Darker Blue: How Small Donors Drive Congressional Polarization

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Abstract

Over the previous two decades, campaign contributions from small donors to congressional elections have surged, and new technologies have transformed the process of political fundraising. How does money from small donors change how legislators take positions and behave in Congress? ActBlue is a digital platform that has lowered the non-monetary costs of individual contributions and has processed billions of dollars in donations for Democratic candidates and causes. Using a difference-in-differences design based on staggered ActBlue adoption by House candidates, I find that when candidates join ActBlue, they raise more money from individual donors. This is predominantly driven by growth in small-donor contributions. These new donor networks are more liberal than they previously were. Those elected to Congress tend to behave more liberally across multiple metrics, relative to their own previous behavior. These findings suggest that the pursuit of small and individual donors can contribute to congressional polarization.

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1 Introduction

The cost of Congressional elections has surged in past years, and fundraising is a critical component of running for office. Concerns about responsiveness to donors have led researchers to study contributions from access-seeking groups and political insiders (Barber, 2016; Bonica, 2020; Desmarais et al., 2015; Fouirnaies & Fowler, 2022; Fouirnaies & Hall, 2018; Fowler et al., 2020; Grier et al., 2023; Powell & Grimmer, 2016), but these types of donors are only a portion of candidates' donor pools. As contributions from smaller donors have risen in recent years, it is increasingly important to understand the interaction between legislators and small donors.

The correlation between small donor contributions and legislator extremity is well-established: legislators who raise more from small donors tend to be more ideologically extreme (Albert & La Raja, 2020; Culberson et al., 2019; La Raja & Schaffner, 2015). How might donors drive ideological extremity? The prevailing mechanism within the literature is that individual and small donors, who themselves are more extreme than the electorate, prefer supporting non-moderate candidates (Barber et al., 2017; Keena and Knight-Finley, 2019; Meisels et al., 2022). Extreme candidates, aided by these donors, then enter office (Barber, 2016; Kujala, 2020). Because the supply of political donations is tied to candidate extremity, it is difficult to establish whether money from small donors also pushes legislators to shift their own ideological positioning.

In this paper, I find that when Democratic candidates receive a larger share of contributions from smaller donors, their donor pools become more liberal, and their legislative behavior shifts to the left. This paper is the first to show that legislative behavior shifts after receiving contributions from small donors, providing evidence on the impact of money on legislative behavior. I use ActBlue adoption among Democratic candidates running in federal House general elections as a shock in order to examine how small donor involvement impacts overall donor pool ideology and legislative behavior. ActBlue is the preeminent website to process payments for Democratic candidates and progressive causes. It combines tools for effective fundraising, regulatory compliance, and donor data management for candidates, as well as lowers the non-monetary costs of making a political contribution for donors. ActBlue adoption provides an ideal case for studying the effects of small donors on legislative behavior, as the platform encourages contributions from small donors and has been widely embraced by Democrats in Congress in recent years.

I introduce a new dataset on ActBlue adoption among general election House candidates within the Democratic party. I combine this dataset with existing data on candidate and district attributes and fundraising metrics. Using a two-way fixed effects (legislator and time) difference-in-differences strategy based on staggered ActBlue adoption among House candidates, I find that when candidates join ActBlue, contributions from individual donors substantially increase, primarily driven by unitemized donors, who give less than $200 to candidates. Smaller donors become a larger share of candidates' fundraising portfolios. When candidates start fundraising with ActBlue, the ideological balance of their donors also shifts to the left. Once in office, legislators who raise money on ActBlue position themselves and vote more liberally on key issues, evidenced by leftward shifts in their interest group-based ideology scores. Ideology scores based on cumulative voting records move to the left on average, as candidates on ActBlue tend to vote more with the majority of Democratic legislators and more against the majority of Republican legislators.

This article proceeds as follows. First, I describe ActBlue's role in the fundraising process and discuss how money from small donors brought about by ActBlue may spark donor and congressional polarization. The data section describes the data collection process, empirical methods, ActBlue adoption, and possible issues for causal inference. In the results section, I investigate candidates' financial returns to ActBlue adoption, by donor type. I show that candidates see the largest increases in contributions from small donors, and that smaller donors become a larger component in candidates' fundraising portfolios. I then examine the interaction between ActBlue adoption and the ideological bend of congressional donors. Finally, the paper investigates whether congressional behavior moves leftward when House members use ActBlue. The concluding section contextualizes these results against the broader backdrop of trends in fundraising, technology, and congressional behavior.

1.1 ActBlue technology enables candidates to effectively reach smaller individual donors

Internet-based giving has transformed the way that candidates solicit and receive money from individual donors (Green & Kingsbury, 2011; Magleby, 2011; Magleby et al., 2018). ActBlue, founded in 2004, is a widely-used online platform that facilitates contributions to Democratic and liberal candidates and causes. Most Democratic congressional candidates from the early 2000s raised money on the internet through firms like PayPal, Google, or NGP,[1] and throughout the late 2000s to mid-2010s, slowly joined the ActBlue platform (Figure 1 and A2). ActBlue altered how individuals make campaign finance transactions by making it easier for prospective smaller donors to give and re-give (Cigler, 2011). The platform increased the types of payments accepted and enabled individuals to schedule recurring contributions. Creating an ActBlue Express account enabled prospective donors to give in a single click, bypassing the need to input payment or employment information. The group has also invested in maintaining and testing a modern aesthetic and simple, mobile-compatible user experiences, to "make [the contributing process] as frictionless as possible," according to ActBlue's executive director (Reilly, 2019).

In addition to making it easier to donate once a prospective donor lands on the site, ActBlue enables campaigns to create more opportunities for donors to give. Like corporate advertisers and activist organizations (Karpf, 2016), campaigns can use ActBlue tools to A/B test which messages effectively convert prospective donors into donors. The organization conducts experiments and reports its findings to campaigns, enabling campaigns to skip over

[1] In 2010, NGP merged to become NGP-VAN, but fundraising was initially a core NGP function.

ineffective solicitation strategies (Willis, 2014). The platform enables bundling, or the ability to donate to curated sets of candidates in a single transaction (Malbin, 2013). Furthermore, ActBlue provides tools for campaigns to identify and keep tabs on potential donors.

These innovations center around converting prospective donors into donors and current donors into recurring donors. Since the largest donors are bound by FEC contribution limits, there is little ActBlue can do to aid campaigns in squeezing more money out of larger donors. Since larger donors are more likely to be donating for access-seeking reasons, the impersonal nature of making an online contribution is additionally unappealing, relative to attending an in-person fundraising event with the opportunity to network with the candidate.

Finally, ActBlue also expands the universe of candidates who can use sophisticated fundraising tools. ActBlue provides its services to campaigns by taking a fixed percentage of contributions, whereas access to similarly advanced tools traditionally required contract-based payment. For campaigns without substantial cash reserves, entering into a contract with upfront costs is often not financially feasible. Nor can lower-profile campaigns employ or regularly consult with marketing professionals or data analysts. James Cargas, a candidate from Texas, explained[2] that if not for ActBlue, campaigns without war chests would likely have turned to other solutions without upfront costs, like PayPal or credit card processing through a local bank. Without ActBlue, candidates would still be able to fundraise online, but the Democratic online fundraising landscape would have remained decentralized for a longer period, with fewer innovative tools available to all candidates, especially those unable to raise substantial sums of early money. Taken together, ActBlue enables more campaigns to identify and engage with more prospective donors, more frequently. Notably, these innovations center around smaller individual donors.

[2] In conversation with the author

1.2 Smaller donors and legislative behavior

Candidates have strong incentives to adopt fundraising strategies that reliably attract donations. Over the past two decades, both the composition of the donor pool and the cost of running for office have changed dramatically. By 2020, the average Democratic congressional general election candidate raised over $4 million, nearly four times what candidates raised two decades earlier.[3] These rising costs can shape who chooses to run (Carnes, 2018) and affect electoral outcomes (Thomsen, 2023). As campaigns become more expensive, electoral competition degrades and incumbents tend to be more advantaged (Fouirnaies, 2021), though the marginal returns on spending diminish slower for challengers – if they can raise enough money (Bonneau & Cann, 2011). Given the centrality of fundraising to electoral viability, candidates have clear incentives to behave in ways that maximize campaign contributions.

The role of large (particularly corporate) donors and lobbyists is more extensively examined within the field since corporations have the ability to make attention-getting large contributions or lobby extensively, and legislators might be willing to amend donor-relevant legislation in connection to these donor-related activities. Since contributions from small donors are inherently small, theoretical mechanisms surrounding the small donor-legislator relationship are less established. In this paper, I offer an explanation for how money from small donors can also shape legislative behavior.

What happens when candidates raise more from small donors? I expect that an increase in small-dollar fundraising may coincide with greater ideological extremity among both the donorate and candidates/legislators (La Raja, 2014; La Raja & Schaffner, 2015; Pildes, 2019). This expectation is grounded in two key premises. The first is on small donor preferences. Work on the recipients of small contributions is consistently suggestive: though extreme candidates do not suggest that donors make smaller contributions (S.-Y. S. Kim, 2025), small donors are drawn to ideologically extreme candidates (Albert & La Raja, 2020;

[3] https://www.opensecrets.org/elections-overview

Culberson et al., 2019; Johnson, 2010; Meisels et al., 2022) and may even reward extreme legislative behavior (Keena & Knight-Finley, 2019) and extreme campaign rhetoric (S.-Y. S. Kim et al., 2023). Both unitemized and itemized donors have more ideologically extreme preferences than access-seeking PACs (Barber, 2016) and voters (Albert & La Raja, 2026; Bafumi & Herron, 2010; Broockman & Malhotra, 2020; Magleby et al., 2018). If a candidate's donor pool shifts towards small donors, this could mean the donor pool shifts away from the ideological middle.

The second premise concerns responsiveness to donors' preferences. Legislators are responsive to both individual and group-based donors (Canes-Wrone & Miller, 2021; Grier et al., 2023; Kalla & Broockman, 2016; Kujala, 2020; Stratmann, 1995), but there are additional reasons to expect that legislators will be particularly responsive to small donors. If legislators are strong partisans, then donors might be better aligned with a legislator's true ideological positioning, and new contributions from small donors may enable lawmakers to ignore the preferences of moderating PACs donors (the reverse case of Li and DiSalvo, 2023). While smaller, individual contributions are typically conceptualized as consumptive and expressive for the donor (Ansolabehere et al., 2003; Bouton et al., 2024), small donors' collective importance in fundraising portfolios may also create incentives for direct responsiveness from legislators. Candidates, staffers, and parties are drawn to the democratic, bottom-up nature of individual contributions ("because campaigns are won on the strength of their grassroots")," [4] often touting large quantities of small donors while campaigning,[5] and arguing that it is a metric that "campaigns should be judged on."[6] In both situations, legislators face pressure to raise and retain funds from small donors. Since small donors are reactive to candidate positioning (Keena & Knight-Finley, 2019),[7] candidates should shift

[4] https://publicintegrity.org/politics/elections/democrats-small-dollar-donors-president-campaign/

[5] https://www.pbs.org/newshour/politics/can-you-chip-in-a-dollar-2020-democrats-race-for-small-donors

[6] https://publicintegrity.org/politics/elections/democrats-small-dollar-donors-president-campaign/

[7] Unlike this study, Keena and Knight-Finley (2019) do not find that legislative behavior shifts when candidates raise more from small donors. There are many possible reasons their results from the Senate differ from mine in the House, including asymmetry across parties (see Appendix Section 24), different settings, and their lack of a similar "shock" to the supply of small donors. My empirical strategy does not

their behavior in order to align with the preferences of small donors and to retain their support.

While small donors lack the direct access to legislators that lobbyists and large donors enjoy, they can still make their preferences known through several pathways. Though these donors contribute smaller amounts, identifying as a donor improves access to legislative staff (Kalla & Broockman, 2016). If smaller donors are more likely to reach out to legislators than constituents, then these imbalances in contact can shape legislators' beliefs on constituent support (Broockman & Skovron, 2018). Furthermore, since online campaign messaging can be extensively tested, campaigns can learn the types of messages that maximize small donor giving. In fact, S.-Y. S. Kim et al. (2023) find that campaign Facebook ads targeted towards donors have converged on using particularly polarized language, suggesting that campaigns do indeed understand the polarized preferences of small donors. Though specific mechanisms on responsiveness are outside the scope of this paper, there are ample reasons to expect that a shift in the quantity of contributions from small donors will correspond to a shift in legislative behavior.

Still, these expectations may not hold in the context of ActBlue. The platform may not substantially increase small donor participation. For instance, high-profile but uncompetitive Democratic challengers have drawn millions from small donors, raising concerns about the efficiency of Democratic donor behavior (Hersh, 2020; Sokolove, 2022). Small donors brought in via new technologies may diverge from the ideologically intense archetype or may not push candidates towards extremity, especially if small donors crowd out contributions from itemized individual donors, who are characterized as similarly or more extreme than unitemized donors in survey work (Albert & La Raja, 2020, 2026; Barber et al., 2026; Graf et al., 2006; Magleby et al., 2018). Indeed, small donors are more representative of the overall population than itemized individual donors (Bouton et al., 2022; Malbin, 2013). Legislators

directly test their conclusion that donors are responsive to prior-session legislative behavior, and it is entirely possible that legislators are responsive to donor preferences *and* donors are responsive to legislator behavior.

may not be responsive to shifts in the donor pools, as contributions do not always translate to preferred policy outcomes (Fouirnaies & Fowler, 2022; Fowler et al., 2020).

Even if patterns of polarization do emerge following ActBlue adoption, they may result from broader changes in donor composition rather than just increases in the quantity of smaller donors. Because internet campaigning enables donors to learn about and give to candidates beyond their congressional district, it is plausible that results actually stem from out-of-state, nationalized donor pools. Baker (2016) and Canes-Wrone and Miller (2021) have shown that legislators who are more reliant on out-of-district donors are more likely to side with their party's national donors, on average. I discuss itemized out-of-state donors, serial donors, and new donors in Table A21, but find that ActBlue adoption does not increase participation among these other types of donors.[8] Beyond out-of-state donors, other explanations for within-legislator change cannot fully be ruled out, though in following sections and the appendix, I discuss possible alternate reasons for adoption such as competition (Tables A12-A16) and candidates' pre-adoption ideological positioning (Table A9).

While "small donor" typically refers to the technical definition of an unitemized donor, applicable to donors who give less than $200 per election, the mechanisms that I describe in this paper are not confined to this threshold. Nor do results substantively change when taking inflation into account (Table A7). Rather, the effects identified in this paper reflect behavioral patterns that are strongest among unitemized donors, but extend to larger individual contributors as well. I show that individual donors giving larger amounts exhibit weaker but directionally similar trends as unitemized donors.

[8] The biggest shifts in out-of-state donor fundraising actually appear the cycle following this paper's period of study (https://www.opensecrets.org/news/reports/out-of-state-donations)

2 Data and Methods

I used the Database on Ideology, Money in Politics, and Elections (DIME) from Bonica (2014) to obtain candidate congressional district, CFScores, itemized contributors, and incumbency status. I used OpenSecrets datasets on the sum and share of contributions raised by candidates from unitemized donors. Some general election candidates are missing from the OpenSecrets data. For these candidates, I manually recorded their receipt totals and their totals of unitemized contributions from the FEC website or verified that they did not raise enough funds to report data to the FEC. Because Senate elections are comparatively infrequent, I subset the data to only House elections. I used data from 2002-2016.[9] To ensure the focus on candidates who are actively fundraising, I restricted the sample to candidates raising over $20,000 in a given cycle. I also removed candidates who have switched in or out of the Democratic party. Table A3 shows results are robust to varying restrictions.

I appended data on candidates and their congressional districts. I used interest group ratings from Vote Smart and roll call voting data or scalings from Clinton et al. (2004), Fowler (2024), and Lewis et al. (2023). Data on legislator and candidate ideology are described in more detail alongside Tables 5-7. For regressions with controls, I used Daily Kos calculations on presidential Democratic vote share by congressional district to calculate district safety.

2.1 ActBlue adoption

Measuring ActBlue adoption is not necessarily straightforward. I consider a candidate to be an ActBlue adopter when they use ActBlue to process online contributions originating from their campaign website. To determine whether a candidate encouraged prospective donors into the ActBlue environment, I used the Internet Archive's Wayback Machine and the Library of Congress' archive of candidate websites. After obtaining a candidate's website URL for a given campaign year, I navigate to the website's contribution page. From there,

[9] By 2018, ActBlue essentially gained market dominance.

it is usually clear what service the candidate uses to process payments.

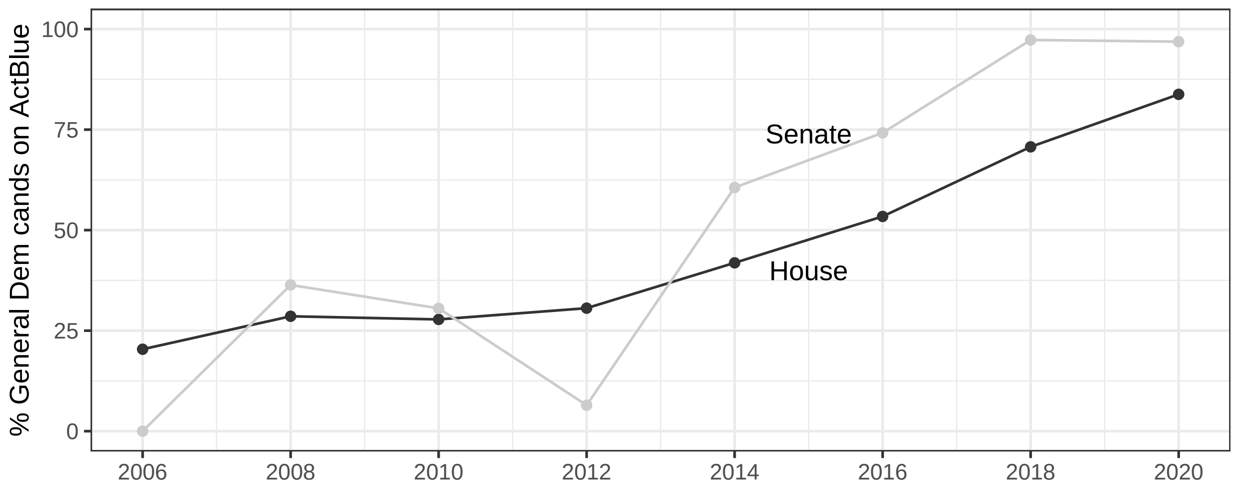
There is some uncertainty in this data-collection process, as some donation pages and some complete websites were never fully captured by the archives. Not all candidates had websites or solicited donations on their websites. Candidates in districts with little electoral competition were among the last to build websites, and long-term incumbents with robust offline contribution networks, such as Rep. Nancy Pelosi, were among the last to solicit contributions on their websites. I code these uncertain and non-soliciting instances (about 8% of observations) as non-adopters.

The website-based strategy has drawbacks. Some candidates actively solicited contributions via ActBlue (through emails, texts, or ads) but directed website visitors to other payment processors. For example, Hillary Clinton's 2016 presidential campaign website brought donors to NGP-VAN's FastAction, while still hosting a landing page (and raising money) through ActBlue. Earlier in ActBlue's history, supporters even raised money for candidates without the candidate's knowledge of the platform – making the strategy used in S.-Y. S. Kim and Li (2025) for WinRed adoption unviable for the ActBlue case. I code candidates as adopters only when their campaign websites redirect visitors to ActBlue, ensuring that adoption reflects an active campaign decision. This approach avoids false positives that would arise from relying solely on FEC data, where candidates might passively receive ActBlue funds. However, it also means that some known users (including some raising over $100k via the platform) are coded as non-adopters if their websites did not redirect to the platform. Misclassifying true ActBlue users as control units potentially biases estimates towards zero, and a placebo test on ActBlue timing in Table A8 shows that results dwarf in size when a candidate's adoption timing is perturbed. Indeed, the main estimates do indeed hinge on the timing of ActBlue's appearance on candidate websites.

2.1.1 When and why did candidates join ActBlue?

The vast majority of Democratic general election candidates now use ActBlue as their online contributions processor. However, in ActBlue's early days, candidates wanting to fundraise online had many competitors to choose from (Figure A2). Unlike WinRed, where Republicans quickly coalesced on a single platform endorsed by party leadership (See Section 24 and S.-Y. S. Kim and Li, 2025), Figure 1 shows that ActBlue convergence took years.

Figure 1 – ActBlue adoption among general election Democratic candidates over time, by chamber



What factors do campaigns cite for choosing ActBlue? Sam Spencer,[10] who has worked in key finance roles in Democratic and left-leaning campaigns across multiple levels of government, characterizes the movement towards ActBlue as multi-faceted, with inertia and user-friendliness for both campaign workers and donors serving as major reasons that campaigns used the platform. In many cases, processing online contributions through ActBlue offered better value, with a predictable fee based on contributions raised. When running for House in Texas, James Cargas[11] decided to use ActBlue because he had previous experience with the platform as a treasurer for state PACs, and that the platform, especially compared to other options without upfront costs, had better customer service and made legal compli-

[10] in conversation with the author
[11] in conversation with the author

ance easier. Jan McDowell,[12] another House candidate from Texas, found ActBlue "easy and responsive to work with." Spencer stated that candidates chose to adopt ActBlue because ActBlue was superior to products offered by competitors, and not with intention of tilting their donor pool towards ideological donors. In Tables A12-A16 I fail to find that candidates switch to ActBlue when they face external pressure to move to the ideological left, but it cannot be ruled out that some switchers had ideological considerations in mind. While making the switch to ActBlue seems prompted by convenience and financial considerations, I additionally cannot fully separate adoption from other within-cycle strategic changes that might co-occur with adoption.

2.2 Methods

All regressions in Tables use the two-way fixed effects (TWFE) difference-in-differences modelling strategy. TWFE are a generalization of the canonical two-period difference-in-differences estimator. Candidate-level regressions are of the following form:

$$y_{it} = \beta * \text{ActBlue candidate}_{it} + \alpha_t + \theta_i + \epsilon_{it} \tag{1}$$

In Equation 1, β represents the average treatment effect on the treated of adopting ActBlue on outcome y_{it}. I define being an ActBlue candidate$_{it}$ as a binary: 1 when candidate i in year t directs website visitors to ActBlue and 0 otherwise. The outcomes y_{it} represent a candidate's contributions by donor type, average donor ideology, and behavior-based ideology. Time and candidate fixed effects are represented by α_t and θ_i respectively. Each observation is a general election House Democratic candidate, for each electoral cycle, 2002-2016.

Tables in the main body also feature up to three additional specifications, space permitting. In order to evaluate pre-trending, I add in a lead term λ on ActBlue adoption. If there is little pre-trending, then the lead term will be indistinct from zero. Because non-website

[12] in conversation with the author

based ActBlue adoption occurs, I also include a dummy "FEC" for periods in which the candidate reports money from ActBlue in their Federal Election Commission forms but do not use ActBlue on their website. This helps distinguish the lead term from uncertainty arising from a candidate's true timing of ActBlue adoption.

$$y_{it} = \beta * \text{ActBlue candidate}_{it} + \lambda * \text{ActBlue candidate}_{i(t-1)} + \text{FEC}_{it} + \alpha_t + \theta_i + \epsilon_{it} \tag{2}$$

While I include candidate fixed effects θ_i, some candidate attributes may also vary over time. For example, we might expect candidate who goes from a very Democratic district to a lean-Republican district, via redistricting or over-time shifts in district preferences, to moderate their legislative behavior. I include controls on district safety and incumbency:

$$y_{it} = \beta * \text{ActBlue candidate}_{it} + \text{District Safety}_{it} + \text{Incumbency}_{it} + \text{FEC}_{it} + \alpha_t + \theta_i + \epsilon_{it} \tag{3}$$

I use candidate-specific linear time trends (CLST). This enables each candidate to generate linear trends in behavior over time, while standard TWFE assumes a static (slope zero) fixed effect for each candidate. For example, if a wholly responsive candidate's district becomes more conservative over time, this behavior can be accounted for by $\gamma_i * t$:

$$y_{it} = \beta * \text{ActBlue candidate}_{it} + \alpha_t + \theta_i + \gamma_i * t + \epsilon_{it} \tag{4}$$

Finally, I replace candidate fixed effects with district-decade (δ_i) fixed effects. Since districts are redrawn ahead of the 2012 election, a decade component is necessary. Doing so reduces the reliance on incumbents, but does risk conflating effects from candidate/legislator replacement together with effects on within-individual changes.

$$y_{it} = \beta * \text{ActBlue candidate}_{it} + \alpha_t + \delta i + \epsilon_{it} \tag{5}$$

Taken together, these specifications allow for the evaluation of the robustness and plausibility of the assumptions underlying the TWFE strategy, which are further discussed below.

2.3 Assumptions and interpretation

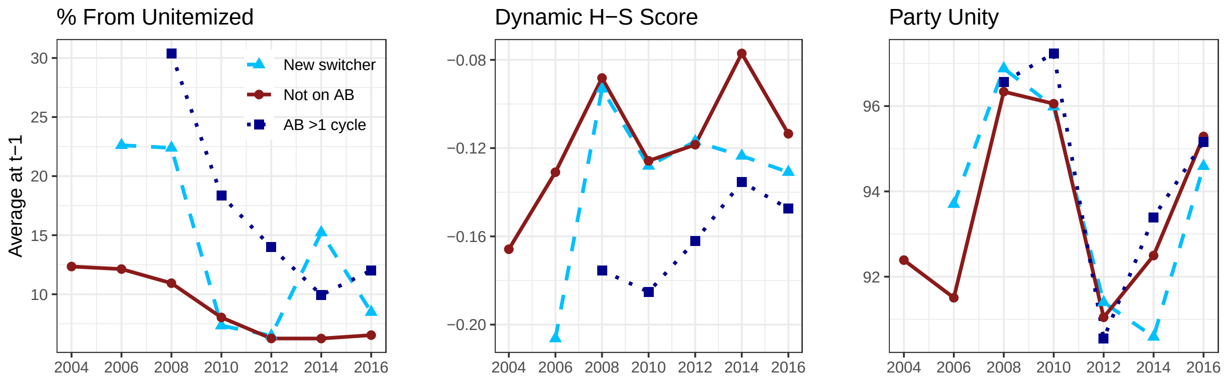
This subsection discusses methodological assumptions underlying the TWFE method and concerns on endogeneity. I take these potential threats to inference seriously. In this paper, I use a within-candidate difference-in-differences design, so that treatment effects already take into account candidate-invariant traits as well as time trends, but concerns may still arise regarding when a candidate adopts the fundraising platform and who gets excluded within the TWFE process.

2.3.1 ActBlue adoption and endogeneity

Because the types of candidates who raise the most from small donors tend to be extreme, a key concern interpreting the Average Treatment Effects on the Treated as true population-wide Average Treatment Effects is that ActBlue adoption is driven by extremity-prone candidates joining the platform. While my conversations with candidates and staffers did not cite ideology as a reason for adopting ActBlue, it is true that candidates with progressive credentials were earlier adopters: in 2008, only 24 ActBlue-using House candidates were elected, including nine legislators with (past or future) Congressional Progressive Caucus membership. Figure 2 shows that in ActBlue's earliest years, the type of candidates who joined ActBlue had more liberal H-S Scores (low values indicate more liberal scores, H-S Scores are defined and discussed extensively in Section 3.2) and higher proportions of small donors prior to adoption. That said, party unity among adopters and non-adopters remains similar throughout time.

Since selection into ActBlue is somewhat skewed, at least on the basis of some metrics, one concern is that results are driven by liberal legislators becoming more liberal. A similar

Figure 2 – Donor pool characteristics of early ActBlue adopters across time



	2004	2006	2008	2010	2012	2014	2016
Not on AB	202	209	216	193	133	115	97
New switcher	0	11	11	21	10	21	20
AB >1 cycle	0	0	19	36	36	57	80

2004	2006	2008	2010	2012	2014	2016
191	198	212	188	129	110	95
0	9	9	21	10	21	20
0	0	17	35	32	50	73

2004	2006	2008	2010	2012	2014	2016
186	188	206	186	119	109	87
0	4	8	19	9	21	16
0	0	7	25	27	49	64

concern is that liberal and moderate candidates may follow different trajectories over time, leading to a violation in the parallel trends assumption. Table A9 classifies candidates as "moderate" or "progressive" based on pre-ActBlue attributes, and allows for moderates and progressives to develop their own separate time fixed effects. Tables 5-7 additionally show results for moderate-only regressions with leads. I find that the effects in this paper are just not about very liberal candidates becoming even more liberal. In fact, candidates who score in the "moderate" half of pre-ActBlue attributes tend to have somewhat larger treatment effects for ActBlue adoption.

An additional potential issue is that this study covers a significant period of time – eight congressional cycles – and that those who chose to refrain from ActBlue adoption throughout this entire period of study (see Figure A1 for all ActBlue adoption trajectories) did so strategically, and therefore may also follow different trajectories than candidates who did eventually join the platform. Table A10 drops candidates who never make the switch and again recovers coefficients similar to those in the results section.

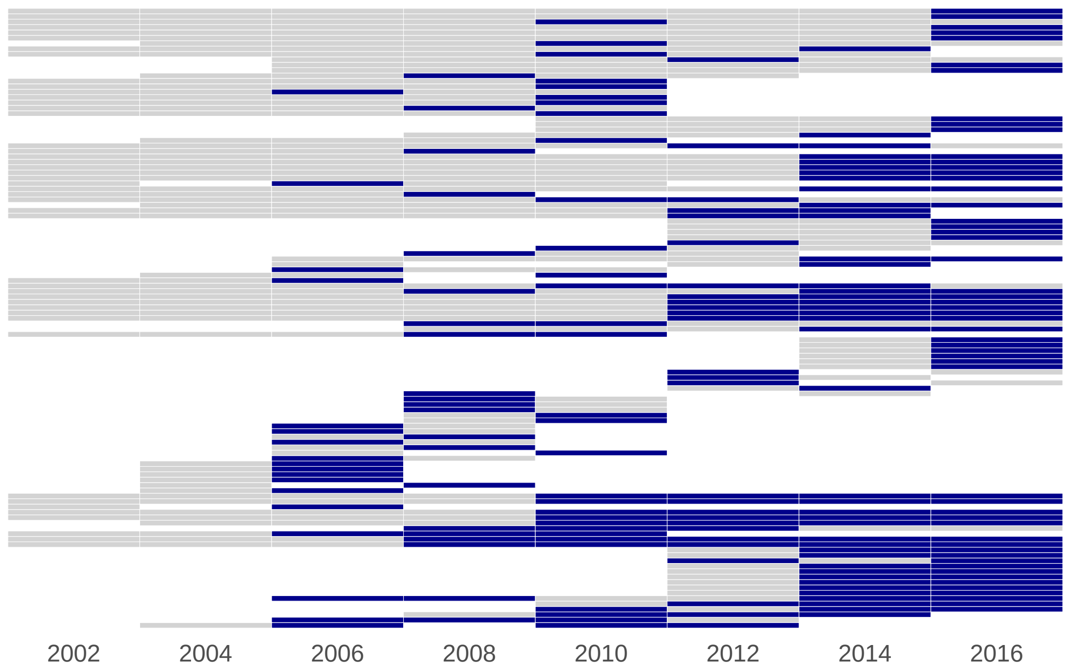
While rollout is fairly even across the period of study (Figure 3), in-text estimates could rely too heavily on early adopters, who may have been the most enthusiastic about activating and being responsive to small donors. If results are strong among early adopters and weak among late adopters, the results may still be significant, on average. In Figure A5, I break results out by the year a candidate first used ActBlue and find that coefficient estimates are generally similar across adoption years. Though ActBlue adoption is correlated with ideology, results are not driven by selection into ActBlue by early or extreme candidates.

Finally, electoral competition could induce ActBlue usage. For example, Democratic incumbents redistricted into competitive districts might take the task of fundraising more seriously and prefer ActBlue's modern interface and research into strategies to maximize contributions. If this were the case, results would not necessarily reflect the effect of ActBlue adoption. Table A12 considers the case of 2010-2012 congressional redistricting and finds that House candidates are not particularly more likely to join ActBlue after being drawn into competitive districts. Similarly, candidates might want to join ActBlue as well as shift their legislative behavior to the left if they encounter primary competition (Anderson et al., 2020; Brady et al., 2007) or being redistricted into a more Democratic seat (Kaslovsky & Kistner, 2024). Descriptive analyses in Table A13 show that candidates are not substantially more likely to join ActBlue when they encounter primary opponents or when primary elections are close. Tables A14-A15 consider financial competition and competitor fundraising strength, and again do not find that competition induces adoption. Table A16 shows that Democratic district safety imposed by redistricting also does not result in significant ActBlue adoption.

2.3.2 Effectively omitted data under two-way fixed effects

Since I focus on within-candidate variation, I can only recover a treatment effect on those who appear within the dataset at least twice. I refer to this as the 2+ set. Candidates who only run once cannot contribute to the calculation of the main effect, as their individual fixed effect completely reflects their observed outcome. Candidates who run at least twice, but have not yet started (or never start) using ActBlue act as control cases. Likewise, those who run at least twice and always use ActBlue aid in the development of time fixed effects,

Figure 3 – ActBlue adoption and usage over time by switchers. Gray denotes that the candidate ran in the cycle, but did not use ActBlue. Blue denotes the usage of ActBlue. White sections indicate that the candidate did not run in a general election.



but again do not aid in the estimation of the effect of ActBlue adoption. The coefficient of interest, β, is calculated based on the outcomes of candidates who have run at least twice, and who have run for office both with and without ActBlue. This amounts to 127 unique candidates, whose ActBlue usage trajectories are shown in Figure 3. The universe of candidates who have run at least twice is visualized in Figure A1. Tables A1-A2 compare the 2+ set to the entire set of general election Democratic House candidates, and show that the 2+ set comes from more Democratic districts, are more likely to be incumbents, raise more from out of state, and raise money from a more moderate network of donors.

Because of this imbalance in which candidates are used to develop β, the ATT should be interpreted as a treatment effect among mostly incumbents or electoral winners, not necessarily as a treatment effect on Democratic House candidates as a whole. As a way to present values that better reflect patterns from the entire sample, I repeat analyses with district-decade instead of candidate fixed effects within the final column of each set of results. While the district-time fixed effects strategy allows for the comparison between different candidates in the same district, selection into the treatment becomes a larger concern, since candidate-level attributes are no longer controlled for.

2.3.3 Parallel trends and two-way fixed effects

The causal interpretation of β is based on a generalized difference-in-difference approach, which relies on the assumption of equal trends to recover the average treatment effect on the treated. For an ActBlue-using candidate i, I assume that if i had not used ActBlue as their primary payment processor, then i would follow the same trends as candidates who did not use ActBlue. While the parallel trends assumption cannot be proved, it can be investigated. In main text tables, I report alternate regression specifications with candidate-specific linear time trends as well as specifications that use the leads of treatment adoption.

These specifications often corroborate results from the default TWFE specification, but do differ on occasion. Both using a lead term or candidate-specific linear trends places additional constraints on my model, which calculates the ATE using 127 switchers. The inclusion of a lead term necessarily drops data from my last year, 2016, as well as the year of the candidate's first House run. The use of candidate-specific time trends necessitates that switchers be present in the data for at least 3 electoral cycles. Lead and CSLT strategies drop the effective number of switchers to 103 and 88, respectively.

The visual assessment of the parallel trends is difficult because my data is characterized by staggered adoption of an unbalanced panel of candidates, but event study-style plots can further aid in the investigation of parallel trends. Event study plots using TWFE are shown in Figure A3, and event study plots based on estimators from Liu et al. (2024) are presented in A4.

The TWFE estimator has recently received attention due to its unclear treatment of heterogeneous fixed effects. I examine alternative difference-in-differences strategies in the appendix. Figure A5 discusses why the Goodman-Bacon (2021) estimator cannot be calculated in this case (and provides by-year treatment effects), Table A5 discusses why treatment reversals prevent directly comparable treatment effects from the Callaway and Sant'Anna (2021) estimator, Table A4 shows results using three estimators from Liu et al. (2024), and Table A6 presents results using the estimator from De Chaisemartin and d'Haultfoeuille (2020), and estimates are often near those shown in this manuscript and are always directionally consistent.

3 Results

This section presents results in three sections. I begin by establishing that when candidates begin using ActBlue, they see the largest increases in cash from smaller donors. I then examine if candidates raise more money from ideologically extreme sources after ActBlue adoption, and therefore appear more "extreme" as measured by contribution-based metrics of candidate ideology. These first two findings establish that as it becomes easier and commonplace for small donors to give in Democratic congressional elections, the donor pool becomes skewed towards smaller donors and fundraising networks shift towards liberal donors. I then ask whether this shift in the donor pool is associated with leftward shifts in legislative behavior. I find that elected legislators, particularly moderates, are more extreme in their congressional behavior post-ActBlue adoption.

3.1 Candidates raise more money from smaller donors after ActBlue adoption

ActBlue is often credited with boosting small donor fundraising, especially following Bernie Sanders' 2016 presidential campaign. But does the platform systematically increase small-dollar contributions, or is this reputation driven by a few high-profile fundraisers in high-salience races? Table 1 tests this by examining changes in logged contributions from non-large individual donors after candidates adopt ActBlue.

Table 1 – When candidates join ActBlue, they receive more money from smaller donors. Unitemized donors (under \$200) have the largest increases.

	Log \$ from Unitemized						Log \$ from \$200-500			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AB Year	0.48	0.42	0.63	0.30	0.23	0.22	0.34	0.35	0.05	-0.01
	(0.11)	(0.14)	(0.12)	(0.18)	(0.09)	(0.06)	(0.08)	(0.07)	(0.08)	(0.09)
Lead		0.14					0.05			
		(0.14)					(0.07)			
Cand FE	✓	✓	✓	✓		✓	✓	✓	✓	
Dist-Dec FE					✓					✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
FEC		✓	✓				✓	✓		
Controls			✓					✓		
CSLT				✓					✓	
Obs	2793	1474	2724	2793	2793	2745	1453	2697	2745	2745

Note: Standard errors are clustered by candidate. CSLT = candidate-specific linear time trends.

Table 1 shows that when a candidate starts using ActBlue, they will, on average, raise about 61% (exp(0.48) = 1.61) more dollars from unitemized donors than they did prior to ActBlue adoption, even after accounting for individual and time-varying factors. Most models show that candidates also raise more from donors giving \$200-\$500, but these increases are smaller than the increases from unitemized donors. A critical question is whether candidates are also receiving more from larger donors when they start using ActBlue: perhaps candidates aggressively solicit money from all sources when they join ActBlue. Table 2 examines whether candidates raise more money from large individual donors as well as Political Action Committees when they start using the fundraising platform.

Table 2's first five columns aggregate campaign contributions from individual donors giving 85% or more of a given year's campaign contribution limit.[13] I find that candidates,

[13]Donors must give 85%-100% of the cycle's campaign contribution. For example, 2002's contribution

Table 2 – After joining ActBlue, candidates experience substantially smaller increases from near-maximizing individual donors and PACs than from unitemized donors.

	Log $ from Near Max					Log $ from PACs				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ActBlue Year	0.16	0.23	0.32	-0.03	-0.07	0.01	0.03	0.16	0.01	-0.39
	(0.07)	(0.09)	(0.08)	(0.08)	(0.09)	(0.07)	(0.11)	(0.07)	(0.09)	(0.11)
Lead		0.12					-0.07			
		(0.07)					(0.07)			
Cand FE	✓	✓	✓	✓		✓	✓	✓	✓	
Dist-Dec FE					✓					✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
FEC		✓	✓				✓	✓		
Controls			✓					✓		
CSLT				✓					✓	
Obs	2652	1438	2606	2652	2652	2648	1448	2606	2648	2648

Note: Standard errors are clustered by candidate. CSLT = candidate-specific linear time trends.

on average, receive increases in contributions from near-maximizing individual donors when they begin using ActBlue, but these results are somewhat fragile, with sign flips in columns 4 and 5.[14] Table 2's final five columns consider funds originating from Political Action Committees. In contrast to other dependent variables, the majority of estimates hover near zero. It is clear from Tables 1 and 2 that campaign fundraising gains after ActBlue adoption are largest for unitemized donors. Given that I find differential changes in contributions by donor type, I next consider whether small and individual donors actually account for a larger proportion of funds within a candidate's fundraising portfolio in Table 3.

Table 3 reports the aggregate percentage of contributions by donor category. When a candidate starts using ActBlue, their share of money from unitemized donors increases by about four percentage points. Changes for all other donor types are substantially smaller.

limit was $1000 per election (primary and general elections are separate), so to be counted, a donor must give at least 0.85*(1000+1000)=$1700.

[14]Column 5 also encompasses candidate replacement, and the discrepancy between columns 5 and 1 emphasizes that one-time candidates who use ActBlue have a tendency to raise substantially less from near-maximizers than one-time candidates on other platforms.

Table 3 – After ActBlue adoption, the smallest individual donors comprise of a larger share of candidate's fundraising portfolios.

	% Unitemized	% $200-500	% Near Max	% Committee
	(1)	(2)	(3)	(4)
ActBlue Year	3.97	0.74	0.23	-1.53
	(0.96)	(0.35)	(0.76)	(1.76)
Cand FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Obs	2829	2829	2829	2829
Mean $\bar{y}$ (%)	14.21	10.10	17.75	33.65

Note: Standard errors are clustered by candidate.

Smaller donors do appear responsive to changes in candidate fundraising technology. When it becomes easier to donate, smaller donors give more to congressional campaigns relative to other types of donors, thereby playing a larger part in congressional fundraising. ActBlue adoption, and the technological improvements that adoption represents, clearly contributes to the rise of small donors in Democratic congressional fundraising.

3.2 Candidate donor networks shift left after ActBlue adoption

The composition of donors shifts when candidates join ActBlue, and a straightforward question is whether the ideological lean of the donor network also shifts. Since smaller donors have been shown to be similarly extreme to other individual donors, and more extreme than the populace or PAC donors, I anticipate that a switcher's donor network will shift left post-adoption.

This section analyzes two metrics of the ideological lean of donor network after candidates begin using the fundraising platform. While these scores are typically used in order to measure candidate ideology, operating under the assumption that a candidate's ideology is revealed by the average ideology of their contributors, I set the assumption of revealed preferences aside. Dynamic CFScores differ for each candidate each year and represent a candidate's ideology in the CFScore common space (Bonica, 2014). I generate a second outcome using contributions data with a methodology similar to Hall (2015) and Hall and Snyder Jr (2015). This procedure imputes candidate DW-NOMINATE by using overlapping donors. I refer to these scores as H-S scalings. I outline how H-S scalings are calculated, how my procedure slightly differs from Hall and Snyder Jr (2015), and discuss researcher degrees of freedom in Table A17. For results in Table 4, H-S Scores are based on the contributory behavior of all itemized donors who have given to at least 3 candidates, and all candidates who have received at least 10 contributions from these donors.

The H-S procedure is ideal because I can control what types of contributions are used in calculating donor extremity scores, and this flexibility allows me to investigate what types of donors are responsible for the underlying over-time shifts in donor ideology in Figure A7. Notably, results are robust when constructing Hall–Snyder Scores using only committee contributions. This reduces concerns that the estimated leftward shift is driven mechanically by ActBlue-induced changes in the individual-donor contribution network.

Table 4 – When candidates start using ActBlue, they raise money from more liberal sources.

	Dynamic CFScores					Hall-Snyder Scores				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AB Year	-0.059	-0.061	-0.080	-0.021	-0.123	-0.025	-0.031	-0.024	-0.026	-0.029
	(0.015)	(0.022)	(0.017)	(0.021)	(0.018)	(0.007)	(0.009)	(0.007)	(0.009)	(0.006)
Lead		-0.025					-0.010			
		(0.017)					(0.006)			
Cand FE	✓	✓	✓	✓		✓	✓	✓	✓	
Dist-Dec FE					✓					✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
FEC		✓	✓				✓	✓		
Controls			✓					✓		
CSLT				✓					✓	
Obs	2798	1480	2754	2798	2798	2456	1420	2411	2456	2456

Note: Standard errors are clustered by congressional candidate. Both Dynamic CFScores and the H-S scores are temporally dynamic. CSLT = Candidate-specific linear time trends.

In Table 4, I find that candidates raise money from more ideologically extreme (more liberal) networks when they start using ActBlue, both with CFScores and the H-S scaling. The magnitudes of these results are substantial relative to the distribution of congressional candidates. Relative to the dependent variable's 2004 distribution (2004 was the last year without ActBlue switchers in the data), a -0.059 Dynamic CF Score shift represents a 25-candidate shift to the left of the median Democratic candidate, out of 336 in-sample Democratic candidates with CFScores. Similarly, a -0.025 H-S score shift in 2004 represents a 33-candidate shift to the left of the median candidate, out of 291 in-sample with H-S Scores. These changes represent 14.7% (CFScores) and 23.9% (H-S) of a standard deviation in the distribution of 2004 Democratic scores.

While average candidate's network of donors moves to the left, it remains unclear whether certain types of donors are responsible for this shift. At first glance, it seems like these results could be the result of a mundane technicality: because ActBlue is a conduit, scores might shift leftwards because the contributions from unitemized donors that flow through ActBlue must be publicly reported (see Alvarez et al., 2020 for a fuller discussion of reporting), and can thereby enter the ideology score calculation process. While CFScores involve an adjustment for the percentage of conduit donations while calculating CFScores, they are not removed. This means that the act of using ActBlue may impact CFScores, even if donor pools are exactly the same before and after ActBlue adoption.

However, this logic does not apply to H-S score shifts, as the contributions that are used in my H-S procedure are always over the itemization threshold of $200 (Table A7 additionally shows that H-S scores are stable after accounting for inflation). Because unitemized contributions are inherently unitemized prior to the rise of campaign finance conduits, I cannot compare pre-ActBlue and post-ActBlue giving among unitemized donors. I can, however, examine how committee or itemized individual donors contribute to the shifts observed in Table 4. I recalculated H-S scores, using only certain subsets of donors in Figure A7. All donor types shift leftward, even committee donors, who are likely not directly impacted by changes to small donor fundraising technology.

Interpreting shifts in the lean of donor networks requires accounting for both the composition of the donor pool (Table 3) and the ideological shift (Figure A7) of each donor group. I explain this in terms of H-S scores. A candidate's overall H-S score may shift if ideological donor groups become more prominent within the donor pool (for example, individual donors become a larger proportion of funds raised, at the expense of PAC donors) and if the within-type donor portfolios shift left (for example, moderate PACs may stop giving to a candidate). When a candidate joins ActBlue, they raise somewhat higher percentage of funds from individual donors, who are known to be more extreme than PACs and the populace. In Figure A7, I show that the candidate's network of itemized individual donors separately also shifts to the left. In other words, the candidate's post-switch individual donors will have given to more liberal candidates (calculated using DW-NOMINATE) than their pre-switch individual donors. Committees become a smaller share of the donorate, and when a candidate starts using ActBlue, Figure A7 shows that their post-adoption network of committee donors gives to more extreme candidates (based on DW-NOMINATE scores), on average, than their pre-adoption network. In sum, the shift left of Democratic donor networks is not solely due to a donation type compositional change where individual donors replace PACs. Within each group, donor networks also shift left. These findings suggest that the ActBlue-related influx of contributions from smaller donors came alongside a real leftward shift in the ideological lean of donor networks.

3.3 Does congressional behavior shift after ActBlue adoption?

The results from the previous sections may not necessarily translate to a leftward shift in observed congressional behavior for three reasons. First, those with the biggest ActBlue-related ideological shifts may not win office.[15] Second, shifts in financial constituencies do not always produced aligned policy responses (Ansolabehere et al., 2003; Fouirnaies & Fowler,

[15]Table A11 finds similar effects to Tables 1-4 using only winners.

2022; Fowler et al., 2020). Third, the changes in donor composition may possibly too small an effect to shift legislative behavior, especially in a within-legislator design. In this section, I test whether legislative behavior shifts to the left once a candidate joins the fundraising platform. Congressional behavior is measured in the term after ActBlue adoption: if a legislator starts using ActBlue ahead of the November 2012 elections, 2013-2014 is her first "treated" term.

Measuring within-legislator behavioral change can be difficult, and very few studies have been able to provide explanations for within-legislator behavioral change. Many standard metrics of legislator behavior, such as DW-NOMINATE, do not vary by Congress, and cannot be used when by-legislator temporal variation is necessary.[16] Other scores may allow legislators to earn new scores each session independent of their previous legislative behavior, but an underlying assumption in my regressions is that over-time variation can be controlled through year fixed effects.[17] Given these caveats, Tables 5-7 examine five measures of congressional behavior.

Table 5 focuses on party unity (the rate of voting alongside the median Democrat). This dependent variable gets to the core of my argument: Democratic Members of Congress are more polarized after ActBlue adoption. Tables 6-7 shows results for four additional dependent variables: the rate of voting against the median Republican legislator, aggregated interest group scores using scores collected by Project Vote Smart, Conservative Vote Probability (CVP) scores (Fowler, 2024; Fowler & Hall, 2012), and scores derived using IRT ideal point estimates from Clinton et al. (2004), abbreviated as CJR. While the development of ideology or position-taking scores is an active endeavor within the field of political science, most other new scores or scores in development either have limited time frames or are currently unavailable to the public. For the CVP, CJR, and interest group scores, a

[16] I discuss Nokken-Poole DW-NOMINATE scores (Nokken & Poole, 2004) in Table A19. In short, Nokken-Poole scores are somewhat anchored by career-length DW-NOMINATE.

[17] For example, I must assume that time-varying characteristics like partisan agenda control can be differenced out with cycle fixed effects, and do not otherwise impact the distribution of dependent variables.

more negative score indicates a more liberal position. For the measures on party unity and Republican disagreement, a positive coefficient indicates more cohesion with the Democratic consensus and voting against the Republican consensus.

In this section (as well as Table A9), I also show results that consider a legislator's pre-ActBlue ideological positioning. "Moderate" and "Progressive" ideological positioning are based on pre-ActBlue positions, with legislators with below-median values of party unity coded as "moderate," and those with above-median values of party unity coded as "progressive." This breakdown serves two purposes: it helps assess for which subsets of legislators the parallel trend assumption is most plausible, and also indicates whether moderates and progressives behave differently post-ActBlue adoption.

Table 5 – When Democratic legislators use ActBlue, they exhibit higher levels of party unity.

	Party Unity (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
AB Year	0.639	0.542	0.823	0.411	0.507	0.597
	(0.231)	(0.386)	(0.326)	(0.343)	(0.468)	(0.258)
Lead		0.187			0.039	
		(0.330)			(0.600)	
Cand FE	✓	✓	✓	✓	✓	
Dist-Decade FE						✓
Time FE	✓	✓	✓	✓	✓	✓
FEC		✓	✓		✓	
Controls			✓			
CSLT				✓		
Moderates only					✓	
Obs	1661	1330	1643	1661	533	1661

Note: Standard errors are clustered by candidate. In 2004 (prior to any ActBlue adoption), the mean party unity was 91.6%.

I first analyze House roll call votes to measure how often House members vote with the Democratic majority (party unity). This measure indicates a legislator's commitment to voting with the party. I use all House votes (Lewis et al., 2023) to create this measure. Table 5 shows that when a House member begins raising money through ActBlue, they begin voting alongside the majority of the Democratic party about 0.64% (pp) more often. This represents a modest increase, as the average 2004 Democrat agreed with the median Democrat on 91.6% of all bills. In the 2004 House, this coefficient corresponds to a 19-congressperson shift to the left of the median 2004 House Democrat, or about 15.6% of a standard deviation (within Congress). Column 2 indicates that on average, the inclusion of a lead term only slightly lowers the estimate, and the estimate from Column 4 with candidate-specific linear time trends is similar other estimates. The lead term in Column 2 is statistically insignificant, though about a third the magnitude of β, indicating that on average, there is not substantial pre-trending for Members of Congress who will soon begin using ActBlue. Column 5 examines considers only moderates, and shows that moderates exhibit similar effects and much less pre-trending, indicating that the assumption of parallel trends is most plausible among moderates. Column 6 uses district-decade fixed effects instead of candidate fixed effects, and recovers an effect similar to those in other columns.

Tables 6 uses two additional dependent variables that measure legislative behavior. Similar to Party Unity from Table 5, Republican Disagreement indicates the proportion of votes that a Democrat makes in opposition to the Republican majority. To obtain a measure of aggregate interest group rating, I take the first principal component from over 35 interest group ratings, which itself explains about half of all variation among Democrats in interest group ratings. These groups are listed in Table A18, and the procedure is described there in more detail. Interest group ratings are created in order to help voters make policy-informed decisions and are centered around issues of national salience, whereas other scores in Tables 5-7 consider all roll call votes. Groups will often consider position-taking and roll call votes, which helps skirt issues of agenda control and strategic roll call voting.[18]

In addition to developing scores to measure legislative behavior, I use two additional scores from the political science literature in Table 7. In general, these scores are highly

[18] A common critique of roll call-based scores are that they treat co-nay voting as agreement, though in practice some members of Congress vote nay for widely different reasons.

correlated (see Figure A8) but are built with different assumptions and methods. Conservative Vote Probability (CVP), developed in Fowler and Hall (2012), is a simple measure that reflects a legislator's probability of making a conservative vote relative to a fixed median legislator. The CVP method requires the manual determination of what a conservative vote entails, and I use updated estimates from Fowler (2024). CVP is easy to interpret: a 0.10 increase in CVP is equivalent to a 10 percentage point increase in voting conservatively, relative to the median member, and this relationship scales linearly. The Bayesian IRT method from Clinton et al. (2004) serves as the basis for many further advancements in the measurement of ideal points beyond just Congress. I calculate CJR scores for each congressional cycle using votes from VoteView and the pscl R package, and manually set the direction of coefficients such that the Democratic mean is negative and the Republican mean is positive (as the rotation of ideal points is not identified in IRT).

Table 6 – Effects of ActBlue adoption on legislators' ideological and partisan positioning (Models 1–8)

	Republican Disagreement					Interest Group Rating				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AB Year	1.499	0.617	1.056	1.606	1.331	-0.333	-0.401	-0.010	-0.581	-0.295
	(0.468)	(0.435)	(0.723)	(0.828)	(0.477)	(0.129)	(0.161)	(0.126)	(0.223)	(0.111)
Lead		0.585		0.662			-0.152		-0.160	
		(0.399)		(0.624)			(0.155)		(0.242)	
Cand FE	✓	✓	✓	✓		✓	✓	✓	✓	
Dist-Decade FE					✓					✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
FEC		✓		✓			✓		✓	
CSLT			✓					✓		
Moders only				✓					✓	
Obs	1661	1330	1661	536	1661	1525	1253	1525	471	1525

Note: Standard errors are clustered by candidate. "Moderate" is based on a candidate's pre-ActBlue value of the dependent variable.

Columns 1-5 of Table 6 consider how voting against the median Republican. On average, when Representatives begin using ActBlue, they exhibit about a 1.5% (pp) increase in disagreement with the Republican consensus. This change represents a 25-congressperson shift to the left from the median. Taken together, the results from Table 5 and Columns 1-4 of

Table 7 – Effects of ActBlue adoption on legislators' ideological and partisan positioning (Models 9–16)

	Conservative Vote Prob					CJR				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AB Year	-0.010	-0.004	-0.006	-0.010	-0.009	-0.054	-0.043	-0.042	-0.027	-0.065
	(0.003)	(0.004)	(0.005)	(0.006)	(0.004)	(0.034)	(0.037)	(0.042)	(0.033)	(0.035)
Lead		-0.004		-0.003			-0.030		-0.007	
		(0.003)		(0.006)			(0.024)		(0.029)	
Cand FE	✓	✓	✓	✓		✓	✓	✓	✓	
Dist-Decade FE					✓					✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
FEC		✓		✓			✓		✓	
CSLT			✓					✓		
Moders only				✓					✓	
Obs	1661	1330	1661	524	1661	1674	1333	1674	538	1674

Note: Standard errors are clustered by candidate. "Moderate" is based on a candidate's pre-ActBlue value of the dependent variable.

Table 6 could represent higher unity in only low-salience situations, but results using interest group ratings convey that this is not the case. Interest groups, who evaluate Members of Congress based both on voting and position-taking on specific issues, assign legislators more extreme ratings when House members begin using ActBlue. Columns 6-10 of Table 6 show that interest group ratings do substantially shift when candidates begin using ActBlue. The 0.33 average shift leftwards in 2004 represents a 5 Representative shift away from the median Democrat (of 182 House members with scores).

Table 7's columns 1-5 consider Conservative Vote Probability scores, and the 1% decrease in CVP (within the main TWFE model) when a candidate uses ActBlue is equivalent to about a 14-legislator shift from the 2004 median House Democrat. Columns 6-10 use the Clinton, Jackman, and Rivers score and finds leftward movement equivalent to a 12-legislator shift from the median 2004 Democrat.

Under all conditions, the relative difference between the lead term and the main effect are more favorable within the moderate subset than when using the entire sample. Effects are generally similar and more causally credible among moderates, a finding echoed in Table A9. While the earliest adopters were somewhat more progressive (see Figure A5 for further discussion on timing and Table A10 for results considering only eventual adopters), these results are not primarily driven by progressive drift to the left.

Although legislative behavior is typically treated as fixed during a legislator's term, the observed shifts reported in this paper are within-legislator. Such effects are rare, and many within-legislator designs yield null results (Fouirnaies & Hall, 2022; K. Kim, 2024). This makes it difficult to benchmark the size of the ActBlue effect against other drivers of ideological change for all dependent variables. However, to give a sense of scale, the estimated effect of ActBlue adoption on CVP is similar in size to a 115th Congress House leadership shift from Nancy Pelosi to Barbara Lee or Janice Schakowsky (the 8-9th most liberal House members) or Senate leadership changing from Chuck Schumer to Ron Wyden or Mazie Hirono (the 7-8th most liberal Senators) (Fowler, 2025). ActBlue adoption effects on legislator CVP are also similar in size to the effect of a congressperson's district becoming 20% (pp) more Democratic post-redistricting (Myers, 2024).

While the results in Tables 5-7 somewhat diverge in magnitude because they pick up on somewhat different behavior and are produced by measures with varying underlying assumptions, the consistent pro-Democrat and liberal direction of results make it clear that when legislators start using ActBlue and raising more from small donors, their own behavior in Congress shifts left. This is especially true for more moderate House Democrats (as measured by pre-ActBlue behavior), and the parallel trends assumption is most plausible among moderates as well. Previous scholarship has suggested that the link between small donors and legislative extremism occurs through legislative turnover, where more moderate candidates are replaced by extreme candidates who are aided by small donors (Barber, 2016). However, these results suggest that under a wide variety of measures, legislators shift their own behavior in a way that aligns with the ideological lean of their new donors.

Limits to interpretation

An important limit to this work is that I cannot fully trace out why legislators appear responsive to the policy preferences of small donors. Responsiveness could be fully intentional, done in order to appease small donors. Responsiveness could be incidental – a decreased reliance on moderate PAC money could allow legislators to vote how they personally prefer, which happens to align with the more-extreme preferences of their new donor pool. Furthermore, since candidate campaign strategy, particularly the motives behind fundraising choices, is not fully observed, it remains possible that co-occurring campaign strategies contribute to the effects in this paper.

Another key limitation is that this study focuses on a single setting, and it is not clear whether these pattens generalize to other parties or to the subnational level. Appendix 24 considers the case of WinRed adoption, and fails to find effects consistent with those in this paper. It is impossible to pinpoint exactly why WinRed adoption differs, but I find that there is evidence of selection into the platform, echoing the work of S.-Y. S. Kim and Li (2025). I also find that WinRed did not represent a substantial change in campaign fundraising technology: since WinRed wasn't created until 2020, about 70% of candidates were already using small donor friendly technology. Candidates across all levels of government are using ActBlue, but since this paper only focuses on the US House case, it is unclear if small donor friendly campaign technology is associated with state-level polarization. On one hand, the technology is similar across levels of government. However, news environments, the partisan balance of power, and the influence of corporations in the fundraising and lawmaking process vary wildly across states. This paper shows that more contributions from small donors can lead to more polarized lawmaking, but cannot prove that this is the case in every context.

4 Discussion

Raising money is a crucial component of a successful modern congressional campaign, and American political campaigns have become increasingly expensive. How can political donations shape congressional behavior? One way is that political donations enable donors to support like-minded candidates, and money helps candidates win elections. Previous researchers have shown that candidates tend to raise money from individuals and groups who have similar viewpoints as themselves, so when these candidates reach office, they behave in ways that align with both their donors' and own interests.

Another way that political donations may impact congressional behavior is through lawmakers changing their legislative behavior to align with the preferences of their donors. The case of corporate donations and pro-corporation legislative behavior has featured prominently within political science research and in mass media. Of course, corporations are not the only entities that give to campaigns. Increasingly larger shares of political contributions are originating from individuals and small donors, with unitemized donor cash accounting for over one-quarter of the money raised in the 2020 presidential and congressional races.[19] Through technological innovations like ActBlue, candidates are constantly making appeals to prospective individual donors. This paper asks whether lawmakers change their legislative behavior towards alignment with the preferences of their smaller donors. Since individual donors (including smaller donors) are known to be more politically extreme and partisan than the populace and electorate, I focus on ideological and partisan legislative behavior.

Because ActBlue adoption is staggered over time and because I utilize a battery of time-variant legislative behaviors, I am able to analyze legislator behavior before and after raising more money from smaller donors. Examining ActBlue adoption among general election Democratic candidates running for House seats, I find that campaign fundraising technology increases the percentage of funds that legislators raise from individual donors, and partic-

[19] https://www.followthemoney.org/research/institute-reports/joint-report-reveals-record-donations-in-2020-state-and-federal-races

ularly those giving under $200. When Democratic candidates use ActBlue and earn more from smaller donors, their congressional behavior shifts to the left: they begin voting more with the median Democrat, voting less with the median Republican, and they receiving increasingly liberal ratings from interest groups. The results in this paper are the first to establish that lawmaker behavior may polarize as donor pools become more comprised of small and individual donors. Campaign contributions, including contributions from smaller donors, not only impact who wins office, but also appear to be linked to how legislators behave once in office.

Adopting ActBlue is associated with a leftward shift in measures of polarized donor networks and legislator behavior. Though the precision of estimates varies, most point estimates place the effect of adopting ActBlue at about a 4-10 percentile leftward shift relative to the median candidate or legislator. What do these shifts mean, over time, considering that nearly all Democratic candidates now use ActBlue? In terms of interest group scores, the mean has shifted from 1.63 to -0.55 within the period of study, so ActBlue's -0.3 effect is substantial. Similarly, Dynamic CFScores have moved from -0.78 to -1.11 over the same time span, and ActBlue's -0.06 shift again represents a meaningful component in leftward donor polarization. Democratic voting against the Republican median has shifted considerably within the period of study, from 48.5% to 68%, and ActBlue adoption explains about 7.7% of this shift. Notably, the estimates in this paper explain within-legislator behavioral changes, indicating that congressperson ideology is not completely static. Future work should seek explanations for both within-legislator and replacement-based legislative polarization.

Rapid technological change is happening in new digital venues, like campaign fundraising conduits, messaging apps, and social media sites, and with new strategies, like micro-targeting, experimentation, and cross-entity data sharing. Politics is increasingly practiced in the digital space, and the use of small donor-centric fundraising platforms is one of many notable changes in the digital campaigning landscape. These ActBlue results, in conjunction with weak results from WinRed adoption in Appendix Section 24, shed light on how new technologies shape political participation and legislative politics. Like S.-Y. S. Kim and Li (2025), this paper provides evidence on an important facet of campaign technological change, but much remains to be learned about how digital technologies reshape politics.

This work provides important evidence related to campaign finance reforms that impact small donor participation. Campaign finance vouchers (Yorgason, 2025), donation matching (Malbin et al., 2012), full public financing (Harden & Kirkland, 2016; Kilborn & Vishwanath, 2021; Malhotra, 2008), spending limits (Fouirnaies, 2021), and contribution limits (Barber, 2016; Gulzar et al., 2022; Primo & Milyo, 2020) are all ways in which governments have tried elevate the role of smaller individual donors. Within the United States, these innovations have been proposed at all levels of government, but implementation has primarily been confined to state and local elections. Those empowered by governmental or private reforms that boost the role of small donors are very political (Yorgason, 2025), and in the case of congressional elections, are highly polarized. A critical challenge for policymakers and political scientists is to consider whether additional institutional attributes influence who participates in the campaign finance process, and further evaluate how variations in participation shape legislative behavior.

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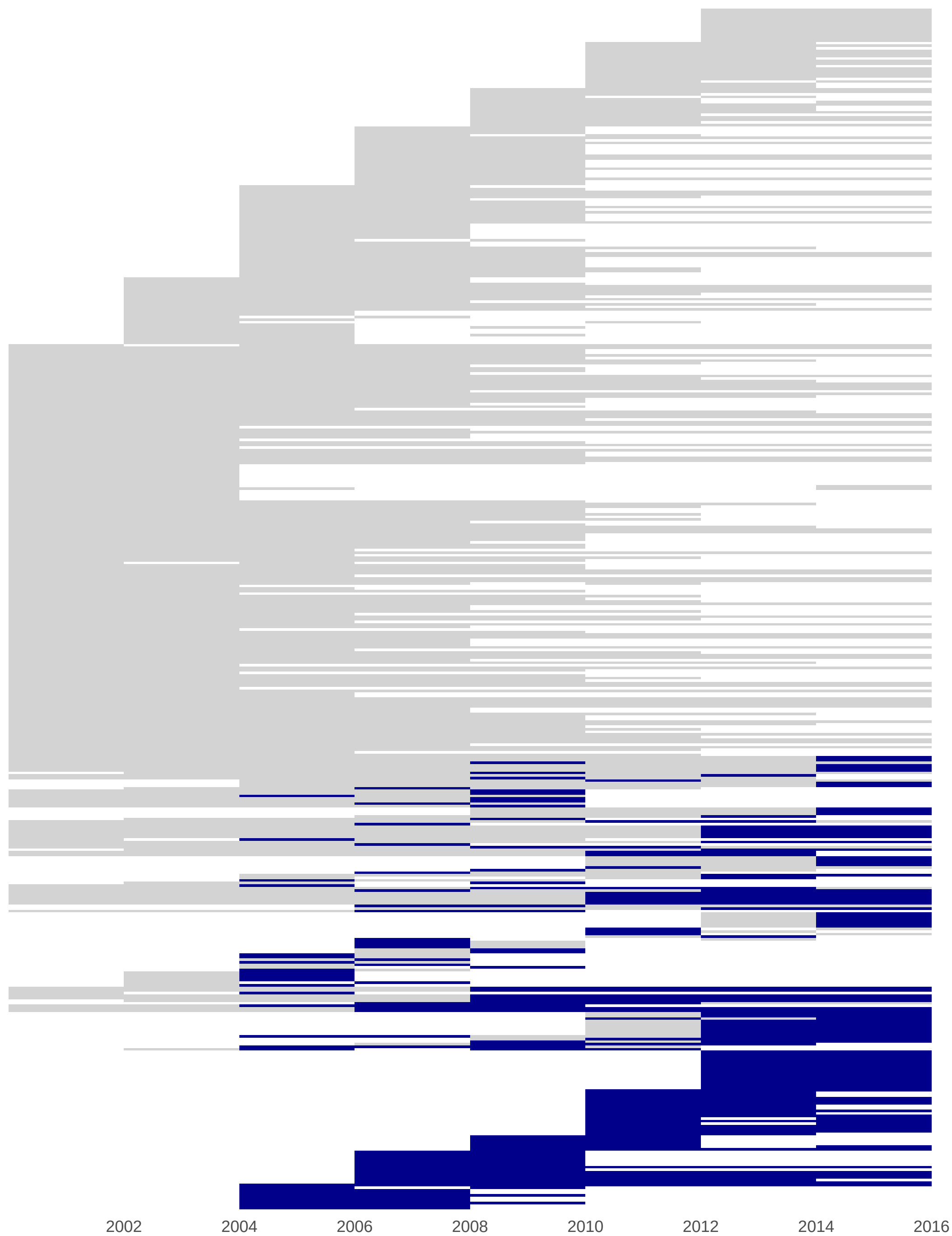
Online Appendix for Darker Blue: How Small Donors Drive Congressional Polarization

Appendix contents

1 Adoption graph for candidates who run 2 or more times

Figure A1 – Most candidates remain ActBlue users after switching on, though there is some on-off switching in the treatment. Red denotes non-ActBlue usage, and blue denotes ActBlue adoption. White=candidate was not on the general election ballot in a given year.



2 Campaign fundraising platform trends

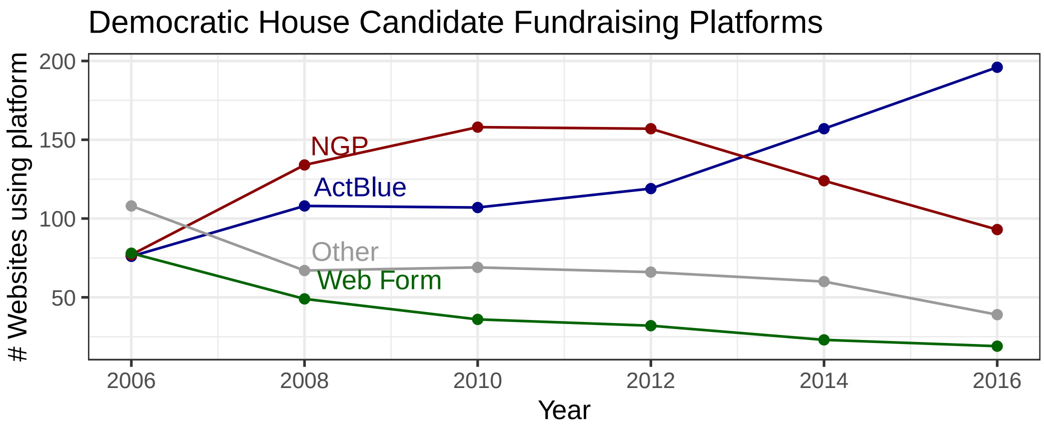


Figure A2 – Campaign fundraising platform by year among Democratic House candidates

3 Sample characteristics and omitted observations

The main analyses in this paper involve subsetting the universe of Democratic House candidates, due to both the omission of less-applicable cases (low fundraisers and non-persistent Democrats) and the mechanical omission of candidates who run once due to the TWFE strategy. This section compares the full universe of candidates to the candidates effectively used within the main text's primary specifications.

Table A1 – Universe and sample candidate attributes

	% Incum	$ Raised (mil)	% Dist Dem (pres)	% Vote share	% $ Out of state	CF Score	HS Score	# Obs
Universe	50.41	1.01	7.81	53.21	24.98	-0.95	-0.15	3073
Used	54.59	1.09	10.30	55.09	25.63	-0.93	-0.15	2830
β Cands	87.16	1.34	26.85	67.30	29.17	-0.78	-0.11	1674
β Electeds	90.58	1.32	27.73	67.82	29.39	-0.77	-0.11	1593

Table A2 – Universe and sample candidate attributes – elected behavior

	Incum	$ Raised (mil)	Party Unity	Repub Disagree	IG Rating	CVP	CJR	# Obs
Universe	86.38	1.39	93.74	59.73	0.47	-0.67	-1.15	1784
β Electeds	90.58	1.32	93.93	60.10	0.39	-0.68	-1.17	1593

The Tables A1 and A2 describe sample characteristics against the characteristics of all general election Democratic House candidates (or electeds) within the time frame. Lines labeled "universe" describe all candidates within the dataset, and subsequent lines describe the sample as it moves through the process. "Used" denotes data used in the regressions, and omits non-persistent Democrats and very low fundraisers. Low fundraisers, raising less than \$20k, include both long-time incumbents without meaningful competition, as well as long-shot candidates, and are further described in Table A3. β candidates describes observations effectively used in calculating β: those within "Used" who are present within the data 2+ times (since a requirement for candidate-based TWFE). β Electeds repeats the process, requiring a candidate be elected twice within the dataset.

There are substantial differences between the universe/used rows and the β rows, highlighting that the ATT in this paper is concentrated primarily on incumbents and those who are eventually elected into office. These units are from more Democratic districts, raise 1/4-1/3 of a million more dollars, and are a little more moderate by CF/HS score metrics than the universe of Democratic candidates.

A strategy taken to hedge against potential issues with the omission of candidates who run once is to use district fixed effects instead of candidate fixed effects. These are presented in the final column of most main text tables, and results generally hold with their inclusion.

4 Regression results without restricting data

Table A3 reports coefficients as the sampling thresholds used in the main text vary. "Dems" indicates dropping candidates who are known to have switched party affiliation, and dollar thresholds indicate a fundraising threshold that I require candidates to reach. Under all thresholds, coefficients are quite stable. That said, on a theoretical level, and when using more complex specifications that draw heavily on past periods (like when using CSLT), the inclusion of what are essentially no competition, non-fundraising years is not ideal, which is why the main text uses a constant Democrat and \$20k fundraising threshold.

Table A3 – ActBlue Year coefficients under various data restrictions

	Log \$ < 200	Log \$ 2-500	Log \$ near max	Log \$ PAC	HS	CF	Dem Agree	Rep Disagr	CVP	CJR	IG Rating
None	0.481	0.221	0.162	0.014	-0.024	-0.057	0.594	1.481	-0.333	-0.010	-0.051
	(0.107)	(0.059)	(0.065)	(0.069)	(0.007)	(0.015)	(0.233)	(0.464)	(0.129)	(0.003)	(0.033)
Num.Obs.	2796	2748	2655	2651	2459	2801	1664	1664	1525	1664	1677
Dems	0.483	0.217	0.160	0.007	-0.025	-0.059	0.639	1.499	-0.333	-0.010	-0.054
	(0.108)	(0.059)	(0.066)	(0.069)	(0.007)	(0.015)	(0.231)	(0.468)	(0.129)	(0.003)	(0.034)
Num.Obs.	2793	2745	2652	2648	2456	2798	1661	1661	1525	1661	1674
Dems+\$10k	0.483	0.217	0.160	0.007	-0.025	-0.059	0.639	1.499	-0.333	-0.010	-0.054
	(0.108)	(0.059)	(0.066)	(0.069)	(0.007)	(0.015)	(0.231)	(0.468)	(0.129)	(0.003)	(0.034)
Num.Obs.	2793	2745	2652	2648	2456	2798	1661	1661	1525	1661	1674
Dems+\$30k	0.471	0.205	0.150	0.004	-0.025	-0.061	0.639	1.499	-0.333	-0.010	-0.054
	(0.108)	(0.059)	(0.065)	(0.069)	(0.007)	(0.015)	(0.231)	(0.468)	(0.129)	(0.003)	(0.034)
Num.Obs.	2701	2661	2596	2590	2449	2711	1661	1661	1525	1661	1674
Dems+\$50k	0.471	0.206	0.157	0.029	-0.025	-0.059	0.639	1.499	-0.333	-0.010	-0.054
	(0.110)	(0.059)	(0.065)	(0.068)	(0.007)	(0.015)	(0.231)	(0.468)	(0.129)	(0.003)	(0.034)
Num.Obs.	2596	2559	2527	2513	2434	2604	1661	1661	1525	1661	1674
Cand, t FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note: Standard errors are clustered by congressional district- decade (eg CA-01, 2002-2010).

5 Event study graphs

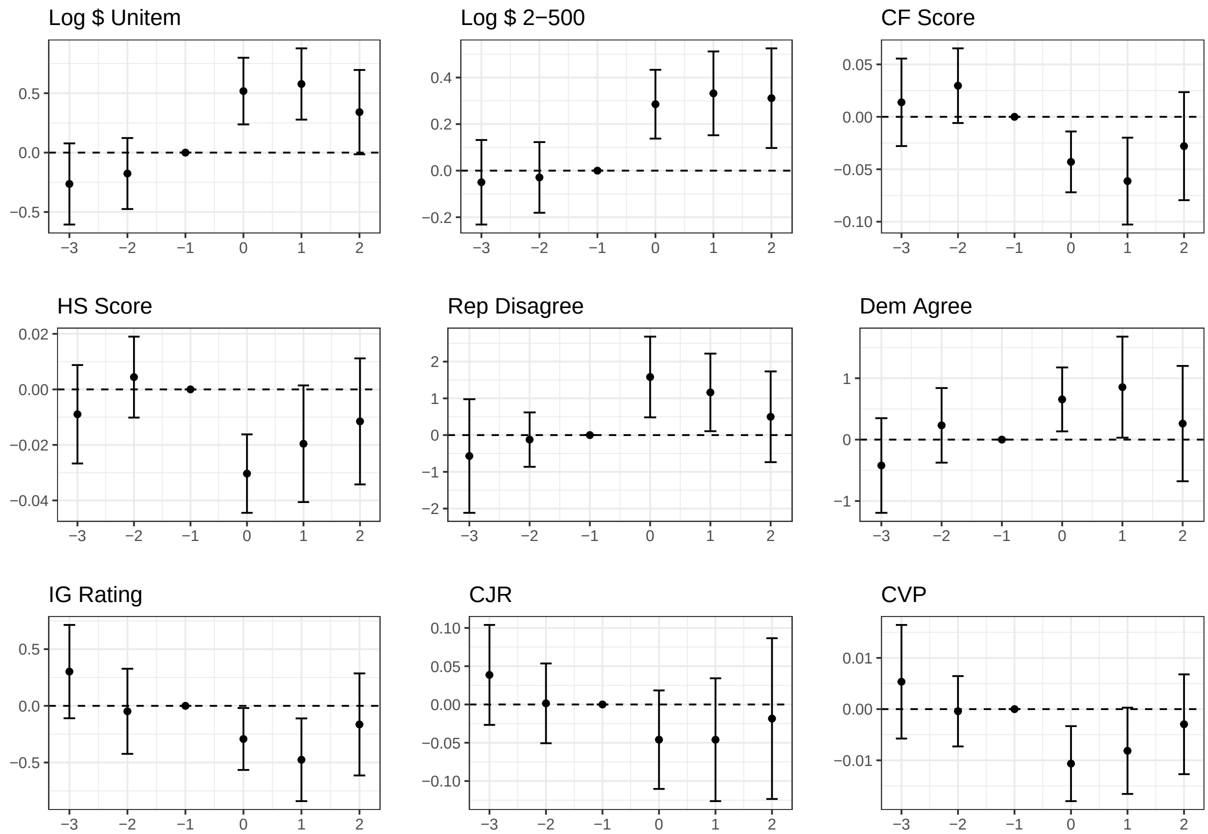


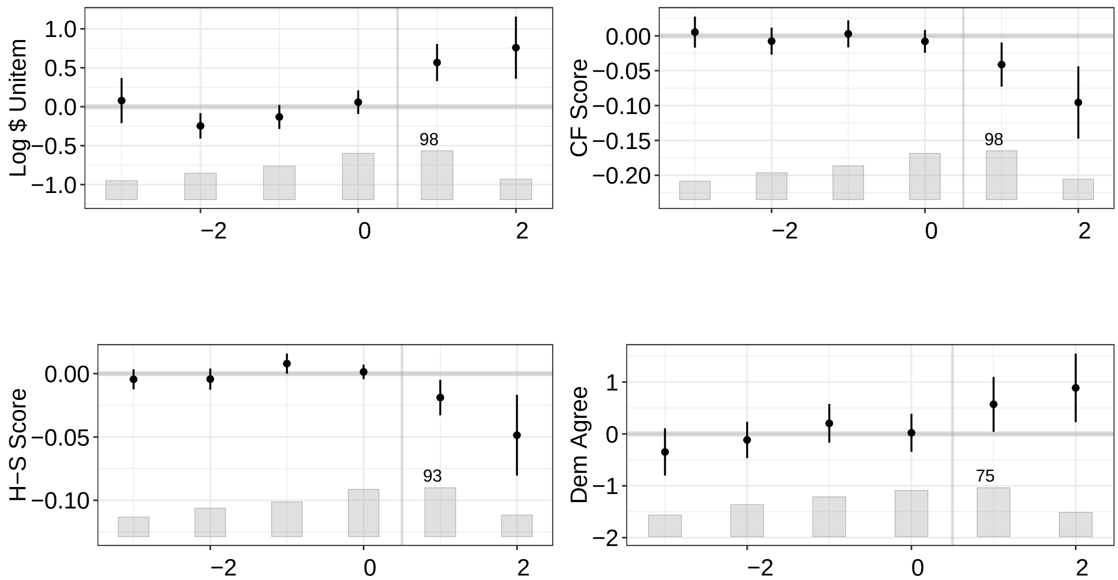
Figure A3 – TWFE event study graphs. Non-switchers are used in the development of year time trends only. X=0 denotes the first treated period.

6 Liu, Wang, and Xu Estimators

Table A4 – Liu, Wang, and Xu estimators by dependent variable and estimator type. FE = TWFE counterfactual (which is different from TWFE in the main text), IFE = Interactive fixed effects counterfactual, MC= Matrix completion method.

Dep Var	Estimator	Coef	SE	Dep Var	Estimator	Coef	SE
Log $ Unitem	FE	0.52	0.12	H-S Score	FE	-0.02	0.01
Log $ Unitem	IFE	0.54	0.21	H-S Score	IFE	-0.03	0.01
Log $ Unitem	MC	0.47	0.20	H-S Score	MC	-0.03	0.01
CF Score	FE	-0.06	0.02	Party Unity	FE	0.60	0.23
CF Score	IFE	-0.09	0.03	Party Unity	IFE	0.41	0.27
CF Score	MC	-0.08	0.02	Party Unity	MC	0.29	0.22

Figure A4 – Liu et al. (2024) Event-study style plots using the LWX "FE" estimator. Post-treatment effects differ from pre-treatment "effects" and are often distinct from 0. Pre-treatment periods exhibit no consistent trending. X=1 denotes the first treated period.



7 The Callaway and Sant'Anna estimator

The Callaway and Sant'Anna (2021) estimator is a commonly used alternative estimator for staggered difference-in-differences designs. A clear issue with the estimator, as it relates to this paper, is that it cannot accommodate for treatment reversals. That is, once a unit is treated, they must remain treated. Within the dataset, 33 candidates (spanning 140 observations) reverse their treatment status. Reversals should matter – a candidate not on ActBlue cannot use the full suite of ActBlue tools. The clearest solution is to use the Callaway and Sant'Anna (2021) estimators and subset the dataset to units whose trajectories do not include a treatment reversal, and results are in Table A5. The size of coefficients vary somewhat from the main TWFE estimates (for example, Party Unity is substantially closer to 0 and CF Scores are substantially further from 0), but coefficients are in the expected direction. I allow unbalanced panels and generate ATT, averaged across time.

Table A5 – Results using the Callaway and Sant'Anna estimator

	Log Unitem	HS	CF	Party Unity	Rep Disag	CVP	CJR
Average	0.390	–0.030	–0.177	0.168	0.863	–0.007	–0.019
	(0.233)	(0.015)	(0.065)	(0.688)	(0.744)	(0.010)	(0.05)

8 The de Chaisemartin and D'Haultfœuille estimator

For these estimators, Placebo 1 and 2 correspond to the first and second years prior to ActBlue adoption. Year 1-3 indicate the effect within the first through third year of ActBlue adoption.

Table A6 – de Chaisemartin and D'Haultfœuille estimators

	Log < 200	HS	CF	Pty Unity	Rep Disag	CVP	CJR
Average	0.47	–0.044	–0.018	0.87	1.29	–0.010	–0.030
	(0.13)	(0.018)	(0.009)	(0.35)	(0.53)	(0.004)	(0.044)
Year 1	0.42	–0.026	–0.014	0.77	1.66	–0.011	–0.036
	(0.13)	(0.013)	(0.006)	(0.24)	(0.62)	(0.004)	(0.034)
Year 2	0.42	–0.055	–0.021	0.80	0.58	–0.006	–0.021
	(0.13)	(0.024)	(0.013)	(0.47)	(0.58)	(0.005)	(0.049)
Year 3	0.37	–0.055	–0.013	0.61	0.62	–0.006	–0.005
	(0.21)	(0.038)	(0.015)	(0.65)	(0.70)	(0.006)	(0.081)
Placebo 1	–0.32	0.025	0.008	0.31	–0.11	–0.000	–0.006
	(0.14)	(0.018)	(0.007)	(0.32)	(0.40)	(0.004)	(0.028)
Placebo 2	–0.52	0.023	0.013	0.33	0.03	–0.000	0.041
	(0.18)	(0.029)	(0.009)	(0.49)	(1.25)	(0.008)	(0.044)
N Switch	191	191	185	150	150	150	150

9 Inflation

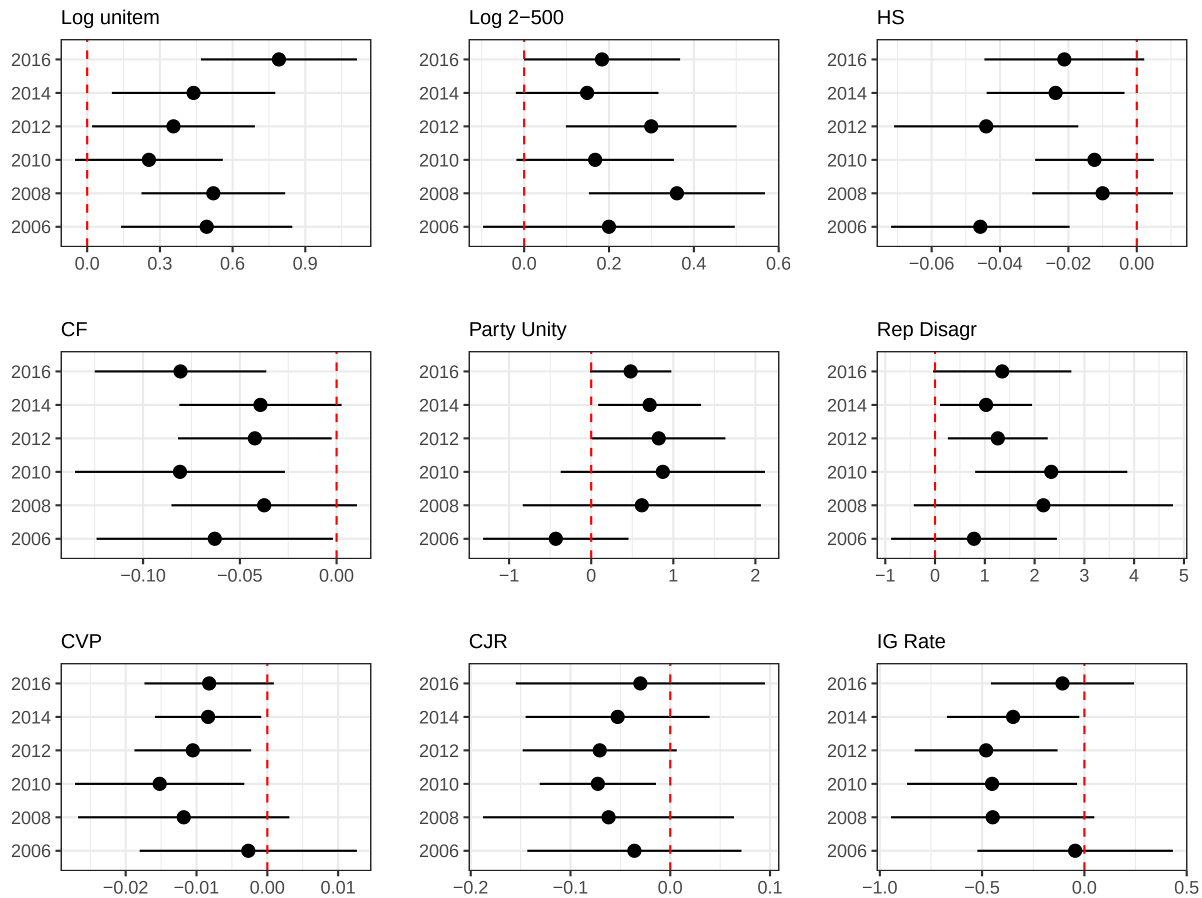
The colloquial definition of a "small donor" in campaign terminology has remained constant over the period of study, as it is tied to the itemization threshold of $200. A $200 contribution in 2016 dollars is worth about $149.89 in 2002 dollars. Table A7 verifies that results about small donors remain similar even after counting for inflation. Since small donations (pre-conduits) did not have to be itemized, the only way to make this comparison is to reclassify donations equivalent to $200 in 2002 as "small-ish." I use the inflation calculator from the Minneapolis Federal Reserve.

Table A7 – Coefficients from donation-driven metrics do not substantively change after acaccounting for inflation of the $200 itemization limit

	Log $ from small-ish	% $ from small-ish	H-S Score
ActBlue Year	0.41 (0.09)	5.50 (1.29)	-0.025 (0.007)
Cand, Time FE	✓	✓	✓
Observations	2,661	2,669	2,431

10 Do effects vary by timing?

Figure A5 – While certain types of individuals are more likely to join ActBlue early, there is no consistent pattern wherein only late or early adopters consistently drive the effects found in the main text. Red lines are at 0.



One potential concern is that early or late ActBlue adopters are driving the effects. There are plausible stories about both early and late adopters: perhaps early adopters are young and progressive and very excited about technology that empowers small donors, or perhaps early iterations of ActBlue software were not effective. Figure 2 shows that the types of candidates who start using ActBlue in its earliest years are quite different from both non-adopters and later adopters. Only 3 incumbents joined in 2006: John Spratt, Ciro Rodriguez, and Ed Towns. None of these three had particularly high levels of small donors or CF Scores, and the extreme 2006 trends are driven by candidates who started using ActBlue as challengers. In 2008, some candidates with very liberal CF Scores (including Mark Schauer and Hilda Solis), high levels of small donors (like Frank Pallone), progressive reputations (Marcy Kaptur), and (past/present) Congressional Progressive Caucus membership (Raul Grijalva, Andre Carson, Carol Shea Porter, Chellie Pingree, Eric Massa, Jared Polis, and others) joined the platform, both as incumbents and first-time candidates.

A model-related timing-based concern is the issue of possible negative weights under staggered adoption. Essentially, using TWFE may result in treatment effects based on clean comparisons (untreated and treated groups) as well as forbidden comparisons (groups treated earlier against groups treated later). If there are heterogeneous treatment effect (by time) β will be mis-estimated – and β could even have the incorrect sign. To address this, the calculation of Goodman-Bacon (2021) estimators is ideal but not possible because my dataset is not a balanced panel.[20] However, I can interrogate if effects vary by timing. Figure A5 presents results. While estimates vary and standard errors are imprecise (expected given that few candidates switch in a given year), I find no consistent pattern suggesting that the results are driven by specific cohort(s).

11 Placebo test

This section conducts a placebo test for core results. A possible concern is that results are driven by candidates who were trending towards small donors/liberal donors/liberal legislative behavior, and that adoption just happens to occur during these leftward trajectories. I randomize adoption year across adopters, with the constraint that their placebo adoption year must be prior to their true adoption year (since doing otherwise would conflate placebo and true effects), and subset out post-adoption years. I repeat this exercise 500 times, and report medians and the middle 95% of predictions for $\beta_{placebo}$. All intervals include zero, and many medians are very close to zero. Even when medians and the in-text treatment effects are directionally similar, the placebo effects are substantially smaller. The final column reports the ratio of the placebo median to the effects recovered in the main text. In sum, over-time leftward trajectories of adopters do not generate effects of comparable magnitude under placebo timing, suggesting that the main estimates are not mechanically driven by existing ideological drift.

Table A8 – Placebo test with simulated values for $\beta_{placebo}$

	2.5 %ile	50 %ile	97.5 %ile	Median/True
$ from small	-0.102	0.048	0.216	0.1
$ from 200-500	-0.103	-0.007	0.085	-0.03
H-S Score	-0.008	0.000	0.008	0
Dynamic CF Score	-0.023	-0.002	0.021	0.08
Party Unity	-0.738	-0.054	0.532	-0.08
Rep Disagreement	-0.575	0.238	0.951	0.16
Int Grp Rating	-0.328	-0.031	0.237	0.09
Conserv Vote Prob	-0.008	-0.002	0.006	0.2
CJR	-0.050	-0.009	0.030	0.17

[20] Even with district instead of candidate FE, I cannot recover a balanced panel due to redistricting.

12 Are there heterogeneous effects based on pre-ActBlue attributes?

One concern is that the theory and evidence presented in the main paper is only applicable to a certain type of candidate. Here, I analyze by moderation/progressivism and allow for time-liberalness FE. Table A9 classifies candidates by pre-ActBlue dependent variables (for percent unitemized, candidates who raise more from small donors are considered "progressive"). Results are similar or stronger for moderates, suggesting that effects are not concentrated on progressives.

Table A9 – Effects are typically somewhat higher, not lower, for moderate candidates.

	% $ from Unitemized	H-S Score	Dynamic CF Score	Dem Agree	Rep Disagree	Conserv Vote Prob
ActBlue Year × Moderate	5.428	-0.033	-0.068	0.518	2.629	-0.011
	(1.399)	(0.011)	(0.026)	(0.369)	(0.790)	(0.004)
ActBlue Year × Progressive	0.486	-0.011	-0.059	-0.031	0.904	-0.005
	(0.432)	(0.010)	(0.016)	(0.194)	(0.899)	(0.004)
Cand FE	✓	✓	✓	✓	✓	✓
Time-Group FE	✓	✓	✓	✓	✓	✓
Obs	2829	2098	2322	1355	1355	1355

Note: Standard errors are clustered by candidate. Time-group FE allow moderates and progressives to develop separate time trends.

13 What if never-adopters serve as improper controls?

One concern is that candidates who never adopt ActBlue are different than those who eventually do. As I discuss pre-trends above, the parallel trends assumption assumes that after ActBlue adoption, ActBlue users would follow similar trends to non-adopters if they hadn't made the switch. Table A10 below considers that this assumption isn't true for candidates who never make the switch. Results are similar to the main text.

Table A10 – Estimates remain similar when candidates who never use ActBlue are dropped.

	Log $ from Unitem	Log $ from PAC	H-S Score	Dynamic CF Score	Dem Agree	Rep Disagree	CVP
AB Year	0.445	-0.073	-0.030	-0.048	0.490	1.257	-0.009
	(0.112)	(0.069)	(0.008)	(0.015)	(0.229)	(0.448)	(0.003)
Candidate FE	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓
Drop Never Treat	✓	✓	✓	✓	✓	✓	✓
Obs	994	928	850	992	551	551	551

Note: Standard errors are clustered by candidate.

14 Are analyses on only winners biased?

Table A11 – Tables 6-7 remove electoral losers. While I cannot show how losers would vote, this table shows that non-legislative results are similar with the exclusion of losers – suggesting that losers dropped between the contribution results and legislative results are likely not observably different or a large enough contingency to expect that results are driven by their exclusion.

	Log \$ Unitem	Log \$ 200-500	Log \$ near max	Log \$ PAC	HS Score	CF Score
AB Year	0.470	0.178	0.178	0.003	-0.024	-0.058
	(0.132)	(0.068)	(0.074)	(0.078)	(0.008)	(0.017)
Cand FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Obs	1645	1634	1632	1631	1633	1661

Note: Standard errors are clustered by candidate.

15 Joining ActBlue when expecting a tight general?

Using House candidates who ran in both 2010 (2002 boundaries) and 2012 (2012 boundaries), I consider if anticipated competition is driving candidates' selection into ActBlue. Columns 1-4 of Table A12 use a TWFE DiD model to show that when candidates are redistricted into competitive districts, they do not join ActBlue at particularly higher nor lower rates. Columns 5-6 use the whole set of 2010 and 2012 candidates with state fixed effects instead of individual candidate fixed effects. Standard errors are clustered by candidate (columns 1-4) and state (columns 5-6). ActBlue adoption seems to be unrelated to expectations of electoral competition.

Table A12 – Being redistricted into a competitive district does not predict ActBlue entry

	Probability that a Candidate uses ActBlue					
2012 Competitive district	0.09	0.06	0.05	0.05	0.09	0.02
	(0.08)	(0.09)	(0.06)	(0.08)	(0.07)	(0.05)
Candidate FE	✓	✓	✓	✓		
State FE					✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓
Competitive threshold	10%	10%	15%	15%	10%	10%
Observations	350	346	350	346	720	701

Note: Competitive threshold = being redistricted into a district where absolute difference in Obama-Romney vote choice is within 10% or 15% (such that a 55-45 race is a 10% difference).

16 Do candidates join ActBlue when there is leftward pressure?

When candidates have tight primary races

Candidates might join ActBlue when they are concerned about within-party competition during primaries. If true, this could indicate that the changes observed in the main text are not the result of joining ActBlue, but rather the result of facing serious primary competition. In Table A13, I investigate whether or not candidates are more likely to join ActBlue in years where they face competition in primary elections. Candidates are not more likely to join ActBlue when their primary is close (columns 1-4). Additionally, candidates are not more likely to join ActBlue when they face any primary competitor (columns 5-6). Finally, columns 7-8 show that there is no significant relationship between primary closeness (represented by 1 minus the primary margin, so that closer races have higher values) and ActBlue adoption. Primary results data comes from Miller and Camberg (2020) and Pettigrew et al. (2014). The number of observations is lower than in the main text because states with jungle or nonpartisan primaries (WA, CA, LA) are excluded.

Table A13 – Candidates are not more likely to join ActBlue during years where they face primary competition.

	Probability that a Candidate uses ActBlue							
Tight primary	0.04	0.05	0.03	0.04				
	(0.04)	(0.04)	(0.04)	(0.04)				
Any prim oppo					0.003	-0.001		
					(0.02)	(0.02)		
1 - prim margin							0.02	0.01
							(0.04)	(0.04)
Candidate, Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓		✓
Tight race thresh.	10%	10%	15%	15%				
Observations	2,616	2,542	2,616	2,542	2,616	2,542	2,616	2,542

Note: Standard errors are clustered by candidate. The tight race threshold means that the primary is within 10% or 15% (such that a 55-45 race is a 10% difference).

When candidates face primary financial competition

Candidates do not *a priori* know election outcomes, and a candidate may respond to the threat of a competitor by joining ActBlue even if the race turns up to not be close. On the other hand, the "any primary opposition" variable will often include highly unviable candidates. To examine primary election competition viability, Table A14 examines whether candidates are more likely to use ActBlue when their primary competition gets substantial financial backing. I use two primary independent variables: the number of itemized donors and total contributions for the losing candidate (if there are > 1 losing candidates, I take the maximum among the losing candidates), both logged. I consider whether primary winners are more likely to use ActBlue when they face financial competition in a given term (columns 1-2) and in the previous term (columns 3-4). Columns 5-6 consider up until a candidate first joins ActBlue, and drops subsequent years. Data on competitor financing is from DIME.

Across all specifications, Table A14 shows that financial competition does not induce ActBlue usage. Results remain substantively similar with the exclusion of candidate fixed effects. These effects are small (not shown in the interest of space). For example, column 1 indicates that as losers raise money from 10% more donors, the competitor's (eventual winner's) likelihood of joining ActBlue increases by around 0.08 percentage points. When a candidate's competitor goes from 1 donor in t-1 to 60,000 donors in t (above the maximum amount of competitor donors), a candidate is only about 8.80 percentage points more likely to join ActBlue. In sum, primary electoral competition is uncommon, and primary financial competition is not meaningfully associated with ActBlue adoption.

Table A14 – Being subject to financial competition does not predict ActBlue entry

	Probability that a Candidate uses ActBlue					
Loser log # donors	0.008	0.01	-0.001			
	(0.006)	(0.009)	(0.006)			
Lag loser log # donors		0.0004				
		(0.008)				
Loser log $ raised				0.004	0.005	0.0001
				(0.003)	(0.003)	(0.003)
Lag loser log $ raised					0.002	
					(0.004)	
Cand, Time FE	✓	✓	✓	✓	✓	✓
Observations	2,829	2,829	1,487	1,487	2,601	2,601
First AB use only					✓	✓

Note: Standard errors clustered by candidate. "First AB use only" considers only candidates until they use ActBlue for the first time.

Even after logging the amount raised and number of donors, the distribution of the independent variable remains highly skewed, and it is highly plausible that primary threat is better measured by some type of non-linear threshold instead of continuous logged dollars or itemized donor count. Table A15 considers a competitor's fundraising quartile against other primary-losing Democratic competitors in a given congressional cycle. Winning candidates are coded 1 if a losing primary competitor was among the top quarter or half of fundraisers that year (those with low-raising competitors and no competitors are coded as 0). To put winning candidates and their challengers head-to-head, I also use the threshold from Thomsen (2023), where a race is deemed financially competitive if the "top fundraiser raised less than 57.5% of preprimary receipts or whether their fundraising margin is within 20 points of the second highest fundraiser."

The results mirror those in Tables A13-A14: candidates who end up in actually financially or electorally competitive races are not more likely to join ActBlue. Only when we focus

Table A15 – Primary competitor fundraising strength and ActBlue adoption

	Probability that a Candidate uses ActBlue				
	Competitor amount raised			*Competitor # of Donors*	
Top half	0.038			0.043	
	(0.032)			(0.031)	
Top quarter		0.077			0.078
		(0.042)			(0.042)
Thomsen financial competition			0.016		
			(0.033)		
Cand, Time FE	✓	✓	✓	✓	✓
Observations	2,829	2,829	2,829	2,829	2,829

Note: Standard errors clustered by candidate. Top quarter/half values are calculated by year.

on the very highest-raising eventual losers, without comparing them to their corresponding primary winners, does it seem that eventual-loser fundraising success is even somewhat related to eventual-winner ActBlue adoption. The magnitude of this relationship is small: eventual-winners with the best-fundraising competition are at most on average about 8% (pp) more likely to be on ActBlue. Not many eventual-losers are top quarter fundraisers (≤ 20 each cycle), so the combined magnitude and small scope of these results are unable to be the driving force behind the main paper results. These results should be interpreted descriptively: winning candidates may have actually adopted ActBlue well before the primary season.

When constituencies become more liberal

Similarly, candidates might want to join ActBlue when their constituency becomes more liberal. This would pose a problem if candidates both joined ActBlue and raised more money from liberal donors and behaved liberally in office because they are responsive to constituency shifts. Table A16 evaluates this possibility. Using the redistricting case, where some legislators will be newly assigned to safe Democratic districts (where the Democratic presidential candidate amasses 15%+ or 20%+ of the vote over the Republican candidate), I find null effects on ActBlue adoption. Columns 4-5 allows Democratic safety within districts to move for any reason. Causally this is a much weaker design, but I obtain similar results.

Table A16 – Candidates are not more likely to join ActBlue when their district liberalizes.

	ActBlue adoption (0/1)				
Safe Dem District	0.08	0.002		0.05	
	(0.05)	(0.07)		(0.03)	
Pres. Dem Margin			0.002		0.0001
			(0.002)		(0.001)
Candidate, Time FE	✓	✓	✓	✓	✓
Safe race threshold	15%	20%		20%	
Redist obs only	✓	✓	✓		
Observations	720	720	708	2,829	2,785

Note: Standard errors are clustered by candidate. The safe Democratic district threshold means that the most recent presidential election is beyond a 20% or 15% margin (a 55-45 race is a 10% margin).

17 Donor network lean based on the method of Hall and Snyder Jr (2015)

Table A17 shows how my construction of H&S scores differs from Hall and Snyder Jr (2015). The general method for constructing a Hall-Snyder score for candidate q in a given legislative term is the following. Start with a dataset of contributions and ideology/partisanship data for legislators. For each of q's donors, assign a temporary score based on a dollar-weighted average of the scores for candidates they give to (excluding q) in the same term. The H-S score for q is the dollar weighted average of the temporary scores of q's donors. Repeat for all legislators. This method is attractive because it allows for customization (choice of starting ideology scores or the imposition of contribution thresholds), but produces easy-to-calculate time-varying measures.

Table A17 – Researcher Degrees of Freedom in Generating Candidate Ideology Scores, Based on the Method in Hall and Snyder Jr (2015)

Step	**H&S Procedure**	**My Procedure**
Choose contributions	Focus on primary or all contributions and donor type	All contribs, both individual and committee
Choose ideology	Party affiliation or DW-NOMINATE	Use DW-NOMINATE
Contrib recipients	Non-incumbents or all candidates	All candidates
Contribution threshold	Only donors who make >19 distinct contributions and candidates who receive >19 distinct contributions	Make 2 or 3, receive 10 (higher similar)

18 Aggregating candidate interest group ratings

Table 6 uses a dependent variable of standardized legislator interest group ratings. Using a single interest group rating is often difficult: sometimes interest groups do not rate certain legislators, and interest group ratings tend to crowd around 0% or 100% (see Snyder Jr (1992)). I use the following procedure to aggregate these ratings:

1. Select interest group ratings within the applicable time period (many only rate candidates for a few years)

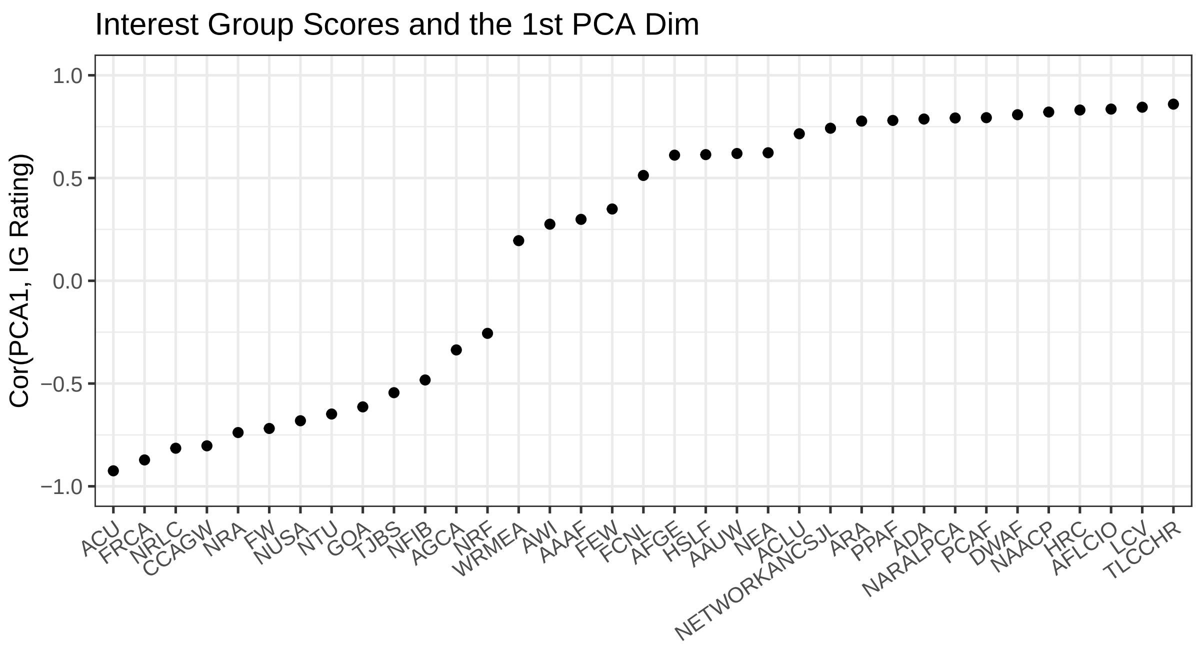
2. For each interest group i, I impute missing values by finding the interest group rating with the highest correlation (j), and predicting a legislator's i score with their j score using linear regression. This is necessary to run Principal Component Analysis without missing values.

3. Run PCA and select the first dimension (this dimension alone represents about 50% of all interest group rating variation **among Democrats** and further dimensions offer only incremental improvements)

Table A18 – List of Interest Group ratings used

Alliance for Retired Americans	Human Rights Campaign
American Association of University Women	Humane Society Legislative Fund
American Civil Liberties Union (ACLU)	League of Conservation Voters
American Conservative Union (ACU)	NARAL Pro-Choice America
American Federation of Government Employees	National Association for the Advancement of Colored People (NAACP)
American Federation of Labor and Congress of Industrial Organizations (AFL-CIO)	National Education Association (NEA)
Americans for Democratic Action (ADA)	National Federation of Independent Business (NFIB)
Americans for the Arts Action Fund	National Retail Federation (NRF)
Animal Welfare Institute	National Rifle Association (NRA)
Associated General Contractors of America	National Right to Life Committee
Council for Citizens Against Government Waste	National Taxpayers Union
Defenders of Wildlife Action Fund	NETWORK, A National Catholic Social Justice Lobby
Family Research Council (FRC) Action	NumbersUSA
Federally Employed Women	Planned Parenthood Action Fund
FreedomWorks	Population Connection Action Fund
Friends Committee on National Legislation	The John Birch Society
Gun Owners of America (GOA)	The Leadership Conference on Civil and Human Rights
Human Rights Campaign	Washington Report on Middle East Affairs (WRMEA)

Figure A6 – The first dimensions of the Interest Group PCA appears to be primarily ideological in nature. Conservative groups are bunched together, liberal groups are bunched together, and groups with primarily non-polarized and non-partisan interests have the weakest correlations with the first PCA dimension.



19 Partisan voting and the computation of Nokken-Poole DW-NOMINATE scores

One notable omission from Table 6-7 are DW-NOMINATE scores, perhaps one of the most ubiquitous measures of legislator ideology within the field. NOMINATE-based scores consider who legislators share votes with (regardless of party), within the framework of a spatial model. Congresspeople receive more liberal scores when they frequently vote alongside other legislators with liberal scores. DW-NOMINATE is the predominant score from the family of NOMINATE-based scores, but cannot be used in this case as only one score is computed per legislator, even if they serve multiple terms. Nokken-Poole scores are period-specific, with fixed cutting lines established by standard DW-NOMINATE scores. Essentially, this procedure calculates by-cycle legislator scores by using boundaries drawn by stationary DW-NOMINATE scores. This procedure was initially used in order to analyze congressional behavior after party switches (a rare occurrence), and because of its reliance on fixed boundaries, it may underestimate ideological shifts if multiple legislators shift simultaneously. I present results using Nokken-Poole scores in Table A19.

A reason Nokken-Poole DW-NOMINATE scores might yield smaller results than other measures is that they were not directly designed to measure simultaneous ideological movement by multiple members of the legislature. For each legislator i, Nokken-Poole scores are calculated by letting legislators retain their "classic" DW-NOMINATE score to establish ideological boundaries, and then calculating i's by-congress ideal point "against the background of the fixed cutting lines." If multiple legislators change ideologies at once, fixed cutting lines would bias this change toward zero. In their paper, Nokken and Poole (2004) study party defections, a process which is rare and under which the assumption of one legislator's ideological change against the static ideologies of legislators is highly plausible. However, this process might be less well-suited in instances in which multiple legislators shift their ideal point simultaneously.

Table A19 – When a legislator i joins ActBlue, the mean Nokken-Poole DW-NOMINATE scores of legislators who i votes with shifts to the left.

	Nokken-Poole DW	N-P Score of Voting Allies
ActBlue Year	−0.008	−0.009
	(0.006)	(0.003)
Candidate FE	✓	✓
Time FE	✓	✓
Observations	1653	1,646
'04 Leg Shift from Med	5	22

Note: Standard errors are clustered by candidate.

Table A19 highlights this issue by considering the ideological alliances (seeded on Nokken-Poole ideology scores) that candidates enter into after joining ActBlue within the second column.[21] When a legislator joins ActBlue, their voting alliances (all votes) shift to the left substantially (equivalent to a 24-legislator shift in the 2004 distribution of voting alliances). In sum, a Democratic legislator who joins ActBlue will have their average voting coalition substantially move to the left but still not have their Nokken-Poole DW-NOMINATE score move substantially to the left. Other values in Tables 6-7 enable legislator scores to be independent each new legislative session. This "stickiness" makes it such that Nokken-Poole scores are not particularly well-calibrated for a staggered difference-in-differences design where multiple candidates adopt treatment simultaneously.

20 Does the public perceive ActBlue candidates as more liberal?

CCES respondents do not perceive their local House candidates as more liberal once they begin using ActBlue. Evaluations using means of the 7-point ideology scale[22] and using the proportion of respondents who place candidates as "very liberal" remain unmoved when candidates start using ActBlue. That said, three substantial issues are present with this

[21] I define voting alliances as the mean score of the legislators that vote together, where each bill is given equal weight.

[22] The 2006 and 2008 CCES used a 100 point scale, and I have re-binned these to the seven point scale. Distributions look similar.

Table A20 – Using CCES data from 2006-2016, I find no change in public perceptions of local candidate ideology when candidates start using ActBlue.

	7-Pt Ideology		% Saying Cand Very Lib	
ActBlue adoption	0.01	0.03	−0.90	−1.00
	(0.04)	(0.05)	(1.05)	(1.29)
Cand FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Controls		✓		✓
Observations	2,328	2,259	2,328	2,259

Note: Standard errors are clustered by candidate.

strategy. First, these regressions have relatively low power. The CCES starts in 2006, making it so that I cannot develop non-treated fixed effects for the first cohort of switchers. Second, the seven-point scale may not provide enough nuance to capture small changes in perceived candidate ideology. Third, public evaluations of candidates are limited by public knowledge of candidates. Nearly 46% of CCES respondents do not rate the ideology of the Democratic candidate. Even among those who do claim enough familiarity to rate candidates, familiarity and perceived ideology are not orthogonal. Less-well-known candidates are substantially more likely to be rated as moderates than well-known candidates.

21 Other donor types

This Table repeats similar analyses in Table 3 with different dependent variables. ActBlue adoption is not related to higher rates of funds coming from outside of state. The proportion of new donors (who haven't given to congressional races in the past two cycles) brought in is small and imprecisely measured. When candidates start using ActBlue, they do receive somewhat more from serial donors (giving to > 1 congressional candidate in a cycle), though the coefficient is insignificant. Candidate in the most partisan-split districts ($< 5\%$ $|Dem - Rep|$ presidential margin) do on average raise 2% (pp) more of their contributions from out-of-state contributions, though standard errors are very large. Unfortunately, though ActBlue adoption is highly effective at activating unitemized donors, this data only focuses on individual (human) itemized donors: we cannot rule out that ActBlue adoption increases these out of district/state, new, or serial unitemized donors.

Broadly, the largest shifts in contributions from itemized out of state donors came after my period of study, during the 2018 elections.[23] ActBlue adoption alone seems unlikely to be responsible for this shift, especially since the shift is also visible, though smaller, for Republican contributions. Given the results in A21, it is possible that ActBlue might responsible for large shifts toward more nationalized out of state donors in highly covered races (those that determine the congressional balance of power or those featuring nationally prominent politicians), but since these regressions are aggregated at the candidate level,

[23] https://www.opensecrets.org/news/reports/out-of-state-donations

	% Out of State					% New	% Serial
ActBlue Yr	-0.064	0.110	-0.029	-0.192	-0.253	−0.477	0.8781
	(0.902)	(1.147)	(1.069)	(0.954)	(0.917)	(1.233)	(0.879)
Comp Dist			1.367	1.107	0.479		
			(1.084)	(0.945)	(1.167)		
AB*Comp Dist			-0.109	0.699	2.197		
			(1.661)	(1.685)	(2.281)		
Cand FE	✓		✓	✓	✓	✓	✓
Dist-Dec FE		✓					
Time FE	✓	✓	✓	✓	✓	✓	✓
Comp			15%	10%	5%		
Obs	2,752	2,752	2,752	2,752	2,752	2,752	2,752

Table A21 – ActBlue adoption does not significantly increase the proportion of funds from itemized out-of-state, new donors, or serial donors.

the average change in out of state contributions might remain near zero. Additional work should seriously consider the preferences and behavior of out of state donors, especially in comparison to small donors.

22 Which donor types shift to the left?

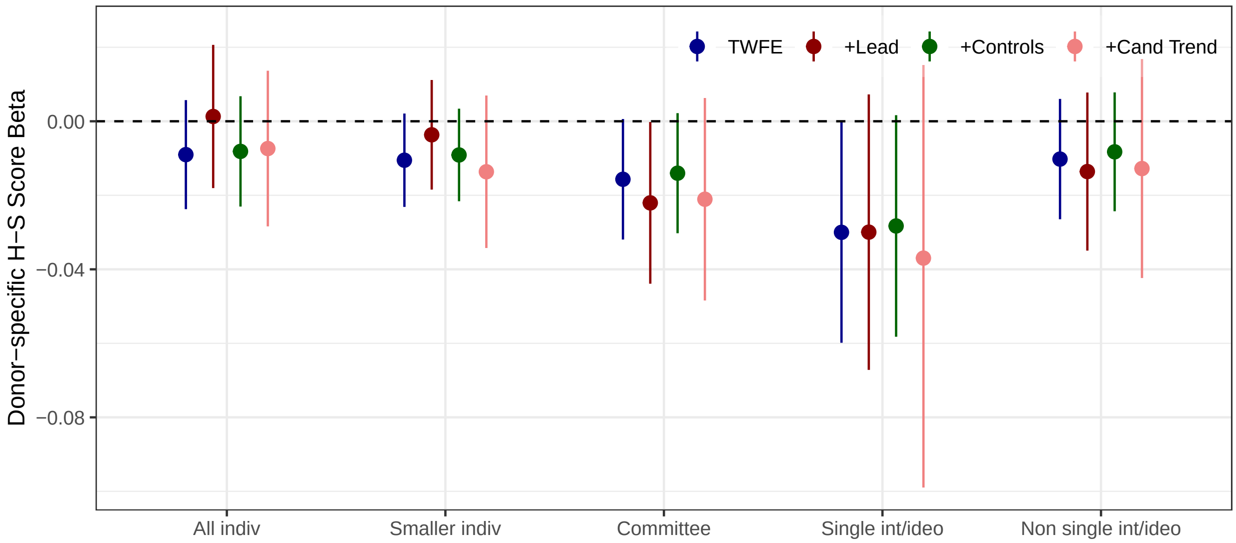
H-S scores built only on a single donor type can help me interrogate how the ideological lean of individual donor networks and PAC donor networks shift after ActBlue adoption. Figure A7 repeats the exercise from Table 4, but builds H-S scores by donor type.

The first two clusters in Figure A7 show that H-S scalings based on all individual donors and based on only smaller individual donors shift to the left after a candidate starts using ActBlue, though at about half the magnitude found among all donors in Table 4. The values in Figure A7 exclude data from unitemized donors (whose contributions prior to ActBlue are unobservable), as well as donors who have given less than twice within a single cycle – behavior that characterizes a sizable proportion of individual contributions.

Within the literature, single interest groups and strongly ideological groups, such as the National Rifle Association or Nancy Pelosi's PAC, are conceptualized as focused on supporting candidates who are allies. Contributions coming from non-single interest and ideological sources, such as those from corporations, are often thought of as vehicles for congressional access and as ideologically moderating forces (Li & DiSalvo, 2023). The final three clusters in Figure A7 consider whether contributions from committees become more ideologically extreme in origin after a candidate joins ActBlue by using committee sector labels from OpenSecrets.[24]

[24] To enter the regressions in Figure A7, a donor must have given as described in Table A17, appear in the DIME "Candidate/Recipient Database" and have a valid FEC ID, and be given a label by Open Secrets. Alternate matching methods that do not rely on appearing in the DIME Candidate/Recipient Database, such

Figure A7 – When a candidate joins ActBlue, they tend to raise funds from more liberal networks. This remains true when considering only specific types of donor networks.



Note: Standard errors are clustered by congressional candidate. Controls are district competitiveness and incumbency status. Committee groupings as single interest/ideological are from Open Secrets, and not all committees are classified by Open Secrets. Cluster 4 uses only contributions from groups labelled as "Single Interest/Ideological," plus party committees, as labelled by Open Secrets. Cluster 5 uses all other PAC contributions, including those that are unlabelled by Open Secrets. When examining committee names, it is clear that most unlabelled groups are not single interest/ideological in nature.

While ActBlue-using candidates raise money from more liberal individual donors (and this fact itself can cause donor H-S and CF scores to shift left), Figure A7 shows that candidates are also funded by more liberal committees when they start using ActBlue. This is true both for committees as a whole (third cluster), committees that are affiliated with national parties/those labeled single-interest or ideological (fourth cluster), as well as those labeled as other committee types (final cluster). The biggest changes come from party, single-interest, and ideological committees, who themselves might also be raising money on ActBlue. Though movement from other PAC sources is smaller, the effects on average donor ideology from other PAC sources are not dissimilar to average effects from individual donors. In short, when candidates start using ActBlue, they consistently raise money from more ideologically liberal networks across all donor types.

Why does money become more liberal from *all* donor types after candidates join ActBlue? One possibility has to do with candidate messaging when they know that small donor contributions are on the table. When House candidates use ActBlue to raise funds, they often employ language that is toxic, invoking fear, disgust, and anger (S.-Y. S. Kim et al., 2023). Since campaigns may tailor messaging to maximize contributions, this polarizing

as using Jaro-Winkler distance to compare Open Secrets committee names with donor committee names, both introduce false positives and significantly reduce n due to false negative matches from name shortening and abbreviations.

language appeals to ideologues with a high propensity to give, but it may alienate more moderate individuals and committees. During the fundraising process, campaigns may also quickly learn that ActBlue adoption brings in more cash from individual donors, and choose to take on liberal stances that appease both ideological interest groups and smaller individual donors. Alternatively, legislators may actively desire to distance themselves from more moderate or conservative donors, and realize that doing so is viable with a new source of smaller donor cash.

23 Dependent variables and their correlations

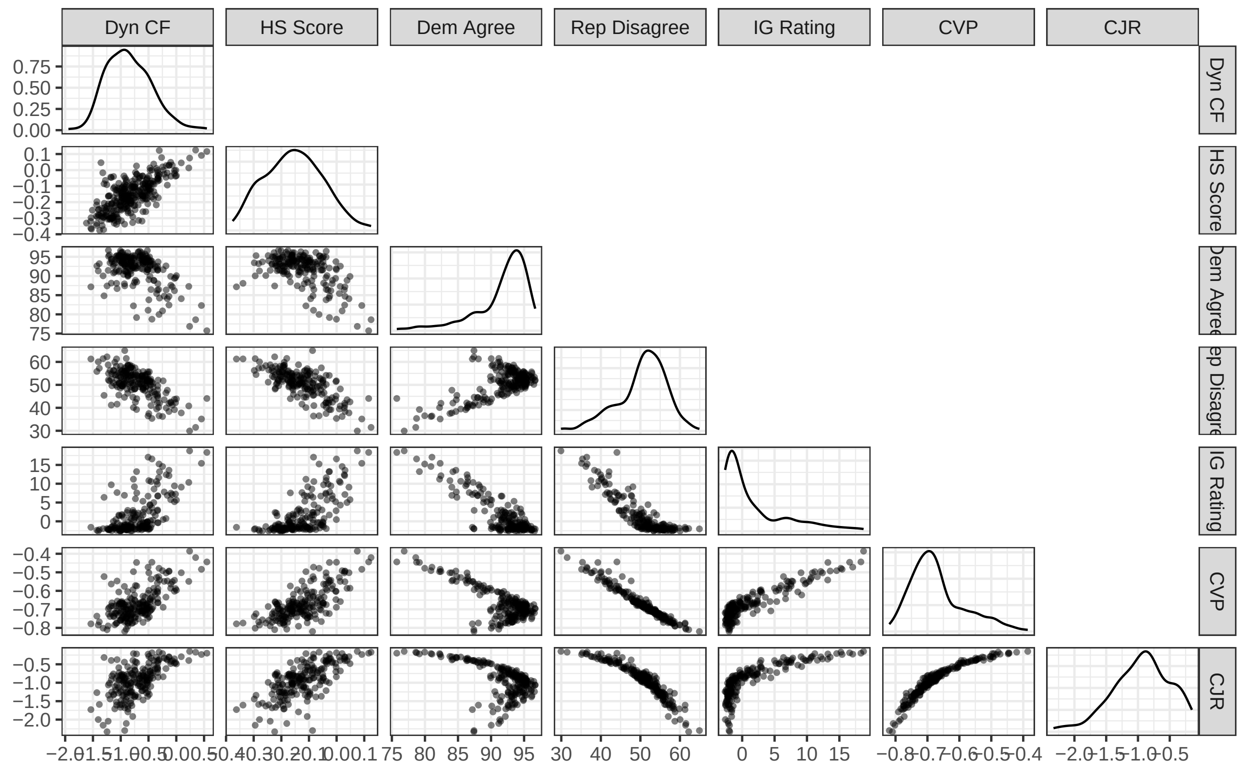


Figure A8 – Scatterplot of 2004-era (last year without and ActBlue adoption) dependent variable correlations. Density plots on the 45 degree line represent that dependent variable's distribution of observations.

24 WinRed Analysis

The main text focuses exclusively on Democrats and ActBlue. This section examines if similar dynamics came about with Republican fundraising through WinRed (see S.-Y. S. Kim and Li (2025) for a much more comprehensive treatment of the topic). Both platforms serve as each party's dominant conduit and offer comparable tools for soliciting individual contributions. As such, WinRed may also increase small donor participation and influence legislative behavior. In Table A22, I present results on WinRed adoption, based on 2016-2022 electoral cycles. WinRed adoption is staggered over 2020 and 2022, and by 2022 about

62% of House candidates directed website visitors to donate on WinRed.[25]

Table A22 – The effects of Republican WinRed adoption differ from the effects of Democratic ActBlue adoption.

	% $ Unitemized (1)	CF Score (2)	% Votes Against Dems (3)	Party Unity (4)	CVP (5)
WinRed Year	0.807	0.029	−1.095	0.368	−0.018
	(1.368)	(0.015)	(0.620)	(0.501)	(0.007)
Observations	1,453	1,476	854	854	638
Candidate FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓

Note: Standard errors are clustered by candidate. N is lower for the CVP regression as estimates are not yet available beyond the 117th Congress/2020 electoral cycle.

Republican adoption of WinRed does not mirror the Democratic experience with ActBlue. On average, WinRed adopters raised just 0.8% more of their funds from small donors—far below the nearly 4% increase observed among Democrats. While WinRed donor networks became slightly more conservative than those of non-WinRed Republicans, this shift was smaller than the leftward movement among Democratic donor networks. Notably, Republican legislators using WinRed voted *less* conservatively on average, with a nearly 2 percentage point decline in conservative vote probability. Voting alignment with Democrats also *increased* modestly, with no substantial changes in party unity.

Why do results differ between the Democratic and Republican case? Below I offer two explanations.

Republican party control of the platform and resulting selection into treatment

One explanation has to do with party involvement. The Republican party exercises much more control over WinRed (in 2019 the RNC was "threatening to withhold support from party candidates who refuse to use WinRed" (Isenstadt, 2019)), meaning that fundraising strategies are more coordinated on the right (S.-Y. S. Kim & Li, 2025). If WinRed adoption is some sort of proxy for party compliance, then the use of dependent variables like roll call voting, where party influence is known to be important, risks conflating the effects of WinRed adoption and party compliance.

We might expect that those who capitulate to party pressure to join the platform are on different over-time trends than those who do not. Since adoption was much less staggered,

[25] This counting method differs from that of (S.-Y. S. Kim & Li, 2025), who count adoption by getting the first quarter a candidate reports raising money from WinRed. Totals vary because candidates can set up a profile and raise money from WinRed while still directing website visitors to a platform like Anedot.

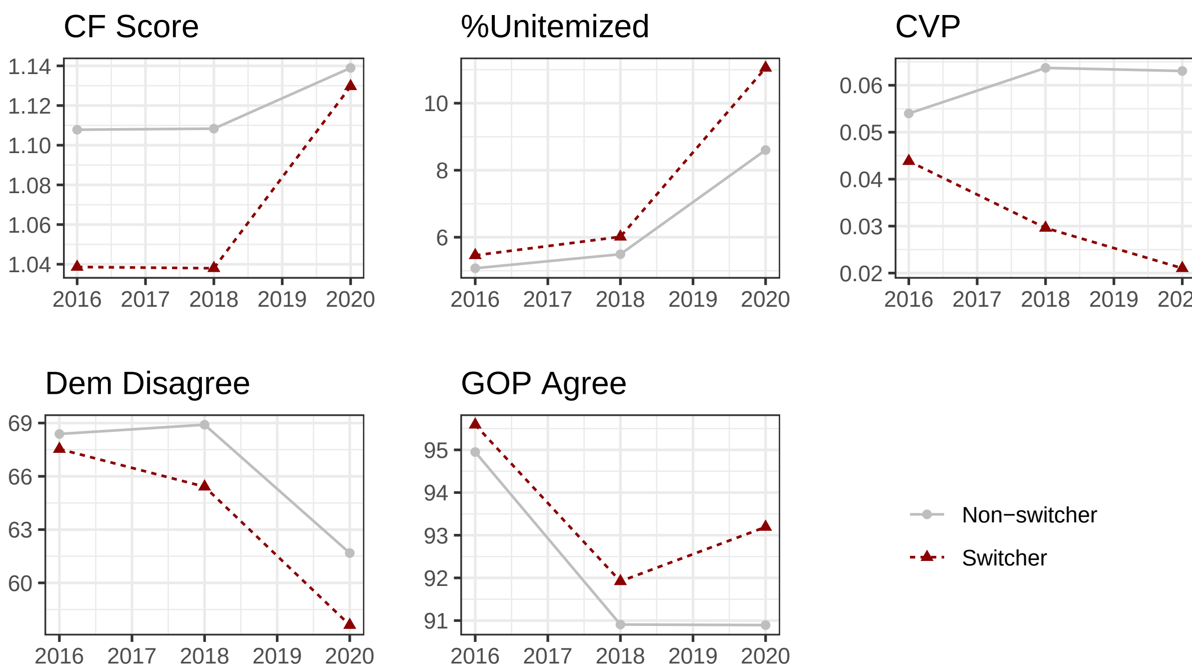


Figure A9 – Trends for 2020 WinRed adopters: Even prior to the WinRed rollout, 2020 WinRed adopters were trending towards more liberal values of conservative vote probabilities and towards less disagreement with Democrats.

the parallel trends assumption can be visually assessed. While Figure A9 cannot test for all possible factors, non-parallel trends on CVP and Democratic disagreement, in conjunction with S.-Y. S. Kim and Li (2025) plus anecdotal evidence on incentives towards adoption, certainly suggest that switchers were on a different trajectory than non-switchers. Results in Table A22 certainly should be interpreted cautiously with these methodological issues in mind.

Further evidence that some type of selection was in play during WinRed adoption is that results are very much driven by the first cohort of adopters. This is not the case in ActBlue adoption (see Table A5). Table A23 shows that effects, in any direction, are virtually non-existent for 2022 adopters and are much stronger for 2020 adopters.

A weak treatment for raising money from small donors

Another explanation for partisan imbalances in effects has to do with technology. WinRed was founded much later, and was first used in the 2020 congressional election. Much of the digital infrastructure that ActBlue brought to Democratic campaigns, like a low-friction donation interface for contributors and A/B testing on messaging existed for Republican campaigns through other payment platforms prior to 2020. If the technological donor-side changes are responsible for ActBlue's effects, it is logical that a 2020 Republican adoption would not bring about the same changes.

Table A23 – Candidates who adopted WinRed in 2020 instead of 2022 have larger effects.

	% \$ Unitemized	CF Score	% Votes Against Dems	% Votes w/ Rs
WR*2020	1.148	0.034	−1.753	1.089
	(1.488)	(0.016)	(0.671)	(0.638)
WR*2022	0.351	0.022	−0.239	−0.572
	(1.619)	(0.018)	(0.750)	(0.602)
Candidate, Time FE	✓	✓	✓	✓
Observations	1,453	1,476	854	854

Note: Standard errors are clustered by candidate. CVP is omitted as a dependent variable in this table as CVP scores beyond the 2020 electoral cycle are not available.

I look into this possibility by considering what fundraising platform Republican candidates switched from, when switching into WinRed. Table A24 considers all 2018-2020 switchers. The vast majority (70.5%) were already using one of three small donor friendly platforms (Anedot, Revv, and Victory Pass) with ActBlue-style technology.[26]

	Already had tech	WinRed = tech improvement	Indeterminable
Count	55	23	11
Proportion	70.5%	29.5%	

Table A24 – Most 2018→2020 WinRed switchers already used small donor-friendly fundraising technology prior to switching platforms.

A related treatment-strength concern that also has to do with party control is that the party strategically decided to prioritize larger contributions. WinRed candidates emphasized FEC limit-maximizing contributions more than ActBlue candidates (S.-Y. S. Kim & Li, 2025) and some defaulted to recurring monthly contributions (Posner et al., 2023), possibly encouraging both very large contributions as well as a series of small contributions that eventually become itemized. As such, Republican WinRed outreach strategy might focus on contributors who are willing and able to make near-maximum and recurring contributions, not just unitemized donors.

If WinRed did not deliver small donor-friendly tech improvements to candidates, or if WinRed prioritized both large and small donors, then it is logical that adopting WinRed does not substantially move the proportion of cash coming from unitemized donors or legislative behavior that would follow from earning money from a more conservative donorate. Of course, this evidence is suggestive, not definitive, and a non-WinRed design is likely needed to assess the role of technology on Republican small donors and legislative behavior.

[26] These are the three vendors mentioned in a Politico article that were used to raise money from small donors (https://www.politico.com/story/2019/01/21/republican-fundraising-patriot-pass-1116642) on the planning process for the platform that would ultimately become WinRed.