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SMALL CAMPAIGN DONORS

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ABSTRACT

We assemble the first comprehensive dataset on small campaign donors in the U.S. from 2005 to 2020, leveraging the fact that small, previously unobservable contributions now largely flow through fundraising platforms required to report them. Although the number of small donors has surged, their aggregate contributions have not grown faster than large donors'. Small donors are more representative of the population but remain disproportionately white and affluent. They support similar candidates as large donors, do not target competitive races more, and are more reactive to salient events and political advertising. We conclude that they are unlikely to transform U.S. elections.

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A data appendix is available at http://www.nber.org/data-appendix/w30050

1 Introduction

Citizens contributing small amounts of money to political campaigns have become a topical issue in U.S. politics in recent years. Some media have portrayed the rise of small donors as a "revolution"[1] that may mitigate the capture of the political process by interest groups and wealthy individuals and reshape which candidates run and win elections.[2] Others see small donors as a driver of ideological extremism, polarization, and the nationalization of U.S. politics.[3] Local governments have implemented public matching programs of small contributions, and parties and candidates have brought small donors to the center of their communication strategies.[4] Yet, despite these signs of small donors' growing importance, we lack systematic evidence on their number, characteristics, and behavior.

In this paper, we build the first comprehensive dataset on small donors from 2005 to 2020 to assess whether they truly have the potential to transform U.S. politics. We answer this question through four sets of analyses. First, we produce reliable estimates of the rise in small donors' numbers and contribution amounts over time. Second, we compare small donors' sociodemographic characteristics to those of the overall population and those of large donors, who have traditionally dominated the fundraising scene. Third, we investigate whether small donors contribute to candidates and races that differ from those targeted by large donors. Finally, because small donors may be less likely to drive change if they simply react to external events and fundraising requests from candidates, we compare the timing of small and large donors' contributions and their response to social media and TV ads.

Our novel dataset contains all 340 million contributions made by individuals and reported to the U.S. Federal Election Commission (FEC) between 2005 and 2020. A key aspect of our data is that they include contribution-level information for the vast majority of donations, no matter how small. We leverage the fact that most (76.4%) contributions during that period were made through channeling organizations called conduits, such as ActBlue, an online platform launched in 2004 that now dominates Democratic fundraising, and WinRed, its Republican counterpart launched in 2019. Conduits have more stringent reporting requirements than traditional campaign committees: they must report detailed information on all the contributions they collect, whereas other committees only disclose donors who give more than $200 during an electoral cycle. By processing these contributions, we more than double the number of observable contributions (i.e., those

[1] See, e.g., "Campaign Reforms May Never Pass, But the Low-Dollar Revolution Has Already Begun" (*American Prospect*, Feb. 28, 2019); "Small dollars, big changes" (*The Washington Post*, Feb. 6, 2020); "How online donations are fueling the election" (*Politico*, Apr. 30, 2024).

[2] See, e.g., "'Not the billionaires': why small-dollar donors are Democrats' new powerhouse" (*The Guardian*, Mar. 10, 2019); "Why Famous, Powerful Presidential Candidates Are Begging You for Five Dollars" (*The New Yorker*, Jun. 10, 2019); and "How small donors have become a destructive, dividing force in American politics" (*Los Angeles Times*, Apr. 15, 2023).

[3] See e.g., Pildes (2019), Vandewalker (2024), "For $200, a Person Can Fuel the Decline of Our Major Parties" (*The New York Times*, Aug. 30, 2023), "Small-Dollar Donors Didn't Save Democracy. They Made it Worse" (*The Washington Post*, May 1, 2023), and "How Small Donors Have Become a Destructive, Dividing Force in American Politics" (*Los Angeles Times*, Aug. 15, 2023).

[4] In various states and cities (e.g., NY and DC), there are minimum requirements on the number of individual donors giving to a candidate for them to be eligible for public funding of campaigns (see Brennan Center for Justice, 2025, for more detail).

for which we have contribution-level information).

We use donors' full names and addresses provided for each observable contribution to create unique donor identifiers and differentiate small from large donors based on their total contributions. We categorize as small the donors who do not give more than $200 to any committee they contribute to over a two-year election cycle. Out of 42.9 million unique donor-cycles in our data, 23.2 million are small donors. In addition, we leverage donors' names, occupations, and addresses to infer their gender and ethnicity (using probabilistic methods and census data), their administrative and political districts (using current and historical maps), their home values (using the list of all U.S. properties provided by Zillow Inc.), and their incomes (using Bureau of Labor Statistics' classifications of occupations and wage estimates).

The extent to which small donors could transform U.S. politics first depends on their number and on the total amounts of their contributions. Accordingly, our first set of analyses track changes in both quantities over time. Existing estimates of total small donor contributions rely on unitemized contribution totals reported by campaigns, which aggregate all contributions that are not subject to traditional committees' reporting requirements (see, e.g., Johnson, 2010a; Culberson et al., 2019; Albert and La Raja, 2020). We show that these totals vastly overestimate small donors' contributions (by a factor of 1.8 to 3.1) because they include contributions made by donors giving large amounts to other candidates or to the same candidate later on. Additionally, unitemized contribution totals are silent on the number of individuals making these contributions. Using our novel dataset, we find that the number of small donors increased from 5.0 million in the 2006 election cycle to 21.8 million in the 2020 cycle. During that period, the number of large donors increased from 2.3 million to 7.0 million. However, even though small donors vastly outnumber large donors, they only accounted for 12.8% of overall contributions in the 2020 cycle. In fact, small donors and large donors' total contributions have grown at similar rates since 2006.

Our second set of results provide systematic evidence on small donors' sociodemographic characteristics including gender, race, income, occupation, and geographic location. These characteristics are strong predictors of political views (see e.g., Edlund and Pande, 2002; Kuziemko and Washington, 2018; Gethin et al., 2022; Autor et al., 2020; Cagé and Piketty, 2023) and of candidate support, with many studies finding that citizens lean towards candidates that look like them (Wolbrecht and Campbell, 2007; Dolan, 2008; Washington, 2006; Grumbach and Sahn, 2020). Small donors may thus be more likely to facilitate the emergence of new types of candidates and to transform campaign platforms and actual policies if they differ from large donors along those characteristics. Furthermore, to the extent that large donors steer politicians and policies away from the electorate's preferences (Gilens, 2012; Kalla and Broockman, 2016; Cox, 2026), small donors may be more likely to balance this influence if they are more representative of the electorate as a whole. This analysis and the next ones focus on donations made to congressional Democratic candidates between the 2012 and

2020 elections, for whom we observe the vast majority of small donor contributions.[5] Gender is the only characteristic for which small donors fully close the representation gap between large donors and the U.S. voting-age population. The fraction of non-white citizens is larger among small donors than among large donors, but it remains much lower than in the voting-age population. Similarly, small donors' occupations and home values indicate that their socioeconomic status is lower than that of large donors but much higher than that of the average U.S. adult. Finally, small donors are more concentrated on the coasts and in large metropolitan areas than the voting-age population, like large donors.

Our third set of results investigates the types of candidates and races that small donors contribute to. Small donors' ability to influence electoral outcomes hinges on several aspects: whether they target close races, where they are more likely to play a pivotal role, whether they back different (types of) candidates than large donors, and how concentrated or dispersed their contributions are. We first show that small and large donors often support the same candidates, yet the share of a candidate's money coming from small donors varies substantially. We then exploit the fact that each donor can donate to any candidate to explore the influence of multiple candidate- and race-specific factors on contribution amounts in multivariate regressions. We use the full set of existing and potential donor-candidate pairs – a total of 2.7 billion observations in general elections and 4.8 billion in primaries – and control for election, state, and donor fixed effects. Our specification allows us to study the role of matches between the district, gender, or race of donors and candidates, among other factors.

Differences between the types of candidates targeted by small and large donors in the general elections are generally small and non-significant. Even if 88% of their contributions go to out-of-district candidates, small donors contribute more to the Democratic candidate from their district than to an average candidate from another district, like large donors, and they are not significantly more likely to support non-incumbents and ideologically extreme candidates. They do not show a stronger preference than large donors for candidates of the same gender and race either and do not contribute more to women and minority candidates, despite being more representative of the electorate. Small donors contribute more money to close races than to sure winners and losers but, if anything, they do so less than large donors. We obtain similar results for primary elections and when using donor deciles rather than the simple dichotomy between small and large donors. Finally, small donors' contributions are more concentrated on candidates holding a leadership position in the Democratic party or running against prominent and divisive Republican figures.

Our fourth set of results considers the effects of external events and political ads on small donors' contributions, using again large donors as a comparison point. This is motivated by the idea that small donors may be less likely to drive change if they simply react to external events and fundraising requests instead of choosing which candidates to support based on their independent policy preferences and active political

[5] In secondary analyses, we consider donations to Republican candidates in the 2020 election cycle, after WinRed had been launched.

agency. We start by examining the timing of contributions. We find that small donors' contributions are more concentrated towards the end of the election cycle than large donors', and that they are more responsive to salient events such as the death of Justice Ruth Bader Ginsburg in 2020.

We then estimate the effects of TV ads by comparing adjacent counties exposed to different volumes of ads because they are located in different media markets, following Spenkuch and Toniatti (2018). We find that Democratic and Republican ads have effects of opposite signs on donations to Democratic candidates. An additional 1,000 Democratic ads increase small donors' total contributions by 6.3% of the mean during the general elections. For large donors, the effect is not significant and much smaller as a share of the mean. We find similar results during the primaries.

We finally use an event study to estimate the effects of ads made by Democratic candidates on Facebook and Instagram during the 2020 election. These ads substantially increase contribution amounts during the first week, with lower but persistent effects in the following weeks. Similar to TV ads, the effects of social media ads are larger for small donors. However, the effects on contributions are only significant in the primaries: there, a week of ads in a state by a specific candidate increases small and large donors' contributions to that candidate in that state by factors of 1.3 and 0.5, respectively, relative to their mean value.

Taken together, our findings support the conclusion that, contrary to frequent claims, small donors are unlikely to fundamentally transform U.S. politics.

Contribution to the literature The literature on campaign finance has mostly focused on the patterns and motives of political donations by large individual donors (Ansolabehere et al., 2003; Gordon et al., 2007; Bonica, 2014; Barber et al., 2017; Cagé, 2018) or firms (Snyder, 1990; Bombardini and Trebbi, 2011; Bertrand et al., 2014, 2020, 2026). This focus can be explained by these actors' potential to influence policy and get access to politicians, which has been theorized (Grossman and Helpman, 1994; Prat, 2002; Hall and Deardorff, 2006; Chamon and Kaplan, 2013) and, in some cases, empirically confirmed (Mian et al., 2010; Kang, 2016; Barber, 2016; Canes-Wrone and Miller, 2022; Dwyer and Stratmann, 2023; Babenko et al., 2024),[6] as well as by data-availability constraints: the censoring of smaller donors in campaign finance reports. However, the motives underlying large donor contributions uncovered by previous studies may not extend to small donors (see, e.g., the discussion in Bouton et al., 2024). To address this gap, we construct a novel dataset covering the near universe of *both* small and large donors, allowing for a unified analysis across the full donor distribution.

Existing empirical work on small donors has attempted to overcome data limitations in several ways. A set of studies (Panagopoulos and Bergan, 2006; Malbin, 2013; La Raja and Schaffner, 2015; Albert and La Raja, 2020) and policy reports (Graf et al., 2006; Joe et al., 2008) rely on survey data, such as the American National Election Studies (ANES), the Cooperative Election Survey (CES), or smaller surveys directly targeting small

[6]Besides, studies have shown that campaign spending affects electoral competition and outcomes (see, e.g., Fouirnaies, 2021; Avis et al., 2022; Bekkouche et al., 2022; Broberg et al., 2025).

donors. Instead, our paper uses exhaustive administrative data, thereby circumventing well-known limitations of surveys, including misreporting and lack of representativeness. Other studies consider small donors in an aggregate way, by analyzing unitemized contribution totals (Culberson et al., 2019; Albert and La Raja, 2020). But as mentioned above, both unitemized contribution and ActBlue contribution totals are substantially different from small donor contribution totals. Finally, a third set of studies focus on contributions to specific campaigns: Magleby et al. (2018) consider a random sample of donors to the 2008 and 2012 presidential general election candidates, and, closer to our paper, Alvarez et al. (2020) use ActBlue data to study the small donors who contributed to Bernie Sanders's 2016 campaign. Studying the universe of candidates and political action committees (PACs) between 2005 and 2020, as we do, not only paints a more comprehensive picture, but also provides the variation in campaign strategies and characteristics that is required to explore the push and pull factors influencing small donor contributions.

Our results also contribute to the broader literature on the effects of electoral campaigns on political behavior (see, e.g. Gerber and Green, 2000; Braconnier et al., 2017; Pons, 2018; Le Pennec and Pons, 2023). The behavior we study, donating to a campaign, can be seen as intermediate between casting a vote and actions such as protesting. The literature studying the effect of TV advertising on voter behavior finds little effect on turnout but substantial effects on vote shares (Huber and Arceneaux, 2007; Krasno and Green, 2008; Da Silveira and De Mello, 2011; Spenkuch and Toniatti, 2018; Sides et al., 2021). A recent literature suggests similar effects of social media ads (see, in particular, Hager, 2019; Zhuravskaya et al., 2020; Coppock et al., 2022; Haenschen, 2023; Enríquez et al., 2024), which are used by a much larger share of candidates (Fowler et al., 2021). Yildirim et al. (2024) also use Spenkuch and Toniatti (2018)'s design to measure the impact of TV ads on donations, though with a different focus: investigating the substitutability between political and charitable giving. Relatedly, Petrova et al. (2021) find a positive impact of opening a Twitter account on contributions to candidates between 2009 and 2014, and Boken et al. (2023) find that Twitter likes and contributions received by congressional candidates are positively correlated. Our study is the first to assess the effect of campaign ads on small donors and to estimate the causal impact of political ads on Facebook and Instagram – the largest social media platform in the U.S. – on campaign contributions.

2 Number and total contributions of small donors

To assess small donors' role in U.S. politics, we build a novel dataset including the contributions of uniquely identified individual donors, both small and large, as well as detailed sociodemographic characteristics of these donors and of the candidates they support. We see this dataset as an important contribution of our paper.

The raw data feeding into our dataset are all the contributions made by individuals and reported to the U.S. Federal Election Commission (FEC) between January 1, 2005 and December 31, 2020. This period covers eight distinct two-year election cycles, which we delimit using calendar years (e.g., the 2006 cycle runs from

January 1, 2005 to December 31, 2006). The FEC data contain a total of 340 million unique contributions, corresponding to all contributions to entities raising more than $5,000 for federal elections, whether they are candidates, parties, or any other political committee, including PACs.

Below, we provide more information on the key features of the data that allow us to observe the vast majority of political contributions, irrespectively of their amount (Section 2.1). We then explain how we identify and define small donors, and measure the change in their number and in total contributions over time (Section 2.2), which is the first step in assessing the importance of small donors in U.S. politics. Appendix A provides additional details on the construction of the dataset.

2.1 The rise of conduit contributions

Any candidate, party, or interest group that raises or spends money with a political purpose is required to create a FEC-registered committee. Whenever the total contributions of an individual to a committee since the beginning of the election cycle exceed $200, the committee must report contributions from this individual as itemized: it must provide detailed information to the FEC on the donor (their full name, address, occupation, and employer) and their contributions (their date and amount). By contrast, contributions from individuals that have not (yet) reached the $200 reporting threshold are said to be unitemized. Committees' financial summaries only report the total amount of unitemized contributions they received, aggregated across all donors.

Most existing empirical research on individual political donors has been limited to itemized donations above the $200 threshold, as reported by committees. We overcome this limitation by including and processing contributions to conduits, which are intermediary individuals or organizations that channel contributions to other committees. The largest conduit is ActBlue, an online nonprofit fundraising platform created in 2004 that now dominates Democratic fundraising. As of 2020, 96% of all Democratic candidates used ActBlue.[7] In 2019, a similar (though for-profit) platform was launched on the Republican side: WinRed. The rapid adoption of these conduits was driven by explicit recommendations from the parties, which recognized their ease of use and scaling potential.[8] Conduits are not allowed to directly promote or favor any candidate, and contributions made to them are earmarked, in the sense that donors clearly designate the destination committee.[9]

We leverage two key features of conduits to build our dataset. First, like other committees, conduits must register with the FEC and report the contributions they receive. But crucially, unlike other committees, conduits need to report *all* the contributions they collect on behalf of candidates, including those below

[7] Appendix B provides more information on ActBlue, the number of candidates using it over time, and their characteristics. Other conduits on the Democratic side, such as MoveOn.org and Swing Left, are much smaller.

[8] See, e.g., "How ActBlue Became a Powerful Force in Fund-Raising" (*The New York Times*, Oct. 9, 2014), or "GOP reaches landmark agreement to juice small-dollar fundraising "(*Politico*, Jan. 21, 2019).

[9] This distinguishes them from contributions made to PACs, given that PACs can discretionarily choose to allocate contributions to candidates or other committees.

\$200. Conduits report these contributions in their financial accounts and indicate the committee to which the contribution is earmarked in the memo texts or receipt descriptions attached to the contributions. Through a thorough cleaning of these memos, explained in Appendix A.3.1, we are able to add earmarked contributions to the set of itemized contributions flowing from an individual donor to a recipient committee.

Second, contributions made through conduits have steadily increased over time and now account for the overwhelming majority of contributions. Between 2006 and 2020, more than 76.4% of the individual contributions in our data were made through conduits, a fraction that reached 91.1% in the 2020 election cycle (see Appendix Figure E.1a). The vast majority (81.2%) of these contributions do not appear in destination committees' reporting and would thus remain unobserved if not reported by conduits. Our processing of conduits' data thus more than doubles the number of observed contributions. Since many of the contributions they channel are small, conduits account for a smaller portion of contribution amounts, but that share has been increasing as well. They accounted for 54.5% of the money contributed by individuals to committees in the 2020 cycle, up from 28.2% in 2018 and 4.1% in 2012 (see Appendix Figure E.1b).

The growing number of contributions made through conduits, together with the fact that conduits report all contributions, implies that we now observe the vast majority of individual contributions. Figure 1 shows the share of total contribution amounts (both itemized and unitemized) that these visible contributions account for. This share has steadily increased over time. In the 2020 election, the contributions that we observe accounted for 82.0% of the total amounts contributed to all campaign committees and for 94.3% of the total amounts contributed to Democratic congressional candidates (Democratic candidates in House and Senate races).[10] Without conduits, the share of visible contributions would be much lower: in 2020, it would only be 61.0% and 62.0% for all campaign committees and for Democratic congressional candidates, respectively.

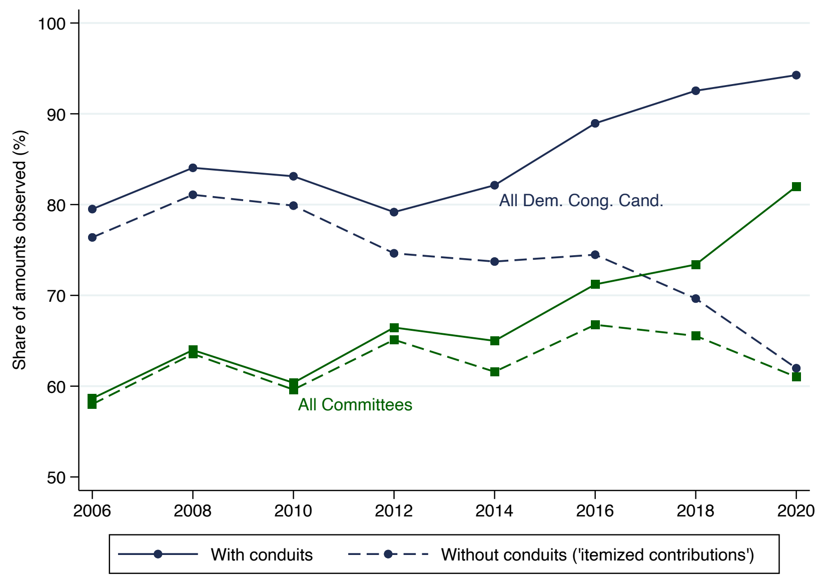
2.2 The growing number of small donors

The fact that we observe the vast majority of individual contributions, including small donations, enables us to identify small donors, the focus of our analysis.

While the FEC assigns unique IDs to candidates, it does not do so for individual donors. To build unique donor IDs, we first clean four variables identifying donors: their first name, last name, street, and zip code. We then assume that the individuals associated with two distinct contributions are the same if they match exactly on three of these characteristics and if they obtain a high fuzzy match score on the fourth.[11] Overall,

[10]The share is smaller for all campaign committees than for Democratic congressional candidates because fewer Republican candidates and non-affiliated PACs use conduits. The sample of Democratic congressional candidates includes all committees that can be linked to one (and only one) Democratic congressional candidate for either the primary or the general election. It excludes non-affiliated committees and joint committees (i.e., committees associated with multiple candidates), which account for 65.8% of all committees and 54.6% of the total amount of contributions; presidential candidate committees, which account for 0.7% of all committees and 15.7% of all contributions; and Republican congressional candidate committees, which account for 14.5% of all committees and 14.8% of all contributions.

[11]For additional details on this procedure, see Appendix A.4.1.



Notes: The figure plots the share of total contribution amounts for which we have contribution-level information, separately for all committees (green lines) and all Democratic congressional candidates (blue lines), in each electoral cycle between 2006 and 2020. Total contribution amounts are computed as the sum of committees' itemized and unitemized contributions, which are aggregate data provided by committees. The solid lines include all visible contributions (i.e., both itemized contributions and contributions made through conduits). The dashed lines only include itemized contributions.

Figure 1: The share of observed contributions, 2006-2020

we identify a total of 30 million unique donors who donated at least once between 2006 and 2020. In the 2020 cycle, this number was 20 million, which corresponds to 8.5% of the adult U.S. citizen population.

Then, we define as small donors all individuals who contributed no more than \$200 to any single committee during a specific cycle. Our definition uses the \$200 threshold as it corresponds to the reporting threshold for non-conduit committees of the FEC.[12] All other donors are called large. The distinction that we draw between small and large donors is election-cycle-specific: a donor may be small in one cycle and large in the next one if the maximum amount they gave to a committee was lower than \$200 in the first cycle but larger in the second. Overall, our data include a total of 42.9 million donor-cycles: 19.7 million large donor-cycles and 23.2 million small donor-cycles (54.1%). Small donors account for 61.0%, 57.4%, and 44.0% of the donor-cycles to presidential, Senate, and House committees. Only 6.1% of all unique individual donors have both small and large donor-cycles.

Our definition of small donors implies that contributions by these donors are a subset of all small (i.e., below \$200) contributions. Contributions by small donors also differ from unitemized contribution totals. Indeed, many of the small contributions included in these totals are made by donors giving large amounts to other candidates or to the same candidate later on. For instance, in the 2020 election cycle, the

[12] In that sense, small donors are the donors that are "invisible" absent conduit data. Appendix A.4.3 provides more details on how we identify donors giving less than \$200. In Section 4, we consider multiple donation thresholds.

share of observable unitemized contributions (i.e., contributions for which we have individual-level data) to Democratic congressional candidates made by small donors was 37.2%. Furthermore, this share has varied between 32.6% and 54.6% in the 2006-2020 period (see Appendix Figures E.2 and E.3, which summarize the share of earmarked and small donor contributions among itemized and unitemized totals for each election cycle). Therefore, using unitemized contribution totals as a proxy for small donor contributions, as many studies and media outlets do,[13] leads to overestimating the extent of small donor contributions by a factor of 1.8 to 3.1 over that period and prevents from measuring their evolution properly.

The left panels of Figure 2 plot the number of small and large donors that we observe and our estimates of the total number of unique small and large donors, in each election cycle. The total number of donors is the sum of the number of donors that we observe and of our estimate of the number of small and large donors who made unitemized contributions that are unobserved (i.e., for which we do not have individual-level data because they were not made through conduits).[14] Panel (a) includes donors to all committees (i.e., all donors) while Panel (c) restricts the sample to donors to Democratic congressional candidates.

We find, first, that the number of observed donors, whether small or large, increased substantially and steadily between 2006 and 2020, from 1.5 million to 20.0 million. Second, this trend was primarily driven by small donors. Third, the increase in the number of observed small donors does not merely result from the improved ability to observe them. Indeed, the total estimated number of small donors, including observed and unobserved ones, also increased dramatically, from 5.0 million to 21.8 million. Meanwhile, the estimated number of large donors increased more slowly, from 2.3 to 7.0 million. Finally, even in the most recent cycles, a substantial share of donors remain unobserved, when considering all committees. By contrast, we observe 67.3% and 79.6% of the small and large donors to Democratic congressional candidates on average, and 88.9% and 91.1% in 2020.

As shown in Table 1, the mean donation amount of the average small and large donor has decreased slightly between 2006 and 2020, but this decline has been more than offset by a growing number of donations: from 3.8 to 23.1 donations per cycle, for the average large donor, and from 2.6 to 4.8 donations for the average small donor. The average number of recipients that large donors contribute to has also increased, but it has remained stable for small donors.

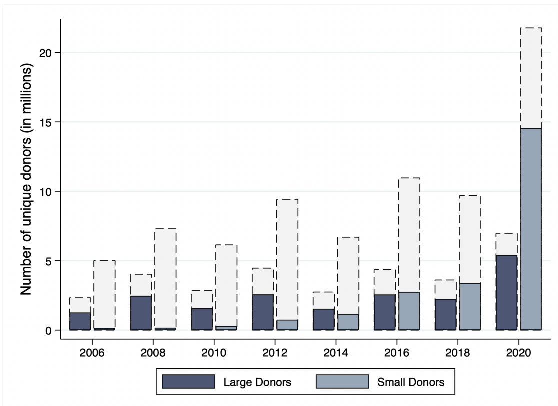
The right panels of Figure 2 plot the observed and estimated aggregate contributions (in dollar amounts)

[13]For academic articles see, e.g., Culberson et al. (2019), Albert and La Raja (2020), and Johnson (2010b); for newspaper articles see, e.g., "Big money, small donors, and burn rates: what to watch for in 2020 campaigns' new fundraising reports" (*Vox*, Apr. 15, 2019); "Sinema's grassroots donor pool dries up" (*Politico*, Jan. 31, 2022); "How GOP donors can get the best value for their money" (*The Washington Post*, Mar. 15, 2023).

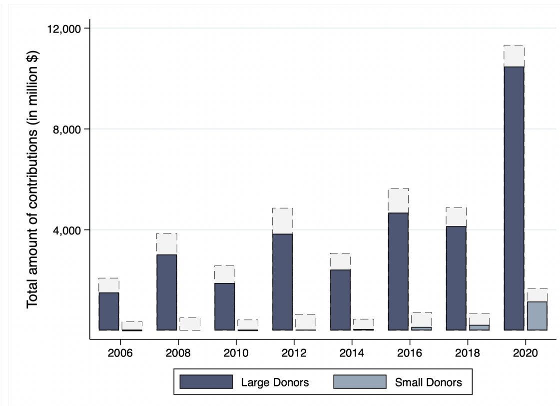
[14]To estimate these numbers, we proceed as follows. First, we compute the weighted average, across election cycles, of the shares of observed unitemized contributions made by small and large donors. Second, we use these shares as proxies of the shares of total unobserved unitemized contributions that were made by small and large donors in each cycle and estimate the amounts of unobserved unitemized contributions made by small and large donors accordingly. Third, we divide these amounts by the weighted average of total unitemized contributions made by a small or a large donor to estimate the number of unique small and large donors responsible for the unobserved unitemized contributions.

Figure 2: The number of small and large donors and the total amount of their contributions, 2006-2020

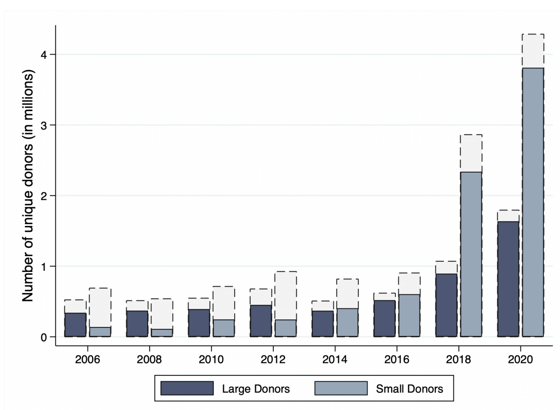
(a) **All Committees:**
Unique donors



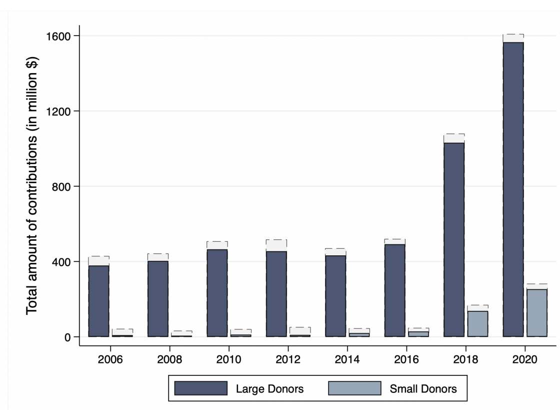
(b) **All Committees:**
Total contribution amounts



(c) **Cong. Democratic Candidates:**
Unique donors



(d) **Cong. Democratic Candidates:**
Total contribution amounts



Notes: The figure represents, for each election cycle between 2006 and 2020, the number of small and large unique donors (left-wing panels); and the total amount of their contributions (right-wing panels). Small and large donors are defined in the text. Panel (a) and Panel (b) include all committees with campaign contributions reports, whereas Panel (c) and Panel (d) focus on congressional Democratic candidate committees, which we define as all committees that can be linked to one (and only one) congressional Democratic candidate at either the general or the primary election. Solid bars display observed quantities (including those in conduits); dashed bars show estimates of the total quantities, based on reported figures of total unitemized contributions and the observed share and average donation of small and large donors in unitemized contributions revealed by conduit data.

Table 1: Contributions by small and large donors, 2006-2020: Descriptive statistics

	Large Donors				**Small Donors**			
Cycle	Mean Donation	# Donations	# Recipients	# Donors	Mean Donation	# Donations	# Recipients	# Donors
2006	512.3	3.8	1.4	1,274,689	32.2	2.6	2.4	152,780
2008	506.6	4.0	1.4	2,470,785	36.5	2.1	1.8	168,644
2010	465.4	4.5	1.5	1,579,621	29.3	2.9	2.3	289,169
2012	516.9	5.5	1.7	2,577,146	22.4	3.0	1.9	753,474
2014	502.3	7.8	2.0	1,538,099	20.6	4.0	1.9	1,147,959
2016	498.1	10.3	2.2	2,570,615	21.1	3.9	1.8	2,753,410
2018	444.1	14.9	3.4	2,244,448	22.1	5.2	2.7	3,394,574
2020	313.2	23.1	5.1	5,405,791	23.8	4.8	2.5	14,556,410

Notes: The table reports the mean donation, number of donations, and number of recipient committees (# Recipients) for each observed donor. The table shows the average of these variables among small and large donors as well as the number of unique donors, for each election cycle between 2006 and 2020.

of small and large donors to all committees and to Democratic congressional candidates. Small donors' contributions have increased more than four-fold between 2006 and 2020, from \$362 million to \$1.664 billion, but large donors' contributions have increased as rapidly, from \$2.084 billion to \$11.307 billion. The share of contributions coming from small donors in the 2020 cycle thus remained modest: 12.8% overall, and 14.9% when focusing on Democratic congressional candidates, for whom we observe the vast majority of contributions.

In sum, while small donors now vastly outnumber large donors, the aggregate amounts they contribute remain dwarfed by large donors, which could limit their political role.

3 Characteristics of small donors

We now use our novel dataset to provide systematic evidence on the sociodemographic characteristics of small donors and compare them to those of large donors and of the entire electorate. This evidence is key to determine whether the rise of small donors amplifies or mitigates longstanding imbalances in political giving and voice along racial, gender, and income lines. In addition, because sociodemographic characteristics are strong predictors of political preferences, the rise of small donors may benefit certain types of candidates at the expense of others and generate incentives for politicians to change their campaign platforms and the policies they implement, once elected. The more small donors differ from large donors and the more they resemble the broader electorate, the more likely they are to balance the influence of large donors and to increase the representativeness of policies.

In this and the next sections, we restrict the sample to donations made to the committees of congressional Democratic candidates between the 2012 and 2020 election cycles, for which we observe the vast majority of small donor contributions, as shown in Section 2.2. This sample includes 11.3 million donor cycles and contributions totaling 4.4 billion dollars. Appendix A.4.2 provides additional details about the cleaning of the data used in this section.

Gender and ethnicity distribution We start by comparing the gender and ethnicity distribution of small donors, large donors, and the overall population. Following the procedure of Imai and Khanna (2016), we infer donors' gender and ethnicity as a probability based on their name and address, combined with U.S. Social Security data on the proportion of men and women for each first name and U.S. Census statistics on the distribution of ethnic groups by surname and census blocks (see Appendix A.4.2 for more details on the procedure and its validation).

As shown in Table 2, small donors tend to be more representative of the population than large donors along ethnic lines: 23.1% of small donors are non-white donors, which is 13.2% more than for large donors but 42.1% less than the corresponding fraction in the overall voting-age population. Turning to gender, we find that women are underrepresented among large donors (47.2%) but overrepresented among small donors (56.9%).

Occupation and income We study donors' socio-economic status by sorting their occupations into the Standard Occupation Classification (SOC) of the U.S. Bureau of Labor Statistics (BLS). The share of small donors with managerial or other high-education occupations ("High SOC")[15], 44.5%, is double the corresponding share in the overall adult population but 18% lower than the share among large donors. Relative to large donors, small donors are more likely to have a "low SOC" occupation and to be inactive (retired, student, etc.) or unemployed.

We also proxy the yearly wage of each employed donor by using BLS data on the median income of their SOC in the state where they live. Small donors' estimated median wage is, once again, lower than large donors' (by 20%) but higher (by 64%) than the median wage in the overall adult population.

Home value We link donors' residential addresses to the market value of the corresponding property using the ZAsmt (ZTRAX) dataset provided by *Zillow, Inc*. As these data only have a large coverage for recent years, we assign to each donor-cycle their 2020 cycle home value. As shown in Table 2, the median value of the property in which a small donor lives is 40% lower than that of a large donor's property, but 64% higher than the median home value in the country.

Appendix Table F.1 replicates Table 2 for donations to congressional Republican candidates' committees in the 2020 election cycle, which is the only cycle for which we observe a substantial share of donations by small donors to Republican candidates, thanks to the creation of WinRed. Differences between the sociodemographic characteristics of small and large Republican donors all go in the same direction as for

[15] "High SOC" covers SOC 11-000 (Management Occupations) to 29-0000 (Healthcare Practitioners and Technical Occupations), which the BLS refers to as "Management, Business, Science, and Arts Occupations."

Table 2: The characteristics of small and large donors, Democratic congressional candidates, 2012-2020

	Large Donors	Small Donors	18+ Population
Demographics (.^{i} = *imputed*)			
Female	0.472^i	0.569^i	0.514
White	0.796^i	0.769^i	0.601
Black	0.076^i	0.086^i	0.115
Hispanic	0.054^i	0.076^i	0.149
Asian	0.049^i	0.043^i	0.054
Other Race	0.025^i	0.026^i	0.081
Socio-economic characteristics			
High SOC occupation	0.541	0.445	0.222
Low SOC occupation	0.070	0.101	0.475
Inactive & Unemployed	0.387	0.452	0.302
Median Annual Wage (2020 dollars)	99,834	79,662	48,469
Median 2020 Home Value (dollars)	419,910	289,900	176,838
Observations	3,870,491	7,402,949	988,614,976

Notes: The table provides summary statistics on the demographic and socio-economic characteristics of large donors, small donors, and the voting-age population. Time period is 2012-2020. An observation is a unique individual-cycle. Variables are discussed in more details in the text. Characteristics indicated with an "i" are imputed using the method explained in Appendix Section A.4.2, which assigns each individual a probability for each gender and race. The statistics shown in the table are the averages of these probabilities. Figures for the voting-age population demographics come from the U.S. Census Bureau ACS estimates. Fractions are calculated on the number of unique individual-cycles for which the corresponding variable is not missing. Wage variables are computed on the employed population and converted to constant 2020 dollars using the U.S. historical price index provided by the World Inequality Lab.

Democratic donors.

Geographical location Using donors' exact addresses, Figure 3 maps the number of small and large donors as a share of the population in each county in 2020. The spatial distributions of small and large donors are strikingly similar, with a correlation of 0.945.[16] Donors of both types are heavily concentrated in the Northeast, along the coasts, and in major metropolitan areas such as Atlanta, Dallas–Fort Worth, Chicago, and Minneapolis. Despite the recent expansion of the donor pool, contributing to electoral campaigns remains rare in large swaths of the country, particularly in most of the Midwest and the South. These spatial disparities are an order of magnitude larger than those observed for voter registration and turnout.[17]

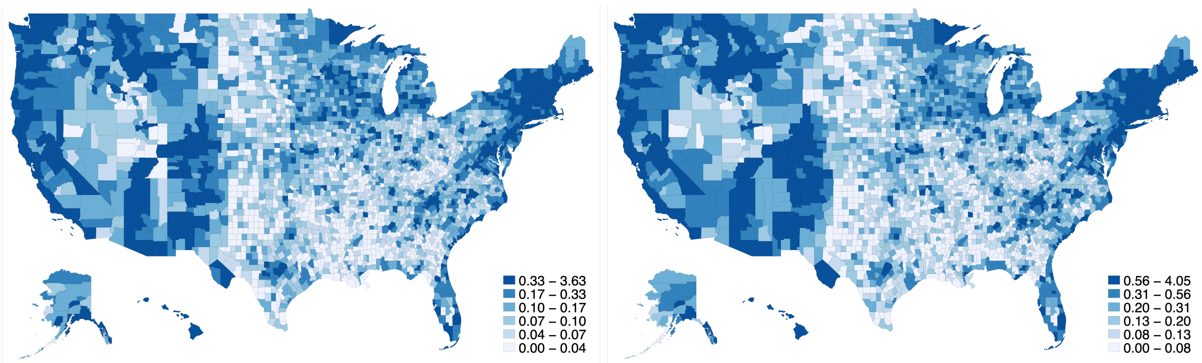
Our findings deliver a consistent picture: while small donors' sociodemographic characteristics are less skewed than those of large donors, they remain far from representative of the electorate. To bring further evidence on small donors' potential to balance the influence of large donors and generate political change, we now compare the types of candidates they support.

[16] Appendix Figure E.4 shows that the same is true for the 2012, 2014, 2016, and 2018 election cycles.

[17] Appendix Figure E.5 maps donors to Republican congressional candidates. Reflecting the well-known differences in partisanship across the U.S., the spatial distributions of these donors differ from those observed in Figure 3. However, they are again very similar for small and large donors.

Figure 3: The geographic distribution of small and large donors, Democratic congressional candidates, 2020

(a) **% of large donors among all donors 2020** (b) **% of small donors in population 2020**



Notes: The figures map the large donors (panel 3a) and small donors (panel 3b) to Democratic congressional candidates of the 2020 election cycle, in the U.S. county these donors live in, as a share of the county population.

4 Candidates supported by small donors

Small donors are more likely to influence election outcomes if they target competitive races rather than expected landslides, where additional funds are unlikely to be pivotal, and if they support candidates with a different demographic profile, ideology, or political background than those funded by large donors. Since the total share of campaign money coming from small donors remains low, their contributions may also be more impactful if they are concentrated on a few candidates rather than spread thinly across many.

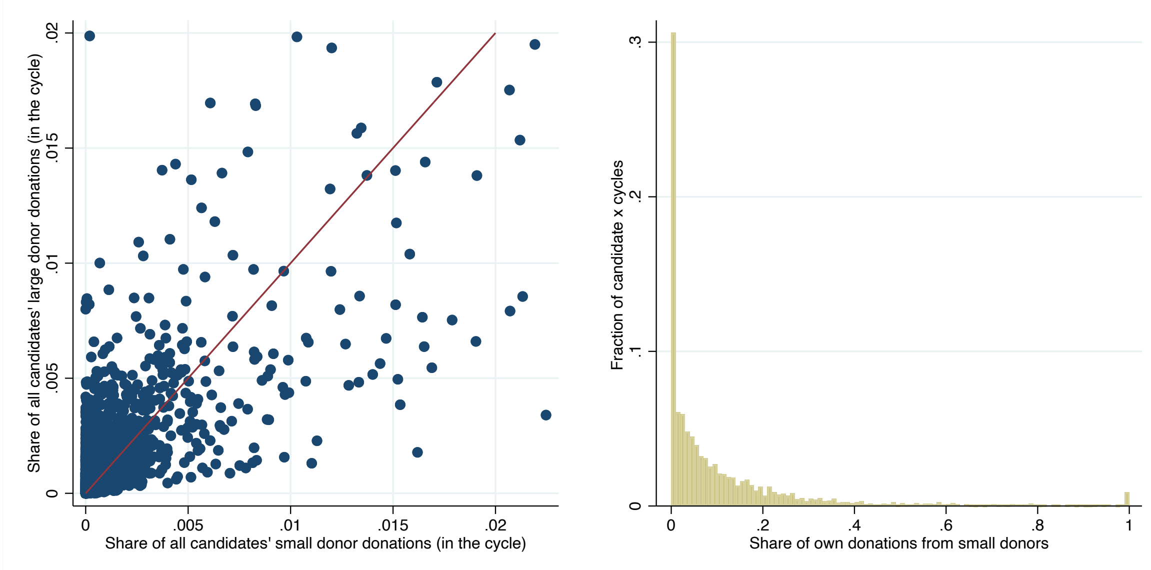
4.1 Overlap between candidates supported by small and large donors

We first ask whether small and large donors tend to support the same candidates or different ones. As in the previous section, we focus on contributions made to congressional Democratic candidates between the 2012 and 2020 elections.

In the left panel of Figure 4, we use one observation per candidate and plot the relationship between the share of small and large donor contributions going to the candidate, out of the total amounts contributed by small and large donors to all candidates during the corresponding cycle.[18] Many points are located close to the 45-degree line, reflecting the fact that small and large donors often support the same candidates. However, a substantial fraction of candidates are close to the vertical axis, indicating that they receive nearly no contributions from small donors, even though some of these candidates attract many large donors' contributions. Conversely, candidates located close to the horizontal axis receive a much larger share of small donor than large donor contributions. This is particularly true in the bottom left part of the figure. The overall

[18] When multiple committees are associated to the same candidate (e.g., Nancy Pelosi's "Nancy Pelosi For Congress" and "Nancy Pelosi Victory Fund," or Elizabeth Warren's "Elizabeth for MA, Inc" and "Massachusetts Senate Victory 2018"), we aggregate the donations made to all these committees.

Figure 4: The relationship between small and large donors' support for candidates, 2012-2020



Notes: The left panel plots, for each congressional Democratic candidate and at each election cycle from 2012 to 2020, the relationship between the share of large donor contributions to this candidate (out of the total amount of large donor contributions to all candidates in that cycle) on the y-axis, and the share of small donor contributions to this candidate (out of the total amount of small donor contributions) on the x-axis. For readability, these shares are trimmed at 0.0208 and 0.0227 (which corresponds to the 99th percentiles of the distributions for large and small donors, respectively). The 45 degree line is shown in red. The right panel plots the distribution of the share of donations received by a candidate that come from small donors, for the sample of Democratic congressional candidates in election cycles from 2012 to 2020.

correlation between the two shares is 0.821, but it drops to 0.345 for candidates receiving a below-median share of total contributions.

In the right panel of Figure 4, we plot the distribution of the share of donations received by a candidate that come from small donors. This share varies substantially, with a standard deviation of 0.17 and a mean of 0.11. While some candidates receive little to no funding from small donors, as reflected by the sharp spike at the lower end of the distribution, there is a long and thin upper tail, with 12.2% of candidates receiving more than one fourth of their donations from small donors.

4.2 Types of candidates and races targeted by small donors

We now use multivariate regressions to characterize and compare the types of races and candidates targeted by small and large donors.

Sample of analysis We distinguish contributions in general and primary elections since the pool of candidates competing in them differ. We define primary election contributions as those made until the date of the primary election in the corresponding state and contributions to the general election as those made between that date (or the first date of the two-year election cycle, if no primary was held), and one week after the general election.[19] We drop contributions made after the general election and those made to candidates who did not compete in the election, e.g., because they withdrew from the race before Election Day. Overall, the resulting sample includes 3,046,894 large and 4,380,584 small donor cycles for general elections, and 2,253,629 large and 2,033,597 small donor cycles for primary elections.

Empirical specification Unlike voters, who can only cast their vote for a candidate running in their constituency, donors can contribute to any candidate competing in any House or Senate race nationwide. We can thus study all donor-candidate dyads and consider a rich set of race- and candidate-level determinants. Our outcome $Y_{ij(s,r)t}$ is the share of contributions made by donor i in election t that went to candidate j competing in state s and race r. This share varies between 0 (for the candidates that the donor did not donate to) and 1 (in case a donor only donated money to a single candidate in a certain election cycle). The choice of this outcome enables us to easily compare the types of candidates and races targeted by small and large donors.[20] Instead, using donations' dollar amounts as the dependent variable would mechanically generate larger coefficients for large donors.

We regress $Y_{ij(s,r)t}$ on explanatory factors separately for small and large donors, using the following model:

$$Y_{ij(s,r)t} = \alpha + \mathbf{X'}_{jt}\beta + \mathbf{V'}_{ijt}\gamma + \mu_t + \delta_s + \eta_r + \zeta_i + \epsilon_{ij(s,r)t}, \tag{1}$$

where $\mathbf{X}_{jt}$ is a vector of race and candidate characteristics, $\mathbf{V}_{ijt}$ is a vector of indicator variables indicating whether a donor's characteristics match with those of the candidate in the pair, and μ_t, δ_s, η_r, and ζ_i are election cycle, state, House vs. Senate, and donor fixed effects.[21] We cluster the standard errors two-way, at the seat and donor level, to account for correlations in contributions across donors to the same candidate and across candidates supported by the same donor.[22]

For general elections, $\mathbf{X}_{jt}$ includes an indicator variable for closeness, equal to one if the mean Democratic winning margin over the last two elections for that seat was between -10% and 10% or if there was a change in the party of the winner in the last two elections; an indicator for safe Republican seat, equal to one if the mean Democratic winning margin over the last two elections for that seat was below -10% and there was no change in the party of the winner in the last two elections; an indicator equal to one if the Democratic candidate is the incumbent; congressional seniority, indicating the number of consecutive cycles for which the candidate has been a member of Congress, if any; and two indicator variables for ideology, indicating whether the candidate

[19] For more details on this classification, see Appendix A.5.3.

[20] While our sample includes donor-candidate pairs for candidates that a donor did not give money to, it is restricted to donors who made at least one contribution in a certain cycle. Because the pool of citizens who considered making a donation but ended up not to is unknown, we cannot study the factors that lead a potential donor to make one rather than no campaign contribution.

[21] We include a unique fixed effect per donor, irrespective of the number of election cycles in which that donor was active. For each variable in $\mathbf{X}_{jt}$ and $\mathbf{V}_{ijt}$, we control for an indicator equal to one when the variable is missing and set the variable to 0.

[22] Primary election candidates competing for the same seat are included in the same cluster.

is in the first and second terciles of the ideology distribution of all Democratic candidates in the sample, as measured by CF-scores from Bonica (2014).[23]

$\mathbf{V}_{ijt}$ includes indicators equal to one when the gender, ethnicity, and geography of the donor match those of the candidate.[24] We hand-coded candidates' gender and ethnicity after searching online for pictures and pronouns used in their biographies and related news articles. Geographic match indicates that the donor is from the congressional district in which the candidate is competing. Appendix Table F.2 provides descriptive statistics on our main explanatory variables.

Our specification greatly improves on studies exploring the determinants of total campaign contributions received by a candidate (see, e.g., Gimpel et al., 2008; Thomsen and Swers, 2017; Culberson et al., 2019; Grumbach and Sahn, 2020) and those that use survey data but fail to record the full set of candidates supported by each donor or the contributions made to each of them (e.g., Albert and La Raja, 2020; Barber et al., 2017). The fact that our data are structured at the candidate-donor level enables us, first, to estimate the effect of matches between donor and candidate characteristics and, second, to control for whether a donor and candidate are from the same district, which is critical to interpret the effects of the other variables. To illustrate that point, suppose that races in districts with more donors tend to be competitive and that donors support candidates in their own district more than candidates in other districts. Then, an aggregate analysis would uncover a positive association between donations and race closeness even if donors do not particularly target close races. By controlling for district match, we avoid this pitfall.

Our specification also enables us to include donor fixed effects, which control for all donor-level invariant factors. We thus estimate the effect of the match variables included in the vector $\mathbf{V}_{ijt}$ by comparing the level of support of a given donor for candidates who have the same gender, ethnicity, or location as them versus other candidates from that year or from another year who have a different gender, ethnicity, or location.[25]

We may be omitting other factors correlated with our independent variables, in which case our estimates do not just capture the impact of the latter but also the influence of the former. Nonetheless, the comparison of the effects observed for small and large donors yields a rich characterization of the differences between the types of candidates they support.

4.3 Donors to Democratic candidates, general elections

Baseline results We first estimate equation (1) using the sample of donors to Democratic candidates in general elections. Table 3 presents the results separately for large donors (columns 1 to 3) and small donors

[23]The CFscores (short for campaign finance scores) estimate candidates' ideal points on the left-right axis based on the contributions they receive from individual donors and PACs, in both federal and state elections. We cannot use NOMINATE scores, which are only available for politicians who have held office (see e.g., McCarty et al., 2006).

[24]We do not observe donors' ideology, preventing us from estimating the effect of ideological affinity between donors and candidates.

[25]By contrast with the effects of the match variables, the inclusion of donor fixed effects affects the coefficients on the race- and candidate-level variables included in the vector $\mathbf{X}_{jt}$ only minimally since all donors active in a given election cycle are paired with the exact same set of races and candidates.

(columns 4 to 6).

Columns 1 and 4 include all donor-candidate pairs. We find that the largest driver of donations is geography. Contributions made by small donors to the candidate running in their congressional district (or in their state, for Senate races) account for a share of their total contributions that is 16.8 percentage points (p.p.) larger than the share of their contributions going to an average candidate outside of their district. This difference is significant at the 1% level. Compared to the mean, it implies that small donors give 73 times more money to the candidate in their district than to the average non-district candidate. For large donors, the difference is 20.4 p.p., which is also significant at the 1% level and corresponds to a ratio of 85. Yet, given the large number of out-of-district candidates, the overall share of donations made to same district candidates remains limited: small and large donors allocate 12.2% and 11.2%, respectively, of their campaign contributions to the Democratic general election candidate running in their district (Appendix Table F.2). These shares reach 18.1% and 20.5% when one includes other candidates running in their state.

Many contributions go to sure winners and sure losers. But compared to candidates in safe Democratic districts (the reference category), those competing in close races receive a share of donations that is larger by 0.11 p.p. for small donors (which amounts to 48% of the mean but is not statistically significant), and 0.18 p.p. for large donors (75% of the mean and significant at the 5% level). Sure losers (relative to sure winners) and more senior candidates also receive more contributions from both small and large donors, while incumbents get fewer contributions, but these effects are generally not significant.

Differences across candidates of varying ideology are larger and significant at the 5 or 10% level. Small donors give 135% and 52% more money (relative to the mean) to candidates in the left and center terciles of the ideology distribution of Democratic candidates than to those in the right tercile (the reference category). These differences are also present for large donors but slightly smaller.[26]

Finally, donors contribute slightly more to candidates of the same gender than those of the opposite gender, but this difference is only significant for large donors. The difference between the contributions received by candidates of the same race or another race is significant neither for small nor for large donors.

Restriction to same state or same district candidates The importance of geographic proximity suggests that many donors do not consider the entire pool of candidates but only local ones when they decide whom to support and by how much. Estimates based on the full sample of donor-candidate pairs may then attenuate the true influence of some contribution drivers. Columns 2 and 5 and columns 3 and 6 thus restrict the sample to donor-candidate pairs from the same state and from the same district, respectively.[27]

[26] Examples of prominent candidates falling in the left, center, and right terciles of the ideology distribution are Elizabeth Warren and Alexandria Ocasio-Cortez, Mark Kelly and Nancy Pelosi, and Joe Manchin and Pete Gallego, respectively.

[27] We keep the definition of the dependent variable unchanged, so the sum of contribution shares made by a donor in a cycle is no longer mechanically equal to 1 and it may be null (for donors who only contributed to candidates outside of their state). Given the inclusion of donor fixed effects, the regressions restricted to donor-candidate pairs from the same district only use variation between the characteristics of the House candidate running in a donor's congressional district and the Senate candidate from that state, and

The effects generally go in the same direction as in the full sample but are more pronounced. The shares of donations from large donors going to close races are 2.4 and 16.4 p.p. larger, in the same-state and same-district samples. The difference between close races and safe Democratic seats remains slightly smaller for small donors, but it is now significant at the 1% level and much larger than in the full sample, both in percentage points and as a share of the mean: 1.7 and 12.6 p.p. (103% and 64% of the corresponding means). In the same-district sample, the surplus of donations going to Democratic candidates competing in safe Republican districts relative to those present in safe Democratic districts and the negative effect of incumbency are now significant and of similar magnitude for small and large donors. The effect of congressional seniority is more modest but significant for small donors.

Differences across candidates of varying ideology remain slightly larger for small donors than large donors. They are estimated more precisely and larger than in the full sample, in terms of percentage points, but smaller as a fraction of the mean. In the same-district sample, small donors contribute 39% and 34% more to candidates in the left and center terciles of the distribution than to those in the right tercile, with percentages of 28% and 26% for large donors.

Finally, the differences between a donor's contributions to candidates of the same gender or race relative to candidates of a different gender or race remain small and they are generally not significant.[28] To estimate these effects more precisely and control for all factors varying at the electoral race level such as the intensity of media coverage or the polarization of political discourse, we run an additional specification including electoral race fixed effects.[29] In that specification, we have to drop the independent variables varying at the electoral race level, but we can continue estimating the effect of matches between donors and candidates. As shown in Appendix Table F.3, the point estimates on the same gender and same race dummies are of similar magnitude as in Table 3 but with smaller standard errors. Controlling for electoral race fixed effects, large donors' contributions to candidates of the same gender or race running in their state or district are significantly larger than their contributions to candidates of the opposite gender or race. Small donors' contributions to candidates of the same race in their district are also significantly larger.

Differences between small and large donors Overall, the types of races and candidates targeted by small donors appear more likely to limit than to magnify their ability to influence election outcomes. Small donors' contributions are not more (and if anything slightly less) concentrated on close races than those of large donors. There is substantial preexisting evidence that, like voters (e.g., Pons and Tricaud, 2018), large donors are often driven by expressive motives – supporting candidates they like, irrespective of the odds of affecting the election

between the different candidates running in this district over time, for donors active in multiple election cycles.

[28] The only exception is that large donors make larger contributions to same-gender candidates in the same-state sample.

[29] This approach rules out a larger set of confounding factors than our baseline specification, but not all of them. For instance, to the extent that female donors and candidates have similar policy preferences, point estimates on gender match may capture the effect of a match on that other dimension.

outcome – rather than strategic considerations – increasing the victory chances of their party in tight contests (e.g., Ansolabehere et al., 2003). Our results show that small donors do not behave more strategically. In addition, they fund slightly more left-wing candidates but do not support incumbent candidates less. Rather than providing more funding to outsider candidates, they are more drawn to senior members of Congress. Furthermore, even though small donors are more representative of the population demographically, they do not support candidates who share their gender or race more than large donors do and do not end up favoring more diverse candidates.[30]

Except for small donors' lower propensity to donate to candidates from their district and of the same gender, in the same-state sample, we cannot reject the null that their contribution patterns are identical to those of large donors (Appendix Table F.4, columns 1 to 3).

Finer donor categories Our results so far distinguish small from large donors based on the rule specified in Section 2, namely, whether their maximum contribution to any candidate is above or below \$200. We now use a finer categorization. We rank donors according to their maximum contribution in a cycle and estimate equation (1) separately for each decile of this distribution. As shown in Figure 5, the effects of the different drivers of campaign contributions tend to vary monotonically, either increasing or decreasing slightly as we move from bottom to top deciles. In other words, the results shown in Table 3 do not hide non-linearity associated with increases in contribution size.

Furthermore, the differences between the types of races and candidates targeted by donors remain modest even when comparing donors in the first and last deciles, whose maximum contribution amounts are lower than \$12.5 and higher than \$800, respectively. We do not reject the null that the contribution patterns of these two sets of donors are identical on any dimension. However, the behavior of donors in the first and last deciles differs significantly on three dimensions, in the same-state sample: first-decile donors contribute less to same-district and same-gender candidates, mirroring the overall difference between small and large donors, and they contribute significantly less to close races (Appendix Table F.4, columns 4 and 5).[31]

4.4 Primary elections and Republican donors

Donors to Democratic candidates, primary elections We extend these results by considering two additional sets of donors. First, we study contributions to Democratic candidates in primary elections. We estimate a specification in the form of equation (1) that includes an additional predictor in $\mathbf{X}_{jt}$: an indicator

[30]We estimate an alternative specification in which we replace the same gender and same race indicator variables with indicator variables equal to one for female candidates and minority candidates, and do not find significant effects of these variables on small and large donors' contributions.

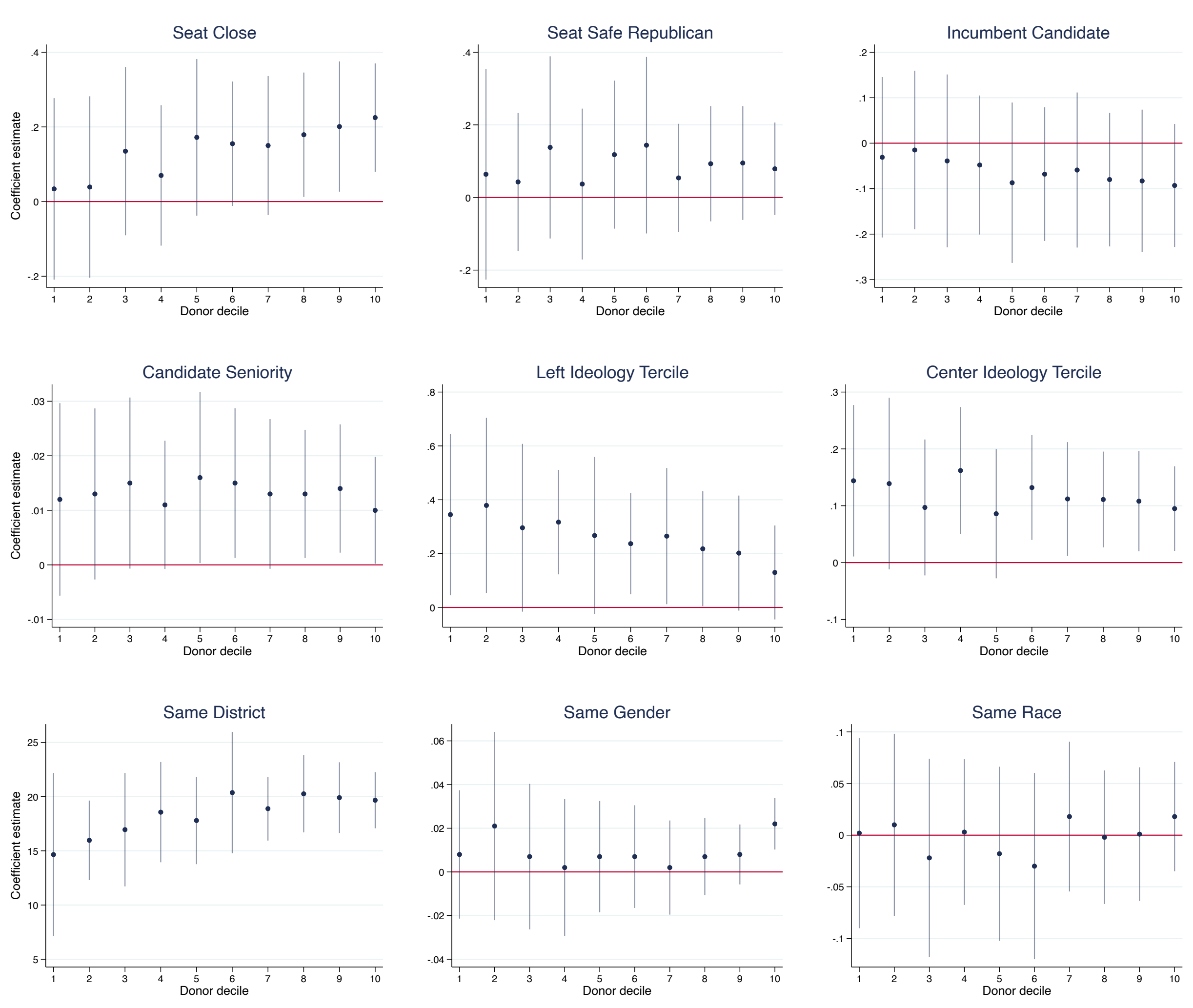
[31]Contributions to close races remain significantly lower among donors in the first decile than those in the tenth decile when we focus on donor-candidate pairs from the same district. In addition, in that sample, donors in the first decile contribute significantly less to sure losers and more to incumbent candidates, senior congresspeople, and left-wing candidates (Appendix Table F.4, column 6).

Table 3: The races and candidates targeted by donors, Democratic congressional candidates, 2012-2020 general elections

	Large			Small		
	(1)	(2)	(3)	(4)	(5)	(6)
Close Seat	0.18**	2.38***	16.38***	0.11	1.69***	12.58***
	(0.07)	(0.42)	(2.44)	(0.11)	(0.47)	(2.49)
Safe Republican Seat	0.06	0.43	8.06***	0.11	0.95	9.17***
	(0.06)	(0.35)	(2.34)	(0.12)	(0.53)	(2.14)
Incumbent Candidate	-0.08	-0.88**	-6.23***	-0.05	-0.64	-4.93*
	(0.07)	(0.32)	(1.78)	(0.08)	(0.36)	(2.07)
Congressional Seniority	0.01*	0.03	0.29	0.02	0.06*	0.72***
	(0.01)	(0.02)	(0.15)	(0.01)	(0.03)	(0.22)
Left Ideology Tercile	0.19*	0.18	6.32***	0.31*	0.23	7.63**
	(0.09)	(0.27)	(1.68)	(0.15)	(0.38)	(2.35)
Center Ideology Tercile	0.11**	0.32	5.79***	0.12*	0.25	6.64**
	(0.04)	(0.23)	(1.39)	(0.06)	(0.28)	(2.39)
Same District	20.45***	14.01***		16.79***	8.48***	
	(1.43)	(0.81)		(2.74)	(0.58)	
Same Gender	0.01*	0.15***	0.61	0.01	0.01	-0.16
	(0.01)	(0.04)	(0.37)	(0.02)	(0.05)	(0.50)
Same Race	0.01	0.22	1.56	-0.02	0.13	1.03
	(0.03)	(0.17)	(1.20)	(0.04)	(0.18)	(1.22)
Election Year FE	✓	✓	✓	✓	✓	✓
House/Senate FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Donor FE	✓	✓	✓	✓	✓	✓
Sample	All Pairs	In-State	In-District	All Pairs	In-State	In-District
Sample Mean	0.24	2.27	22.21	0.23	1.64	19.65
N	998,443,983	42,784,266	2,653,417	1,682,512,593	75,103,840	4,289,535
R2	0.09	0.23	0.42	0.08	0.28	0.53
Within-R2	0.08	0.06	0.06	0.05	0.06	0.14

Notes: Models are estimated using OLS. The time period is 2012-2020. An observation is a donor-candidate pair at each election cycle. In columns (1) and (4), the sample includes, for each donor who gave during a cycle, all the possible pairs of that cycle. We restrict the sample to donor-candidate pairs of the same state, in columns (2) and (5) and to donor-candidate pairs of the same district, in columns (3) and (6). The dependent variable is the share of the total amount contributed by the donor to the candidate during the general election. Regressors are described in the text. The race of a donor is the one, if any, that had an assigned probability greater than 50%, based on the imputation described in Appendix A.4.2. For each characteristic, we create and control for an indicator equal to one when the characteristic is missing and set the corresponding variable to 0. Standard errors are shown in parentheses and two-way clustered at the seat and donor levels. Appendix Table F.4 shows the p-values associated with the t-tests of equality between the effects observed in the small and large donor samples. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Figure 5: The races and candidates targeted by donors, by donors' deciles, Democratic congressional candidates, 2012-2020 general elections



Notes: The figure plots the values and 95% confidence intervals of the coefficients obtained from estimating equation (1) for different deciles of donors, based on the distribution of the maximum contributions made to any candidate during an election cycle. A donor making a maximum contribution of $200, the threshold used to split our sample between small and large donors in the regression tables, would be included in the 8th decile. The estimations include election year, state, House/Senate and donor fixed effects.

variable for the closeness of the primary, equal to one if the mean margin of victory of the winner in the last two primary elections for that seat was between -10% and 10%.

We observe many similarities with donations in the general elections: competitive general election races already attract larger donations during the primary, and like general election donors, primary donors provide more support to candidates in their district, candidates on the left and the center, and candidates with the same gender or race (Appendix Table F.5). A notable difference is that primary donors support incumbent candidates more, which balances the fact that those candidates receive fewer contributions during the general election. Once again, the estimates are generally not significantly different for small and large donors except for small donors' lower contributions to candidates from their district and of the same gender, as in the general elections (Appendix Table F.6).

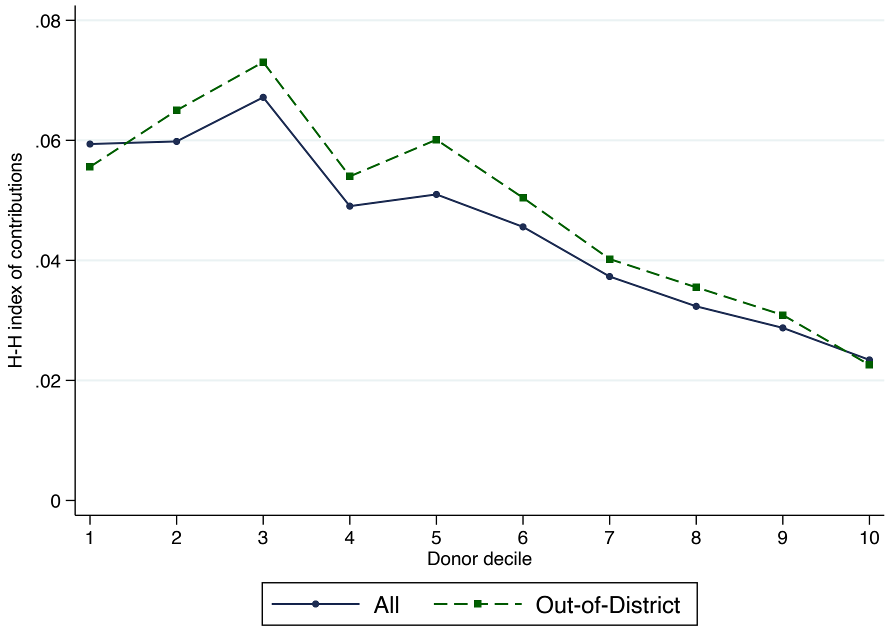
Donors to Republican candidates, general elections Second, we consider donations to Republican candidates in the 2020 general elections, which followed the creation of WinRed. The main predictors of Republican contributions are race closeness and same district, as for Democrats, and more right-wing Republican candidates (the omitted category) receive more contributions, mirroring the effect observed for left-wing Democrats. Differently than Democratic donors, Republicans support incumbent candidates slightly more and senior congresspeople as well as same gender and same race Republican candidates from their district less (Appendix Table F.7).[32] Most importantly, the variables for which we observe significantly different effects for small and large Republican donors are same district, with small donors being more likely than large donors to support candidates from other districts, and race closeness, which increases small donors' contributions less, echoing differences observed among Democratic donors (Appendix Table F.8).

4.5 Concentration of small donors' contributions

Herfindahl-Hirschman index of contributions Whichever set of donors we consider, the main difference between small and large donor contributions is that the former flow substantially more to out-of-district races than the latter. One possible explanation is that some prominent candidates receive the support of small donors located throughout the country. To test whether this is the case, in each decile and election cycle, we calculate the share of contributions going to a candidate out of the total contributions across all Democratic candidates, and compute the Herfindahl-Hirschman index of that variable. We then average the HHI across election cycles in each decile. As shown in Figure 6, donor contributions in general elections are much more concentrated in the bottom than in the top deciles, whether we consider all contributions or focus on those made out of district. A similar pattern is present in primary elections (Appendix Figure E.6).

[32]The negative effect of gender match remains, in regressions including seat x election year fixed effects, but the negative effect of race match disappears and becomes positive and significant in some samples (Appendix Table F.9).

Figure 6: The concentration of contributions by donors' deciles, Democratic congressional candidates, 2012-2020 general elections



Notes: The figure plots the Herfindahl-Hirschman index of concentration of all (continuous blue line with dots) and out-of-district (dashed green line with squares) contributions to Democratic congressional candidates, for different deciles of donors grouped based on the maximum total contributions they make to a candidate during an election cycle, for each election cycle between 2012 and 2020 and then averaged over all cycles.

Many of the Democratic candidates attracting a large share of small donations either hold a leadership position within the party or one of its sub-groups (e.g., Elizabeth Warren in 2012 and 2018) or run against a Republican candidate that is a nemesis of the Democratic Party (e.g., Beto O'Rourke, who sought to unseat Ted Cruz in 2018, or Amy McGrath, who challenged Mitch McConnell in 2020).[33]

Interpretation While small donors support similar types of candidates as large donors and do not contribute more to close races, limiting their ability to influence electoral outcomes, they may still prompt changes in campaign platforms and in the policies implemented by election winners. Their willingness to support out-of-district candidates may increase politicians' incentives to talk about national issues rather than local matters (Cagé et al., 2024), contributing to the nationalization of U.S. politics (e.g., Hopkins, 2018; Sievert and McKee, 2019). In addition, small donors may be particularly influential in the high-profile races in which their contributions are concentrated.

However, their ability to drive policy change (as in Grossman and Helpman, 1994, 1996; Coate, 2004; Ashworth, 2006) is likely to remain modest if, rather than actively choosing certain candidates and pushing for certain agendas, they passively react to external events or campaign solicitations(as in Bouton et al., 2024).

[33] We list the candidates that received the most small and large donors' contributions in general and primary elections in Appendix Tables F.10 and F.11.

Differences in visibility and campaign outreach activities across candidates could help explain why small donors' contributions are more concentrated than those of large donors and more often flow to races outside their district. To assess the role of pull factors, we now investigate whether surges in campaign contributions coincide with salient events and increases in campaign ads, and we estimate the effects of television and social media ads on contributions from both types of donors.

5 Timing of small donor contributions and effects of political ads

5.1 Timing of contributions

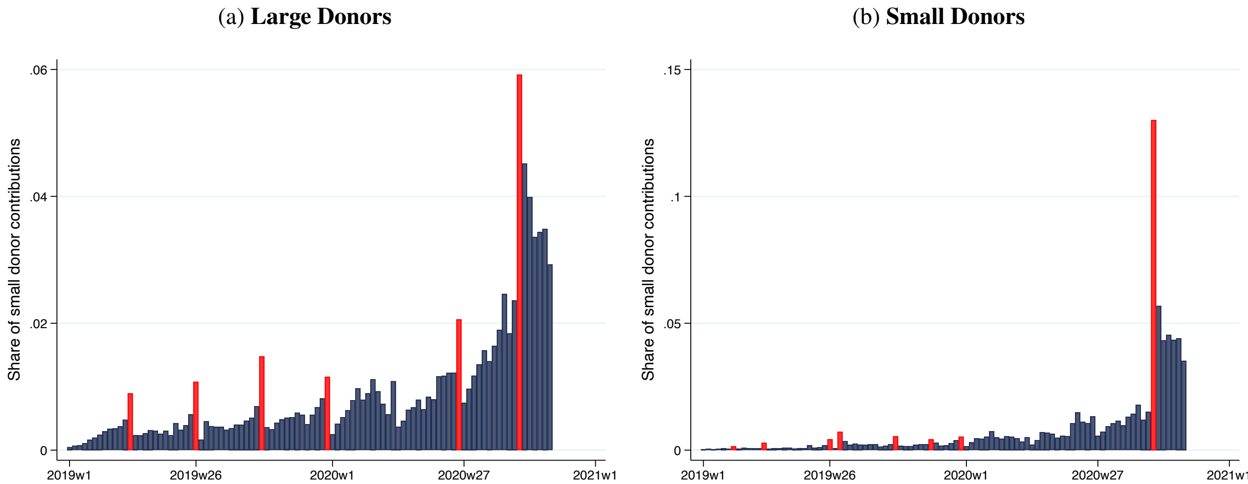
Figure 7 compares the timing of the contributions made by small and large donors. We plot the share of total contributions made by both sets of donors on each week of the 2020 election cycle. The corresponding graphs for other election cycles are shown in Appendix Figure E.7.

Two main patterns emerge. First, small and large donors' contributions steadily increase over time, during the two-year election cycle, but the concentration toward the end of the cycle is larger for small donors. This pattern suggests that small donors are more sensitive to the intensity of the campaign and the salience of the election, and it may further limit their influence. Indeed, the closer the election is, the less scope candidates have to change their platform or to use small donors' contributions as seed money to raise their profile.

Second, we observe different peaks in the two series. For large donors, the peaks coincide with quarterly campaign finance reporting deadlines. By contrast, small donor activity surges more after key events. For instance, about 13.0% of all small donors' contributions during the 2020 election cycle were made during the week of the death of Justice Ruth Bader Ginsburg. By contrast, this surge in activity only accounted for 5.9% of all contributions by large donors.

To complement this visual inspection, we define abnormal weeks as weeks during which contributions were 50% higher than the mean in the previous and following months or twice as high as in the previous and following weeks. We color these weeks in red and identify the event that is the most likely trigger of the surge. Across all cycles, 30 of the 31 abnormal weeks identified for large donors coincide with end-of-quarter reporting deadlines, against 27 of the 43 abnormal weeks identified for small donors. Other abnormal weeks for small donors were triggered by nationally salient external events that raised outrage or concern among Democrats, such as the December 2017 adoption of the TCJA Tax Bill or Newt Gingrich's South Carolina Primary Victory in 2012, suggesting that small donors are more sensitive to these events (Appendix Table F.12).

Figure 7: The timing of small and large donor contributions, Democratic congressional candidates, 2020 election cycle



Notes: The figures plot the share of small and large donor contributions in dollar amounts to Democratic congressional candidates on each week of the 2020 election cycle up to the week of the election, as a share of the total contributions made over the cycle to these candidates. We highlight in red the weeks during which contributions were higher than 1.5 times the mean of the previous and following months or 2 times the level of the previous week and the following week.

5.2 The effects of TV ads

We now estimate the effects of candidates' political ads on campaign contributions. In the U.S., political advertising accounts for a large fraction of all candidate expenses (55% in 2020, according to Opensecrets.org). The vast majority of these advertising expenditures still go to TV ads, but expenditures on digital ads have substantially increased in recent elections (Ridout et al., 2021).

Empirical strategy We first estimate the effects of TV political ads using Spenkuch and Toniatti (2018)'s identification strategy, which exploits variation in the number of TV ads across adjacent counties located in the same state or in the same district but in different media markets (referred to as "Designated Market Areas," or DMAs).[34] This variation is plausibly exogenous given that candidates determine the volume of TV ads at the level of the DMA, based on market-level factors, and each DMA encompasses many counties. Because each border county accounts for a small share of the population living in its DMA (5% on average), its composition, partisanship, and past contribution amounts should have a minimal influence on the volume of ads it is exposed to, and differences in TV ads across adjacent counties located in different DMAs should be orthogonal to differences in their characteristics. Spenkuch and Toniatti (2018) show that this is indeed the case for many variables.

[34] Krasno and Green (2008) and Gerber et al. (2011) find that the effects of political ads on voter turnout and vote choice are short-lived at best but Spenkuch and Toniatti (2018) uncover a substantial impact on vote shares, which they attribute to the stronger mobilization of supporters of the candidate disseminating more ads. If ads sent by candidates motivate their supporters to vote, then they may also increase political engagement on another margin, contributing money to the campaign, which we investigate.

We restrict the sample to pairs of neighboring counties in different DMAs and use the following specification:

$$Y_{c(p)t} = \phi \text{Ads}_{ct} + \mu_{pt} + \mathbf{X'}_{ct}\gamma + \psi \text{OtherAds}_{ct} + \alpha_c + \epsilon_{ct}, \tag{2}$$

where $Y_{c(p)t}$ is the amount of contributions for a specific race in county c of county-pair p in election t,[35] Ads_{ct} is the number of TV ads for that race broadcasted in the county's DMA, μ_{pt} is a year-specific county-pair fixed effect, equal to one for the two counties sharing a common border, $\mathbf{X}_{ct}$ is a vector of county-level time-varying controls, OtherAds_{ct} is the number of ads aired in the same DMA for all other races,[36] and α_c is a county fixed effect.[37] We cluster standard errors at the DMA level.

For Senate races, which are state-wide, the sample includes border-counties located in the same state, like in Spenkuch and Toniatti (2018). For House races, we further restrict the sample to border-counties located in the same constituency. Since counties can span multiple constituencies, we require that at least 90% of the surface area of each of the border-counties be included in the constituency so that the race relevant to the county is defined unambiguously. Some counties have multiple neighboring counties located in a different DMA but in the same state or constituency. We follow Spenkuch and Toniatti (2018) and include these counties multiple times in the sample.[38]

We measure the number of TV political ads aired in each county based on data from the Wesleyan Media and Wisconsin Advertising Projects. It includes ads sponsored by candidates and their parties as well as ads by PACs and other interest groups that support a specific candidate and are categorized as pro-Democratic or pro-Republican. In DMAs overlapping multiple congressional districts, people receive ads promoting candidates of their county's congressional district(s) as well as ads promoting candidates of other districts in the DMA. Our main specification estimates the effects of both types of ads on contributions to both types of candidates.[39] In our sample of border county pairs, people receive, on average, 3,600 Democratic general election ads supporting Senate candidates and 1,800 ads supporting House candidates per election cycle between 2012 and 2020 (see Appendix Table F.13).

We validate our empirical strategy by replicating the results of Spenkuch and Toniatti (2018) for turnout and vote shares. We obtain the same point estimates for the 2012 presidential elections, and qualitatively similar results for the 2012-2020 congressional elections. Our results corroborate the conclusion of Sides et al. (2021) that TV ads have larger effects on electoral outcomes in down-ballot elections than in presidential

[35] We do not estimate the effects of ads on donations to Republican races because the combined restriction of the sample to the 2020 election cycle and to border counties severely limits statistical power.

[36] The definition of OtherAds depends on the type of race we consider. It includes presidential and Senate ads when we consider House races, and presidential and House ads when we look at Senate races. Ads related to gubernatorial and down-ballot races (such as state legislatures, supreme courts, or ballot initiatives) are always included in OtherAds.

[37] In years in which a Senate race takes place in the state in which a county is located, we replace the county fixed effect and county-pair-by-year fixed effect with two sets of fixed effects (one for the House race and the second for the Senate race).

[38] All these observations are included in the same cluster, since we cluster standard errors at the DMA level, but the county-pair fixed effect that takes value 1 is different for each of these observations.

[39] In rare cases, candidates advertise in DMAs not overlapping with their congressional districts. We include these ads in OtherAds_{ct}.

ones. Appendix C details the data, empirical specifications, and results of this exercise.

Results Table 4 shows the impact of TV ads on contributions to Democratic candidates in general and primary elections. In general elections, an increase in Democratic ads by 1,000 (corresponding to 27% of the mean number of Senate ads and 56% of the mean number of House ads) increases the total contributions by large and small donors by 27.9 and 10.9 dollars per 10,000 adult inhabitants (columns 1 and 2), which corresponds to 2.3% and 6.3% of their mean. The effects in primary elections are 2.1 and 3.6 dollars per inhabitant, corresponding to 0.2% and 3.7% of the mean. In both sets of elections, the effects are only statistically significant (at the 1 and 5% level, respectively) for small donors. However, using a seemingly unrelated regressions framework, we find that the difference between the effects on small and large donors is not statistically significant. By contrast with Democratic ads, Republican ads have non-significant effects on the contributions of both small and large donors. We obtain similar results when using the number of donors as the dependent variable (Appendix Table F.14).

Table 4: The effects of TV ads on small and large donor contributions, Democratic congressional candidates, 2012-2020

	General Elections		Primary Elections	
	(1) Large	(2) Small	(3) Large	(4) Small
Democratic Ads (Total number, in 1000s)	27.87	10.86***	2.12	3.65**
	(32.49)	(3.78)	(28.72)	(1.66)
Republican Ads	-22.33	-4.91	15.46	1.18
	(37.99)	(5.32)	(24.25)	(1.97)
County-Pair x Year x Office FE	✓	✓	✓	✓
County x Office FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
R-sq (within)	0.004	0.027	0.006	0.017
Observations	31,162	31,162	31,162	31,162
Clusters	204	204	204	204
Mean DepVar	1,191.04	172.10	1,085.14	98.91

Notes: Models are estimated using OLS. An observation is a county-cycle-office. We combine House and Senate races for the 2012 to 2020 elections. Columns 1 and 2 and columns 3 and 4 show the results for the general and primary elections, respectively. The sample includes all county-pairs with border-counties located in the same congressional district for House races, and all county-pairs in which a Senate race took place. The dependent variable considers contributions to all Democratic congressional candidates in the DMA, and is the total dollar amount of contributions per 10,000 adult inhabitants. Controls include all other political ads aired in the county (for senatorial elections, presidential, House, non-DMA Senate, governor, and other down-ballot races' ads; and for House elections, presidential, Senate, non-DMA House, governor, and other down-ballot races' ads), measured in the same way as the main dependent variable and separately for Democratic and Republican candidates, together with a set of socio-demographic characteristics at the county level (total population, share of high-school dropouts, share of college graduates, share of ethnic minority population, share of foreign-born population, median household income, share of population below the poverty line, and employment-to-population ratio). Standard errors are shown in parentheses and clustered at the DMA level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

In Appendix Table F.15, we check the robustness of our results to an alternative specification, measuring the effects of ads promoting the candidates running in the district corresponding to the county of the donor on contributions to these candidates.[40] The effects of Democratic ads are qualitatively similar as in Table 4

[40] In a few states and years (five in total in the sample), two Senate races took place at the same time. In these cases, TV ads and

and, if anything, more pronounced, suggesting that the connection between local ads and local contributions is slightly stronger.

5.3 The effects of social media ads

Empirical strategy We now turn to social media ads, which account for a smaller share of campaign budgets than TV ads but can be better targeted and often include links to online conduits. We collected data on political ads posted on Facebook and Instagram using Meta's API, as in Fowler et al. (2021). We match the names of pages posting ads to the corresponding congressional candidates.[41] We study ads placed in the 2020 election, which is the only cycle fully covered by these data starting in May 2018.

We estimate the effect of these ads using an event study. Social media ads often target a single state or a handful of states. Therefore, we define events at the candidate-state-week level.[42] We compute the total number of ads for each candidate, state, and week and define an event as a week in which the candidate launched at least one ad in the state. We exclude events which are separated by less than three weeks from each other or which fall in the last three weeks before the incoming election, to be able to estimate effects up to three weeks after. This leaves us with 20,579 events for 402 candidates: 2,753 events for general elections (corresponding to 5% of the number of weeks with ads in this period) and 17,826 for primary elections (12.5%).[43] In alternative specifications, we only exclude events separated by less than two weeks or one week (rather than three). We can then only inspect pre-trends and measure effects over shorter periods, but the fraction of Democratic social media ads that we keep reaches 10% and 19% in general elections, and 17 and 29% in primary elections. Summary statistics on these events are shown in Appendix Table F.16.

Our sample is restricted to candidate-states with one event or more. For each event, we use one observation per week. If there are multiple events for a candidate-state, the same set of weeks is included multiple times. We use the heterogeneity-robust event-study estimator proposed by de Chaisemartin and D'Haultfoeuille (2024).[44] For each switcher group g – candidate-states with an event in a given week – let F_g denote the week

the contribution amounts are summed over the two races, and the number of donors counts all people who donated to at least one of the two races.

[41] See Appendix D for more information on the data collection and cleaning.

[42] Ads sometimes generate a few impressions in states that were not targeted by the candidate. Accordingly, for each ad, we compute the ratio between the share of the ad's impressions in a state and the state's share of the U.S. adult population. We consider states for which the ratio is below 0.17 (the bottom 5%) as not targeted by the ad. Inhabitants of these states are more than six times less likely to see the ad than if it had been disseminated indifferently in all states.

[43] Louisiana does not hold primary elections before Election Day. Since our specification controls for week-state fixed effects, including observations corresponding to weeks for which only one state is observable would pose an issue. We thus focus, for all general election estimations, on the period between the first week of April 2020 (i.e., three weeks after the earliest primary election date in other states with events) and Election Day.

[44] This estimator improves on the "classical" event-study estimator that would be obtained by running a specification of the following form:

$$Y_{jw} = \sum_{k=-3}^{-2} \mu_k + \sum_{k=0}^{3} \mu_k + \theta_w + \gamma_j + \epsilon_{jw},$$

where Y_{jw} is the outcome for candidate-state-event j in week w, μ_k (-3 $\leq$ k $\leq$ 3) are indicator variables for the number of weeks in which the event occurs. The group-level estimator of the event's effect at different horizons $\ell \in \{1, 2, 3, 4\}$ is the following 2×2 difference-in-differences:

$$\text{DID}_{g,\ell} \;=\; \Big(Y_{g,\,F_g-1+\ell} - Y_{g,\,F_g-1}\Big) \;-\; \frac{1}{N^g_{F_g-1+\ell}} \sum_{\substack{g':\, D_{g',1}=D_{g,1} \\ F_{g'}>F_g-1+\ell}} \Big(Y_{g',\,F_g-1+\ell} - Y_{g',\,F_g-1}\Big), \tag{3}$$

where $N^g_{F_g-1+\ell}$ is the number of control groups g' in which the event has not taken place yet by week $F_g-1+\ell$.

The aggregate event-study effect at horizon ℓ is then:

$$\text{DID}_{\ell} \;=\; \frac{1}{N_\ell} \sum_{g:\, F_g-1+\ell \leq T_g} \text{DID}_{g,\ell}, \tag{4}$$

where N_ℓ is the number of events for which this effect is estimated. We assess the plausibility of the parallel-trends assumption using placebo estimators of pre-event effects. The fact that candidates run ads at different times enables us to control flexibly for the calendar week and to ensure that our effects are not biased by the overall increase in donations over the election cycle or by other time trends or national events. We include week-state fixed effects to allow time trends in donations to vary across states. Candidates' advertising campaigns often run in multiple states at the same time, so we cluster the standard errors at the candidate x week of the event level.

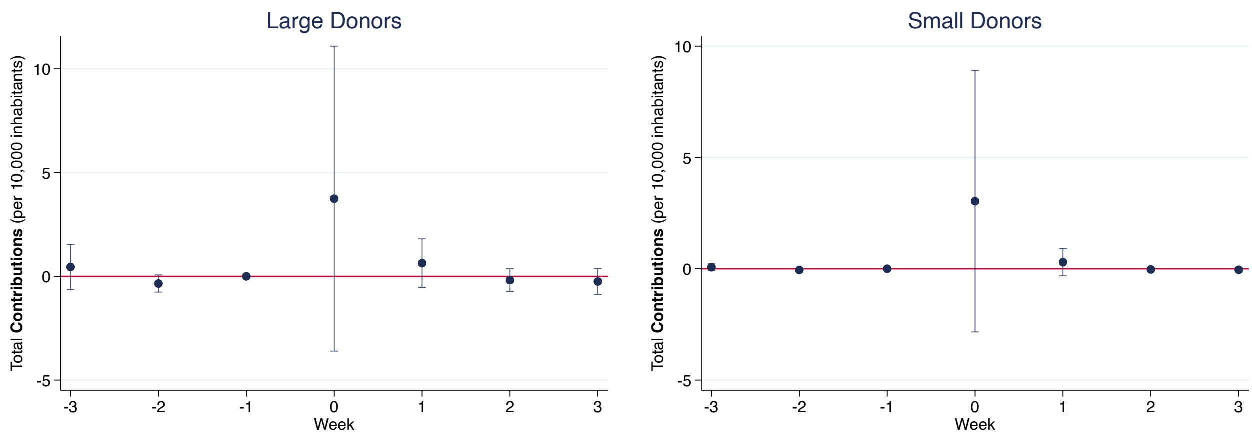
Results Figure 8 plots the effects of ads by Democratic candidates on small and large donors' contributions in general and primary elections to the candidate who posted the ad from three weeks before to three weeks after. We do not find any clear pre-trend in these outcomes in the three weeks before the ad. Instead, the ads have immediate positive effects on all four outcomes. The effects decrease in the three subsequent weeks but remain positive up to three weeks later in the primary elections, which may be due to the fact that ads often run for multiple weeks.

We report the corresponding point estimates in Appendix Table F.17, Panel (a). On average, in general elections, an event increases the total contributions to the candidate per 10,000 inhabitants by \$3.7 for large donors in the state and \$3.0 for small donors during the first week, compared to the preceding week. These effects correspond to 2.5 and 8.3 times the mean level of contributions, respectively, but they are not statistically significant (columns 1 and 2). In primary elections, the effects are smaller but estimated more precisely, thanks to the larger number of events included in the estimation, and they are significant. They correspond to 0.5 and 1.3 times the mean (columns 3 and 4). The difference between effects on small and large donors echoes the one observed for TV ads: the effects are larger for small donors, but the difference is not statistically significant. We observe comparable effects on the number of donors (Appendix Figure E.8 and Table F.17,

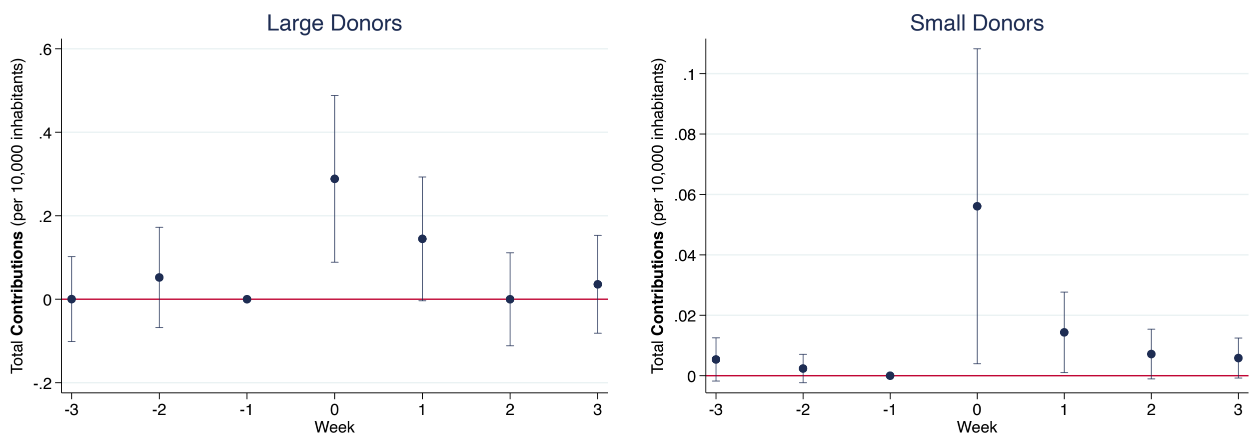
relative to the first day of the ad, γ_j are event fixed effects, and θ_w are week-state fixed effects.

Figure 8: The effects of social media ads on small and large donor contributions, Democratic congressional candidates, 2020 election cycle

(a) **General Elections**



(b) **Primary Elections**



Notes: The figure shows point estimates and 95% confidence intervals associated with the event-study results of the estimator developed by de Chaisemartin and D'Haultfoeuille (2024). An observation is a candidate-state-event-week. The sample includes all congressional Democratic candidates who ran at least one ad-event on Meta's platform during the 2020 election cycle. Estimations also include week-state fixed effects. The dependent variable is the total dollar amount of contributions made that week by small and large donors from the corresponding state to the candidate posting the ad, per 10,000 state inhabitants. The top panel focuses on the general elections and the bottom panel on the primary elections. Standard errors are clustered at the candidate x week of the event level. The corresponding point estimates are shown in Appendix Table F.17, Panel (a).

Panel (b)).

We obtain qualitatively similar results when excluding new advertising weeks separated by less than two weeks or one week, thereby increasing the number of events included in the estimation (Appendix Figures E.9 and E.10); when dropping ads with a number of impressions per inhabitant in the state in the top 5 percentiles of the distribution, thereby ensuring that the effects are not driven by a few extremely salient ads (Appendix Figure E.11); and when dropping ads with a number of impressions falling in the bottom 25 percentiles of the distribution, which are unlikely to have sizable effects (Appendix Figure E.12).[45]

Next, we focus on the 57.6% of ads that include a hyperlink to ActBlue, allowing viewers to directly make an online donation. We find larger effects in the sample restricted to events including those ads (Appendix Figure E.13). This result provides additional evidence that we are capturing a causal impact rather than a spurious relationship.

These findings suggest that, together with the advent of online conduits, the growing political importance of social media is one of the key determinants underlying the small donor phenomenon.

Overall, the results in this section paint a consistent picture: small donors are more responsive to pull factors than large donors.

6 Conclusion

Small campaign donors were long largely invisible, but now their contributions overwhelmingly flow through conduits that are required to report them individually. We processed these data to provide the first comprehensive evidence on the number of small donors, their geographic and demographic distribution, the candidates and races they target, and the timing and magnitude of their contributions.

Taken together, our findings suggest that the rise of small donors is unlikely to be as transformative as often claimed. Although the number of small donors and their total contributions have increased rapidly, contributions from large donors have grown at a similar pace. Small donors are somewhat more representative of the U.S. population than large donors, but their rise cannot be characterized as a grassroots movement. Their racial composition and socioeconomic status remain closer to those of large donors than to those of the average citizen, and they are not significantly more likely than large donors to support women, minority candidates, non-incumbents, or ideologically extreme politicians.

Small donors do not target close races to a greater extent than large donors, and their contributions are largely driven by pull factors: they surge late in campaigns and in the aftermath of salient political events, are concentrated in high-profile races, and are more responsive than the contributions of large donors to TV and

[45]The results obtained on subsamples selected based on the number of impressions should be interpreted with caution since that number may be endogenous to ad quality. Our main specification does not suffer from this issue since it includes all events, irrespective of the number of people reached.

social media advertising. In sum, small donors appear to occupy the passenger seat rather than the driver's seat.

Overall, these findings provide little reason to expect small donors to substantially transform U.S. politics.

References

Albert, Z. and La Raja, R. (2020). Small donors in us elections. *Politique américaine*, (2):15–45.

Alvarez, R. M., Katz, J. N., and Kim, S.-y. S. (2020). Hidden Donors: The Censoring Problem in U.S. Federal Campaign Finance Data. *Election Law Journal: Rules, Politics, and Policy*, (1):1–18.

Ansolabehere, S., de Figueiredo, J. M., and Snyder, J. M. J. (2003). Why is There so Little Money in U.S. Politics? *Journal of Economic Perspectives*, 17(1):105–130.

Ashworth, S. (2006). Campaign finance and voter welfare with entrenched incumbents. *American Political Science Review*, 100(1):55–68.

Autor, D., Dorn, D., Hanson, G., and Majlesi, K. (2020). Importing political polarization? the electoral consequences of rising trade exposure. *American Economic Review*, 110(10):3139–3183.

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

Babenko, I., Fedaseyeu, V., and Xu, G. (2024). Mega-donors and representation of the wealthy in the wake of citizens united. *Available at SSRN*.

Barber, M. J. (2016). Ideological Donors, Contribution Limits, and the Polarization of American Legislatures. *The Journal of Politics*, 78(1):296–310.

Barber, M. J., Canes-Wrone, B., and Thrower, S. (2017). Ideologically sophisticated donors: Which candidates do individual contributors finance? *American Journal of Political Science*, 61(2):271–288.

Bekkouche, Y., Cagé, J., and Dewitte, E. (2022). The heterogeneous price of a vote: Evidence from multiparty systems, 1993-2017. *Journal of Public Economics*, 206:104559.

Bertrand, M., Bombardini, M., Fisman, R., and Trebbi, F. (2020). Tax-Exempt Lobbying: Corporate Philanthropy as a Tool for Political Influence. *American Economic Review*, 110(7):2065–2102.

Bertrand, M., Bombardini, M., Fisman, R., Trebbi, F., and Yegen, E. (2026). Investing in influence: Investors, portfolio firms, and political giving. *The Review of Economic Studies*, page rdag010.

Bertrand, M., Bombardini, M., and Trebbi, F. (2014). Is It Whom You Know or What You Know? An Empirical Assessment of the Lobbying Process. *The American Economic Review*, 104(12):3885–3920.

Boken, J., Draca, M., Mastrorocco, N., and Ornaghi, A. (2023). The returns to viral media: the case of us campaign contributions. Technical report. CAGE Working Paper 681. Conditionally accepted at the *Journal of the European Economic Association*.

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

Bonica, A. (2014). Mapping the Ideological Marketplace. *American Journal of Political Science*, 58(2):367–386.

Bouton, L., Castanheira, M., and Drazen, A. (2024). A theory of small campaign contributions. *The Economic Journal*, 134(662):2351–2390.

Braconnier, C., Dormagen, J.-Y., and Pons, V. (2017). Voter registration costs and disenfranchisement: experimental evidence from france. *American Political Science Review*, 111(3):584–604.

Brennan Center for Justice (2025). Guide to public financing programs nationwide. https://www.brennancenter.org/our-work/research-reports/guide-to-public-financing-programs-nationwide. Originally published June 29, 2023; updated August 18, 2025.

Broberg, N., Pons, V., and Tricaud, C. (2025). Spending limits, public funding, and election outcomes. *Journal of the European Economic Association*, page jvaf043.

Cagé, J. (2018). *Le prix de la démocratie*. Fayard (English version: The Price of Democracy, Harvard University Press, 2020).

Cagé, J. and Piketty, T. (2023). *Une histoire du conflit politique. Elections et inégalités sociales en France, 1789-2022*. Le Seuil (English version: A History of Political Conflict. Elections and Social Inequalities in France, 1789-2022. Harvard University Press, forthcoming), Paris.

Cagé, J., Pennec, C. L., and Mougin, E. (2024). Firm donations and political rhetoric: Evidence from a national ban. *American Economic Journal: Economic Policy*, 16:217–256.

Canes-Wrone, B. and Miller, K. M. (2022). Out-of-district donors and representation in the us house. *Legislative Studies Quarterly*, 47(2):361–395.

Chamon, M. and Kaplan, E. (2013). The Iceberg Theory of Campaign Contributions: Political Threats and Interest Group Behavior. *American Economic Journal: Economic Policy*, 5(1):1–31.

Coate, S. (2004). Political Competition with Campaign Contributions and Informative Advertising. *Journal of the European Economic Association*, 2(5):772–804.

Coppock, A., Green, D. P., and Porter, E. (2022). Does digital advertising affect vote choice? evidence from a randomized field experiment. *Research & Politics*, 9(1):20531680221076901.

Cox, C. (2026). The equilibrium effects of campaign finance deregulation on us elections. *Econometrica*. Forthcoming.

Culberson, T., McDonald, M. P., and Robbins, S. M. (2019). Small Donors in Congressional Elections. *American Politics Research*, 47(5):970–999.

Da Silveira, B. S. and De Mello, J. M. P. (2011). Campaign Advertising and Election Outcomes: Quasinatural Experiment Evidence from Gubernatorial Elections in Brazil. *The Review of Economic Studies*, 78(2):590–612.

de Chaisemartin, C. and D'Haultfoeuille, X. (2024). Difference-in-differences estimators of intertemporal treatment effects. *The Review of Economics and Statistics*, pages 1–45.

Dolan, K. (2008). Is there a "gender affinity effect" in american politics?: Information, affect, and candidate sex in u.s. house elections. *Political Research Quarterly*, 61(1):79–89.

Dwyer, K. and Stratmann, T. (2023). Effect of campaign contributions on legislator behavior: Intra–dairy industry interest group competition. *Journal of Political Economy Microeconomics*, 1(4):746–780.

Edlund, L. and Pande, R. (2002). Why have women become left-wing? the political gender gap and the decline in marriage. *The Quarterly Journal of Economics*, 117(3):917–961.

Enríquez, J. R., Larreguy, H., Marshall, J., and Simpser, A. (2024). Mass political information on social media: Facebook ads, electorate saturation, and electoral accountability in mexico. *Journal of the European Economic Association*, 22(4):1678–1722.

Fouirnaies, A. (2021). How Do Campaign Spending Limits Affect Elections? Evidence from the United Kingdom 1885–2019. *American Political Science Review*, 115(2):395–411.

Fowler, E. F., Franz, M. M., Martin, G. J., Peskowitz, Z., and Ridout, T. N. (2021). Political advertising online and offline. *American Political Science Review*, 115(1):130–149.

Gerber, A., Gimpel, J., Green, D., and Shaw, D. (2011). How Large and Long-lasting Are the Persuasive Effects of Televised Campaign Ads? Results from a Randomized Field Experiment. *American Political Science Review*, 105(01):135–150.

Gerber, A. S. and Green, D. P. (2000). The Effects of Canvassing, Telephone Calls, and Direct Mail on Voter Turnout: A Field Experiment. *The American Political Science Review*, 94(3):pp. 653–663.

Gethin, A., Martínez-Toledano, C., and Piketty, T. (2022). Brahmin Left Versus Merchant Right: Changing Political Cleavages in 21 Western Democracies, 1948–2020. *The Quarterly Journal of Economics*, 137(1):1–48.

Gilens, M. (2012). *Affluence and Influence: Economic Inequality and Political Power in America*. Princeton University Press.

Gimpel, J. G., Lee, F. E., and Pearson-Merkowitz, S. (2008). The Check Is in the Mail: Interdistrict Funding Flows in Congressional Elections. *American Journal of Political Science*, 52(2):373–394.

Gordon, S. C., Hafer, C., and Landa, D. (2007). Consumption or investment? on motivations for political giving. *The Journal of Politics*, 69(4):1057–1072.

Graf, J., Reether, G., Malbin, M. J., and Panagopoulos, C. (2006). Small Donors and Online Giving. A Study of Donors to the 2004 Presidential Campaigns. Report, Institute for Politics Democracy and the Internet.

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

Grossman, G. M. and Helpman, E. (1996). Electoral Competition and Special Interest Politics. *The Review of Economic Studies*, 63(2):265–286.

Grumbach, J. M. and Sahn, A. (2020). Race and Representation in Campaign Finance. *American Political Science Review*, 114(1):206–221.

Haenschen, K. (2023). The conditional effects of microtargeted facebook advertisements on voter turnout. *Political Behavior*, 45(4):1661–1681.

Hager, A. (2019). Do online ads influence vote choice? *Political Communication*, 36(3):376–393.

Hall, R. L. and Deardorff, A. V. (2006). Lobbying as legislative subsidy. *American Political Science Review*, 100(1):69–84.

Hopkins, D. J. (2018). *The Increasingly Unites States. How and Why American Political Behavior Nationalized*. Chicago Studies in American Politics.

Huber, G. A. and Arceneaux, K. (2007). Identifying the Persuasive Effects of Presidential Advertising. *American Journal of Political Science*, 51(4):957–977.

Imai, K. and Khanna, K. (2016). Improving ecological inference by predicting individual ethnicity from voter registration records. *Political Analysis*, 24(2):263–272.

Joe, W. Y., Malbin, M. J., Wilcox, C., Brusoe, P. W., and Pimlott, J. P. (2008). Do Small Donors Improve Representation? Some Answers from Recent Gubernatorial and State Legislative Elections. The cfi small donor project, Campaign Finance Institute.

Johnson, B. (2010a). Individual contributions: A fundraising advantage for the ideologically extreme? *American Politics Research*, 38(5):890–908.

Johnson, B. (2010b). Individual contributions: A fundraising advantage for the ideologically extreme? *American Politics Research*, 38(5):890–908.

Kalla, J. L. and Broockman, D. E. (2016). Campaign Contributions Facilitate Access to Congressional Officials: A Randomized Field Experiment. *American Journal of Political Science*, 60(3):545–558.

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

Krasno, J. S. and Green, D. P. (2008). Do televised presidential ads increase voter turnout? Evidence from a natural experiment. *Journal of Politics*, 70(1):245–261.

Kuziemko, I. and Washington, E. (2018). Why did the democrats lose the south? bringing new data to an old debate. *American Economic Review*, 108(10):2830–2867.

La Raja, R. J. and Schaffner, B. F. (2015). *Campaign Finance and Political Polarization: When Purists Prevail*. University of Michigan Press.

Le Pennec, C. and Pons, V. (2023). How do Campaigns Shape Vote Choice? Multicountry Evidence from 62 Elections and 56 TV Debates*. *The Quarterly Journal of Economics*, 138(2):703–767.

Magleby, D. B., Goodliffe, J., and Olsen, J. A. (2018). *Who donates in campaigns?: The importance of message, messenger, medium, and structure*. Cambridge University Press.

Malbin, M. J. (2013). Small Donors: Incentives, Economies of Scale, and Effects. *The Forum*, 11(3):385–411.

McCarty, N., Poole, K. T., and Rosenthal, H. (2006). *Polarized America: The Dance of Ideology and Unequal Riches*. Walras-Pareto Lectures. MIT Press.

Mian, A., Sufi, A., and Trebbi, F. (2010). The political economy of the us mortgage default crisis. *American Economic Review*, 100(5):1967–1998.

Panagopoulos, C. and Bergan, D. (2006). Contributions and contributors in the 2004 presidential election cycle. *Presidential Studies Quarterly*, 36(2):155–171.

Petrova, M., Sen, A., and Yildirim, P. (2021). Social media and political contributions: The impact of new technology on political competition. *Management Science*, 67(5):2997–3021.

Pildes, R. H. (2019). Small-donor-based campaign-finance reform and political polarization. *Yale LJF*, 129:149.

Pons, V. (2018). Will a five-minute discussion change your mind? A countrywide experiment on voter choice in France. *American Economic Review*, 108(6):1322–1363.

Pons, V. and Tricaud, C. (2018). Expressive Voting and Its Cost: Evidence From Runoffs With Two or Three Candidates. *Econometrica*, 86(5):1621–1649.

Prat, A. (2002). Campaign Advertising and Voter Welfare. *The Review of Economic Studies*, 69(4):999–1017.

Ridout, T. N., Fowler, E. F., and Franz, M. M. (2021). Spending fast and furious: Political advertising in 2020. *The Forum*, 18(4):465–492.

Sides, J., Vavreck, L., and Warshaw, C. (2021). The effect of television advertising in unites states elections. *American Political Science Review*, page 1–17.

Sievert, J. and McKee, S. C. (2019). Nationalization in u.s. senate and gubernatorial elections. *American Politics Research*, 47(5):1055–1080.

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

Spenkuch, J. L. and Toniatti, D. (2018). Political Advertising and Election Results. *The Quarterly Journal of Economics*, 133(4):1981–2036.

Thomsen, D. M. and Swers, M. L. (2017). Which women can run? gender, partisanship, and candidate donor networks. *Political Research Quarterly*, 70(2):449–463.

Vandewalker, I. (2024). *Do Small Donors Cause Political Dysfunction?* Brennan Center for Justice at New York University School of Law.

Washington, E. (2006). How Black Candidates Affect Voter Turnout. *The Quarterly Journal of Economics*, 121(3):973–998.

Wolbrecht, C. and Campbell, D. E. (2007). Leading by example: Female members of parliament as political role models. *American Journal of Political Science*, 51(4):921–939.

Yildirim, P., Simonov, A., Petrova, M., and Perez-Truglia, R. (2024). Are political and charitable giving substitutes? evidence from the united states. *Management Science*, 70(11):8030–8043.

Zhuravskaya, E., Petrova, M., and Enikolopov, R. (2020). Political effects of the internet and social media. *Annual Review of Economics*, 12(1):415–438.

Small Donors

Supplemental Appendix

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Contents

A Data construction

A.1 Scrapping the FEC's website

Background Committees registered with the FEC have to file paper or electronic forms reporting their financial activity over periods varying from 24 hours to 6 months, depending on committees' type and the stage of the election cycle. The FEC uploads these filings on its website, and processes most of their information, including the list of all contributions received and disbursements made, which it renders browsable and accessible for download. These data are already partially formatted: in their filings, the committees have to sort the contributions they received along "lines," which designate the different sources of contributions. Lines 11A(i) (and lines 17A(i), for presidential committees) of forms 3 and 3X gather all contributions from *individuals, partnerships and other persons who are not political committees*. In addition, the FEC identifies, among these contributions, all those coming from *physical* individuals (as opposed to partnerships, for instance), and stores them under the category "*Individual Contributions*" (is_individual=t in tabulated format). These are the data we scraped. They are accessible at `https://www.fec.gov/data/receipts/individual-contributions`. Note that this repository contains about 0.6% of non-11A(i)/17A(i) lines, likely due to processing errors. We deleted them.

Procedure The FEC website allows to export detailed contributions data for no more than 500,000 records at a time. It enables the filtering of the data on intervals of date of receipt (e.g., between the 02/01/18 and 02/04/18) and contribution amounts (e.g., below 200 dollars), among other fields. To extract the full set of records, we implemented the following procedure:

- We retrieved, for each day, the number of contributions that were registered for the day.
- If the number of contributions made on that day was below 500,000, we extracted the data by selecting them through the following URL requests: `?two_year_transaction_period=PERIOD`, `&min_date=[MINDATE]`, and `&max_date=[MAXDATE]`; where `MINDATE`, `MAXDATE` are the same date and `PERIOD` is the identifier of the two-year period containing the interval of interest (e.g., 2017-2018).
- If the number of contributions made on that day was above 500,000 (all these days but one were during the 2020 election cycle), we divided the set of contributions in sets of records with fewer than 500,000 elements using amount brackets (e.g., below 2 dollars, between 2 and 100 dollars, over 100 dollars) and extracted the data using the URL requests `min_amount=[a]&max_amount=[b]` where [a] and [b] are the different contribution amount thresholds.
- To retrieve the contributions for which the date was missing, we pulled each cycle's list of contributions using the FEC API, and selected contributions for which the "receipt date" variable was null.

A.2 Verifying the exhaustivity of the data

We verified the exhaustivity of these data by comparing, for each committee, the aggregate amount of itemized contributions they reported in their financial summaries with the amounts obtained by summing all the contributions to this committee within our dataset. The process revealed two types of issues: errors in either FEC or committee reporting, and missing reports.

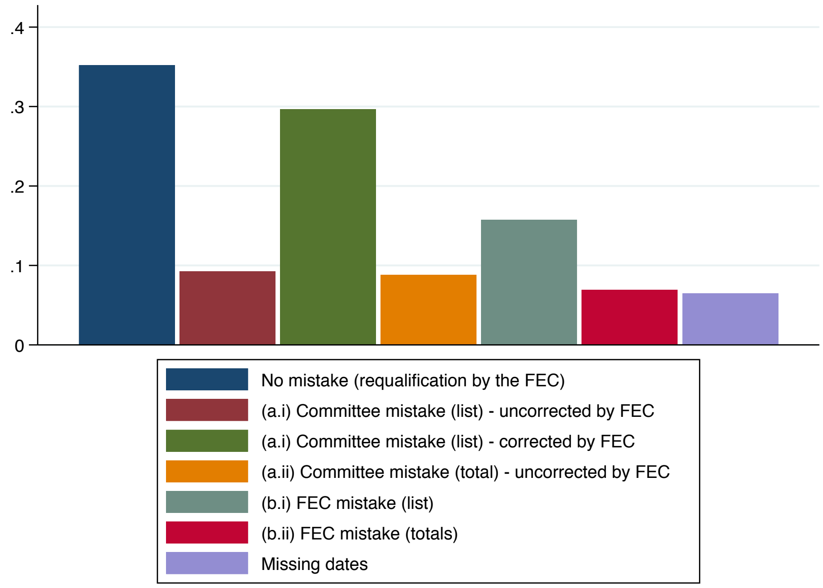
A.2.1 Issues in reporting

Among the 42,245 committee-cycles that filed reports with non-zero figures during the 2007-2018 period,[1] 18,082 (42.8%) have totals that do not match. We manually identified the sources of these mismatches for a stratified sample of 216 of those committees. We did it by looking at the list of all contributions, both in the pdf version of committees' reports and in the .csv tables generated by the FEC processing of these reports. The results are summarized in Figure A.1. About 36% of mismatches ("No Mistake (requalification)") were due to contributions from partnerships or other entities that qualify as 11A(i) donors, but are not individuals *per se*. For this reason, the FEC did not include them in its "Individual Contributions" data section (the data we scraped), even though they are still included by committees in the reported totals. These mismatches thus did not indicate erroneous filing or missing contributions. Another 6% of mismatches ("Missing dates") came from the few contributions for which committees did not indicate a receipt date: we had not found a way to scrape these contributions at the time of this verification (we have found a solution since, see Section A.1).

The remaining differences were due to errors in the data. These errors originated either in committees' filings (in their list of itemized contributions (i) or in their reported totals (ii)), or in the FEC's processing of these filings (in the sense that the pdf versions of the reports were correct, but the data tabulated by the FEC were not). In about 38% of the committee-cycles for which there was a mismatch ("Committee mistake (list)"), the committee reported, in the list of 11A(i) contributions, contributions that are *not* 11A(i) contributions – such as transfers from another committee – thereby providing an incorrect list of contributions. Three-fourths of these wrong categorizations had been identified by the FEC and the appropriate contributions had been removed from the list (labeled "-corrected" in the figure), but without changing the totals reported by the committee, meaning that these totals became un-representative of the – correct – available list of individual contributions. In the other fourth ("-uncorrected"), the browsable list of individual contributions still included these wrongly categorized donations, but the totals reported by the committee did not (so that the totals in fact accurately represent the sum of individual contributions).[2] Finally, in 8% of the cases ("Committee mistake

[1] We conducted this verification exercise in 2020, before the 2020 data became available in full.

[2] There could also be committees for which the list of contributions was not corrected by the FEC *and* for which the totals amounts computed include the erroneous contributions. Because the two are then equal, one cannot systematically count the number of committees with such mistakes. We can nevertheless delete (parts of) the erroneous contributions (see below).



Notes: The figure represents the reasons why committees' list of individual contributions do not add up to the total amounts they reported, for all committees of the 2008 to 2018 electoral cycles. Each bar corresponds to a different error type, and represents the share of committees that include this error. One committee can display multiple errors and error-types.

Figure A.1: The reasons for mismatch between total itemized contributions reported and computed, 2008-2018

(total)"), the list of individual contributions seemed, on the contrary, accurate but differed nonetheless from the totals reported, meaning that either contributions were missing, or the totals computed and reported by the committee were incorrect.

Similar mistakes were made by the FEC in making the reports' information available for browsing and download. About 16% of totals' mismatches ("FEC-mistake (list)") were due to misprocessing of contributions' lists, so that they differed from those reported by the committees in their original filings. Another 7% of committee-cycles ("FEC-mistake (totals)") showed, on their financial summary webpage, totals that differed from those in the original filings, meaning that the FEC processed them incorrectly.

Overall, we thus estimated that 25% of mismatching committees (11% of all committees) have an inaccurate list of individual contributions, and 44% (18%) have an incorrect total. As most of our analyses are conducted at the contribution-level, we were interested in having the most accurate list of individual contributions possible. Hence, we implemented several strategies to correct the inaccurate lists:

- Contributions that were wrongly categorized by committees could often be spotted through their name (that are not in the form first name-surname): after dropping the obvious keywords ("INC.", "INVESTMENTS",...), we navigated "manually" through the 240,000 first names that failed to have a gender assigned, in order to spot the non-individuals.

- The wrong processing of lists by the FEC was, in several cases, due to multiple imports of the same pdf report, which resulted in duplicate contributions. We thus dropped all donations that are from the same donor, amount, date, description, and report type, but with a different “file number,” which is an automatic number assigned to a file when uploaded on the server.

A.2.2 Missing filings

Several campaigns failed to report their financial data to the FEC. Out of the 19,029 candidate-cycles with positive official vote counts at either a primary or a general election between 2006 and 2018 cycles, 4,342 have no receipt declared. One possible explanation is that these campaigns may not have surpassed the 5,000$ reporting threshold. Yet, for those with relatively high vote counts, this seems very unlikely. In these cases, the FEC sends a “Administrative Termination” letter, which, without further action from the committee, effectively terminates its activities. Contribution data for these missing filings remains unavailable. We do not include these committees in our analyses.

A.3 Cleaning the contributions data

A.3.1 Earmarked contributions

Background An earmarked contribution is a contribution made by an individual donor through an intermediary, called conduit, with a clear designation of the final recipient committee. Conduits can be individuals as well as organizations. They need not be registered with the FEC to be subjected to reporting rules. Conduits registered with the FEC need to itemize and report *all* their contributions, whatever their amount. For each contribution, they need to provide information on the name and address of the original donor, the date of the receipt, the identity of the recipient, the date of the transfer of the contribution to this recipient, and the type of payment (cash, check, etc.). If the contribution is from an individual and exceeds $200, the conduit must also report the individual’s employer and occupation. In practice, most conduits include these latter elements for all donors.

For the recipient committees, earmarked contributions are treated like a direct contribution from the individual donor (and not the conduit) in terms of reporting threshold and contribution limits. This means that committees have to report earmarked contributions of donors whose total contributions since the beginning of the election cycle (independently of whether they are earmarked) exceed $200. These contributions will thus appear both in the committee reports and in the conduit reports.

Processing The data we scraped include the list of all 11A(i) contributions in conduits’ reports, i.e. earmarked contributions from individual donors. In this list, the contributions are recorded as going from donors to conduits, but most of them also include a field called “memo text” with information on the recipient committee. The format of this memo text varies over time and across conduits. To extract the information, we screened all possible patterns of reporting. Some included the full committee ID; others included its name or the name of the affiliated candidate.[3] We managed to identify the recipient committee of 98% of all earmarked contributions.

In the second step, we identified which of these contributions were also itemized by their recipient committee, in order to remove the duplicates. This pairing exercise was even less straightforward as the conduits do not always transfer contributions on the day they receive them (hence, duplicate contributions could be registered on different dates). Moreover, the reports by the conduit and the candidate committee may identify the donors differently, and the candidate committee does not always record the contribution as earmarked. After manually addressing as many of these issues as possible, we managed to couple 87% of all the earmarked committee-itemized donations with their conduit-itemized equivalent, and dropped the committee-itemized part of these pairs. The remaining committee-itemized donations (representing 3% of all contributions) remain in our data as earmarked contributions (with the caveat that we are generally not able to identify the name of the specific conduit earmarking the donation).

Special cases As a non-profit, the conduit "ActBlue" offers donors to top-up their contributions with small amounts to support their own operations. These donations are recorded in the conduit data as "Contributions to ActBlue." We dropped them from our analysis. We also dropped contributions to the conduit "It Starts Today," a 2018 special conduit that divides contributions equally across all 468 Democratic congressional candidates, thus artificially boosting the number of very small earmarked contributions.

A.3.2 Refunded contributions

Contributions refunded by committees to donors, which appear in the data as one positive contribution and one negative contribution, were removed. For partial refunds, we took away the appropriate amount from the initial contribution. There are multiple reasons for a contribution to be refunded. For instance, the donor could have exceeded the legal contribution limit, or the contribution may not permissible or may be unwanted by the committee (e.g., the Democratic Party refunded a contribution from Harvey Weinstein after revelations on his sexual misconducts).

[3] Earmarked contributions made early in the election cycle are sometimes designated to seats, before the official candidate is announced/running (e.g. "for the Democratic nominee for TX-02 district"). We assigned these to the candidate that will eventually contest the seat.

A.4 Collecting and processing the data on donors

A.4.1 Grouping

For each contribution, committees report the donor with their full name, address, occupation, and employer. In theory, this information is sufficient to identify any given individual across contributions, committees, and years. However, donors' information can be collected and recorded by committees in many different ways: orally at an event, through an app, on a paper form, etc. Hence, in practice, the information about the same donor can vary across contributions, and a grouping procedure relying on exact matching would generate a large fraction of false negatives.

Instead, we proceeded in two steps. First, we chose key identifying variables, which we cleaned and homogenized, sometimes by fuzzy matching string segments. Second, we established a set of explicit rules based on these variables that define an exact matching procedure of identification. Each step reflects a detailed inspection of the microdata and our contextual understanding of mistakes or inconsistencies that humans make in reporting contributions.[4]

Step 1 We focused on four main variables: *first name*, *surname*, *street* (including house number), and *zipcode*. Occupation and employer are too inconsistently reported to be used as grouping variables.

- First names were cleaned of all prefixes, suffixes, grades, and titles. In addition, we built an index of first name variants (e.g., Rebecca, Beck, and Becky).
- Surnames were fuzzy grouped within addresses to account for typos.
- Street suffixes were homogenized (Drive, Dr, Drv,...) and street names (that include house numbers) were fuzzy grouped by donors' name. In addition, we created a variable that is the street name alone, to account for variation in the presence of suffixes, coordinates, etc. Building units were extracted from street strings, when applicable.
- Zipcodes were forced to their 5-digit format, and cities' and states' names were cleaned manually.

Step 2 We considered that two individuals were the same person if they matched exactly on three main characteristics and fuzzy matched on the fourth. In the case of first names, "fuzzy" meant using the first name variant index and in the case of zipcodes, it meant using the city and state instead. In other words, two individuals were considered to be the same person if they shared one of the following:

[4] The reason why we did not proceed with a fuzzy matching on the whole data is twofold. First, computational considerations: fuzzy grouping on strings require calculation of between-string distances and thus the computational task grows at $O(N^2)$. Given the size of our data and the length of the variables, it would require a lot of data segmentation. Second, the rules we specified are conservative and transparent, so we expect the false positive rate to remain very small.

- *first name*, *surname*, *full street*, and *zipcode*.
- *first name variant index*, *surname*, *full street*, and *zipcode*.
- *first name*, *fuzzy surname*, *full street*, and *zipcode*.
- *first name*, *surname*, *fuzzy street*, and *zipcode*.
- *first name*, *surname*, *full street*, and *city-state*.

A.4.2 Donor characteristics

Geography We used cleaned donors' addresses to get their geographic coordinates. To do so, we used an MIT-licensed US address locator on ArcMap 10.1. Addresses that did not match (because they were erroneous, incomplete, or were absent from the locator) were geolocalized based on their 5-digit zipcode or their state. The shares of donor-cycles matched in each step were 82%, 15.5%, and 2%.[5]

Once mapped, addresses localized at the building level were overlapped with GIS maps of census blocks' boundaries and with maps of congressional districts for each election cycle, both obtained from the U.S. Census Bureau. For addresses localized at the zipcode level, we used HUD-USPS crosswalks provided by the US Office for Policy Development and Research (Din and Wilson, 2020) to obtain both county and congressional district information.[6]

Demographics We used the surname and address of each donor to compute the probabilities that they belong to the different ethnic categories (white, hispanic, black, asian, other). We followed the method proposed by Imai and Khanna (2016), which originates from the public health literature (see, e.g., Elliott et al., 2009) and has since then been used by other social scientists (see, e.g., Grumbach and Sahn, 2020). Assuming that one's surname is uninformative of one's address once controlling for ethnicity, the posterior probability of belonging to ethnicity r =1,..,R can be written using Bayes' rule:

$$P(R_i = r|N_i = n, G_i = g) = \frac{P(G_i = g|R_i = r)P(R_i = r|N_i = n)}{\sum_{j=1}^{R} P(G_i = g|R_i = r_j)P(R_i = r_j|N_i = n)} \tag{1}$$

with

$$P(G_i = g|R_i = r) = \frac{P(R_i = r|G_i = g)P(G_i = g)}{\sum_{j=1}^{G} P(R_i = r|G_i = g_j)P(G_i = g_j)} \tag{2}$$

We used census data, obtained through the NHGIS (Manson et al., 2019), to compute the quantities

[5] About 0.5% of addresses are in foreign countries. Their coordinates were left missing.

[6] We used this correspondence only for zipcodes for which more than 98% of the zipcode territory lies in the same county/congressional district.

$P(R_i = r|N_i = n)$, $P(R_i = r|G_i = g)$, and $P(G_i = g)$ for each census geography (i.e., block-, tract-, county-, and state-levels). For donors that have a surname listed in the census lists (about 87%), we applied Bayes' rule using the smallest geographical level for which we had geolocalization. This produced probabilities for about 84% of the donor-years, 80% of which are estimated at the census block-level.

The last step required setting up a decision rule for assigning an ethnic group to each individual based on their inferred race probabilities. We chose the ethnicity of a donor as the one, if any, that had an assigned probability greater than 50%. Imai and Khanna (2016) discuss the reliability of this method in detail. Using voter registration data from Florida, they report that this decision rule achieves very low false positive rates for non-white individuals: 2.6% for Black individuals, 3.8% for Hispanic individuals, and .7% for Asian individuals. For White individuals, the decision rule is less precise and achieves 26% false positives. Hence, when studying donors' profiles in the aggregate, in Section 3, we use each of their race probabilities. For individual level analyses studying the effect of a match between the race of donors and candidates, in Section 4, we use the above decision rule in order to make the results interpretable.

To obtain gender probabilities, we merged donors' first names with the list of U.S. Social Security Administration historical baby names, using the R package `gender` (Mullen, 2021). Donors' first name was available for 97% of them. We then defined the donor's gender as the one, if any, with an assigned probability larger than 75%.

Occupation classification and income We sorted the (self-reported) occupations of donors using the 6-digit Standard Occupation Classification (SOC) of the U.S. Bureau of Labor Statistics (BLS). More precisely, we first classified occupations using the SOC 2018, which we used for the 2018 and 2020 cycles, and then mapped them into SOC 2000 (for the 2006-2008 cycles) and SOC 2010 (for the 2010-2016 cycles) using official crosswalks. Aside from the SOC, we also included categories for students, retirees, "not employed",[7] government employees (which lack a corresponding SOC), and "too vague" occupations (e.g., "INVENTOR"). Because the list of donors' unique occupations is extremely large (1,718,000) but a few occupations are shared by many individuals, we proceeded as follows: we ranked occupations by frequency of appearance and classified manually each occupation until the 2,500th most frequent one, using a keyword matching procedure. That is, we identified the smallest segment of the occupation string that would unambiguously classify that occupation without creating false positives. This meant that the procedure also classified a large number of occupations with lower frequency (e.g., classifying "COMMUNITY COLLEGE PROFESSOR" through the "COLLEGE PROFESSOR" segment also classifies "COLLEGE PROFESSOR OF ECONOMICS"). Overall, we classified the occupations of 93.6% of all unique donor-cycles (9% of which were allocated to the "too vague" category). Note that the occupation of the same donor can vary over

[7] Unfortunately, the extensive use of the "not employed" category prevents us from separating unemployed workers from inactive individuals and from distinguishing different types of inactivity.

time.

We then obtained information on the average and median wages of the 6-digit SOC categories using the "Occupational Employment and Wage Statistics (OEWS) Surveys" of every even year between 2006 and 2020 (Bureau of Labor Statistics, 2020), both at the state level and at the national level. We used the following procedure to merge these data: if available, we used the state-level wage of the same 6-digit SOC category (82.2% of cases); otherwise, if available, we used the state-level wage of the 5-digit SOC category; otherwise, if available, we used the national-level wage of the 5-digit SOC category; otherwise, if available, we used the state-level wage data of the 3-digit SOC category. Overall, this procedure provided wage information for 96% of all state-cycle-SOC categories.

House Value We merged donors' home addresses with the ZAsmt dataset of the ZTRAX Database, made available to researchers between 2016 and 2023 by *Zillow, Inc*. The ZAsmt dataset contains assessment data from local government (counties or cities) on real estate properties, which are regularly appraised for tax purposes (for more details, see Nolte et al., 2024).[8] The dataset covers the full list of properties in over 3,100 counties. Among a large set of home characteristics, it includes variables on the "Assessment Value" and "Market Value" of these properties. The Market Value of a property is a dollar amount appraisal meant to represent its value on the current housing market. The Assessment Value is calculated based on the Market Value by applying a conversion formula (more details below) and is used by governments to calculate taxes. Note that each local government uses its own methods to compute Market and Assessment Values.[9]

The ZAsmt dataset is divided between "current" data, which provide property values starting 12/30/2018 and is updated several times a year; and "historical" data, with property values dating back to 1999 and updated at most once a year. We extracted Assessment and Market Values for each year between 2005 and 2020, taking the data point that is the closest to December 31st when multiple updates per year were available.

Merger of Addresses. We matched donors' addresses using their house number, street name, city (or zipcode) and state, allowing for a fuzzy matching on the street name to account for typographic mistakes and abbreviations (more precisely, we require a restricted Damerau-Levenshtein distance in the street name of 0.9 or greater). In both the FEC and ZAsmt data, the reporting of the property's unit within a multi-home dwelling (when applicable) is not consistent. It thus happened that one donor's address matched with multiple properties in ZAsmt (or conversely), because one is in fact an entire building and the other a unit/apartment. We dropped the cases when one or multiple donors' apartments match an entire building in ZAsmt, as the

[8]The ZTRAX database also includes data on properties' transactions (ZTrans), but their geographical coverage is smaller.

[9]The City of Cambridge, for instance, reports that it "*must collect, record and analyze a great deal of information, including property and market characteristics, sales verification analysis, up-to-date construction costs and any changes in zoning, financing and economic conditions. The City of Cambridge Assessing Department uses the three nationally recognized appraisal approaches to value: cost, income and market. This data is then correlated into a final value. Prior to the issuing of tax bills, the City must submit the values to the State Department of Revenue for annual and triennial certifications.*"

property value imputed would be irrelevant. When a donor's address without a reported unit matched multiple units of the same building in the ZAsmt data, we selected the median property value of the matched units. Overall, we were able to match the addresses of 83.3% of our unique donor-cycles with at least one year-entry in the ZAmst dataset.

Attribution of Market Value. Not all entries in ZAsmt have non-missing Market Value, in particular in the years covered by the historical dataset. In fact, the share of merged properties in our sample with a non-missing Market Value ranges from 4.5% for 2007 values to 47.1% for 2019 values. We thus decided to focus on 2019-2020 values: to each address, we assigned the Market Value of 2019, 2020, or the mean of the two, depending on data availability. Assessment Values are available for a larger fraction of addresses (up to 69.83% in 2019). We thus implemented a procedure to complete Market Values with a proxy based on Assessment Values when the former are missing but the latter are available. Our goal was to reverse engineer the county-specific formula applied by local governments, based on the cases in which both Assessment and Market Values are available (this formula is often a simple ratio). Concretely, in county-years for which we have 20 or more observations with both Assessment and Market Values in the ZAsmt dataset, we computed the modal conversion rate between the two. We then used these county-year-specific rates to calculate estimated Market Values on the sample of observations with *both* Assessment and Market Values. We averaged within each county-year these estimated Market Values and compared them to the average, real Market Value using a t-test of difference in means. We kept only conversion rates of county-years for which the p-value of this test is greater than 0.9, and we used them to compute estimated Market Values for all entries for which the Assessment Value is available but the Market Value is missing. Overall, we obtained a consistent 2020-cycle Market Value for 41.2% of all donor-cycles.

A.4.3 Building a consistent classification of small donors

To determine whether an individual's contribution to a committee is below $200, we distinguished two sets of committees. The first set, accounting for the vast majority of committees, only itemizes direct contributions of an individual when their total during the electoral cycle reaches more than $200, in compliance with the FEC mandate described in Section 2.1. In this case, we determined that the individual gave less than $200 if we do not observe any direct contribution to the committee and if the sum of all their contributions to the committee through conduits was lower than $200. The second set includes the committees that choose to itemize all the contributions they receive.[10] In that case, we determined that an individual gave less than $200 if the sum of all their direct and earmarked contributions to the committee is lower than $200.

Note that there are two data-driven imperfections in our identification of small and large donors and their

[10]Culberson et al. (2019) call these committees "serial reporters." We identified committees in this category by the fact that their total unitemized contributions are null. They account for about 12% of all committee-cycles.

contributions. First, we miss a small subset of small donors, namely donors who do not use conduits and who contribute less than $200 to all the candidates they contribute to directly. We do not know the exact number of these "hidden donors" (a terminology proposed by Alvarez et al., 2020), but we know that it is small, especially in recent years: recall from Figure 1 that, thanks to the growing use of conduits, we observe the vast majority of contributions in the last elections. Second, the observed total contributions of a large donor may be lower than the actual total, and even under $200. This issue arises for donors who made their contributions in several installments, with the first ones being below $200. We are not too concerned with these cases since (i) for the same reasons as for hidden donors, they only represent a small share of total contributions; and (ii), even though their computed total contribution is incorrect, they are correctly labeled as "large" and not "small" donors.

It is interesting to note that, as it appears clearly in Figures E.2 and E.3, our definition of small donors implies that contributions made by small donors are not equal to committees' aggregate unitemized contributions. This is because the latter also include (i) contributions to committees that total less than $200 but were made by donors who contributed more than $200 to at least one other committee, as well as (ii) contributions made by donors to committees to which they would give more than $200 in total, before that threshold was reached.

A.5 Processing the data on committees and candidates

A.5.1 Mapping between committees and candidates

All contributions in our data indicate a recipient committee. We mapped these committees to the individual candidate they are connected to, if any.

All candidates must have one committee that is solely linked to their campaign, called the *principal* committee. In addition, they can have other *authorized* committees, either dedicated to themselves or shared with other candidates or parties. These committees can transfer unlimited funds to each other and are grouped together for the purpose of contribution limits.[11] Authorized committees shared by multiple candidates and/or parties are called *joint* committees. They are usually created to facilitate fundraising, as they are allowed to raise large contributions that are then split across committees' participants (candidates and/or parties), taking into account their respective limits.[12]

As a result of these features, the mapping between candidates and committees is of the form many-to-many. There are at least two reasons why this is not ideal for our analysis. First, it is not clear how we should interpret a contribution that is made to several candidates at the same time (even assuming that the

[11] Like individuals, all committees face specific limits on how much they can contribute to a single candidate or to other committees.

[12] This is possible since *McCutcheon v. FEC 2014*. Beforehand, contributions to a joint committee counted towards the joint committee's limit.

donor is aware of all the candidates they give to, which is not certain). Second, not all committees indicate properly that a contribution is joint and how it will be split across committee participants, rendering the attribution difficult. Hence, we did not link joint committees (11% all committee-cycles, accounting for 4% all individual contributions) to their affiliated candidates, thereby turning the mapping between candidates and committees into a 1-to-m setting.[13] This allowed us to map each contribution to at most one recipient candidate, using the crosswalks provided by the FEC in its "bulk files" section.

A.5.2 Electoral and demographic characteristics

Electoral data We obtained candidates' vote counts from FEC official election results tables.

Demographics We manually coded the ethnicity of all candidates running in any election between 2006 and 2020 using Internet searches.[14] We also collected manually the gender of candidates whose first name is less than 99% predictive of their gender, based on the method described above to determine the gender of donors.

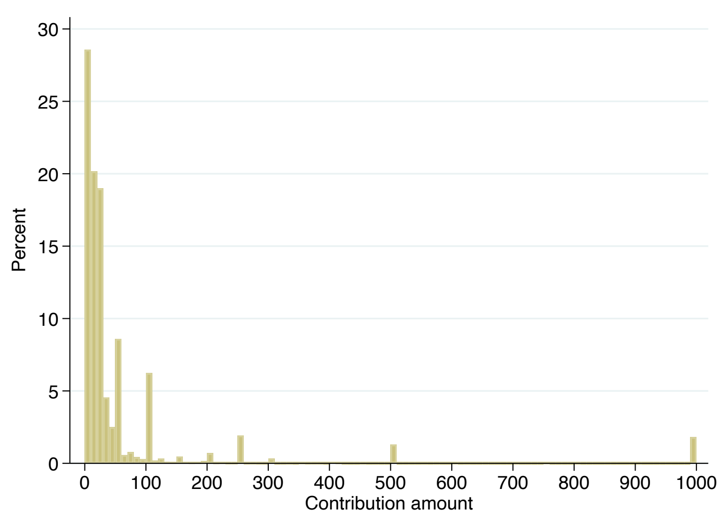
A.5.3 General vs. primary elections

To differentiate between general and primary election contributions, we used the date contributions were received by committees and compared it to the official primary dates of the relevant election provided by the FEC. We use this method instead rather than on the election type variable provided by the FEC because that variable is often missing or incorrect or records the election that the contribution was assigned to by the committee even though the contribution was made for a previous election. We defined congressional primary election contributions as those made before or on the date of the primary election in the corresponding state, and presidential primary contributions as those made before or on the day of the de facto nomination (i.e. when all other candidates retracted and / or the eventual candidate was declared the presumptive nominee). Contributions to the general election are those made between the date of the primary (or the first date of the two-year election cycle, if no primary was held) and a week after the general election date. This classification remains imperfect because (i) contribution receipt dates sometimes differ from the date in which the contribution was actually made, which we partially address by including contributions made up to one week after the general election, and (ii) some contributions made before the end of the primary are designated by the donor for the general election, and vice versa. Our reading of the data is that measurement errors induced by these two imprecisions are very limited.

[13]Some joint committees split their proceeds between a candidate and a party (such as "TRUMP MAKE AMERICA GREAT AGAIN," between Donald Trump and the Republican Party). We do link these to the relevant candidate.

[14]We do not use the automatic method we used for donors because candidates are much more likely to be non-representative of their underlying population than donors.

A.6 Summary statistics of the final dataset



Notes: The figure plots the distribution of the dollar value of contributions made by individual donors and reported to the U.S. Federal Election Commission for the 2006 to 2020 election cycles. We use bins of $10 and winzorize the variable at the 99th percentile (i.e. $1,000).

Figure A.2: The distribution of contributions made by individual donors and reported to the U.S. Federal Election Commission, 2006-2020

Table A.1: Summary statistics on all observable contributions by election cycle, 2006-2020

	Mean	St.Dev	P25	Median	P75	Obs
2006	292.1	972	25	60	250	5,220,840
2008	299.2	1,161	25	75	250	10,135,950
2010	237.7	1,915	22	50	154	8,014,443
2012	237.0	6,841	15	38	100	16,379,566
2014	149.9	7,765	8	25	50	16,592,807
2016	129.6	8,222	6	20	50	37,253,535
2018	85.7	8,476	5	12	26	51,068,028
2020	59.7	5,988	5	15	35	195,015,888

Notes: The table provides summary statistics for all observable contributions by individual donors included in our dataset, separately by two-year election cycle, from 2006 to 2020. Amounts are in current US dollars.

B ActBlue, WinRed, and the candidates using them

ActBlue was created in 2004 to help the Democrats raise political contributions. Formally, ActBlue is a nonprofit organization. Its stated mission is to "empower small-dollar donors." Groups that use ActBlue pay a 3.95% transaction fee to cover processing costs. As a nonprofit, ActBlue also runs its own, separate fundraising program and accepts tips on contributions to cover its own expenses.[15] Candidates which adopt ActBlue can receive online contributions without having to set up their own fundraising platform. They simply need to include a link on their website which redirects potential donors to a page dedicated to them on ActBlue's website.[16] In some cases, this page is so customized that nothing but the url suggests to the viewer that they are on a third party (ActBlue) website.

ActBlue also facilitates political contributions on the donors' side.[17] Donors can contribute to candidates seamlessly, from their computer or their smartphone. Once they have entered their personal information and payment card number, an additional contribution is just one click away. Moreover, on ActBlue's website, users can browse and search for candidates and groups to donate to. This is done without ActBlue favoring any candidate or cause (if ActBlue did that, it would endanger its conduit status).

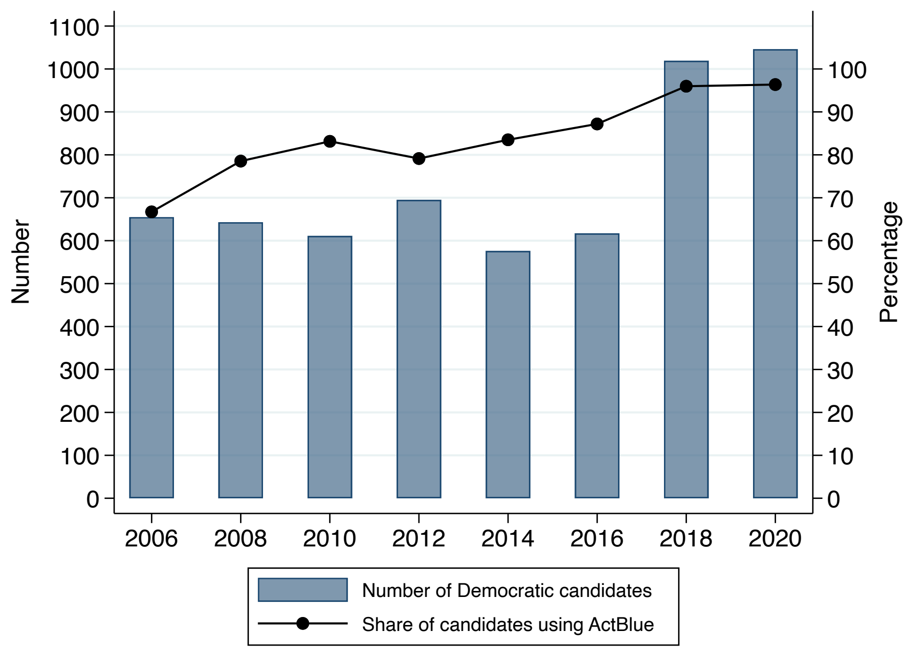
WinRed was launched in February 2019, with the explicit aim of being the Republican equivalent of ActBlue, thus mimicking many of ActBlue's features. Contrary to ActBlue, WinRed is registered as a for-profit organization. Its launch was immediately followed by active efforts from the Republican Party's leadership to disseminate its use among Republican congressional candidates (many of whom were using competing online payment services at the time).

Unsurprisingly, the increase in the number of ActBlue and WinRed contributions was concomitant with an increase in the fraction of candidates using these conduits. The share of Democratic congressional candidates receiving at least one contribution through ActBlue rose from 67% in 2006 to 96% in 2020 (Figure B.1). On the Republican side, around one third of candidates used WinRed during the first election cycle after it was launched (2020). As shown in Figure B.2, the fraction of candidates using ActBlue and WinRed is slightly higher among incumbents and, interestingly, among women candidates. It is also higher among White candidates than Blacks and Hispanics, but this difference has slightly receded over time.

[15] See e.g., "How ActBlue Is Trying To Turn Small Donations Into A Blue Wave," *FiveThirtyEight*, Carrie Levine and Chris Zubak-Skees, 25 October 2018.

[16] See e.g., "How ActBlue Became a Powerful Force in Fund-Raising," *The New York Times*, Derek Willis, 9 October 2014.

[17] See e.g., "How Small Donations Gave Underdog Democrats a Fighting Chance for the House," *The Washington Post*, Michelle Ye Hee Lee, 4 November 2018.

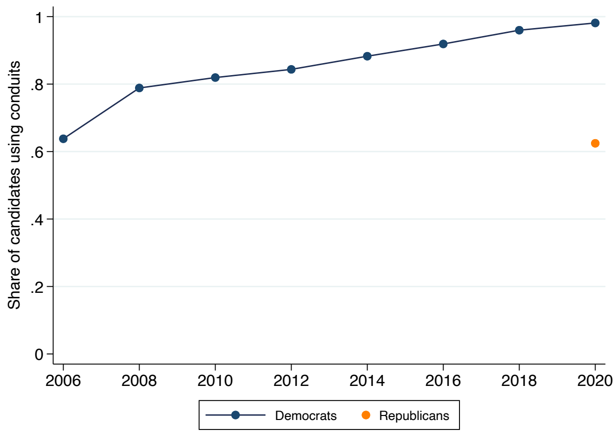


Notes: The figure represents the number of Democratic congressional candidates (left y-axis) and the share of these candidates (right y-axis) using ActBlue by two-year election cycle.

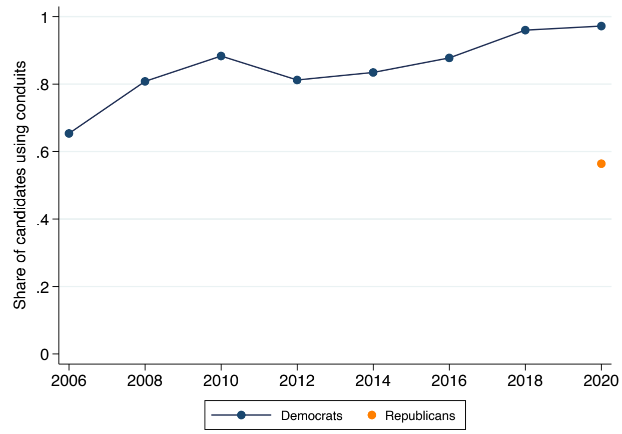
Figure B.1: The share of Democratic congressional candidates using ActBlue, 2006-2020

Figure B.2: The share of congressional candidates using conduits, depending on their characteristics, 2006-2020

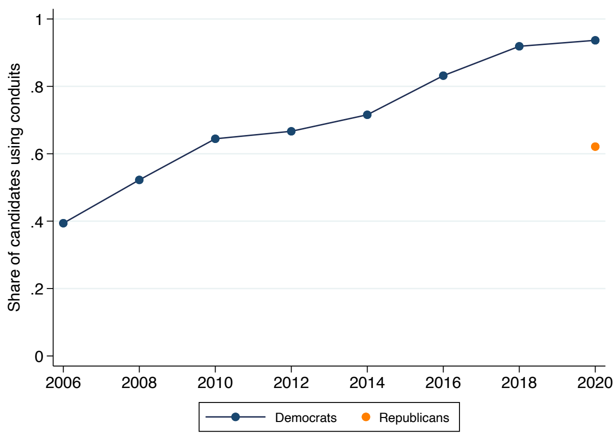
(a) **Female candidates**



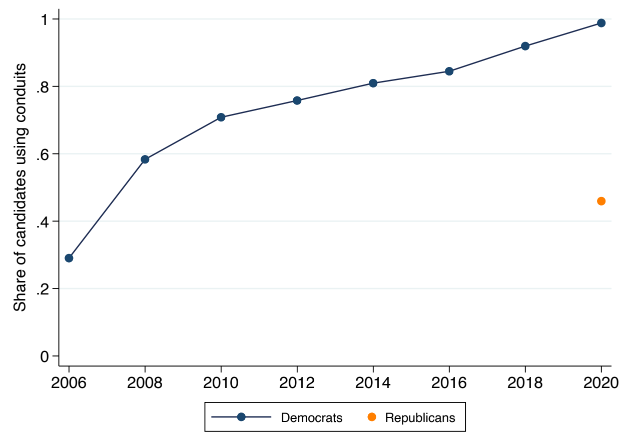
(b) **White candidates**



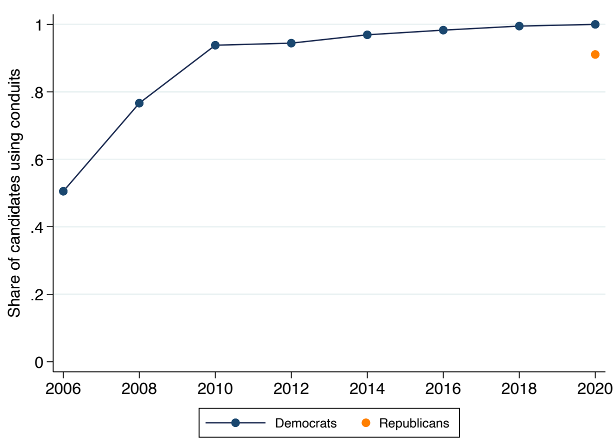
(c) **Black candidates**



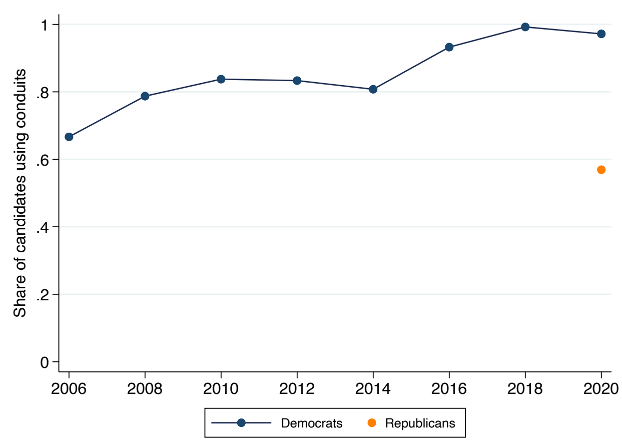
(d) **Hispanic candidates**



(e) **Incumbent candidates**



(f) **Candidates in close races**



Notes: The figure plots the evolution of the share of Democratic congressional candidates using ActBlue (blue line with dots) and the share of Republican congressional candidates using WinRed (red dots), for different groups of candidates, 2006-2020. Since WinRed was introduced in 2019, we only have one observation for Republican congressional candidates, that corresponds to the 2020 election cycle.

C Replication of the results of Spenkuch and Toniatti (2018)

For detailed information on the sources of data used to measure electoral outcomes and covariates and replicate the results in Spenkuch and Toniatti (2018), see their original paper. Electoral results for the presidential and Senate races come from the CQ Voting and Elections Collection. Results for the House races come from the Leip Election Atlas. We use the same specification as Spenkuch and Toniatti (2018) in order to best replicate their results. Specifically, we focus on the 60-day period leading to the general election and we cluster standard errors two-way, by state and by DMA border.

We first measure the effects of TV ads on the results of presidential elections. While Spenkuch and Toniatti (2018) study the 2004, 2008, and 2012 presidential elections, we consider the 2012, 2016, and 2020 elections, corresponding to our sample period. We then measure the effects of TV ads on the results of congressional elections, as in Sides et al. (2021). While Sides et al. (2021) study the 2000-2018 congressional elections, we consider the 2012 to 2020 elections, which correspond to our sample period. In a few states and years (five in total in the sample), two Senate races took place at the same time. In these cases, TV ads are summed over the two races, and voter turnout and the difference between the Democratic and Republican vote shares are averaged over the two races.

As shown in Table C.1, Panel (a), consistently with Spenkuch and Toniatti (2018), we do not find any significant effect of TV ads on aggregate turnout in the 2012, 2016, and 2020 presidential elections (columns 1 to 4). We also find that the difference between the number of Democratic and Republican ads increases the difference between the vote share of the Democratic and Republican candidates (columns 5 to 8), though it is only statistically significant in 2012. Averaged over 2012, 2016, and 2020, an increase in the number of Democratic ads by 1,000, relative to Republican candidates, increases the difference in vote shares by 0.06 p.p.[18]

We now turn to the effects of TV ads on the results of congressional races. As shown in Table C.1, Panel (b), we do not measure any significant impact on voter turnout averaged across all years, despite positive effects on participation in 2014 and 2018 (columns 1 to 6). The effects on vote shares are large and significant (columns 7 to 12). An increase by 1,000 in the difference between the number of local ads aired by Democratic and Republican candidates increases the difference between the Democratic and Republican vote shares by 0.55 p.p. on average, in the five Senatorial and House elections between 2012 and 2020.

Put together, the estimates in Panels (a) and (b) of Table C.1 corroborate Sides et al. (2021)'s conclusion that TV ads have larger effects on electoral outcomes in down-ballot elections than in presidential ones.

[18] The point estimates for the effects on turnout and vote shares in 2012, which is the one year in common with Spenkuch and Toniatti (2018), are nearly exactly identical as in their paper, as should be expected.

Table C.1: The effects of TV ads on electoral outcomes, 2012-2020

(a) **Presidential elections**

	Turnout				Dem-Rep Votes			
	(1) 2012	(2) 2016	(3) 2020	(4) 2012-2020	(5) 2012	(6) 2016	(7) 2020	(8) 2012-2020
All Parties Ads (Total number, in 1000s)	0.04	0.04	0.02	-0.00				
	(0.03)	(0.04)	(0.02)	(0.02)				
Dem-Rep Difference in Ads					0.33***	0.10	0.00	0.06
					(0.09)	(0.13)	(0.02)	(0.06)
County-Pair x Year FE	✓	✓	✓	✓	✓	✓	✓	✓
County FE				✓				✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Lagged Dep.	✓	✓	✓		✓	✓	✓	
R-sq (within)	0.847	0.822	0.863	0.010	0.968	0.958	0.980	0.123
Observations	5,058	5,058	5,058	15,174	5,058	5,058	5,058	15,174
Clusters	450+46	450+46	450+46	450+46	450+46	450+46	450+46	450+46
Mean DepVar	55.46	54.99	57.92	56.12	-23.34	-36.40	-35.93	-31.89

(b) **Congressional elections**

	Turnout						Dem-Rep Votes					
	(1) 2012	(2) 2014	(3) 2016	(4) 2018	(5) 2020	(6) 2012-2020	(7) 2012	(8) 2014	(9) 2016	(10) 2018	(11) 2020	(12) 2012-2020
All Parties Local Ads (Total number, in 1000s)	0.07	0.09***	0.01	0.05***	-0.01	0.01						
	(0.09)	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)						
Dem-Rep Difference in Local Ads							0.56	1.30***	0.99***	0.39	0.13	0.55***
							(0.56)	(0.43)	(0.33)	(0.23)	(0.15)	(0.17)
County-Pair x Year x Office FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
County x Office FE						✓						✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lagged Dep.	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	
R-sq (within)	0.628	0.684	0.737	0.789	0.862	0.017	0.611	0.773	0.762	0.838	0.892	0.026
Observations	6,038	6,384	6,274	5,948	6,518	31,162	6,038	6,384	6,274	5,948	6,518	31,162
Clusters	440+46	412+44	439+44	433+43	413+44	450+46	440+46	412+44	439+44	433+43	413+44	450+46
Mean DepVar	53.46	35.06	48.68	45.17	56.60	47.80	-23.16	-32.69	-35.51	-27.40	-40.53	-32.04

Notes: Models are estimated using OLS. An observation is a county-cycle-office. In Panel (a), the sample includes all county-pairs in the 2012, 2016, and 2020 presidential elections. In Panel (b), we combine House and Senate races for the 2012 to 2020 elections. The sample includes all county-pairs with border-counties located in the same congressional district, for House races, and all county-pairs in which a Senate race took place. In columns 1 to 4 of Panel (a) and 1 to 6 of Panel (b), the dependent variable is turnout; in columns 5 to 8 of Panel (a) and 7 to 12 of Panel (b), it is the difference between the Democratic and Republican candidates' vote shares. Controls include all other political ads aired in the county (for presidential elections, these are House, Senate, governor, and other down-ballot races' ads; for senatorial elections, presidential, House, non-local Senate, governor, and other down-ballot races' ads; and for House elections, presidential, Senate, non-local House, governor, and other down-ballot races' ads), measured in the same way as the main dependent variable (the sum of all parties ads in columns 1 to 4 of Panel (a) and 1 to 6 of Panel (b), and the difference between Democratic and Republican ads in columns 5 to 8 of Panel (a) and 7 to 12 of Panel (b)), together with a set of socio-demographic characteristics of the county (total population, share of high-school dropouts, share of college graduates, share of ethnic minority population, share of foreign-born population, median household income, share of population below the poverty line, and employment-to-population ratio). Single-cycle estimations (columns 1 to 3 and 5 to 8 in Panel (a), and columns 1 to 5 and 7 to 11 in Panel (b)) include the value of the dependent variable in the previous election cycle ("lagged") as a control. Standard errors are shown in parentheses and clustered at the state and DMA border levels. * p<0.10, ** p<0.05, *** p<0.01.

D Processing of Meta's ads data

Using the Facebook API, we scraped all "Political and Issue Ads" diffused on Meta's platforms between May 7, 2018 (when the data start being available) and November 30, 2022. These data include two datasets. The "Ad archive" dataset contains information on the content and reach of all ads since May 7, 2018. We scraped it using a Python script requesting all ads made by a Facebook page (identified with a "page id"), for all Facebook pages issuing at least one ad (as listed in the "lifelong advertisers" file provided by the API). We obtained 14,300,871 ads. The "Ad targeting" dataset contains information on the targeting of all ads since August 3, 2020. We scraped it through FORT, an online Jupyter console, available with a VPN, both provided by Facebook. We obtained a total of 5,484,022 ads.

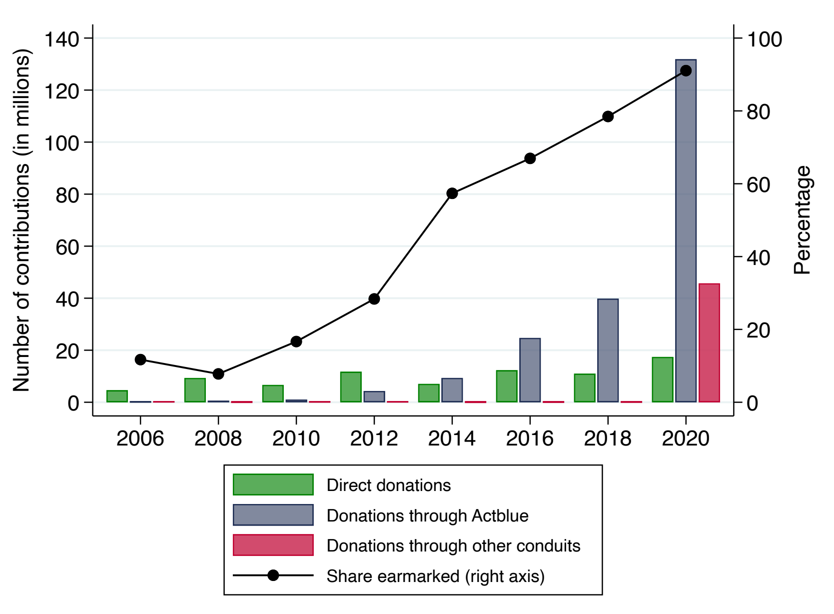
Our analysis uses the "Ad archive" dataset as it covers the entire 2020 cycle. We started by merging the ads with the House and Senate candidates of our contributions dataset, using the names of the Facebook pages that made the ads. This involved cleaning those names as well as, for homonym pages, identifying which page(s) are those of the relevant candidate. Some pages are not matched with a congressional candidate, because they are independent from any candidate, and some candidates are associated with multiple pages. 49% of all candidates receiving donations and all candidates receiving more than $25,000 of individual donations merged with a Facebook page. We then extracted geographical information about the viewing of the ad from the "delivery by region" variable. Information on the share of viewers across U.S. states, our unit of analysis, is available for about 68.5% of ads from congressional candidates. The other ads, for which that information is missing or available at other, unsystematic geographical levels, were dropped from the analysis.

We then computed the number of ads, estimated cost, and total impressions at the candidate-state-week level, our unit of analysis. Meta provides a bracket of the total number of impressions (e.g., 1-999) and estimated cost in dollars (e.g., 1000-5000). We compute the number of impressions in a state by multiplying the mean of the bracket with the state share. The data also includes information on the exact timing of each ad. 316,724 ads were made during the 2020 cycle by Democratic congressional candidates. A candidate can post multiple ads on the same day, targeting different areas or different groups. Ads can run for multiple days, with a medium length of nine days.

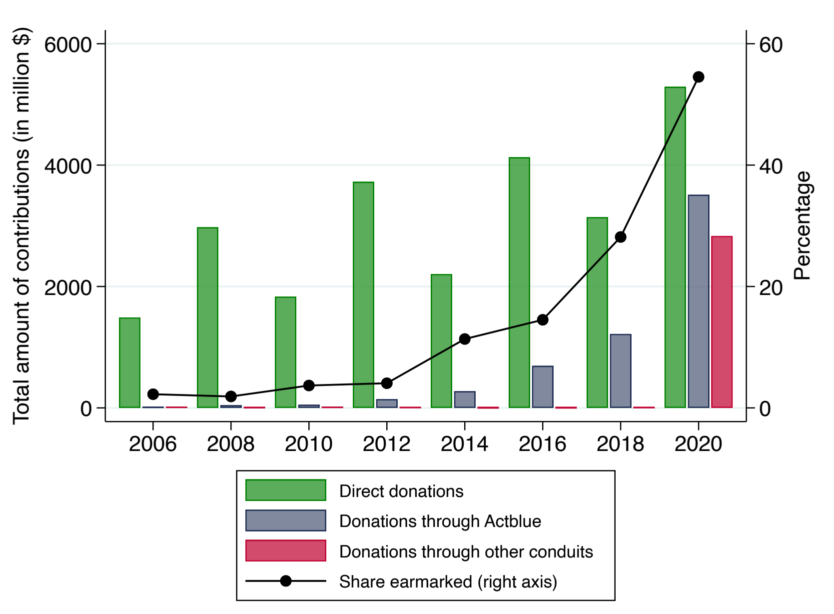
E Additional figures

Figure E.1: The number and total amount of contributions, by conduit, 2006-2020

(a) **Number of donations**

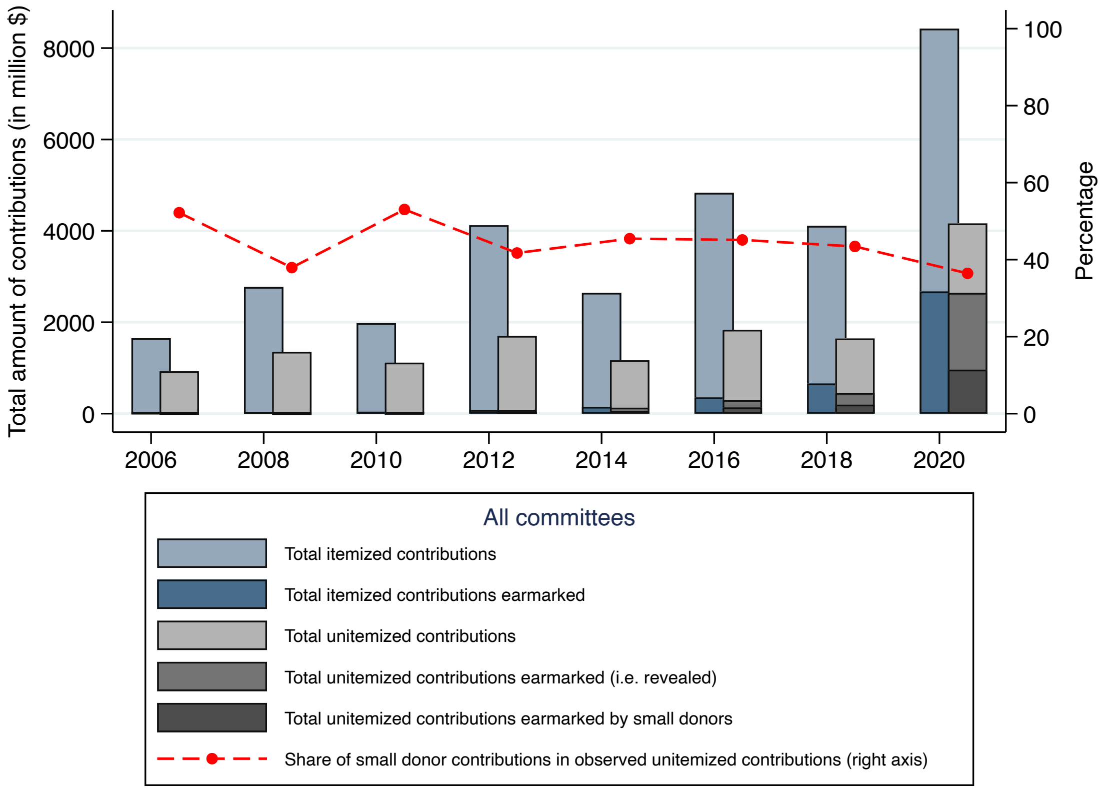


(b) **Total dollar amount**



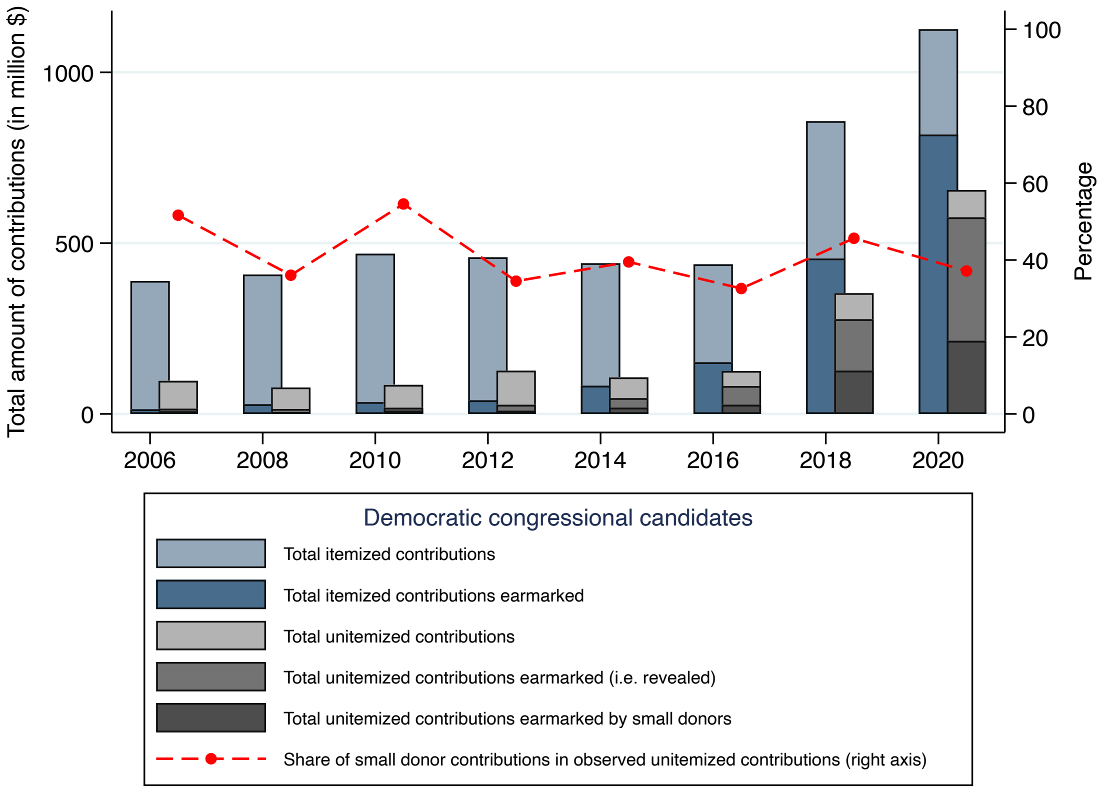
Notes: The figure shows the number (Figure E.1a) and total amount (Figure E.1b) of donations made by individual donors between 2006 and 2020, by two-year election cycle, and depending on whether donations were made directly to committees (i.e., not using a conduit), through ActBlue, or through another conduit (including WinRed). For a small fraction of conduit donations, the conduit name cannot be determined (see Section A.3.1): their totals are assigned to ActBlue totals and to other conduit totals based on these two groups' respective share of total conduit contributions in each cycle. The sample includes all donations with itemized information – that is, it excludes non-earmarked unitemized contributions (for which the total number of donations is unknown).

Figure E.2: Total amount of contributions received by all committees, depending on their type, 2006-2020



Notes: The figure plots the evolution of the donations received by all committees. Light blue and light gray represent the aggregate contributions these committees report in their financial summaries. Darker bars indicate the quantity of these contributions that are earmarked, as observed in our data, and the quantity of these contributions that are made by small donors.

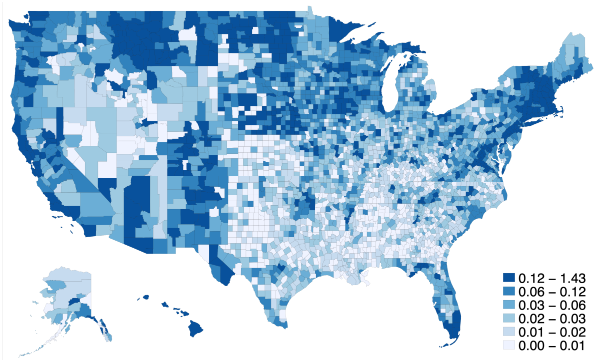
Figure E.3: Total amount of contributions received by Democratic congressional candidates, depending on their type, 2006-2020



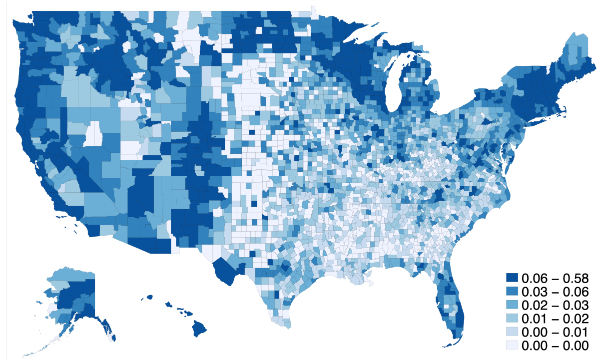
Notes: The figure plots the evolution of the donations received by Democratic congressional candidates. Light blue and light gray represent the aggregate contributions these candidates report in their financial summaries. Darker bars indicate the quantity of these contributions which are earmarked, as observed in our data, and the quantity of these contributions which are made by small donors.

Figure E.4: The geographic distribution of small and large donors, Democratic congressional candidates, 2012-2018

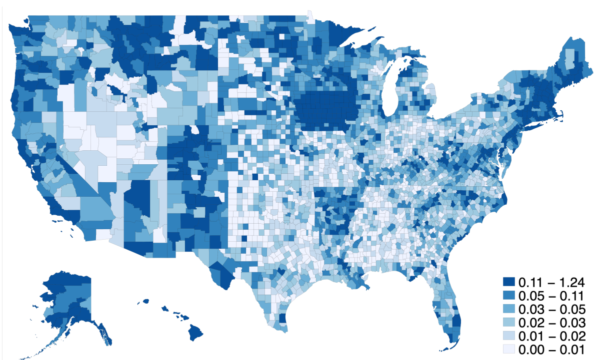
(a) **% of small donors in population 2012**



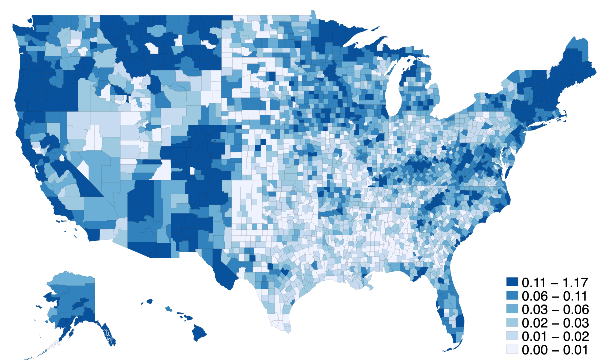
(b) **% of large donors in population 2012**



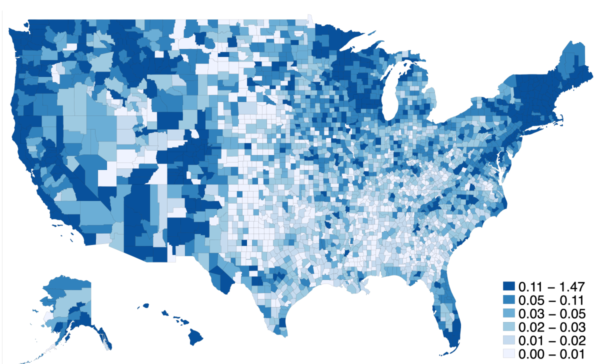
(c) **% of small donors in population 2014**



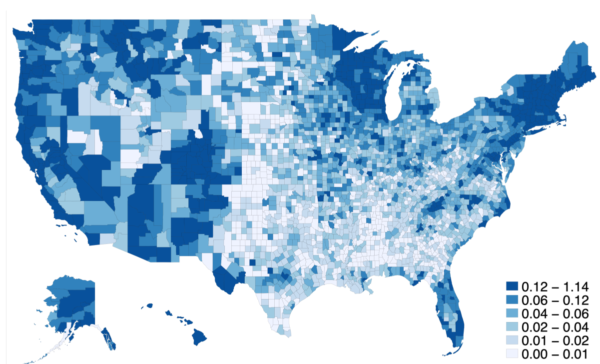
(d) **% of large donors in population 2014**



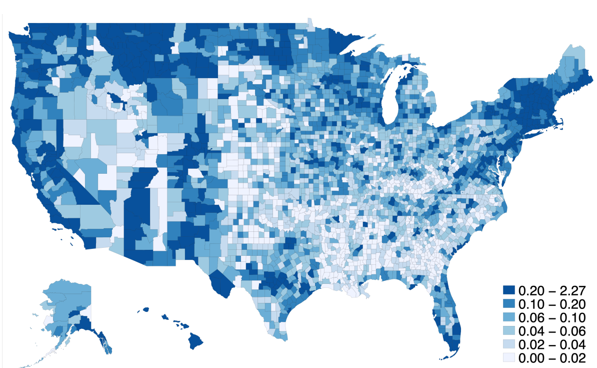
(e) **% of small donors in population 2016**



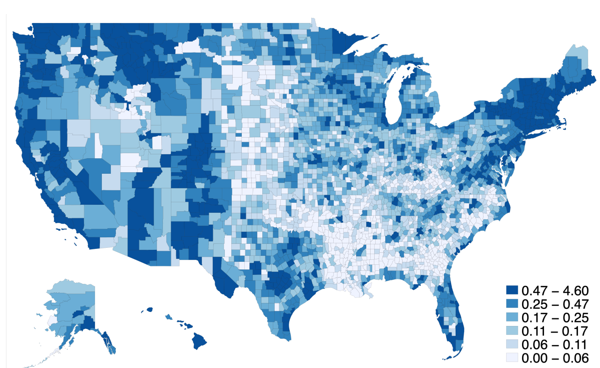
(f) **% of large donors in population 2016**



(g) **% of small donors in population 2018**

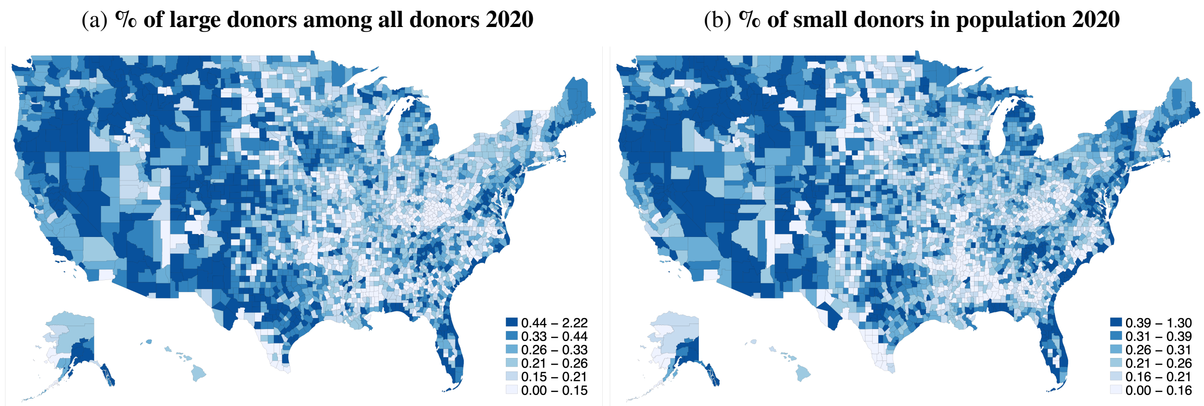


(h) **% of large donors in population 2018**



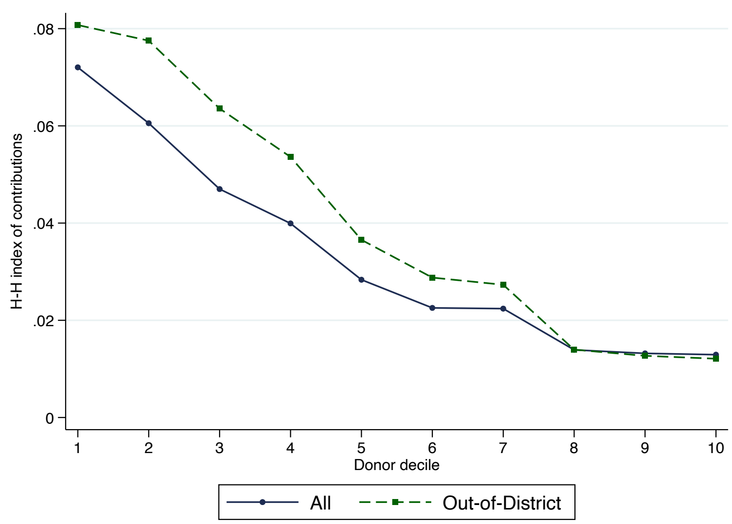
Notes: The figures map the large donors (left panels) and small donors (right panels) to Democratic congressional candidates of the 2012, 2014, 2016, 2018 election cycles, in the U.S. county these donors live in, as a share of the county population.

Figure E.5: The geographic distribution of small and large donors, Republican congressional candidates, 2020



Notes: The figures map the large donors (panel E.5a) and small donors (panel E.5b) to Republican congressional candidates of the 2020 election cycle, in the U.S. county these donors live in, as a share of the county population.

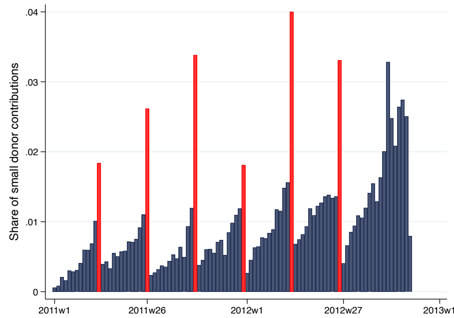
Figure E.6: The concentration of contributions by donors' deciles, Democratic congressional candidates, 2012-2020 primary elections



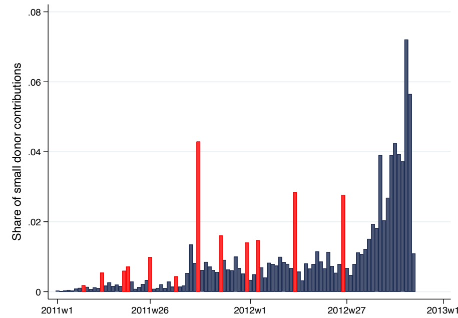
Notes: The figure plots the Herfindahl-Hirschman index of concentration of all (continuous blue line with dots) and out-of-district contributions (dashed green line with squares) to Democratic congressional candidates, for different deciles of donors grouped based on the maximum total contributions they make to a candidate during an election cycle, for each primary election cycle between 2012 and 2020 and then averaged over all cycles.

Figure E.7: The timing of small and large donor contributions, 2012-2018

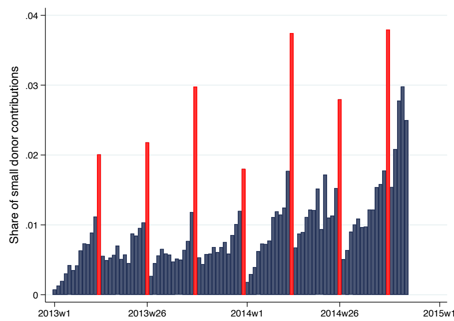
(a) **Large Donors 2012**



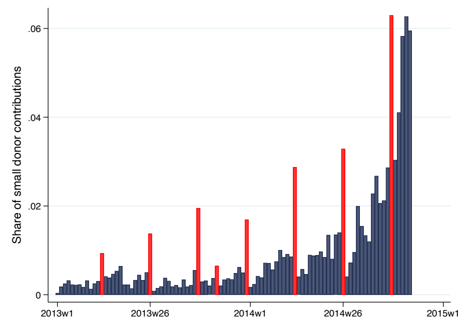
(b) **Small Donors 2012**



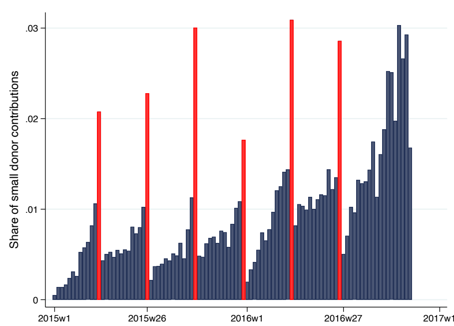
(c) **Large Donors 2014**



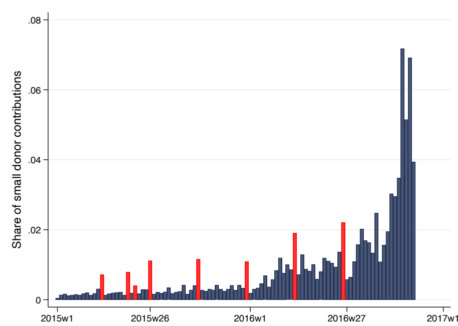
(d) **Small Donors 2014**



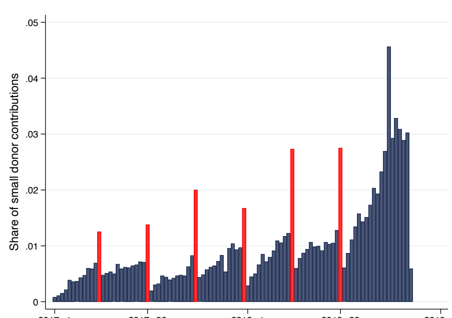
(e) **Large Donors 2016**



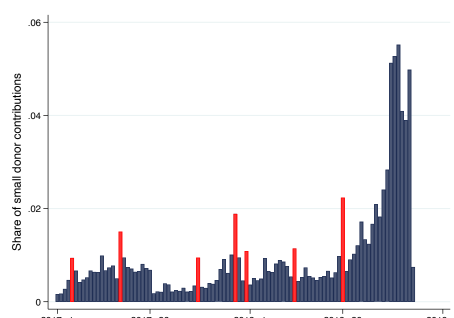
(f) **Small Donors 2016**



(g) **Large Donors 2018**



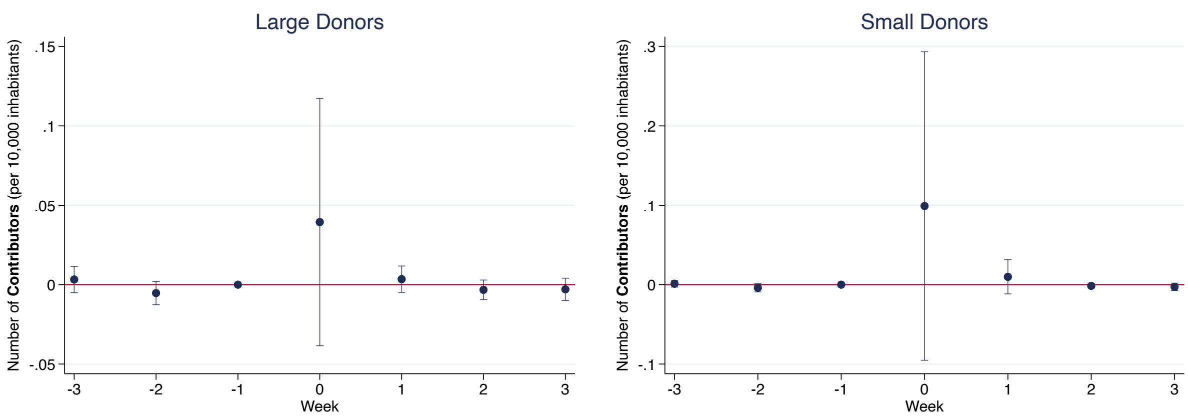
(h) **Small Donors 2018**



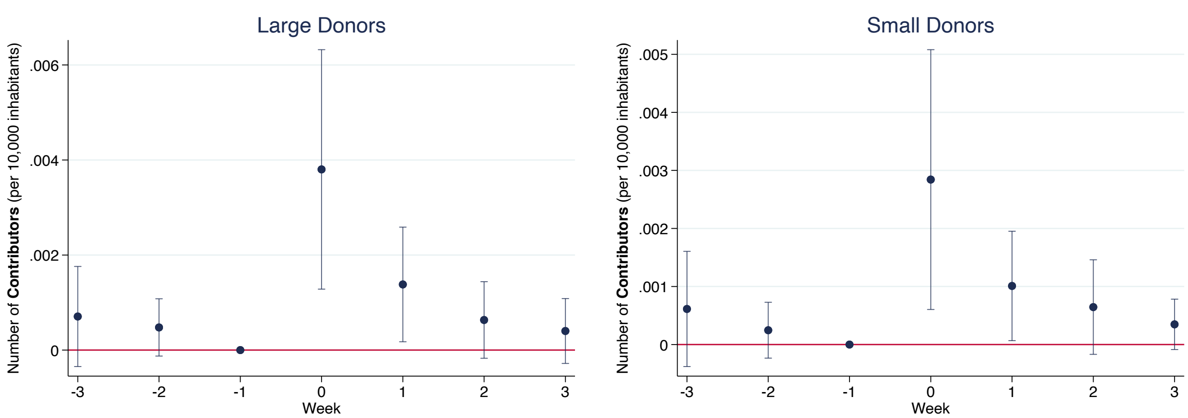
Notes: The figures plot the share of small and large donor contributions made to Democratic congressional candidates on each week of the 2012-2018 election cycles up to the week of the election, as a share of the total contributions made over the cycle to these candidates. We highlight in red the weeks during which contributions were higher than 1.5 times the mean of the previous and following months or 2 times the level of the previous week and the following week.

Figure E.8: The effects of social media ads on the number of small and large donors, Democratic congressional candidates, 2020 election cycle

(a) **General Elections**



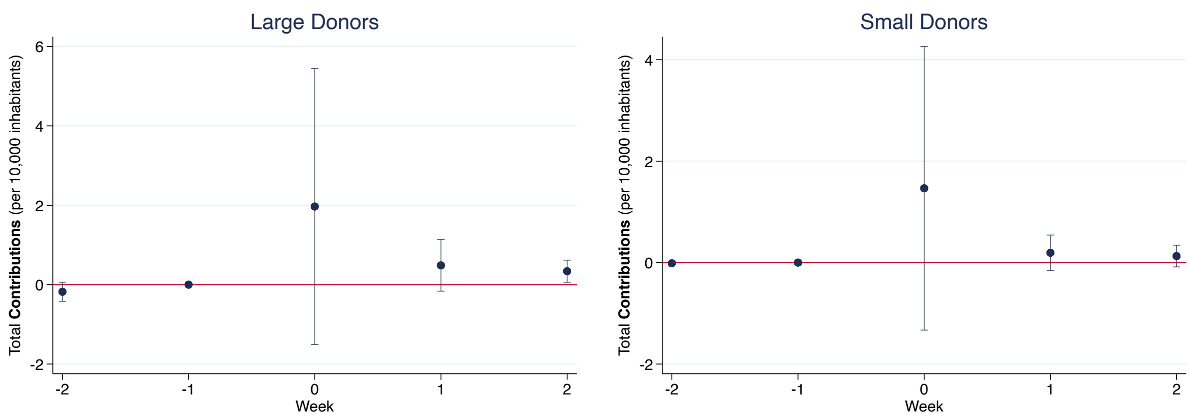
(b) **Primary Elections**



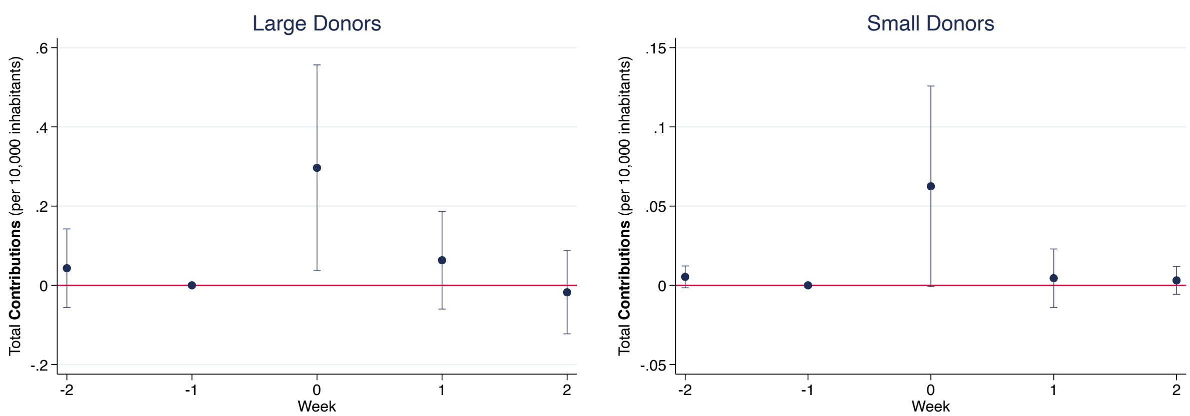
Notes: The figure shows point estimates and 95% confidence intervals associated with the event-study results of the estimator developed by de Chaisemartin and D'Haultfoeuille (2024). An observation is a candidate-state-event-week. The sample includes all congressional Democratic candidates who ran at least one ad-event on Meta's platform during the 2020 election cycle. Estimations also include week-state fixed effects. The dependent variable is the number of unique donors during that week by small and large donors from the corresponding state to the candidate posting the ad, per 10,000 state inhabitants. The top panel focuses on the general elections and the bottom panel on the primary elections. Standard errors are clustered at the candidate x week of the event level. The corresponding point estimates are shown in Table F.17, Panel (b).

Figure E.9: The effects of social media ads on small and large donor contributions, Democratic congressional candidates, 2020 election cycle, shorter time window (events separated by two weeks or more without ads)

(a) **General Elections**



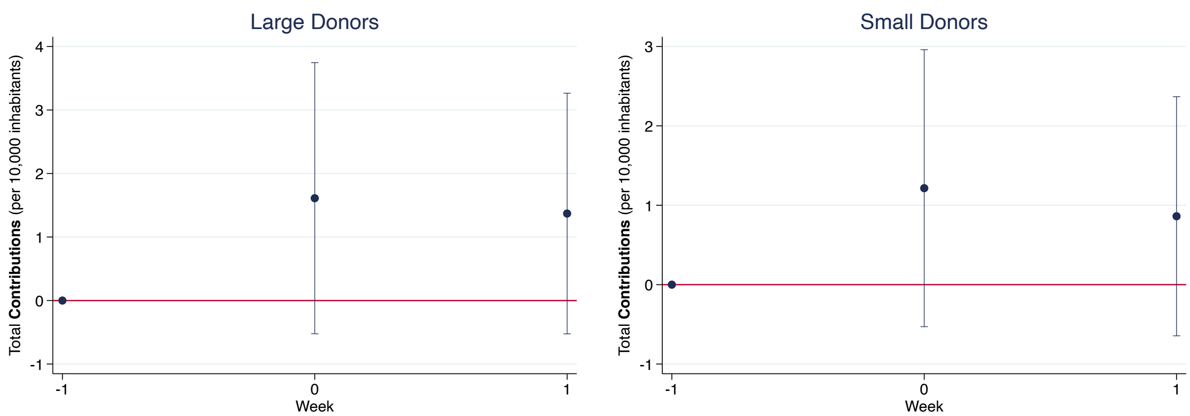
(b) **Primary Elections**



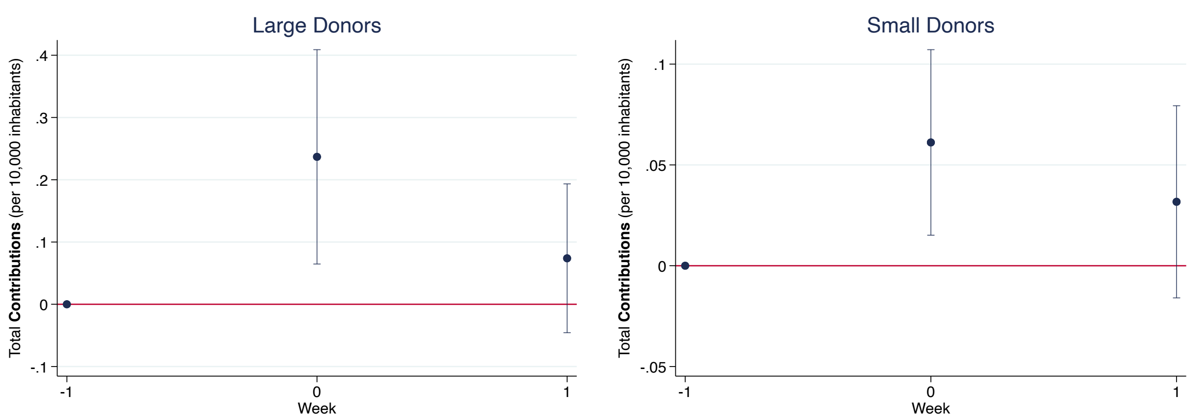
Notes: The figure shows point estimates and 95% confidence intervals associated with the event-study results of the estimator developed by de Chaisemartin and D'Haultfoeuille (2024). An observation is a candidate-state-event-week. The sample includes all congressional Democratic candidates who ran at least one ad-event on Meta's platform during the 2020 election cycle. Estimations also include week-state fixed effects. The dependent variable is the total dollar amount of contributions made that week by small and large donors from the corresponding state to the candidate posting the ad, per 10,000 state inhabitants. The top panel focuses on the general elections and the bottom panel on the primary elections. Standard errors are clustered at the candidate x week of the event level. The corresponding point estimates are shown in Table F.18, Panel (a).

Figure E.10: The effects of social media ads on small and large donor contributions, Democratic congressional candidates, 2020 election cycle, shorter time window (events separated by one week or more without ads)

(a) **General Elections**



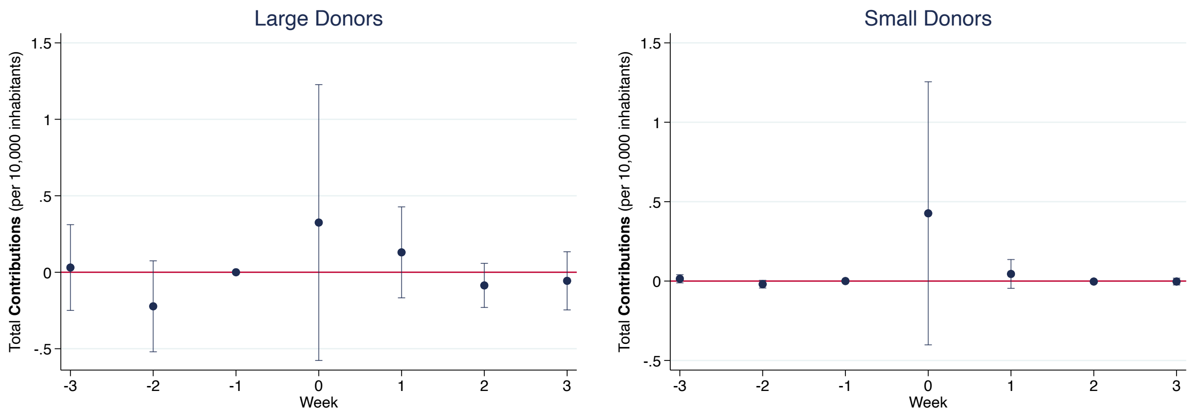
(b) **Primary Elections**



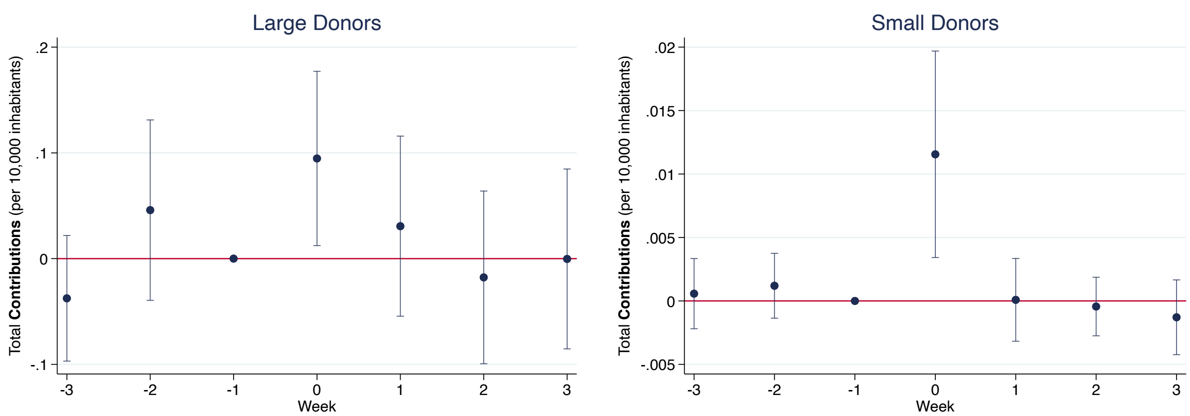
Notes: The figure shows point estimates and 95% confidence intervals associated with the event-study results of the estimator developed by de Chaisemartin and D'Haultfoeuille (2024). An observation is a candidate-state-event-week. The sample includes all congressional Democratic candidates who ran at least one ad-event on Meta's platform during the 2020 election cycle. Estimations also include week-state fixed effects. The dependent variable is the total dollar amount of contributions made that week by small and large donors from the corresponding state to the candidate posting the ad, per 10,000 state inhabitants. The top panel focuses on the general elections and the bottom panel on the primary elections. Standard errors are clustered at the candidate x week of the event level. The corresponding point estimates are shown in Table F.18, Panel (b).

Figure E.11: The effects of social media ads on small and large donor contributions, Democratic congressional candidates, 2020 election cycle, dropping very large events

(a) **General Elections**



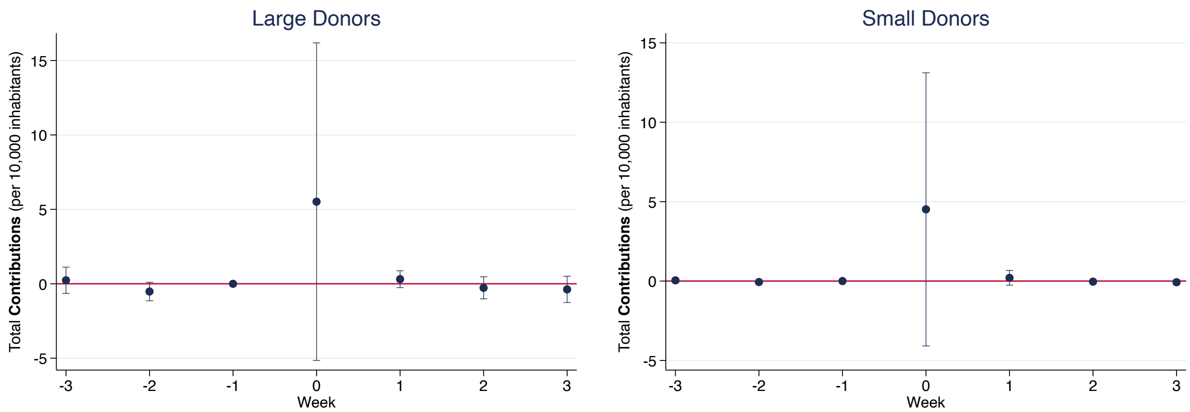
(b) **Primary Elections**



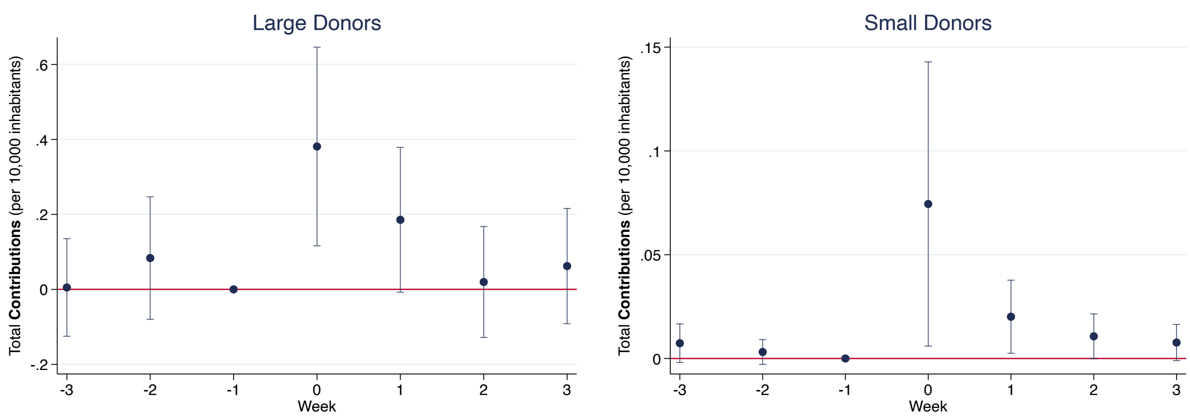
Notes: The figure shows point estimates and 95% confidence intervals associated with the event-study results of the estimator developed by de Chaisemartin and D'Haultfoeuille (2024). An observation is a candidate-state-event-week. The sample includes all congressional Democratic candidates who ran at least one ad-event on Meta's platform during the 2020 election cycle, but excludes ad-weeks in the top 5 percentiles of the distribution of impressions per adult inhabitants. Estimations also include week-state fixed effects. The dependent variable is the total dollar amount of contributions made that week by small and large donors from the corresponding state to the candidate posting the ad, per 10,000 state inhabitants. The top panel focuses on the general elections and the bottom panel on the primary elections. Standard errors are clustered at the candidate x week of the event level. The corresponding point estimates are shown in Table F.19, Panel (b).

Figure E.12: The effects of social media ads on small and large donor contributions, Democratic congressional candidates, 2020 election cycle, dropping very small events

(a) **General Elections**



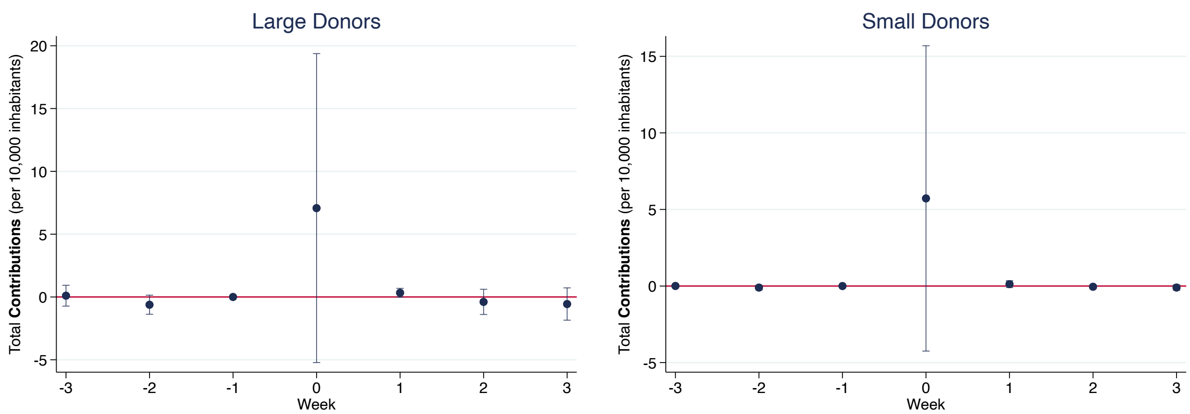
(b) **Primary Elections**



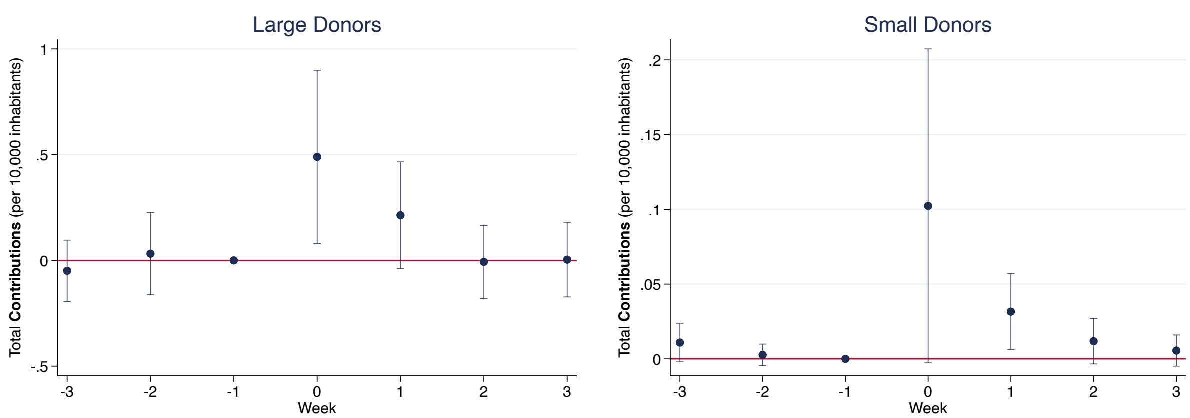
Notes: The figure shows point estimates and 95% confidence intervals associated with the event-study results of the estimator developed by de Chaisemartin and D'Haultfoeuille (2024). An observation is a candidate-state-event-week. The sample includes all congressional Democratic candidates who ran at least one ad-event on Meta's platform during the 2020 election cycle, , but excludes ad-weeks in the bottom 25 percentiles of the distribution of impressions per adult inhabitants. Estimations also include week-state fixed effects. The dependent variable is the total dollar amount of contributions made that week by small and large donors from the corresponding state to the candidate posting the ad, per 10,000 state inhabitants. The top panel focuses on the general elections and the bottom panel on the primary elections. Standard errors are clustered at the candidate x week of the event level. The corresponding point estimates are shown in Table F.19, Panel (a).

Figure E.13: The effects of social media ads on small and large donor contributions, Democratic congressional candidates, 2020 election cycle, conduit-hyperlink ads only

(a) **General Elections**



(b) **Primary Elections**



Notes: The figure shows point estimates and 95% confidence intervals associated with the event-study results of the estimator developed by de Chaisemartin and D'Haultfoeuille (2024). An observation is a candidate-state-event-week. The sample includes all congressional Democratic candidates who ran at least one ad-event on Meta's platform during the 2020 election cycle, considering only ads with a hyperlink leading to an ActBlue webpage. Estimations also include week-state fixed effects. The dependent variable is the total dollar amount of contributions made that week by small and large donors from the corresponding state to the candidate posting the ad, per 10,000 state inhabitants. The top panel focuses on the general elections and the bottom panel on the primary elections. Standard errors are clustered at the candidate x week of the event level. The corresponding point estimates are shown in Table F.20.

F Additional tables

Table F.1: The characteristics of small and large donors, Republican congressional candidates, 2020 election cycle

	Large Donors	Small Donors	18+ Population
Demographics *(.^{i} = imputed)*			
Female	0.375^i	0.439^i	0.510
White	0.839^i	0.835^i	0.589
Black	0.058^i	0.054^i	0.115
Hispanic	0.052^i	0.064^i	0.151
Asian	0.031^i	0.026^i	0.054
Other Race	0.021^i	0.021^i	0.091
Socio-economic characteristics			
High SOC occupation	0.318	0.230	0.182
Low SOC occupation	0.125	0.144	0.356
Inactive & Unemployed	0.556	0.626	0.462
Median Annual Wage (2020 dollars)	94,546	75,409	51,149
Median 2020 Home Value (dollars)	342,800	248,392	176,838
Observations	1,206,054	1,089,274	258,418,464

Notes: The table provides summary statistics on the demographic and socioeconomic characteristics of large donors, small donors, and the voting-age population. Time period is 2020. An observation is a unique individual-cycle. Variables are discussed in more details in the text. Characteristics indicated with an "i" are imputed using the method explained in Section A.4.2. Figures for the voting-age population demographics come from the U.S. Census Bureau ACS estimates. Fractions are calculated on the number of unique individual-cycles for which the corresponding variable is not missing. Wage variables are computed on the employed population and converted to constant 2020 dollars using the U.S. historical price index provided by the World Inequality Lab.

Table F.2: Summary statistics on explanatory variables of interest, Democratic congressional candidates, 2012-2020

(a) **General elections**

	Candidates	Large donors	Small donors
	Share	Share	Share
Electoral characteristics			
Close Races	0.177	0.390	0.348
Sure Winners	0.402	0.176	0.140
Sure Losers	0.401	0.435	0.511
Incumbents	0.416	0.295	0.242
Left Candidates	0.334	0.437	0.481
Center Candidates	0.333	0.487	0.472
Right Candidates	0.332	0.076	0.047
Matching characteristics			
Gender		0.490	0.476
Race		0.618	0.598
District		0.112	0.122
State		0.205	0.181
Observations	2,140	10,394,813	12,674,440

(b) **Primary elections**

	Candidates	Large donors	Small donors
	Share	Share	Share
Electoral characteristics			
Close Races	0.159	0.332	0.286
Sure Winners	0.370	0.336	0.299
Sure Losers	0.440	0.332	0.415
Close Primary Races	0.031	0.022	0.018
Incumbents	0.167	0.300	0.275
Left Candidates	0.334	0.341	0.398
Center Candidates	0.333	0.449	0.444
Right Candidates	0.333	0.210	0.158
Matching characteristics			
Gender		0.504	0.489
Race		0.623	0.621
District		0.175	0.179
State		0.295	0.266
Observations	3,607	4,721,758	4,192,044

Notes: The table provides summary statistics for our main explanatory variables of interest. Time period is 2012-2020. The sample includes all donors to Democratic congressional races. An observation is a candidate-cycle in the first column, and a donor-candidate-cycle pair in the second and third columns. The shares are computed as the number of individuals with each characteristic divided by all individuals for which information on the characteristic is available (i.e., for which the variable is not missing). Small and large donors are defined in the text.

Table F.3: The races and candidates targeted by donors, Democratic congressional candidates, 2012-2020 general elections, controlling for Seat x Election-Year fixed effects

	Large			Small		
	(1)	(2)	(3)	(4)	(5)	(6)
Same District	20.31***	13.96***		15.90***	8.02***	
	(1.36)	(0.78)		(2.17)	(0.54)	
Same Gender	0.02**	0.17***	0.89**	0.02*	0.04	0.23
	(0.01)	(0.03)	(0.33)	(0.01)	(0.04)	(0.41)
Same Race	0.03*	0.18**	1.35***	0.02	0.04	1.47***
	(0.01)	(0.07)	(0.33)	(0.03)	(0.05)	(0.42)
Seat x Election Year FE	✓	✓	✓	✓	✓	✓
Donor FE	✓	✓	✓	✓	✓	✓
Sample	All Pairs	In-State	In-District	All Pairs	In-State	In-District
Sample Mean	0.24	2.27	22.21	0.23	1.64	19.65
N	998,443,983	42,784,266	2,653,416	1,682,512,593	75,103,840	4,289,535
R2	0.13	0.32	0.54	0.16	0.42	0.64
Within-R2	0.0803	0.0565	0.0019	0.0499	0.0287	0.0012

Notes: Models are estimated using OLS. The time period is 2012-2020. An observation is a donor-candidate pair at each election cycle. In columns 1 and 4, the sample includes, for each donor who gave during a cycle, all the possible pairs of that cycle. We restrict the sample to donor-candidate pairs of the same state in columns 2 and 5, and to donor-candidate pairs of the same district in columns 3 and 6. The dependent variable is the share of the total amount contributed by the donor to the candidate during the general elections. Regressors are described in the text. For each characteristic, we create and control for an indicator variable equal to one when the characteristic is missing and set the corresponding variable to 0. Standard errors are shown in parentheses and two-way clustered at the seat and donor levels. * p<0.10, ** p<0.05, *** p<0.01.

Table F.4: The races and candidates targeted by donors, Democratic congressional candidates, 2012-2020 general elections, p-value of the difference in coefficients between donors of different sizes

	p-value					
	Large vs. Small			1st vs. 10th decile		
Variable	All Pairs	In-State	In-District	All Pairs	In-State	In-District
Seat Close	0.596	0.275	0.275	0.186	0.012	0.003
Safe Republican Seat	0.728	0.413	0.725	0.926	0.844	0.038
Incumbent Candidate	0.789	0.621	0.634	0.585	0.213	0.015
Congressional Seniority	0.681	0.337	0.106	0.846	0.282	0.015
Left Ideology Tercile	0.517	0.913	0.651	0.224	0.423	0.070
Center Ideology Tercile	0.825	0.849	0.760	0.529	0.873	0.777
Same District	0.237	2.59×10^{-8}		0.223	1.71×10^{-23}	
Same Gender	0.643	0.033	0.212	0.386	0.004	0.101
Same Race	0.569	0.688	0.756	0.768	0.637	0.736

Notes: The table shows the p-value associated with the two-sided t-test of difference between estimated coefficients of, in Columns (1)-(3), the large donor sample and those of small donor sample, reported in Table 3, and, in Columns (4)-(6), the 1st decile of donors and those of the 10th decile of donors. The coefficients for Column (4) are shown in Figure 5.

Table F.5: The races and candidates targeted by donors, Democratic congressional candidates, 2012-2020 primary elections

	Large			Small		
	(1)	(2)	(3)	(4)	(5)	(6)
Seat Close	0.04	0.94***	8.79***	-0.01	0.67*	7.71***
	(0.04)	(0.25)	(1.26)	(0.06)	(0.30)	(1.51)
Safe Republican Seat	-0.01	0.14	2.19*	-0.01	0.16	2.61*
	(0.03)	(0.19)	(1.11)	(0.04)	(0.20)	(1.21)
Seat Close Primary	-0.06	-0.31	-5.42	-0.06	-0.29	-2.44
	(0.03)	(0.43)	(4.33)	(0.03)	(0.50)	(4.75)
Incumbent Candidate	0.22***	1.85***	13.82***	0.29*	1.54***	10.54***
	(0.05)	(0.32)	(1.57)	(0.11)	(0.40)	(1.70)
Congressional Seniority	-0.01**	-0.10***	-0.81***	-0.01	-0.07	-0.62***
	(0.01)	(0.03)	(0.13)	(0.01)	(0.04)	(0.17)
Left Ideology Tercile	0.08**	0.07	0.24	0.14**	0.44*	1.82**
	(0.03)	(0.15)	(0.82)	(0.05)	(0.19)	(0.69)
Center Ideology Tercile	0.13***	0.59***	3.52***	0.16***	0.61***	4.19***
	(0.03)	(0.14)	(0.93)	(0.04)	(0.18)	(0.85)
Same Congressional District	8.28***	6.27***		6.22***	3.98***	
	(0.97)	(0.40)		(0.73)	(0.25)	
Same Gender	0.01***	0.14***	0.67***	0.01	0.07**	0.25
	(0.00)	(0.02)	(0.13)	(0.01)	(0.03)	(0.17)
Same Race	0.05	0.41*	3.40***	0.05	0.32	2.77**
	(0.02)	(0.19)	(0.81)	(0.03)	(0.18)	(0.88)
Election Year FE	✓	✓	✓	✓	✓	✓
House/Senate FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Contributor FE	✓	✓	✓	✓	✓	✓
Sample	All Pairs	In-State	In-District	All Pairs	In-State	In-District
Sample Mean	0.12	1.19	8.27	0.11	0.84	6.32
N	1,927,698,169	86,810,296	7,962,564	2,774,293,195	122,204,792	11,251,214
R2	0.03	0.10	0.26	0.02	0.10	0.29
Within-R2	0.03	0.02	0.05	0.02	0.01	0.04

Notes: Models are estimated using OLS. The time period is 2012-2020. An observation is a donor-candidate pair at each election cycle. In columns 1 and 4, the sample includes, for each donor who gave during a cycle, all the possible pairs of that cycle. We restrict the sample to donor-candidate pairs of the same state in columns 2 and 5, and to donor-candidate pairs of the same district in columns 3 and 6. The dependent variable is the share of the total amount contributed by the donor to the candidate during the primary elections. Regressors are described in the text. For each characteristic, we create and control for an indicator equal to one when the characteristic is missing and set the corresponding variable to 0. Standard errors are shown in parentheses and two-way clustered at the seat and donor levels. Table F.6 shows the p-values associated with the t-tests of equality between the effects observed in the small and large donor samples. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table F.6: The races and candidates targeted by donors, Democratic congressional candidates, 2012-2020 primary elections, p-value of the difference in coefficients between donors of different sizes

	p-value					
	Large vs. Small			1st vs. 10th decile		
Variable	All Pairs	In-State	In-District	All Pairs	In-State	In-District
Seat Close	0.423	0.485	0.582	0.153	0.242	0.080
Safe Republican Seat	0.997	0.944	0.800	0.254	0.610	0.118
Seat Close Primary	0.959	0.972	0.642	0.629	0.931	0.568
Incumbent Candidate	0.599	0.543	0.156	0.322	0.904	0.523
Congressional Seniority	0.789	0.499	0.391	0.402	0.741	0.893
Left Ideology Tercile	0.265	0.126	0.141	0.034	0.006	0.001
Center Ideology Tercile	0.429	0.939	0.598	0.226	0.936	0.745
Same District	0.089	9.65×10^{-7}		0.031	5.66×10^{-18}	
Same Gender	0.905	0.023	0.047	0.788	0.017	0.013
Same Race	0.990	0.710	0.595	0.491	0.810	0.347

Notes: The table shows the p-value associated with the two-sided t-test of difference between estimated coefficients of, in columns 1 to 3, the large donor sample and those of small donor sample, reported in Table F.5, and, in columns 4 to 6, the 1st decile of donors and those of the 10th decile of donors.

Table F.7: The races and candidates targeted by donors, Republican congressional candidates, 2020 general elections

	Large			Small		
	(1)	(2)	(3)	(4)	(5)	(6)
Seat Close	0.32**	1.89***	16.38***	0.16	1.45**	9.80***
	(0.15)	(0.50)	(2.39)	(0.17)	(0.49)	(1.76)
Safe Republican Seat	0.39	1.29**	9.44***	0.27	0.78	3.20
	(0.36)	(0.48)	(2.60)	(0.34)	(0.45)	(2.25)
Incumbent Candidate	0.06	0.37	4.56*	0.15	0.14	4.76*
	(0.33)	(0.47)	(2.20)	(0.33)	(0.48)	(2.03)
Congressional Seniority	-0.02	-0.03	-0.85*	-0.03	-0.02	-0.70*
	(0.02)	(0.06)	(0.34)	(0.03)	(0.04)	(0.35)
Left Ideology Tercile	0.02	-0.67	1.56	0.16	-0.46	2.45
	(0.17)	(0.38)	(2.59)	(0.24)	(0.40)	(3.21)
Center Ideology Tercile	-0.13	-0.64	-4.63*	-0.09	-0.60	-4.72**
	(0.09)	(0.39)	(1.83)	(0.11)	(0.38)	(1.73)
Same District	12.68***	8.20***		7.14***	3.68***	
	(1.15)	(0.44)		(1.01)	(0.40)	
Same Gender	-0.02	-0.17	-3.45***	-0.03	-0.19*	-2.53***
	(0.03)	(0.12)	(0.98)	(0.02)	(0.09)	(0.73)
Same Race	-0.11	-0.31	-4.87*	-0.13	-0.40	-6.17**
	(0.07)	(0.29)	(2.26)	(0.08)	(0.32)	(2.18)
Election Year FE	✓	✓	✓	✓	✓	✓
House/Senate FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Donor FE	✓	✓	✓	✓	✓	✓
Sample	All Pairs	In-State	In-District	All Pairs	In-State	In-District
Sample Mean	0.28	1.53	14.69	0.28	0.96	9.41
N	371,400,937	14,547,345	756,290	322,989,429	12,323,062	643,710
R2	0.06	0.22	0.47	0.05	0.19	0.50
Within-R2	0.03	0.03	0.03	0.01	0.01	0.03

Notes: Models are estimated using OLS. The time period is 2020. An observation is a donor-candidate pair at each election cycle. In columns 1 and 4, the sample includes, for each donor who gave during a cycle, all the possible pairs of that cycle. We restrict the sample to donor-candidate pairs of the same state in columns 2 and 5, and to donor-candidate pairs of the same district in columns 3 and 6. The dependent variable is the share of the total amount contributed by the donor to the candidate during the general election. Regressors are described in the text. For each characteristic, we create and control for an indicator equal to one when the characteristic is missing and set the corresponding variable to 0. Standard errors are shown in parentheses and two-way clustered at the seat and donor levels. Table F.8 shows the p-values associated with the t-tests of equality between the effects observed in the small and large donor samples. * p<0.10, ** p<0.05, *** p<0.01.

Table F.8: The races and candidates targeted by donors, Republican congressional candidates, 2020 general elections, p-value of the difference in coefficients between donors of different sizes

	p-value					
	Large vs. Small			1st vs. 10th decile		
Variable	All Pairs	In-State	In-District	All Pairs	In-State	In-District
Seat Close	0.493	0.531	0.027	0.215	0.365	0.001
Safe Republican Seat	0.799	0.445	0.070	0.452	0.194	0.093
Incumbent Candidate	0.861	0.731	0.946	0.593	0.844	0.331
Congressional Seniority	0.688	0.912	0.748	0.674	0.941	0.906
Left Ideology Tercile	0.638	0.715	0.831	0.632	0.943	0.728
Center Ideology Tercile	0.767	0.943	0.969	0.556	0.752	0.980
Same District	2.90×10^{-4}	1.98×10^{-14}		5.25×10^{-6}	1.95×10^{-15}	
Same Gender	0.899	0.890	0.451	0.525	0.366	0.233
Same Race	0.828	0.829	0.681	0.779	0.974	0.944

Notes: The table shows the p-value associated with the two-sided t-test of difference between estimated coefficients of, in columns 1 to 3, the large donor sample and those of small donor sample, reported in Table F.7, and, in columns 4 to 6, the 1st decile of donors and those of the 10th decile of donors.

Table F.9: The races and candidates targeted by donors, Republican congressional candidates, 2020 general elections, with Seat x Election-Year fixed effects

	Large			Small		
	(1)	(2)	(3)	(4)	(5)	(6)
Same District	12.68***	8.18***		7.17***	3.72***	
	(1.15)	(0.42)		(0.05)	(0.37)	
Same Gender	-0.04*	-0.09	-1.88**	-0.04	-0.15*	-1.99**
	(0.02)	(0.08)	(0.68)	(0.79)	(0.07)	(0.65)
Same Race	0.01	0.26*	-0.48	0.03***	0.36	0.04
	(0.02)	(0.12)	(0.63)	(0.01)	(0.29)	(0.34)
Seat $\times$ Election Year FE	✓	✓	✓	✓	✓	✓
Donor FE	✓	✓	✓	✓	✓	✓
Sample	All Pairs	In-State	In-District	All Pairs	In-State	In-District
Sample Mean	0.28	1.53	14.69	0.28	0.96	9.41
N	371,400,937	14,547,345	756,290	322,989,429	12,323,062	643,710
R2	0.13	0.26	0.51	0.14	0.26	0.56
Within-R2	0.03	0.03	0.00	0.01	0.01	0.00

Notes: Models are estimated using OLS. The time period is 2020. An observation is a donor-candidate pair at each election cycle. In columns 1 and 4, the sample includes, for each donor who gave during a cycle, all the possible pairs of that cycle. We restrict the sample to donor-candidate pairs of the same state in columns 2 and 5, and to donor-candidate pairs of the same district in columns 3 and 6. The dependent variable is the share of the total amount contributed by the donor to the candidate during the general election. Regressors are described in the text. For each characteristic, we create and control for an indicator equal to one when the characteristic is missing and set the corresponding variable to 0. Standard errors are shown in parentheses and two-way clustered at the seat and donor levels. * p<0.10, ** p<0.05, *** p<0.01.

Table F.10: The largest recipients of donations, Democratic congressional candidates, 2012-2020 general elections

(a) **From small donors**

Candidate	Year	State	Seat	**Small donor donations (% of all candidates')**	Small donor donations (% of own all donations)
O'ROURKE, ROBERT (BETO)	2018	TX	S	**22.60**	30.12
HARRISON, JAIME	2020	SC	S	**18.08**	24.21
MCGRATH, AMY	2020	KY	S	**13.40**	26.49
GRAYSON, ALAN MARK	2012	FL	9	**11.11**	21.44
GRIMES, ALISON LUNDERGAN	2014	KY	S	**9.40**	17.31
MASTO, CATHERINE CORTEZ	2016	NV	S	**8.98**	11.60
ROSS, DEBORAH K	2016	NC	S	**8.91**	10.81
BALDWIN, TAMMY	2012	WI	S	**8.20**	9.20
KELLY, MARK	2020	AZ	S	**8.19**	15.38
JONES, DOUG	2018	AL	S	**7.99**	24.01
FEINGOLD, RUSSELL DANA	2016	WI	S	**7.31**	14.72
HEITKAMP, HEIDI	2018	ND	S	**6.68**	27.05
MCGINTY, KATHLEEN ALANA	2016	PA	S	**6.36**	8.50
GRAVES, JAMES JOSEPH	2012	MN	6	**6.24**	22.79
UDALL, MARK E	2014	CO	S	**5.95**	9.62
Mean Candidate				**.24**	7.82

(b) **From large donors**

Candidate	Year	State	Seat	**Large donor donations (% of all candidates')**	Small donor donations (% of own donations)
HARRISON, JAIME	2020	SC	S	**8.58**	24.21
O'ROURKE, ROBERT (BETO)	2018	TX	S	**8.54**	30.12
KAINE, TIMOTHY MICHAEL	2012	VA	S	**7.47**	0.63
SCHUMER, CHARLES E	2016	NY	S	**6.96**	0.33
KELLY, MARK	2020	AZ	S	**6.83**	15.38
GILLIBRAND, KIRSTEN ELIZABETH	2012	NY	S	**6.51**	0.79
WARNER, MARK ROBERT	2014	VA	S	**5.67**	3.38
MCGRATH, AMY	2020	KY	S	**5.64**	26.49
ROSS, DEBORAH K	2016	NC	S	**5.22**	10.81
GIDEON, SARA	2020	ME	S	**5.04**	13.33
NELSON, BILL	2018	FL	S	**4.88**	13.01
MASTO, CATHERINE CORTEZ	2016	NV	S	**4.85**	11.60
MCGINTY, KATHLEEN ALANA	2016	PA	S	**4.85**	8.50
PRYOR, MARK LUNSFORD	2014	AR	S	**4.33**	4.30
JONES, DOUG	2018	AL	S	**4.12**	24.01
Mean Candidate				**.24**	7.82

Notes: The tables show the largest candidate recipients of small (Panel (a)) and large (Panel (b)) donor contributions, measured by their share of the total amount of small / large donor contributions to all candidates in the cycle (indicated in bold). The rightmost column shows the share of donations received by the candidate that come from small donors. The time period is 2012-2020. The sample is all Democratic congressional candidates at the general elections.

Table F.11: The largest receivers of donations, Democratic congressional candidates, 2012-2020 primary elections

(a) **From small donors**

Candidate	Year	State	Seat	**Small donor donations (% of all candidates')**	Small donor donations (% of own all donations)
WARREN, ELIZABETH	2012	MA	S	**38.49**	8.07
WARREN, ELIZABETH	2018	MA	S	**10.04**	26.23
FEINGOLD, RUSSELL DANA	2016	WI	S	**9.99**	7.80
FRANKEN, AL	2014	MN	S	**9.08**	6.76
SHAHEEN, JEANNE	2014	NH	S	**8.99**	8.92
MERKLEY, JEFFREY ALAN	2014	OR	S	**8.02**	15.20
CANOVA, TIMOTHY A	2016	FL	23	**7.41**	17.82
O'ROURKE, ROBERT (BETO)	2018	TX	S	**7.26**	15.69
GRAYSON, ALAN MARK	2014	FL	9	**6.89**	28.04
GRIMES, ALISON LUNDERGAN	2014	KY	S	**5.94**	6.19
GRAYSON, ALAN MARK	2016	FL	S	**5.82**	14.49
LEWIS, JOHN R	2020	GA	5	**5.81**	14.71
HAGAN, KAY R	2014	NC	S	**4.72**	6.54
ROMANOFF, ANDREW	2020	CO	S	**4.53**	12.16
UDALL, MARK E	2014	CO	S	**4.42**	4.19
Mean Candidate				**.16**	11.12

(b) **From large donors**

Candidate	Year	State	Seat	**Large donor donations (% of all candidates')**	Small donor donations (% of own donations)
WARREN, ELIZABETH	2012	MA	S	**8.41**	8.07
BOOKER, CORY A	2014	NJ	S	**6.61**	0.83
KENNEDY, JOSEPH P III	2020	MA	S	**6.42**	4.22
FEINGOLD, RUSSELL DANA	2016	WI	S	**4.77**	7.80
MARKEY, EDWARD JOHN MR	2014	MA	S	**4.55**	1.92
VAN HOLLEN, CHRIS	2016	MD	S	**4.23**	1.13
MCCASKILL, CLAIRE	2018	MO	S	**4.17**	7.25
FRANKEN, AL	2014	MN	S	**3.99**	6.76
NELSON, BILL	2012	FL	S	**3.84**	0.07
NUNN, MARY MICHELLE	2014	GA	S	**3.82**	1.21
HARRIS, KAMALA D	2016	CA	S	**3.75**	2.62
MURPHY, PATRICK E	2016	FL	S	**3.64**	2.72
MENENDEZ, ROBERT	2012	NJ	S	**3.53**	0.07
BENNET, MICHAEL F	2016	CO	S	**3.38**	2.52
MELTON-MEAUX, ANTONE	2020	MN	5	**3.36**	2.79
Mean Candidate				**.16**	11.12

Notes: The tables show the largest candidate recipients of small (Panel (a)) and large (Panel (b)) donor contributions, as measured in their share of the total amount of small / large donor contributions to all candidates in the cycle (indicated in bold). The rightmost column shows the share of donations received by the candidate that come from small donors. The time period is 2012-2020. The sample is all Democratic congressional candidates at the primary elections.

Table F.12: Weeks of small donor contribution surges and their most likely trigger events, 2012-2020

Week	**Dates**	**Event**	**Share of contributions**
2020w38	Sep 16–22, 2020	Death of Justice RBG (Sep 18)	0.130
2019w46	Nov 12–18, 2019	First Public Impeachment Hearings (Nov 13)	0.004
2019w28	Jul 9–15, 2019	Trump ICE Deportation Raids (Jul 12)	0.007
2019w7	Feb 12–18, 2019	Trump National Emergency Declaration (Feb 15)	0.002
2017w49	Dec 3–9, 2017	TCJA Tax Bill (Dec 2) + Flynn Guilty Plea (Dec 1)	0.019
2017w18	Apr 30–May 6, 2017	AHCA Passes House (May 4)	0.015
2017w5	Jan 29–Feb 4, 2017	Trump Travel Ban Executive Order (Jan 27)	0.009
2015w22	May 28–Jun 3, 2015	USA FREEDOM Act / NSA Surveillance Reforms (Jun 2)	0.004
2015w20	May 14–20, 2015	Amtrak Derailment + De-Funding Vote (May 12–13)	0.008
2013w44	Oct 29–Nov 4, 2013	Special Senate Election in MA and NJ (Nov 5)	0.007
2012w3	Jan 15–21, 2012	Gingrich South Carolina Primary Victory	0.015
2011w45	Nov 5–11, 2011	Ohio Issue 2 Anti-Union Referendum Victory	0.016
2011w33	Aug 13–19, 2011	Rick Perry Presidential Candidacy	0.004
2011w19+20	May 7–20, 2011	NY-26 Special Election (May 24)	0.006
2011w8	Feb 19–25, 2011	Wisconsin Capitol Anti-Union Protests (Feb 14–25)	0.002

Notes: The table lists the weeks during which contributions from small donors to Democratic congressional candidates were higher than 1.5 times the mean of the previous and following months or 2 times the level of the previous week and the following week. The list excludes weeks corresponding to FEC quarterly reporting deadlines. For each week, the table also shows the exact dates, the most likely political trigger (i.e., the event that occurred during that week or the previous one and that is the most likely trigger of the surge), and the campaign contributions made that week as a share of all campaign contributions made by small donors during that election cycle.

Table F.13: Summary statistics on county-level TV advertising and campaign contributions, 2012-2020

(a) **General Elections**

	Mean	Median	sd	Min	Max	N
Democratic Ads (in 1000s)						
– Senate (DMA)	3.65	1.03	6.15	0.00	52.42	16,843
– Senate (Local)	2.88	0.46	5.57	0.00	52.42	16,843
– House (DMA)	1.79	0.02	3.50	0.00	26.06	15,635
– House (Local)	0.34	0.00	1.23	0.00	24.45	15,635
Democratic Donors (nb. per 10,000 inhabitants)						
– Senate (DMA)	9.94	4.47	18.50	0.00	405.96	16,843
– Senate (Local)	9.46	4.02	18.17	0.00	405.96	16,843
– House (DMA)	4.96	0.61	13.74	0.00	271.81	15,635
– House (Local)	4.35	0.00	13.23	0.00	255.82	15,635
Democratic Contributions (dollar amounts per 10,000 inhabitants)						
– Senate (DMA)	1,554	434	3,889	0	92,425	16,843
– Senate (Local)	1,478	397	3,746	0	92,425	16,843
– House (DMA)	1,124	35	4,760	0	173,774	15,635
– House (Local)	984	0	4,532	0	171,637	15,635

(b) **Primary Elections**

	Mean	Median	sd	Min	Max	N
Democratic Ads (in 1000s)						
– Senate (DMA)	1.95	0.22	4.77	0.00	41.46	16,843
– Senate (Local)	1.53	0.02	3.76	0.00	29.76	16,843
– House (DMA)	0.73	0.00	2.28	0.00	26.66	15,635
– House (Local)	0.12	0.00	0.76	0.00	9.33	15,635
Democratic Donors (nb. per 10,000 inhabitants)						
– Senate (DMA)	7.29	2.57	14.06	0.00	283.23	16,843
– Senate (Local)	7.03	2.35	13.82	0.00	283.23	16,843
– House (DMA)	3.58	0.00	9.99	0.00	287.53	15,635
– House (Local)	3.04	0.00	9.37	0.00	276.41	15,635
Democratic Contributions (dollar amounts per 10,000 inhabitants)						
– Senate (DMA)	1,374	220	4,099	0	165,904	16,843
– Senate (Local)	1,335	202	4,049	0	165,876	16,843
– House (DMA)	948	0	3,460	0	114,535	15,635
– House (Local)	794	0	3,153	0	98,645	15,635

Notes: An observation is a county-cycle. The samples include all county-pairs in which a race took place for each election over the 2012-2020 period. For House races, the sample includes only county-pairs with border-counties located in the same congressional district. “Inhabitants” refers to the county adult (i.e., aged 18 and over) population.

Table F.14: The effects of TV ads on the number of small and large donors, Democratic congressional candidates, 2012-2020

	General Election		Primary Election	
	(1)	(2)	(3)	(4)
	Large	Small	Large	Small
Democratic Ads (Total number, in 1000s)	0.13***	0.18***	0.04	0.11***
	(0.05)	(0.06)	(0.03)	(0.03)
Republican Ads	-0.07	-0.07	0.07**	-0.01
	(0.06)	(0.08)	(0.03)	(0.04)
County-Pair x Year x Office FE	✓	✓	✓	✓
County x Office FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
R-sq (within)	0.013	0.031	0.013	0.023
Observations	31,162	31,162	31,162	31,162
Clusters	204	204	204	204
Mean DepVar	3.43	4.23	2.77	2.82

Notes: Models are estimated using OLS. An observation is a county-cycle-office. We combine House and Senate races for the 2012 to 2020 elections. Columns 1 and 2 and columns 3 and 4 show the results for the general and primary elections, respectively. The sample includes all county-pairs with border-counties located in the same congressional district for House races, and all county-pairs in which a Senate race took place. The dependent variable considers contributions to all Democratic congressional candidates in the DMA, and is the number of unique donors per 10,000 adult inhabitants in the county. Controls include all other political ads aired in the county (for senatorial elections, presidential, House, non-DMA Senate, governor, and other down-ballot races' ads; and for House elections, presidential, Senate, non-DMA House, governor, and other down-ballot races' ads), measured in the same way as the main dependent variable and separately for both Democratic and Republican congressional candidates, together with a set of socio-demographic characteristics of the county (total population, share of high-school dropouts, share of college graduates, share of ethnic minority population, share of foreign-born population, median household income, share of population below the poverty line, and employment-to-population ratio). Standard errors are shown in parentheses and clustered at the DMA level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table F.15: The effects of *local* TV ads on small and large donor contributions, *local* Democratic congressional candidates, 2012-2020 general elections

	General Elections		Primary Elections	
	(1)	(2)	(3)	(4)
	Large	Small	Large	Small
Local Democratic Ads (Total number, in 1000s)	42.45	16.52***	29.00	4.02
	(37.77)	(4.96)	(65.50)	(3.73)
Local Republican Ads	-13.20	-9.06	-1.68	1.56
	(52.47)	(7.02)	(47.54)	(3.34)
County-Pair x Year x Office FE	✓	✓	✓	✓
County x Office FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
R-sq (within)	0.004	0.025	0.006	0.015
Observations	31,162	31,162	31,162	31,162
Clusters	204	204	204	204
Mean DepVar	1,096.64	161.39	998.44	92.90

Notes: Models are estimated using OLS. An observation is a county-cycle-office. We combine House and Senate races for the 2012 to 2020 elections. Columns 1 and 2 and columns 3 and 4 show the results for the general and primary elections, respectively. The dependent variable considers contributions to the Democratic congressional candidates of the county, and is the total dollar amount of contributions per 10,000 adult inhabitants in the county. Controls include all other political ads aired in the county (for senatorial elections, presidential, House, non-local Senate, governor, and other down-ballot races' ads; and for House elections, presidential, Senate, non-local House, governor, and other down-ballot races' ads), measured in the same way as the main dependent variable and separately for both Democratic and Republican congressional candidates, together with a set of socio-demographic characteristics of the county (total population, share of high-school dropouts, share of college graduates, share of ethnic minority population, share of foreign-born population, median household income, share of population below the poverty line, and employment-to-population ratio). Standard errors are shown in parentheses and clustered at the DMA level. * p<0.10, ** p<0.05, *** p<0.01.

Table F.16: Summary statistics on social media political advertising and campaign contributions, 2020 election cycle

(a) **General Elections**

	Mean	Median	sd	Min	Max	N
Democratic Impressions (nb. per 10,000 inhabitants)						
– Senate	3.84	0.39	7.40	0.01	49.16	202
– House	2.71	0.43	19.77	0.00	598.51	2,551
Democratic Donors (nb. per 10,000 inhabitants)						
– Senate	0.10	0.00	0.55	0.00	38.31	35,672
– House	0.00	0.00	0.02	0.00	2.50	435,136
Democratic Contributions ($ amounts per 10,000 inhabitants)						
– Senate	4.65	0.00	29.58	0.00	2,686.76	35,672
– House	0.27	0.00	3.11	0.00	453.20	435,136

(b) **Primary Elections**

	Mean	Median	sd	Min	Max	N
Democratic Impressions (nb. per 10,000 inhabitants)						
– Senate	7.35	0.29	62.97	0.00	2,414.73	2,351
– House	2.00	0.23	17.27	0.00	1,056.53	15,475
Democratic Donors (nb. per 10,000 inhabitants)						
– Senate	0.06	0.00	0.74	0.00	154.95	270,816
– House	0.01	0.00	0.06	0.00	11.20	2,089,568
Democratic Contributions ($ amounts per 10,000 inhabitants)						
– Senate	2.73	0.00	34.75	0.00	7,595.79	270,816
– House	0.46	0.00	5.79	0.00	1,102.47	2,089,568

Notes: An observation is an event (i.e., candidate-state-new ad-week) for ads variables, and an event-week for contribution variables. The time period is the 2020 two-year election period. The sample includes all candidates running at least one ad on Meta. For the contributions variables, the samples include weeks up to 3 weeks before and 3 weeks after the event new ad-week. "Inhabitants" refers to the state adult (i.e., aged 18 and over) population.

Table F.17: The effects of social media ads on the number of small and large donors and their total amount of contributions, Democratic congressional candidates, 2020 election cycle

(a) **Contributions**

	General Elections		Primary Elections	
	(1) Large	(2) Small	(3) Large	(4) Small
Week -3	0.452	0.070	0.000	0.005
	(0.553)	(0.077)	(0.052)	(0.004)
Week -2	-0.346	-0.051	0.052	0.002
	(0.211)	(0.035)	(0.061)	(0.002)
Week 0	3.744	3.039	0.288***	0.056**
	(3.749)	(2.998)	(0.102)	(0.027)
Week 1	0.637	0.299	0.145*	0.014**
	(0.596)	(0.313)	(0.076)	(0.007)
Week 2	-0.181	-0.028	-0.000	0.007*
	(0.278)	(0.027)	(0.057)	(0.004)
Week 3	-0.248	-0.047	0.036	0.006*
	(0.317)	(0.051)	(0.060)	(0.003)
Week x State FE	✓	✓	✓	✓
Observations	64512	64512	1346353	1346353
Clusters	217	217	1055	1055
Mean DepVar	1.497	.363	.613	.042

(b) **Number of donors**

	General Elections		Primary Elections	
	(1) Large	(2) Small	(3) Large	(4) Small
Week -3	0.003	0.001	0.001	0.001
	(0.004)	(0.002)	(0.001)	(0.001)
Week -2	-0.005	-0.004	0.000	0.000
	(0.004)	(0.003)	(0.000)	(0.000)
Week 0	0.039	0.099	0.004***	0.003**
	(0.040)	(0.099)	(0.001)	(0.001)
Week 1	0.003	0.010	0.001**	0.001**
	(0.004)	(0.011)	(0.001)	(0.000)
Week 2	-0.003	-0.002	0.001	0.001
	(0.003)	(0.001)	(0.000)	(0.000)
Week 3	-0.003	-0.003	0.000	0.000
	(0.004)	(0.002)	(0.000)	(0.000)
Week x State FE	✓	✓	✓	✓
Observations	64512	64512	1346353	1346353
Clusters	217	217	1055	1055
Mean DepVar	.021	.017	.006	.003

Notes: Models are estimated using the Difference-in-Differences estimator of de Chaisemartin and D'Haultfoeuille (2024). An observation is a candidate-state-event-week. The sample includes all Democratic congressional candidates for the general elections (columns 1 and 2) or for the primary elections (columns 3 and 4) who ran at least one ad-event on Meta's platform during the 2020 election cycle. The dependent variable includes all contributions to the candidate posting the ad. In Panel (a), it is the total dollar amount of contributions made that week by small and large donors from the corresponding state per 10,000 adult inhabitants in the state; in Panel (b), it is the number of unique donors by small and large donors from the corresponding state donating that week per 10,000 adult inhabitants in the state. The independent variables are a series of leads and lags indicator variables. Standard errors are shown in parentheses and clustered at the candidate x week of the event level. * p<0.10, ** p<0.05, *** p<0.01.

Table F.18: The effects of social media ads on small and large donor contributions, Democratic congressional candidates, 2020 election cycle, shorter time windows for the inclusion of events

(a) **2-week window**

	General Elections		Primary Elections	
	(1) Large	(2) Small	(3) Large	(4) Small
Week -2	-0.178	-0.013	0.043	0.005
	(0.123)	(0.017)	(0.051)	(0.004)
Week 0	1.968	1.465	0.297**	0.063*
	(1.774)	(1.427)	(0.133)	(0.032)
Week 1	0.486	0.193	0.063	0.004
	(0.332)	(0.178)	(0.063)	(0.009)
Week 2	0.339**	0.129	-0.018	0.003
	(0.142)	(0.109)	(0.054)	(0.004)
Week x State FE	✓	✓	✓	✓
Observations	129641	129641	1841636	1841636
Clusters	343	343	1398	1398
Mean DepVar	1.425	.239	.717	.059

(b) **1-week window**

	General Elections		Primary Elections	
	(1) Large	(2) Small	(3) Large	(4) Small
Week 0	1.611	1.215	0.237***	0.061***
	(1.089)	(0.890)	(0.088)	(0.023)
Week 1	1.370	0.862	0.074	0.032
	(0.966)	(0.768)	(0.061)	(0.024)
Week x State FE	✓	✓	✓	✓
Observations	241440	241440	3159412	3159412
Clusters	594	594	2232	2232
Mean DepVar	1.871	.332	1.008	.107

Notes: Models are estimated using the Difference-in-Differences estimator of de Chaisemartin and D'Haultfoeuille (2024). An observation is a candidate-state-event-week. The sample includes all Democratic congressional candidates for the general elections (columns 1 and 2) or for the primary elections (columns 3 and 4) who ran at least one ad-event on Meta's platform during the 2020 election cycle. The dependent variable includes all contributions to the candidate posting the ad, and is the total dollar amount of contributions made that week by small and large donors from the corresponding state per 10,000 adult inhabitants in the state. Panel (a) includes all events separated by two or more weeks without ads, and Panel (b) includes all events separated by one or more weeks without ads. The independent variables are a series of leads and lags indicator variables. Standard errors are shown in parentheses and clustered at the candidate x week of the event level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table F.19: The effects of social media ads on small and large donor contributions, Democratic congressional candidates, 2020 election cycle, excluding small / large events

(a) **Excluding bottom 25% of events**

	General Elections		Primary Elections	
	(1)	(2)	(3)	(4)
	Large	Small	Large	Small
Week -3	0.237	0.044	0.005	0.007
	(0.451)	(0.067)	(0.066)	(0.005)
Week -2	-0.519	-0.060	0.084	0.003
	(0.316)	(0.048)	(0.083)	(0.003)
Week 0	5.518	4.516	0.381***	0.074**
	(5.444)	(4.388)	(0.135)	(0.035)
Week 1	0.312	0.203	0.186*	0.020**
	(0.289)	(0.237)	(0.099)	(0.009)
Week 2	-0.271	-0.038	0.020	0.011*
	(0.379)	(0.039)	(0.075)	(0.006)
Week 3	-0.377	-0.072	0.062	0.008*
	(0.451)	(0.077)	(0.078)	(0.004)
Week x State FE	✓	✓	✓	✓
Observations	48377	48377	1009693	1009693
Clusters	158	158	883	883
Mean DepVar	1.963	.481	.789	.054

(b) **Excluding top 5% of events**

	General Elections		Primary Elections	
	(1)	(2)	(3)	(4)
	Large	Small	Large	Small
Week -3	0.031	0.014	-0.038	0.001
	(0.143)	(0.013)	(0.030)	(0.001)
Week -2	-0.223	-0.020	0.046	0.001
	(0.152)	(0.012)	(0.044)	(0.001)
Week 0	0.325	0.427	0.095**	0.012***
	(0.460)	(0.423)	(0.042)	(0.004)
Week 1	0.130	0.045	0.031	0.000
	(0.152)	(0.046)	(0.043)	(0.002)
Week 2	-0.086	-0.003	-0.018	-0.000
	(0.074)	(0.005)	(0.042)	(0.001)
Week 3	-0.056	-0.003	-0.000	-0.001
	(0.097)	(0.011)	(0.043)	(0.002)
Week x State FE	✓	✓	✓	✓
Observations	61279	61279	1278995	1278995
Clusters	205	205	919	919
Mean DepVar	.59	.081	.314	.017

Notes: Models are estimated using the Difference-in-Differences estimator of de Chaisemartin and D'Haultfoeuille (2024). An observation is a candidate-state-event-week. The sample includes all Democratic congressional candidates for the general elections (columns 1 and 2) or for the primary elections (columns 3 and 4) who ran at least one ad-event on Meta's platform during the 2020 election cycle. The dependent variable includes all contributions to the candidate posting the ad, and is the total dollar amount of contributions made that week by small and large donors from the corresponding state per 10,000 adult inhabitants in the state. Panel (a) excludes ad-weeks in the bottom 25 percentiles of the distribution of impressions per adult inhabitants, and Panel (b) excludes the top 5 percentiles. The independent variables are a series of leads and lags indicator variables. Standard errors are shown in parentheses and clustered at the candidate x week of the event level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table F.20: The effects of social media ads on small and large donor contributions, Democratic congressional candidates, 2020 election cycle, conduit-hyperlink ads only

	General Elections		Primary Elections	
	(1)	(2)	(3)	(4)
	Large	Small	Large	Small
Week -3	0.102	0.005	-0.049	0.011*
	(0.423)	(0.042)	(0.074)	(0.007)
Week -2	-0.618	-0.100	0.032	0.003
	(0.388)	(0.079)	(0.099)	(0.004)
Week 0	7.074	5.721	0.489**	0.102*
	(6.275)	(5.087)	(0.209)	(0.054)
Week 1	0.331*	0.125	0.214*	0.032**
	(0.180)	(0.112)	(0.129)	(0.013)
Week 2	-0.391	-0.048	-0.007	0.012
	(0.511)	(0.052)	(0.088)	(0.008)
Week 3	-0.562	-0.098	0.004	0.006
	(0.656)	(0.091)	(0.090)	(0.005)
Week x State FE	✓	✓	✓	✓
Observations	38258	38258	711492	711492
Clusters	113	113	403	403
Mean DepVar	2.277	.598	.73	.055

Notes: Models are estimated using the Difference-in-Differences estimator of de Chaisemartin and D'Haultfoeuille (2024). An observation is a candidate-state-event-week. The sample includes all Democratic congressional candidates for the general elections (columns 1 and 2) or for the primary elections (columns 3 and 4) who ran at least one ad-event on Meta's platform during the 2020 election cycle, considering only ads with a hyperlink leading to an ActBlue webpage. The dependent variable includes all contributions to the candidate posting the ad, and is the total dollar amount of contributions made that week by small and large donors from the corresponding state per 10,000 adult inhabitants in the state. The independent variables are a series of leads and lags indicator variables. Standard errors are shown in parentheses and clustered at the candidate x week of the event level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

References

Alvarez, R. M., Katz, J. N., and Kim, S.-y. S. (2020). Hidden Donors: The Censoring Problem in U.S. Federal Campaign Finance Data. *Election Law Journal: Rules, Politics, and Policy*, (1):1–18.

Bureau of Labor Statistics, U. (2020). Occupational employment and wage statistics. *Division of Occupational Employment and Wage Statistics*, pages 53–0000.

Culberson, T., McDonald, M. P., and Robbins, S. M. (2019). Small Donors in Congressional Elections. *American Politics Research*, 47(5):970–999.

de Chaisemartin, C. and D'Haultfoeuille, X. (2024). Difference-in-differences estimators of intertemporal treatment effects. *The Review of Economics and Statistics*, pages 1–45.

Din, A. and Wilson, R. (2020). Crosswalking zip codes to census geographies. *Cityscape*, 22(1):293–314.

Elliott, M. N., Morrison, P. A., Fremont, A., McCaffrey, D. F., Pantoja, P., and Lurie., N. (2009). Using the census bureau's surname list to improve estimates of race/ethnicity and associated disparities. *Health Services and Outcomes Research Methodology*, 9(2):69–83.

Grumbach, J. M. and Sahn, A. (2020). Race and Representation in Campaign Finance. *American Political Science Review*, 114(1):206–221.

Imai, K. and Khanna, K. (2016). Improving ecological inference by predicting individual ethnicity from voter registration records. *Political Analysis*, 24(2):263–272.

Manson, S., Schroeder, J., Van Riper, D., and Ruggles, S. (2019). *IPUMS National Historical Geographic Information System: Version 14.0 [Database].* Minneapolis, MN: IPUMS.

Mullen, L. (2021). *gender: Predict Gender from Names Using Historical Data*. R package version 0.6.0.

Nolte, C., Boyle, K. J., Chaudhry, A. M., Clapp, C. M., Guignet, D., Hennighausen, H., Kushner, I., Liao, Y., Mamun, S., Pollack, A., et al. (2024). Data practices for studying the impacts of environmental amenities and hazards with nationwide property data. *Land Economics*, 100(1):200–221.

Sides, J., Vavreck, L., and Warshaw, C. (2021). The effect of television advertising in unites states elections. *American Political Science Review*, page 1–17.

Spenkuch, J. L. and Toniatti, D. (2018). Political Advertising and Election Results. *The Quarterly Journal of Economics*, 133(4):1981–2036.