# Across the Aisle: Affective Polarization and Bipartisanship in American Legislatures*

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**Abstract**

Partisan hostility in American legislatures has escalated to the point that some legislators fear violence from their peers across the aisle. Amid this increase in partisan tension, bipartisanship in lawmaking has declined. Existing theoretical frameworks of legislative behavior struggle to explain the extent of inter-partisan animosity, however. In this paper, I argue that partisan identities and affective polarization among legislators can help us understand both inter-partisan animosity and the decline of bipartisanship in lawmaking. Due to the hyper-salience of legislators' political identities, partisan identities may be important in shaping the behavior of American politicians. Using the results of a conjoint experiment in an original survey of state legislative candidates, I show that politicians discriminate against members of the opposing party when selecting partners in the policy process. In particular, more affectively polarized politicians are more likely to choose to work with a copartisan legislator. Even when presented with policy information, more affectively polarized candidates are more likely than their less polarized peers to choose a copartisan partner. These results have important implications for the study of legislative politics, affective polarization, and the democratic system.

legislative politics | bipartisanship | affective polarization | partisan identity

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# Introduction

Partisan conflict in American legislative bodies has reached new heights in the recent years. The threat of partisan violence hangs over interactions between legislators from opposing parties. Inter-partisan disputes in Congress have nearly turned into fist-fights on several occasions (e.g., Griffiths, 2023). In the aftermath of the January 6$^{th}$ insurrection at the Capitol, Republican members of the House regularly evaded newly-installed metal detectors, designed to prevent guns from entering the House chamber (Shabad, Moe and Caldwell, 2021). Rep. Paul Gosar (R-AZ) posted a cartoon video of himself killing Rep. Alexandria Ocasio-Cortez (D-NY) on social media (Constantino, 2021). These behaviors sparked fears of a potentially deadly escalation of partisan conflict and led then-Speaker Nancy Pelosi (D-CA) to declare that "the enemy is within" the House of Representatives (Kaplan, 2021).

Amid the partisan hostility, bipartisanship in co-sponsorship behavior has been declining (Harbridge-Yong, Volden and Wiseman, 2023). In a recent survey of congressional staff, 95% of respondents said they believed that this inter-partisan tension has led to the failure of "otherwise noncontroversial legislative ideas" (Goldschmidt, 2022). What is most puzzling about recent partisan interactions in legislatures is that, in many cases, politicians' behavior no longer seems to be driven solely by policy concerns, ambition, or electoral goals, as existing literature would predict (see e.g., Mayhew, 1974; Rohde, 1979; Fenno, 1973). So intense is this partisan enmity that, according to congressional staff, it has even affected the ability of members of Congress to work across the aisle on "noncontroversial" legislation. This suggests that the influence of partisanship in the policy-making process extends beyond policy disagreements and strategic considerations. Instead, the extent to which distrust, fear, and animosity color legislators' interactions with members of the opposing party seems more consistent with partisan affective polarization—hatred of the opposing party and warmth toward one's own party (Iyengar, Sood and Lelkes, 2012). In this paper, I study whether affective polarization and partisan identity among politicians affect their willingness to work with members of the opposing party.

Scholars have shown that affective polarization and partisan identities are important drivers of mass-level behavior, leading to discrimination in dating (Huber and Malhotra, 2017), scholarship decisions (Iyengar and Westwood, 2015), and hiring decisions (Gift and Gift, 2015). Yet, little work has examined the role of affective polarization in explaining the behavior of elites. Understanding elite behavior, however, is crucial to our understanding of American government. Politicians often lead the public on policy issues (Lenz, 2012), and their behavior and rhetoric suggest to the public the bounds of appropriate behavior in a democracy (Mason and Kalmoe, 2022). If elites regularly discriminate against or engage in hostile behavior toward members of the opposing party, this could signal to the mass public that such behavior is an accepted or even necessary part of political engagement. Moreover, democratic systems are based around the representation of the public's views in policy. If representatives refuse to work with their peers due to their partisan identity, this could degrade the quality of representation in two notable ways. First, previous research has found that bipartisanship is important to passing legislation (Curry and Lee, 2020; Harbridge-Yong, Volden and Wiseman, 2023). Thus, partisan discrimination in policy-making could hinder the ability of representatives to pass legislation, thereby generating gridlock and preventing the implementation of their constituents' preferred policies. Second, partisan discrimination could impede responsiveness to constituents' policy concerns if policy decisions are not based on constituent preferences but instead, on the legislator's partisan identity. In short, understanding affective polarization among politicians is crucial to understanding the functioning of American democracy.

In this paper, I present the results of an original survey of candidates who ran for state legislative office in 2022. Within this survey, I conducted a conjoint experiment which asked respondents to choose, from a pair of legislator profiles, which policy-maker they would prefer to work with in the legislature. This design allows me to estimate the influence of partisanship on policy-making decisions, net of other potential considerations. My results show that state legislative candidates discriminate against members of the opposing party in the legislative process. Moreover, even after accounting for policy information, more affectively polarized candidates are more likely to discriminate against opposing partisans than their less affectively polarized peers—though the gap between the most and least polarized closes with more policy information. These results suggest that affective polarization is crucial to understanding legislative behavior. In sum, recent declines in bipartisanship and increases in partisan rancor in legislative bodies may be attributable, in part, to elite affective polarization.

# Existing Theories of Legislative Behavior

## Re-Election

Mayhew's (1974) book reshaped the study of legislative politics, positing that legislators are "single-minded seekers of reelection" (5). Indeed, it is logical that, to achieve any other goals in the legislature, a politician must be elected and reelected to office. Consequently, Mayhew argued that much of lawmakers' behavior could be explained by their reelection motive. To remain in office, many legislators focused on performing casework for constituents (e.g., Fiorina, 1989) and avoided taking clear positions out of step with constituency preferences (e.g., Arnold, 1990). Still, much has changed since Mayhew's (1974) admonishment that "no theoretical treatment of the United States Congress that posits parties as analytic units will go very far" (27). Foremost among these changes has been the resurgence of partisan identification among the electorate as a key predictor of mass voting behavior (Bafumi and Shapiro, 2009).

Whereas, at the time of Mayhew's writing, legislators could often build individual brands transcending partisanship, legislators' chances of reelection today are more tied to the fate of their party (Hopkins, 2018; Rogers, 2023). At the same time, local news media have been shuttered or decreased their coverage of politics (Hayes and Lawless, 2018), making it harder for the "rationally inattentive public" to learn about their legislators (Downs, 1957). Additionally, geographic sorting and partisan gerrymandering mean that individual legislators rarely face serious electoral challenges (Rogers, 2023; Stephanopoulus and McGhee, 2015). The confluence of all of these forces means that, while individual decisions made by legislators may be electorally important on key issues, they are otherwise not likely determinative of electoral outcomes—especially at the state and local levels. In other words, the reelection goal is likely a less important constraint on legislative behavior than in the past.

## Policy

Other scholars have included additional considerations with Mayhew's (1974) ultimate electoral goal to explain the behavior of legislators. For instance, (Fenno, 1973) argued that policy goals are also key to understanding legislative behavior. Legislators, holding some form of utility function over policies, would like to see their preferred policies enacted and should take actions consistent with the enactment of these policies (e.g., Krehbiel, 1998). Yet, current partisan conflict in legislatures is often directly at odds with successful policy-making (i.e., the enactment of members' preferred policies).

A long line of research suggests that bipartisanship is crucial to the passage of policy (Curry and Lee, 2020; Harbridge-Yong, Volden and Wiseman, 2023). However, bipartisan behavior in Congress is generally quite low on average and is declining over time (Harbridge-Yong, Volden and Wiseman, 2023). In itself, this trend is not inconsistent with parties that are more extreme and better sorted on policy (Levendusky, 2009; McCarty, Poole and Rosenthal, 2016), but as noted above, a sizable majority of congressional staff agree that partisan conflict has hampered the progression of even "noncontroversial" policies.

One recent example illustrates the role of partisanship in shaping inter-partisan interactions, even where policy disagreements were not directly implicated. Rep. Cori Bush (D-MO) opted to move to a different office space—not to find a better or more convenient location, or due to policy considerations, but because of a hostile partisan interaction with Rep. Marjorie Taylor Greene (R-GA) whose office was nearby (Shabad, Moe and Caldwell, 2021). Increasingly, then, it seems that partisan conflict has extended beyond policy disagreements into overt expressions of partisan social distance, hostility, and distrust, which stand to impede the passage of policies even when both parties agree on the content.

## Majority Control and Party Branding

Among other explanations of legislative behavior, perhaps the most prominent is the goal of majority control. To achieve this goal, members take actions to promote the party brand. In turn, a polished and distinct party brand helps them and other members of their party win the majority in Congress (Cox and McCubbins, 1993; Lee, 2009, 2016). For several reasons, however, this consideration is unlikely to constrain the behavior of most legislators. Party brands represent collective action problems: for most politicians most of the time, their individual decisions have imperceptible effects on the party brand. Further, it may be electorally beneficial for some members to distance themselves from the party brand. Solving this collective action problem is left to party leaders who often have few formal powers over their members (Cox and McCubbins, 2005). Thus, instead, majority control becomes more an exercise of negative agenda control, keeping potentially damaging policies off of the floor—more the purview of a few leaders than the membership at large (Cox and McCubbins, 2005).

Additionally, this goal is likely less important at the state legislative level than at the congressional level. Geographic sorting and partisan gerrymandering have generated non-competitive state legislatures—even in states which are nationally competitive (e.g., Wisconsin, Georgia). Indeed, in most state legislatures, the majority party has *supermajority* control (Crampton, 2023). Finally, the nationalization of politics means that national party brands trickle down to the state and local levels rather than the reverse (Hopkins, 2018). Therefore, most state legislative parties and their members likely have little incentive to engage in party branding efforts.

In sum, a decreasing share of legislators faces truly competitive elections, particularly at the state level. Majority control of the legislature is, in most states, rarely in doubt, and the individual efforts of most politicians likely contribute imperceptibly to party brands—if at all. Finally, it appears that some policy-making behavior in legislatures cannot be explained by policy positions alone. Given that legislators are less subject to electoral or majority-control constraints than in the past, traditional theoretical frameworks struggle to explain behavior in legislatures. Specifically, why is it the case that partisanship inhibits policy-making even on noncontroversial issues? I argue that affective polarization and partisan identities among legislators can account for inter-partisan hostility in legislatures and the concomitant decline in bipartisanship.

## Affective Polarization in Legislatures

At the mass level, scholars have recently noted increased feelings of warmth toward one's own party and hatred of the opposing party, a trend known as affective polarization (Iyengar et al., 2019). Affective polarization is rooted in one's partisan social identity (Iyengar, Sood and Lelkes, 2012). It has been shown to predict political engagement (Mason, 2018) and the decision to share fake news on social media (Osmundsen et al., 2021). Moreover, partisan identities generate in-group favoritism and out-group discrimination across a wide variety of domains (Engelhardt and Utych, 2020; McConnell et al., 2018; Shafranek, 2021).

Still, there are reasons to expect that partisan identities might exert even stronger effects among elites. While a large share of the public is politically disengaged (Krupnikov and Ryan, 2022), politicians are, by definition, among the most politically engaged individuals, meaning their political identities are likely more central to their personal identity. West and Iyengar (2022) show that partisan social identities are stronger when politics is more salient to the electorate. In fact, partisan discrimination among the masses appears to decline outside of election periods (Sheffer, 2020). Whereas these periods of salience are intermittent for the masses, politics is perpetually salient for politicians which presumably heightens the importance of partisanship for politicians.

Further, as American elections have nationalized, politicians' prospects for remaining in office have become more attached to their party affiliation. While state legislative elections are often non-competitive, the connection of the individual's position with the position of the party could generate a strong attachment to and identification with the in-group, and perhaps even a sense of partisan linked fate (Dawson, 1994; Webster and Sinclair, N.d.). The perpetual salience of politics and the tethering of individual fates to the broader fate of the group should work to produce stronger partisan identities among elites than among the masses. Canonical work in social identity theory suggests that even randomly assigned groups can generate inter-group discrimination (Tajfel, 1970). Thus, a strong identity like partisanship among politicians should produce inter-group discrimination as well.

In addition, politicians do not interact with a random sample of the population: those who contact politicians tend to be engaged, extreme, and committed partisans (see e.g., Huddy, Mason and Aaroe, 2015; Krupnikov and Ryan, 2022). Copartisan constituents who contact legislators may be more similar to politicians (i.e., engaged, extreme) than average copartisans in the electorate, and constituents from the opposing party contacting legislators may be more dissimilar to the legislator than average out-party members. The slice of the electorate featuring in politicians' interactions with the public generates a biased picture of the public at large among politicians (Broockman and Skovron, 2018). Biases in perceptions about opposing partisans have been shown to be quite consequential for affective polarization (Stone, 2023). For example, correcting misperceptions about the demographic composition of the opposing party can reduce affective polarization among mass partisans (Ahler and Sood, 2018). In short, misperceptions about opposing partisans matter for affective polarization:

overestimation of differences with the opposing party can exacerbate dislike of the opposing party. Politicians, who are confronted with a non-representative sample of partisans in the public, likely have inflated perceptions of inter-partisan difference and believe that members of the public at large are more extreme and committed partisans than they are.

Finally, we should expect politicians to be even more likely to discriminate against their opposing partisan peers than are the masses. Members of the mass public are less likely to express resistance to interacting with a hypothetical opposing partisan when told that the opposing partisan rarely talks about politics (Druckman et al., 2022; Krupnikov and Ryan, 2022). Yet, while the average partisan in the electorate might not be politically engaged, politicians' peers in the legislature are, providing conditions ripe for partisan discrimination. Further, when asked to rate the major political parties on feeling thermometers, members of the mass public are often thinking of political elites and party leaders (Druckman and Levendusky, 2019). It is elites, therefore, who evoke the most partisan hostility. Legislators' peers are precisely those individuals that generate the most affective polarization among the public: engaged elites. Mass-level research on affective polarization, then, suggests that politicians should be even more likely to discriminate against their peers in the legislature than mass partisans against their peers in the electorate.

Overall, mass-level research on affective polarization offers compelling reasons to expect that politicians should be *more* influenced by their partisan identities and affective polarization than the masses. Elites are chronically politically engaged, and politics is always salient for them. For this reason alone, we should expect that political identities like partisanship are more central to their personal identities than to the disengaged masses. In addition, constituents who contact politicians are likely to be engaged and committed partisans (Huddy, Mason and Aaroe, 2015), contributing to biases in perceptions of the opposing party. These biased perceptions of dissimilarity work to increase one's dislike of the opposing party (Stone, 2023). Thus, the biased portion of the American electorate politicians interact with should lead to increased affective polarization among politicians. Finally, since politicians' peers in the legislature are precisely the individuals who evoke the most affective polarization among the masses, we should expect the most partisan hostility to be directed at their opposing partisans in the legislature. Consequently, I hypothesize that when deciding whom to work with in the legislature, politicians should discriminate against members of the opposing party, and that this discrimination should be most pronounced among the most affectively polarized politicians. Moreover, given that affective polarization is rooted in partisan social identity (Iyengar, Sood and Lelkes, 2012), I expect that this discrimination in favor of the in-party and against the opposing party should occur even after accounting for policy positions and ideology.

# Data and Methods

To test my hypothesis that affective polarization and party identities influence bipartisanship in lawmaking, I rely on the results of an original survey of individuals who ran for state legislative office as a Democrat or Republican in 2022 (N=1448).[1] Affective polarization is measured by taking the difference between in-party and out-party feeling thermometer ratings, excluding pure independents from the analysis (Iyengar, Sood and Lelkes, 2012). Ideology was measured on an 11-point scale from extremely liberal (0) to extremely conservative (10). Ideology was transformed into a measure of congruence with the respondent's party by subtracting the ideology value from 10 for Democrats. Higher values of congruence indicate that the respondent's ideology more strongly matches the ideology of their party. I also asked about individual demographic characteristics, including race and ethnicity, religion, age, and education.

I embedded a conjoint experiment in this survey which presented respondents with four to five pairs of hypothetical legislator profiles and asked which profile they would prefer

[1]More information about this survey can be found in Appendix A.1.

to work with in the legislature. I randomly varied characteristics of the profiles, including race, religion, constituency type, age, education, and whether the legislator served on a committee with the respondent. I randomized party at the choice-level such that each choice task contained one Democratic and one Republican profile, following Peterson (2017). Importantly, I also randomly varied the content and number of the policy positions displayed for each profile pair. Respondents could be shown profiles with between two and six policy positions. The seven possible policies included abortion, voter identification laws, government spending, red-flag laws for firearm purchases, sanctuary city policies, school vouchers, and environmental protections, spanning a wide variety of controversial policies.[2] This experimental design allows me to test the extent to which party identity influences legislators' choices in policy-making—above and beyond the effects of policy positions and demographic characteristics. It also provides me with the flexibility to examine the role played by affective polarization in choosing legislative partners.

First, I examine the average marginal component effect (AMCE) of party on respondent choice (Hainmueller, Hopkins and Yamamoto, 2014) and estimate the conditional average marginal component effect (CAMCE) of party, conditional on a respondent's affective polarization. The AMCE is an estimate of the effect of partisanship, averaging across the distribution of the other profile attributes (Hainmueller, Hopkins and Yamamoto, 2014). Following de la Cuesta, Egami and Imai (2022) and Hainmueller, Hopkins and Yamamoto (2014), I randomized attributes with some joint dependence between abortion policy positions, party, and religion, such that extreme party-incongruent abortion policy positions were less likely. Accordingly, I estimated the AMCE and CAMCE using inverse propensity score weighting (de la Cuesta, Egami and Imai, 2022). Additionally, because I randomized party at the choice level, my outcome variable is an indicator variable for whether profile A was chosen in a given pair, and the main treatment of interest is whether profile A is a member

[2] See Appendix A.2 for full details of the conjoint experiment.

of the respondent's party.[3] In all models, I cluster standard errors at the respondent level. While the CAMCE cannot tell us whether affective polarization *causes* different reactions to party information, it can tell us the association between affective polarization and the effects of partisanship.

Second, I demonstrate the robustness of my results to alternate theories of legislative behavior by estimating CAMCEs of party identity, conditional on policy positions, ideology, electoral results, and state partisan control. Finally, recognizing the limitations of linear functional forms, I use nonparametric causal forest models to detect treatment effect heterogeneity (Wager and Athey, 2018). Causal forests fit a large number of trees on different subsamples of the data. These trees are built to best predict treatment effect heterogeneity, and the tree-based structure naturally incorporates nonlinear functional forms and complex interactions among variables (Athey and Imbens, 2016; Wager and Athey, 2018).[4] Causal forest models were fit using individual covariates (age, education, ideological congruence with the respondent's party, party strength, party identification, race and ethnicity, and religion), state-level covariates (partisan control of the state house, state senate, and governorship as well as the share of seats in the respondents' chamber held by the respondents' party), and covariates for Profile A (the number of issues, the number of party-incongruent issue positions, age, constituency type, education, race and ethnicity, religion, and committee membership). The causal forest results confirm both that affective polarization is among the most important predictors of treatment effect heterogeneity and that the effects of party are greatest among the most affectively polarized politicians.

[3]Full details of the identification and estimation of the AMCE and CAMCE are located in Appendix A.3.

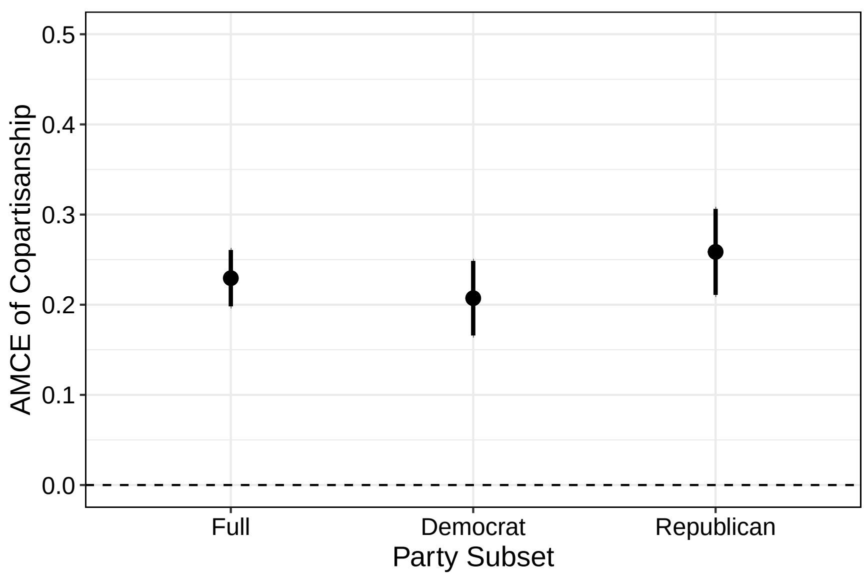
[4]In Appendix A.4, I provide more details on the use of causal forests.

# Analysis

## Partisan Discrimination and Affective Polarization

In this section, I estimate the average marginal component effect (AMCE) of copartisanship on the willingness of state legislative candidates to work with another legislator. Figure 1 displays the AMCE estimates of copartisanship on willingness to work with legislator A. As we can see, the effect of party is consistent and precisely estimated for Democrats, Republicans, and in the full sample. The estimates indicate that state legislative candidates are between 20 and 25 percentage points more likely to choose to work with a member of their own party than with a member of the opposing party.

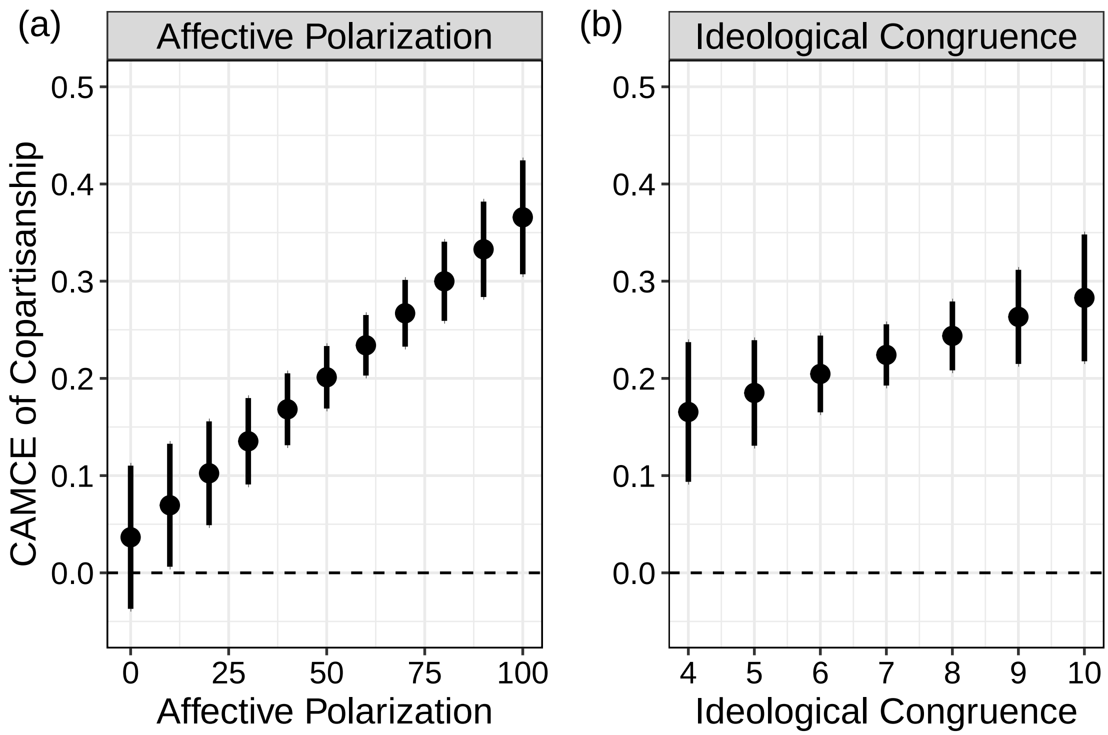
Figure 1: Average Marginal Component Effects of Copartisanship on Legislative Partnership




Note: Coefficient estimates from regressions of a choice indicator variable on an indicator variable for copartisanship.

Next, I examine the effect of copartisanship conditional on affective polarization by interacting the copartisan indicator variable with the difference in party feeling thermometers. For comparison, I also display the relationship between the CAMCE of copartisanship and ideological congruence. I expect that more affectively polarized politicians should have larger treatment effects, if they truly hate the opposing party and feel more warmly toward their own.

Figure 2: Conditional Average Marginal Component Effects of Copartisanship




Note: Marginal effects from a regression of a choice indicator variable on an indicator variable for copartisanship, interacted with (a) affective polarization and (b) ideology.

As we can see in Figure 2, more affectively polarized state legislative candidates are more likely to discriminate in favor of their copartisans when legislating. Similarly, those whose ideology more closely matches their party affiliation are also more likely to discriminate in favor of their party. The variation in the CAMCE of copartisanship is larger for affective polarization than for ideological congruence, suggesting that affective polarization may be more strongly associated with effect of copartisanship than ideology alone. Substantively, these results indicate that the least affectively polarized candidates are only slightly more likely to work with a copartisan legislator, on average; however, the most affectively polarized individuals are more than 35 percentage points more likely to choose their copartisan legislator.

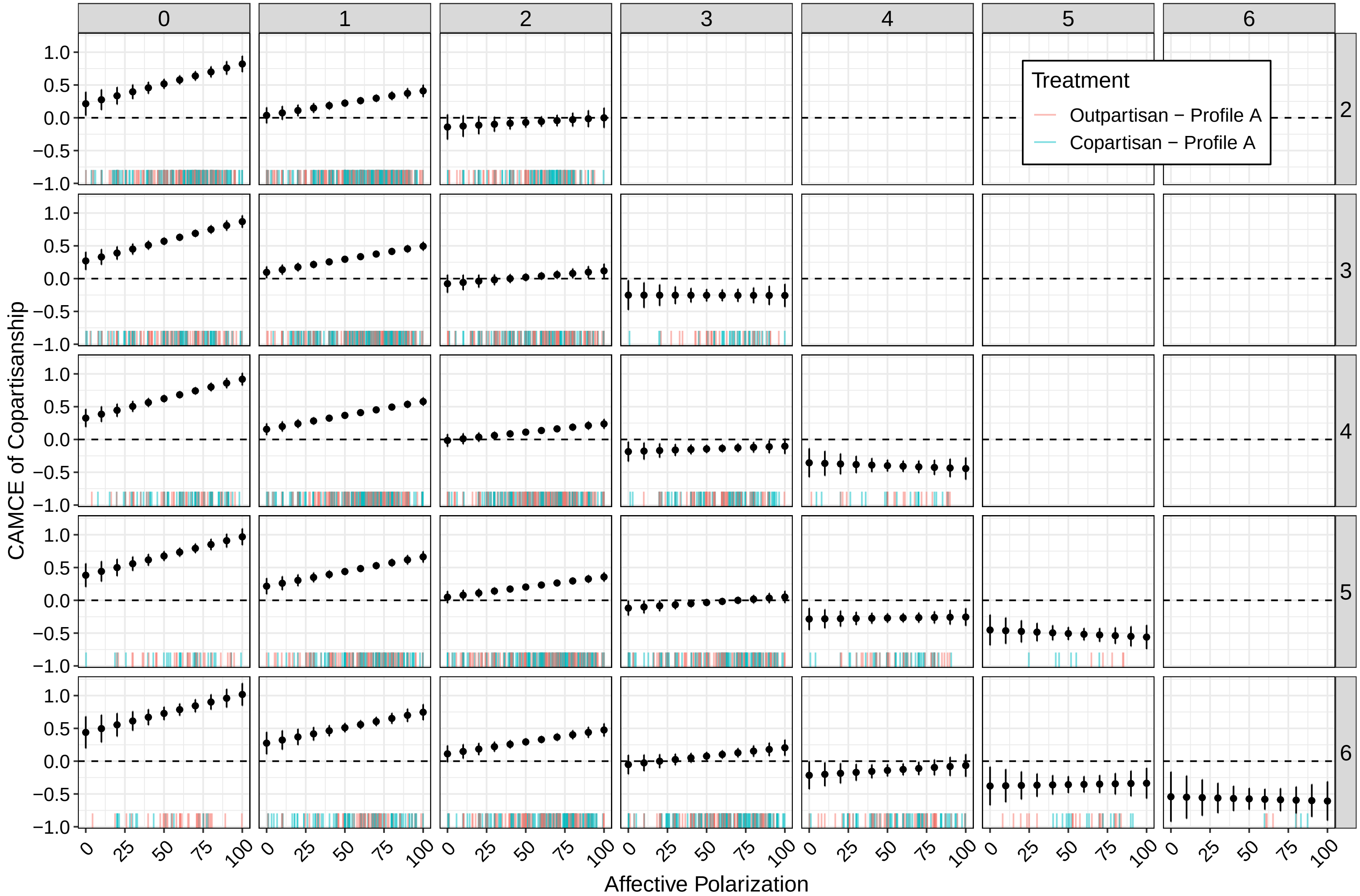
## Alternative Explanations

One concern with these results might be that partisanship is serving as a cue for policy positions, so candidates are merely assuming that they would be more likely to find common ground with a copartisan legislator. The design of my conjoint experiment allows me to test for this possibility, as I randomized both the number of issue positions displayed for each pair and the content of the issue positions at the profile level. Thus, I can see how the effect of copartisanship varies with the issue positions of the profiles.

As a conservative test of the role of affective polarization in partisan discrimination, I examine the relative preference of respondents for copartisans, conditional the number of issues displayed and the congruence of the issue positions with the conjoint profile's partisanship. For example, I estimate the effect of switching from a Democratic profile with six conservative policy positions to a Republican profile with six liberal policy positions on Republican respondents' choice probabilities. This is an especially tough test of my hypothesis because the inparty profile has policy positions which are likely inconsistent with the respondent's, *and* the outparty profile being compared has policy positions which are likely consistent with those of the respondent: there are, at most, 12 pieces of policy information which are incongruent with partisanship. In Appendix B.3 and Appendix B.4, I show that my results are robust to alternative issue codings and to excluding individual issues altogether.

The CAMCE estimates of copartisanship on affective polarization and issue positions are shown in Figure 3. First, policy positions are undoubtedly related to the willingness of state legislative candidates to work with members of opposing parties. As more incongruent policy information about the inparty and outparty legislators' profiles is presented, candidates become more likely to favor the outparty profile over the inparty profile. Interestingly, however, even when the candidates are expected to agree with the outparty profile on six policy positions and to disagree with the inparty profile on all six policy positions, they still choose the inparty profile more than 20% of the time on average. This suggests that politicians' choices of legislative partners are not driven entirely by policy. Second, across 21 of the 25 panes in the figure, the CAMCE of copartisanship is larger for more affectively polarized individuals. While we should be careful overinterpreting any given pane due to potential nonlinearities and potential lack of overlap in the data, it appears that more affectively polarized politicians are more likely to discriminate against opposing partisan legislators—even with high levels of policy information. That said, with larger amounts of party-incongruent policy information, the gap in treatment effects between more affectively polarized candidates and less affectively polarized candidates is smaller than with less policy information, suggesting that policy matters for the affective discrimination gap in partisan discrimination.

Figure 3: CAMCEs of Copartisanship by Issue Positions and Affective Polarization

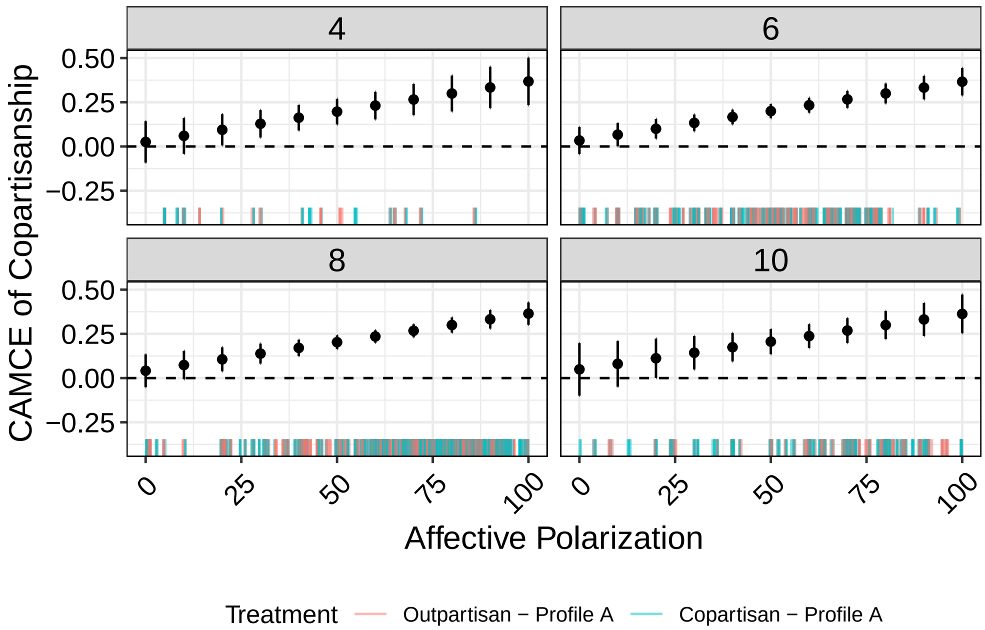



Note: Copartisan CAMCE estimates from regressions of a choice indicator variable on an indicator variable for copartisanship, interacted with affective polarization, the number of issue positions, and the number of issue positions incongruent with the profile's partisanship. The vertical axis of the grid corresponds to the number of issue positions displayed for the profile pair, and the horizontal axis indicates the number of party-incongruent issue positions.

Finally, I show that the relationship between affective polarization and the effect of copartisanship is robust to a variety of alternative theories of legislative behavior. If partisanship and affective polarization are purely proxies for ideology, we should see the relationship between affective polarization and the CAMCE of copartisanship dissipate after accounting for ideological congruence. Contrary to this prediction, in Figure 4, I show that the strong relationship between affect and partisan discrimination holds across the spectrum of ideological congruence, meaning that this discrimination cannot simply be explained by the respondent's ideology. Electoral theories of legislative behavior would suggest that politicians in competitive primaries should be more likely to discriminate in favor of their party to head off future primary challenges (Anderson, Butler and Harbridge-Yong, 2020). Interestingly, Figure 5 shows, overall, that partisan discrimination in lawmaking behavior does not appear to vary by primary election vote margins. Rather, it seems that partisan discrimination in legislatures is strongly related to affective polarization and may not be driven solely by fear of the primary electorate.

The literature on responsiveness suggests that we should expect politicians in competitive general elections to exhibit more bipartisan behavior and to engage in less partisan discrimination (Bafumi and Herron, 2010; Canes-Wrone, Brady and Cogan, 2002; Harbridge, 2015). Yet, the results shown in Figure 5 indicate that those who had the most competitive general elections in 2022 appear to discriminate on the basis of partisanship more than those who had less competitive general elections. This seems inconsistent with traditional electoral accounts of bipartisanship in legislatures: previous research shows that more marginal candidates tend to exhibit more bipartisanship Harbridge (2015). While this pattern seems worthy of further investigation, overall, Figure 5 confirms that the relationship between affect and partisan discrimination persists across different electoral conditions. Indeed, the most affectively polarized politicians have the largest CAMCEs of copartisanship in both marginal districts and safe districts.

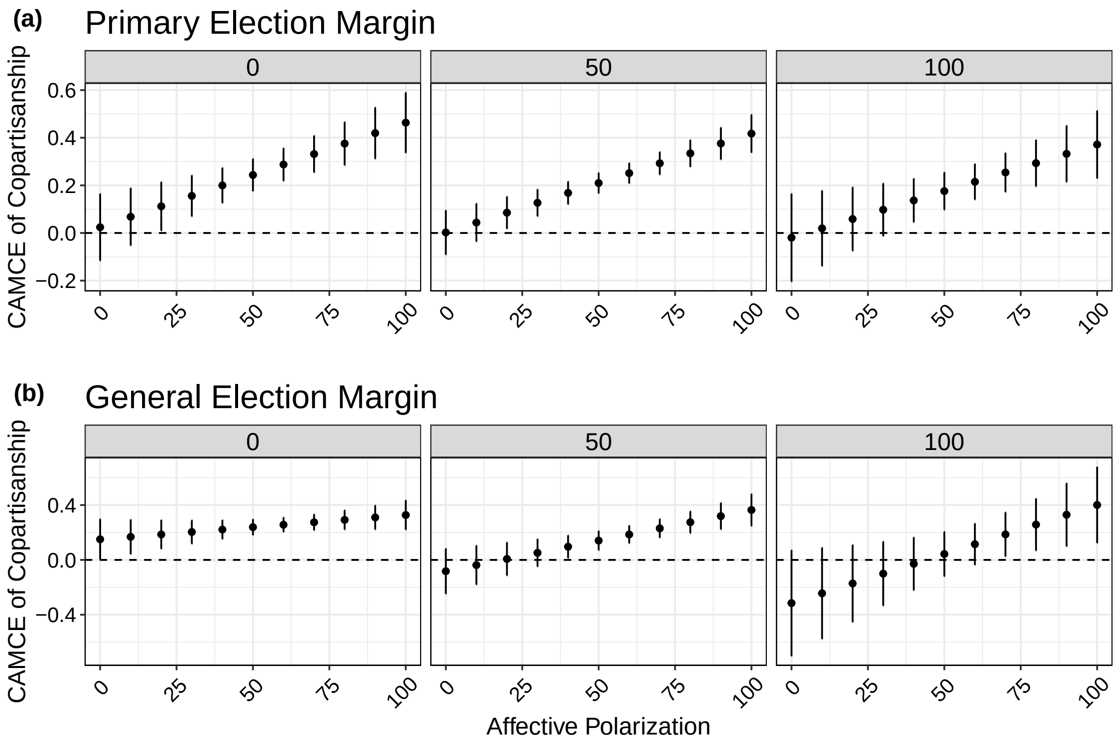
Figure 4: CAMCEs of Copartisanship for Ideology and Affective Polarization




Note: Copartisan CAMCE estimates from regressions of a choice indicator variable on an indicator variable for copartisanship, interacted with affective polarization and ideological congruence with the respondent's party. A value of 0 indicates that the respondent's ideological identification matches the other party, while a value of 10 indicates that the respondent's ideology matches their own party.

We might think that politicians concerned about passing policy would be more likely to discriminate on the basis of partisanship if it will help them pass policy: if the opposing party controls all the levers of the government in their state, they will have to work with the opposing party to pass policy. Instead, in Figure 6, we see robust relationships between affective polarization and discrimination against the opposing party in the legislative process across all configurations of state governmental control. Candidates do appear more likely to discriminate in favor of their own party when their party controls the legislature and the governor's office, but even when the opposing party controls the legislature and governorship, the most affectively polarized politicians discriminate against the opposing party in the policy process.

Figure 5: CAMCEs of Copartisanship by Electoral Competition

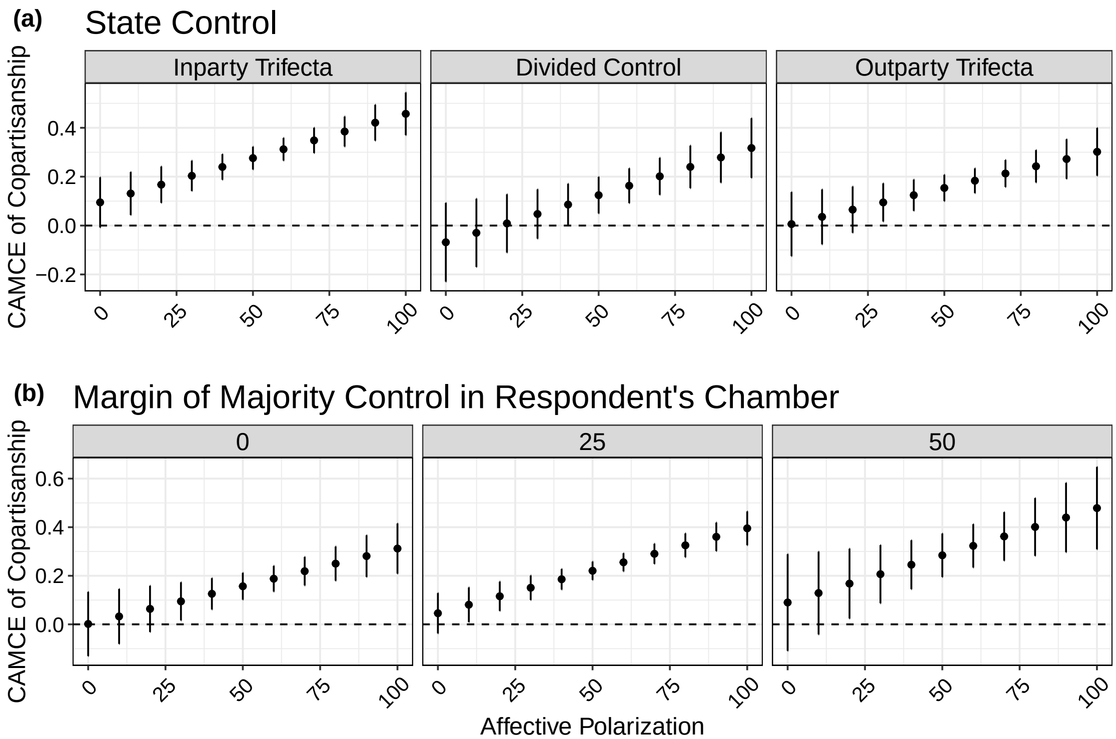



Note: Copartisan CAMCE estimates from regressions of a choice indicator variable on an indicator variable for copartisanship, interacted with affective polarization and candidate electoral margins in the primary (panel A) or general election (panel B). Margins closer to 0 indicate more competitive elections.

## Causal Forests

The results in the previous section show that affective polarization is an important and consistent predictor of partisan discrimination in lawmaking behavior in the conjoint experiment. These results have two limitations, however: (1) they rely on restrictive (and potentially incorrect) assumptions of linearity, and (2) they rely on correct specifications of interactions. To address these concerns, I re-estimate the CAMCEs of the copartisan variable using causal forests (Wager and Athey, 2018). Causal forests rely on the random forest framework, a nonparametric machine learning algorithm, to determine the best splits in the data for predicting treatment effect heterogeneity. Thus, causal forests can handle both nonlinear relationships in the data as well as complex interactions between variables.

Figure 6: CAMCEs of Copartisanship by Control of State Government

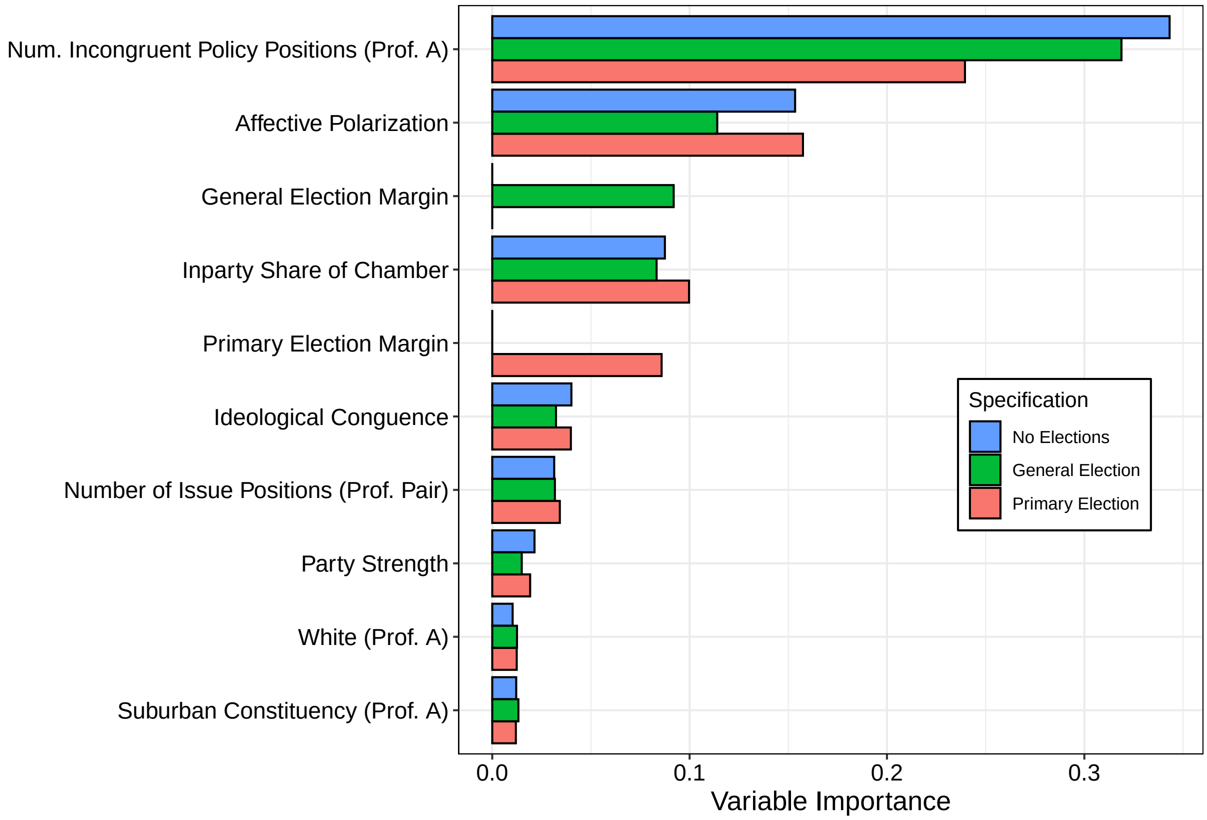



Note: Copartisan CAMCE estimates from regressions of a choice indicator variable on an indicator variable for copartisanship, interacted with affective polarization and measures of state government control. In panel A, control of state government is measured by control of the different branches (trifecta or divided control). In panel B, control is measured by the size of the majority in the respondent's chamber of the state legislature.

I fit causal forest models using key predictor variables from the above analyses, including individual covariates, state-level covariates, and characteristics of profile A. As we can see in Figure 7, across three separate specifications, affective polarization is the second most important predictor of the CAMCE of copartisanship. The most important predictor is consistently the number of party-incongruent policy positions assigned to profile A. Even after accounting for potentially complex interactions and nonlinear relationships in the data, affective polarization is still a strong predictor of partisan discrimination.

As a final test of my hypothesis, I plot out-of-bag CAMCE predictions from the causal forest fit above against affective polarization and policy information. The causal forest

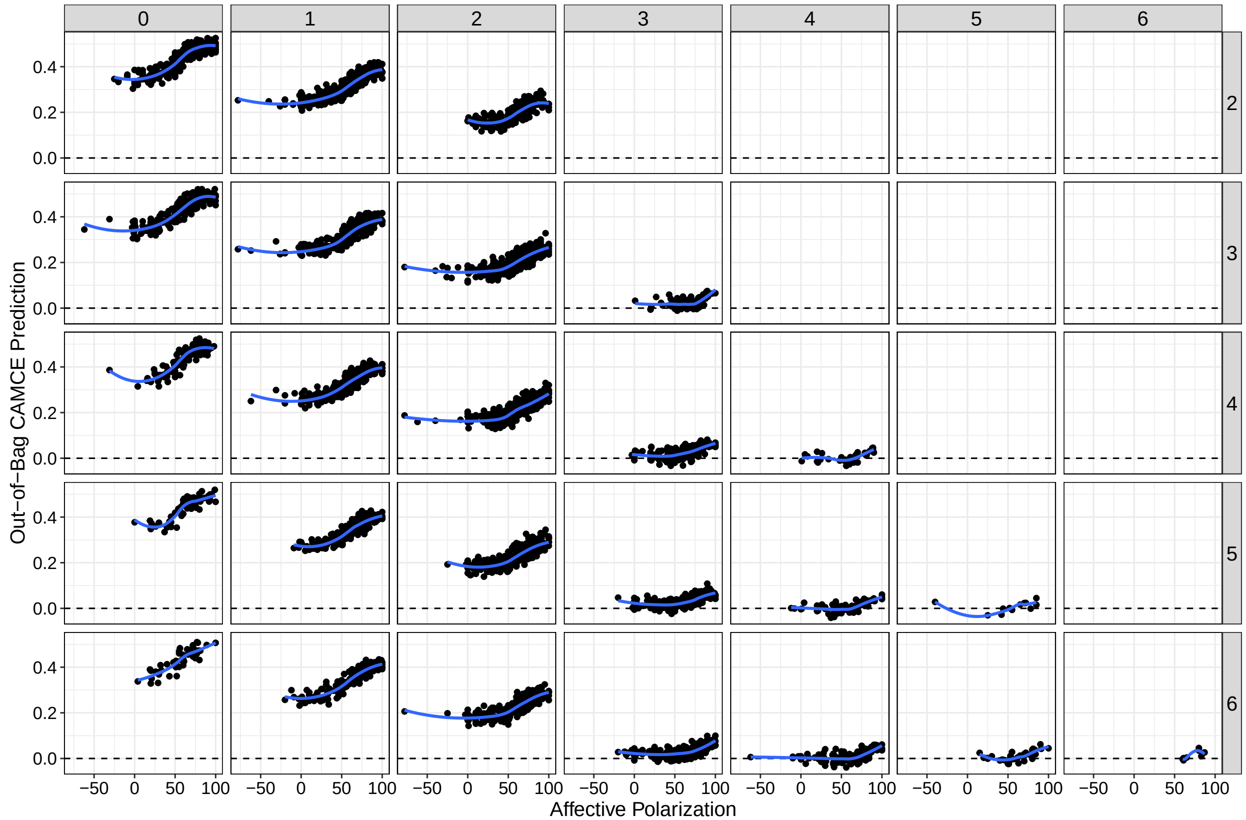
Figure 7: Causal Forest Variable Importance




Note: Variable importance from causal forest fit. Higher values indicate that variables are more important predictors of the conditional average marginal component effect of copartisanship. The primary election specification reflects causal forest fits including primary election margins. The general election specification is based on causal forest fits including general election margins. The no elections specification is based on causal forest fits without the general or primary election variables. The 10 variables with the highest median variable importance scores are shown here for space.

results largely confirm the findings in the previous section; however, there does appear to be some nonlinearity in the relationship between affective polarization and the CAMCE of copartisanship, displayed in Figure 8. In the figure, we can see that the most affectively polarized individuals have the largest predicted CAMCEs (i.e., more affectively polarized individuals are more likely to discriminate against opposing partisans in the policy process—even after accounting for policy information).

Figure 8: Out-of-Sample CAMCE Predictions




Note: Out-of-Bag CAMCE predictions from the causal forest specification with no electoral variables. Electoral variables were omitted to avoid discarding large portions of the sample who appeared in a primary but not a general election or vice versa. The vertical axis of the grid corresponds to the number of issue positions displayed for the profile pair, and the horizontal axis indicates the number of issue positions which are incongruent with the party of profile A. Blue lines fit using LOESS.

# Discussion and Conclusion

Throughout this paper, I presented findings from a conjoint experiment embedded in a survey of state legislative candidates. The results of this experiment show that politicians discriminate against members of the opposing party when choosing their legislative partners. This discrimination is more pronounced among the most affectively polarized politicians: those who express colder feelings toward the opposing party and warmer feelings toward their own appear less willing to work with opposing partisans in the legislature. The relationship between affective polarization and partisan discrimination holds across different levels of competitiveness in both the primary and general elections as well as across different configurations of state partisan control. Contrary to existing theories of legislative behavior, decisions in the policy-making process do not appear wholly conditional on strategic electoral or policy calculations. Moreover, ideological congruence does not appear to condition the relationship between affect and partisan discrimination. Affectively polarized politicians whose ideological identification is incongruent with their party are just as likely to discriminate as affectively polarized politicians with congruent ideological identifications.

Building on previous work (Peterson, 2017; Mummolo, Peterson and Westwood, 2019; Orr, Fowler and Huber, 2023), I find that policy is the most important predictor of partisan discrimination. Partisan discrimination does appear to result, in large part, from policy cues associated with party labels. Comparing an inparty profile with six outparty policy positions to an outparty profile with six inparty policy positions (12 pieces of policy incongruent information), politicians are more likely to work with the opposing partisan. Still, even with fairly high levels of policy information, more affectively polarized politicians are more likely to favor their copartisan legislator than are less affectively polarized politicians. At low levels of policy information and high levels of party-congruent policy information (i.e., what is most likely to occur in real legislatures), affectively polarized candidates are highly likely to discriminate on the basis of partisanship. My results, then, suggest that affective polarization and partisan identities are an important part of understanding legislative behavior. In particular, declining bipartisanship in Congress may not be explained by policy disagreement alone but also by increasing affective polarization.

In this paper, I contribute to a long line of research on the motivations and behavior of legislators. Previous work has identified reelection (Mayhew, 1974; Anderson, Butler and Harbridge-Yong, 2020), the desire for majority control (Cox and McCubbins, 2005; Lee, 2016), and policy preferences (Fenno, 1973; Krehbiel, 1998) as key predictors of legislative behavior. My results indicate that partisan affect and identities are also important to understand legislative behavior. Future work could explore the environments and conditions under which partisan identities are more important for legislative behavior. For example, does partisan affect matter more in certain institutional settings or at different stages of the policy process? Do less salient policy positions produce similar patterns of partisan discrimination? Further, to what extent does partisan discrimination of this sort contribute to further partisan hostility in legislative bodies?

This work also builds upon a burgeoning literature on affective polarization. Scholars of affective polarization have long focused on mass-level partisans to build and test their theories. Yet, my results suggest that politicians should not be neglected in the study of partisan identity and affect. Politicians are subject to a unique set of circumstances which can be used to build and test new theories of affective polarization. Moreover, factors believed to influence affective polarization among the masses have different configurations among elites, meaning politicians can provide more leverage to test theories of affective polarization.

Overall, I find strong evidence that politicians are influenced by identity and affect in the policy-making process. This finding has important implications for American government and representation. Partisan discrimination does not appear to occur solely or even primarily in response to electoral conditions, raising concerns that the representation constituent interests may be hampered by the partisan identities and affect of legislators.

Moreover, given the importance of bipartisanship to successfully passing policy (Curry and Lee, 2020; Harbridge-Yong, Volden and Wiseman, 2023), my results suggest that partisan affect stands to contribute to legislative gridlock. In sum, then, we should take seriously the possibility that elites, like the masses, are influenced by partisan identities.

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# Contents

# A State Legislative Candidate Survey

## A.1 Survey Details

This survey of state legislative candidates was conducted between May and August of 2023. All state legislative candidates who were listed by Ballotpedia as having sought office in 2022 as a Democrat or a Republican were included in the sampling frame. Contact information was collected from Ballotpedia, Statescape, and Votesmart. Where available, I scraped contact information from each state's candidate filings or campaign finance records. Candidates with valid email addresses were contacted up to three times via email for participation. Candidates without valid emails were contacted either via phone by the Survey Research Center at the University of Alabama Birmingham or via mail. A sample of individuals who did not respond to emails were also contacted by mail or phone. In total, 13,682 individuals were contacted by email; 1,500 were contacted by phone; and 2,300 were contacted with a postcard or letter.

In total, 1,235 individuals completed at least one conjoint choice task (omitting tasks with no selected profile), with respondents completing 4.33 on average. After omitting respondents who identified as pure Independents or declined to self-identify their partisanship, there are 1,217 partisans who completed at least one conjoint task, completing 4.33 tasks on average.

Figure A.1.1: Comparison of Nonrespondents and Respondents

| **Characteristic** | **Nonrespondent**, N = 12,292[1] | **Respondent**, N = 1,448[1] |
|---|---|---|
| General Margin | 4 | -5 |
| Primary Margin | 23 | 20 |
| Gender | | |
| Female | 34% | 34% |
| Male | 66% | 65% |
| Neither/Both | 0.1% | 0.2% |
| State Control | | |
| Dem | 37% | 33% |
| Divided | 17% | 18% |
| N/A | 0.5% | 0.7% |
| Rep | 46% | 48% |
| Democratic Share Senate | 45 | 44 |
| Democratic Share House | 46 | 45 |
| Governor Control | | |
| Dem | 50% | 48% |
| Rep | 50% | 52% |
| Incumbent | 37% | 23% |
| Party | | |
| Dem/Rep | 0.2% | 0% |
| Democrat | 44% | 53% |
| Republican | 56% | 47% |

[1]Mean; %

## A.2 Conjoint Experiment Details

Respondents were randomly assigned to view four or five conjoint choice tasks to maximize power while also minimizing potential attrition due to longer questionnaires. For each choice task, respondents were shown two profiles of hypothetical legislators and asked to choose which they would prefer to work with in the legislature. Both profiles in each choice task had identical amounts of information, with all demographic information shown to all respondents.

To minimize attribute order effects and respondent cognitive load, the order of attributes was randomized at the respondent level. Demographic characteristics were shown at the top of each profile and issue positions were shown at the bottom of each profile.

The attribute order randomization thus occurred within the demographic and issue position sections for each respondent. An example choice task is shown in Figure A.2.1. Following (Peterson, 2017), I randomized party at the choice level, so that each choice task contained one Democratic and one Republican profile. Additionally, I randomized the number of issue positions shown at the choice level, such that between 2 and 6 policy positions were shown for each profile. I also randomized religion, race, party, and abortion issue positions with some mutual dependence to make certain profile combinations less common. For example, I made it less likely that Evangelical Christian and Republican profiles would take extreme liberal abortion positions. The full randomization scheme is shown in Table A.2.1 and Table A.2.2.

Figure A.2.1: Example Conjoint Choice Task

| | **Legislator A** | **Legislator B** |
|---|---|---|
| **Race/Ethnicity** | White | White |
| **Religion** | Evangelical protestant | Catholic |
| **Serves on a Committee with You** | No | No |
| **Education** | College | No college |
| **Age** | 65 | 80 |
| **Constituency Type** | Urban | Urban |
| **Party** | Democrat | Republican |
| Issue Positions: | | |
| **Voter ID Laws** | Supports | Opposes |
| **Environmental Protections** | Keep the same | Increase |
| **Red-Flag Laws for Firearms** | Opposes | Opposes |

**Which legislator would you prefer to work with?**

Legislator A ○ Legislator B ○

Table A.2.1: Randomization Scheme

| Attribute | Potential Values | Randomization Probabilities |
|---|---|---|
| Number of Issues | 2, 3, 4, 5, 6 | Uniform (Choice-Level) |
| Issues | Abortion, Environmental Protections, Government Spending, Red-Flag Laws, Sanctuary Cities, School Vouchers, Voter ID Laws | Uniform, Conditional on Number of Issues (Respondent-Level Order and Choice-Level Inclusion) |
| Party | Democrat, Republican | Uniform (Choice-Level) |
| Age | 26, 35, 47, 58, 65, 80 | Uniform |
| Constituency Type | Urban, Rural, Suburban | Uniform |
| Education | No college, Community college, College, Graduate degree | Uniform |
| Same Committee as Respondent | Yes, No | Uniform |
| Race/Ethnicity | White | 0.5 |
| | Black | 0.2 |
| | Hispanic | 0.2 |
| | Asian American | 0.1 |
| Religion | Evangelical protestant\|Race/Ethnicity=Hispanic | 0.2 |
| | Mainline protestant\|Race/Ethnicity=Hispanic | 0.1 |
| | Catholic\|Race/Ethnicity=Hispanic | 0.5 |
| | None\|Race/Ethnicity=Hispanic | 0.2 |
| | Evangelical protestant\|Race/Ethnicity=Asian American | 0.15 |
| | Mainline protestant\|Race/Ethnicity=Asian American | 0.15 |
| | Catholic\|Race/Ethnicity=Asian American | 0.2 |
| | Muslim\|Race/Ethnicity=Asian American | 0.15 |
| | Hindu\|Race/Ethnicity=Asian American | 0.15 |
| | None\|Race/Ethnicity=Asian American | 0.2 |
| | Evangelical protestant\|Race/Ethnicity=Black | 0.1 |
| | Mainline protestant\|Race/Ethnicity=Black | 0.5 |
| | Catholic\|Race/Ethnicity=Black | 0.1 |
| | Muslim\|Race/Ethnicity=Black | 0.1 |
| | None\|Race/Ethnicity=Black | 0.2 |
| | Evangelical protestant\|Race/Ethnicity=White | 0.3 |
| | Mainline protestant\|Race/Ethnicity=White | 0.2 |
| | Catholic\|Race/Ethnicity=White | 0.2 |
| | Jewish\|Race/Ethnicity=White | 0.1 |
| | None\|Race/Ethnicity=White | 0.2 |

Table A.2.2: Randomization Scheme for Issue Positions

| Attribute | Potential Values | Randomization Probabilities* |
|---|---|---|
| Environmental Protections | Increase, Keep the same, Decrease | Uniform |
| Government Spending | Reduce, Keep the same, Increase | Uniform |
| Red-Flag Laws for Firearms | Supports, Opposes | Uniform |
| Sanctuary Cities | Supports, Opposes, Opposes, but opposes cutting funding | Uniform |
| School Vouchers | Supports, Opposes | Uniform |
| Voter ID Laws | Supports, Opposes | Uniform |
| Abortion | No restrictions\|Republican or Evangelical | 0.1 |
| | Restore pre-Roe laws\|Republican or Evangelical | 0.3 |
| | Restrict with exceptions for rape, incest, and to protect the life of the mother\|Republican or Evangelical | 0.3 |
| | Completely ban and criminally charge\|Republican or Evangelical | 0.3 |
| | No restrictions\|Democrat and !Evangelical | 0.3 |
| | Restore pre-Roe laws\|Democrat and !Evangelical | 0.3 |
| | Restrict with exceptions for rape, incest, and to protect the life of the mother\|Democrat and !Evangelical | 0.3 |
| | Completely ban and criminally charge\|Democrat and !Evangelical | 0.1 |

*Probabilities conditional on inclusion of the issue in the choice task.

## A.3 Identification and Estimation of the AMCE and CAMCE

Due to the somewhat interdependent randomization scheme, I estimated the treatment effect of party using inverse probability of treatment weighting, wherein I weighted by the inverse probability of party, conditional on profile attributes (Gerber and Green, 2012; de la Cuesta, Egami and Imai, 2022). The necessary probabilities were calculated as follows:

$$Pr(P_1 = x|N, I, R_1, Rel_1, IP_1, R_2, Rel_2, IP_2) = \frac{Pr(P_1 = x, N, I, R_1, Rel_1, IP_1, R_2, Rel_2, IP_2)}{Pr(P_1 = x, N, I, R_1, Rel_1, IP_1, R_2, Rel_2, IP_2) + Pr(P_1 \neq x, N, I, R_1, Rel_1, IP_1, R_2, Rel_2, IP_2)}$$

$P_1$ is the party of profile 1. $N$ is the number of issue positions shown. $I$ denotes the specific issues shown. $R_1$ and $R_2$ indicate the race and ethnicity of profiles 1 and 2, respectively. $Rel_1$ and $Rel_2$ indicates the religions of profiles 1 and 2, respectively. Finally, $IP_1$ and $IP_2$ indicate the issue positions of profiles 1 and 2, respectively.

The joint probabilities were calculated using the following probabilities:

$$\begin{aligned}
&Pr(P_1 = x, N, I, R_1, Rel_1, IP_1, R_2, Rel_2, IP_2) = \\
&Pr(P_1 = x) * Pr(N) * Pr(I|N) * Pr(R_1) * Pr(Rel_1|R_1) * Pr(IP_1|P_1, I, Rel_1)* \\
&Pr(R_2) * Pr(Rel_2|R_2) * Pr(IP_2|P_1, I, Rel_2)
\end{aligned}$$

Since $Pr(P_1 = x) = 0.5$, for $x \in [Democrat, Republican]$, the conditional probability of party depends only on $Pr(IP_1|P_1, I, Rel_1) * Pr(IP_2|P_1, I, Rel_2)$ and can thus be calculated as:

$$Pr(P_1 = x|N, I, R_1, Rel_1, IP_1, R_2, Rel_2, IP_2) = \frac{Pr(IP_1|P_1 = x, I, Rel_1) * Pr(IP_2|P_1 = x, I, Rel_2)}{Pr(IP_1|P_1 = x, I, Rel_1) * Pr(IP_2|P_1 = x, I, Rel_2) + Pr(IP_1|P_1 \neq x, I, Rel_1) * Pr(IP_2|P_1 \neq x, I, Rel_2)}$$

For all issue positions except abortion, $P_1 \perp\!\!\!\perp \{IP_1, IP_2\}$, and as a result, for these other issues,

$$Pr(P_1 = x|N, I, R_1, Rel_1, IP_1, R_2, Rel_2, IP_2) = Pr(P_1 = x) = 0.5.$$

Using well-known properties of propensity scores (see e.g., Imbens and Rubin, 2015),

$$P_1 \perp\!\!\!\perp \{T_{ijk[-l]}, T_{i[-j]k}\}|Pr(P_1|T_{ijk[-l]}, T_{i[-j]k})$$

Following Hainmueller, Hopkins and Yamamoto (2014), $T_{ijk[-l]}$ is the sub-vector of profile attributes $-l$ for respondent $i$ on profile $j$ for choice task $k$, not including the main treatment $l$ which is party here. Further, $T_{i[-j]k}$ is the vector of attributes of the other profile $-j$ for respondent $i$ on choice task $k$.

Due to the conditional independence of party from other attributes, I am able to estimate the Average Marginal Component Effect using linear regression, weighted by the inverse probability of treatment (Hainmueller, Hopkins and Yamamoto, 2014; de la Cuesta, Egami and Imai, 2022). The same logic holds for the identification of the AMCE, conditional on other profile attributes and respondent characteristics: due to randomization of the profile attributes,

$$P_1 \perp\!\!\!\perp \{Y_{ij1}(1), Y_{ij1}(0), X_i\} | Pr(P_1 | T_{ijk[-l]}, T_{i[-j]k})$$

In short, treatment is independent of potential outcomes and respondent covariates, which allows for the straightforward estimation of the CAMCE, using inverse probability of treatment weighting in regression.

Due to the perfect negative correlation between the party of profile 1 and the party of profile 2 as well as the respondent's profile choice on a given task, I examine $Y_{ij1}$ instead of $Y_{ijk}$. This choice does not substantively affect the point estimates of the AMCE because $Y_{ij1}$ and $Y_{ij2}$ are perfectly negatively related within the choice task, as are $Party_{ij1}$ and $Party_{ij2}$.

To estimate the AMCE of copartisanship, I run the following linear regression:

$$Y_{ij1} = \alpha + \beta * Copartisan_{ij1} + \varepsilon_i$$

This regression is weighted using the inverse of the conditional probability of party discussed above, and errors are clustered at the respondent level. $Y_{ij1}$ is an indicator variable for whether the respondent chose the first profile in the task, and $Copartisan_{ij1}$ is an indicator for whether the first profile was a copartisan profile.

From here, it is straightforward to estimate the best linear approximation of the CAMCE by running linear regressions of the following form:

$$Y_{ij1} = \alpha + \beta * Copartisan_{ij1} + \gamma * X_i + \theta * Copartisan_{ij1} * X_i + \varepsilon_i$$

Again, these regressions cluster errors at the respondent level, and weight by the propensity score. The CAMCE is then estimated as the marginal effect of copartisanship at different levels of the variable or variables $X_i$, using the `marginaleffects` package in R (Arel-Bundock, 2023).

## A.4 Causal Forests

Causal forests are a nonparametric algorithm for estimating heterogeneous treatment effects. They are based on the classification and regression tree (CART) and random forest frameworks of (Breiman et al., 1984; Breiman, 2001). The main difference is that causal forests are designed to detect treatment effect heterogeneity rather than predict outcomes per se. Specifically, the causal tree algorithm developed by Athey and Imbens (2016) builds trees by selecting splits in the data which generate the most treatment effect heterogeneity between leaves, subject to the constraint that there are a minimum number of treated and control observations in each leaf. Causal forests repeat this process multiple times on random subsamples of the data (taken without replacement), and each split is chosen using a random sample of variables. Further, the authors employ "honest estimation" in which the subsample is split in two; one subset of the subsample is used to build the tree, and the other subset is used to estimate the leaf treatment effects (Wager and Athey, 2018). Splitting the subsample into training and estimation samples helps to ensure that the estimated conditional average treatment effects are consistent for the true effects (Wager and Athey, 2018).

One of the benefits of the tree-based framework for the estimation of heterogeneous treatment effects is that trees naturally incorporate nonlinear functional forms and complex interactions between variables. In essence, causal forests learn the most predictive functional form from the data, helping to mitigate some of the challenges of potentially incorrect model specifications. Because of the conditional independence of the partisan treatment from other treatments and from individual potential outcomes given propensity scores, the CAMCE is estimated in the same way as a standard conditional average treatment effect. This means we can use causal forests to estimate the CAMCE, after providing the propensity score.

Causal forests are fit using the `grf` package (Athey, Tibshirani and Wager, 2019). Clustered subsampling for tree building is conducted by drawing a subsample of respondents without replacement. $K$ choice tasks are sampled randomly for each individual, where $K$ is the minimum number of choice tasks for any respondent in a given subsample. I grow 4,000 trees for each forest and provide propensity scores as described in Appendix A.3. The specific covariates used in training are shown in Table A.4.3. Categorical variables were one-hot encoded (i.e., there was one indicator variable for each category).

Variable importance is calculated as the weighted number of times a variable is used to determine splits at a given tree depth, weighting splits at a shallow depth more heavily. Intuitively, this captures how "important" a given covariate is for predicting treatment effect heterogeneity. The CAMCEs were estimated by taking out-of-bag predictions from the causal forests. In other words, each individual estimate was constructed using only trees which were not trained using that individual observation.

Table A.4.3: Causal Forest Model Covariates

| Covariate Type | Covariates |
|---|---|
| Profile 1 | Age, Constituency Type, Education, Race/Ethnicity, Religion, Serves on a Committee with You |
| Respondent | Affective Polarization, Party Strength, Ideological Congruence with Party, Education, Age, Religion, Party ID (D vs. R), Race/Ethnicity, General Election Margin*, Primary Election Margin* |
| State | Inparty's Share of Respondent Chamber, Gubernatorial Control (D vs. R), State House Control (D vs. R), State Senate Control (D vs. R) |

*Only where noted.

# B Robustness Checks

Table B.0.4: Map of Original Figures to Appendix Replications

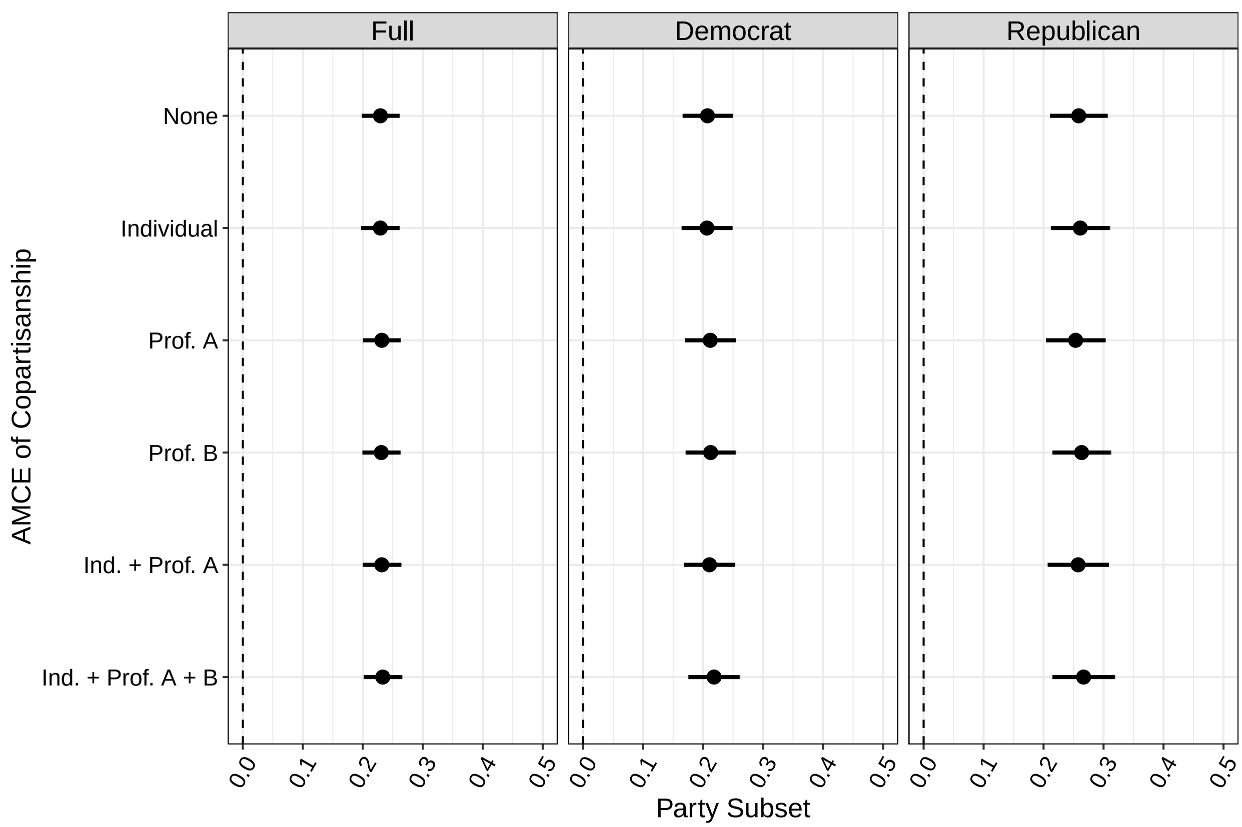
| Estimand | Original Figure | Covariates | Party Results | Issue Coding | Issues | Nebraska's Partisanship | Random Seed | Missing Choices |
|---|---|---|---|---|---|---|---|---|
| AMCE | Figure 1 | Figure B.1.1 | — | — | Figure B.4.1 | — | Figure B.6.1 | Figure B.7.1 |
| CAMCE: Affect | Figure 2 | Figure B.1.2<br>Figure B.1.3 | Figure B.2.1 | — | Figure B.4.2<br>Figure B.4.3 | — | Figure B.6.2 | Figure B.7.2 |
| CAMCE: Affect and Issues | Figure 3 | Figure B.1.4<br>Figure B.1.5<br>Figure B.1.6<br>Figure B.1.7<br>Figure B.1.8 | Figure B.2.3 | Figure B.3.1 | Figure B.4.4<br>Figure B.4.5<br>Figure B.4.6<br>Figure B.4.7<br>Figure B.4.8<br>Figure B.4.9<br>Figure B.4.10 | — | Figure B.6.3 | Figure B.7.3 |
| CAMCE: Affect and Ideology | Figure 4 | Figure B.1.9 | Figure B.2.4 | — | Figure B.4.11 | — | Figure B.6.4 | Figure B.7.4 |
| CAMCE: Affect and Elections | Figure 5 | Figure B.1.10<br>Figure B.1.11 | Figure B.2.5<br>Figure B.2.6 | — | Figure B.4.12<br>Figure B.4.13 | Figure B.5.1 | Figure B.6.5 | Figure B.7.5 |
| CAMCE: Affect and Government Control | Figure 6 | Figure B.1.12<br>Figure B.1.13 | Figure B.2.7<br>Figure B.2.8 | — | Figure B.4.14<br>Figure B.4.15 | — | Figure B.6.6 | Figure B.7.6 |
| Variable Importance | Figure 7 | Figure B.1.14 | Figure B.2.9<br>Figure B.2.10 | Figure B.3.2 | Figure B.4.16<br>Figure B.4.17<br>Figure B.4.18<br>Figure B.4.19<br>Figure B.4.20<br>Figure B.4.21<br>Figure B.4.22 | Figure B.5.2 | Figure B.6.7 | Figure B.7.7 |
| Causal Forest CAMCE | Figure 8 | Figure B.1.15 | Figure B.2.11<br>Figure B.2.12 | Figure B.3.3 | Figure B.4.23<br>Figure B.4.24<br>Figure B.4.25<br>Figure B.4.26<br>Figure B.4.27<br>Figure B.4.28<br>Figure B.4.29 | Figure B.5.3 | Figure B.6.8 | Figure B.7.8 |

## B.1 Robustness to Covariates

In this section, I show that my results are robust to the inclusion of covariates, including individual covariates as well as covariates for the characteristics of Profiles 1 and 2. The individual covariates are education, age, religion, ideology, three-category party identification, and race and ethnicity. Profile 1 and profile 2 covariates are race and ethnicity, religion, age, constituency type, education, and an indicator for whether the profile serves on a committee with the respondent. I fit models using only covariates for individuals, profile 1, and profile 2 separately. I also fit models using covariates for individuals and profile 1 and models using covariates for individuals, profile 1, and profile 2. All of the results including covariates are substantially similar to the specifications without covariates reported in the main text.

### B.1.1 AMCE Results

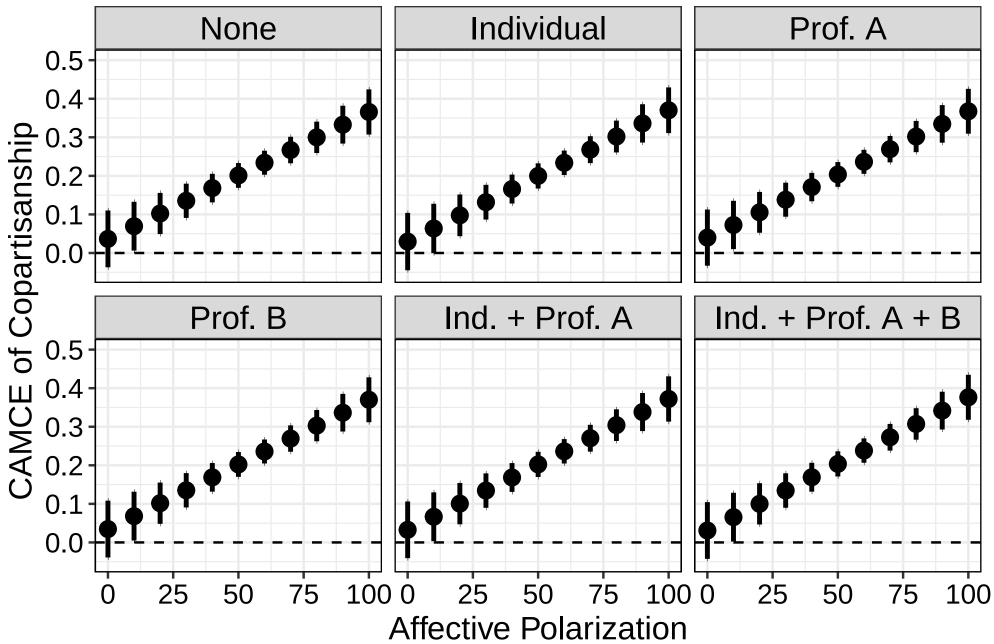
Figure B.1.1: AMCE of Copartisanship by Party




Note: Estimates from models fit using no covariates, individual covariates, covariates for Profile A, covariates for Profile B, and combinations thereof.

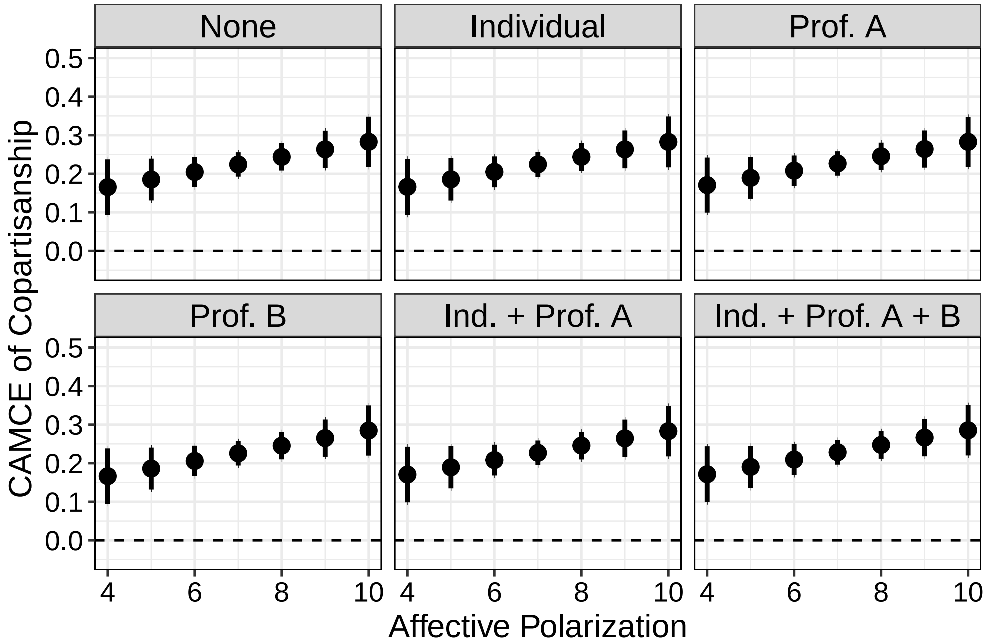
### B.1.2 Simple CAMCE Results

Figure B.1.2: CAMCE of Copartisanship by Affective Polarization




Note: Estimates from models fit using no covariates, individual covariates, covariates for Profile A, covariates for Profile B, and combinations thereof.

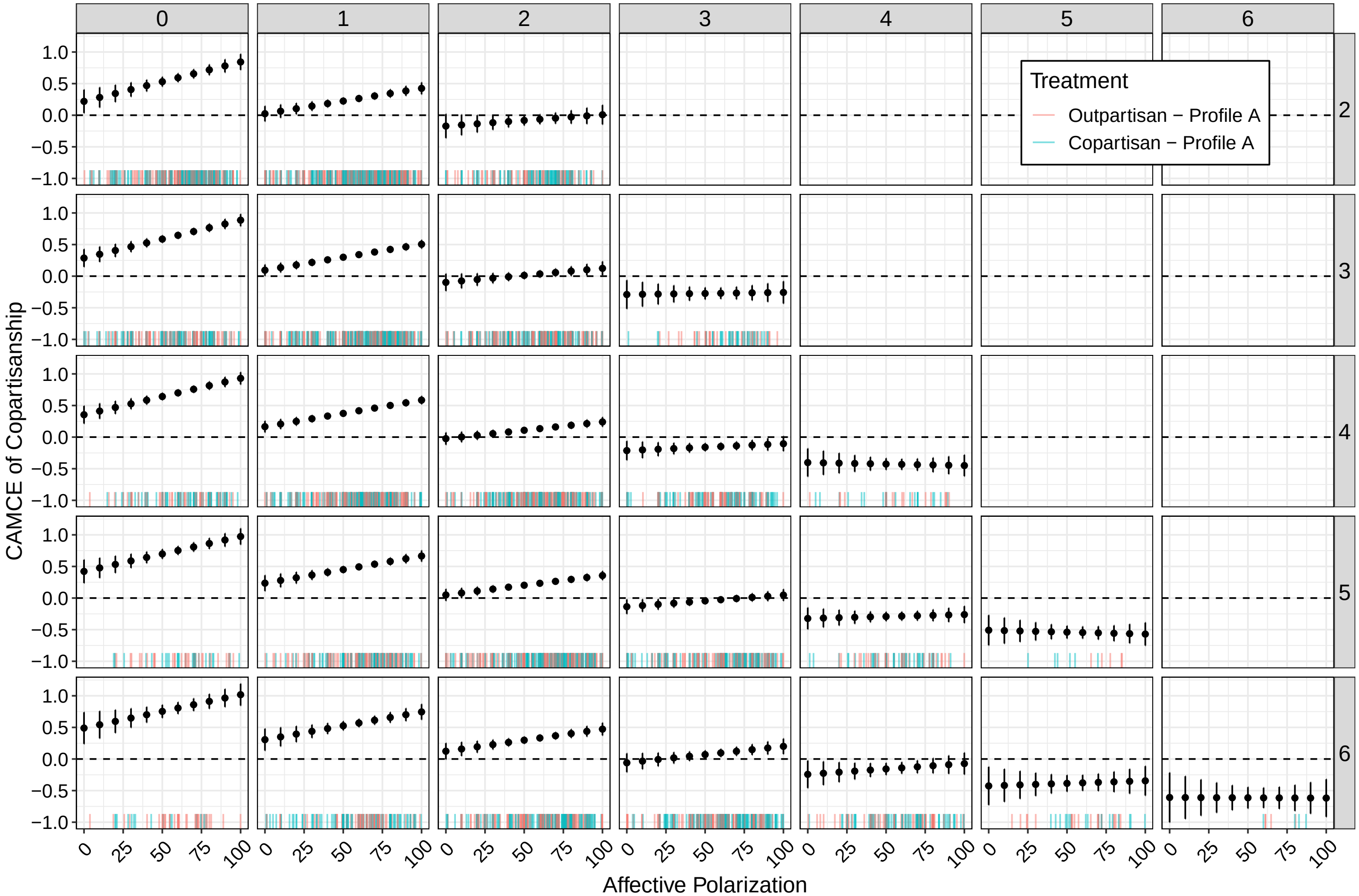
Figure B.1.3: CAMCE of Copartisanship by Ideological Congruence




Note: Estimates from models fit using no covariates, individual covariates, covariates for Profile A, covariates for Profile B, and combinations thereof.

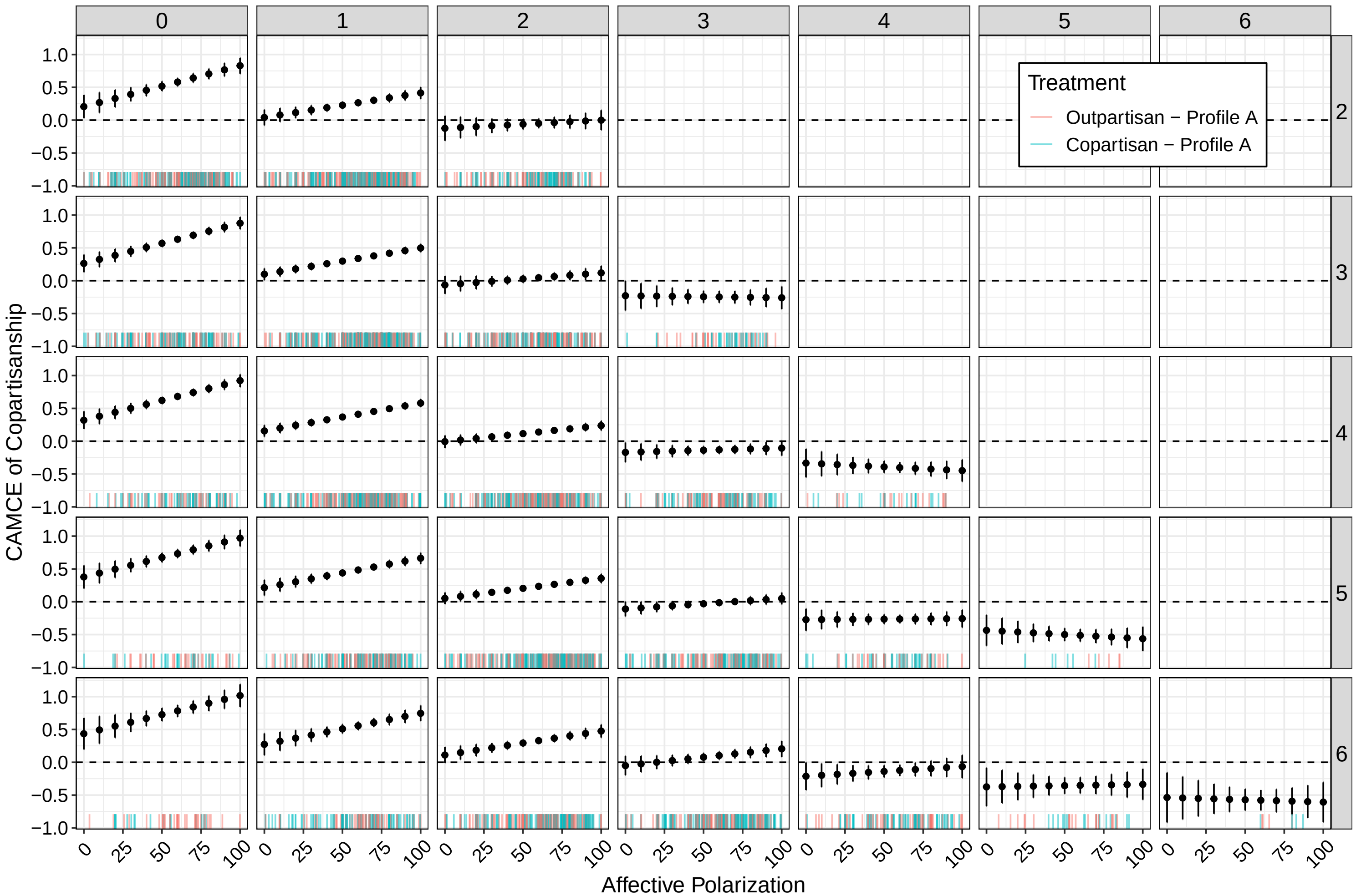
### B.1.3 CAMCE Results by Affect and Issue Content

Figure B.1.4: CAMCE of Copartisanship by Issue Content (Individual Covariates)



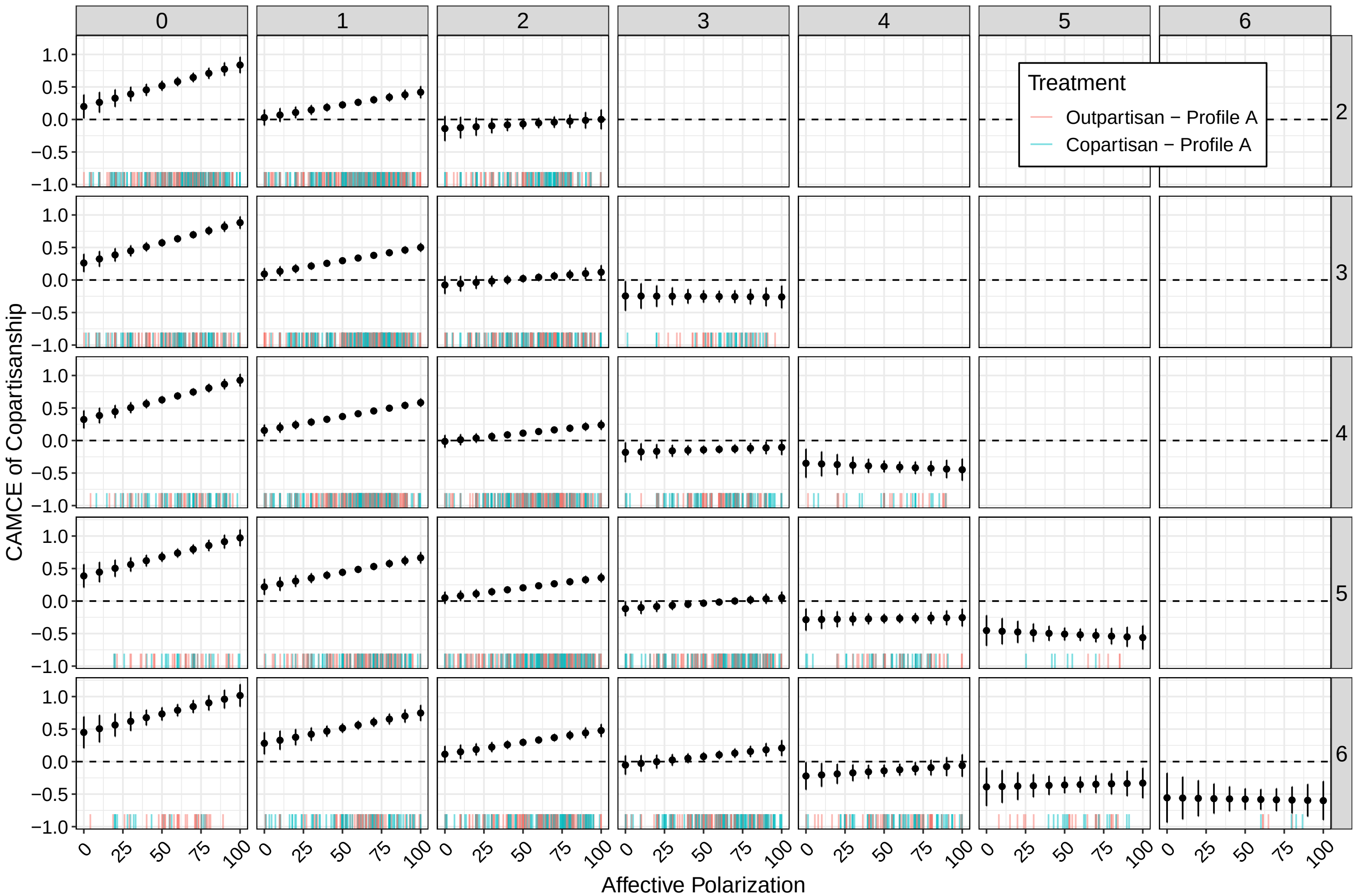

Note: CAMCE estimates from models fit with individual covariates. The vertical pane axis shows the number of issues shown for the profile pair, while the horizontal pane axis shows the number of party-incongruent issue positions shown for profile A.

Figure B.1.5: CAMCE of Copartisanship by Issue Content (Profile A Covariates)



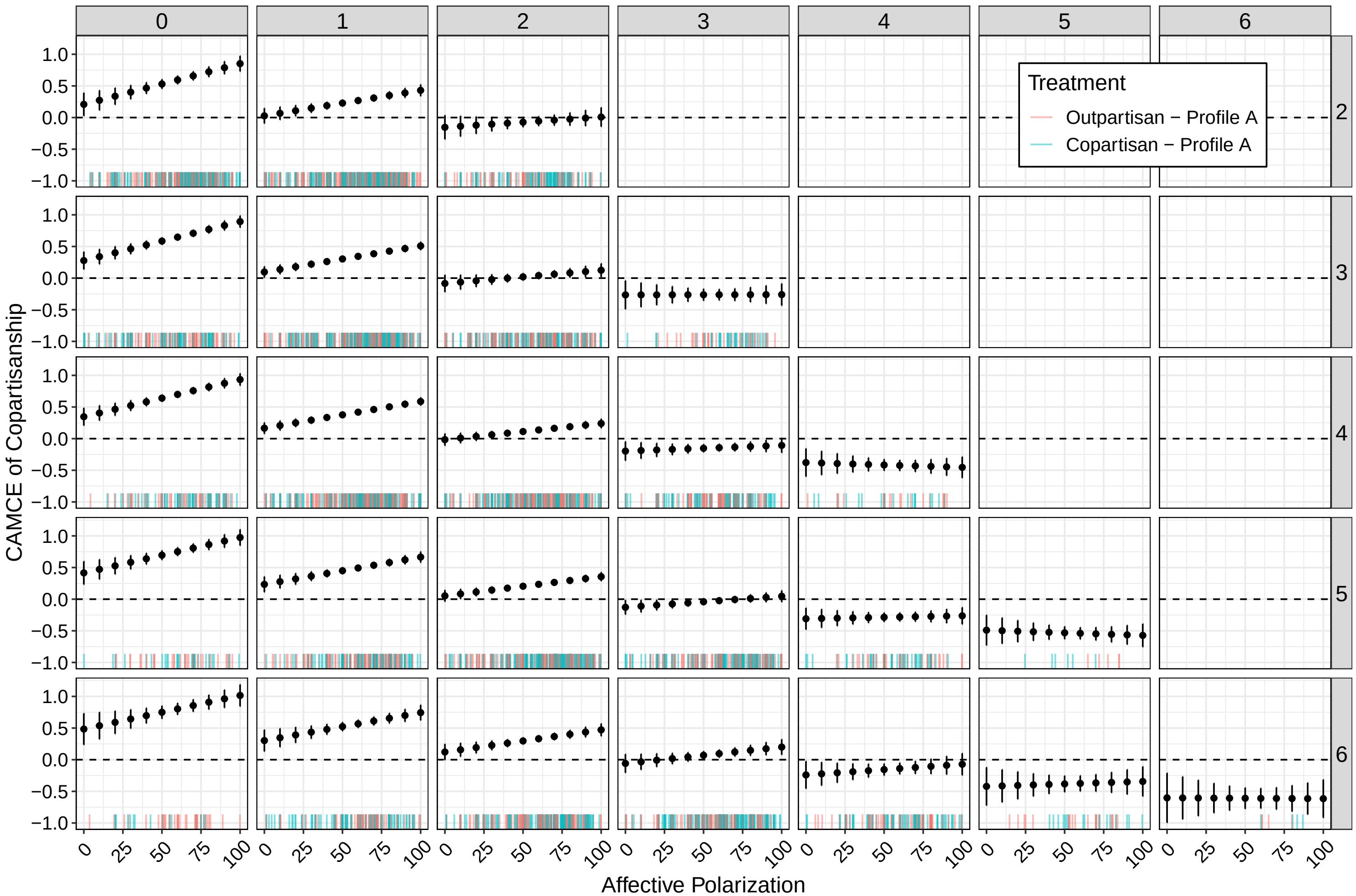

Note: CAMCE estimates from models fit with covariates for profile A. The vertical pane axis shows the number of issues shown for the profile pair, while the horizontal pane axis shows the number of party-incongruent issue positions shown for profile A.

Figure B.1.6: CAMCE of Copartisanship by Issue Content (Profile B Covariates)



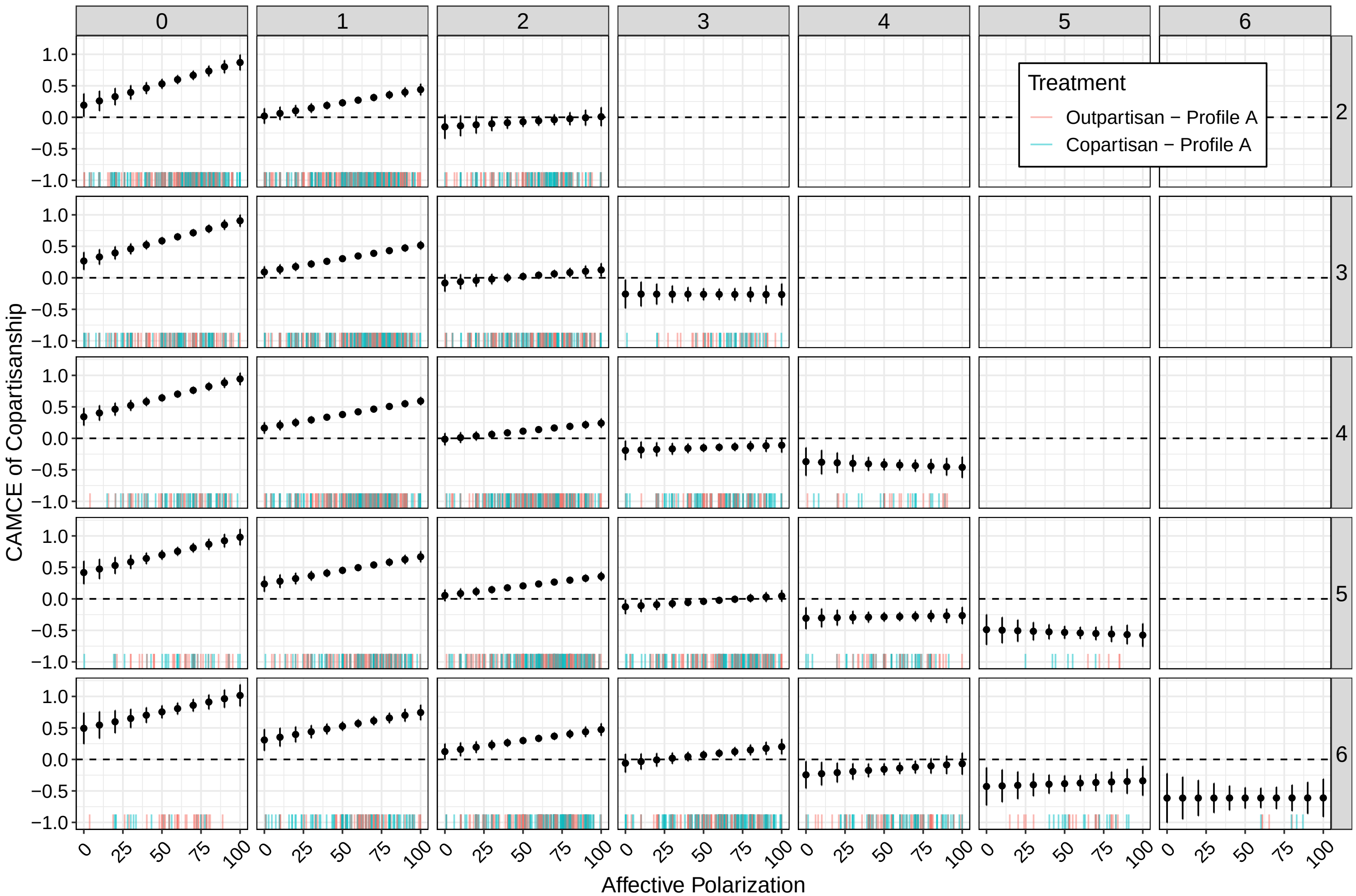

Note: CAMCE estimates from models fit with covariates for profile B. The vertical pane axis shows the number of issues shown for the profile pair, while the horizontal pane axis shows the number of party-incongruent issue positions shown for profile A.

Figure B.1.7: CAMCE of Copartisanship by Issue Content (Individual + Profile A Covariates)




Note: CAMCE estimates from models fit with individual covariates as well as covariates for profile A. The vertical pane axis shows the number of issues shown for the profile pair, while the horizontal pane axis shows the number of party-incongruent issue positions shown for profile A.

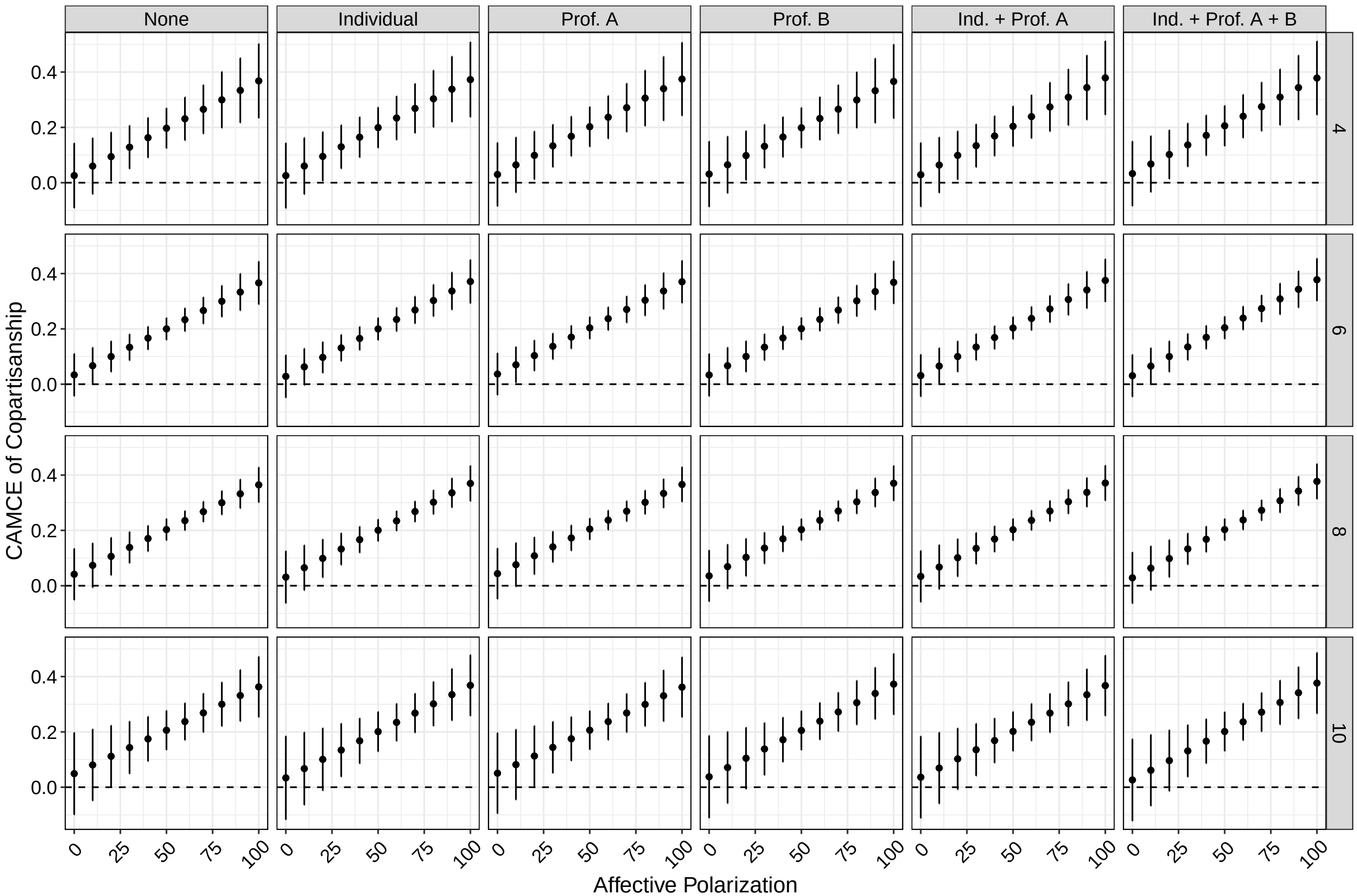
Figure B.1.8: CAMCE of Copartisanship by Issue Content (Individual + Profiles A and B Covariates)




Note: CAMCE estimates from models fit with individual covariates as well as covariates for profiles A and B. The vertical pane axis shows the number of issues shown for the profile pair, while the horizontal pane axis shows the number of party-incongruent issue positions shown for profile A.

#### B.1.4 CAMCE Results by Affect and Ideology

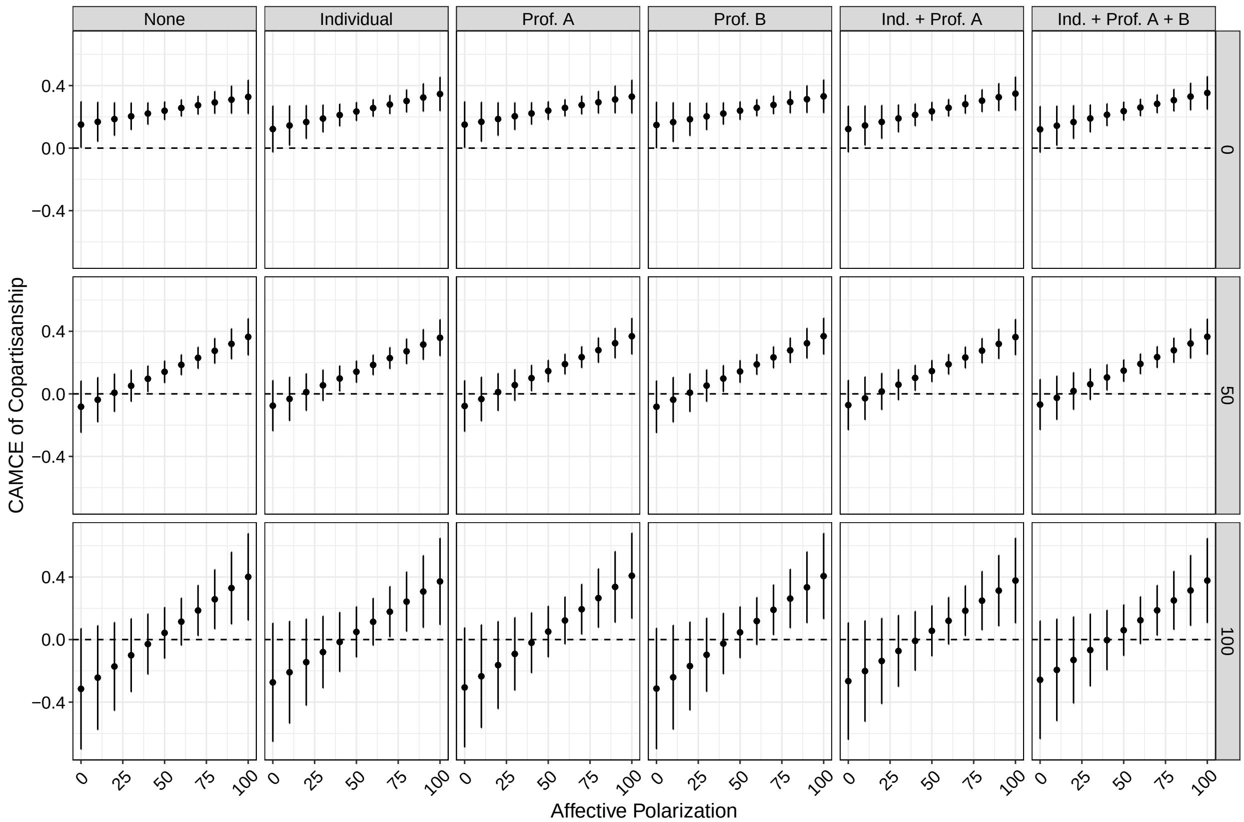
Figure B.1.9: CAMCE of Copartisanship by Ideological Congruence and Party




Note: Estimates from models fit using no covariates, individual covariates, covariates for Profile A, covariates for Profile B, and combinations thereof. The vertical pane axis depicts ideological congruence with the respondent's party (a value of 5 corresponds to moderate ideology while a value of 10 corresponds to extreme ideology consistent with the respondent's party).

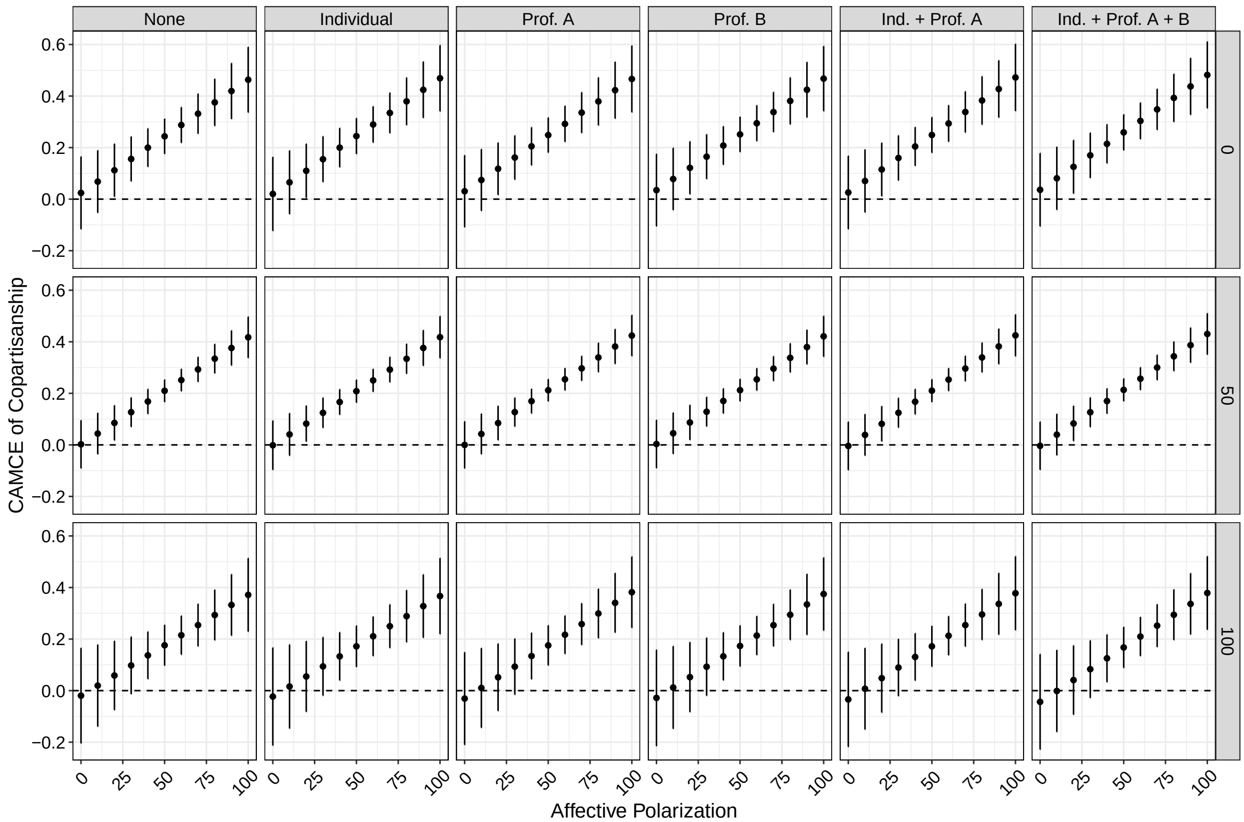
### B.1.5 CAMCE Results by Affect and Election Margins

Figure B.1.10: CAMCE of Copartisanship by Affect and General Election Margin




Note: Estimates from models fit using no covariates, individual covariates, covariates for Profile A, covariates for Profile B, and combinations thereof. The vertical pane axis shows the absolute value of the general election vote share margin from 2022.

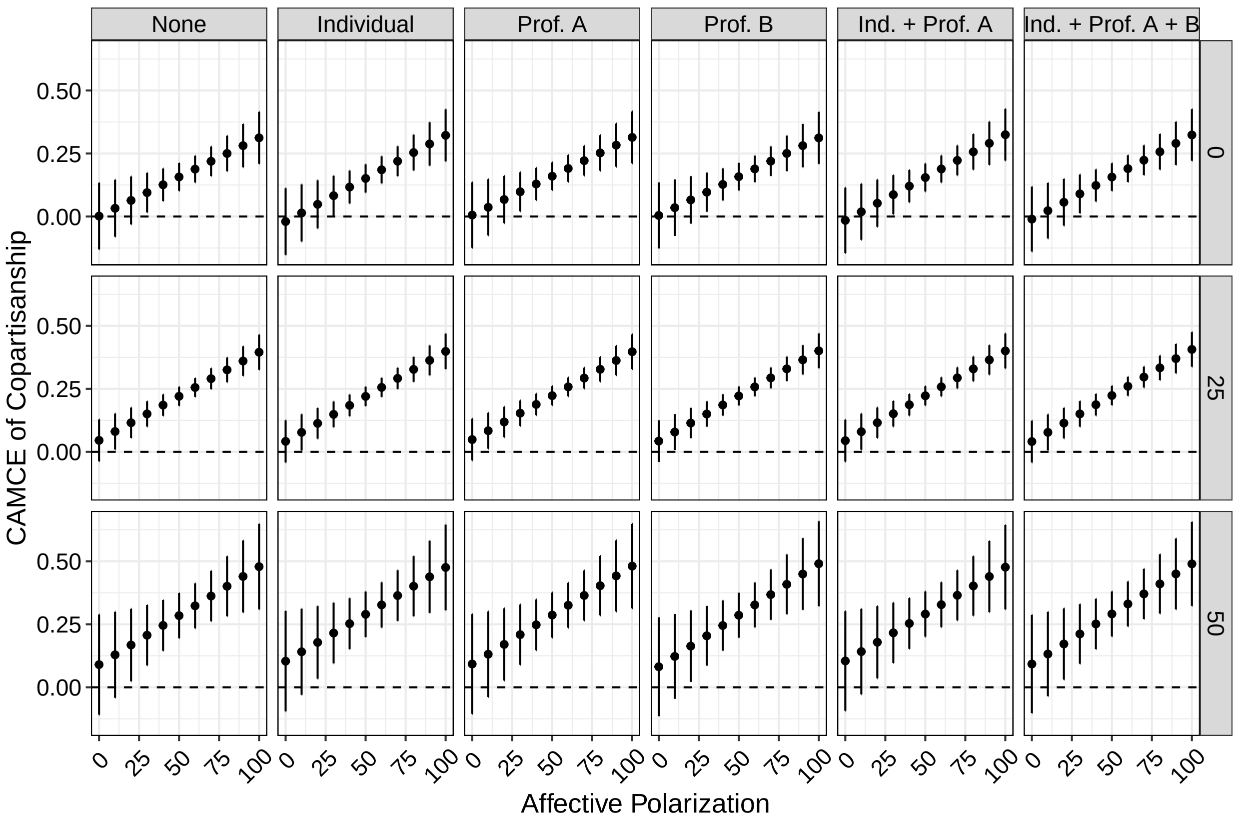
Figure B.1.11: CAMCE of Copartisanship by Affect and Primary Election Margin




Note: Estimates from models fit using no covariates, individual covariates, covariates for Profile A, covariates for Profile B, and combinations thereof. The vertical pane axis shows the absolute value of the primary election vote share margin from 2022.

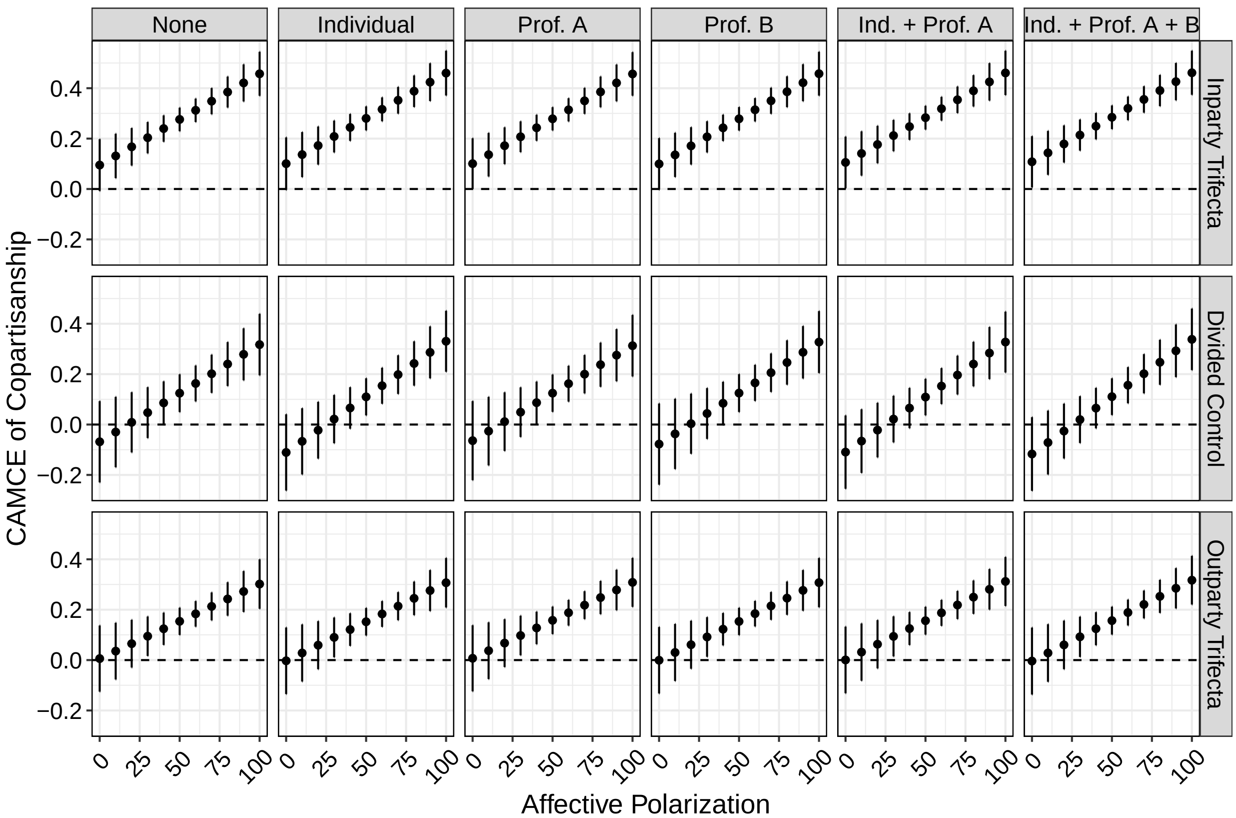
### B.1.6 CAMCE Results by Affect and State Partisan Control

Figure B.1.12: CAMCE of Copartisanship by State Control, Affect, and Party




Note: Estimates from models fit using no covariates, individual covariates, covariates for Profile A, covariates for Profile B, and combinations thereof. The vertical pane axis displays the partisan control of the state government.

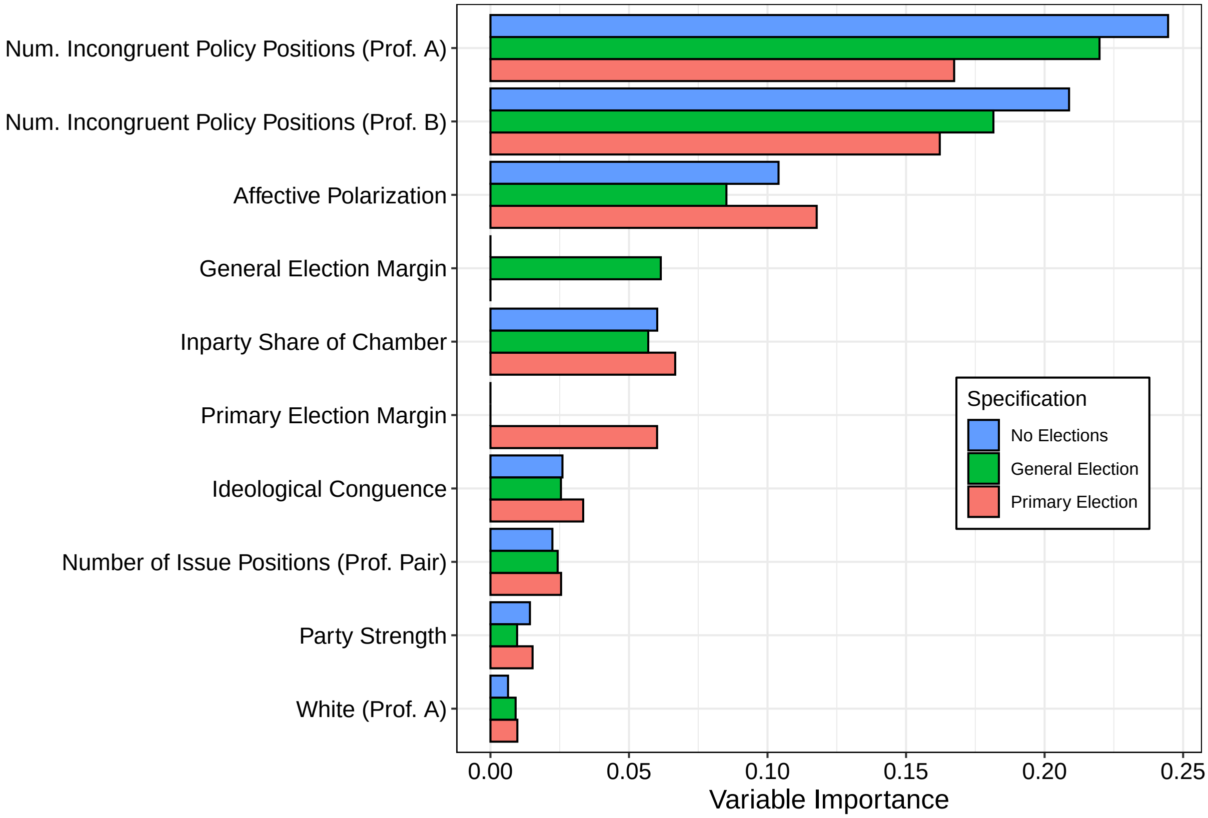
Figure B.1.13: CAMCE of Copartisanship by Chamber Margin, Affect, and Party




Note: Estimates from models fit using no covariates, individual covariates, covariates for Profile A, covariates for Profile B, and combinations thereof. The vertical pane axis displays the margin of control of the majority party in the candidates' chamber of the state legislature.

### B.1.7 CAMCE Results by Affect and State Partisan Control

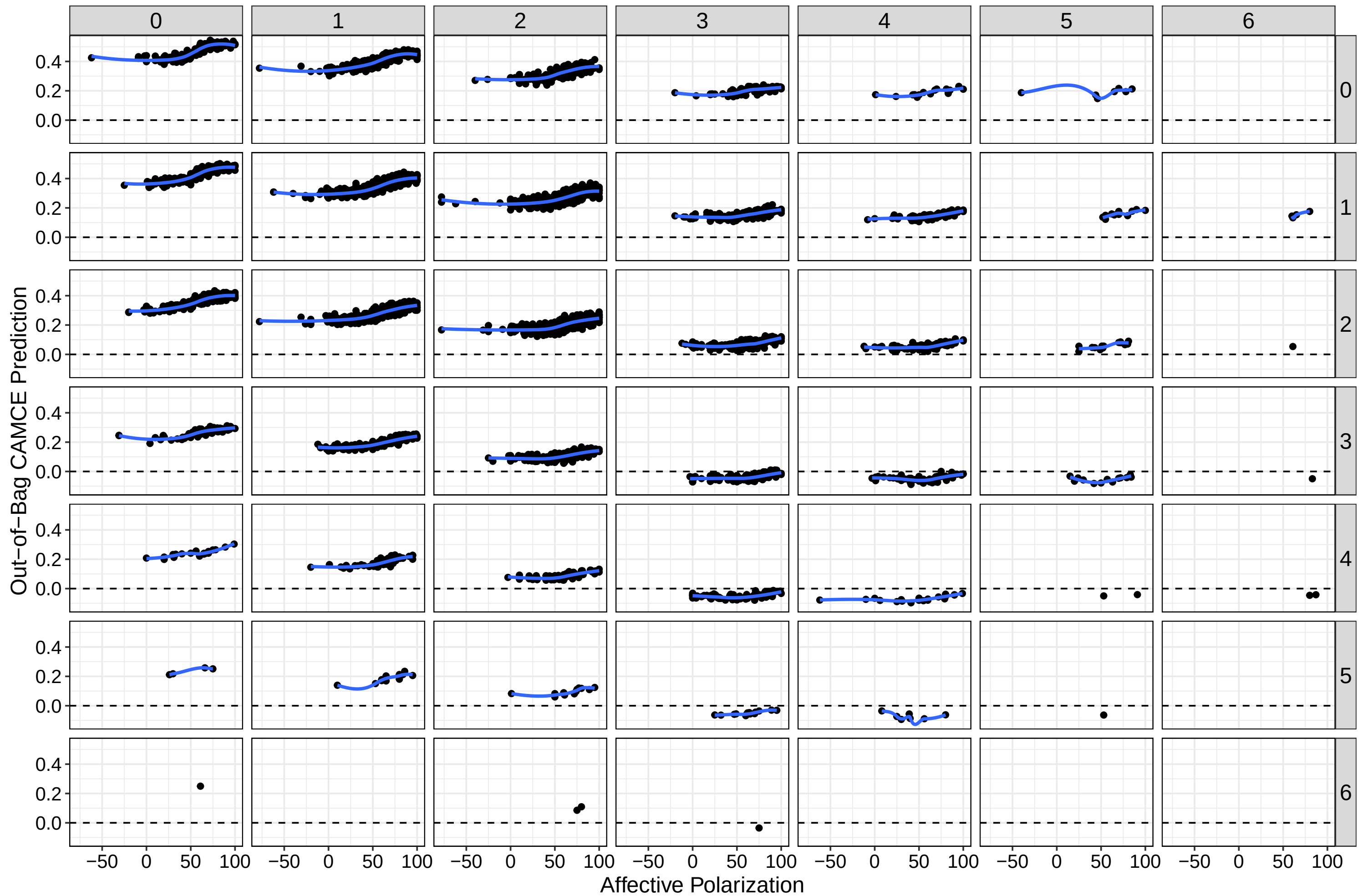
Figure B.1.14: Causal Forest Variable Importance




Note: Variable importance from causal forest fit including individual covariates and covariates for profile A and B. Higher values indicate that variables are more important predictors of the conditional average marginal component effect of copartisanship. The primary election specification reflects a causal forest fit including primary election margins. The general election specification is based on a causal forest fit including general election margins. The no elections specification is based on a causal forest fit without the general or primary election variables. The 10 variables with the highest median variable importance scores are shown here for space.

### B.1.8 CAMCE Results by Affect and State Partisan Control

Figure B.1.15: Out-of-Bag CAMCE Predictions



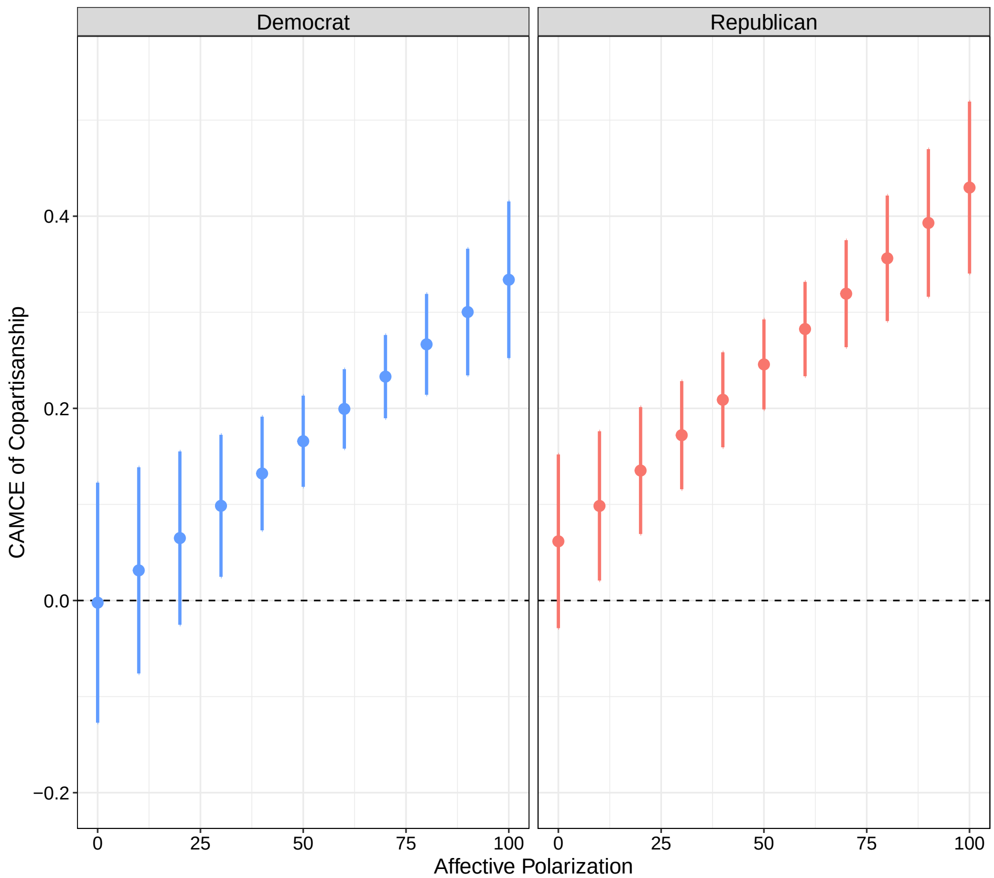

Note: Out-of-Bag CAMCE predictions from the causal forest specification with no electoral variables. Electoral variables were omitted to avoid discarding large portions of the sample who appeared in a primary but not a general election or vice versa. The vertical axis of the grid corresponds to the number of party-incongruent issue positions for profile B, and the horizontal axis indicates the number of party-incongruent issue positions for profile A. Blue lines fit using LOESS.

## B.2 Robustness to Party Subset

Next, I examine whether the relationships between affective polarization and the CAMCE of copartisanship vary by party. To do so, I re-fit the original model specifications on subsets of the data containing only Democrats or Republicans. The relationships between affective polarization and the CAMCE of copartisanship are all quite similar to the full data fits displayed in the main text. Most differences between these results and the main text are in strength of the relationships between affect and the CAMCE of copartisanship, while the substantive conclusions are largely the same as for the full specifications. The main notable difference occurs in Figure B.2.3 which shows a positive relationship between affective polarization and partisan discrimination for both parties; however, this relationship appears to be negative for high levels of incongruent issue content for Democrats but remains positive for Republicans. While this difference is worthy of further exploration, we should be careful in overinterpreting this difference due to the lack of observations in cells with high degrees of incongruent information, which violates the common support assumption, and the potential for nonlinear relationships.

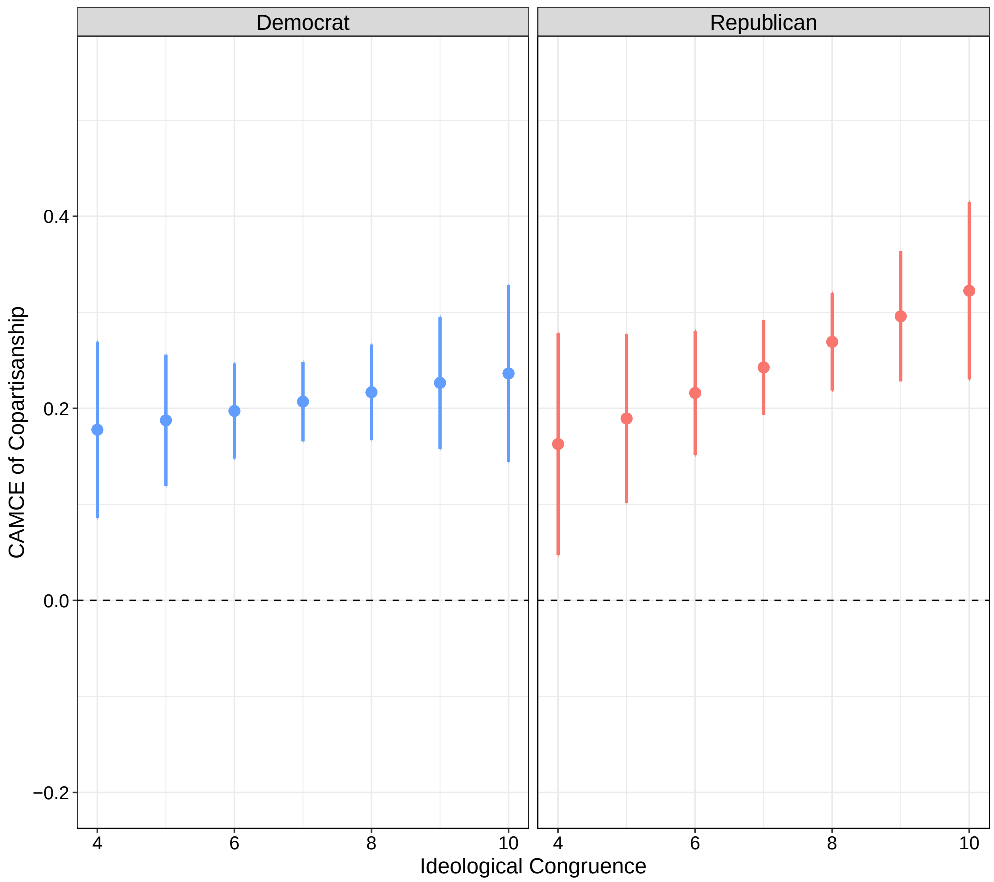
### B.2.1 Simple CAMCE Results

Figure B.2.1: CAMCE of Copartisanship By Party and Affect




Note: Fits from Democratic and Republican subsets of the data are displayed.

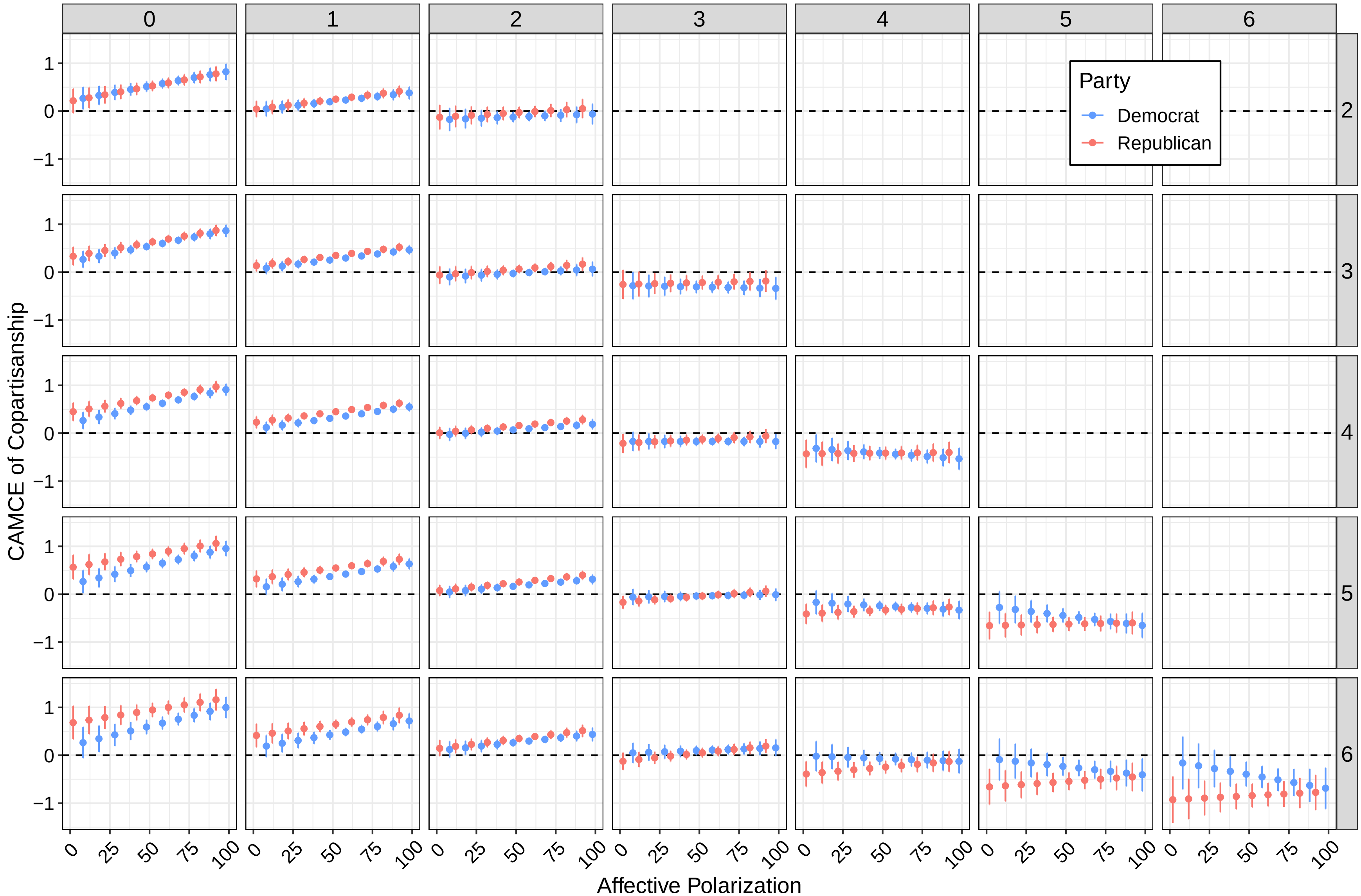
Figure B.2.2: CAMCE of Copartisanship By Party and Ideology




Note: Fits from Democratic and Republican subsets of the data are displayed.

### B.2.2 CAMCE Results by Affect and Issue Content

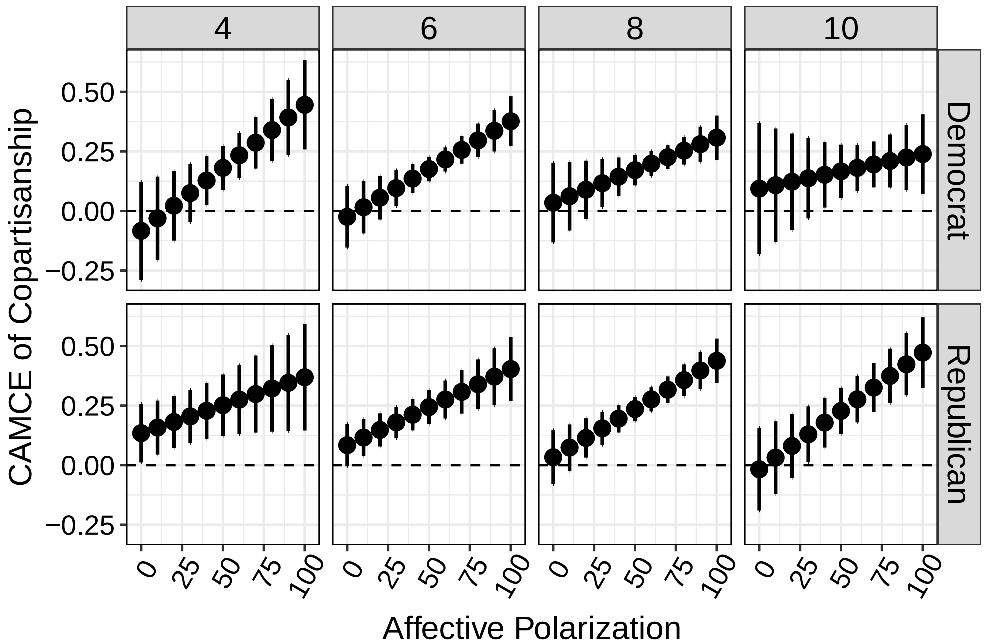
Figure B.2.3: CAMCE of Copartisanship by Affective Polarization and Party




Note: Fits on Democratic and Republican subsets of the data are displayed. The vertical pane progression shows the number of policy positions displayed for the profile pair, and the horizontal pane axis shows the number of incongruent policy positions for profile A.

### B.2.3 CAMCE Results by Affect and Ideology

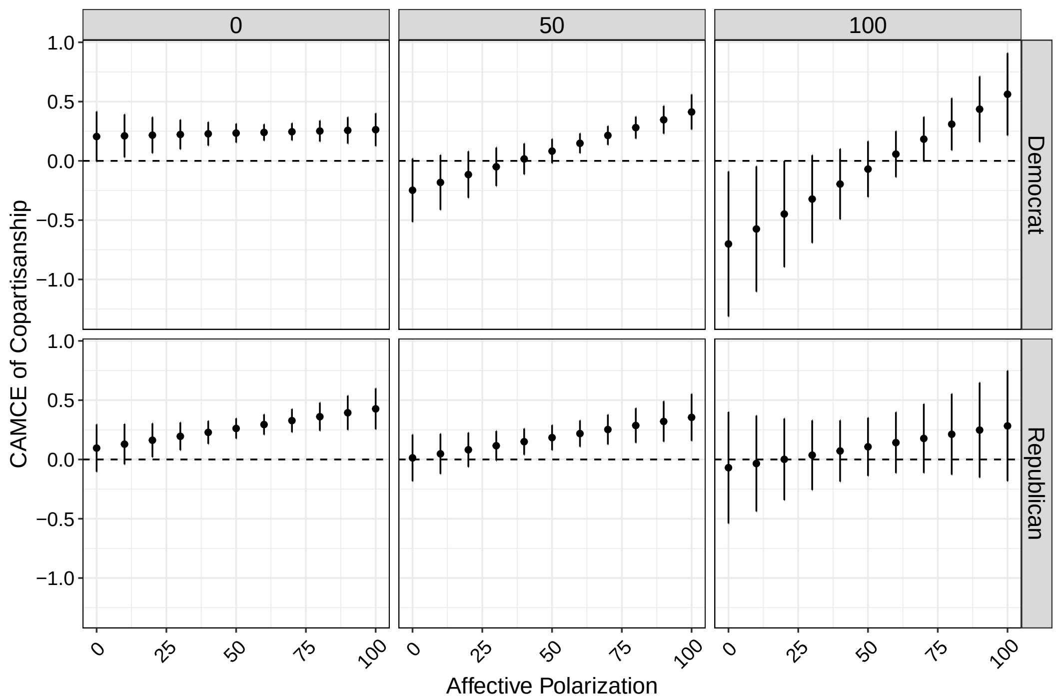
Figure B.2.4: CAMCE of Copartisanship by Ideological Congruence and Party




Note: CAMCE estimates from models fitted on subsets of data containing only Democrats and Republicans. The horizontal pane progression displays the respondent's ideological congruence with their party (a value of 5 represents a moderate individual, while a value of 10 represents someone with an extreme ideology that matches their party).

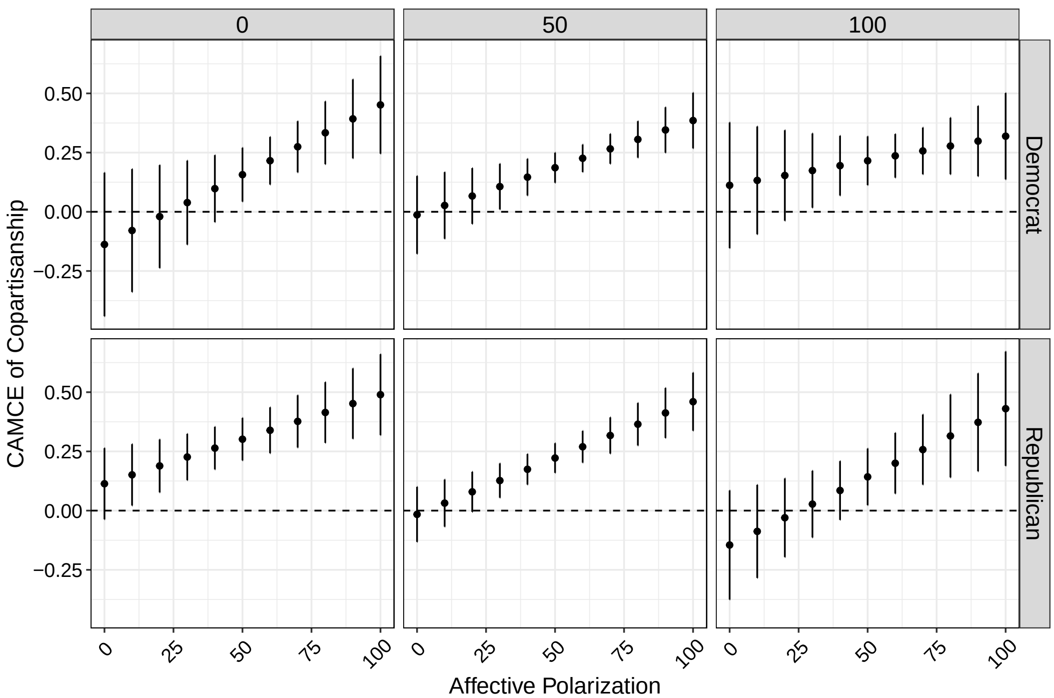
### B.2.4 CAMCE Results by Affect and Election Margins

Figure B.2.5: CAMCE of Copartisanship by Affect and General Election Margin




Note: CAMCE estimates from models fitted on subsets of data containing only Democrats and Republicans. The horizontal pane axis indicates the absolute value of the candidate's vote share margin in the 2022 general election.

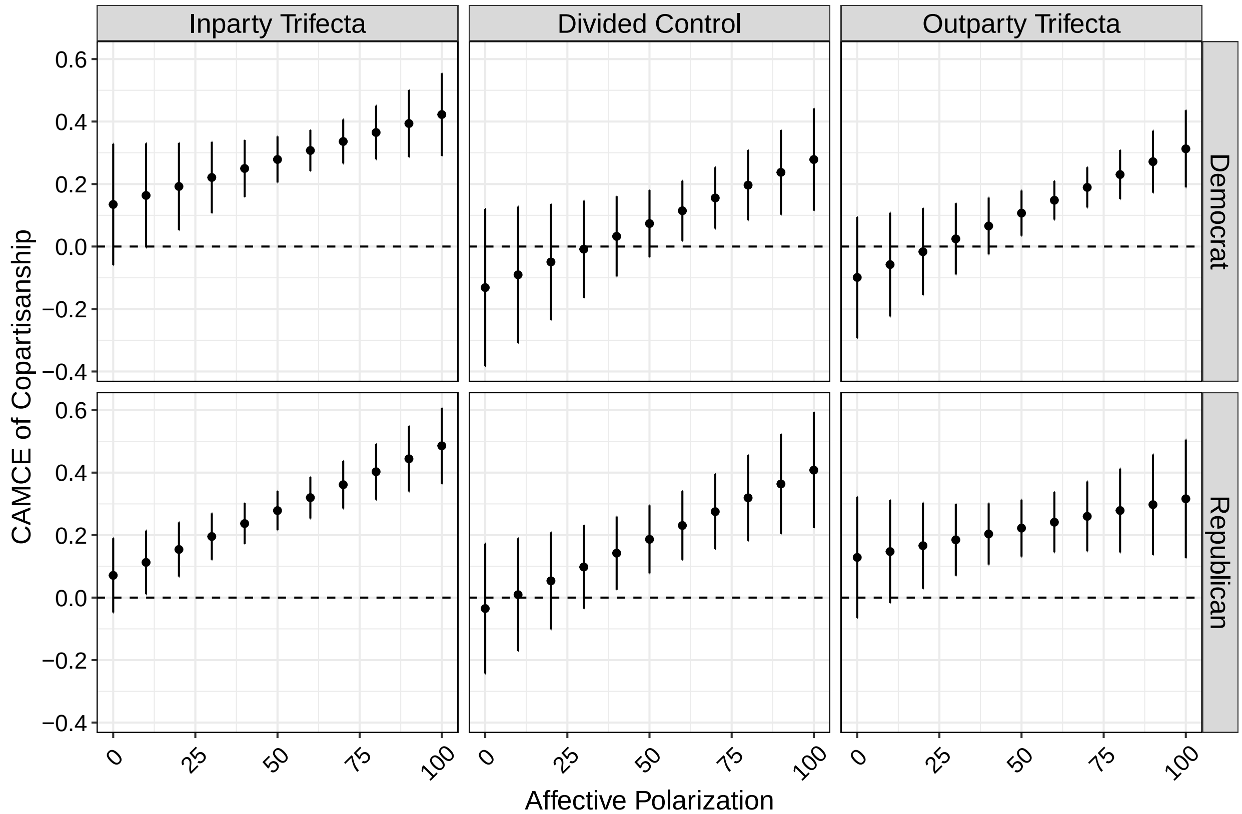
Figure B.2.6: CAMCE of Copartisanship by Affect and Primary Election Margin




Note: CAMCE estimates from models fitted on subsets of data containing only Democrats and Republicans. The horizontal pane axis displays the candidate's vote share margin in the 2022 primary election.

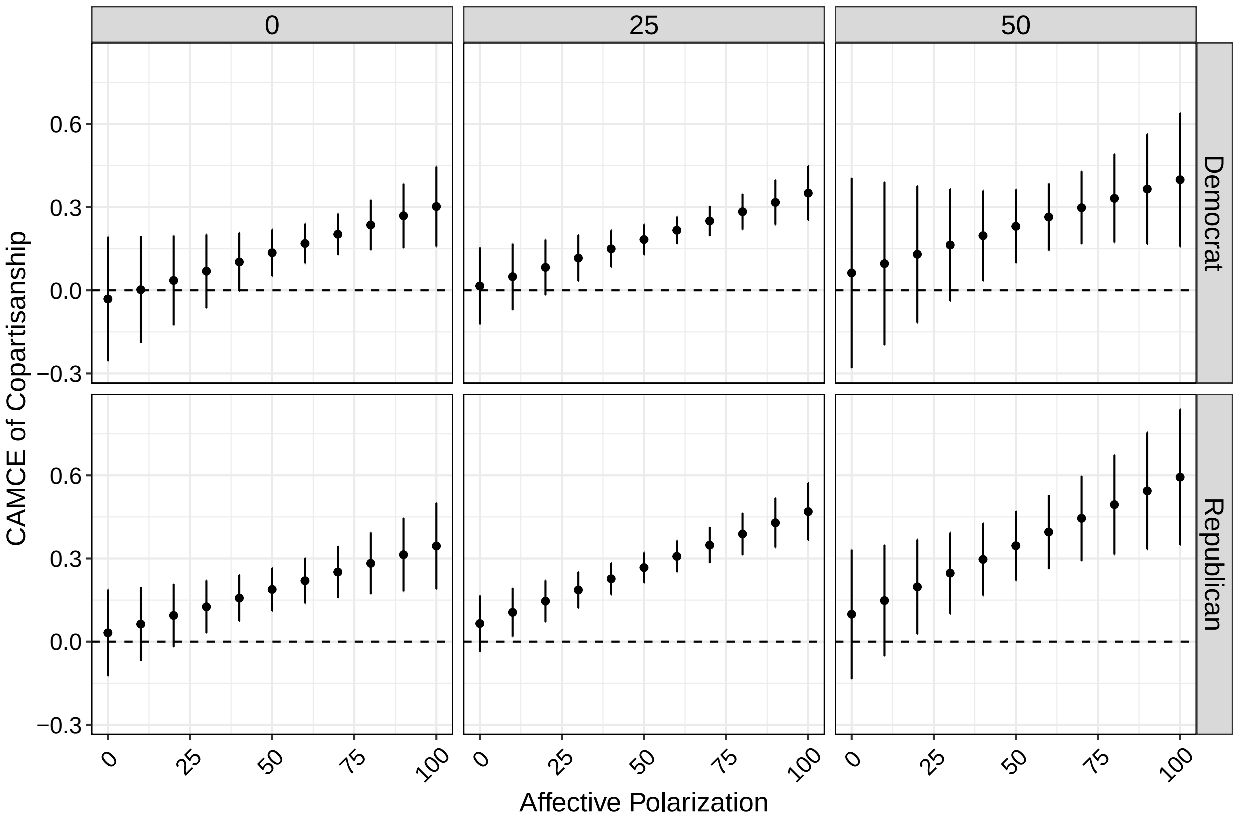
### B.2.5 CAMCE Results by Affect and State Partisan Control

Figure B.2.7: CAMCE of Copartisanship by State Control, Affect, and Party




Note: CAMCE estimates from models fitted on subsets of data containing only Democrats and Republicans. The horizontal pane axis shows the seat margin in the chamber for which the respondent ran in 2022.

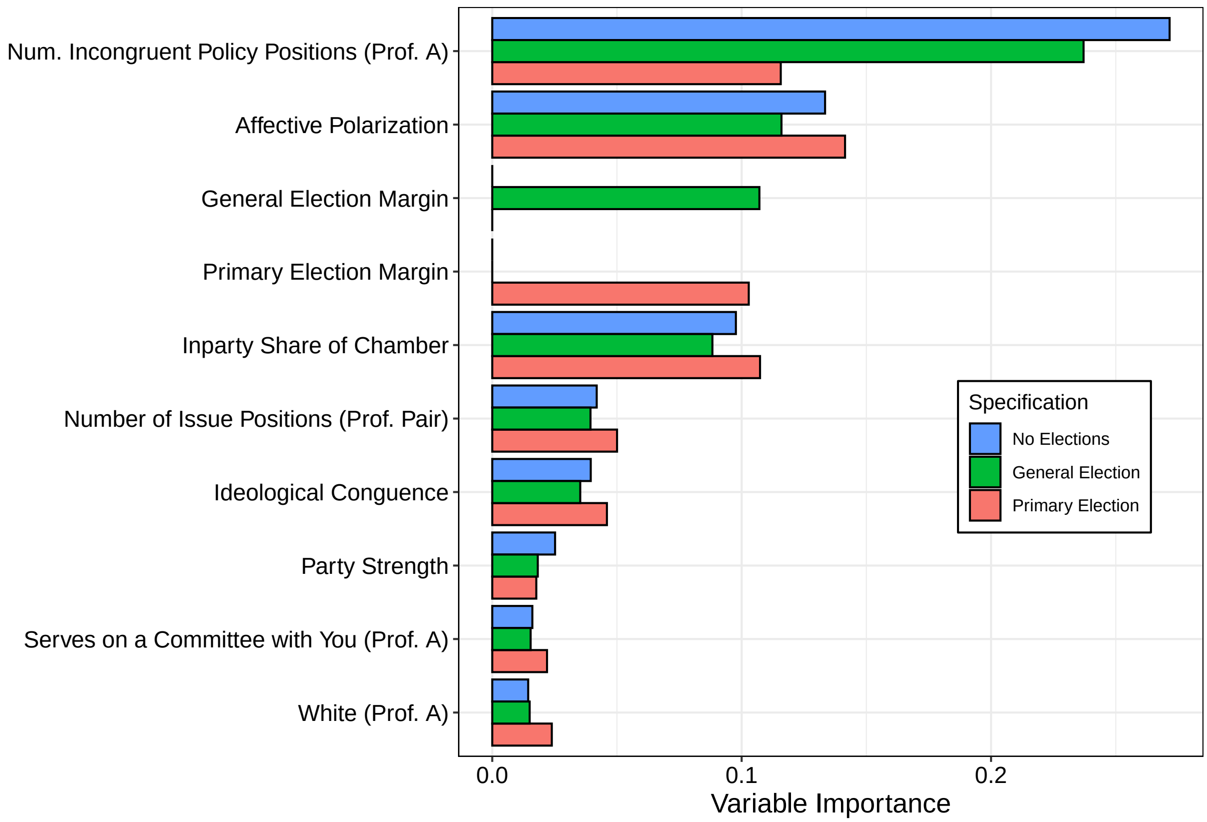
Figure B.2.8: CAMCE of Copartisanship by Chamber Margin, Affect, and Party




Note: CAMCE estimates from models fitted on subsets of data containing only Democrats and Republicans. The horizontal pane axis reflects partisan control of the respondents' state government.

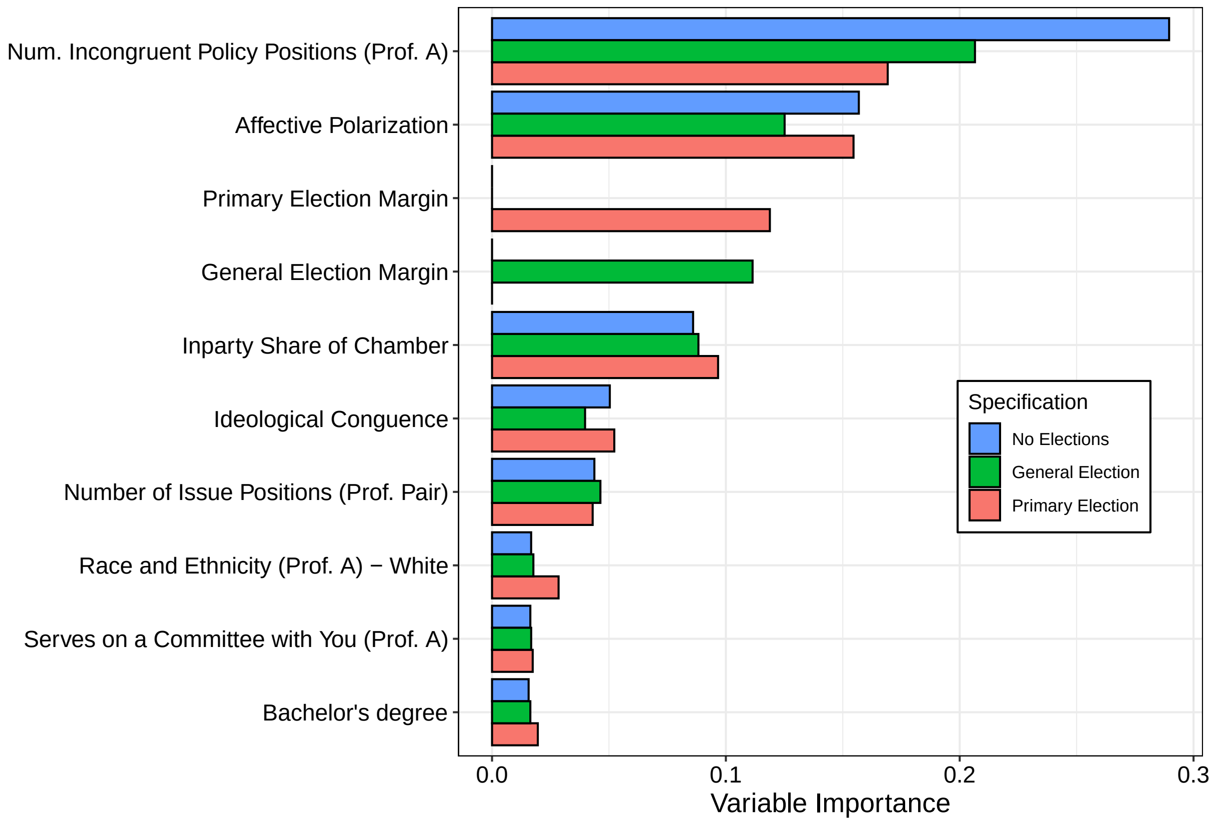
### B.2.6 Variable Importance Results

Figure B.2.9: Causal Forest Variable Importance (Democratic Subset)




Note: Variable importance estimates from causal forests fitted on subsets of data containing only Democrats. Only the 10 variables with the highest median variable importance across specifications displayed for space. The Primary Election model specification was fitted using the candidate's primary election vote margin. The General Election model specification was fitted using the candidate's general election vote margin. The No Election model specification was fitted without vote margins.

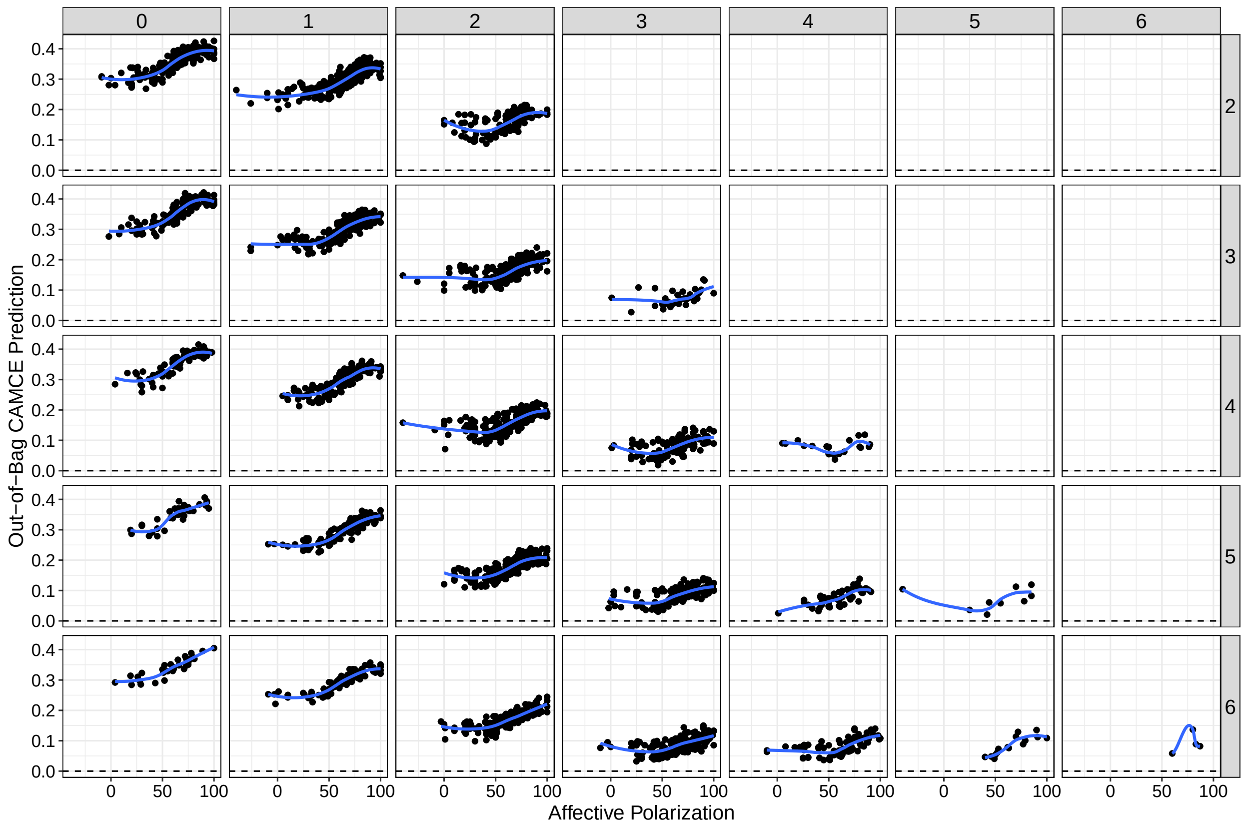
Figure B.2.10: Causal Forest Variable Importance (Republican Subset)




Note: CAMCE estimates from causal forests fitted on subsets of data containing only Republicans. Only the 10 variables with the highest median variable importance across specifications displayed for space. The Primary Election model specification was fitted using the candidate's primary election vote margin. The General Election model specification was fitted using the candidate's general election vote margin. The No Election model specification was fitted without vote margins.

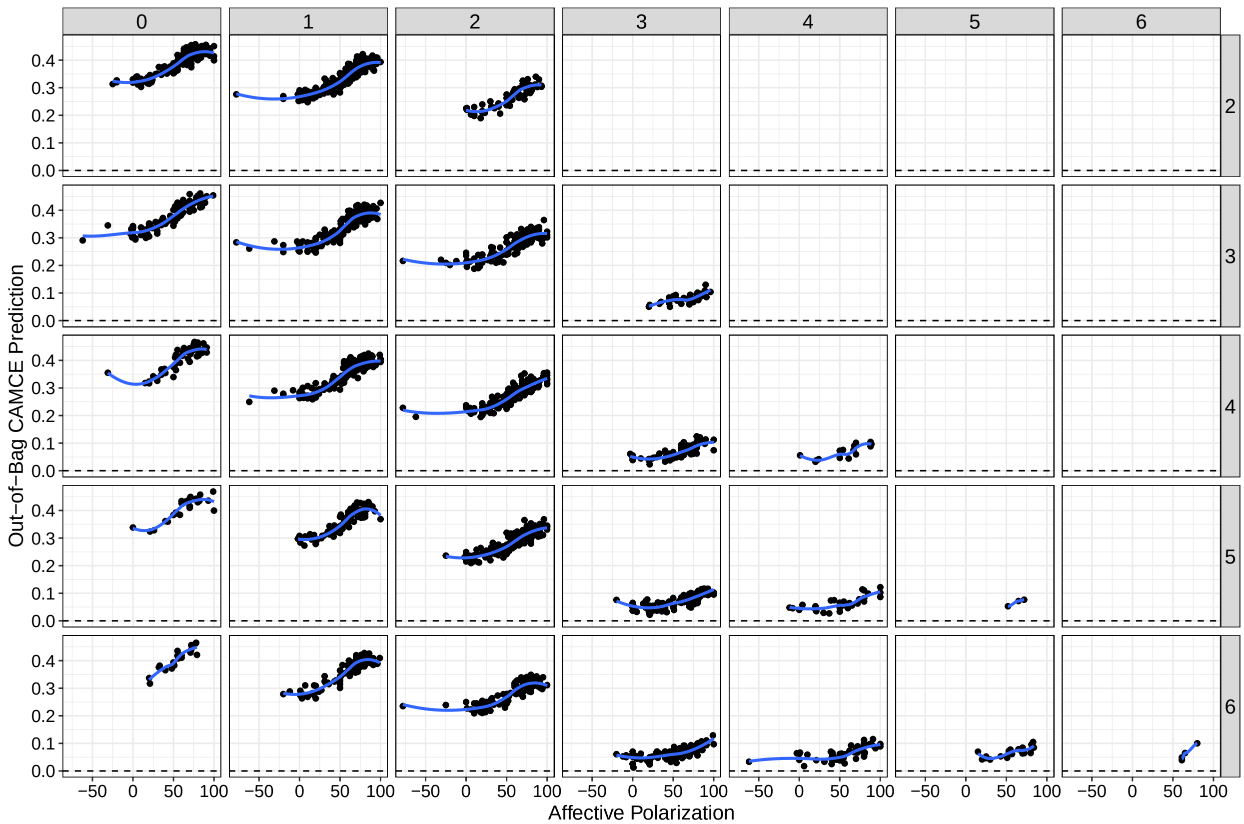
### B.2.7 Predicted CAMCE Causal Forest

Figure B.2.11: Predicted CAMCEs of Copartisanship by Affect and Issues (Democratic Subset)




Note: CAMCE estimates predicted on out-of-bag observations from causal forests fitted on subsets of data containing only Democrats. The vertical pane axis shows the number of issue positions shown for the profile pair, and the horizontal pane axis shows the number of party-incongruent issue positions for Profile A.

Figure B.2.12: Predicted CAMCEs of Copartisanship by Affect and Issues (Republican Subset)




Note: CAMCE estimates predicted on out-of-bag observations from causal forests fitted on subsets of data containing only Republicans. The vertical pane axis shows the number of issue positions shown for the profile pair, and the horizontal pane axis shows the number of party-incongruent issue positions for Profile A.

## B.3 Robustness to Issue Coding

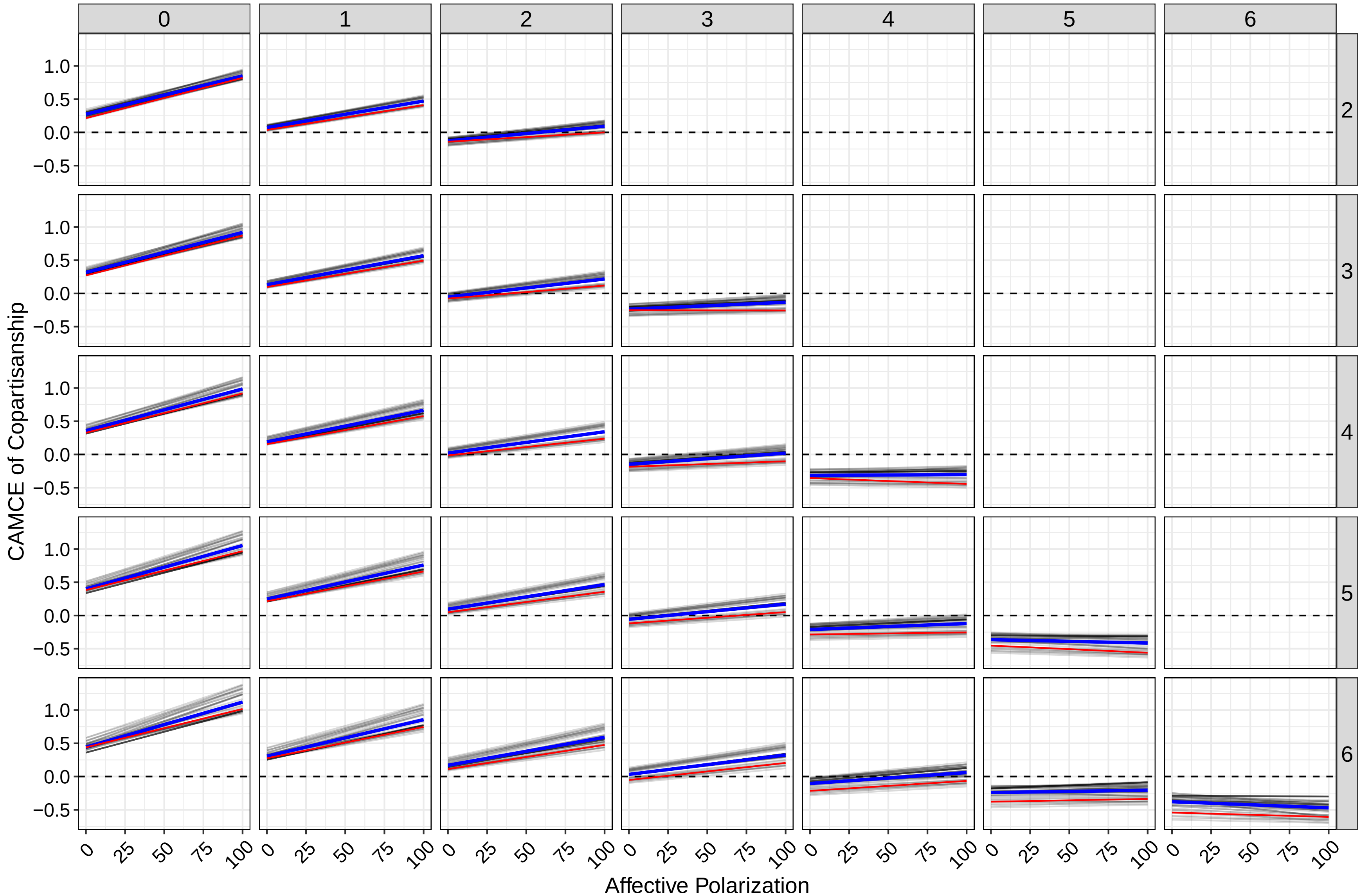
In this section, I test the robustness of my results to various permutations of coding issue positions. In total, 48 ways of coding issue positions were considered. I examined whether coding party-incongruent issue positions differed if I coded issue positions as strictly or "weakly" incongruent: a strict coding of incongruity simply means that issue positions were incongruent only if they matched the opposing party's position, while a weak coding of incongruity includes moderate positions as incongruent. In addition, I examined whether changing the definition of incongruity to a one-sided or a two-sided analysis altered my results. The main text employs a two-sided definition of incongruity under which policies are considered incongruent if they are strictly or weakly congruent with the opposing party's position. A one-sided definition of incongruity counts policies as incongruent for Republicans if they do not match the Republican Party's position under the coding scheme. All other issue positions are coded as being incongruent for Democrats. For example, for a strictly incongruent one-sided coding, the number of strictly liberal policies would become the number of party-incongruent policies for Republican profile versions, while the number of weakly non-liberal policy positions (weakly conservative policies, including moderate positions) would be classified as party-incongruent policies for Democratic profiles.

Finally, I take alternative approaches to coding three issue positions. I code weak opposition to sanctuary cities (which includes opposing cutting funding to sanctuary cities) as either conservative or moderate. I code restricting access to abortion with exceptions as either conservative or moderate. Lastly, I code positions which express support for returning to "pre-Roe laws" as liberal, moderate, or conservative. Several candidates indicated that they had understood this policy position as returning to pre-Dobbs laws instead of pre-Roe laws, so I examine results under a variety of coding schemes.

In sum, I test robustness to codings of strict or weak, one-sided or two-sided, moderate or conservative sanctuary cities policies, moderate or conservative abortion restrictions, and liberal, moderate, or conservative pre-Roe law codings—for a total of 48 possible combinations.

### B.3.1 CAMCE Results by Issue Content

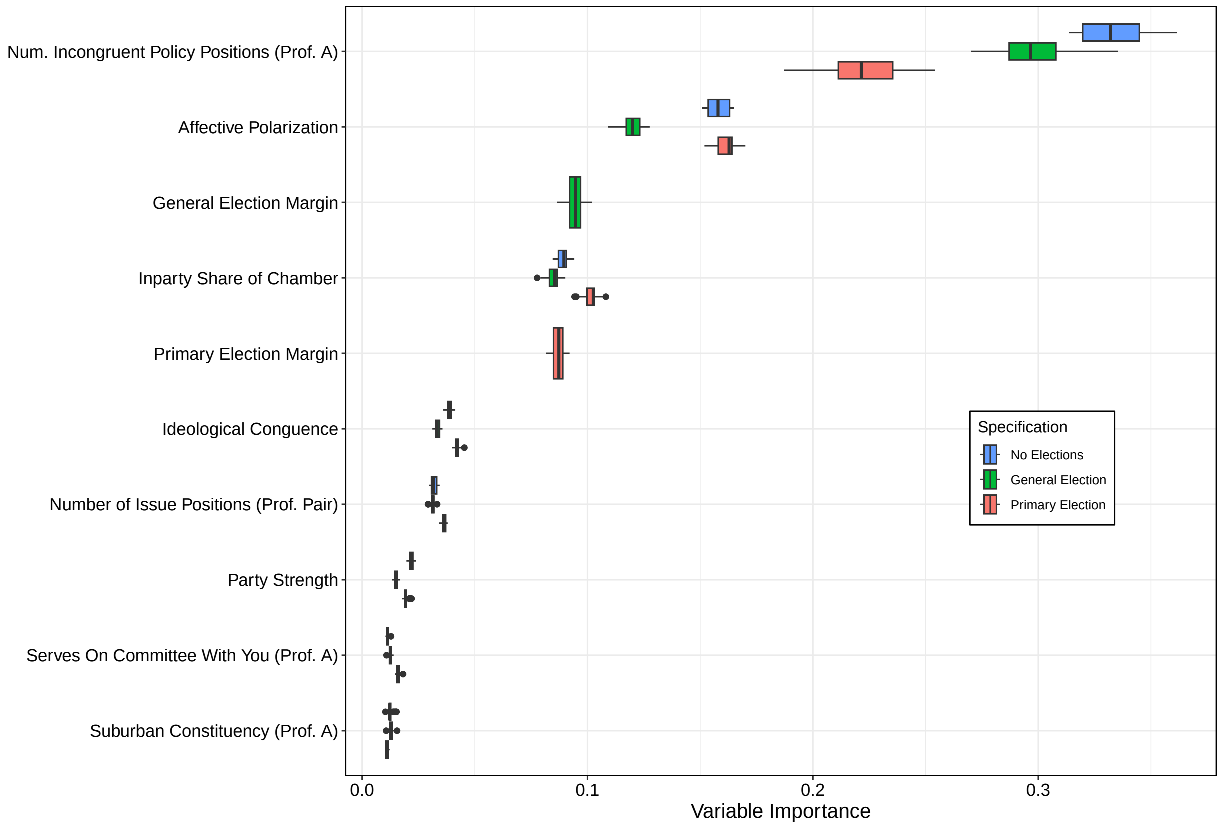
Figure B.3.1: CAMCE of Copartisanship by Affective Polarization and Party




Note: Black lines correspond to CAMCE estimates from different issue codings. The red line corresponds to the CAMCE estimates from the main text. The blue line is a loess fit to the CAMCEs from issue codings not in the main text. The vertical pane progression shows the number of policy positions displayed for the profile pair, and the horizontal pane axis shows the number of incongruent policy positions for profile A.

### B.3.2 Variable Importance Results

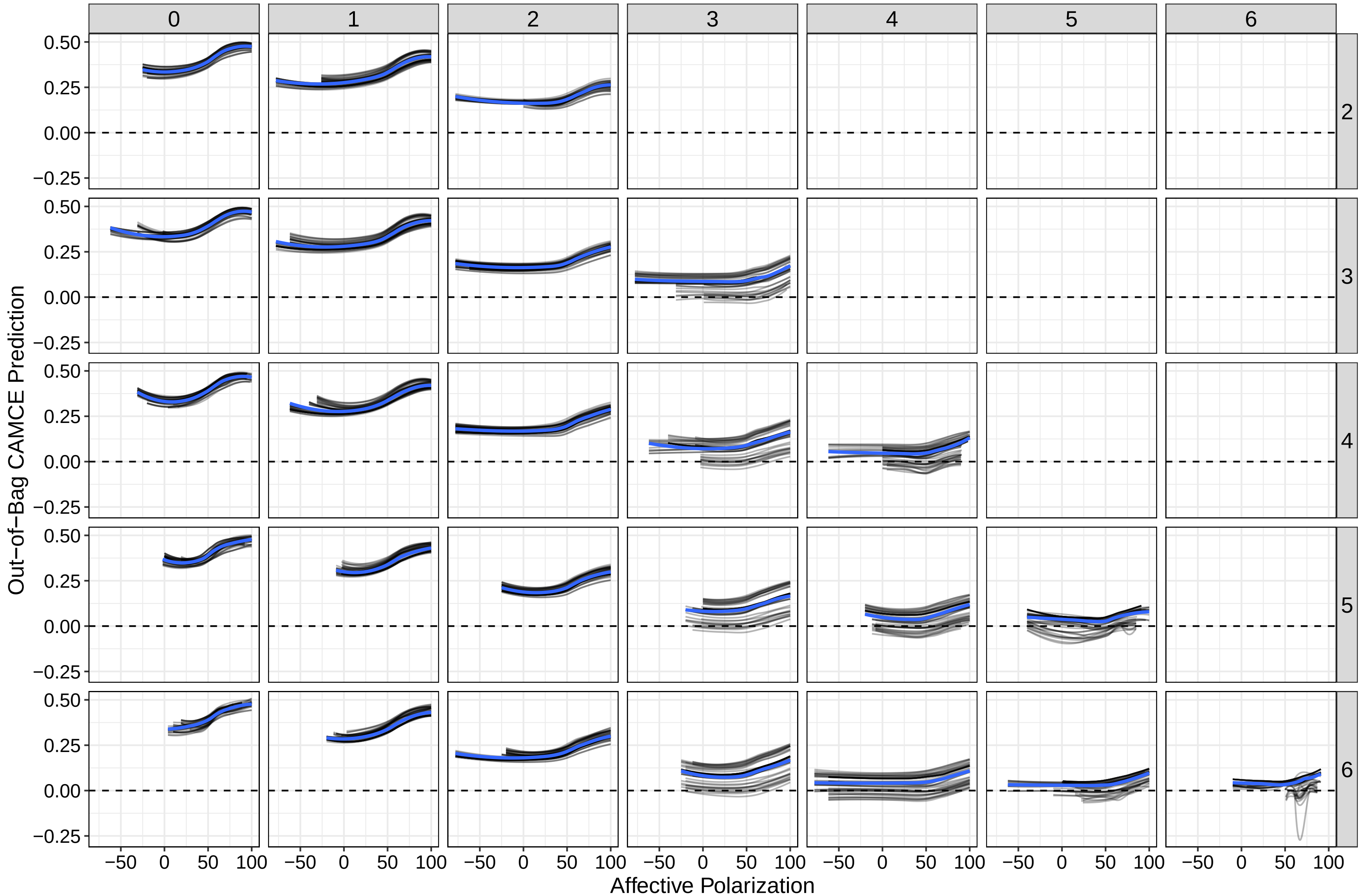
Figure B.3.2: Causal Forest Variable Importance Across Issue Codings




Note: Variable importance estimates from causal forests fitted containing individual covariates and profile A characteristics as well as one of 48 potential issue codings. Only the 10 variables with the highest median variable importance across specifications displayed for space. The Primary Election model specification was fitted using the candidate's primary election vote margin. The General Election model specification was fitted using the candidate's general election vote margin. The No Election model specification was fitted without vote margins.

### B.3.3 Predicted CAMCE Causal Forest

Figure B.3.3: Predicted CAMCEs of Copartisanship by Affect and Issues for Different Issue Codings




Note: CAMCE estimates predicted on out-of-bag observations from causal forests fitted on individual covariates, characteristics of Profile A, and 48 different issue codings. Black lines are loess fits to out-of-bag predicted CAMCEs for each individual issue coding, and the blue line is a loess fit to all predicted CAMCEs across models. The vertical pane axis shows the number of issue positions shown for the profile pair, and the horizontal pane axis shows the number of party-incongruent issue positions for Profile A.

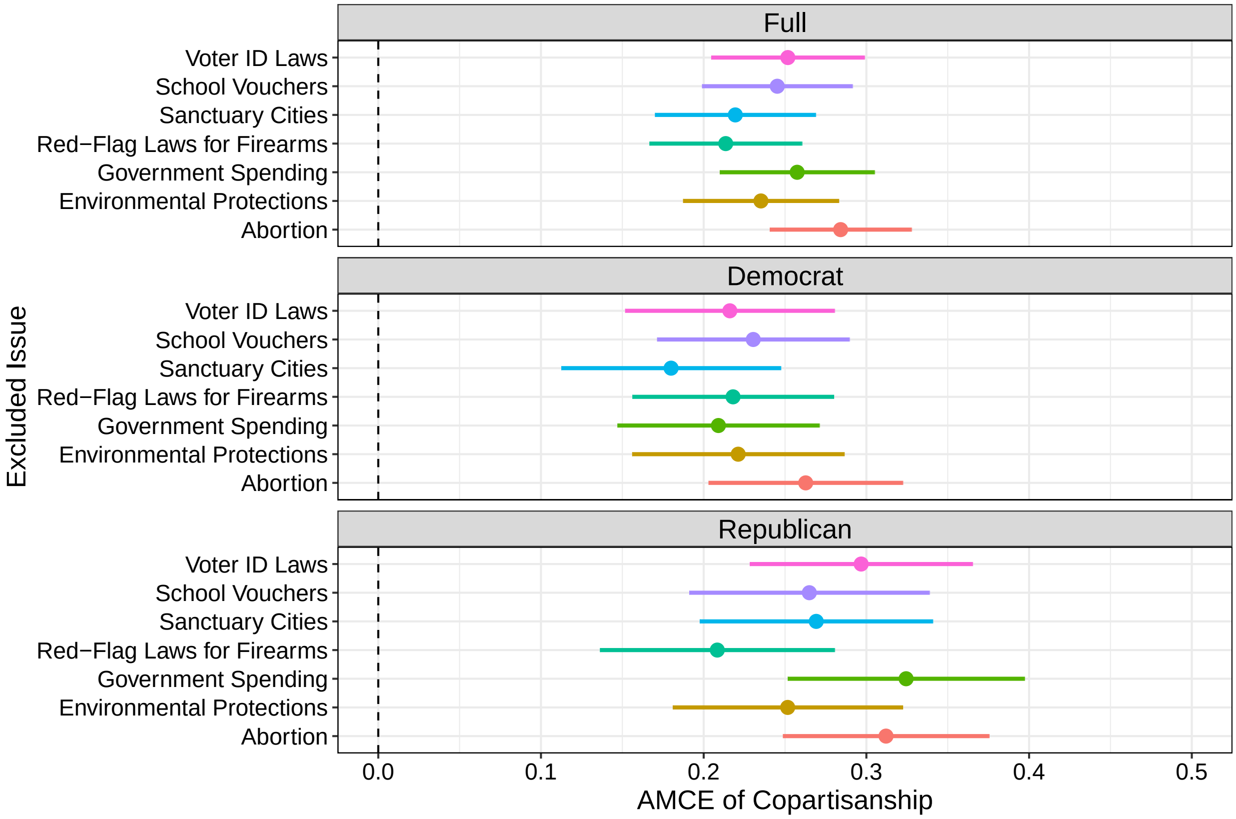
## B.4 Robustness to Issues Included

To ensure that my results do not depend on the specific issues included, I re-fit my main analyses sequentially excluding profiles which displayed an issue position from a given issue area (e.g., Abortion, Governmental Spending, etc.). For example, I excluded all profile pairs which displayed an abortion issue position. The main differences between the figures and those displayed in the main text are the strength of the relationships between affective polarization and the CAMCE of copartisanship, while the substantive interpretation of the results changes little.

There are several things to note in these figures. First, the number of observations in any given pane is smaller than in the full sample due to the omission of roughly half of the choice tasks, so we should be cautious about drawing firm conclusions from these results—due to the lack of statistical power and potential violations of common support. Second, for Figure B.4.4 through Figure B.4.10, which display the CAMCE of copartisanship conditional on affect and issue content, several of the relationships between affective polarization and partisan discrimination appear to be negative. Still, 142 of 175 panes display positive relationships between affective polarization and partisan discrimination. Again, we should avoid overinterpreting these results due to the reduced power from excluding each issue, but the findings in this section are suggestive that the main results are not sensitive to the specific issues excluded.

### B.4.1 AMCE Results

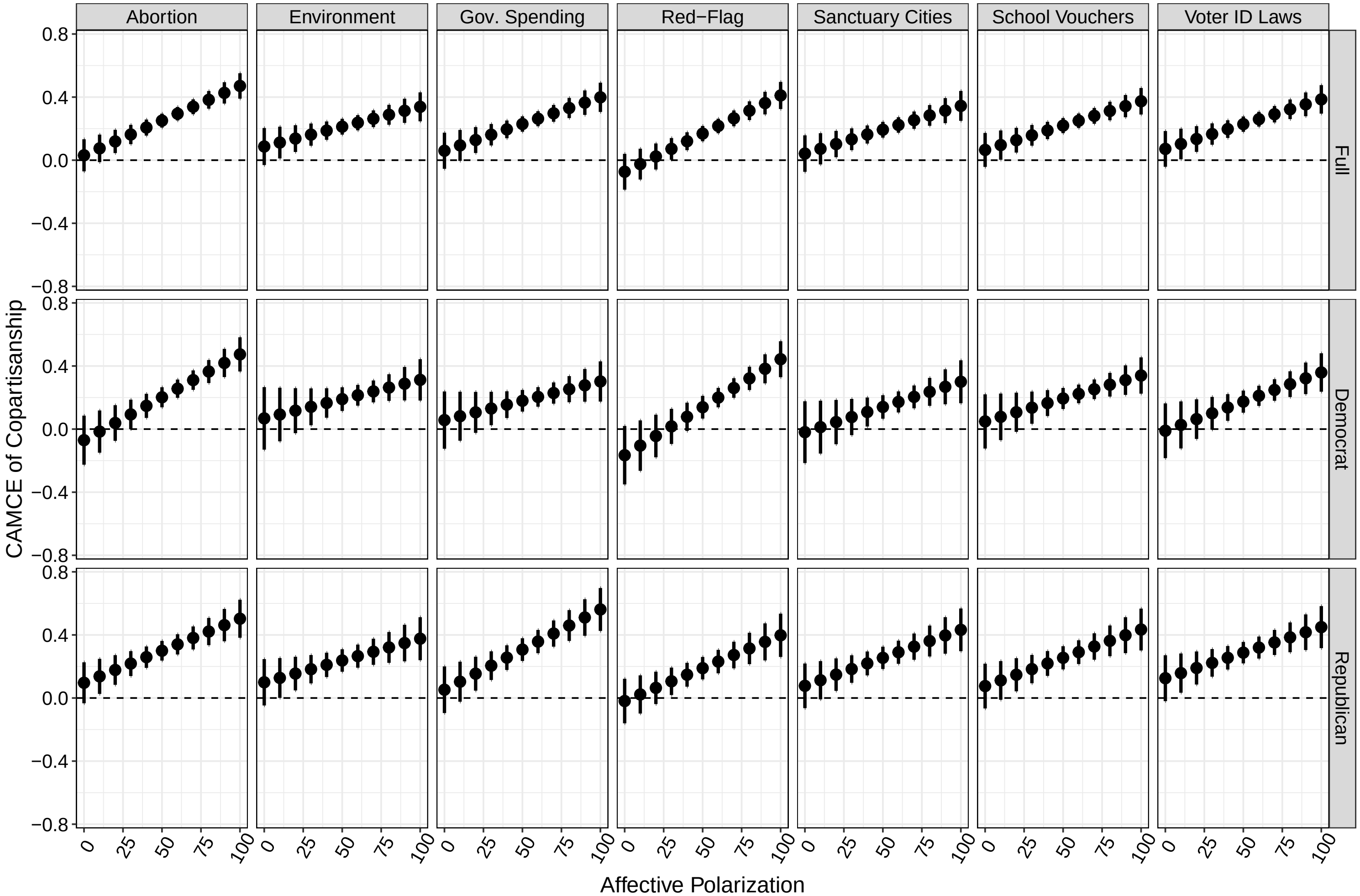
Figure B.4.1: AMCE of Copartisanship by Excluded Issue




Note: AMCE estimates from models fitted on subsets of data excluding profile pairs displaying positions from the specified issue. Full model fit using data for both Democrats and Republicans; fits from Democratic and Republican subsets are also displayed.

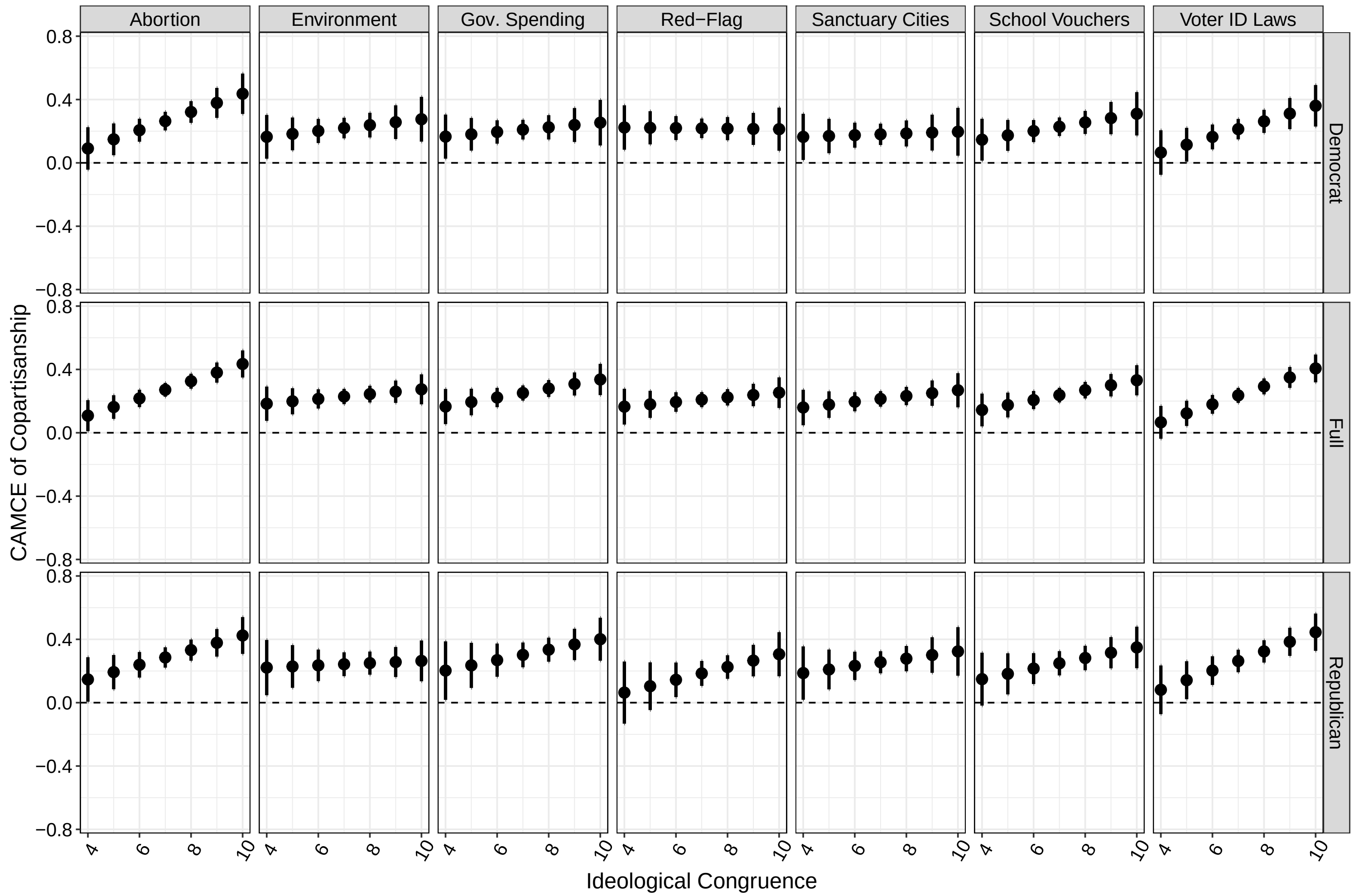
### B.4.2 Simple CAMCE Results

Figure B.4.2: CAMCE of Copartisanship by Affective Polarization and Excluded Issue




Note: CAMCE estimates from models fitted on subsets of data excluding profile pairs displaying positions from the specified issue. Full model fit using data for both Democrats and Republicans; fits from Democratic and Republican subsets are also displayed.

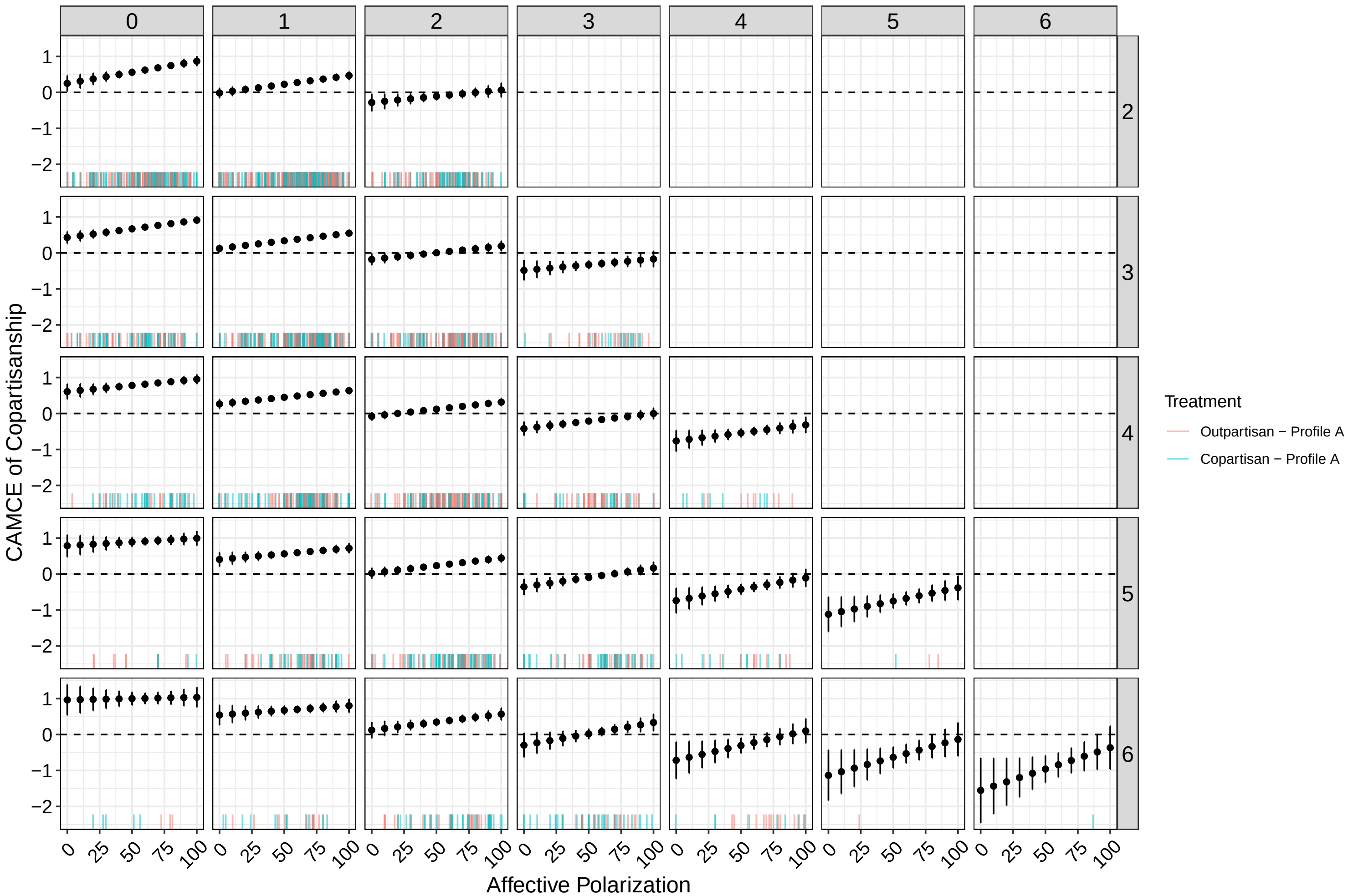
Figure B.4.3: CAMCE of Copartisanship by Ideological Congruence and Excluded Issue




Note: CAMCE estimates from models fitted on subsets of data excluding profile pairs displaying positions from the specified issue. Full model fit using data for both Democrats and Republicans; fits from Democratic and Republican subsets are also displayed.

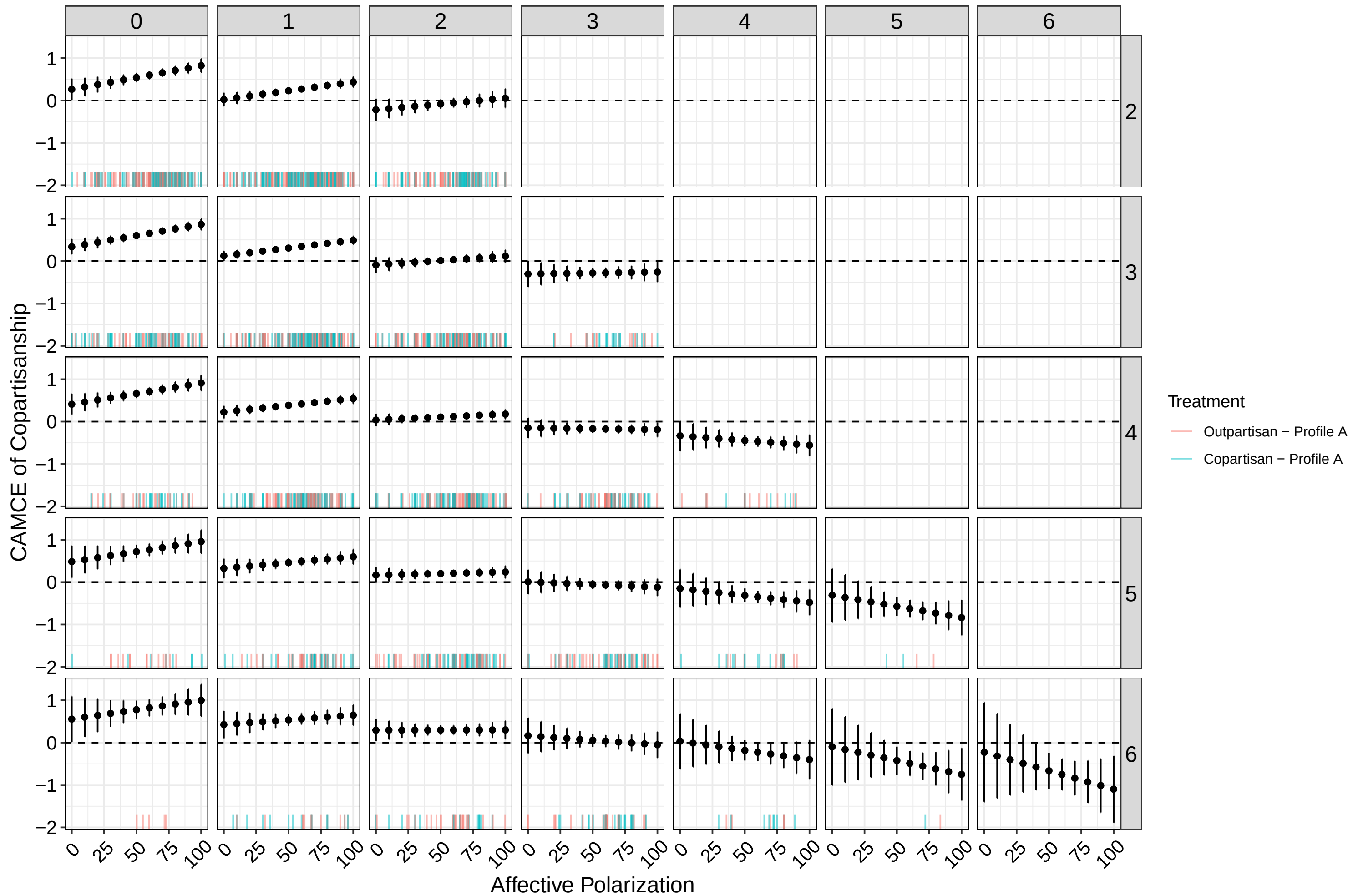
#### B.4.3 CAMCE Results by Issue Content

Figure B.4.4: CAMCE of Copartisanship by Issue Content (Abortion Excluded)



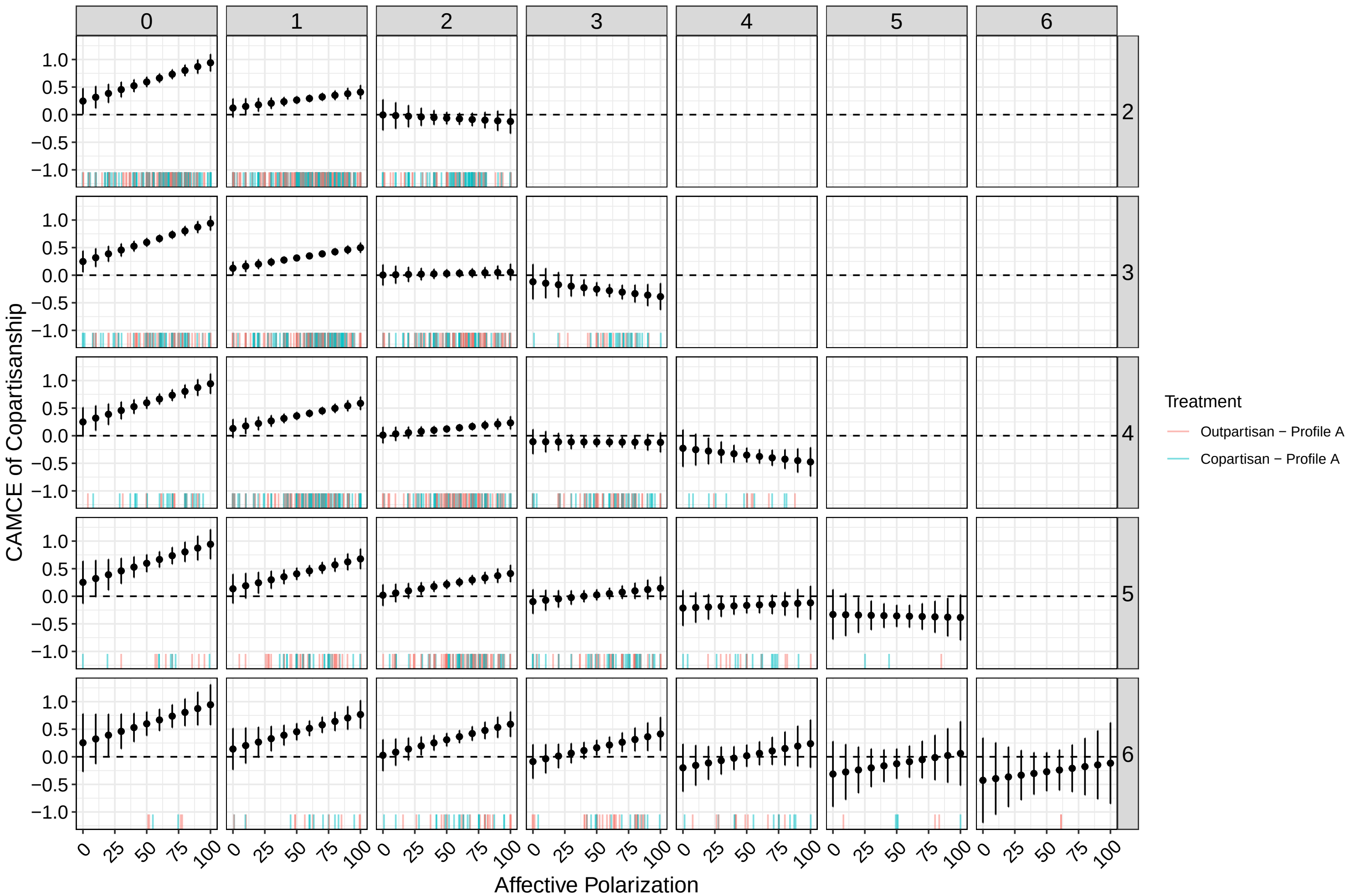

Note: CAMCE estimates from models fitted on subsets of data excluding profile pairs displaying abortion positions.

Figure B.4.5: CAMCE of Copartisanship by Issue Content (Environmental Regulation Excluded)



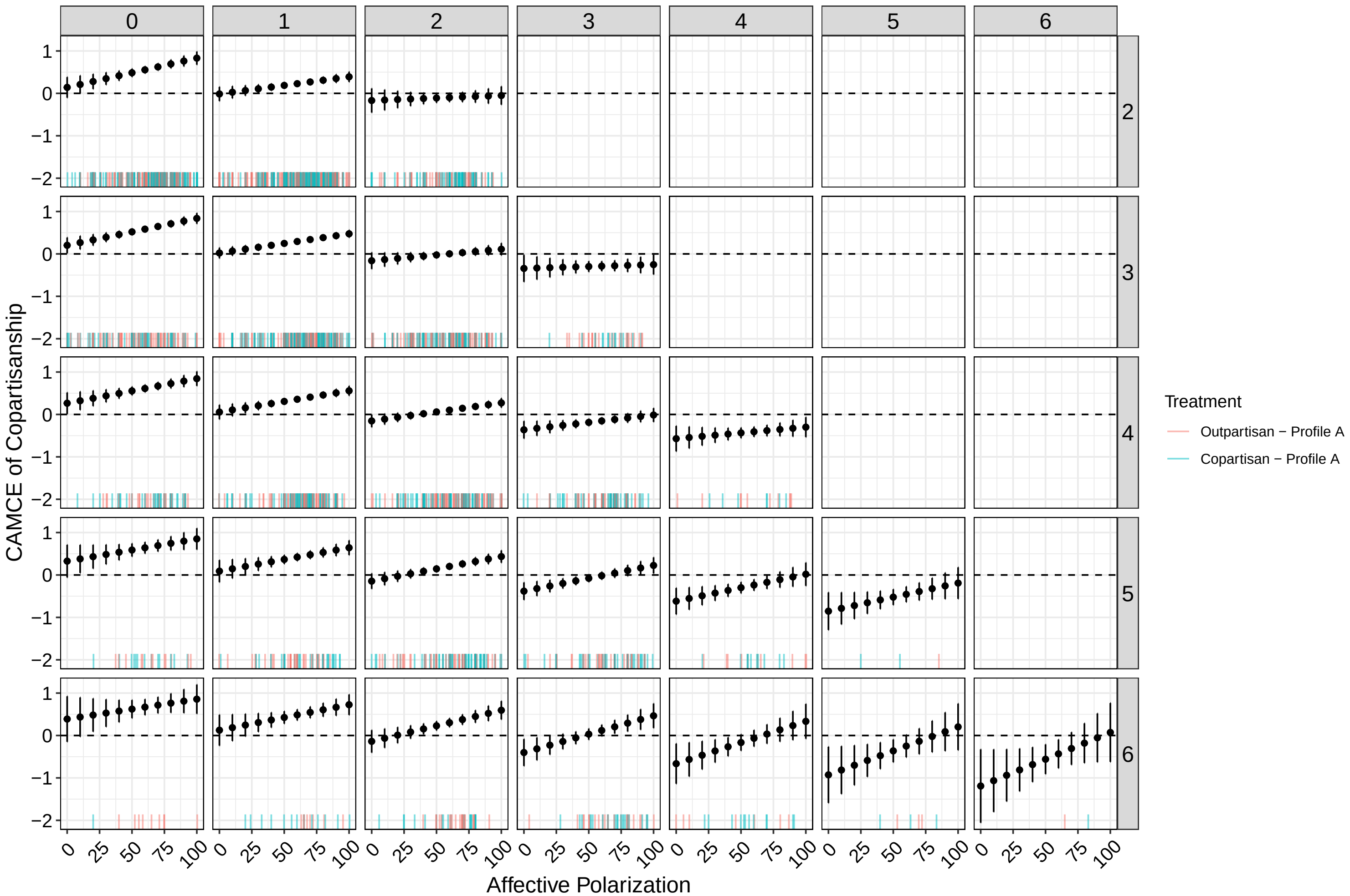

Note: CAMCE estimates from models fitted on subsets of data excluding profile pairs displaying environmental regulation positions.

Figure B.4.6: CAMCE of Copartisanship by Issue Content (Governmental Spending Excluded)



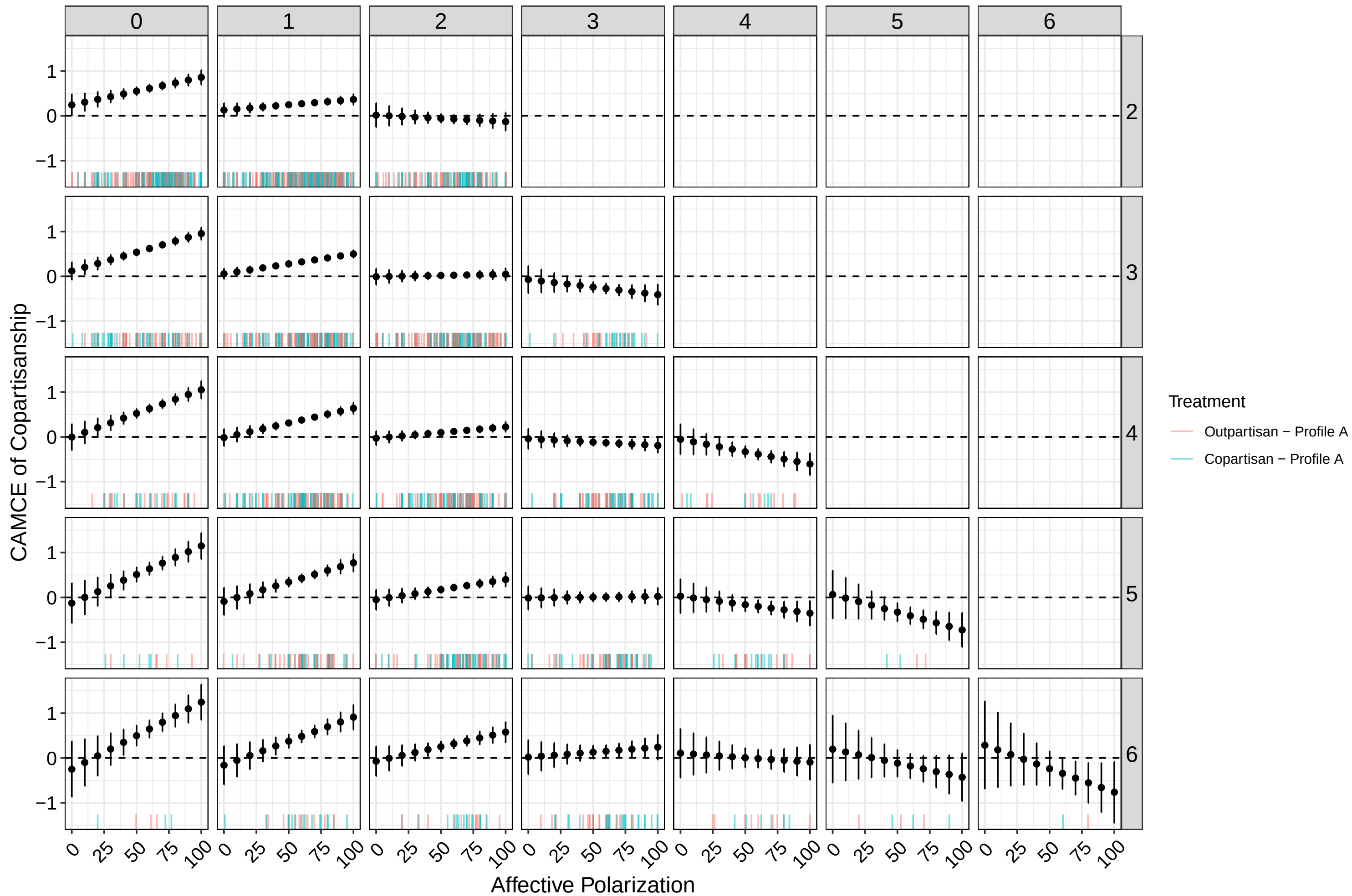

Note: CAMCE estimates from models fitted on subsets of data excluding profile pairs displaying governmental spending positions.

Figure B.4.7: CAMCE of Copartisanship by Issue Content (Red-Flag Laws Excluded)



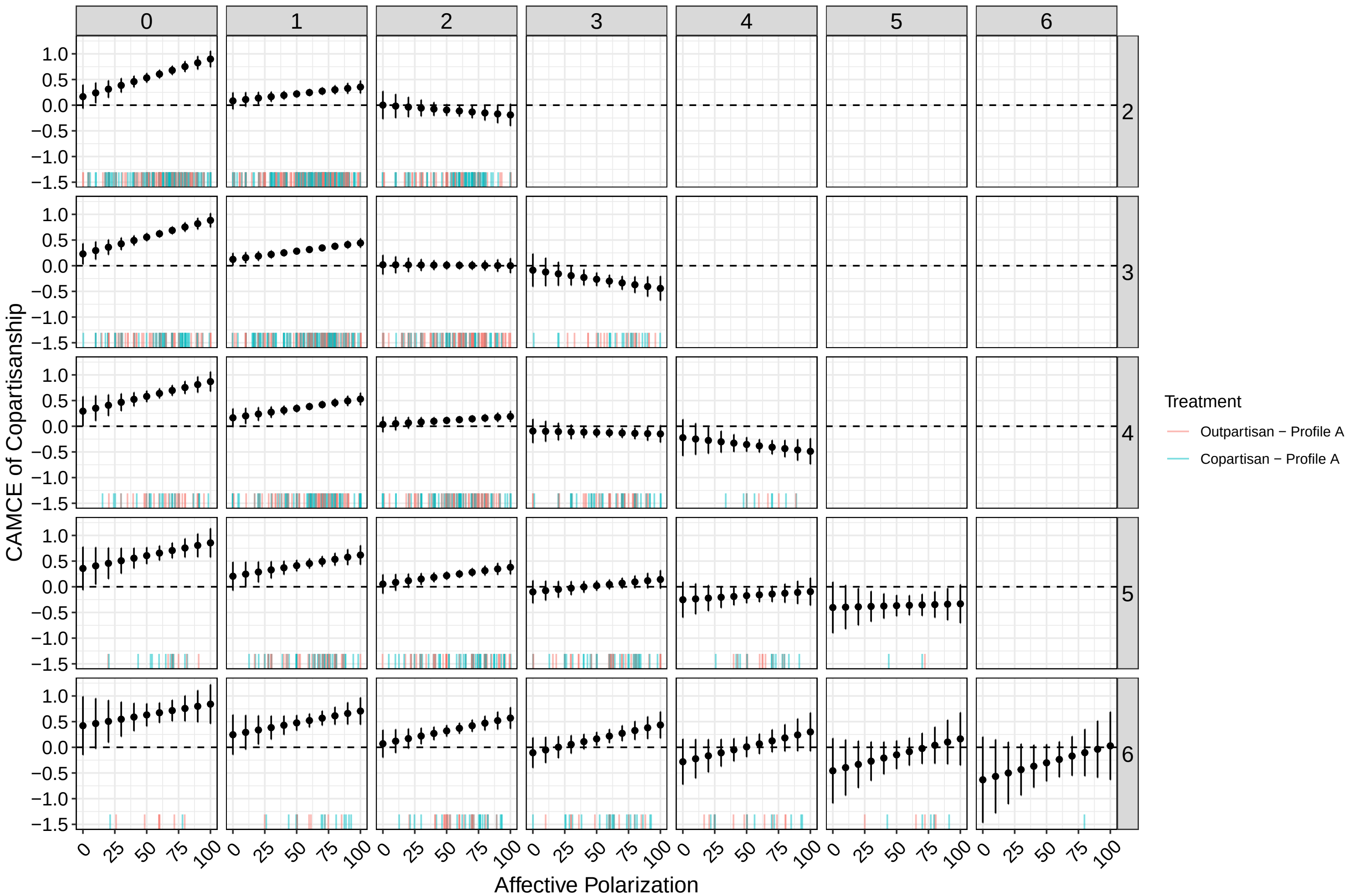

Note: CAMCE estimates from models fitted on subsets of data excluding profile pairs displaying red-flag law positions.

Figure B.4.8: CAMCE of Copartisanship by Issue Content (Sanctuary Cities Excluded)



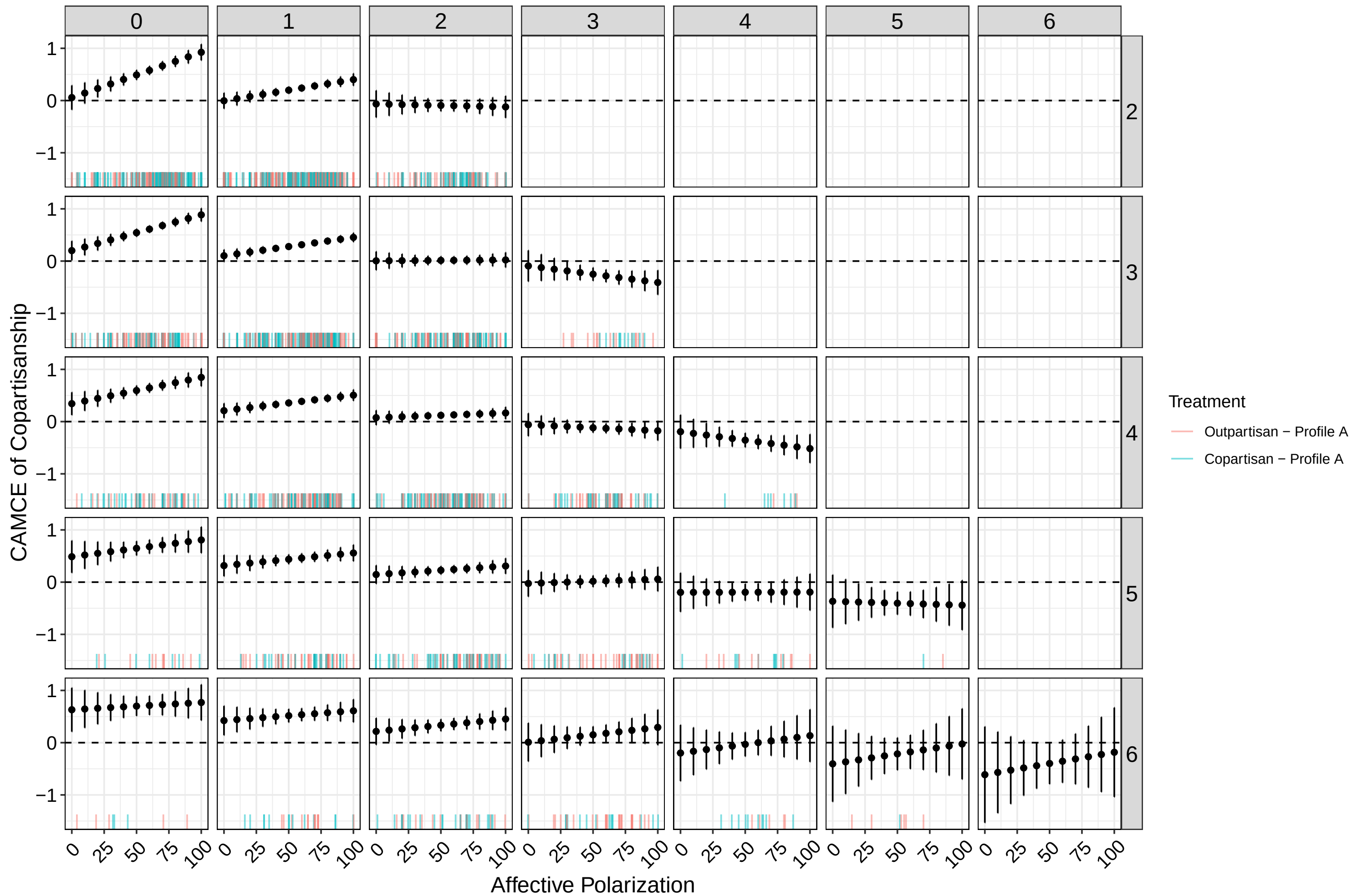

Note: CAMCE estimates from models fitted on subsets of data excluding profile pairs displaying sanctuary cities positions.

Figure B.4.9: CAMCE of Copartisanship by Issue Content (School Vouchers Excluded)




Note: CAMCE estimates from models fitted on subsets of data excluding profile pairs displaying school vouchers positions.

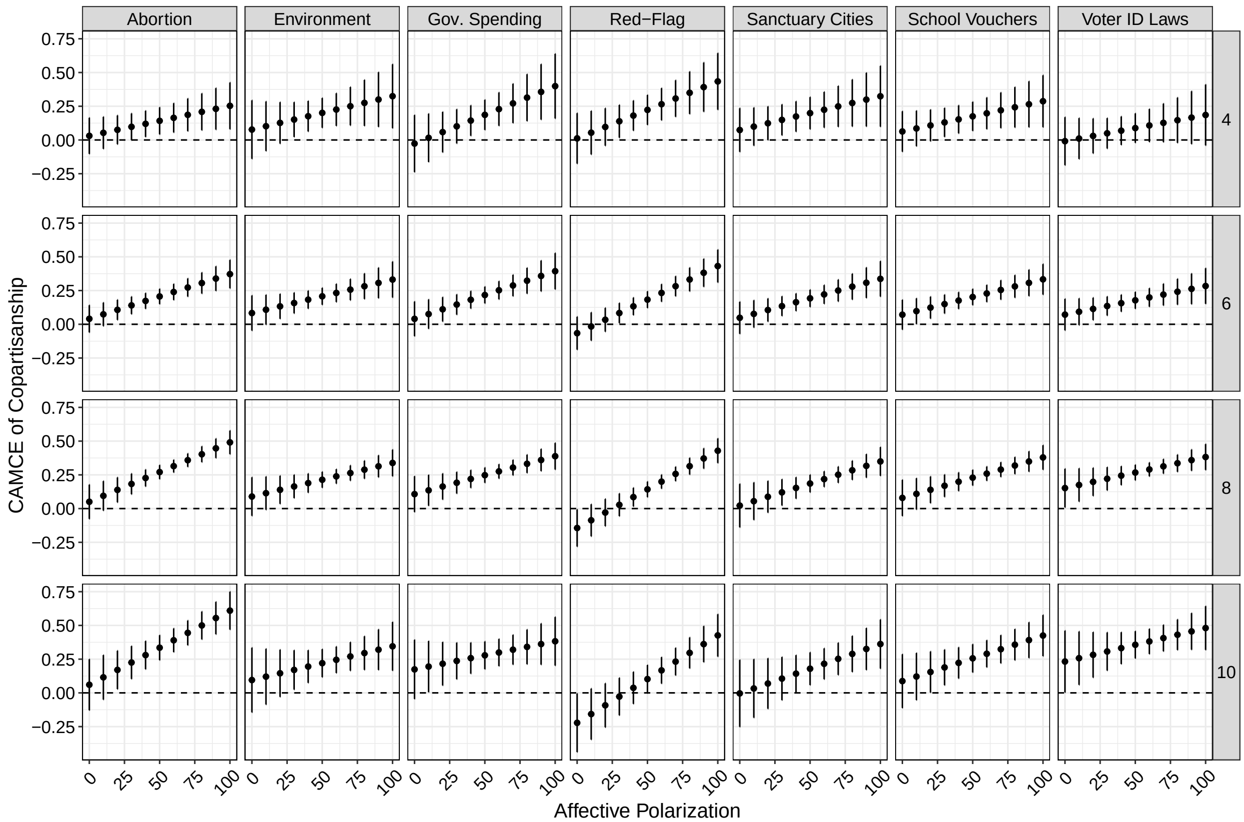
Figure B.4.10: CAMCE of Copartisanship by Issue Content (Voter ID Excluded)




Note: CAMCE estimates from models fitted on subsets of data excluding profile pairs displaying voter ID positions.

### B.4.4 CAMCE By Ideology

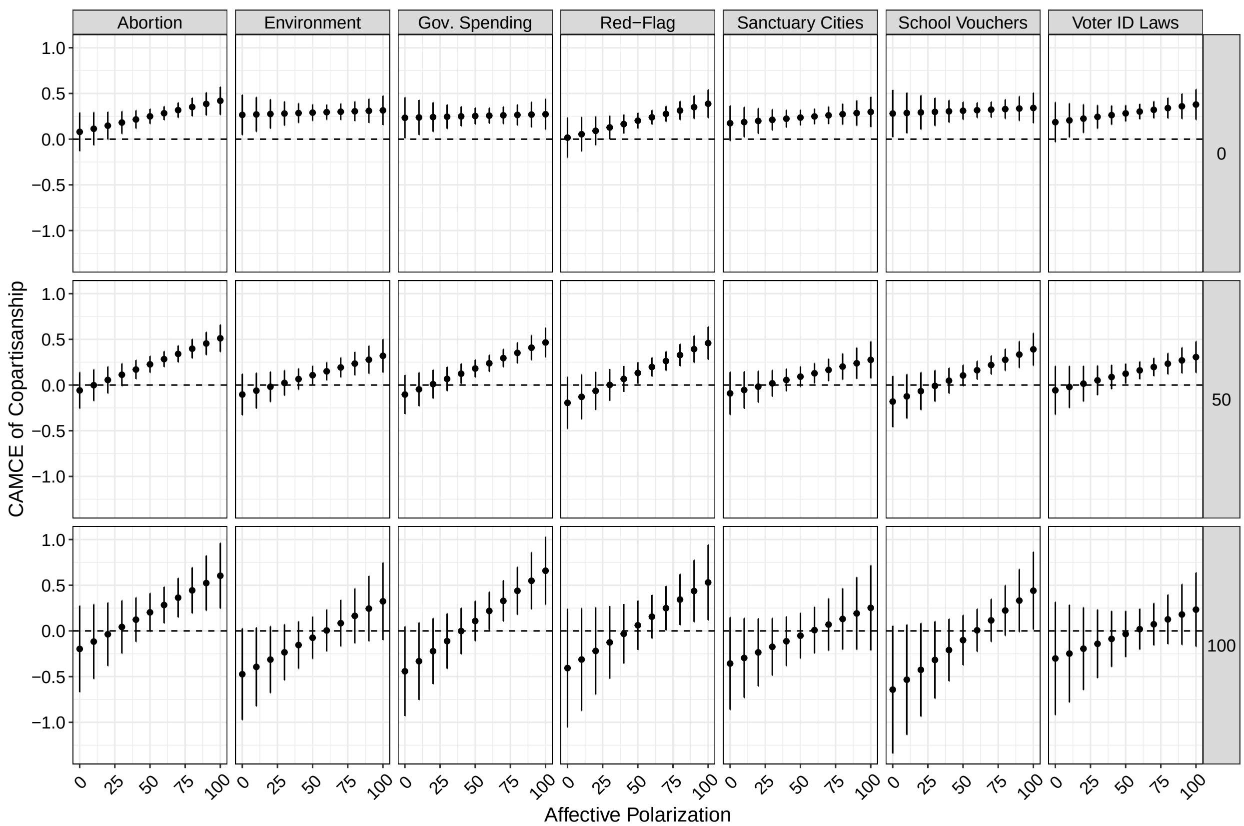
Figure B.4.11: CAMCE of Copartisanship by Ideology, Affect, and Excluded Issue




Note: CAMCE estimates from models fitted on subsets of data excluding profile pairs displaying positions from the specified issue.

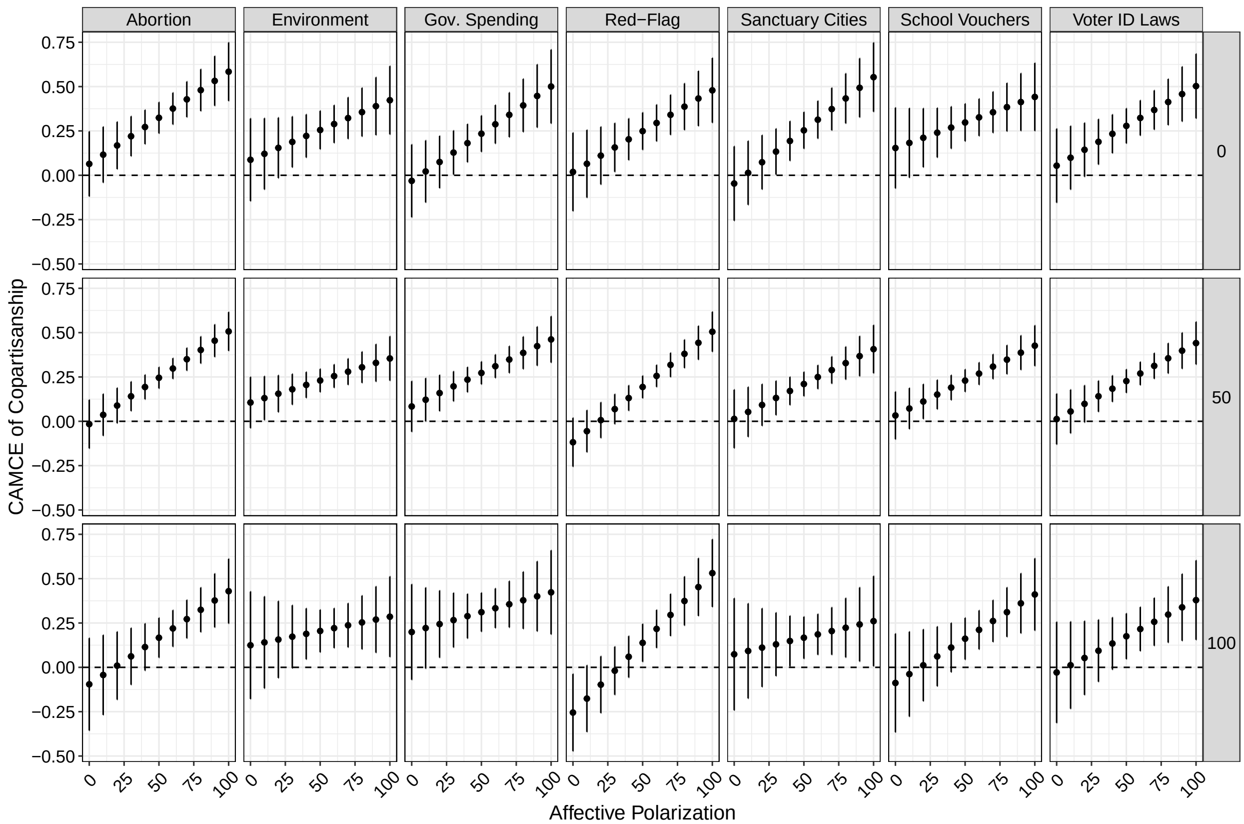
### B.4.5 CAMCE By Affect, Election Results, and Excluded Issue

Figure B.4.12: CAMCE of Copartisanship by General Election Margin, Affect, and Excluded Issue




Note: CAMCE estimates from models fitted on subsets of data excluding profile pairs displaying positions from the specified issue.

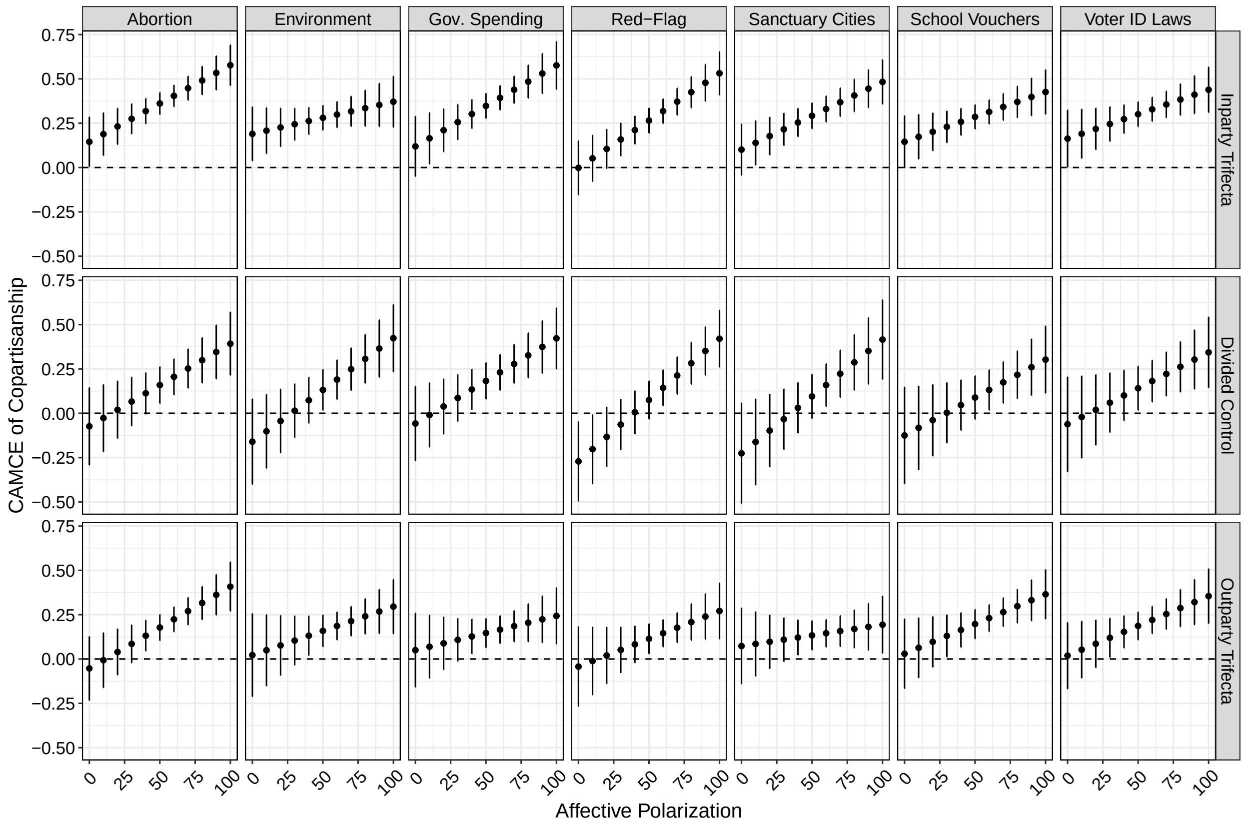
Figure B.4.13: CAMCE of Copartisanship by Primarty Election Margin, Affect, and Excluded Issue




Note: CAMCE estimates from models fitted on subsets of data excluding profile pairs displaying positions from the specified issue.

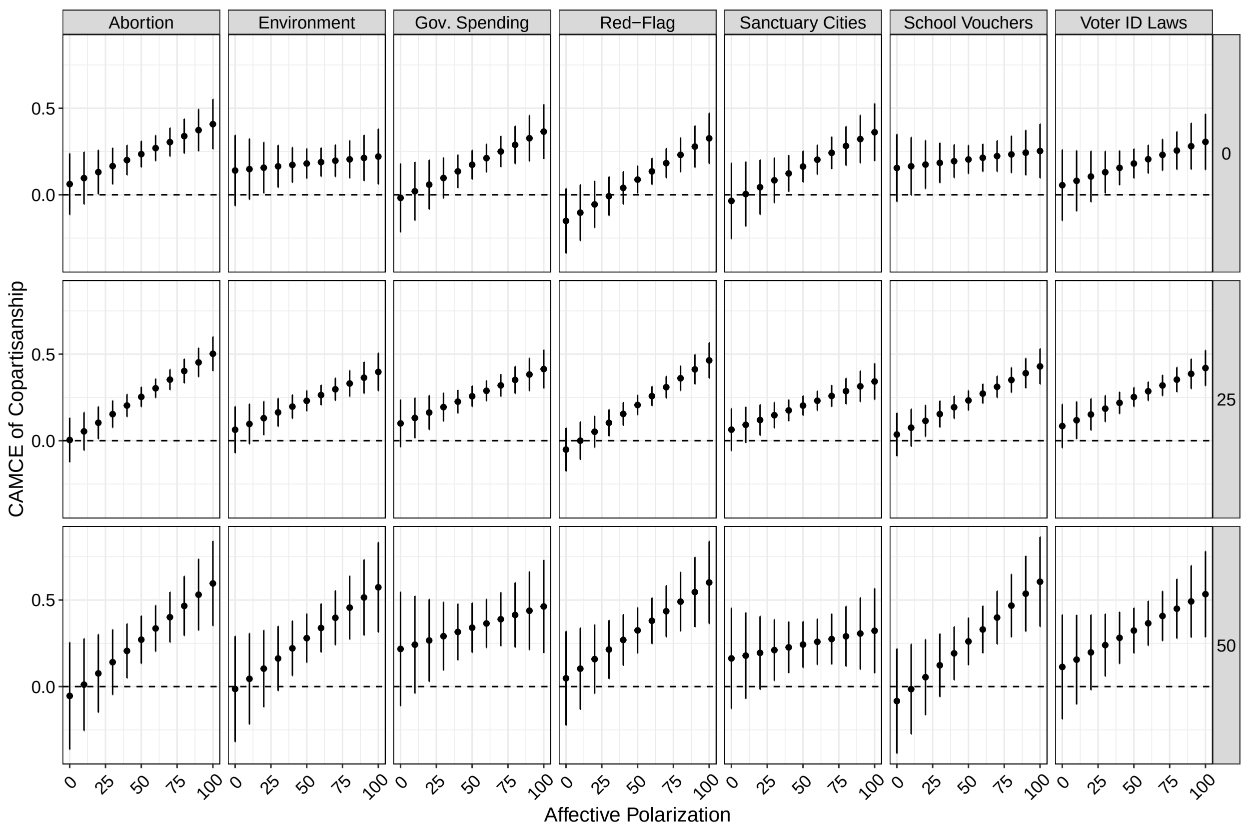
### B.4.6 CAMCE By Affect, State Control, and Excluded Issue

Figure B.4.14: CAMCE of Copartisanship by State Control, Affect, and Excluded Issue




Note: CAMCE estimates from models fitted on subsets of data excluding profile pairs displaying positions from the specified issue.

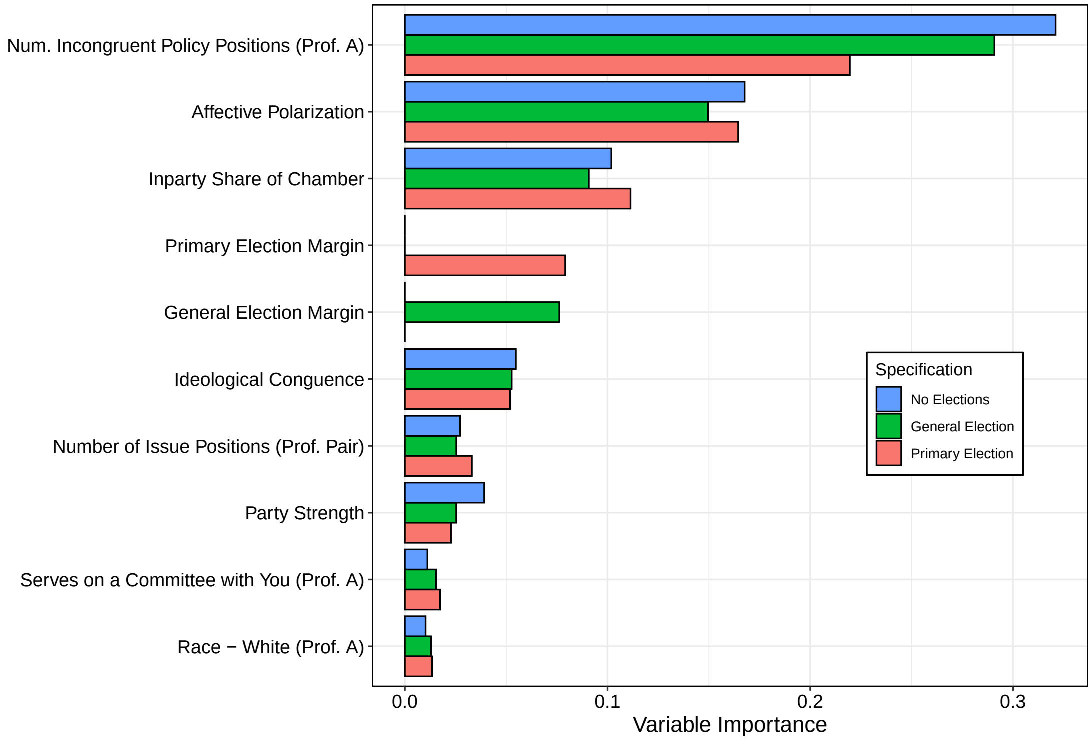
Figure B.4.15: CAMCE of Copartisanship by Chamber Margin, Affect, and Excluded Issue




Note: CAMCE estimates from models fitted on subsets of data excluding profile pairs displaying positions from the specified issue.

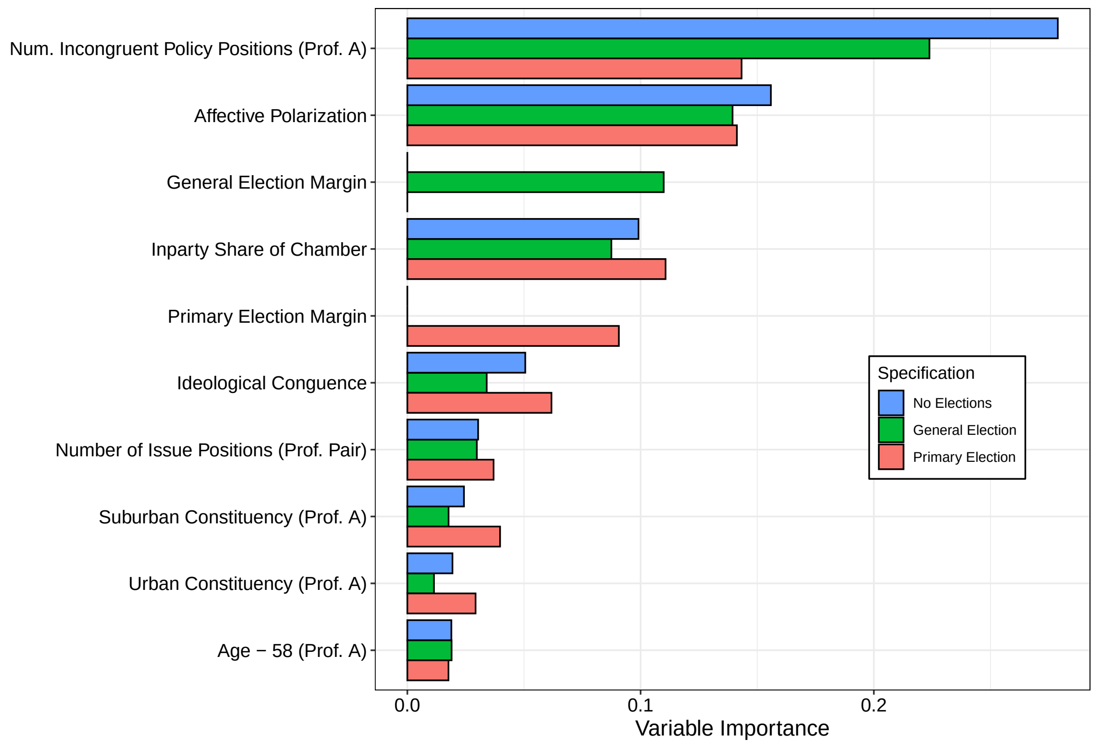
### B.4.7 Variable Importance Results

Figure B.4.16: Variable Importance from Causal Forest Fits (Abortion Excluded)



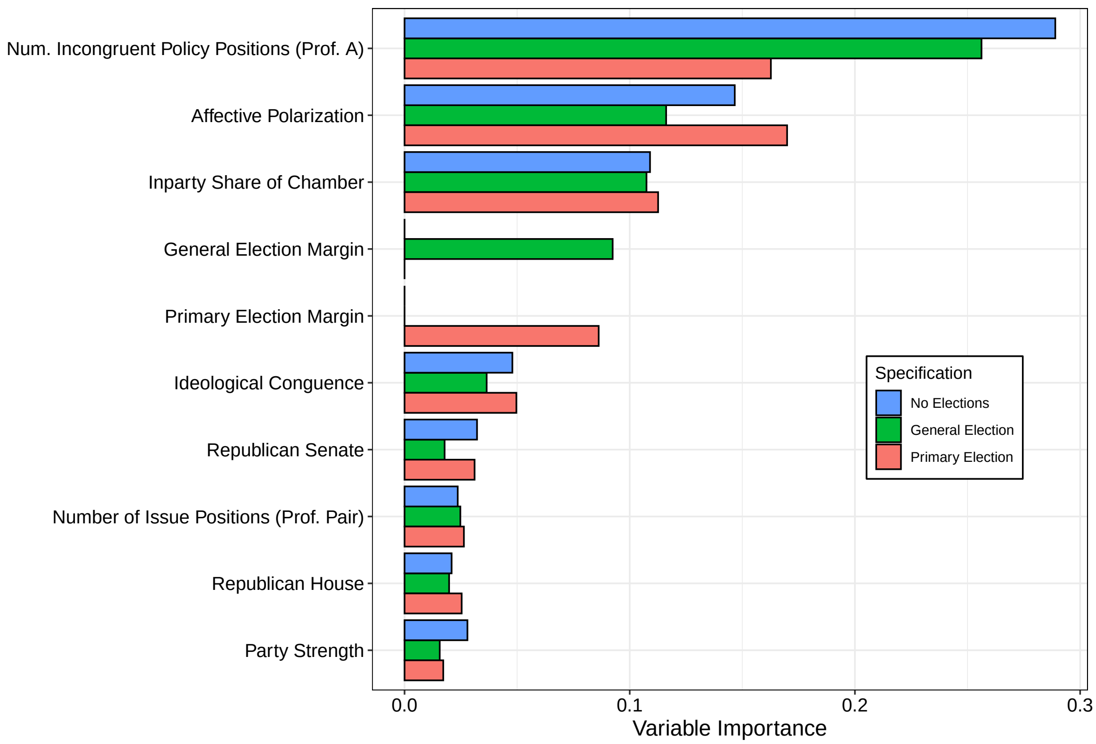

Note: Variable importance from 10-fold causal forest fits on data excluding choice tasks with abortion positions. The 10 variables with the highest median importance across folds and specifications shown for space. Specifications with primary or general election margins have fewer observations due to election missingness (some individuals ran in primaries but not in the general and vice versa).

Figure B.4.17: Variable Importance from Causal Forest Fits (Environmental Regulation Excluded)



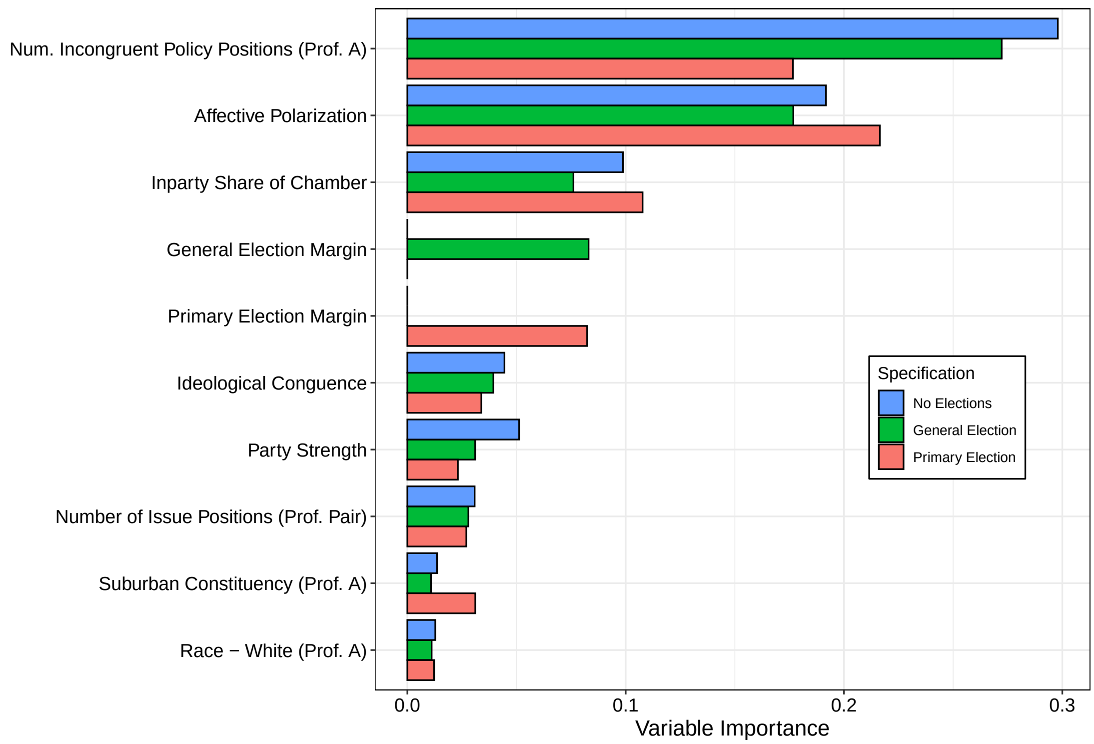

Note: Variable importance from 10-fold causal forest fits on data excluding choice tasks with environmental regulation positions. The 10 variables with the highest median importance across folds and specifications shown for space. Specifications with primary or general election margins have fewer observations due to election missingness (some individuals ran in primaries but not in the general and vice versa).

Figure B.4.18: Variable Importance from Causal Forest Fits (Governmental Spending Excluded)



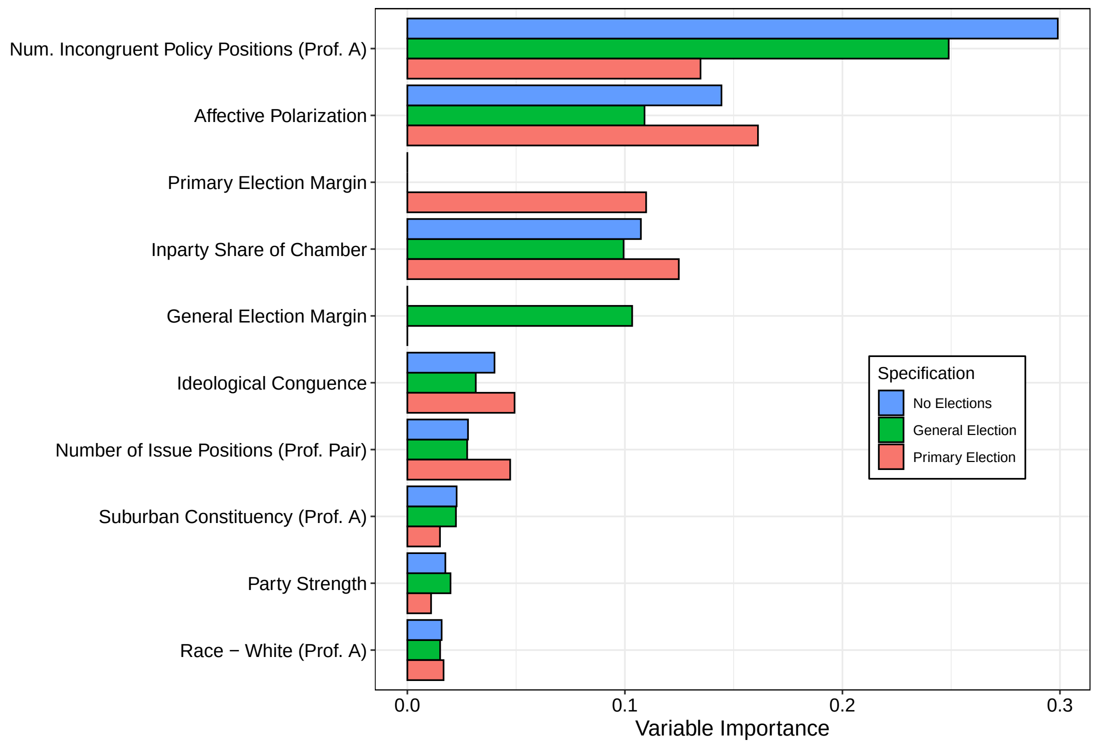

Note: Variable importance from 10-fold causal forest fits on data excluding choice tasks with governmental spending positions. The 10 variables with the highest median importance across folds and specifications shown for space. Specifications with primary or general election margins have fewer observations due to election missingness (some individuals ran in primaries but not in the general and vice versa).

Figure B.4.19: Variable Importance from Causal Forest Fits (Red-Flag Laws Excluded)



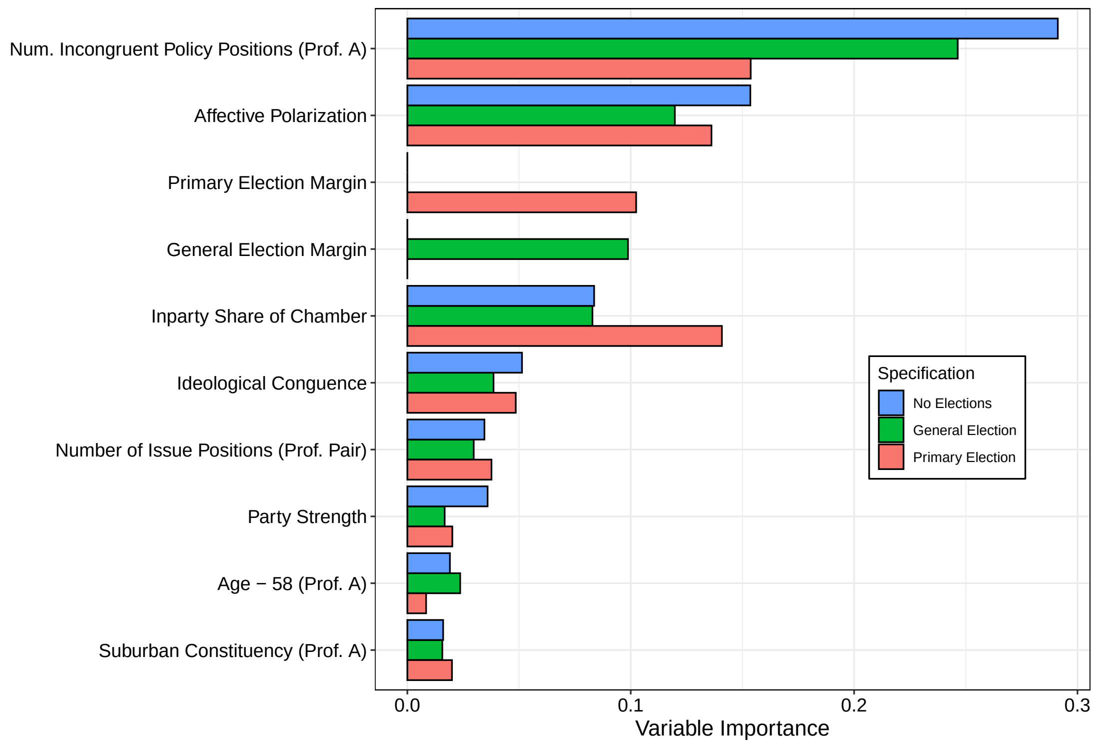

Note: Variable importance from 10-fold causal forest fits on data excluding choice tasks with positions on red-flag laws. The 10 variables with the highest median importance across folds and specifications shown for space. Specifications with primary or general election margins have fewer observations due to election missingness (some individuals ran in primaries but not in the general and vice versa).

Figure B.4.20: Variable Importance from Causal Forest Fits (Sanctuary Cities Excluded)



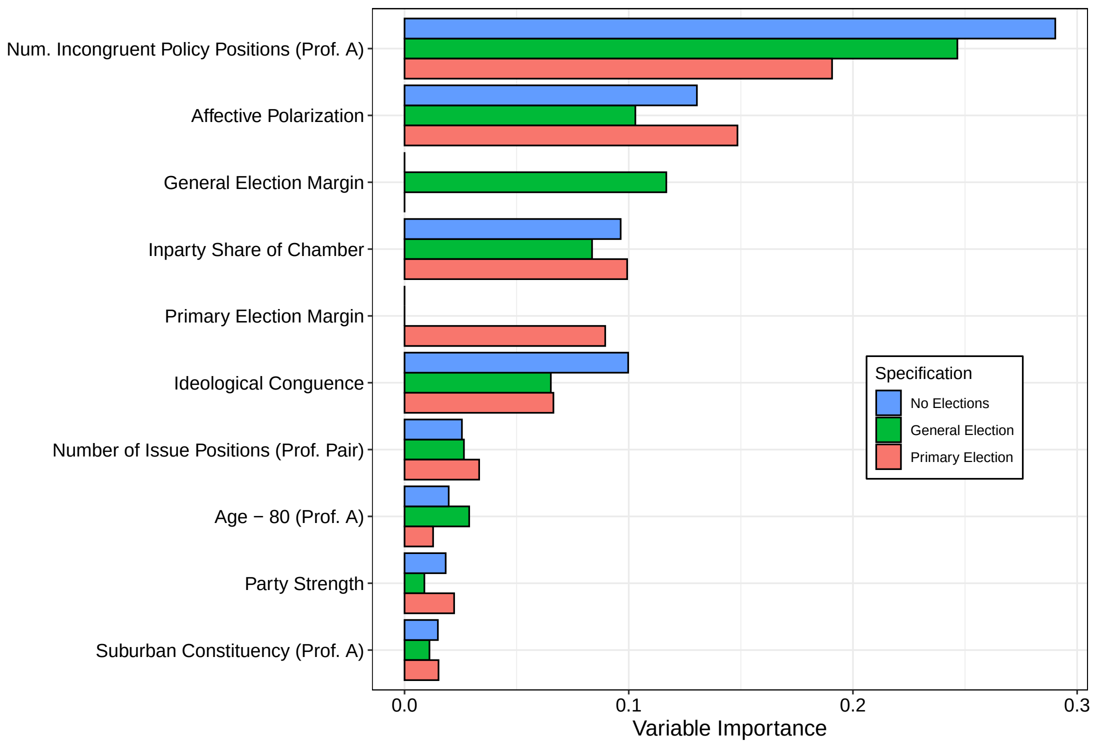

Note: Variable importance from 10-fold causal forest fits on data excluding choice tasks with positions on sanctuary cities. The 10 variables with the highest median importance across folds and specifications shown for space. Specifications with primary or general election margins have fewer observations due to election missingness (some individuals ran in primaries but not in the general and vice versa).

Figure B.4.21: Variable Importance from Causal Forest Fits (School Vouchers Excluded)




Note: Variable importance from 10-fold causal forest fits on data excluding choice tasks with positions on school vouchers. The 10 variables with the highest median importance across folds and specifications shown for space. Specifications with primary or general election margins have fewer observations due to election missingness (some individuals ran in primaries but not in the general and vice versa).

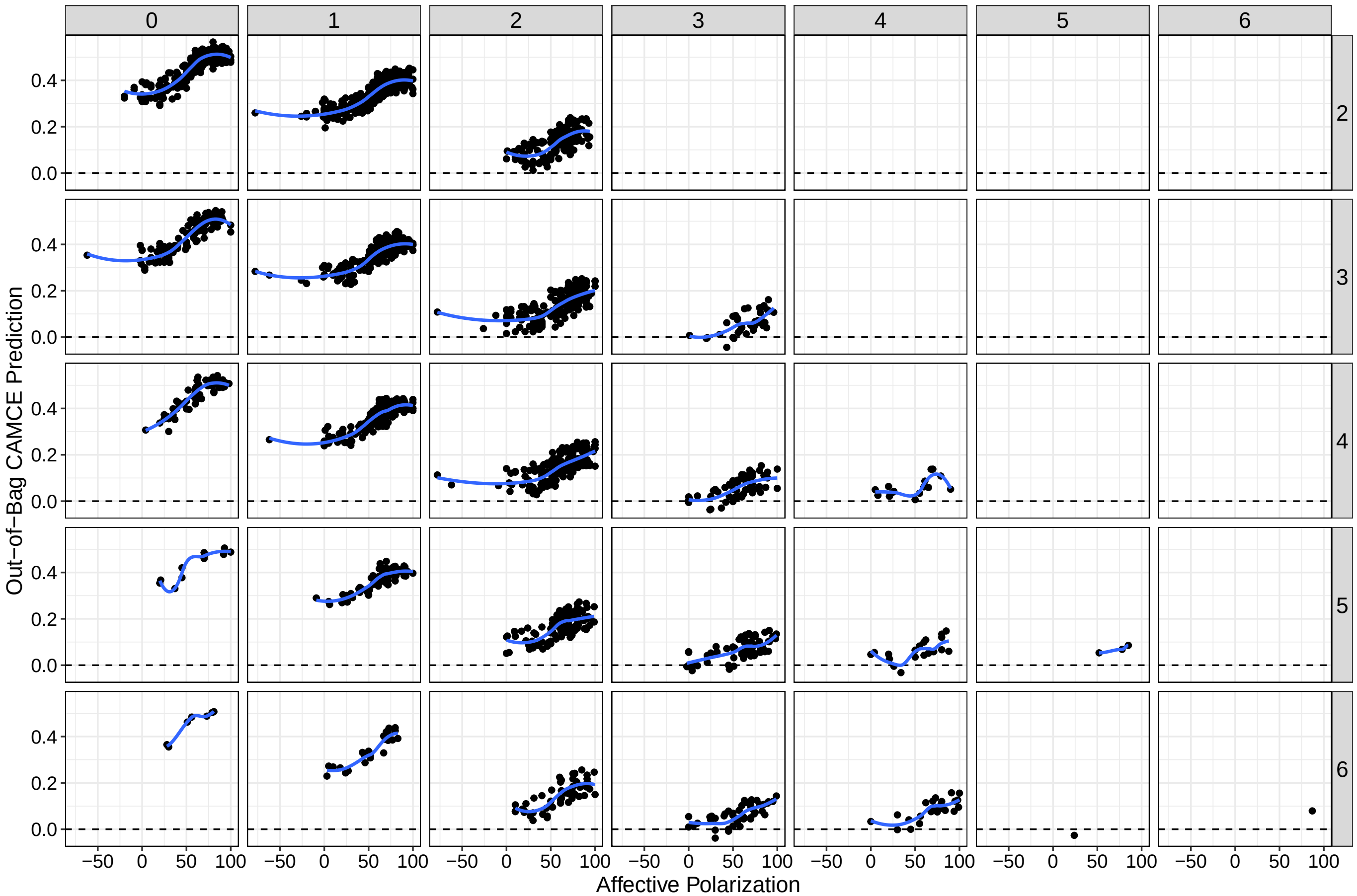
Figure B.4.22: Variable Importance from Causal Forest Fits (Voter ID Excluded)




Note: Variable importance from 10-fold causal forest fits on data excluding choice tasks with positions on voter ID laws. The 10 variables with the highest median importance across folds and specifications shown for space. Specifications with primary or general election margins have fewer observations due to election missingness (some individuals ran in primaries but not in the general and vice versa).

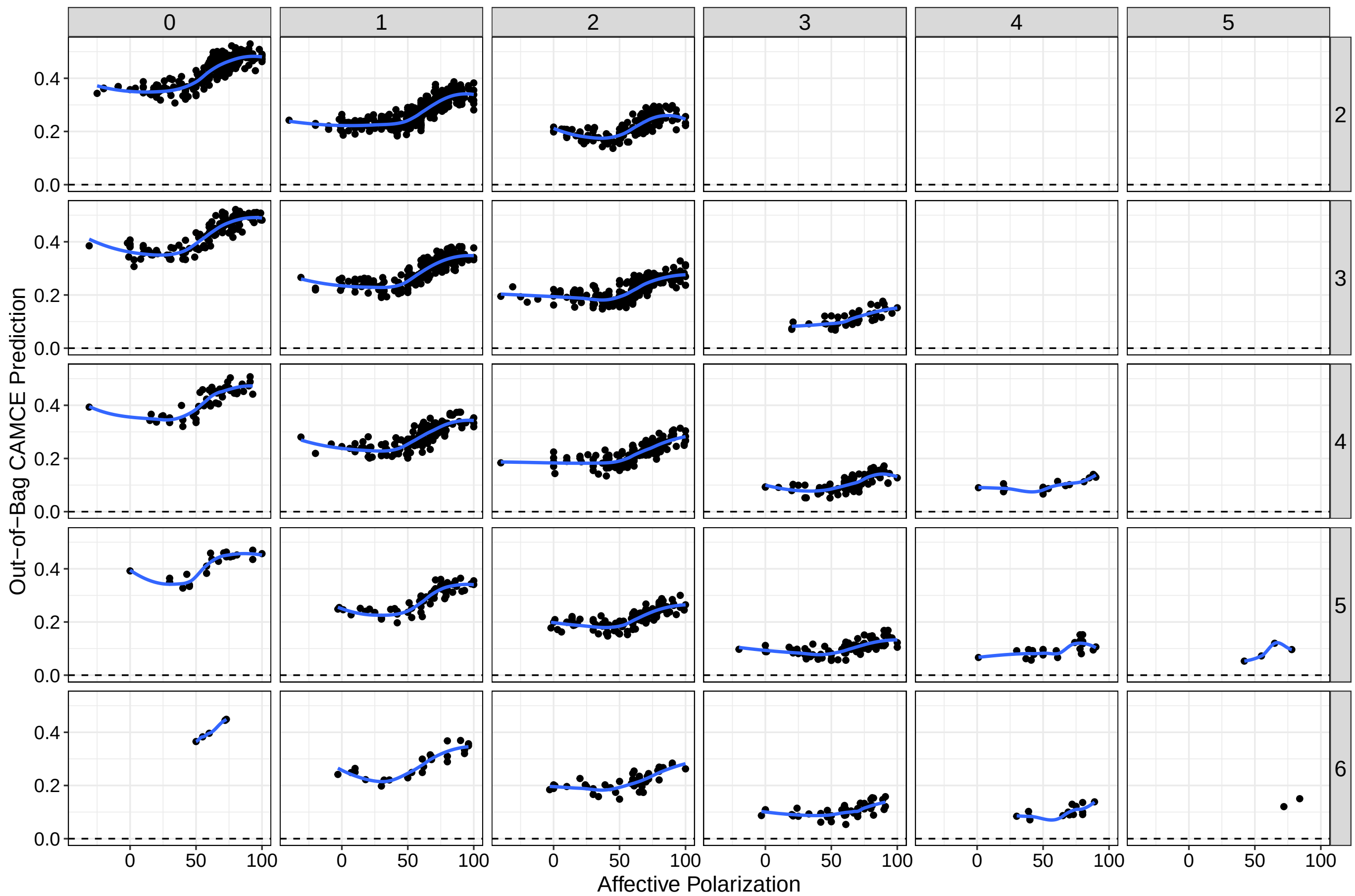
#### B.4.8 Predicted CAMCE Causal Forest

Figure B.4.23: Predicted CAMCEs of Copartisanship by Affect and Issues (Abortion Excluded)



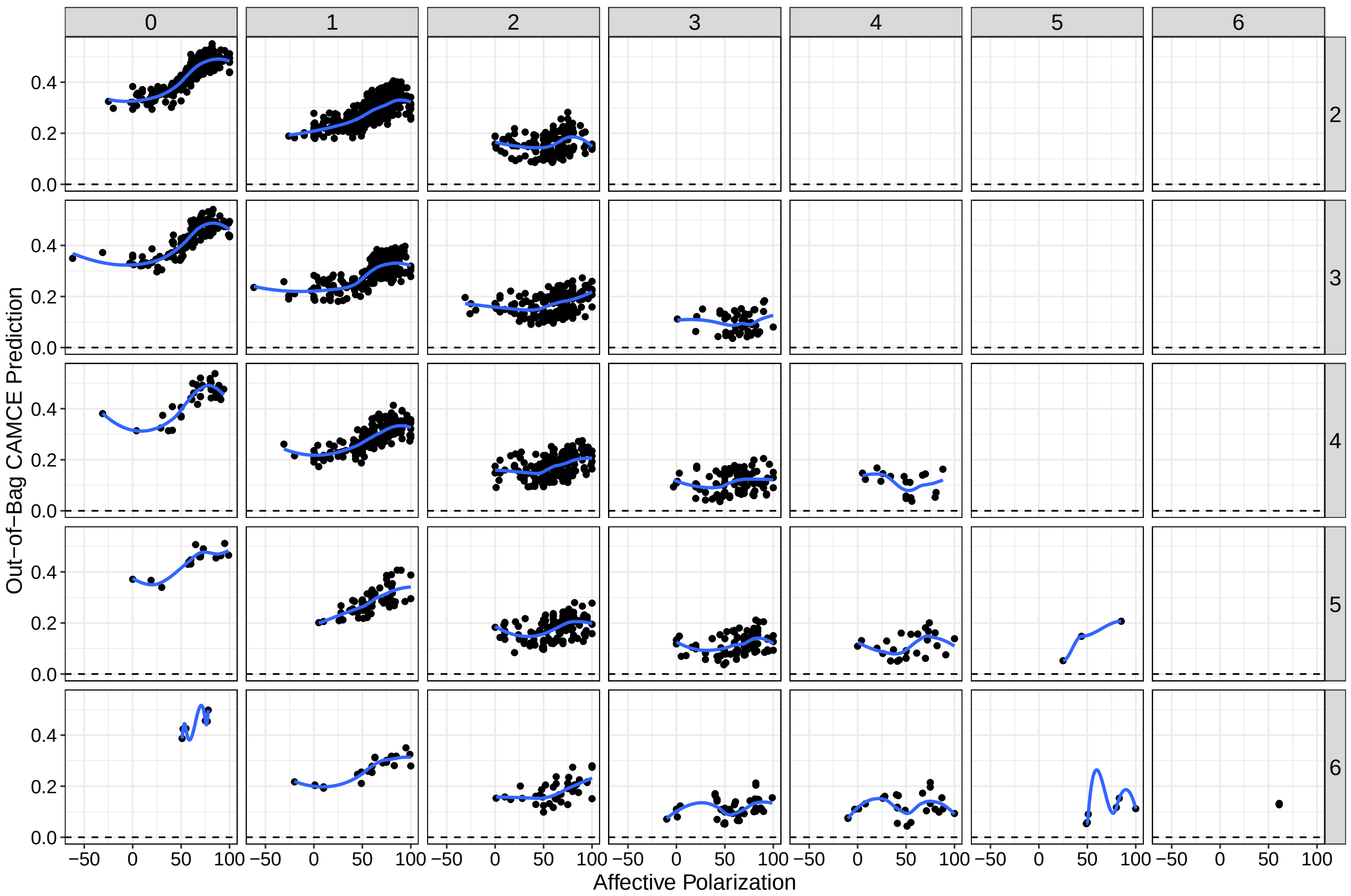

Note: Predicted CAMCEs from 10-fold causal forest fits on data excluding choices displaying abortion positions.

Figure B.4.24: Predicted CAMCEs of Copartisanship by Affect and Issues (Environmental Regulations Excluded)



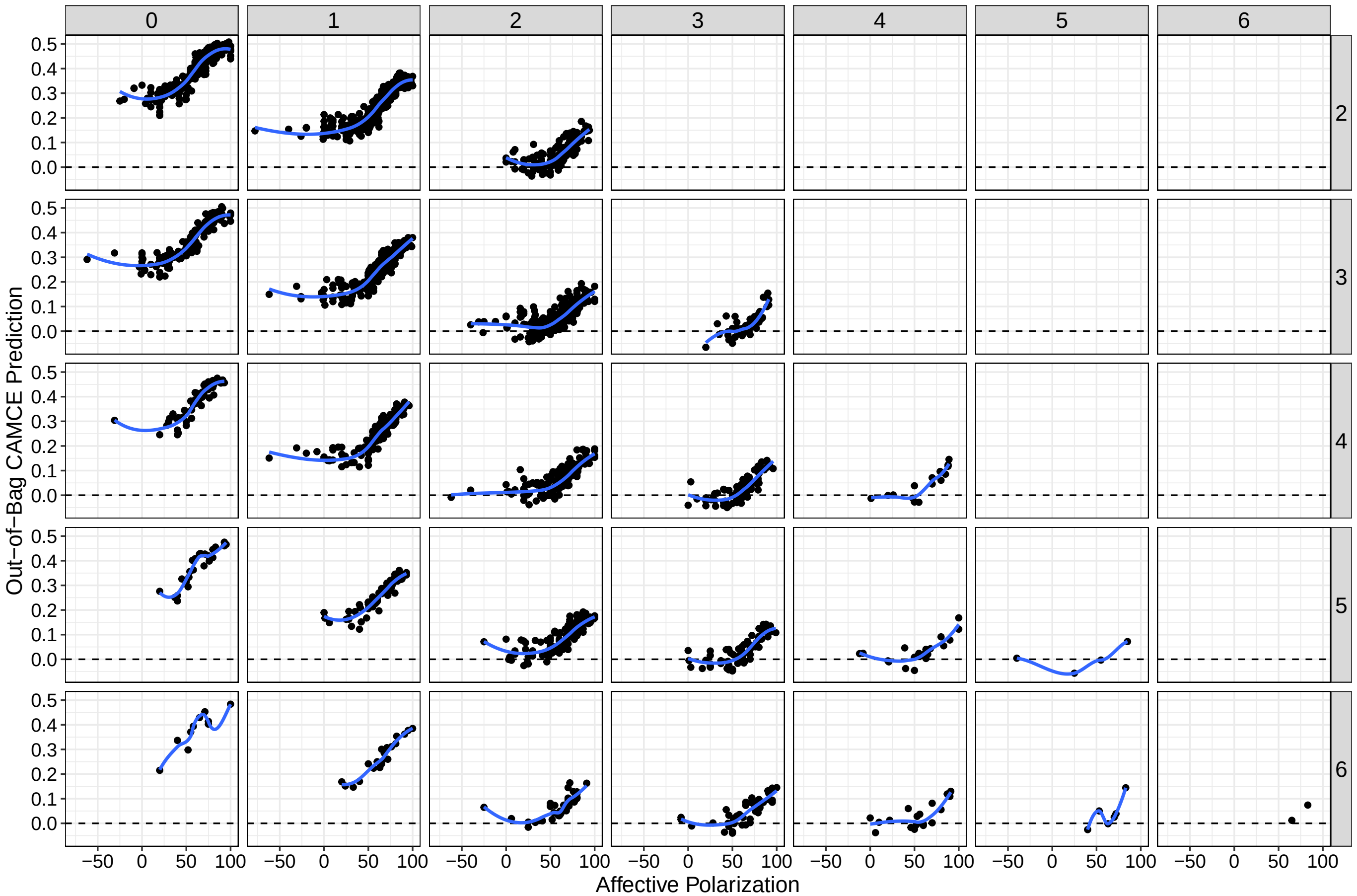

Note: Predicted CAMCEs from 10-fold causal forest fits on data excluding choices displaying positions on environmental regulations.

Figure B.4.25: Predicted CAMCEs of Copartisanship by Affect and Issues (Government Spending Excluded)



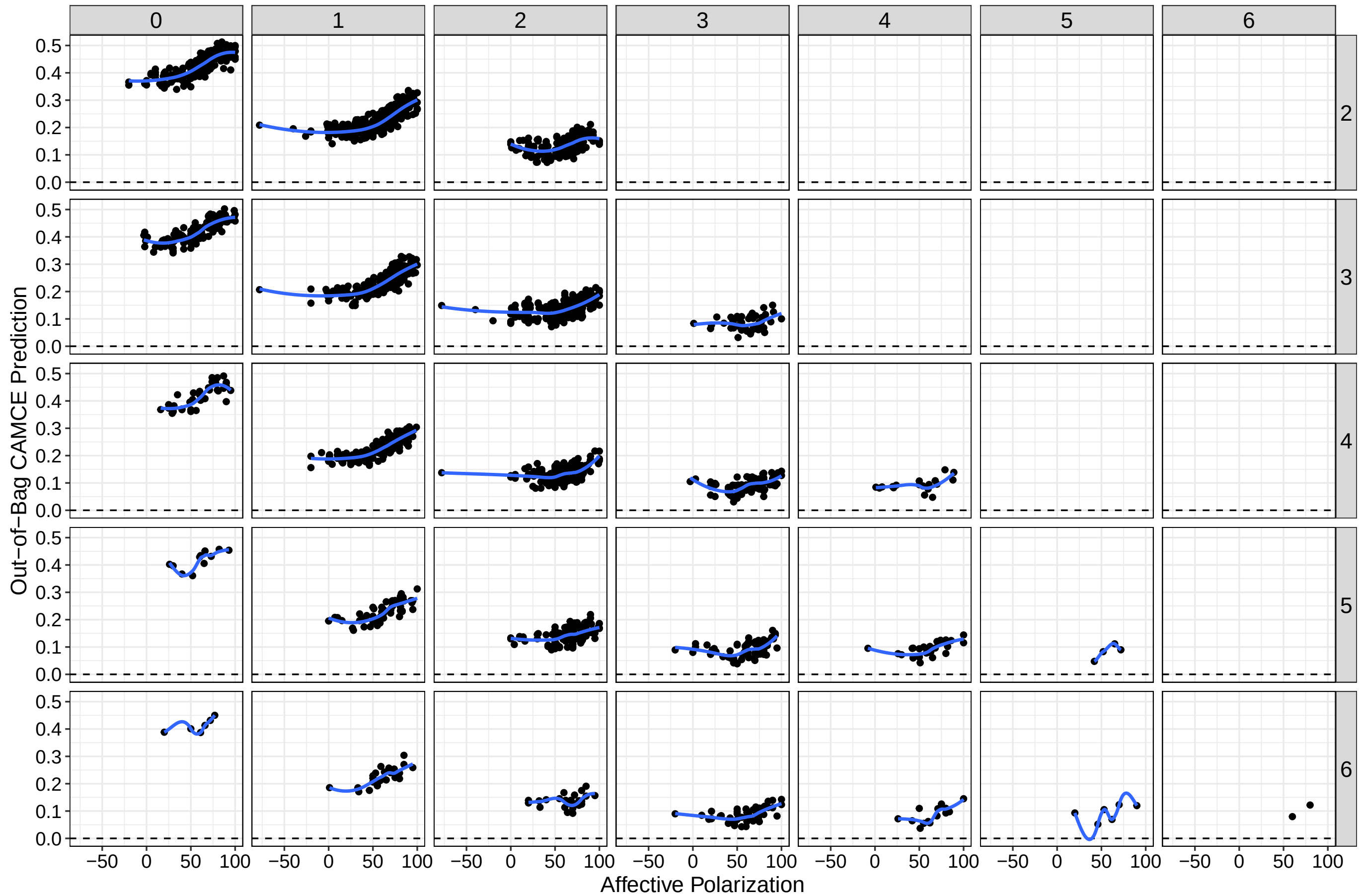

Note: Predicted CAMCEs from 10-fold causal forest fits on data excluding choices displaying governmental spending positions.

Figure B.4.26: Predicted CAMCEs of Copartisanship by Affect and Issues (Red-Flag Laws Excluded)



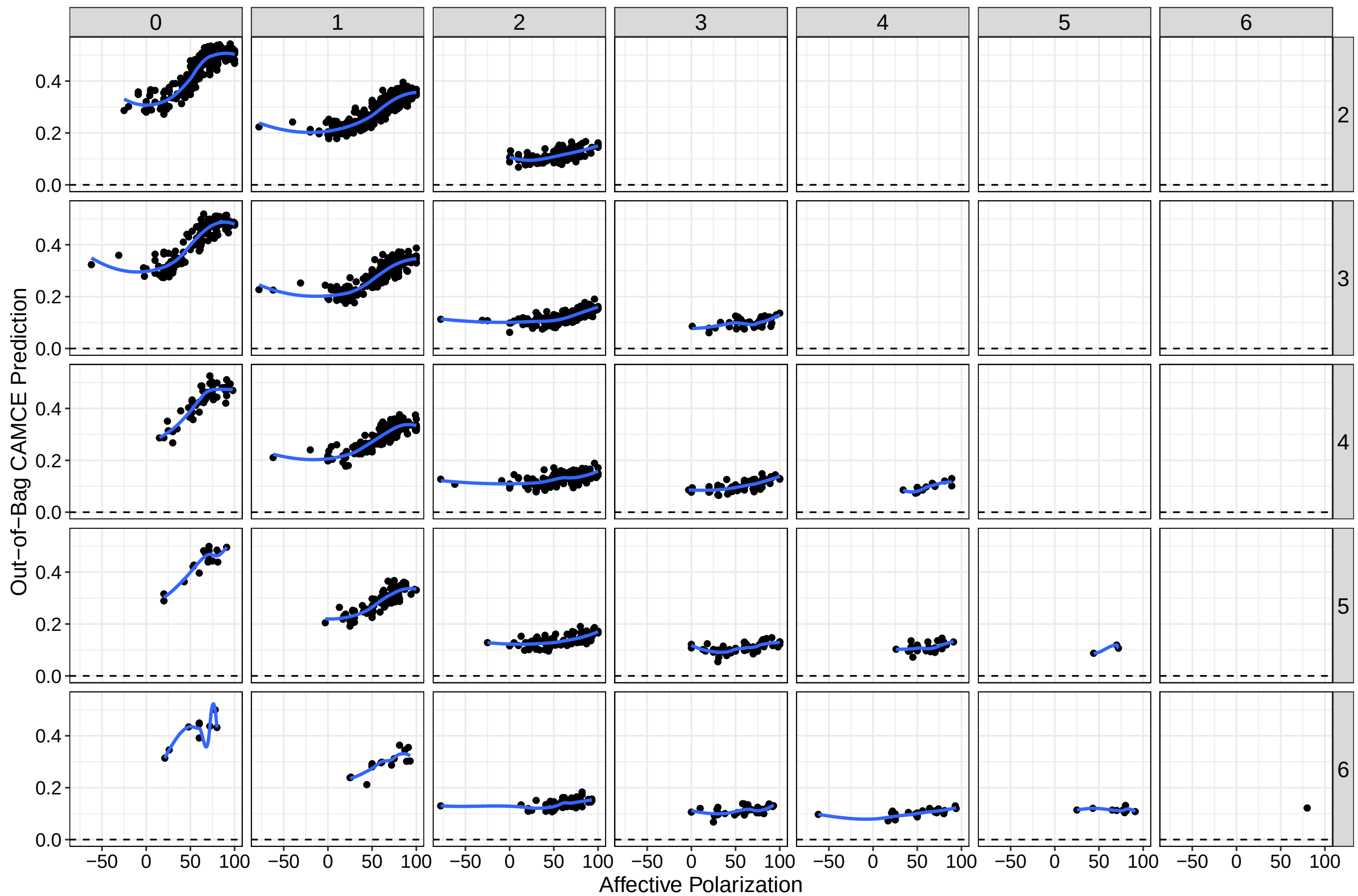

Note: Predicted CAMCEs from 10-fold causal forest fits on data excluding choices displaying positions on red-flag laws.

Figure B.4.27: Predicted CAMCEs of Copartisanship by Affect and Issues (Sanctuary Cities Excluded)



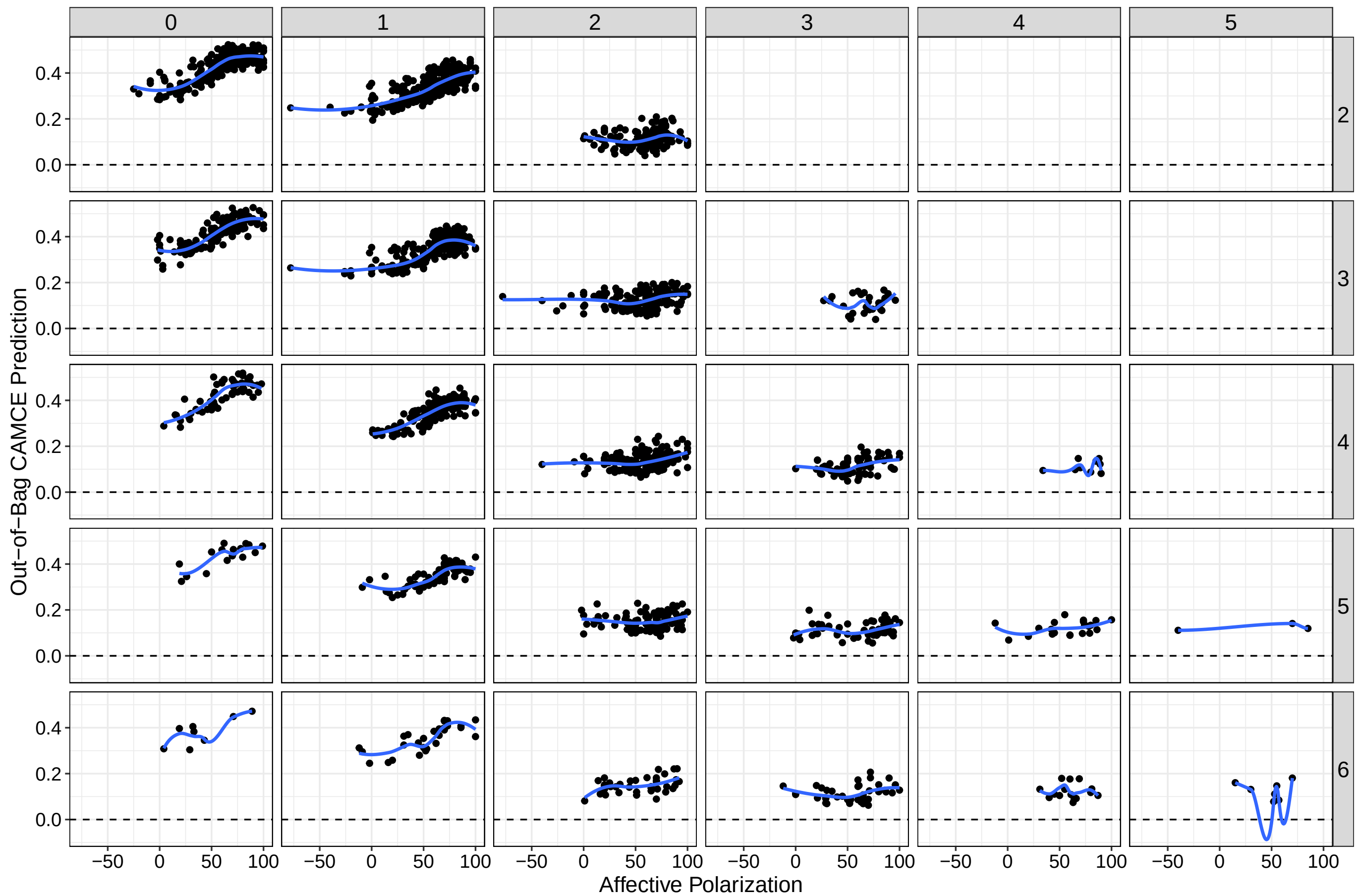

Note: Predicted CAMCEs from 10-fold causal forest fits on data excluding choices displaying sanctuary city positions.

Figure B.4.28: Predicted CAMCEs of Copartisanship by Affect and Issues (School Vouchers Excluded)




Note: Predicted CAMCEs from 10-fold causal forest fits on data excluding choices displaying school voucher positions.

Figure B.4.29: Predicted CAMCEs of Copartisanship by Affect and Issues (Voter ID Excluded)



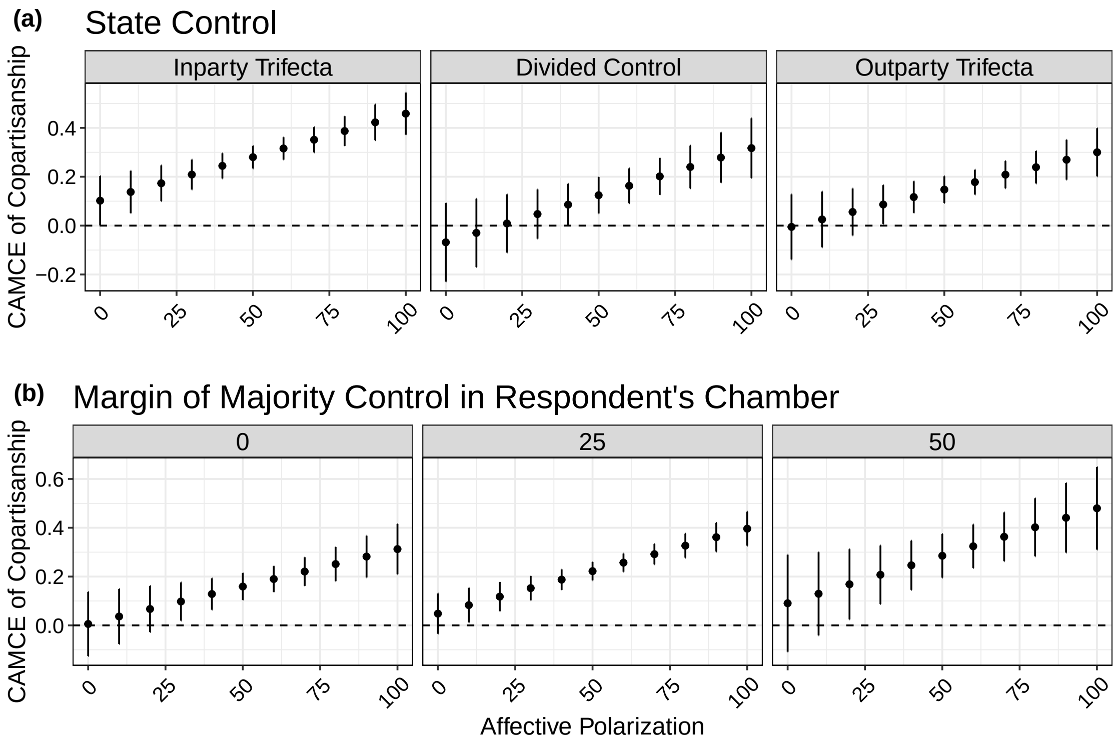

Note: Predicted CAMCEs from 10-fold causal forest fits on data excluding choices displaying voter ID positions.

## B.5 Robustness to Nebraska's Partisanship

Because Nebraska does not formally recognize parties in its legislature or in its legislative elections, I excluded candidates from Nebraska in the main analyses which measured state partisan control. This affects 38 observations from eight candidates. Here, I show that conclusions from the main text do not change when Nebraska is included. The party affiliations of legislators in Nebraska's unicameral have been identified by the media (e.g., Beck, 2023). The Republican Party in Nebraska currently controls both the legislature and the governorship, which I code as a Republican trifecta. Additionally, within the legislature there are 32 Republicans, 16 Democrats, and one independent. Since the main causal forest specifications include separate measures of gubernatorial, house, and senate control, I instead include the trifecta control measure in the robustness analysis because Nebraska's legislature only has one chamber.

### B.5.1 CAMCE Results by Affect and State Partisan Control

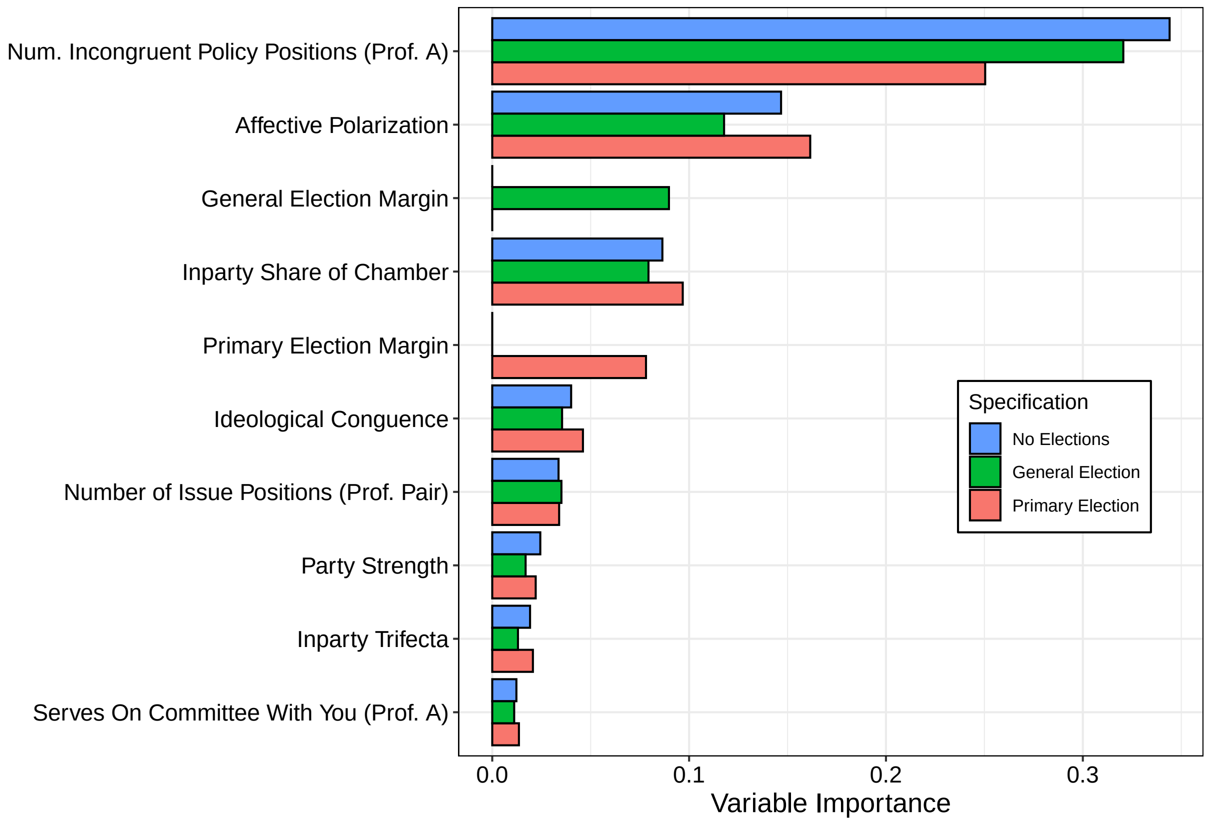
Figure B.5.1: CAMCEs of Copartisanship by Control of State Government (Including Nebraska)




Note: Copartisan CAMCE estimates from regressions of a choice indicator variable on an indicator variable for copartisanship, interacted with affective polarization and measures of state government control. In panel A, control of state government is measured by control of the different branches (trifecta or divided control). In panel B, control is measured by the size of the majority in the respondent's chamber of the state legislature.

### B.5.2 Variable Importance Results

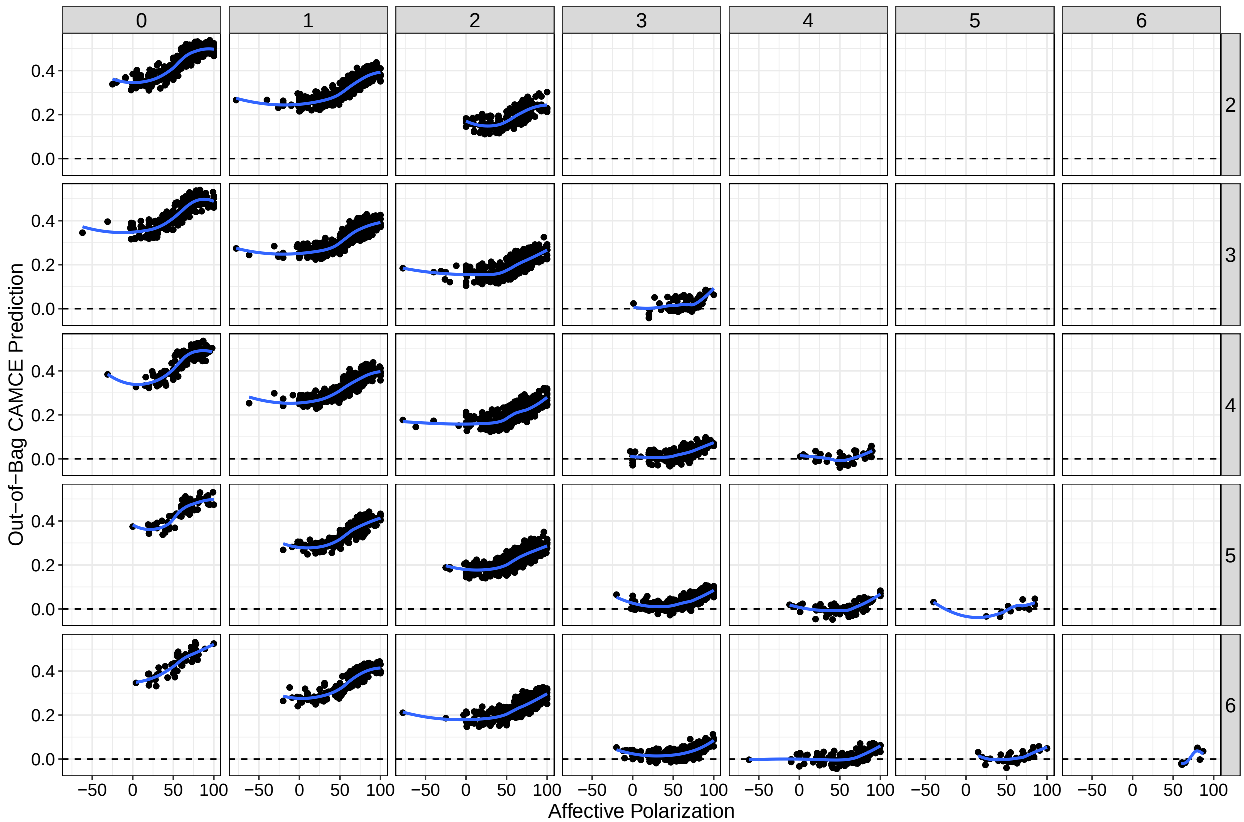
Figure B.5.2: Causal Forest Variable Importance (Including Nebraska)




Note: Variable importance from causal forest fit. Higher values indicate that variables are more important predictors of the conditional average marginal component effect of copartisanship. The primary election specification reflects causal forest fits including primary election margins. The general election specification is based on causal forest fits including general election margins. The no elections specification is based on causal forest fits without the general or primary election variables. The 10 variables with the highest median variable importance scores are shown here for space.

### B.5.3 Predicted CAMCE Causal Forest

Figure B.5.3: Out-of-Sample CAMCE Predictions (Including Nebraska)



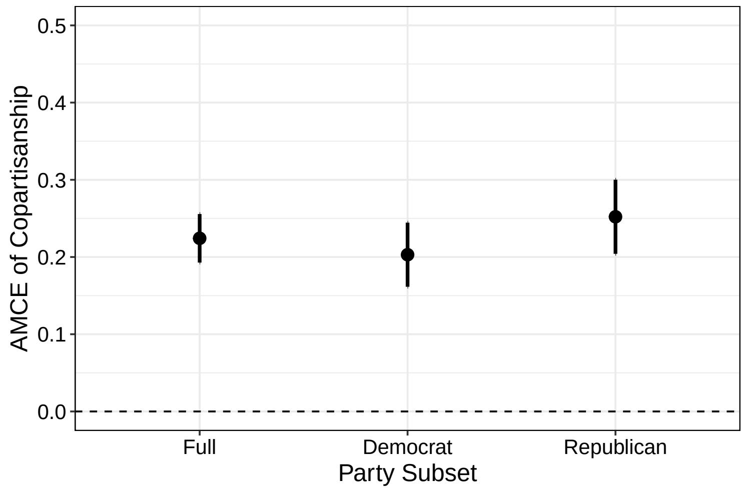

Note: Out-of-Bag CAMCE predictions from the causal forest specification with no electoral variables. Electoral variables were omitted to avoid discarding large portions of the sample who appeared in a primary but not a general election or vice versa. The vertical axis of the grid corresponds to the number of issue positions displayed for the profile pair, and the horizontal axis indicates the number of issue positions which are incongruent with the party of profile A. Blue lines fit using LOESS.

## B.6 Robustness to Individuals with No Random Seed

Six individuals were assigned to treatment in Qualtrics without a random seed, meaning they were repeatedly shown the same profile pair. The main analyses exclude these individuals. Here, I show that results are robust to their inclusion. In Figure B.6.3, 21 of the 25 panes still show positive relationships between affective polarization and partisan discrimination.

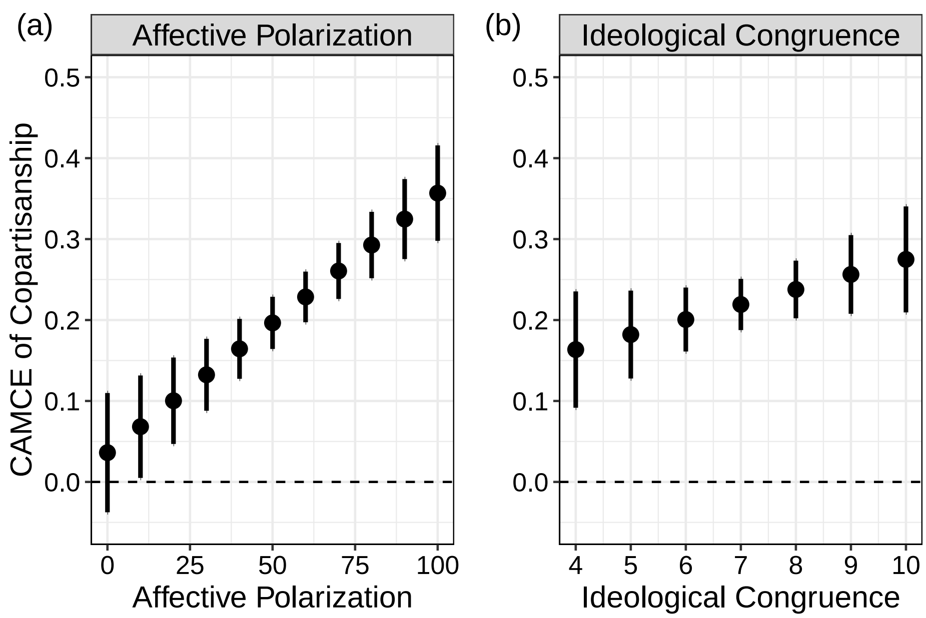
### B.6.1 AMCE Results

Figure B.6.1: AMCE of Copartisanship



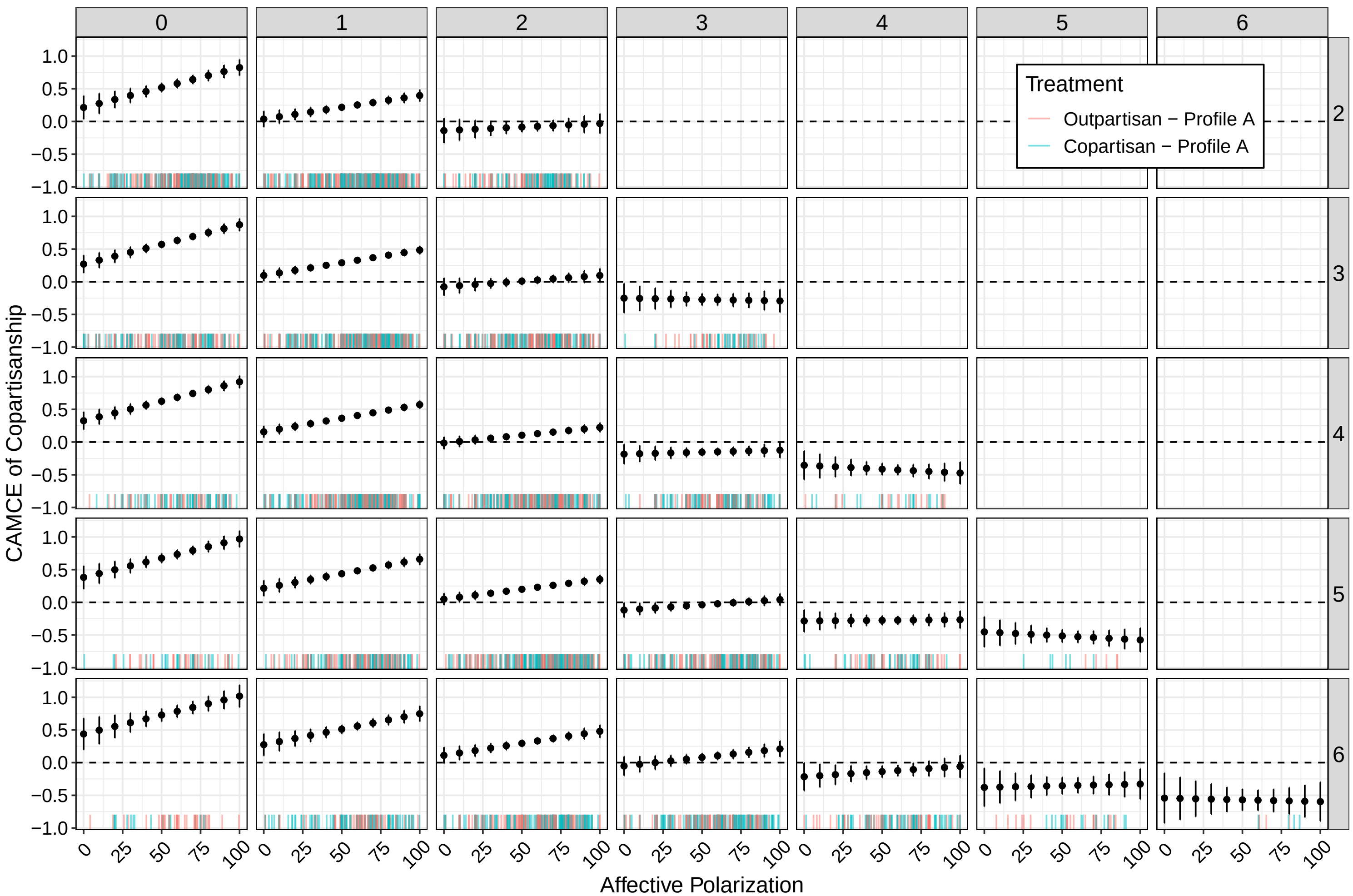

### B.6.2 Simple CAMCE Results

Figure B.6.2: CAMCE of Copartisanship by Affect and Ideological Congruence



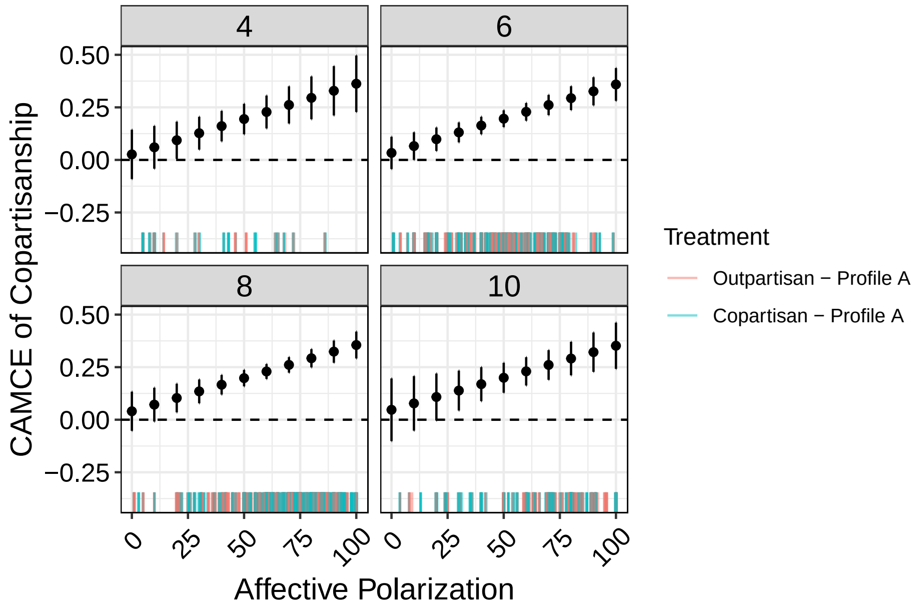

### B.6.3 CAMCE Results by Affect and Issue Content

Figure B.6.3: CAMCE of Copartisanship by Affect and Policy Positions



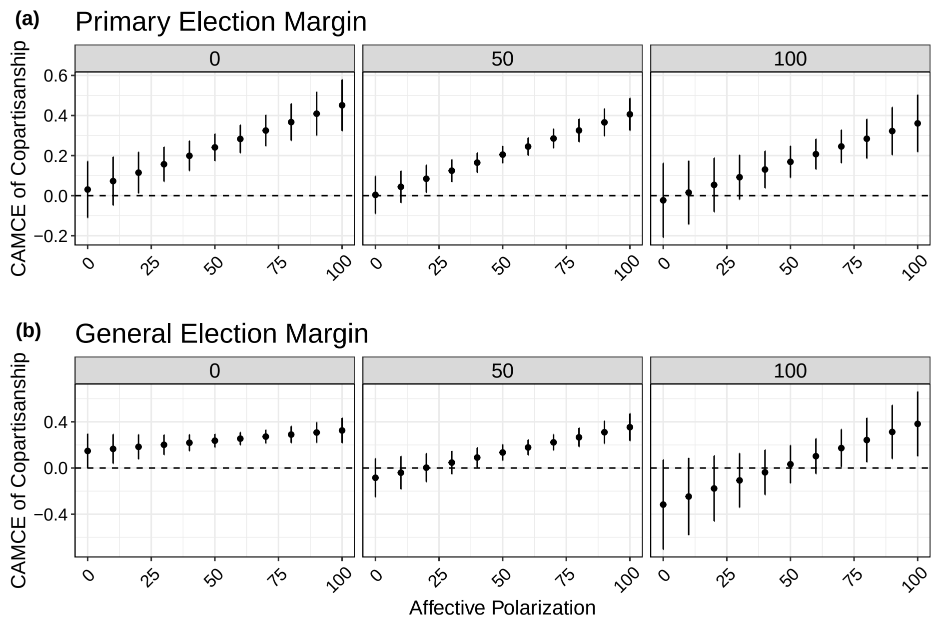
### B.6.4 CAMCE Results by Affect and Ideology

Figure B.6.4: CAMCE of Copartisanship by Affect and Ideological Congruence



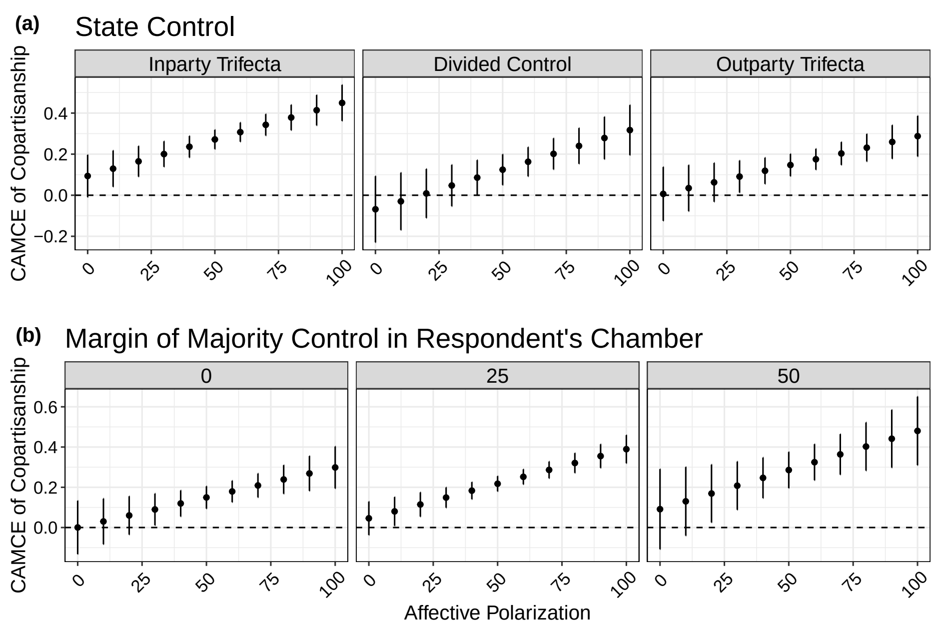

### B.6.5 CAMCE Results by Affect and Election Margins

Figure B.6.5: CAMCE of Copartisanship by Affect and Election Margins



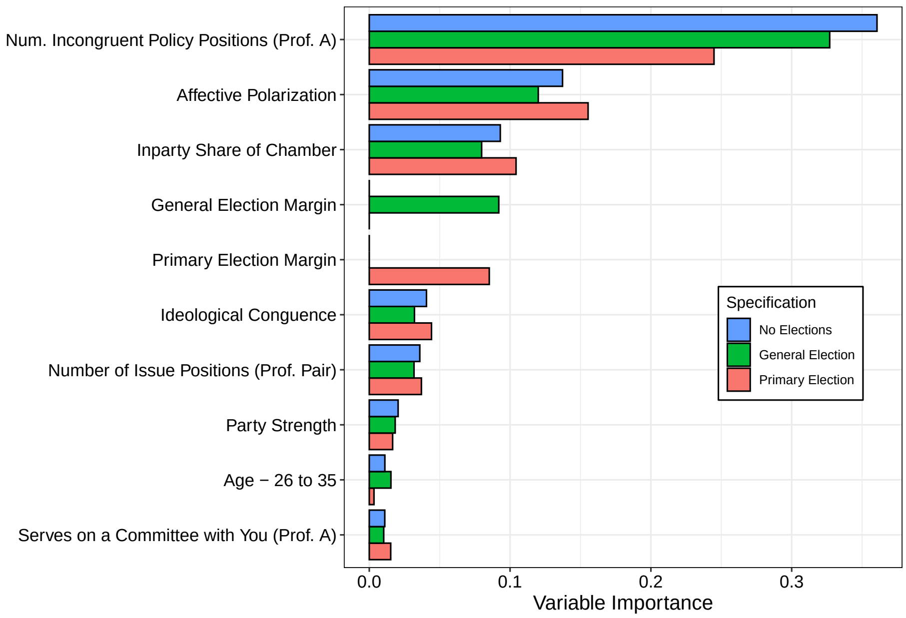

## B.6.6 CAMCE Results by Affect and State Partisan Control

Figure B.6.6: CAMCE of Copartisanship by Affect and Partisan Control




## B.6.7 Variable Importance Results

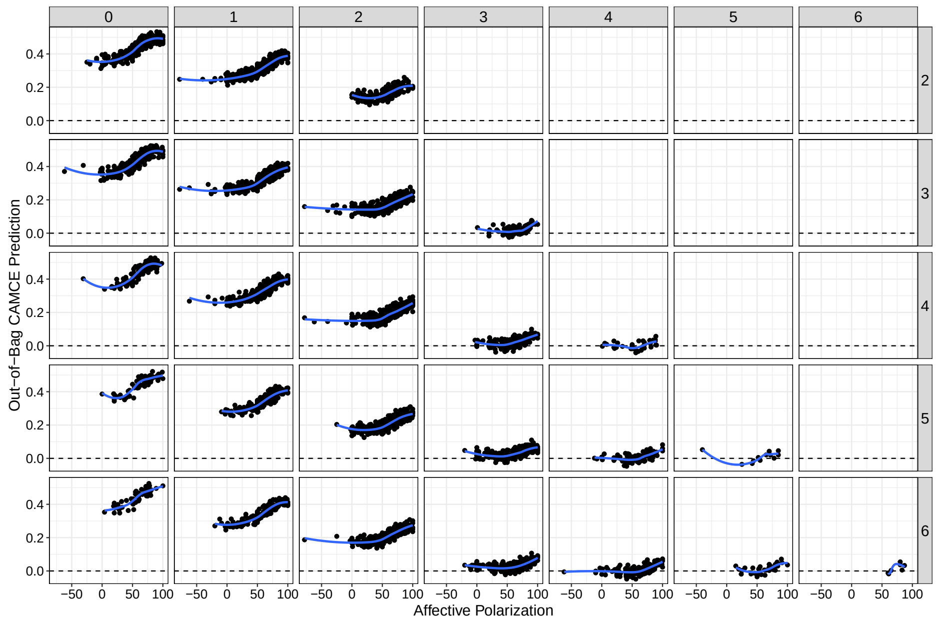
Figure B.6.7: Variable Importance from Causal Forest Fits




Note: Variable importance from 10-fold causal forest fits on data including individuals with no random seeds. The 10 variables with the highest median importance across folds and specifications shown for space.

### B.6.8 Predicted CAMCE Causal Forest

Figure B.6.8: Predicted CAMCEs of Copartisanship by Affect and Issues



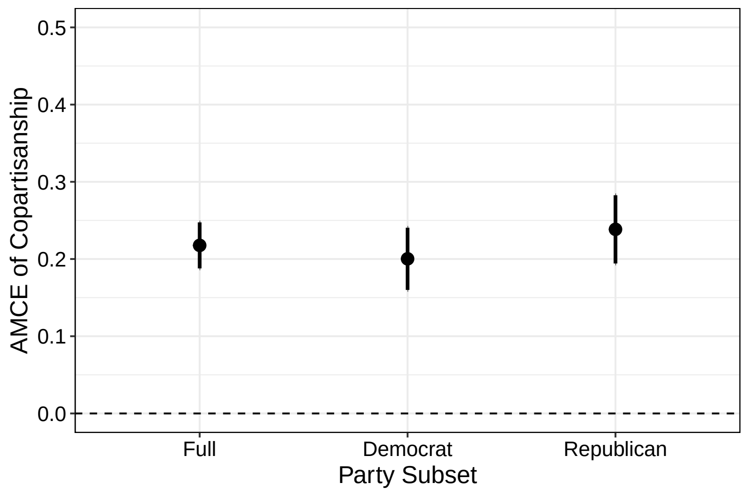

Note: Predicted CAMCEs from 10-fold causal forest fits on data including individuals with no random seeds.

## B.7 Robustness to Missing Choices

Some individuals viewed conjoint profile pairs but did not make a selection. This affects 426 choice tasks from 156 individuals. The main results exclude these individuals. In this section, I show that the main results are robust to including these choice tasks with missing outcomes, coding their outcomes as 0.

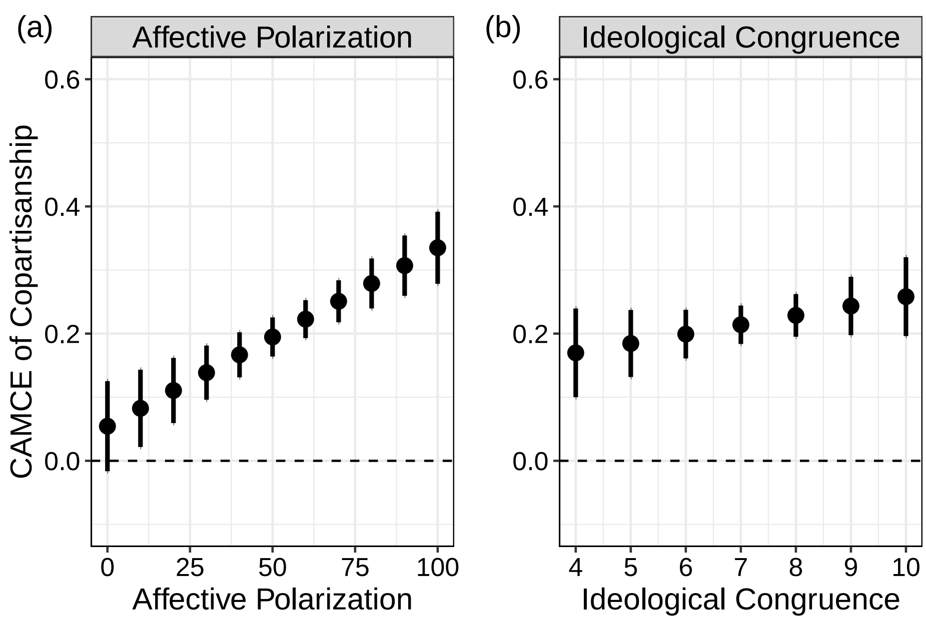
### B.7.1 AMCE Results

Figure B.7.1: AMCE of Copartisanship



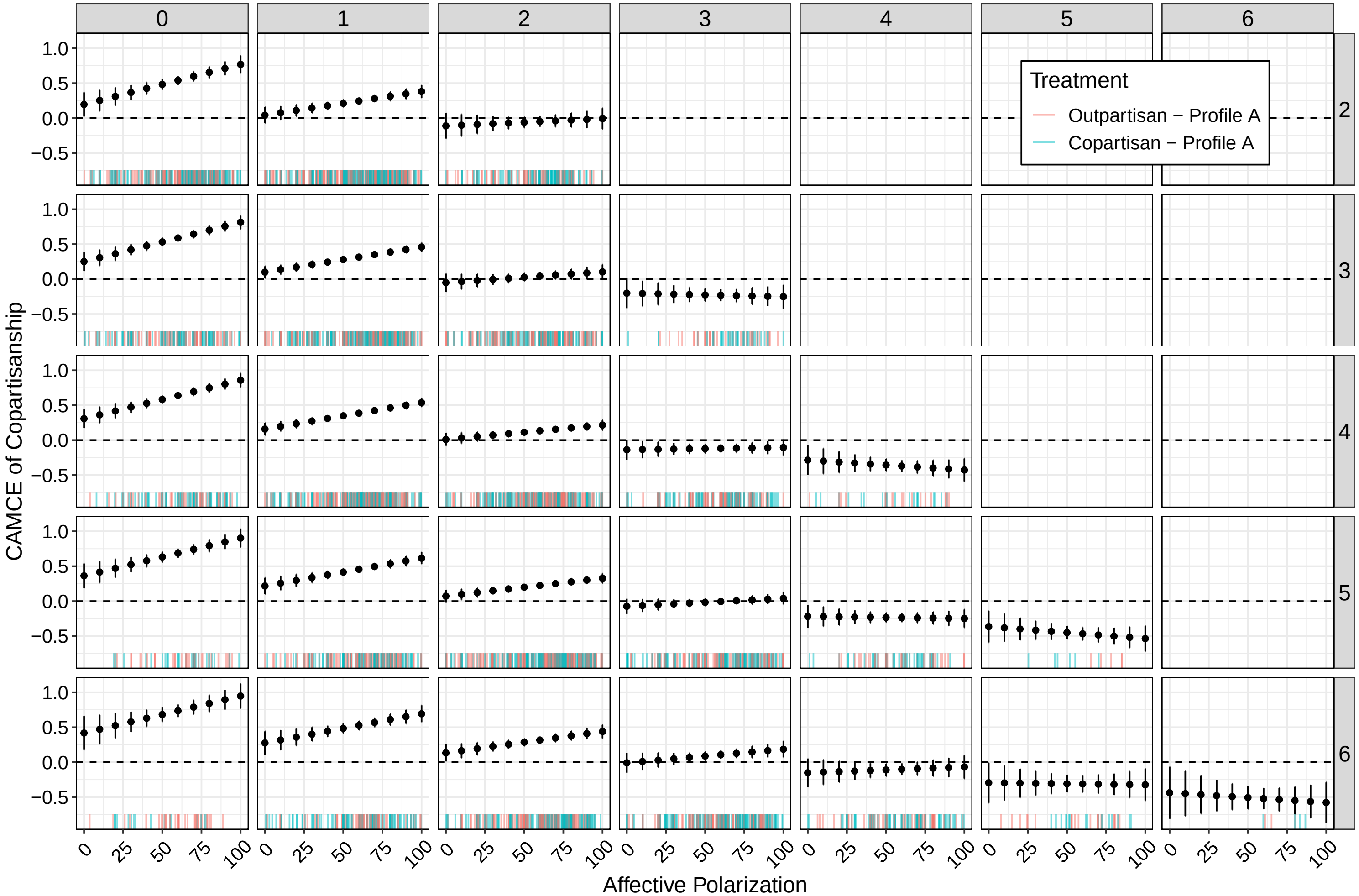

### B.7.2 Simple CAMCE Results

Figure B.7.2: CAMCE of Copartisanship by Affect and Ideological Congruence



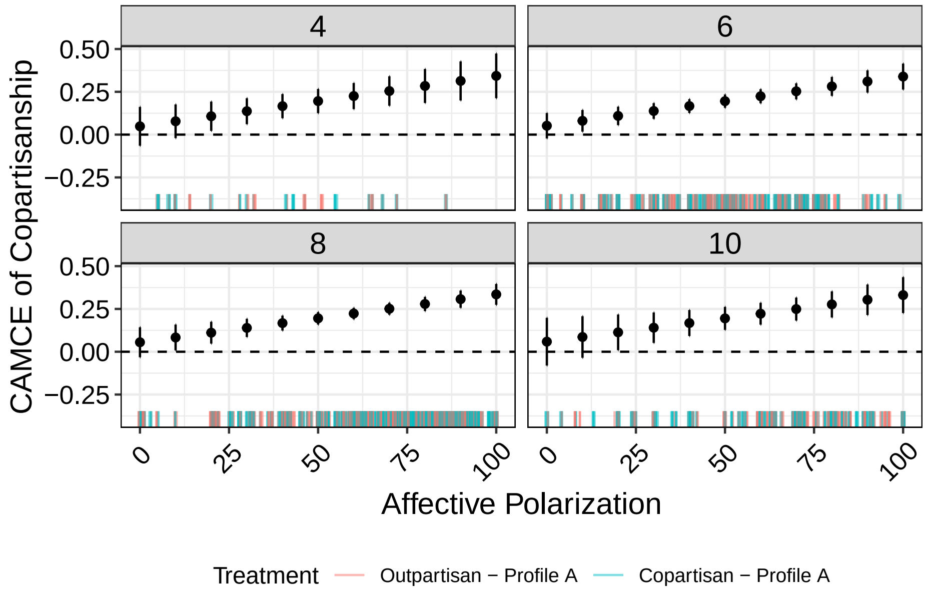

### B.7.3 CAMCE Results by Affect and Issue Content

Figure B.7.3: CAMCE of Copartisanship by Affect and Policy Positions



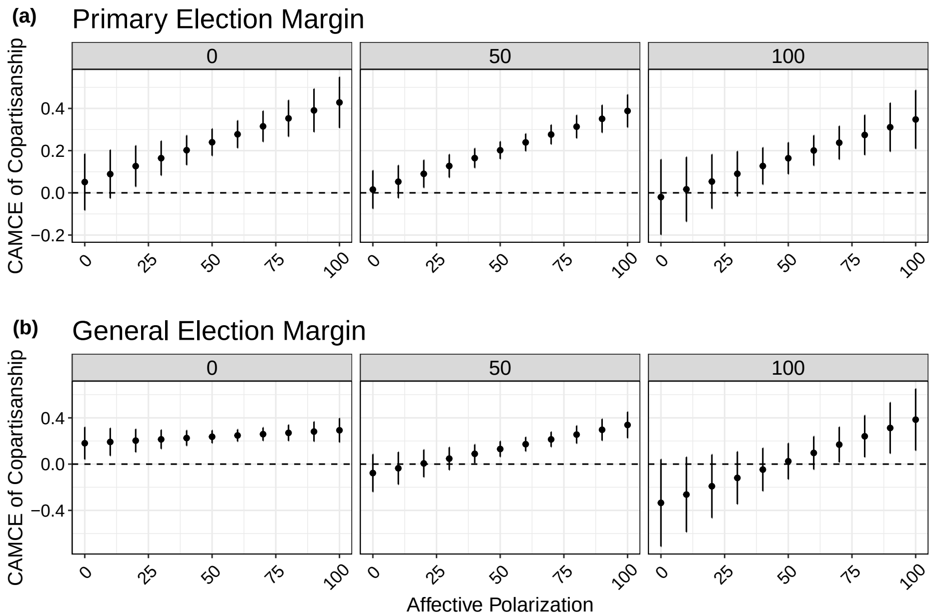
### B.7.4 CAMCE Results by Affect and Ideology

Figure B.7.4: CAMCE of Copartisanship by Affect and Ideological Congruence



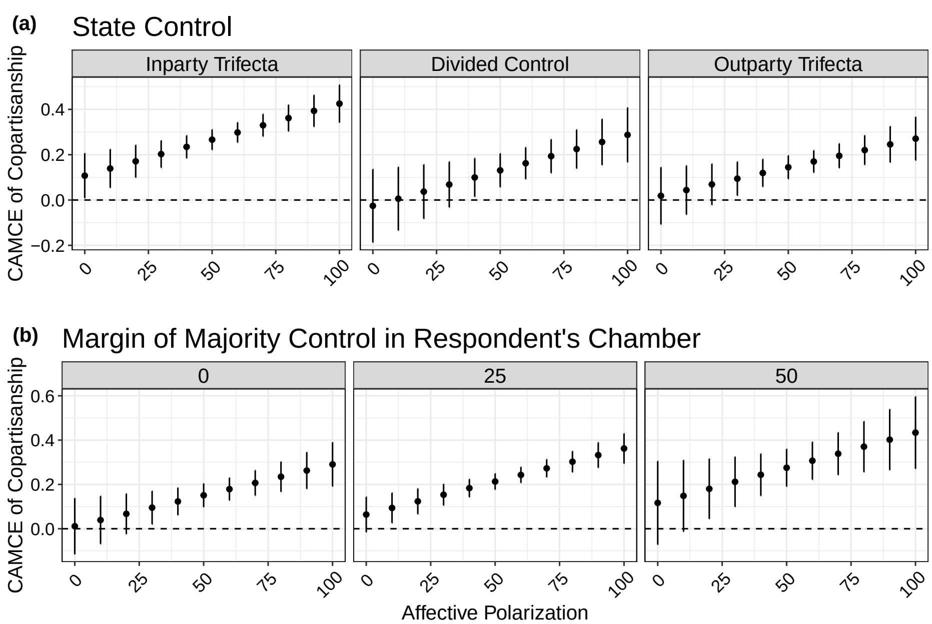

### B.7.5 CAMCE Results by Affect and Election Margins

Figure B.7.5: CAMCE of Copartisanship by Affect and Election Margins



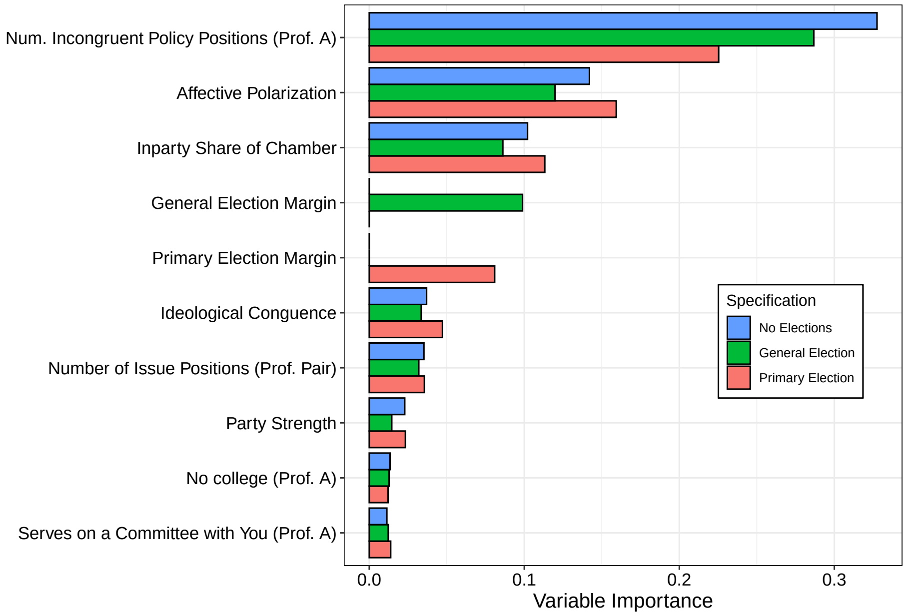

## B.7.6 CAMCE Results by Affect and State Partisan Control

Figure B.7.6: CAMCE of Copartisanship by Affect and Partisan Control




## B.7.7 Variable Importance Results

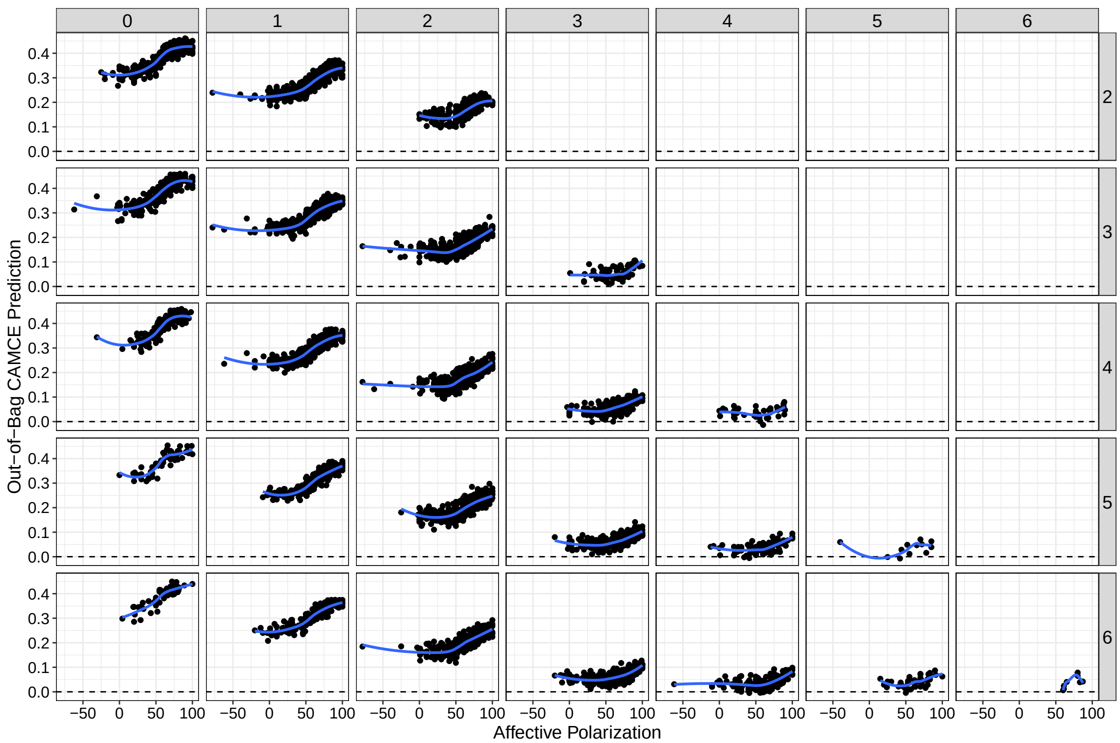
Figure B.7.7: Variable Importance from Causal Forest Fits




Note: Variable importance from 10-fold causal forest fits on data excluding missing choices. The 10 variables with the highest median importance across folds and specifications shown for space.

### B.7.8 Predicted CAMCE Causal Forest

Figure B.7.8: Predicted CAMCEs of Copartisanship by Affect and Issues




Note: Predicted CAMCEs from 10-fold causal forest fits on data excluding missing choices.