Partisan Favoritism in Public Spending: Evidence from Congressional Earmarks*

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Abstract

Representative democracy rests on the principle that elected officials represent their entire constituencies. We study whether members of Congress instead favor their co-partisan voters in federal spending. Pairing an original, geocoded dataset covering U.S. earmark requests and allocations since the resumption of earmarking in FY2022 with a regression discontinuity design in House general elections, we find strong evidence of partisan favoritism. Narrowly electing a Democrat rather than a Republican shifts the average requested earmark dollar toward areas that are 4–8 percentage points more Democratic and increases requests to Democratic strongholds by 19 percentage points. This disparity persists within policy areas, is not explained by socio-demographic correlates of partisanship, extends beyond close elections, and carries through to enacted spending. Our results show that—rather than broadening representation—strong electoral incentives can push legislators to serve their supporters at the expense of their broader constituency.

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1 Introduction

If politics is about "who gets what, when, and how" (Lasswell, 1936), then a fundamental question of political representation is which constituents receive public resources. While representatives are elected to govern on behalf of entire constituencies, they only depend electorally on a subset of the electorate, creating incentives to reward those who helped elect them. Representation may therefore carry unequal material benefits within a constituency, advantaging co-partisans while leaving the opposition behind. We refer to such imbalances in distributive outcomes as partisan favoritism—the allocation of resources in ways that disproportionately benefit co-partisan constituents over others.[1]

Do members of Congress favor co-partisan constituents when allocating federal spending? While a rich literature shows that electoral incentives shape how much effort legislators devote to securing distributive benefits for their districts (Levitt and Snyder Jr, 1995; Bickers and Stein, 1996; Balla et al., 2002; Lee, 2003; Lazarus, 2009; Engstrom and Vanberg, 2010; Albouy, 2013; Dynes and Huber, 2015; Berry and Fowler, 2016; Fagan et al., 2023), we have little evidence on whether they favor co-partisan constituents *within* the districts they represent once those benefits are secured.[2] Identifying such favoritism is difficult because it is challenging to distinguish legislators' choices from the many differences between the districts that elect Democrats and Republicans.[3] Further, because most federal spending is filtered through formula-based rules and shaped by legislative bargaining, realized partisan favoritism in spending rarely allows us to isolate individual legislators' spending priorities (Hammond and Rosenstiel, 2020).

We overcome these challenges by pairing new data on federal spending with a natural experiment. To isolate individual legislators' spending priorities, we examine congressional earmarks, a discretionary mechanism through which individual members of Congress request funding for specific projects in their districts outside standard formula-based or competitive allocation processes. Crucially, the earmark process allows us to observe not only which projects ultimately receive funding, but also the projects each legislator requests

[1]Our outcome-based definition of partisan favoritism parallels the notion of discrimination in law and economics, which is identified by disparate impact—an outcome that disadvantages one group net of legitimate justifications—rather than by demonstrable intent. Favoritism is thus the co-partisan–opposition disparity in outcomes, regardless of whether it arises from animus or from legislator strategy.

[2]Evidence for partisan favoritism comes largely from studies of presidential influence over federal spending (Kiewiet and McCubbins, 1988; McCarty, 2000; Garrett and Sobel, 2003; Larcinese et al., 2006; Bertelli and Grose, 2009; Healy and Malhotra, 2009; Berry et al., 2010; Kriner and Reeves, 2015; Lowande et al., 2018). However, it remains unclear whether the patterns they identify extend to Congress, which holds the power of the purse.

[3]For example, Democratic legislators may represent districts where necessary and fundable projects are disproportionately located in Democratic areas, while Republican members represent electorates where plausible earmark opportunities are in Republican areas, creating an association between legislator party and the partisan geography of requests absent partisan targeting.

and the requested amount. Since earmarks returned in fiscal year (FY) 2022, members of Congress must publicly disclose the project, recipient, amount, and location of each request.[4] We assemble these disclosures, together with enacted earmark allocations, into an original, geocoded dataset covering FY2022–FY2026, allowing us to observe the geography of discretionary spending below the district level. To then distinguish legislators' targeting choices from the underlying differences between Democratic- and Republican-represented districts, we adopt a regression discontinuity (RD) design in U.S. House general elections (Lee, 2008). Near the close-election cutoff, the underlying geography of fundable projects and constituent needs varies smoothly, while the party of the elected representative changes discontinuously. Our design therefore identifies the causal effect of electing a Democrat rather than a Republican on the within-district partisan geography of requested and allocated earmarks.

We find clear evidence of co-partisan favoritism. Narrowly electing a Democrat rather than a Republican shifts the average earmark dollar to areas with a 4–8 percentage-point higher Democratic registration share. This shift reflects a reallocation between partisan strongholds, rather than a uniform tilt across the district. Electing a Democrat raises the share of earmark dollars flowing to Democratic strongholds—defined as areas with at least 60% Democratic registrants—by roughly 19 percentage points, while reducing the share directed to Republican strongholds by 12 percentage points. These reallocations are economically substantial in addition to being politically significant. In dollar terms, our effects are equivalent to roughly $14 million reallocated from opposition- to co-partisan-heavy areas per election cycle.

We then assess whether this pattern reflects partisan differences in policy priorities or the targeting of socio-demographic groups correlated with party affiliation. To assess the first possibility, we classify earmark requests into eleven policy areas and re-estimate the RD separately for each category to isolate legislators' policy priorities. We find evidence of partisan favoritism in ten of eleven policy areas, indicating our main estimates do not appear because Democratic and Republican members request earmarks in different policy areas which are themselves spatially correlated with constituency partisanship. Second, we replace local party registration with other characteristics of the nearby population that are known correlates of partisan preferences, including racial composition, population density, income, and educational attainment. Although Democratic representation also shifts requests toward some groups that are more likely to support Democrats, targeting on the basis of these socio-demographic characteristics is substantially smaller than targeting on the basis of partisanship. To extend these estimates beyond the subset of districts featuring close elec-

[4] In the post-moratorium era starting FY2022, Congress revived earmarks under the label Community Project Funding" for House members and Congressionally Directed Spending" for Senators. We refer to both as earmarks.

tions, and to hold the full set of characteristics constant rather than testing one at a time, we complement the RD with a panel of fixed five-mile grid cells whose party representation changes over time, either due to electoral turnover or the 2022 decennial redistricting process. Within this panel, a cell's partisan composition is the only characteristic that predicts which neighborhoods gain additional earmarks when representation changes hands. Together these results suggest that our central estimates reflect a distinct partisan component in earmark targeting rather than broad differences in policy priorities or socio-demographic targeting alone.

Finally, by matching earmark requests to final appropriations bills, we identify which earmark requests were ultimately funded and in what amount. We find that partisan favoritism persists at nearly the same magnitude in allocated federal earmarks. Overall, our findings show that U.S. House members direct greater discretionary resources towards their core, partisan constituents. More broadly, the results show that co-partisan representation carries material benefits, shaping which constituents receive more from government, in ways which other group identities do not.

This paper contributes to our understanding of distributive politics and partisan representation in American politics. To our knowledge, we provide the first causal test of co-partisan favoritism on the within-district geography of U.S. congressional spending. Prior research on distributive allocations by members of Congress has largely studied how resources are distributed across districts. While important, these analyses cannot address whether additional district spending is broadly distributed or narrowly targeted toward co-partisan constituents.

Second, we advance the study of congressional earmarking by assembling the first comprehensive, geocoded dataset of House earmark requests and allocations across every fiscal year since earmarks returned in FY2022. Building on studies of the first post-moratorium appropriations cycle (Cassella et al., 2023; Fagan et al., 2023; Kaslovsky and Stone, 2025), our data follow the contemporary earmark process over time and locate individual projects within congressional districts. This makes it possible to examine not only how much legislators seek for their constituencies, but where within those constituencies they direct federal resources—a question that existing Congressional spending data have rarely allowed researchers to study.[5]

Finally, our results contribute to research on partisan representation by showing that partisan control determines not only who represents a district, but which constituents within it receive the material benefits of representation. By illustrating that elected members of Congress target co-partisan areas within their district, we provide causal evidence that speaks to long running debates about the targeting strategies politicians adopt (Cox and McCub-

[5] The closest analogues examine senators' within-state or county-level targeting strategies (Martin, 2003; Kaslovsky, 2022; Kaslovsky and Stone, 2025).

bins, 1986; Lindbeck and Weibull, 1987; Dixit and Londregan, 1995). Existing research also finds that voters prefer to be represented by co-partisans, a preference often understood in terms of partisan identity, shared ideological preferences or expressive attachment (Broockman and Ryan, 2016; Mummolo et al., 2021). Our estimates identify an additional instrumental basis for this preference: co-partisan representation also increases the material benefits received. Elections therefore shape whose interests within that constituency receive priority from the federal government.

Overall, our findings complicate a common understanding of democratic accountability. Many theories suggest that elections—especially competitive ones—motivate politicians to work harder, adopt more responsive positions, and deliver for their districts. Empirical evidence that politicians are punished for ideological extremism or poor performance is therefore often interpreted as evidence that electoral competition should induce better representation. Yet this interpretation generally carries an implicit assumption that politicians who work hard for their districts are working for the district as a whole. Our results challenge that assumption. Even in some of the most electorally competitive districts in the country, representatives direct more earmarks toward co-partisan communities than toward opposition communities within the same district. Electoral competition may therefore encourage legislator effort without ensuring equal representation.

This paper proceeds as follows. The next section reviews the literature on distributive politics and political favoritism in the United States and globally. The following section provides background on U.S. congressional earmarks and explains why they offer a useful lens for studying political favoritism. We then introduce our new dataset of geocoded earmark requests and describe how requests are distributed within members' districts. The subsequent section lays out our regression discontinuity design, which uses narrowly decided U.S. House general elections to identify the causal effect of electing a Democrat rather than a Republican. We next present our central results, showing that narrow partisan control shifts requested earmark dollars toward co-partisan areas of the district. The next section distinguishes partisan favoritism from partisan differences in policy priorities or the targeting of sociodemographic constituencies correlated with partisanship. We then examine the extent to which partisan favoritism persists through the earmark allocation process. Finally, we discuss the implications of the findings and conclude.

2 Distributive Politics and Political Favoritism

Elections create incentives for politicians to use public resources strategically. Foundational work in the modern study of distributive politics originated with studies of Congress, where scholars began linking legislative behavior to electoral incentives (Mayhew, 1974; Fenno, 1978). Early studies of congressional spending showed that legislators often sought re-election by "bringing home" federal dollars, known as "pork," to their districts and claiming credit for these distributive benefits (Ferejohn, 1974; Fiorina and Press, 1977; Cain et al., 1987).

This central insight raises a natural question about which voters politicians target with these resources. Formal models of distributive politics offer competing predictions: politicians may reward core supporters, reinforcing the coalitions that brought them to office (Cox and McCubbins, 1986), or target swing voters, whose support can be shifted more efficiently with distributive spending (Lindbeck and Weibull, 1987). Subsequent work shows that these incentives depend on politicians' ability to identify voter needs, deliver benefits effectively, and claim credit for them (Stein and Bickers, 1994; Dixit and Londregan, 1996; Stokes, 2005). Together, these debates motivate a broader empirical question about whether there is systematic favoritism in distributive spending (Golden and Min, 2013). Across a wide range of settings, research finds that politicians direct greater public resources toward co-ethnics, co-partisans, or otherwise politically valuable in-group members (Chandra, 2004; Franck and Rainer, 2012; Jablonski, 2014; Hodler and Raschky, 2014; Burgess et al., 2015; Ejdemyr et al., 2018; De Luca et al., 2018; Dreher et al., 2019; Colonnelli et al., 2020).

Scholars in the U.S. likewise find evidence of partisan favoritism in federal spending. Presidency scholars have shown that American presidents consistently use their influence to direct federal dollars towards co-partisan areas (Kiewiet and McCubbins, 1988; McCarty, 2000; Larcinese et al., 2006; Bertelli and Grose, 2009; Berry et al., 2010; Kriner and Reeves, 2015). For instance, U.S. presidents are more likely to allocate disaster spending (Garrett and Sobel, 2003; Healy and Malhotra, 2009; Reeves, 2011) or extend trade protection (Lowande et al., 2018) in ways that benefit electorally important areas.

It is less clear if similar patterns emerge in congressional spending. Past research primarily examines how factors such as electoral competition, majority-party status, seniority, and committee membership affect legislators' ability and incentives to bring more resources home (Stein and Bickers, 1994; Levitt and Snyder Jr, 1995; Bickers and Stein, 1996; Martin, 2003; Albouy, 2013; Dynes and Huber, 2015; Berry and Fowler, 2016; Hammond and Rosenstiel, 2020). However, few have shown where those resources go within districts once they are secured. Because members of Congress represent entire districts, increased district-level spending cannot reveal whether resources benefit the constituency broadly or favor some groups over others. Evaluating partisan favoritism in the U.S. Congress instead requires observing within-district targeting strategies, which existing congressional spending data rarely permit.

Whether members of Congress exhibit partisan favoritism is critical for understanding representation in the U.S. because Congress possesses constitutional authority over federal spending. In this paper, we study partisan favoritism by House members using congressional earmarks. We are of course not the first to study earmarks with an eye toward these questions. However, to our knowledge, ours is the first to use earmark requests across multiple fiscal years to provide within-district causal evidence of co-partisan favoritism in congressional earmark requests. Like the research on general congressional spending, early studies of congressional earmarks primarily examine allocations across districts (Bickers and Stein, 2000; Balla et al., 2002; Lee, 2003; Lazarus, 2009; Engstrom and Vanberg, 2010; Clemens et al., 2015), leaving them unable to speak directly to whether political favoritism exists within districts. More recent studies using contemporary earmark request data examine the partisan dynamics of earmarking rather than distributive targeting (Cassella et al., 2023; Fagan et al., 2023). Our study is closest to Kaslovsky and Stone (2025), who examine within-constituency targeting by senators in FY2022 and find that senators request more funding for core and swing counties than for opposition counties. We build on this work by examining House earmark requests across all appropriations cycles in the post-moratorium era. By pairing geocoded data on FY2022–FY2026 House earmark requests with a regression discontinuity design, we are able to offer the first within-district causal evaluation of systemic co-partisan favoritism in U.S. House earmarks.

3 New Data on Congressional Earmarks

This section introduces the contemporary earmarking process and the new data that allow us to study its within-district geography. We first explain how the post-moratorium rules—including limits on the number of requests, community-originated proposals, and project-level disclosure—make earmark requests an unusually direct way to examine legislators' distributive priorities. We then describe how we assemble the first comprehensive dataset of all Community Project Funding (CPF) requests submitted by U.S. House members between fiscal years 2022 and 2026, covering every year since Congress resumed earmarking after the ten-year moratorium. The dataset records the requesting member, project description, recipient, requested dollar amount, subcommittee, policy area, and geocoded recipient location for each request. This data provides the first systematic project-level account of the spatial allocation of contemporary House earmark requests. We conclude the section by documenting the principal descriptive patterns in requests and allocations. Appendices A and B provide full details on data sources, collection procedures, geocoding, policy area classification, and additional descriptive statistics for both requests and allocations.

3.1 Contemporary Earmarks Reveal Legislator Priorities

Congressional earmarks provide an unusually direct window into how legislators prioritize constituencies within their districts. Earmarks are discretionary appropriations for specific projects or recipients that are awarded outside standard formula-based or competitive processes (Doyle, 2011; Fagan et al., 2023). After expanding substantially during the 1990s and 2000s, earmarks became the subject of criticism over excessive spending and limited transparency. Congress adopted a series of disclosure reforms between 2006 and 2009 before imposing a moratorium beginning with the 112th Congress in 2011.[6] Earmarks returned in 2021 under a substantially revised institutional framework that makes legislators' distributive choices considerably more transparent.

House earmarks, now formally called "Community Project Funding," must originate with local governments or eligible nonprofit organizations, which submit project proposals to their congressional representatives. Members then decide which proposals to forward (i.e., "request") to the Appropriations committee. These choices are meaningfully constrained. The number of requests each House member may submit is capped, as is total earmark spending, requiring legislators to choose among competing projects rather than support every proposal they receive.[7] The contemporary earmark process therefore reveals legislators' priorities precisely because members cannot support every potential recipient or project.

New disclosure requirements accompanying the return of earmarks make those choices observable at an unusually fine geographic level. Appropriations committees release consolidated records of submitted requests, while individual members must disclose each project's purpose, recipient, requested amount, and location on their official websites.[8] Beginning with the FY2022 cycle, we can therefore observe the projects individual legislators choose to support before those requests are filtered through committee bargaining, negotiations between the chambers, and the broader appropriations process.

For this reason, our analysis focuses primarily on members' requests. Requests most directly capture the projects for which legislators actively seek federal support, whereas final allocations reflect both those initial choices and the influence of downstream institutional actors. We nevertheless collect and analyze final allocations as well. Examining both stages allows us to distinguish the partisan geography of legislators' initial distributive priorities from the geography of spending ultimately enacted into law.

[6] See Doyle (2011) and Lynch (2026) for a discussion of the politics of this era.

[7] House members could submit up to 10 requests in FY2022, 15 in FY2023, and 20 in each fiscal year from FY2024 through FY2026. Total earmark allocations were capped at 1% of discretionary spending in FY2022 and FY2023 and 0.5% from FY2024 through FY2026 (House Appropriations Committee, 2021, 2022, 2023, 2024, 2025).

[8] Earlier disclosure rules generally identified the requesting member only after an earmark was included in appropriations legislation.

A further advantage of earmarks is their substantive breadth. House members may submit requests across the appropriations portfolio, including infrastructure, public safety, health, education, housing, environmental projects, and community development. Our analysis therefore does not depend on a single federal program or type of public good whose geographic distribution may be unusually well suited to targeting particular constituencies (Kramon and Posner, 2013). Contemporary earmarks combine constrained legislator choice, unusually detailed disclosure, and broad policy coverage, making them a particularly informative setting in which to examine how members of Congress distribute discretionary federal resources within their districts.

3.2 Construction of Earmarks Dataset

Our primary sources are materials released by the Democratic and Republican House Appropriations Committees, supplemented by individual legislators' disclosure forms and websites. Contemporary earmark disclosure rules require the House Appropriations Committee to release consolidated CPF request tables for each fiscal year and individual legislators to publicly disclose their requested projects on their websites. Across FY2022–FY2026, House members submitted 23,510 CPF requests totaling $85.38 billion.

The Committee's consolidated records provide most of the information included in the final dataset, although recipient location information is missing for many requests in FY2022 and FY2023, the first years after earmarks resumed. To recover this information, we use an LLM-assisted retrieval, extraction, and matching procedure to collect members' public disclosure materials from official websites and archived webpages, extract project-level locations, and match recovered records to the corresponding request from Committee records. We observe or recover sub-state location information for 23,110 requests, which we geocode using the ArcGIS USA geocoder. We successfully geocode 98% of these requests, with more than 90% matched at the point or street level. This fine spatial resolution allows us to observe where members seek resources within their districts, rather than only the total amount they seek for their districts as a whole.

Although each request is assigned to an appropriations subcommittee, subcommittee designations are too coarse to capture the substantive purpose of individual projects.[9] For example, requests assigned to the "Transportation, Housing and Urban Development" sub-

[9] The relevant House appropriations subcommittees are: Agriculture, Rural Development, Food and Drug Administration, and Related Agencies; Commerce, Justice, Science, and Related Agencies; Defense; Energy and Water Development, and Related Agencies; Financial Services and General Government; Homeland Security; Interior, Environment, and Related Agencies; Labor, Health and Human Services, Education, and Related Agencies; Military Construction, Veterans Affairs, and Related Agencies; and Transportation, Housing and Urban Development, and Related Agencies.

committee may support projects as varied as road improvements, public transit, affordable housing, airport facilities, and community development. To identify different policy priorities, we classify each project into one of eleven major policy areas using OpenAI's GPT-5.5 large language model. To validate this classification, we independently hand-coded a random sample of 150 requests. Our human-coded labels agreed with the model's on 88% of projects, corresponding to a Cohen's κ of 0.86. Appendix A describes this process in detail and visualizes the projects included in each category.

Finally, we merge the request data with Voteview's congressional membership records for the 117th, 118th, and 119th Congresses, which span our period of analysis.[10] These records provide standardized identifiers and information on each member's state, congressional district, and party affiliation. Of the 610 House members who served across these three Congresses, 519 (85%) submitted at least one earmark request. As we discuss in the following section, non-requesting members are overwhelmingly Republican and concentrated in the 117th Congress, and the share of members submitting no requests declines over time within both parties.

Allocations We primarily focus on earmark requests because they better capture legislator intent. However, we also collect final earmark allocations data, which allow us to observe whether each requested project was funded and the amount ultimately provided by Congress. Our data source for allocations is the Senate Appropriations Committee's website, which releases subcommittee-level reports listing enacted Community Project Funding and Congressionally Directed Spending projects. These records report the project name or description, recipient, requesting members, state, appropriations account and agency where available, and final amount provided. Because the format and column structure vary across fiscal years and subcommittees, we use an LLM-assisted extraction procedure to convert the reports into a standardized project-level dataset. We extract each funded project, standardize member names and dollar amounts, and combine the records across subcommittees within each fiscal year. We then use an LLM-assisted matching procedure to link funded projects to the corresponding records in our requests dataset.[11] The resulting data preserve the full request-level records while adding measures of whether each project received funding and the amount ultimately allocated.[12]

[10]The 117th Congress covers the FY2022 and FY2023 appropriations cycles, the 118th Congress the FY2024 and FY2025 cycles, and the 119th Congress the FY2026 and FY2027 cycles.

[11]Within each member and fiscal year, we compare project names, recipients, locations, subcommittees, and dollar amounts across the two sources, while requiring each allocation to match at most one request. We manually review low-confidence matches. Requests linked to an enacted allocation are coded as funded and assigned the final amount provided; requests without a plausible match are coded as unfunded.

[12]Importantly, no earmarks were funded in FY2025. Congress failed to pass an appropriations bill and instead operated through a series of continuing resolutions which explicitly excluded earmark funding.

3.3 Characteristics of Earmark Requests

Geographic Coverage Earmark requests achieve broad geographic reach. As Figure 1 shows, members of Congress in 48 of 50 states submitted earmark requests during our period of study.[13] At the state level, the partisanship of the areas surrounding a state's projects largely tracks the partisanship of the state as a whole: requests in heavily Democratic states tend to fall near Democratic-leaning areas, and requests in heavily Republican states near Republican-leaning ones.[14] Yet, this mechanical aggregate correlation masks substantial within-district variation in the partisan composition of areas near requested projects. Figure 2 illustrates this pattern in three states chosen to span the partisan spectrum: New York, which leans Democratic; Texas, which leans Republican; and Pennsylvania, whose congressional delegation is closely divided. In each state, districts represented by a single party nonetheless contain requests sited near neighborhoods of varying partisanship. Republican-held districts, for instance, include projects near strongly Democratic areas as well as strongly Republican ones (and vice versa for Democratic-held districts).

Growth Over Time Earmarking expanded rapidly on both the extensive and intensive margins over the FY2022–FY2026 period. As Figure 3 shows, the number of submitted projects rose from 3,041 in FY2022 to 5,414 in FY2026, and total requested funding more than tripled, from $7.1 billion to $23.4 billion. Both more members submitting requests and larger individual requests drove this growth: the average member submitted roughly 9 projects per year in FY2022 and about 14 in each subsequent year, while the median request grew from $975,000 to $2.1 million. Requested amounts are highly right-skewed: a few infrastructure projects reach hundreds of millions of dollars, while most remain below $2 million.

Partisan Differences Democrat and Republican legislators diverge along both the extensive and intensive margins: Democrats submitted more projects, while Republicans requested more money. Across the full period, Democrats submitted 64% of all projects, yet Republicans requested more total funding—$47.0 billion (55%) against the Democrats' $38.4 billion (45%). The count gap reflects initial Republican reticence toward earmarks that faded over time. When earmarks returned in FY2022, Republican leadership apprehension and House Freedom Caucus opposition to new spending (Shutt and McPherson, 2021) meant only about half the Republican conference submitted requests,[15] compared with nearly all

[13] Republicans Kelly Armstrong of North Dakota and Dusty Johnson of South Dakota did not make any earmark requests between FY2022 and FY2026.

[14] Appendix Figure C.1 shows that these patterns hold individually in each fiscal year, FY2022–FY2026.

[15] This finding aligns with other work on FY2022 (Cassella et al., 2023).

Figure 1 – Geographic Distribution of Earmark Requests, Colored by Democratic Registration Share Within 5 Miles. Each dot represents an individual earmark request. Appendix Figure C.1 presents this map broken out by fiscal year.

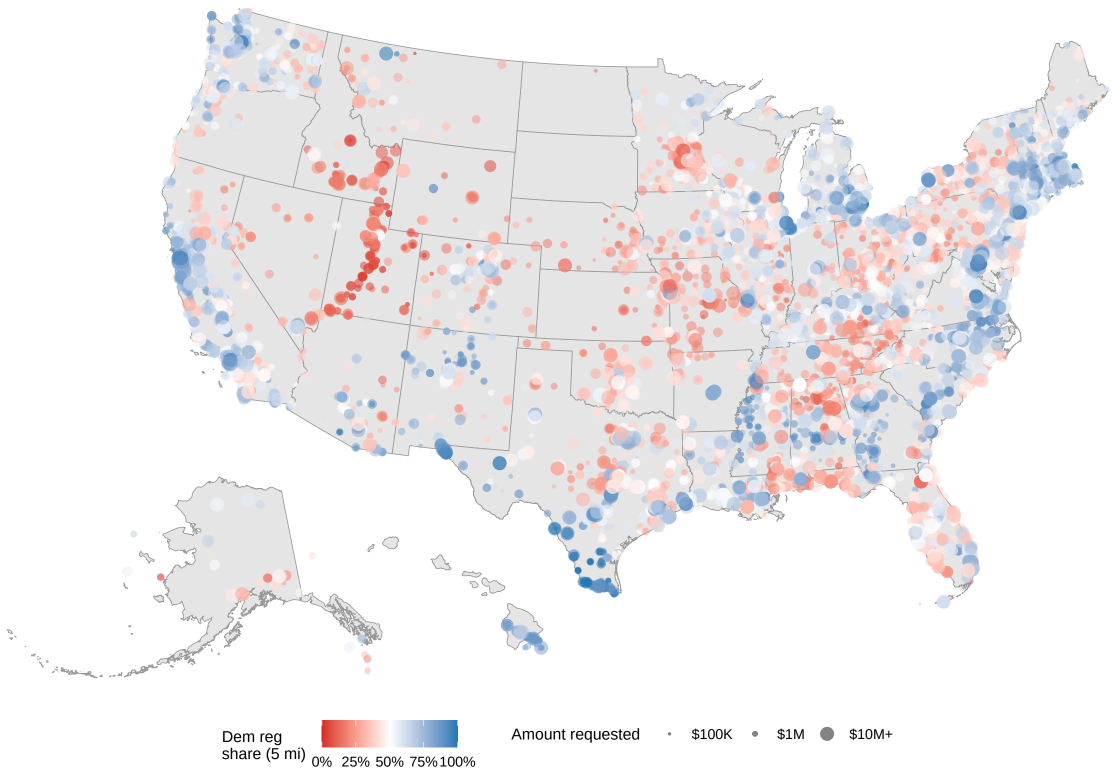


Figure 2 – Earmark Requests in New York, Pennsylvania, and Texas, FY2024. Each dot is an individual FY2024 request, sized by its requested amount and shaded by the Democratic registration share within five miles of the project. Congressional districts are outlined by the requesting member's party.

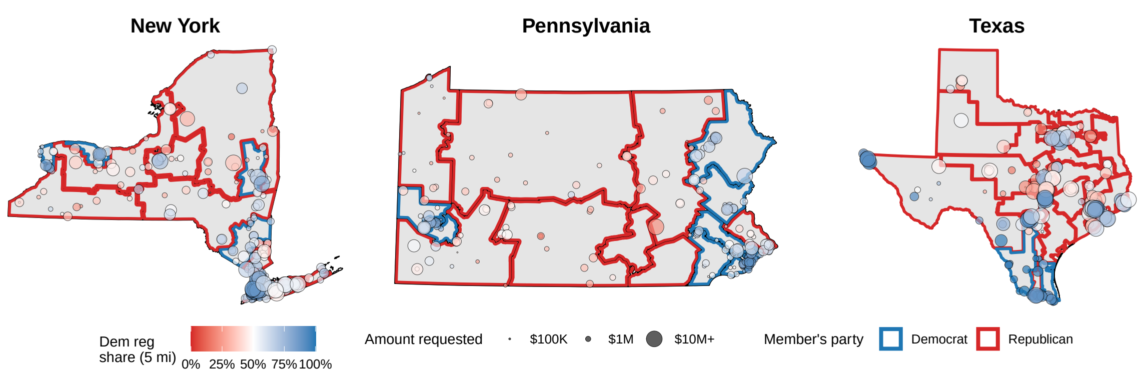
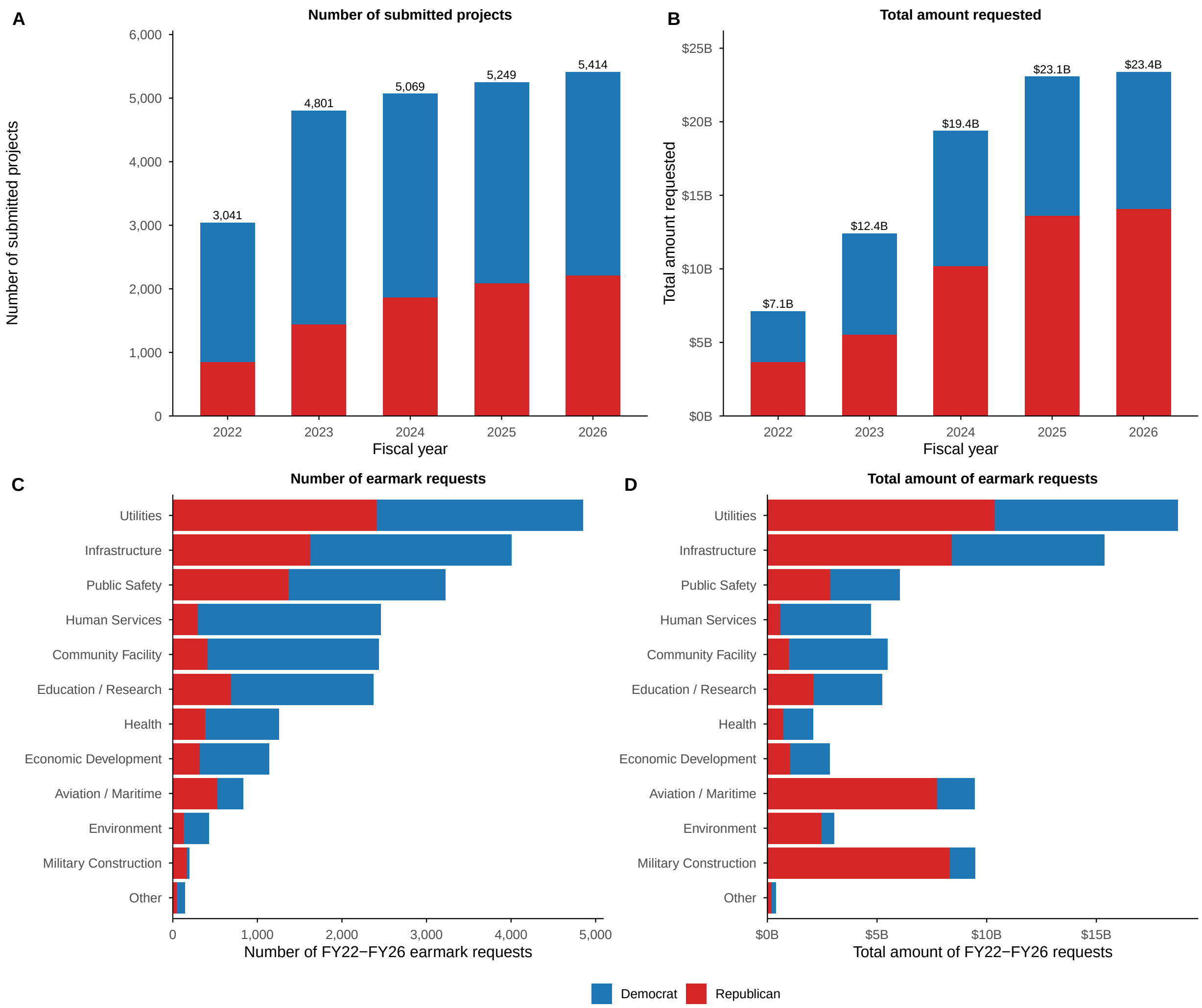


Figure 3 – Volume and Composition of House CPF Submissions. Panels A–B show, by fiscal year, the count of submitted CPF projects (A) and the total dollar amount requested (B). Panels C–D show the count (C) and total amount (D) requested in each policy category. Party for FY2022–FY2023 requests, which the source files omit, is assigned from Voteview's 117th Congress roster. In every panel, bars are stacked by the submitting member's party.



Democrats. The share of Republicans submitting requests then climbed steadily to roughly 78% by FY2026, narrowing the gap. Though Republican legislators submit fewer projects, their requested projects are of higher value. While the number of requests per member was capped, the dollar amount of any individual project was not. The average Republican request ($5.6 million; median $2.4 million) was more than twice the average Democratic request ($2.5 million; median $1.6 million), so despite submitting fewer projects, Republicans accounted for the larger share of requested dollars.

Policy Areas Despite contentious debates over spending priorities, Democratic and Republican members of Congress prioritize similar top policy areas. Panels C and D of Figure 3 show that members of both parties concentrate their requests on utilities, infrastructure, and public safety, which collectively make up 59% of total requests and 50% of requested dollars. There are pronounced partisan differences, however, outside of these three largest categories. Democratic legislators account for the vast majority of requests for community facilities, human services, and education/research, while Republicans tend to disproportionately prioritize military construction and aviation/maritime requests.[16]

4 Empirical Design

We combine our geocoded earmarks data with voter registration records to examine whether legislators disproportionately direct requests toward co-partisan areas of their districts. We first describe how we measure the local partisan composition of each request, then introduce the regression discontinuity (RD) design that identifies the causal effect of legislator partisanship on the geography of requests, and finally discuss the assumptions under which we interpret that effect.

Measuring Local Partisan Composition We measure the partisan composition of each earmark request by combining our earmarks data with geocoded voter-file records from the data vendor L2.[17] L2 is a large commercial voter-data vendor, widely used in economics and political science research, that standardizes official state registration files into a national database of registered voters and geocodes their residential address (Hersh, 2015; Fraga, 2018; Fos et al., 2022; Allcott et al., 2020). These data allow us to measure the partisan composition of registered voters surrounding each earmark request.

Our primary outcome is the dollar-weighted average Democratic registration share within an r-mile radius of a district's earmark requests in each cycle. Formally, let P_{dt} denote the

[16] Earmarks cannot fund direct military spending—procurement, operations, personnel, or contracts to defense firms. Military earmarks are instead limited to construction of physical facilities on installations (e.g., National Guard readiness centers), funded through the Military Construction and Veterans Affairs subcommittee.

[17] In 33 states, L2's partisan classification reflects voters' self-declared party affiliation as recorded in the state's official voter-registration file, or the party of the most recent primary in which they participated. In the remaining 17 states, L2 imputes partisan classification using a proprietary model trained on primary-ballot choice and demographic data. In Appendix E, we show that our substantive conclusions are unchanged when we instead measure neighborhood partisanship using geocoded precinct-level presidential vote share.

set of earmark projects requested in district d and general-election cycle t. We define

$$Y^r_{dt} = \frac{\sum_{p \in P_{dt}} Amount_{pdt} \cdot Democratic\ Registration\ Share^r_{pdt}}{\sum_{p \in P_{dt}} Amount_{pdt}}, \tag{1}$$

where p indexes an earmark project, $Amount_{pdt}$ is the dollar amount requested for project p, and $Democratic\ Registration\ Share^r_{pdt}$ is the two-party share of Democratic registrants within r miles of project p. To ensure this measure does not capture downstream effects of earmarks on registration, we use a voter-file snapshot from the year preceding the first cycle in our data. Our outcome therefore measures the Democratic registration share surrounding the average requested dollar, rather than the average project.

We use a dollar-weighted outcome given our theoretical interest in the intensive margin of requested spending, not merely where projects are located. Whereas a project-weighted measure treats all requests equally regardless of size, Y^r_{dt} captures whether members direct larger requests disproportionately toward areas with different partisan compositions. Thus, even if a member submits the same number of projects in Democratic- and Republican-leaning areas, the outcome will reflect a partisan tilt when the requested dollar amounts in one set of areas are systematically larger. In Appendix F, we show that our substantive conclusions are unchanged when we weight each project equally.

This construction also distinguishes the within-district geography of requests from partisan differences in overall earmark activity. Thus, the fact that Republican members submit fewer requests, or that Democratic members request fewer total dollars, does not mechanically generate a partisan difference in our outcome among district-cycles with at least one request. Because Y^r_{dt} is normalized by total requested dollars, a proportional increase in requested amounts across all locations leaves it unchanged. The outcome changes only when the relative allocation of requested dollars shifts toward areas with different partisan compositions. Thus, Y^r_{dt} captures partisan differences in how requested dollars are targeted within districts.

Regression Discontinuity Design To identify whether legislators disproportionately funnel earmark requests to co-partisan areas, we adopt a regression discontinuity design in U.S. House general elections (Lee and Lemieux, 2010). The design compares the distribution of earmark requests across districts that narrowly elect a Democratic versus a Republican legislator. Specifically, we estimate equations of the form

$$Y^r_{dt} = \beta_0 + \beta_1\, Dem\ Win_{dt} + f(Dem\ Win\ Margin_{dt}) + \varepsilon_{dt}, \tag{2}$$

where $Dem\ Win_{dt}$ indicates that the Democratic candidate won district d's election in cycle t, and $f(\cdot)$ is a flexible function of the Democratic candidate's win margin. We assign each request to the election cycle corresponding to the term of the member who submitted it. The outcome Y^r_{dt} measures the partisan composition of voters within an r-mile buffer of the district's requests, as defined in Equation 1.

The key parameter of interest, β_1, captures the causal effect of electing a Democratic legislator on the spatial composition of earmark requests in 50–50 elections. Although closely contested races represent a narrow slice of U.S. House elections, they offer a particularly demanding test of partisan favoritism. In closely divided electorates, legislators have the strongest incentive to direct requests toward out-party supporters in order to gain an electoral edge (Levitt and Snyder Jr, 1997; Bickers and Stein, 1996; Stratmann, 2013; Kriner and Reeves, 2012). Observing partisan favoritism even here gives us confidence that the pattern extends to less competitive races.

Identification The identifying assumption is that parties' potential earmark requests are continuous near the victory cutoff (Imbens and Lemieux, 2008; Lee and Lemieux, 2010). Although the party of the elected representative changes discontinuously when a Democrat narrowly wins rather than loses, the underlying partisan geography of constituent needs and fundable projects does not. This assumption is especially plausible in close elections, where candidates rarely have polling precise enough to locate themselves relative to the discontinuity. Consistent with this expectation, Eggers et al. (2015) find little evidence of strategic sorting across the electoral threshold in a large set of contests, including U.S. House races. In Appendix D, we supplement this evidence with our own data and find no evidence of imbalance.

The design's central advantage is that baseline differences in the earmark opportunity structure across districts are balanced at the threshold. Because contemporary CPF requests are community-originated, a naive comparison between Democratic and Republican members' requests would conflate legislators' targeting strategies with the geographic distribution of the proposals their offices receive. Democratic legislators could appear to target more Democratic areas simply because such areas have greater administrative capacity, more potential recipients, distinct local needs, or a greater propensity to submit viable proposals. These pre-existing differences are part of the baseline opportunity structure, and they vary smoothly through the close-election threshold. Comparing districts that narrowly elect a Democrat to those that narrowly elect a Republican thus isolates the effect of representative party from cross-sectional differences in the availability and location of potential projects.

This design does not, by itself, distinguish all mechanisms that could generate a non-zero point estimate. In particular, while the RD provides balance on the pre-treatment geography of earmark opportunities, it does not balance the *type* of projects Democratic and Republican legislators request. If, for example, Democratic legislators prioritize health, education, and public transit spending, and these categories are disproportionately located in Democratic-leaning areas, Democratic representation would shift earmark requests toward Democratic areas because they have different policy priorities than Republicans, rather than as a result of direct partisan targeting.[18] To probe this possibility, in Section 6.1 we classify every earmark request in our database into eleven distinct policy areas and reestimate our central RD design separately for each category. This approach isolates partisan favoritism within narrow policy domains. Second, if representatives target demographic groups that are correlated with partisanship, the resulting geographic pattern could also resemble partisan favoritism.[19] To evaluate this mechanism, in Section 6.2 we re-estimate our central RD design, but replace local Democratic registration share with other characteristics of the population surrounding each earmark request, including racial composition, population density, income, and educational attainment. These analyses allow us to assess whether co-partisan targeting exceeds targeting on the basis of other electorally salient constituencies that are correlated with partisanship. In Section 6.2.2, we show that our results generalize beyond the set of close, contested elections that underlie our RD design.

5 Partisan Favoritism in Congressional Earmark Requests

5.1 Legislators Target Co-Partisan Voters

We begin with the central question: do members of Congress direct earmark requests toward co-partisan voters? Figure 4 plots our estimates of β_1 from Equation 2 using the method from Calonico et al. (2014).[20] The vertical axis reports the effect of a narrow Democratic win on the dollar-weighted Democratic registration share, Y^r_{dt}; the horizontal axis varies the project radius r.

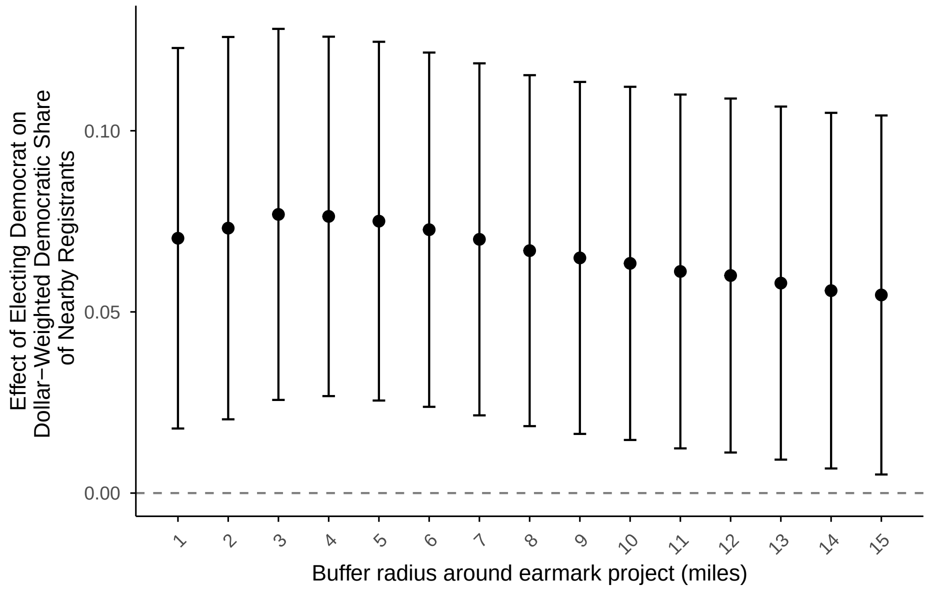
We find clear evidence of partisan favoritism. At every buffer radius from 1 to 15 miles, the estimated effect of a narrow Democratic win on co-partisan earmark requests is positive and statistically distinguishable from zero. Focusing on the estimate using a 5-mile radius, we find that the narrow election of a Democratic member of Congress increases the dollar-weighted two-party share of registered voters within 5 miles of earmark requests by 8 percentage points

[18]Similarly, Republican legislators may prioritize categories such as rural infrastructure, water systems, or public safety projects that are disproportionately located in Republican-leaning areas.

[19]For example, Democratic legislators may target non-white, urban, or highly educated communities, which are also more likely to be Democratic-leaning.

[20]This method uses kernel regression with a triangular kernel and a bandwidth that minimizes mean squared error. We implement the method using the R package *rdrobust*.

Figure 4 – Effect of Electing Democrat on Democratic Share of Registrants Near Earmark Requests. The narrow election of a Democratic member of Congress increases the dollar-weighted two-party Democratic share of registered voters in the vicinity of earmark requests by 6 to 9 percentage points relative to electing a Republican. The horizontal axis reports the radius of voters included around each project.



relative to a narrow Republican victory. The estimates are largest at smaller radii, declining from 9 percentage points at 1 mile to 6 percentage points at 15 miles. This gradient is consistent with within-district targeting, since smaller buffers isolate co-partisan voters most sharply while larger ones average over a more heterogeneous population.

As is standard in RD analyses, Table 1 reports estimates of β_1 across a variety of bandwidths and functional forms. For simplicity, we focus here on our preferred 5-mile radius specification. The first column in Table 1 replicates the 5-mile CCT estimate from Figure 4. In the second column, we use a local-linear specification of the running variable, $Dem\ Win\ Margin_{dt}$, and a 10% bandwidth fit separately on either side of the discontinuity (i.e., a spline). The third column fits a third-order polynomial using all available data and a spline. Finally, column four reports the estimate from Imbens and Wager's (2019) *optrdd* R package, which uses convex optimization to construct the finite-sample minimax linear estimator of the discontinuity, given a bound on the curvature of the conditional expectation function.[21] Across all four specifications, we find precise, uniform evidence that legislators disproportionately funnel earmark requests to areas with more co-partisan voters.

[21] Following Imbens and Wager (2019), we obtain a conservative estimate of the second derivative of the conditional expectation function, B, using a global quadratic regression and multiplying the estimate by 2.

Table 1 – Effect of Electing Democrat on Democratic Share of Registrants Near Earmark Requests, 5-mile Radius. The narrow election of a Democratic member of Congress increases the dollar-weighted two-party Democratic share of registered voters within 5 miles of earmark requests by 4 to 8 percentage points relative to electing a Republican.

	Dollar-Weighted Democratic Registration Share			
	(1)	(2)	(3)	(4)
Democratic Win	0.08	0.05	0.05	0.04
	(0.03)	(0.02)	(0.02)	(0.02)
N	261	355	993	993
Specification	CCT	Linear	Cubic	IW
Spline	-	Yes	Yes	-
Bandwidth	0.07	0.10	-	-

Note: Robust standard errors clustered by district are reported in parentheses. The running variable is the Democratic candidate's general-election margin of victory. Spline indicates that the regression function was fit separately on either side of zero. Cubic refers to a third-order polynomial regression. CCT refers to the method from Calonico, Cattaneo, and Titiunik (2014). IW refers to the method from Imbens and Wager (2019).

5.2 Targeting Operates by Defunding Out-Party Strongholds

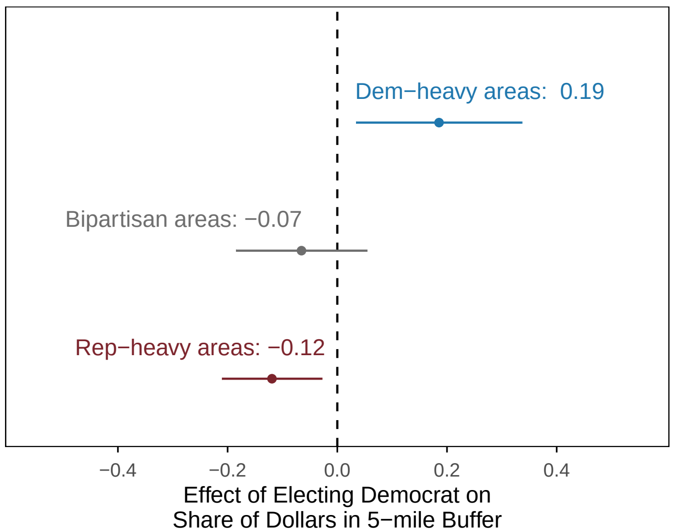
Our headline results establish that legislators direct earmark requests towards areas with more co-partisan voters, but not which areas within the district drive this shift. Legislators could reallocate dollars away from evenly divided neighborhoods with a mix of in- and out-partisans or away from out-party strongholds—a distinction that reveals whether favoritism operates by courting a district's marginal areas or by withdrawing resources from the opposition's base.

To localize the shift, we classify each district's requests into three neighborhood types by local partisan composition: Dem-heavy (≥60% Democratic registration), bipartisan (40–60%), and Rep-heavy (≤40%). We then re-estimate our RD design separately for each neighborhood, but, because we now condition on the political composition of nearby voters, our outcome is the share of a legislator's total earmark requests flowing to a given neighborhood type.[22]

Figure 5 reports the results and shows that reallocation is financed by defunding out-party strongholds, not bipartisan areas. The first row shows that a narrow Democratic win

[22] Formally, we define $Z_{dt}^{N} = \frac{\sum_{p \in N} Amount_{pdt}}{\sum_{p \in P} Amount_{pdt}}$, where d and t index district and election cycle, respectively, P stands in for the set of all projects in dt, and N is the subset of P situated in a given neighborhood type (i.e., Democratic-heavy, Bipartisan, or Republican-Heavy).

Figure 5 – Effect of Electing a Democrat on the Share of Project Dollars Placed in Each Neighborhood Type, 5-Mile Radius. Robust bias-corrected RDD estimates (Calonico et al., 2014) of the effect of a narrow Democratic win on the district-year share of earmark project dollars whose 5-mile buffer falls in each partisan bucket: Dem-heavy ($\geq 60\%$ Dem registration), Bipartisan (40–60%), or Rep-heavy ($\leq$ 40%). 95% robust confidence intervals shown. The narrow election of a Democratic member of Congress increases the share of earmark dollars requested in Democratic-heavy areas by 19 percentage points, while decreasing the share in Republican-heavy areas by 12 percentage points; the smaller drop in bipartisan areas (7 percentage points) is not statistically distinguishable from zero.



raises the share of a legislator's earmark portfolio flowing to Democratic-heavy areas by 19 percentage points. The second and third rows show that this shift is financed in large part by reductions in Republican strongholds, where electing a Democrat lowers the share of requested dollars by 12 percentage points. The drop in bipartisan areas (7 percentage points) is smaller and not statistically distinguishable from zero. Co-partisan favoritism in U.S. House earmark requests therefore operates primarily by diverting resources away from out-partisan neighborhoods, rather than by trimming flows to politically heterogeneous ones.

The magnitude of the effect is economically meaningful. In our data, the average request is \$2.5 million and the average legislator submits roughly 30 requests per election cycle, for a portfolio of about \$75 million.[23] The first row in Figure 5 indicates that a narrowly elected legislator funnels an additional 19 percentage points of requested funds to co-partisan areas. This means that, on average, the narrow election of a Democrat leads to \$14.2 million in requests re-directed from Bipartisan and Republican-heavy areas to Democratic strongholds.

[23] The number of requests and total earmark spending change across fiscal years. Total earmark allocations were capped at 1% of discretionary spending for FY2022–FY2023 and 0.5% for FY2024–FY2027, and House members could submit 10 requests in FY2022, 15 in FY2023, and 20 in each of FY2024–FY2027.

In Appendix Figure F.2, we show that this effect translates into roughly 4 additional projects in Democratic-heavy areas.

5.3 Proposal Supply and Participation

We now address the concern that our estimates reflect proposal supply rather than targeting. As discussed earlier, representative party may shape not only which projects a member selects but which constituencies bring proposals forward in the first place. If co-partisans submit at higher rates when their party holds the seat, the pool a member draws from would itself tilt toward co-partisan areas, and neutral selection from that pool could reproduce our estimates without deliberate targeting. Because the universe of submitted proposals is unobserved, we cannot rule this channel out directly; instead, we calibrate how much of the effect differential participation could plausibly generate.

We benchmark against Broockman and Ryan (2016), an influential study of how co-partisan representation in U.S. Congress shapes voter participation. Using a regression discontinuity in close U.S. House elections, they find that having a co-partisan representative raises the probability a citizen contacts their representative by roughly 23%. This benchmark is conservative for our setting. Broockman and Ryan (2016) measure an individual-level contact asymmetry rooted in the discomfort of engaging out-partisans, whereas CPF proposers are institutional actors, as requests primarily originate with an eligible nonprofit or a local government. Such institutions seek federal funds instrumentally and have been documented to be far less partisan-attached than individual citizens (Barber, 2016; Fouirnaies and Hall, 2018; Li, 2018). Their estimate therefore likely overstates the participation asymmetry among proposers in our data. We nonetheless adopt it because their design closely matches ours and can provide a useful ceiling on participation's contribution.

We map this estimate into our setting under the assumption most favorable to the participation account. Suppose a close 50–50 district's underlying proposal pool is split evenly between in-party and out-party areas, and that representative party changes only how often each area submits, not which proposals members select. Broockman and Ryan (2016) estimate that citizens contact a co-partisan representative about 7.2 percentage points more often than an out-partisan one, relative to a baseline contact rate of roughly 31%. Absent partisan favoritism, this estimate implies that the difference in the co-partisan share of requested projects would be $7.2/(38.2+31) \approx 0.10$.[24] In Appendix Figure F.2, we show that narrowly electing a Democrat increases the share of projects in co-partisan areas by 0.13, or about four additional projects. Differential participation therefore accounts for roughly

[24] An even split maximizes this shift, so the exercise is generous to the participation account.

$\frac{0.10}{0.13} \times 4 \approx 3.1$ of these four projects.[25] Equivalently, for differential participation to explain away the entire estimated effect, co-partisan areas would need to submit about 29% more proposals than out-party areas—above the roughly 23% gap implied by Broockman and Ryan's estimate.

Finally, participation also cannot speak to the intensive margin of partisan targeting. Differential participation in CPF submissions can add co-partisan projects to the pool of considered projects, but it cannot make any one of them larger. Our results show that the partisan favoritism tilt is greater in requested dollars than counts, as the dollar-weighted effect (19pp) exceeds the project-count effect (13pp). Differential participation thus explains at most part of the extensive margin, but not the intensive margin. Co-partisan favoritism, not proposal supply, better explains the pattern we document.

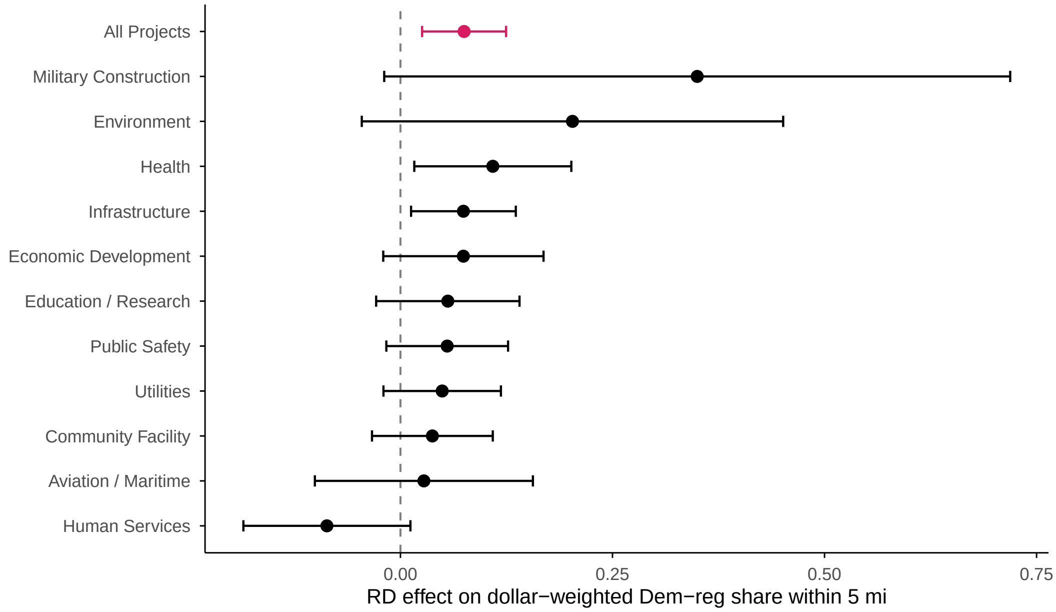
6 Mechanisms

The results thus far establish that narrowly electing a Democrat rather than a Republican changes who stands to benefit from requested discretionary federal spending. Our RD design ensures this disparity does not reflect pre-existing differences in the geography of earmark opportunities across districts represented by the two parties. Whatever the underlying process, this distributive pattern is consequential, since constituents in opposition neighborhoods receive less when represented by the other party.

As we describe in Section 1, however, our definition of partisan favoritism focuses on the co-partisan–opposition disparity that remains after accounting for need, relevant demographics, and policy. This section performs that accounting. We ask whether the headline effects we identify are absorbed by two ostensibly non-partisan allocation priorities. First, Democratic and Republican legislators may simply request different types of projects, and those project types may sit in different neighborhoods. Second, legislators may target constituencies defined by race, density, education, or economic need that are spatially correlated with partisanship. These analyses do not alter the finding that representation carries unequal material benefits within the district. Instead, they determine what kind of disparity these patterns reflect.

[25] A participation gap in proposal supply also need not be innocent. Partisan differences in who submits CPF proposals could operate through the member's own office, by encouraging in-party organizations to apply, directing outreach, or assisting favored applicants. Under our estimand, that channel is not an alternative to favoritism but a form of it.

Figure 6 – Effect of Electing a Democrat on the Democratic Share of Registrants Within 5 Miles by Project Policy Area. The narrow election of a Democratic member of Congress increases the dollar-weighted two-party Democratic share of registered voters within 5 miles of earmark requests, even within policy areas.



6.1 Co-Partisan Targeting Persists Within Policy Area

Democratic and Republican legislators often pursue systematically different policy priorities, a pattern documented across decades of work on partisan issue ownership (Petrocik, 1996; Egan, 2013) and on the distributive spending the two parties pursue on behalf of their districts (Albouy, 2013; Lazarus, 2009; Clemens et al., 2015). If Democratic and Republican legislators prioritize different policy areas when requesting earmarks, and these project types are spatially correlated with the partisan composition of the electorate, what looks like partisan favoritism might simply reflect different policy priorities. For example, if Democratic legislators prioritize health, education, and public transit spending, and hospitals, universities, and transit stations tend to be located in Democratic-leaning areas, a narrow Democratic win could shift the partisan geography of requested earmarks mechanically.

To probe this possibility, we re-estimate Equation 2 separately within each of the eleven policy categories introduced in Section 3. Hence, the outcome becomes

$$Y^{cr}_{dt} = \frac{\sum_{p \in C_{dt}} Amount_{pdt} \cdot Dem\ Registration\ Share^{r}_{pdt}}{\sum_{p \in C_{dt}} Amount_{pdt}}, \tag{3}$$

where C_{dt} represents the set of projects in a given policy category, c. Each project is assigned to exactly one category, and the categories are granular enough that variation in project location is unlikely to reflect differential partisan priorities.

Figure 6 plots our estimates of policy-specific earmark distribution using a 5-mile project radius and the estimator from Calonico et al. (2014). As the figure shows, we find evidence of co-partisan targeting in ten of eleven policy areas. Across these categories, the estimated shift in the dollar-weighted Democratic registration share ranges from roughly 3 to 36 percentage points, with the largest effects in military construction and environment and the most precisely estimated effects in health and infrastructure.

Taken together, these policy-level estimates suggest that differences in policy priorities between Democratic and Republican legislators cannot account for our headline result. A second alternative interpretation remains, however: legislators may target demographic constituencies that are correlated with partisanship. We turn to that possibility next.

6.2 Co-Partisan Targeting Exceeds Demographic Targeting

A second, ostensibly non-partisan, explanation for the central effects we identify is that legislators may target constituencies on the basis of demographics in ways that are correlated with partisanship. For example, Democratic legislators may direct earmark requests toward predominantly minority, urban, poor, or college-educated communities, each of which we show in Appendix G is correlated with Democratic registration. The partisan geography of requested earmarks would then shift toward Democratic-leaning areas without legislators explicitly targeting co-partisans. In this subsection, we benchmark demographic-based targeting relative to partisan targeting using two complementary research designs.

6.2.1 Alternative Regression Discontinuity Outcomes

We begin by using our regression discontinuity design to evaluate the extent to which the parties differentially target individual demographic groups. To do so, we re-estimate Equation 2 replacing the dollar-weighted Democratic registration share, $\textit{Dem Registration Share}^{r}_{pdt}$, with each of four placebos: the share of non-white residents, population density, the share of residents with a bachelor's degree or greater, and the share of residents in poverty (household income below the poverty line), each measured within a 5-mile radius of requested projects.[26] Because these outcomes are measured on different scales, we make the RD estimates comparable by converting each outcome to its sample percentile before estimation, so that every effect is expressed in common percentile points, or the number of percentiles by which electing a Democrat moves the targeted area up that outcome's distribution.

[26]Since state voter files do not consistently report race, educational attainment, or income, we impute these variables using block-group level data from the Census Bureau. Our point estimates are highly similar, however, when using the modeled education and race variables provided by L2.

Figure 7 – Effect of Electing a Democrat on Earmark Targeting by Party, Race, Population Density, Education, and Economic Need, 5-Mile Radius. Each point is the regression-discontinuity effect on the targeted area's percentile in the given outcome's distribution (percentile points), a common scale robust to differences in scale and skew across outcomes. Electing a Democrat significantly increases targeting on the basis of party, whereas the demographic and economic-need placebos—race, population density, education, and poverty—are not individually distinguishable from zero.

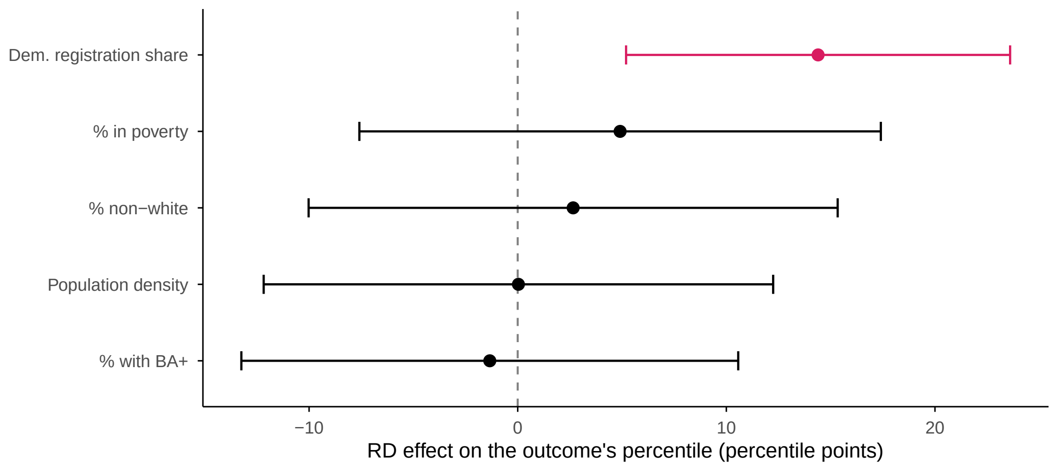


Figure 7 reports the results. Electing a Democrat moves the targeted area roughly 15 percentiles up the Democratic-registration distribution, a large and statistically significant shift. The corresponding effects on the demographic and economic-need placebos—race, population density, education, and poverty—are all smaller and none is statistically distinguishable from zero. Co-partisan targeting therefore does not appear to be a by-product of parties differentially targeting these correlated neighborhood characteristics. The raw point estimates underlying the figure, in each outcome's native units (including population density), are reported in Appendix Table G.1 and show the same substantive conclusion.

6.2.2 Grid-Cell Panel of Fixed Neighborhoods

The results in the previous subsection indicate that our RD design results do not reflect Democratic and Republican legislators differentially targeting individual demographic groups. While this design matches our main approach, the demographic-based RD can only test one demographic characteristic at a time, making it impossible to hold the other covariates fixed and challenging to assess their relative importance. The RD also focuses on a small subset of districts featuring close, contested elections.

To overcome these challenges, we adopt a second, panel-based identification strategy. This design leverages two sources of variation in the party representing a given geographic area. First, a district's representation can switch parties through election outcomes, when a seat flips from one party to the other. And second, we take advantage of the 2022 decennial redistricting process, which caused portions of districts previously represented by Democratic legislators to be reassigned to Republican representation (or vice versa).

More specifically, we run a grid-cell panel analysis, following a large political-economy literature that studies disaggregated outcomes on a fixed spatial grid (Tollefsen et al., 2012; Michalopoulos and Papaioannou, 2013; Berman et al., 2017; Harari and La Ferrara, 2018). To do so, we lay a single national five-mile-by-five-mile grid over the U.S. in an equal-area projection for the period of study. Because district boundaries change and cells do not, each cell is assigned in each Congress to the congressional district containing its centroid. We then measure the partisan composition of each cell using the data introduced in Section 4.[27] Our resulting estimation sample is a panel of 53,104 cells observed in each of five fiscal years. Roughly 9.5% of these cells receive an earmark at some point between FY2022 and FY2026.[28] Appendix I reports additional details.

We use these data to compare the same five-mile grid cells across fiscal years in which their party representation changes. Our design asks whether the same cell becomes more likely to receive earmark support when its representation switches to the party its voters favor, and whether any such gain tracks the cell's partisan composition or its demographic profile, once each is conditioned on the other. Because the cell and its characteristics are fixed over the panel, a differential gain cannot reflect the location's permanent attractiveness as a project site; it can only come from the change in who represents it.

Specifically, we estimate equations of the form

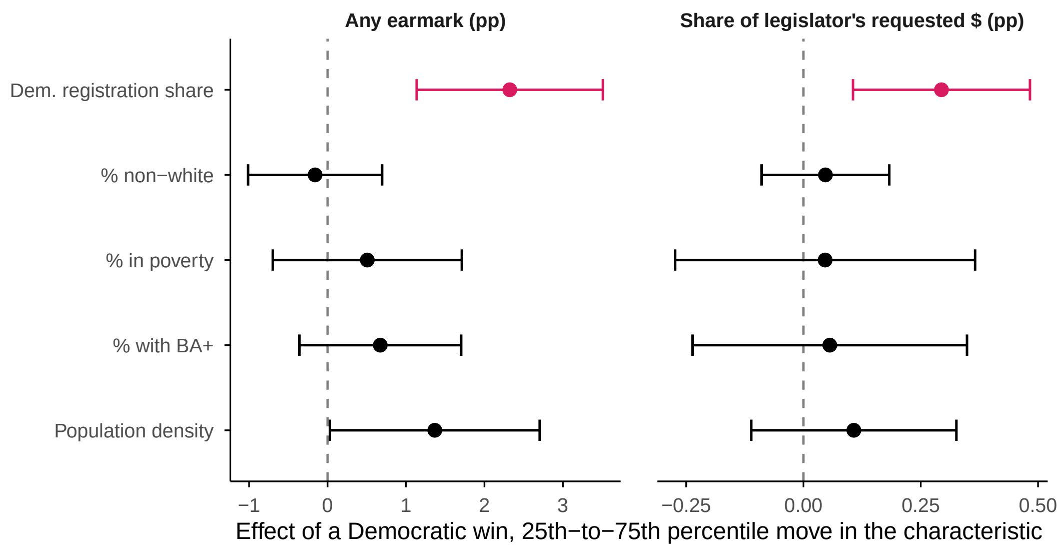
$$
\begin{aligned}
Y_{it} = \alpha_i + \delta_t + \beta \, \mathit{Dem\ Win}_{dt} + \gamma \, \mathit{Dem\ Win}_{dt} \times \mathit{Dem\ Registration\ Share}_i \\
+ \sum_{k=1}^{4} \theta_k \, \mathit{Dem\ Win}_{dt} \times X_{ik} + \varepsilon_{it},
\end{aligned}
\tag{4}
$$

where i indexes gridcells, t indexes fiscal years, and d denotes the district containing cell i in year t. $\mathit{Dem\ Registration\ Share}_i$ is the cell's two-party Democratic registration share. The characteristics X_{ik} include the same demographic covariates from Section 6.2.1, namely the cell's non-white share, poverty rate, share of residents aged twenty-five and over holding a bachelor's degree or higher, and its population density. Gridcell fixed effects α_i absorb time-

[27] We use areal interpolation to impute the demographic composition of each cell using block-group data from the Census Bureau.

[28] The national five-mile-by-five-mile lattice contains roughly 144,000 cells, but many are close to unpopulated. Over half of all cells hold fewer than 100 residents, and the median cell falling below our registration threshold holds about 15 people across its 25 square miles. Because we require at least a combined total of 25 registered Democrats or Republicans in a cell before computing its Democratic registration share, we retain 45.6% of cells, but 99.7% of all cell-assigned earmark dollars and 99.2% of the cells that ever receive an earmark.

Figure 8 – Effect of Electing a Democrat on Within-District Earmark Targeting by Party Registration, Race, Economic Need, Education, and Population Density, 5-Mile Grid Cells. Each point is the interaction between a Democratic win and one fixed characteristic of a grid cell, reported for a move from the 25th to the 75th percentile of that characteristic, from a regression with grid-cell and fiscal-year fixed effects that compares cells whose representation changes over FY2022–FY2026. Standard errors clustered by district election.



invariant differences across cells, while fiscal-year fixed effects δ_t absorb shocks common to all cells in a given fiscal year. The coefficient β captures the average difference in earmark activity under Democratic representation, common to all cells in the district. The outcome Y_{it} is alternatively an indicator for whether the cell receives at least one earmark request in fiscal year t or the cell's share of the legislator's requested dollars.[29] The term γ then captures the extent to which cells with a larger Democratic registration share receive an additional relative boost under Democratic representation, conditional on the other observable characteristics. Similarly, θ_k measures the extent to which higher values of characteristic k receive a relatively larger gain from Democratic representation, holding the Democratic registration share and the remaining characteristics constant.

Figure 8 reports the results from this analysis. The first row plots our estimate of γ, while subsequent rows plot θ_k. Since our covariates are on different scales, we follow the same approach as in Figure 7 and convert each characteristic to its percentile in the sample distribution before estimation. Each reported coefficient then measures the change in earmark activity when a cell moves from the 25th to the 75th percentile of the characteristic

[29]Because a project is credited to a cell only when it falls inside the requesting member's own district, the denominator comprises the legislator's geocoded, in-district requested dollars, and shares sum to one across each district's cells within a fiscal year.

under Democratic relative to Republican representation.

The left panel of Figure 8 studies the probability a gridcell receives at least one earmark request in a given fiscal year. In our estimation sample, 4.84% of cell-years receive at least one earmark request. The first row then shows that a shift from the 25th to 75th percentile of Democratic registration share raises the probability of receiving an earmark under Democratic representation by an additional 2.3 percentage points relative to Republican representation, or roughly half of the base rate. The subsequent rows plot the corresponding estimates for the demographic covariates. With the exception of percent non-white, these point estimates are positive, consistent with Democratic legislators requesting earmarks in denser, poorer, and more educated areas. None of these estimates, however, is statistically distinguishable from zero at conventional levels, and each is a fraction of the size of the direct partisan gradient.

While the left panel of Figure 8 studies the extensive margin of earmark requests, the right panel studies the intensive margin, or the share of a legislator's requested earmarks in a given cell. Because each legislator's dollars are divided across potentially many cells, the average cell accounts for just 0.80% of the average district's requested earmark funding. Against this baseline, the estimates in the right panel mirror those on the extensive margin. Moving from the 25th to the 75th percentile of Democratic registration share raises a cell's share of the legislator's requested dollars by an additional 0.29 percentage points under Democratic representation—or a third of the average cell's share—while none of the demographic characteristics approaches statistical significance.

Overall, the results using the grid-cell panel design mirror our conclusions using the RD design with demographic outcomes. In addition to leveraging different sources of variation, the panel design allows us to study the broader set of areas where the incumbent switches parties. That our results are similar suggests that our central results generalize beyond the set of districts featuring close, contested general elections that we focus on using the RD design.

Taken together, the results presented in this section illustrate that our headline results do not reflect the two parties requesting different types of projects, since co-partisan targeting persists within ten of eleven policy areas. Nor does it reflect the demographic correlates of partisanship. Electing a Democrat does not meaningfully shift requested dollars toward more non-white, denser, poorer, or more educated areas, and when partisan and demographic characteristics compete directly within fixed neighborhoods, only partisan composition predicts which cells gain when representation changes hands. What remains is precisely what we define as partisan favoritism. In the next section, we ask whether this favoritism survives the appropriations process to shape enacted spending.

7 Partisan Favoritism in Enacted Earmarks

The results thus far show that legislators disproportionately direct earmark requests to areas with stronger co-partisan support. While we focus on earmark *requests* rather than *allocations* to isolate legislators' intent net of other institutional actors, it is nevertheless important to assess whether partisan favoritism survives the allocation process and ultimately shapes the distribution of federal spending. This section examines whether the geographic patterns evident in legislators' requests persist in the earmarks that are passed into law.

7.1 Characteristics of Allocated Earmarks

Using the data introduced in Section 3.2, Figure 9 compares legislators' requested earmarks to the allocations ultimately included in each year's appropriations bill.[30]

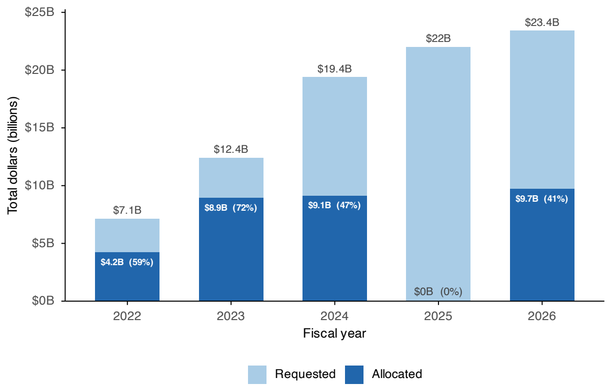
As Panel A of Figure 9 illustrates, enacted earmark allocations range from 41% (FY2026) to 72% (FY2023) of requested dollars. In FY2022—the first year under the new earmark regime—Congress allocated approximately $4.2 billion of the $7.1 billion requested. Allocated dollars subsequently remained relatively stable at roughly $9–10 billion in FY2023, FY2024, and FY2026, even as requested dollars rose from $12.2 billion to $23.4 billion. Because FY2025 was ultimately funded through a full-year continuing resolution, Congress did not enact new earmarks for that fiscal year. We therefore exclude FY2025 from the analyses in this section.

Panel B of Figure 9 plots each earmark's allocated amount as a share of the amount the member requested. As the figure illustrates, the vast majority of requests received at least some funding, with only 8.0% of requests receiving zero funding. Nearly half (45%) of requested projects are funded in the exact amount requested. Another 43% were funded below the requested amount, with haircuts spread fairly evenly across the distribution, while 4.0% received more than requested.

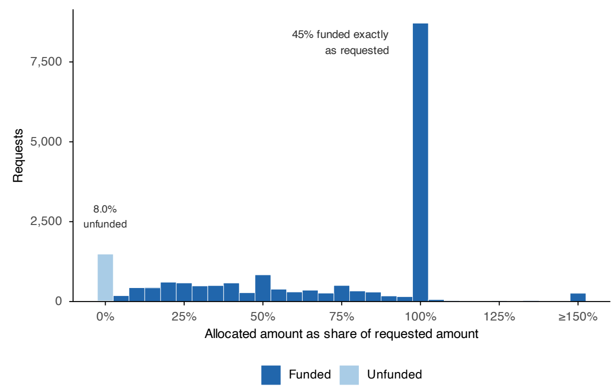
Finally, Panel C plots the percent of each party's requests that received at least some funding, while Panel D reports the percent of each party's requested dollars that were ultimately allocated. Control of the U.S. House switched from Democrats in FY2022–FY2023 to Republicans in FY2024–FY2026. Interestingly, Panel C shows that Democratic requests are more likely than Republican requests to receive non-zero funding in every fiscal year,

[30] Our allocation data measure the earmark amounts provided in enacted appropriations legislation rather than actual outlays, which we cannot observe at the project level. Prior work shows that allocations and outlays can diverge when the executive branch influences which allocations are ultimately disbursed (Angell, 2026; Wlezien and Soroka, 2003). Because this section studies whether the congressional appropriations process preserves the favoritism documented in requests, enacted allocations are the appropriate outcome. Any slippage between allocation and disbursement reflects executive-branch implementation rather than congressional choice.

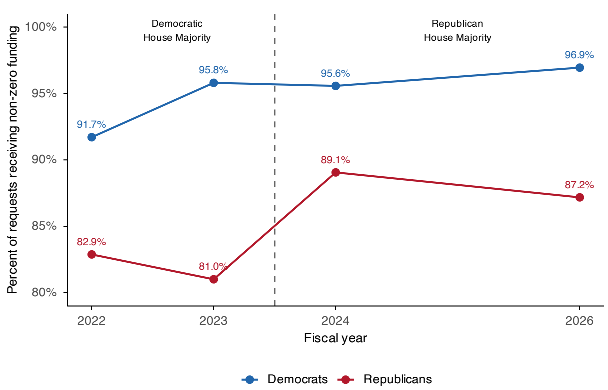
Figure 9 – Earmark Requests vs. Enacted Allocations. Panel A compares the total dollars House members requested to the dollars ultimately enacted in each fiscal year's appropriations bills. FY2025 shows zero allocated dollars because it was funded through a full-year continuing resolution and no earmarks were enacted. Panel B shows each funded request's allocated amount as a percent of the requested amount, pooling all fiscal years. Panel C plots the percent of each party's requests receiving any funding, by fiscal year. Panel D plots the percent of each party's requested dollars that were ultimately allocated. FY2025 is omitted from Panels B–D.



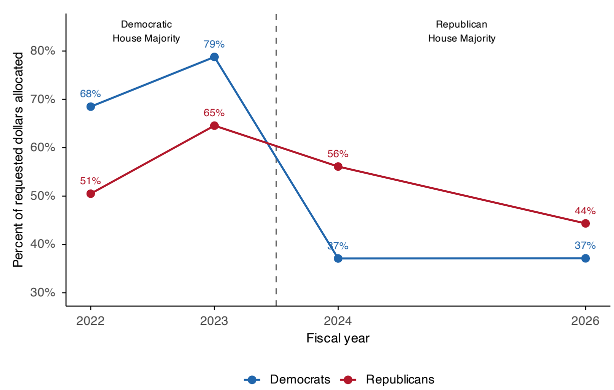
(a) Dollars requested vs. allocated



(b) Allocated share of requested amount



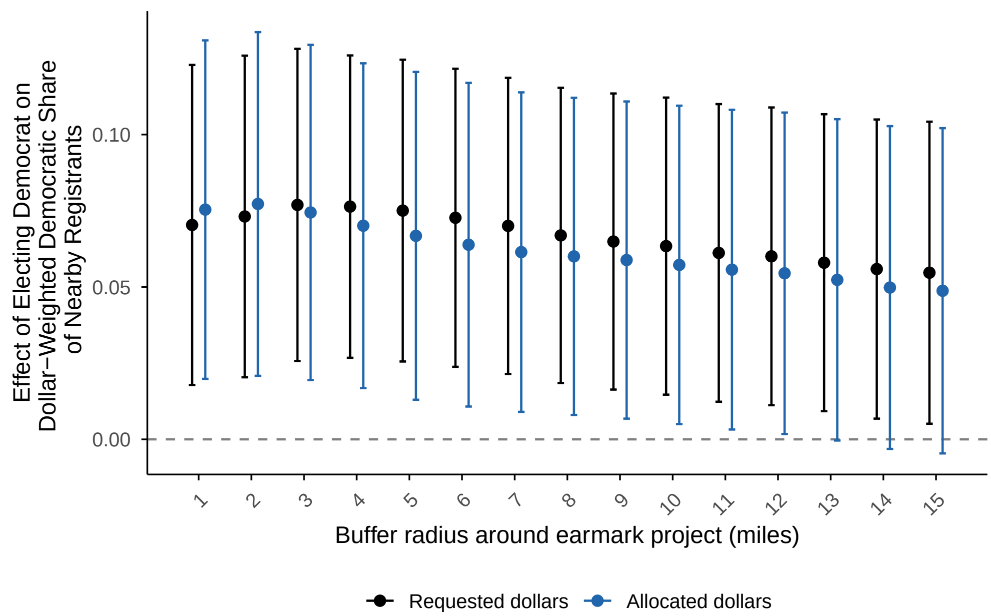
(c) Percent of requests funded at least in part, by party



(d) Percent of requested dollars allocated, by party

and this pattern is unchanged when control of the chamber shifts in FY2024. Panel D, however, shows that Democrats' share of requested dollars falls dramatically from 79% to 37% when the new Republican majority takes control. Together, the two panels suggest that the majority party exercises its control over the appropriations process not by rejecting the minority's projects outright, but by cutting the size of their awards.

Figure 10 – Effect of Electing a Democrat on the Democratic Share of Registrants Near Requested vs. Allocated Earmarks. Black points replicate the headline estimates from Figure 4, in which each project is weighted by its requested dollars. Blue points re-estimate the same RD using only funded projects, weighting each by its enacted allocation; FY2025 requests, which were never fundable, drop out of the allocated series along with unfunded requests. 95% robust confidence intervals shown.



7.2 Partisan Favoritism Persists in Allocated Earmarks

Does the political favoritism documented in earmark requests survive the appropriations process? To answer this question, we re-estimate Equation 2 using only funded projects, weighting each project by its enacted allocation rather than its requested amount when constructing the outcome in Equation 1. The blue points in Figure 10 plot these allocation-based estimates, while the black points reproduce the request-based estimates from Figure 4. We find that partisan favoritism persists in allocated earmarks. As the figure shows, our point estimates are highly similar across all project radii. At five miles, electing a Democrat increases the allocation-weighted Democratic registration share near funded projects by 6.7 percentage points ($p = 0.02$), similar to the 7.7 percentage-point effect for requested dollars.

These results show that, whatever trimming the appropriations process imposes on individual projects, it does not undo legislators' partisan targeting. As a result, the patterns identified in this paper materially affect the distribution of public spending across the country and within districts.

8 Conclusion

Whether elected officials distribute public resources evenly across their constituency is a central question for democratic representation. Pairing new data on congressional earmark requests and allocations with a regression discontinuity design in general elections, we show that members of the U.S. House do not. In districts that narrowly elect a Democrat (Republican), the average earmark dollar goes to an area which has 4 to 8 percentage points more (fewer) registered Democrats (Republicans). This pattern is driven in large part by incumbents reallocating earmark dollars out of opposing stronghold areas and into co-partisan areas within their district. This disparity persists within policy areas, is not explained by the demographic correlates of partisanship, appears wherever representation changes hands rather than only in close districts, and carries through the appropriations process into enacted spending.

These findings complicate a common understanding of democratic accountability. Many theories suggest that elections—especially competitive ones—motivate politicians to work harder, adopt more responsive positions, and deliver for their districts. Empirical evidence that politicians are punished for ideological extremism or poor performance is therefore often interpreted as evidence that electoral competition should induce better representation. Yet this interpretation generally carries an implicit assumption that politicians who work hard for their districts are working for the district as a whole. Our results challenge that assumption. Even in some of the most electorally competitive districts in the country, representatives direct more earmarks toward co-partisan communities than toward opposition communities within the same district. Electoral competition may therefore encourage legislator effort without ensuring equal representation.

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Online Appendix:

Partisan Favoritism in Public Spending: Evidence from Congressional Earmarks

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Contents

A Congressional Earmarks Data

Our analysis uses project-level data on House Community Project Funding (CPF) requests for fiscal years 2022–2026. This period covers the post-moratorium years for which systematic House request data are available. Congress observed an earmark moratorium beginning with the 112th Congress (2011–2012). The moratorium ended for the FY2022 appropriations cycle, when the House Appropriations Committee revived earmarks under the new label "Community Project Funding."[31] The revived process introduced several disclosure requirements. Members were required to post their CPF requests on their official House websites, the House Appropriations Committee released consolidated tables of submitted requests, and House rules required subcommittees to identify approved earmarks and their sponsors in the reports accompanying appropriations bills. We therefore begin with FY2022, the first fiscal year after the moratorium, and end with FY2026, the latest fiscal year for which a consolidated House request table was available when the dataset was constructed.

Under the post-moratorium regime, the CPF process begins when local governments, nonprofit organizations, and other eligible project sponsors submit proposals to congressional offices. Project sponsors often submit the same proposal to both their House representative and their senators, while many members publish detailed application guidelines and outreach materials to solicit requests from their districts. In a typical appropriations cycle, applications to House offices are due in mid-March. Members then review the proposals they receive, select those they wish to sponsor, and transmit their requests to the relevant House Appropriations subcommittees, generally within approximately two weeks. The subcommittees subsequently determine which member-sponsored projects to include in the appropriations bills. Once the relevant bill is approved, funds are generally disbursed several months later. From the initial solicitation of constituent proposals through the eventual distribution of funds, the process therefore commonly extends for more than a year.

Several institutional rules constrain this process. House members may submit requests across multiple appropriations bills, but the total number of requests permitted per member increased over time: members could submit no more than 10 requests for FY2022, 15 for FY2023, and 20 in each fiscal year from FY2024 through FY2027. Senators face no equivalent submission cap. The 117th Congress administered the FY2022 and FY2023 appropriations cycles, the 118th Congress administered FY2024 and FY2025, and the 119th Congress administered FY2026 and FY2027. Aggregate earmark allocations were also subject to spending limits, with total allocations capped at 1 percent of discretionary spending in FY2022 and FY2023 and at 0.5 percent from FY2024 through FY2027. Within these constraints, individual appropriations subcommittees retain authority to establish their own eligibility requirements and evaluation criteria. Although these rules vary across subcommittees, funding decisions are intended to follow pre-established substantive guidelines rather than member-specific considerations.

A.1 Primary Sources and Harmonization

The primary sources are the House Appropriations Committee's consolidated CPF request tables for FY2022–FY2026. The FY2022 and FY2023 files are hosted on the Democratic

[31] The Senate uses the term "Congressionally Directed Spending."

House Appropriations Committee website, while the FY2024–FY2026 files are hosted on the Republican House Appropriations Committee website. These tables report, for each CPF request, the member name, subcommittee, project name and/or description, requested amount, recipient name, and, depending on the year, the member's district, party, disclosure website, and the project recipient's address.

We harmonized the annual files into a common schema containing congress session, fiscal year, member name, district, party, project, recipient, address, requested amount, member disclosure website, and geocoordinates. The source files differ in the variables reported. While the FY2024–FY2026 files contain the full set of variables described above, the FY2022 and FY2023 files do not contain member information beyond member names. Critically, FY2023 does not include recipient addresses in the consolidated table, requiring us to recover address information from member disclosure pages and other project-level source materials. The raw stacked dataset contains 23,510 CPF requests totaling $85.38 billion in requested funds. Table A.1 summarizes the source data before address recovery.

Table A.1 – House Community Project Funding Requests Before Address Recovery

FY	Number of Requests	Requested Amount	Missing Address in Source
2022	3,019	$7.13b	95
2023	4,761	$12.40b	4,761
2024	5,067	$19.38b	34
2025	5,249	$23.07b	72
2026	5,414	$23.39b	71
Total	23,510	$85.38b	5,033

A.2 Recovering Missing Addresses

For projects missing addresses, we collected project-location information from member disclosure materials. Our address-recovery process involved four steps. First, for each member-fiscal-year with at least one missing address in the consolidated source tables, we used an iterative retrieval-and-screening procedure to identify the relevant disclosure material. We began with the member's official CPF disclosure page, using the live page when available and otherwise querying the Internet Archive Wayback Machine for snapshots from July–December of the year preceding the fiscal year. This window follows the closing of the request process, when members were expected to have posted their CPF disclosures on their official House websites. Member disclosure URLs are included in the consolidated data for FY2024–FY2026. For FY2022 and FY2023, which do not include these links, we scraped the Democratic Committee's centralized member-link pages to recover members' disclosure URLs.

We then used a large language model (LLM) to screen each retrieved document for project-level CPF information for the target fiscal year.[32] To pass screening, a document had to list at least one specific project for that fiscal year, including a project name or description and a recipient or project address. The implementation used separate HTML and

[32]The screening step used Claude Sonnet 4.6.

PDF screening prompts to identify the input type, but both applied the same substantive screening prompt. If a retrieved document was too thin to contain project-level content, failed screening, or pointed to separate disclosure materials, we searched for a relevant CPF subpage or downloaded linked financial certification PDFs, which members are required to submit to certify that they and their immediate families have no financial interest in the requested projects. Retrieved subpages and PDFs were then screened using the same criteria. When the automated search returned an incorrect or incomplete page and no linked PDF or relevant subpage could be found, we allowed manual URL overrides as a final fallback. Of the 479 member-fiscal years with at least one missing address, we identified usable disclosure documents for 461 (96.2%).

Screening prompt

This is a document from a US House member's Community Project Funding disclosure for FY `{fy}`.

Does this document contain project-level information for FY `{fy}`? To qualify, the document must list at least one specific project covering FY `{fy}` with (1) a project name or project description and (2) a recipient address or project address.

Note: Formal project request letters dated `{fy - 1}` and written by the member to the Appropriations Committee always qualify if they contain the above information.

Reply with only: YES or NO.

For documents that passed the screening step, we used a second LLM call to extract structured project-level fields.[33] These fields include the project name, project description, project purpose, recipient, project address, recipient address, and the requested amount. The model extracted 6,372 projects from the retrieved documents, of which 6,136 (96.3%) contained location information.

Extraction prompt

Extract project-level information from U.S. House member `{member}`'s disclosure document for FY `{fy}` Community Project Funding requests.

Cover letter check: If this document is a member letter to a congressional committee or subcommittee, extract only projects from letters dated in `{fy - 1}`. Skip letters dated in other years. If no letters are dated in `{fy - 1}`, return:

```
{
  "projects": [],
  "note": "incorrect FY - letters dated [year]"
}
```

Extract one object for each distinct project mentioned in the document. Return JSON with one key, `"projects"`, containing one object per distinct project:

```
{
  "projects": [
```

[33]The extraction step used Claude Opus 4.7.

```
    {
      "project_name": null,
      "project_description": null,
      "project_purpose": null,
      "recipient": null,
      "project_address": null,
      "recipient_address": null,
      "amount_requested": null,
      "source_notes": null
    }
  ]
}
```

Use `null` for any field that is not stated.

Rules:

- Return one object per distinct project.
- Do not merge multiple projects into one object.
- Do not infer facts not explicitly stated.
- Preserve dollar amounts exactly as written.
- If the same project appears more than once, extract it only once using whichever instance has the most complete information.
- Use `project_description` for the main descriptive text by default.
- Use `project_purpose` only if the document separately states a purpose or use of funds.
- Use `project_address` as the default address field.
- If it is unclear whether the address is for the project or recipient, put it in `project_address`.
- Use `recipient_address` only when the document clearly states a recipient address that is different from `project_address`.
- Use `source_notes` only for brief notes about ambiguity or unusual wording.

If there are no projects to extract, return:

```
{
  "projects": []
}
```

When `projects` is empty, you may include a top-level `"note"` field briefly explaining why, for example:

```
{
  "projects": [],
  "note": "<brief reason>"
}
```

Return ONLY valid JSON, no other text. Do not wrap the output in markdown code fences.

Finally, we matched the extracted projects back to the harmonized source data using a constrained LLM matching prompt.[34] For each member-fiscal-year, the prompt listed source projects with missing addresses (with project name, recipient, and requested amount) alongside all extracted projects for the same member-fiscal-year with available address information

[34] The matching step used Claude Opus 4.7.

(with project name, description, purpose, recipient, and requested amount). The model was instructed to match each source project to the best corresponding extracted project, with each extracted project assigned to at most one source row. This matching process recovered addresses for 4,663 of the 5,033 projects that initially lacked addresses, including 4,408 high-confidence matches, 243 medium-confidence matches, and 12 low-confidence matches. We manually reviewed all low-confidence matches and a 10% random sample of medium-confidence matches. All reviewed matches were correctly assigned. Table A.2 summarizes the distribution of recovered and remaining missing addresses by fiscal year.

Matching prompt

You are helping fill in missing addresses for earmark projects requested by `{member}` for FY `{fy}`.

Below are projects missing addresses, labeled REQUESTED, and projects scraped from official disclosure documents that have addresses, labeled EXTRACTED. For each requested project, find the best extracted match so we can obtain its address. Return `null` if no extracted project is a plausible match.

REQUESTED PROJECTS (missing addresses):

```
[1]
    Project:     <project name>
    Description: <project description, if available>
    Recipient:   <recipient name>
    Amount:      <amount requested>

...

[N]
    Project:     <project name>
    Description: <project description, if available>
    Recipient:   <recipient name>
    Amount:      <amount requested>
```

EXTRACTED PROJECTS (have addresses):

```
[1]
    Project:         <project name>
    Description:     <project description>
    Purpose:         <project purpose, if available>
    Recipient:       <recipient name>
    Project address: <project address>
    Amount:          <amount requested>

...

[N]
    Project:         <project name>
    Description:     <project description>
    Purpose:         <project purpose, if available>
    Recipient:       <recipient name>
    Project address: <project address>
    Amount:          <amount requested>
```

Each extracted project may only be matched to one requested project. If two requested projects could match the same extracted project, assign it to the closer match and return `"ex": null` for the other.

Return ONLY valid JSON in the following format:

```
{
  "matches": [
    {
      "stk": 1,
      "ex": 2,
      "confidence": "high"
    }
  ]
}
```

Use `"ex": null` if no extracted project is a plausible match.

Confidence definitions:

- `"high"`: certain same project.
- `"medium"`: likely same project.
- `"low"`: possible same project.

Table A.2 – Address Recovery from Member Disclosure Materials

FY	Missing in Source	Recovered	Remaining Missing
2022	95	88	7
2023	4,761	4,435	326
2024	34	24	10
2025	72	62	10
2026	71	54	17
Total	5,033	4,663	370

A.3 Classifying Policy Area

Although each request is assigned to an appropriations subcommittee, subcommittee labels are too coarse to capture the substantive purpose of individual projects. For example, a single subcommittee such as "Transportation, Housing and Urban Development" receives requests for projects including road improvements, public transit, affordable housing, and community development. To support the within-category analysis in Section 6.1, we classify every request into one of twelve substantive policy areas that are finer than the subcommittee designation.

To do so, we identify eleven major policy areas and develop a codebook listing representative projects in each area.[35] Table A.3 reproduces the codebook. For the classification step, we prompt OpenAI's GPT-5.5 large language model to classify each earmark request based on the project title using the codebook. The third column in Table A.3 reports the number

[35]We also construct a residual *Other* category. Only 0.6 percent of requests fall into this category.

of projects classified into each policy area. To validate our classifications, we independently hand-coded a random sample of 150 requests using the same codebook, blind to the model's classifications. Our human coding and the model agreed on 88 percent of requests. Because some agreement is expected by chance, we summarize concordance with Cohen's κ, which adjusts for chance agreement. The resulting κ of 0.86 indicates strong agreement between human coders and the model.

To further describe the policy areas, Figure A.1 shows the most frequent project-name words within each policy area.

Table A.3 – Policy-Area Codebook

Category	Description	Requests
Utilities	Water, sewer, and stormwater systems; flood control, levees, and dam safety; broadband and last-mile internet	4,949
Infrastructure	Roads, bridges, highways, and bike/pedestrian paths; buses, rail, and transit hubs	4,014
Public safety	Police, fire, and EMS equipment and facilities; emergency operations and communications	3,231
Human services	Affordable housing; food banks, homeless services, and family, youth, and senior programs	2,479
Community facility	Community centers, libraries, parks, trails, recreation facilities, and museums	2,450
Education & research	K–12 and higher education, workforce-training programs, and research facilities	2,386
Health	Hospitals, clinics, community health centers, and mental-health and substance-use treatment	1,256
Economic development	Downtown revitalization, business incubators, workforce facilities, and public-works buildings	1,145
Aviation & maritime	Airports and runways; ports, harbors, dredging, and navigation channels; freight rail	873
Environment	Habitat and watershed restoration and land and marine conservation	440
Military construction	Military bases, barracks, and on-base training and construction	209
Other	Unclassifiable, multi-purpose, or insufficient information	142
Total		23,574

A.4 Member Matching and Geocoding

We matched each request to Voteview House rosters for the 117th, 118th, and 119th Congresses. This step supplied Bioguide identifiers, member state, district, and party for all rows, including FY2022–FY2023 observations for which district and party were not reported in the original source tables. The matching procedure used a cascade of name and state keys. The final match rate was 100% across 519 unique members serving in the 117th, 118th, or

Figure A.1 – Most Frequent Words in Earmark Project Names, by Policy Category. Each panel shows the top 35 words from the project names within the labeled policy category. Word size and color encode the within-category rank of each word's frequency.

119th Congress. These members represent 85% of the 610 Voteview House members who served across the three Congresses.

We geocoded CPF requests using the ArcGIS USA geocoder. For the 17 projects that listed multiple distinct sites in a single address field, we expanded the data to one row per location and divided the requested amount equally across sites.[36] The final dataset therefore contains 23,574 location rows corresponding to 23,510 distinct project requests, and the geocoder returned coordinates for 23,132 of 23,574 location rows, a 98% match rate. Most matches are highly granular: over 90% were matched at the street- and point-level. The level of granularity in geocoordinates by fiscal year is shown in Table A.4. We also flag cases in which the geocoded state differs from the sponsoring member's state. This occurs for 237 location rows (1.0%), often reflecting headquarters or administrative addresses rather than project sites.

[36]For example, Representative Jimmy Gomez's FY2023 CPF request for "Community Empowerment Learning Pods" was designated for three YMCAs in the Los Angeles area: Weingart East Los Angeles YMCA at 2900 Whittier Boulevard, Ketchum-Downtown YMCA at 401 South Hope Street, and Anderson-Munger Family YMCA at 4301 West Third Street. We split this request into three location rows with a common project identifier.

Table A.4 – Geocoding Results

FY	Total	Point	Street	City/Postal	Unmatched
2022	3,041	2,662	242	130	7
2023	4,801	3,631	522	308	340
2024	5,069	4,360	518	154	37
2025	5,249	4,559	498	151	41
2026	5,414	4,700	529	168	17
Total	23,574	19,912	2,309	911	442

B Final Earmark Allocations

We supplement the House request data with project-level records of enacted earmark allocations. These records allow us to identify whether each requested project was ultimately funded and, when it was funded, the amount provided by Congress. Our primary sources are the subcommittee-level Community Project Funding and Congressionally Directed Spending tables released as PDFs on the Senate Appropriations Committee's website. Unlike the House request tables, which record all projects submitted by House members, the Senate tables contain only projects included in the final appropriations legislation. Depending on the fiscal year and subcommittee, the tables report the appropriations agency and account, project name or description, recipient, state, requesting House and Senate members, chamber of origination, and final amount provided. We recover allocations for FY2022, FY2023, FY2024, and FY2026, however, for FY2025, allocations are unavailable because Congress did not fund any earmarks due to a series of continuing resolutions.

B.1 Sources for Funded Projects

The allocation PDFs differ across fiscal years and subcommittees in their layout, column names, and treatment of project and recipient information. Some files contain separate project and recipient columns, while others combine both in a single description field. The files also differ in whether dollar amounts are reported in dollars or thousands of dollars, and some are scanned documents without a usable text layer. We therefore use an LLM-assisted procedure to extract each funded project into a common schema.[37]

For each fiscal year, we process every available subcommittee PDF in batches of eight pages. The model reads the PDF pages directly, including pages that must be rendered as images, and returns one structured record for each funded project. The standardized fields are fiscal year, subcommittee, agency, account, project, recipient, amount, state, House requester, Senate requester, and chamber of origination. The prompt instructs the model to preserve the table's distinctions when they are available, leave fields empty when the source contains no corresponding information, and avoid combining, summarizing, or inferring project records. Each page batch is saved separately, and the annual file is assembled only after every expected batch has been successfully extracted.

Allocation extraction prompt

You are extracting a U.S. congressional appropriations earmarks disclosure table from a PDF or a page-range fragment of one. Read every page of the PDF at `pdf path`.

It is a Community Project Funding or Congressionally Directed Spending allocations table. Each data row is one funded project. These tables appear in several layouts and do not all contain the same columns. Map whatever columns this PDF contains onto the fixed target schema below; if a target field has no corresponding column or content, use an empty string.

Return a JSON object with exactly two keys. The first is `amounts in thousands`: use `true` if a header or subtitle visible on these pages states that dollar amounts are reported in thousands; `false` if a table header or subtitle is visible and does not state that amounts are

[37] The allocation extraction step used Claude Opus 4.8.

in thousands; and `null` if these pages show no header text about units. Do not infer units from the size of the numbers. The second key is `rows`, a JSON array containing one object per funded project:

```
{
"amounts_in_thousands": true | false | null,
"rows": [
{
"agency": "",
"account": "",
"project": "",
"recipient": "",
"amount": "",
"state": "",
"house_member": "",
"senate_member": "",
"origination": ""
}
]
}
```

Field rules:

- Use `agency` for the agency or department and `account` for the appropriations account. Use an empty string when either field is absent.
- Use `project` for the project description or name. If the table combines the project and recipient in a single column, place the full combined text in `project` and leave `recipient` empty.
- Use `recipient` only when the table contains a distinct recipient column. If it instead reports a project site or base location in a separate location column, place that location in `recipient`.
- Record `amount` exactly as printed using digits only. Do not convert values reported in thousands.
- Record `state` as a two-letter postal abbreviation. Prefer an explicit state column; otherwise use clear location text or a requester state annotation when unambiguous.
- Separate multiple House or Senate requester names with semicolons and preserve state annotations attached to names. If the table has a single combined requester column, place the names in the chamber field indicated by `origination`.
- Record `origination` as `H`, `S`, or `H/S`.

Rejoin words hyphenated across line breaks while preserving genuine hyphens. Ignore repeated page headers, section-title banners, column-header rows, and subtotal or total lines. Extract every project row; do not invent, merge, or summarize rows. Return only valid JSON.

After extraction, we combine the page-level records within each fiscal year and assign a standardized subcommittee name based on the source file. We also standardize the units in which allocations are reported. For each page batch, the model records whether an explicit header states that amounts are in thousands of dollars. Batches containing continuation pages without a table header inherit the unit designation from other batches belonging to the same subcommittee; when no batch contains unit information, the values are treated as dollars. As an independent check, we search the PDF text layer for language indicating that values are reported in thousands and flag disagreements with the model's classification. If different header-bearing batches from the same subcommittee produce contradictory unit designations, the annual file is not assembled until the discrepancy is resolved. Amounts from subcommittees identified as reporting in thousands are then multiplied by 1,000, producing a common measure of final dollars allocated.

The enacted-earmark universe we extract comprises 28,775 allocation records worth $58.09 billion across FY2022–FY2024 and FY2026. Annual volume rises over the panel, from 4,975 records and $9.69 billion in FY2022 to 8,485 records and $16.72 billion in FY2026, with the median award steady at roughly $1 million; Table B.1 reports the breakdown. Of these, 16,755 records worth $30.59 billion list at least one House sponsor and are therefore in scope for matching to House members' requests.

Table B.1 – Allocation records and enacted spending. Projects which received funding as extracted from the Senate Appropriations Community Project Funding / Congressionally Directed Spending disclosure tables, before any match to requests. FY2025 is absent due to Congress not funding any requests for that fiscal year. Amounts are reported in dollars. Columns denoted "House-sponsored" restrict to allocations listing at least one House sponsor, the subset the matcher operates on; the remainder are Senate-only.

FY	Allocations	Allocated Amount	Median Award	House-Sponsored Allocations	House-Sponsored Amount
2022	4,975	$9.69b	$0.93m	2,724	$4.22b
2023	7,218	$15.92b	$1.00m	4,357	$8.80b
2024	8,097	$15.77b	$0.97m	4,686	$8.59b
2026	8,485	$16.72b	$1.00m	4,988	$8.96b
Total	28,775	$58.09b	$1.00m	16,755	$30.59b

B.2 Matching Final Allocations to House Requests

We next match the extracted allocations to the corresponding projects in the House requests data. The matching procedure is conducted separately for each House member and fiscal year. We first restrict the possible matches to allocations from the same fiscal year for which the member is listed as a House requester. To accommodate differences in how member names are printed across sources, we normalize capitalization, diacritics, and apostrophes before identifying surname matches. We also use the allocation state and state annotations attached to requester names to distinguish members who share a surname.

For each member-fiscal-year, we use a constrained LLM matching prompt to compare the member's requests with the resulting pool of possible allocations.[38] The request records include the project name, recipient, cleaned address, subcommittee, and requested amount. The allocation records include the project name, recipient, state, subcommittee, agency, account, final amount, and listed House requester. The model is instructed to consider these fields jointly, rather than treating agreement on any single field as sufficient, and to return no match when an allocation does not plausibly fund the same project. Each allocation may

[38]The allocation matching step used Claude Opus 4.7.

be linked to at most one request within a member-fiscal-year. The code separately enforces this restriction after the model returns its proposed matches.

Allocation matching prompt

You are matching earmark requests submitted by U.S. Representative `member` for FY `fy` to enacted allocations in the same fiscal year. Below are the member's requested projects and the pool of allocations for which this member is listed as a House sponsor. For each request, identify the allocation that funds the same project. Match on the project name, recipient, address or state, subcommittee, and dollar amounts together; no single field is definitive. Return `null` if no allocation plausibly matches.
REQUESTS:

```
[1]
Project:      <project name>
Recipient:    <recipient name>
Address:      <cleaned project address>
Subcommittee: <subcommittee>
Amount req:   <requested amount>
```

ALLOCATIONS:

```
[1]
Project:      <project name>
Recipient:    <recipient name>
State:        <state>
Subcommittee: <subcommittee>
Agency:       <agency>
Account:      <account>
Amount:       <final allocation>
House member: <listed House requester>
```

Each allocation may be matched to only one request. If two requests could match the same allocation, assign it to the closer match and return `null` for the other. Return only valid JSON in the following format:

```
{
"matches": [
{
"req": 1,
"alloc": 2,
"confidence": "high"
}
]
}
```

Use `"alloc": null` when no allocation is a plausible match. Classify confidence as `high` when the records certainly describe the same project, `medium` when they likely describe the same project, and `low` when the match is only possible.

Requests linked to an enacted allocation are coded as funded and assigned the final amount reported in the allocation table. Requests for which the member has no candidate allocations, or for which no candidate plausibly describes the same project, are coded as unfunded. Because the resulting data remain organized around House requests, Senate-only allocations and other allocation records that cannot be linked to a House request are not added as separate observations. When a funded project lists multiple House requesters, the allocation may be linked separately to the corresponding request of each listed member; the one-to-one restriction applies within each member-fiscal-year. The matching procedure records high-, medium-, and low-confidence matches and produces a separate file containing all low-confidence assignments for manual review. The final request-level dataset preserves the original request information and adds two variables: an indicator for whether the request was funded and the amount ultimately provided by Congress.

Table B.2 reports that the allocations-to-requests match rate is extremely high. Of the collected allocations, 16,596 of 16,755 House-sponsored allocations (99.1%) correspond to a House request. The match rate rises monotonically from 97.8% in FY2022 to 99.6% in FY2026.

Table B.2 – Enacted Earmarks Matched to a Member's Funding Request. Of all enacted earmarks listing a House sponsor, the share linked to a request filed by that sponsor. Amounts are de-duplicated across jointly sponsored earmarks.

FY	House-Sponsored Allocations	Matched to a Request	Share Matched	Share Low-Confidence
2022	2,724	2,665	97.8%	0.08%
2023	4,357	4,311	98.9%	0.00%
2024	4,686	4,651	99.3%	0.02%
2026	4,988	4,969	99.6%	0.00%
Total	16,755	16,596	99.1%	0.02%

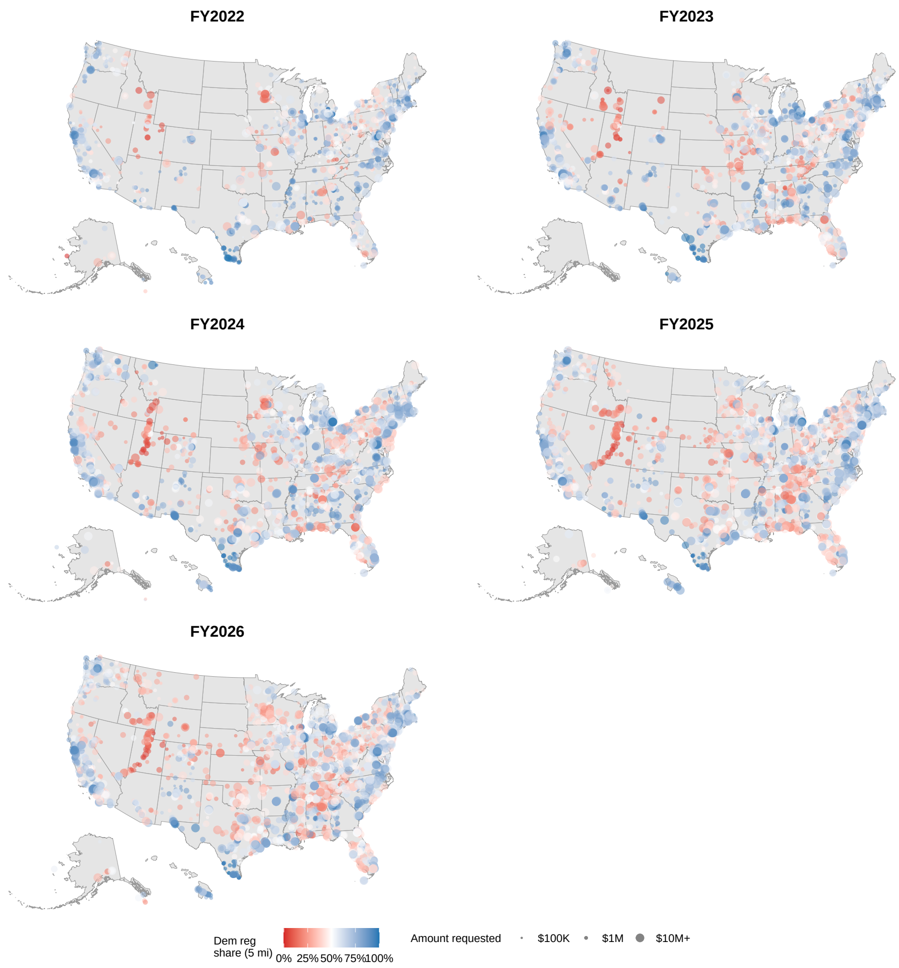
C Additional Earmark Descriptives

This appendix reports additional descriptive information on where earmarks are requested and allocated.

C.1 Earmark Requests

Figure C.1 breaks the results in Figure 1 out by fiscal year.

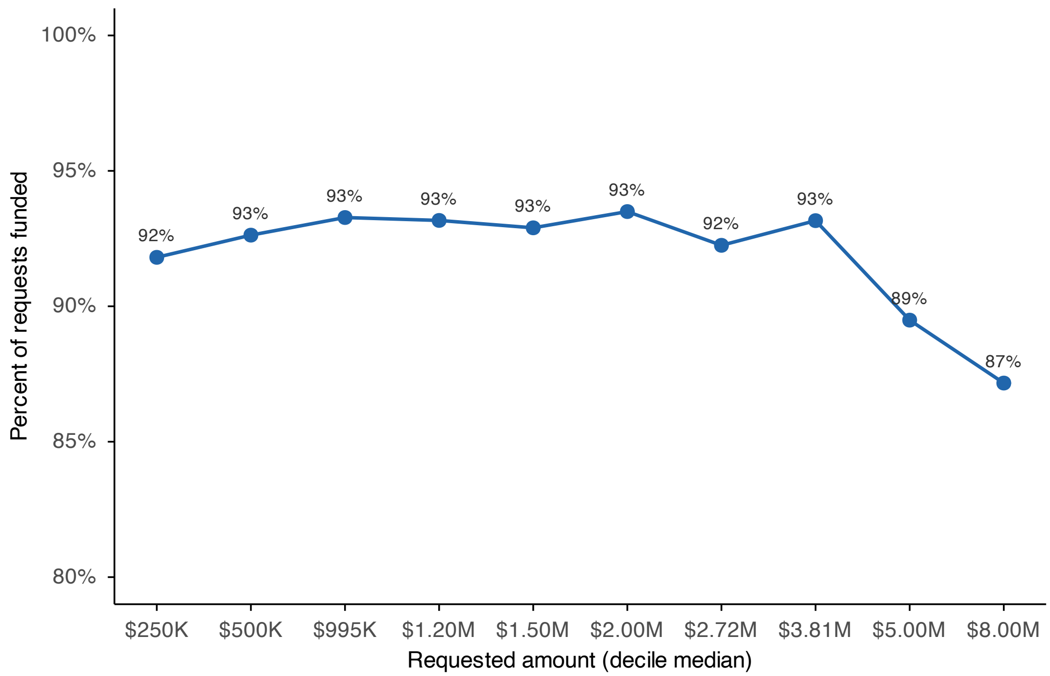
Figure C.1 – Geographic Distribution of Earmark Requests by Fiscal Year, Colored by Democratic Registration Share Within 5 Miles. Each dot represents an individual earmark request; dot area is proportional to the requested amount (capped at $10 million for scaling) and color encodes the Democratic registration share within five miles of the project. Panels break out the pooled map in Figure 1 by fiscal year, FY2022–FY2026. Alaska and Hawaii are repositioned beneath the continental United States.



C.2 Earmark Allocations

Figure C.2 examines whether larger requests are less likely to be funded. It plots the percent of requests receiving any allocation by decile of the requested amount, pooling all fiscal years with enacted earmarks. Funding rates are flat at roughly 92–93% through the first eight deciles and decline only for the largest requests, falling to 87% in the top decile.

Figure C.2 – Funding Rate by Size of Request. Percent of earmark requests receiving any funding, by decile of the requested amount (FY2022–FY2026 pooled; FY2025 excluded because no earmarks were enacted). The horizontal axis reports each decile's median requested amount.



D RD Balance Tests

In this appendix, we probe the identifying assumptions of the regression discontinuity design used in the main text.

First, Table D.1 examines balance on pre-treatment covariates. Because these outcomes are determined before the cycle-t election takes place, the conditional expectation function should be smooth across the discontinuity. In the first row we replace the outcome from Equation 2 with its analog from the prior election cycle, the dollar-weighted Democratic registration share within five miles of the earmark requests filed by district d's representative in cycle $t-1$.[39] The remaining rows repeat the exercise for the four demographic and economic placebos from Figure 7: the share of residents in poverty, the share of non-white residents, the share with a bachelor's degree or greater, and population density near requested projects. All five estimates are small and statistically indistinguishable from zero.

Second, we evaluate whether the running variable is continuous across the discontinuity using the density test proposed by McCrary (2008). Applying this test to our sample, we obtain a p-value of 0.164, providing no evidence of manipulation around the close-election threshold. These results match prior work finding little evidence of strategic sorting around the threshold (Eggers et al., 2015).

Table D.1 – Pre-Treatment Balance and Placebo Outcomes. Each row applies the cubic specification from Table 1 to an outcome that should be unaffected by the cycle-t election: the dollar-weighted Democratic registration share within five miles of the district's earmark requests filed in the prior election cycle ($t-1$), and the four placebo characteristics from Figure 7, each in its raw units. The lagged outcome exists only for the 2022 and 2024 cohorts (the modern earmark program has no 2018-cycle requests to lag to), hence its smaller N.

Outcome	RD estimate	SE	N
Lagged Dem. reg. share	0.021	(0.031)	610
% in poverty	0.005	(0.009)	993
% non-white	0.015	(0.038)	993
% with BA+	0.001	(0.014)	993
Population density	713	(420)	993

Note: Robust standard errors clustered by district in parentheses.

[39] Because the new earmarking regime began following the 2020 election, there are no lagged outcomes for this cycle. Hence, the first row in Table D.1 uses only elections in 2022 and 2024. The remaining rows also include 2020.

E Measuring Partisanship Using Geocoded Presidential Election Returns

In 33 states, L2's partisan classification reflects voters' self-declared party affiliation as recorded in the state's official voter-registration file, or the party of the most recent primary in which they participated. In the remaining 17 states, L2 imputes partisan classification using a proprietary model trained on primary-ballot choice and demographic data. To evaluate the robustness of our results, we replicate our main analysis using a measure of voters' political preferences as revealed through presidential election returns. Using geolocated precinct-level returns from the 2020 presidential election collected by the Voting and Election Science Team (VEST), we calculate $Dem\ Presidential\ Vote\ Share^{r}_{pdt}$, the Democratic candidate's two-party vote share within r miles of project p in district d and cycle t. When precincts are not entirely contained within a given radius, we weight each precinct by the share of its area lying inside the r-mile buffer. We then substitute this measure into Equation 1.

Table E.1 reports the results using this alternative measure of partisanship. Our point estimates remain statistically distinguishable from zero across all four specifications, but are slightly smaller than the estimates using voter registration data. This smaller magnitude is consistent with the fact that presidential vote share is a coarser proxy for neighborhood partisanship than registration.

Table E.1 – Effect of Electing Democrat on Democratic Two-Party Presidential Vote Share Near Earmark Requests, 5-Mile Radius. This table replicates Table 1 using the two-party Democratic presidential vote share instead of party registration to measure partisanship. Our substantive conclusions remain unchanged using this measure of revealed political preferences.

	Dollar-Weighted Democratic Presidential Vote Share			
	(1)	(2)	(3)	(4)
Democratic Win	0.03	0.02	0.03	0.02
	(0.01)	(0.01)	(0.01)	(0.01)
N	388	355	993	993
Specification	CCT	Linear	Cubic	IW
Spline	-	Yes	Yes	-
Bandwidth	0.11	0.10	-	-

Note: Robust standard errors clustered by district are reported in parentheses. The outcome is the dollar-weighted Democratic two-party presidential vote share within five miles of a district-year's requested earmark projects. The running variable is the Democratic candidate's general-election margin of victory. Spline indicates that the regression function was fit separately on either side of zero. Cubic refers to a third-order polynomial regression. CCT refers to the method from Calonico, Cattaneo, and Titiunik (2014). IW refers to the method from Imbens and Wager (2019).

F Extensive Margin Estimates

A potential concern in Equation 1 is that a small number of large earmark requests might be driving our results. In this section we re-estimate our main results after weighting each project equally. Formally, our outcome becomes

$$Y^r_{dt} = \frac{\sum_{p \in P} \textit{Dem Registration Share}^r_{pdt}}{|P|}, \tag{F.1}$$

where $|P|$ represents the cardinality of P. In words, each requested project enters the district-year outcome with equal weight, regardless of the size of the request.

We first replicate Table 1 using this unweighted outcome at the 5-mile radius. Table F.1 reports the resulting estimates. The point estimates are highly similar to their dollar-weighted counterparts in Table 1, indicating that the headline result is not driven by variation in the size of individual requests.

To confirm that this finding is not specific to the 5-mile buffer, Figure F.1 replicates Figure 4 using the unweighted outcome across radii 1–15 miles. The point estimates closely track those in Figure 4 and are positive and statistically distinguishable from zero at every radius, confirming that the headline pattern is robust to dropping the dollar weighting.

The same logic applies to the bucketed composition result in Figure 5, which reports the effect of electing a Democrat on the share of *dollars* flowing to Dem-heavy, Bipartisan, and Rep-heavy neighborhoods at the 5-mile radius. Figure F.2 replicates that figure using the share of *projects* in each neighborhood type rather than the share of requested dollars. The point estimates are similar in sign and magnitude to those in Figure 5, again confirming that the headline composition pattern does not depend on the dollar weighting.

Table F.1 – Effect of Electing Democrat on Unweighted Democratic Registration Share, 5-Mile Radius. The narrow election of a Democrat shifts the average share of Democratic registrants within 5 miles of requested projects by 4 to 6 percentage points.

	Unweighted Dem Registration Share			
	(1)	(2)	(3)	(4)
Dem. Win	0.06	0.05	0.04	0.05
	(0.03)	(0.02)	(0.02)	(0.02)
N	276	352	983	983
Specification	CCT	Linear	Cubic	IW
Spline	-	Yes	Yes	-
Bandwidth	0.08	0.10	-	-

Note: Robust standard errors clustered by district are reported in parentheses. The outcome is the average Democratic registration share within 5 miles of a district-year's requested earmark projects (unweighted). The running variable is the Democratic candidate's general-election margin of victory. Spline indicates that the regression function was fit separately on either side of zero. Cubic refers to a third-order polynomial regression. CCT refers to the method from Calonico, Cattaneo, and Titiunik (2014). IW refers to the method from Imbens and Wager (2019).

Figure F.1 – Effect of Electing a Democrat on the Project-Equally-Weighted Democratic Share of Nearby Registrants, by Radius. The narrow election of a Democratic member of Congress increases the unweighted two-party Democratic share of registered voters in the vicinity of earmark requests by 5 to 7 percentage points relative to electing a Republican. The horizontal axis reports the radius of voters included around each project. Replicates Figure 4 after replacing dollar weighting with equal weighting across projects.

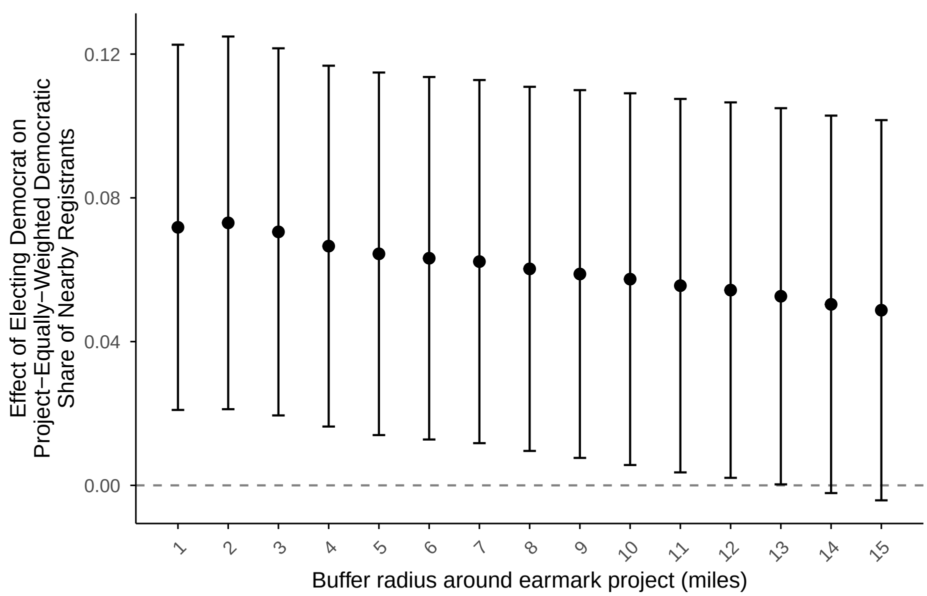
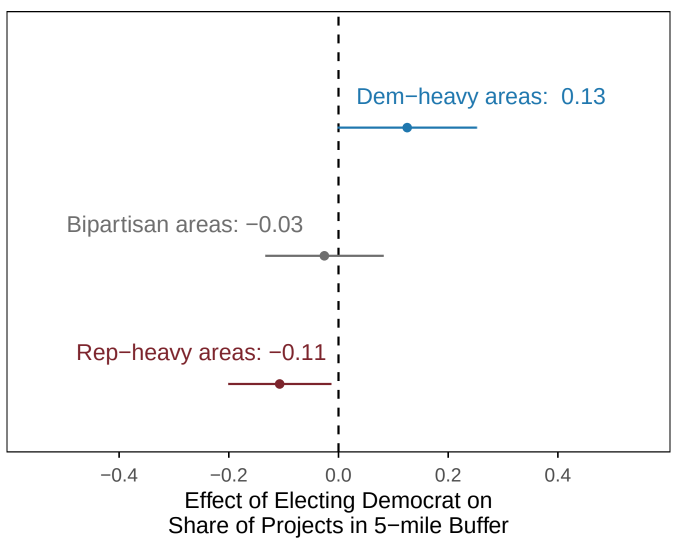


Figure F.2 – Effect of Electing a Democrat on the Share of Projects Placed in Each Neighborhood Type, 5-Mile Radius. Robust bias-corrected RDD estimates (Calonico et al., 2014) of the effect of a narrow Democratic win on the district-year share of earmark projects (rather than requested dollars) whose 5-mile buffer falls in each partisan bucket: Dem-heavy ($\geq$ 60% Dem registration), Bipartisan (40–60%), or Rep-heavy ($\leq$ 40%). 95% robust confidence intervals shown. The narrow election of a Democratic member of Congress increases the share of earmark projects requested in Democratic-heavy areas by 13 percentage points, while decreasing the share of projects in Republican-heavy areas by 10 percentage points, with essentially no change in bipartisan areas.



G Correlation Between Partisan and Demographic Characteristics

Figure G.1 – Correlation Between Democratic Registration Share and Placebo Neighborhood Characteristics. Each point reports the Pearson correlation, across earmark requests filed in FY2022–FY2026, between the Democratic registration share and one placebo characteristic—the non-white share, population density, the share of residents with a bachelor's degree or greater, and the share of residents in poverty—each measured within five miles of the request. All four placebos are positively correlated with Democratic registration, so a legislator who targeted any of them rather than partisanship directly could still shift requests toward more Democratic-leaning areas. Figure 7 shows that electing a Democrat significantly shifts requests toward co-partisan areas but not toward these placebo characteristics.

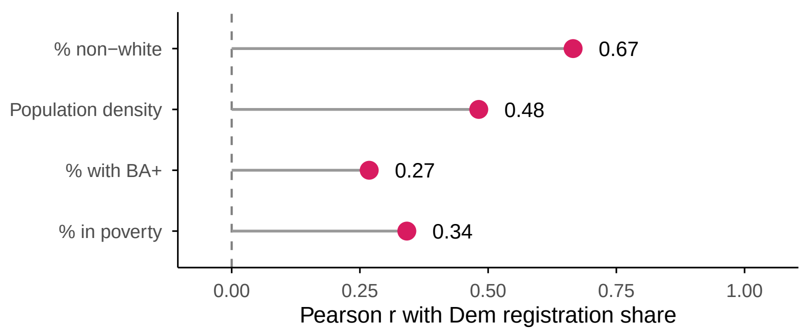


Table G.1 – Raw RD Point Estimates Underlying Figure 7. Regression-discontinuity estimates of the effect of narrowly electing a Democrat on each Figure 7 outcome, in the outcome's native units (including population density). Because the units differ across rows, the point estimates are not comparable across rows; Figure 7 places them on a common percentile scale.

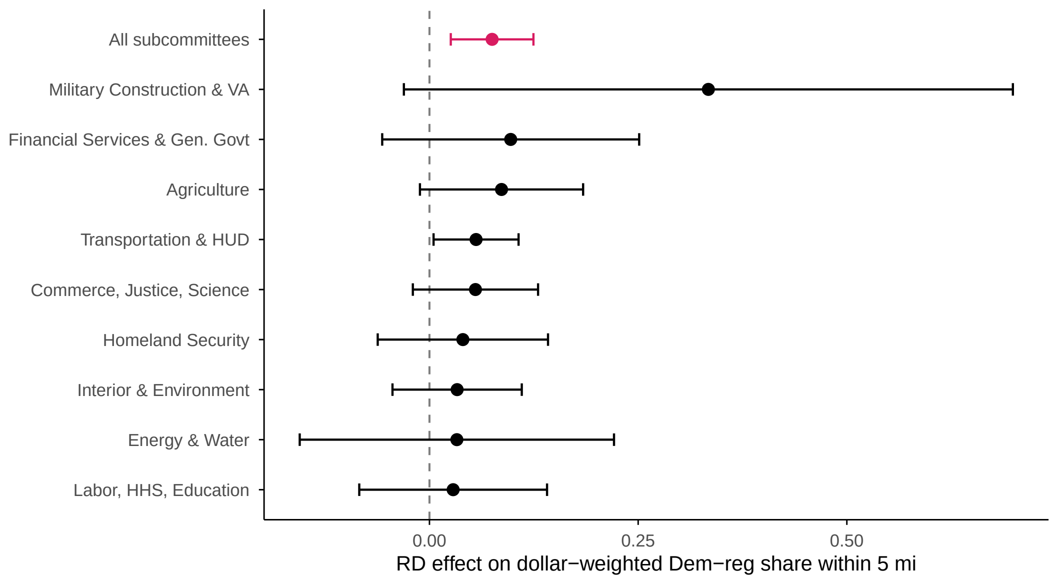
Outcome	RD estimate	Robust SE	N
Dem. registration share	0.075***	0.025	993
% non-white	0.015	0.041	993
Population density	47.6	307.3	993
% with BA+	−0.002	0.016	993
% in poverty	0.007	0.010	993

Note: Raw Calonico, Cattaneo, and Titiunik (2014) RD estimates of the effect of narrowly electing a Democrat, in each outcome's native units: registration and demographic outcomes are shares (proportions in $[0, 1]$), while population density is registered persons per square mile. Because the units differ across rows, the point estimates are not comparable across rows; Figure 7 places them on a common percentile scale. Robust bias-corrected standard errors in the third column. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

H Estimates by Subcommittee

A natural question is whether the co-partisan targeting documented in Figure 4 is confined to a handful of spending areas or holds broadly across the appropriations process. Figure H.1 re-estimates Equation 2 separately within each House Appropriations subcommittee to which requests were directed, using the dollar-weighted Democratic registration share within a 5-mile radius and the estimator from Calonico et al. (2014). The top row (in red) reproduces the pooled estimate from Figure 4.

Figure H.1 – Effect of Electing a Democrat on the Dollar-Weighted Democratic Registration Share Near Earmark Requests, by Appropriations Subcommittee (5-Mile Radius). Each point is a separate CCT regression-discontinuity estimate of β_1 from Equation 2, restricting the earmark requests to those directed to the labeled subcommittee; horizontal bars are robust 95% confidence intervals. The pooled "All subcommittees" estimate (red) matches Figure 4.



I Grid-Cell Construction

We overlay the fifty states with a single national grid of five-mile by five-mile cells the US National Atlas Equal Area projection. Because the projection is equal-area, every cell covers exactly 25 square miles. The grid is anchored at the projection origin and laid down once, so cell boundaries and identifiers are fixed for the whole study period and a cell retains its identity across with redistrictings. The resulting panel contains 144,057 distinct cells and 720,186 cell fiscal-year observations over FY2022–FY2026. Quantities recorded on polygons (census block groups) are allocated to cells by converting each additive count to a per-square-metre density, rasterising it onto a 500 m grid nested within each cell and snapped to the cell origin, multiplying back by fine-cell area, and block-summing; the nesting makes the block sum exact. Point quantities—registered voters and geocoded earmark projects—are indexed to a cell directly from their projected coordinates. Cells are used whole and never clipped to district boundaries, so a cell's characteristics describe a neighbourhood that may extend past the district it is assigned to.

For each cell we calculate five time-invariant characteristics. *Non-white share* is one minus non-Hispanic white-alone population over total population, from the 2020 Decennial Census PL 94-171 redistricting file at block-group level (mean 0.298). *Poverty share* is persons below 100 % of the federal poverty level over the poverty universe, from the 2019–2023 American Community Survey five-year estimates, table C17002 (mean 0.144). *Share with a BA or higher* is persons holding a bachelor's, master's, professional or doctoral degree among those aged 25 and over, from the 2019–2023 ACS five-year estimates, table B15002 (mean 0.214). *Democratic registration share* is registered Democrats over registered Democrats plus Republicans, from the L2 VM2 national voter file, 2021 snapshot, geocoded to individual addresses (mean 0.377). The census and ACS measures are non-missing for 99.6% of cell-years. Democratic registration is defined only where a cell holds at least 25 major-party registrants, a floor imposed to suppress mechanical rates off very small denominators; it is therefore available for 45.6% of cell-years, which are the populated ones.

Each cell is then finally assigned to the congressional district containing its centroid, using TIGER/Line cartographic boundary files: the 2021 vintage for the 117th Congress, the 2022 vintage for the 118th, and the 2024 vintage for the 119th. The assignment is recomputed for each Congress to allow for redistricting. Therefore cell identity and characteristics are fixed while district membership can change over time in our panel. A cell straddling two or more districts is assigned in its entirety to the district containing its centroid, never split or weighted. This yields 436 districts per fiscal year. Because the grid is uniform in area, cells per district vary with geographic size: mean 330.4, median 88, minimum 1, maximum 23,387 (Alaska's at-large seat), with 119 district-Congresses holding five cells or fewer. Ten district are smaller than a single gridcell—MA-7 and NY-14 in the 117th, NY-12 in the 118th and 119th, and NY-10 and NY-13 in all three. Each is assigned the cell it overlaps most and flagged; the flagged observations are excluded from estimation rather than allowed to duplicate a cell. They account for 0.41% of cell-level requested dollars.