Polarizing the Electoral Connection: Partisan Representation in Supreme Court Confirmation Politics

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Do senators respond to the preferences of their state's median voter or only to the preferences of their copartisans? We develop a method for estimating state-level public opinion broken down by partisanship so that scholars can distinguish between general and partisan responsiveness. We use this to study responsiveness in the context of Senate confirmation votes on Supreme Court nominees. We find that senators weight their partisan base far more heavily when casting such roll call votes. Indeed, when their state median voter and party median voter disagree, senators strongly favor the latter. This has significant implications for the study of legislative responsiveness and the role of public opinion in shaping the members of the nation's highest court. The methodological approach we develop enables more nuanced analyses of public opinion and its effects, as well as more finely grained studies of legislative behavior and policy making.

Whom do legislators represent? Most scholars agree that constituents' preferences shape the behavior of their representatives in Congress (e.g., Mayhew 1974). There is, however, no consensus about whose opinion matters. Are some constituents better represented than others? Are lawmakers more responsive to the median voter or to subconstituencies, particularly their own partisans? The answers to these questions are important for understanding American democracy: if members of Congress are primarily (or only) responsive to their same-party constituents, it raises normative concerns of democratic performance and has implications for the study of legislatures and elections. As Clinton (2006, 397) puts it, "If representatives are most responsive to the preferences of only some constituents, the representativeness of the system and the legitimacy of resulting outcomes may be lacking."

The possibility that lawmakers are most responsive to their copartisans has long been recognized (Clausen 1973; Fenno 1978) and perhaps believed to be true. Still, there is very little systematic evidence for this claim; in large part, this lack of evidence is due to the challenges associated with measuring preferences across subconstituencies. Researchers have compensated with demographic and economic proxies or diffuse survey measures such as averaged preferences or general ideology. Such measures can be problematic in two ways, and their limitations are often explicitly recognized by the scholars that invoke them. First, these measures do not directly capture constituent prefer-

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ences on the specific roll call votes being studied. Second, they do not share a common metric with roll call votes, sharply limiting the inferences that can reasonably be drawn. The difficulty of measuring subconstituency opinion means that the question of whose opinion matters is far from settled. Indeed, as we discuss below, the existing literature reveals conflicting findings.

Our article makes both methodological and substantive contributions. We overcome existing methodological limitations by generating opinion estimates on specific votes broken down by partisan subconstituencies in each state. To do so, we build on recent advances in opinion estimation based on "multilevel regression and poststratification" (MRP). We develop novel extensions of this method that allow more fine-grained estimates of public opinion by subgroup—a senator's in-party, opposite-party, and independent constituents. In addition, in contrast to most research that takes survey responses as measured without error, we incorporate the underlying uncertainty in our estimates at every stage of our empirical analysis, developing new tools for doing so. Finally, we develop an MRP extension for measuring three-way splits in opinion compatible with this uncertainty analysis.

The immediate goal for these innovations is to conduct a fine-grained substantive case study of responsiveness and representation: how senators cast votes on Supreme Court nominees. We connect senatorial roll call votes to roll call–specific subconstituency preferences. Since our opinion estimates and roll call votes are on a common scale, we estimate not only the strength of the relationship between opinion and senatorial vote choice by subconstituency but also how often a senator's vote is congruent with the preferences of same-party, opposite-party, and independent voters. This generates more nuanced assessments of responsiveness than previously possible. Our extensions—creating substate estimates when census data necessary for basic MRP are not available—will be useful for many further applications of MRP and for studying a wide range of substantive questions. It will make possible the generalization of our substantive research on nomination voting to other types of votes.

From a substantive perspective, the question of who gets represented is most important when evaluating key votes cast by legislators: these votes are likely to have a lasting impact on their constituents. Not many decisions are as consequential for and visible to the public as a vote to confirm or reject a nominee to the US Supreme Court. While the outcomes of many votes are ambiguous or obscured in procedural detail, the result of a vote on a Supreme Court nomination is stark. From a research design perspective, public opinion can vary

widely across states and nominees and has been shown to influence senatorial voting on nominees (Kastellec, Lax, and Phillips 2010). Thus, we are not looking for a disparate impact where no impact of opinion exists at all.

We document that opinion on Supreme Court nominees varies strongly across partisan groups. Given this divergence, to whom senators listen can mean the difference between a vote to confirm and a vote to reject. We show clear and robust evidence that senators give far more weight to the opinion of their fellow partisans. After controlling for ideology and party, we find that Democrats still listen more to Democrats and Republicans more to Republicans. Just changing the composition of a nominee's supporters (holding constant total support) has striking effects on the likelihood that a senator votes to confirm. Increasing support in the senator's party can have almost six times the effect of support outside the party. Overall, senators do what their copartisans want 87% of the time. This is even more than the 80% of the time that senators vote for nominees made by a president of the same party. When the preferences of the median voter and the party median voter differ, senators side with their copartisans 75% of the time. The method we develop to analyze partisan opinion within states leads us to the conclusion that the extra weight given to partisan subconstituencies polarizes the electoral connection, which both pulls policy away from the median voter and results in far more contentious confirmation politics.

CONSTITUENCIES AND LEGISLATORS: THEORY AND MEASUREMENT

The natural starting point for linkages between voters and legislators—the median voter theorem—predicts that if representatives are motivated solely by office seeking, they will locate at the ideal point of the median voter of the lawmaker's constituency (Downs 1957). However, as discussed in Clinton (2006), empirical evidence suggests that lawmakers often do not converge to the median voter. For example, House candidates from the same district often adopt divergent ideological positions (Ansolabehere, Snyder, and Stewart 2001), and same-state senators frequently disagree (Bullock and Brady 1983).

Theoretical work on representation offers many reasons why the Downsian empirical predictions might not hold. First, if candidates and politicians are also policy seeking, they will have incentives to diverge from the median voter. Second, pleasing extreme activists and interest groups may induce divergence (Miller and Schofield 2003). Third, representatives may adopt extreme positions to advance the party's "brand" (Aldrich 1995). Fourth, the fact that challengers and incumbents often must first win a primary

election before running in a general election may lead an officeholder to favor her "primary" constituency over the median voter, especially if she serves in a jurisdiction with a closed primary in which only self-identified partisans may vote. Primary voters are more extreme relative to those who participate in general elections, which may pull representation toward the primary (and thus partisan) constituency (Gerber and Morton 1998). And, in general elections, partisan voters exhibit greater intensity and thus are more likely to vote (especially in off-year elections), making their support particularly valuable. Finally, if there exists a high degree of preference heterogeneity across a state or district, it may be difficult to accurately represent the median voter. In contrast, "partisans are more homogeneous, probably more communicative, and hence easier to represent than the full constituency" (Wright 1989, 469).

The empirical literature on this question (with respect to representation rather than elections) has largely flowed from Fenno's (1978) canonical work on how members of Congress respond to different subconstituencies. Whereas the median voter can be thought to represent what Fenno calls the "geographical constituency" (i.e., the entire district or state), members of Congress will also focus on both the "reelection constituency" and the "primary constituency" (see also Fiorina 1974). The former comprises the people in a district or state that a member thinks will vote to support her, while the latter comprises a subset of these voters—those who are the member's strongest supporters. These supporters, of course, are most likely to be members of the legislator's party. As Clausen (1973, 128) notes, "Given the overwhelming importance of party affiliation as a basis for choosing among candidates for office, and given the long term exposure of most candidates to the people, and views of a single party, the expectation is that the legislator will represent his partisan followers best."

We give here a brief sense of the conflicting findings on partisan representation. While some might strongly believe that nonmedian representation exists, and despite many reasons to believe that it exists, actual empirical evidence is scant at best. One reason for this dearth of evidence is the difficulty in obtaining clean measures of subgroup opinion. Examining the responsiveness of senators to different constituencies, Shapiro et al. (1990) find that senators' votes are strongly related to the preferences of their in-party constituents, while Wright (1989) finds that same-party preferences have no direct effect on representation. More recently, Clinton (2006) finds that House Republicans in the 106th Congress were strongly responsive to the preferences of Republicans in their districts. However, he also finds that Democrats do not follow the preferences of their partisan

constituency, but oddly that they too are more responsive to Republicans. Finally, in a study of representation in California, Gerber and Lewis (2004) find responsiveness to the median voter (especially when preferences within a district are homogeneous) but no effect of in-party preferences on members' voting behavior. Thus, more than three decades after Fenno made famous the idea of separate constituencies, there exists little empirical evidence—and certainly no consensus—that congressional partisans are more responsive to their copartisans.

Methodological challenges. Testing differential representation raises several methodological concerns. Foremost among these is the difficulty of accurately measuring the preferences of various subconstituencies. This challenge arises from a harsh constraint: the frequent lack of comparable public opinion polls across states or congressional districts. To compensate for this, scholars have pursued several alternatives, each with its own limitations.

Early empirical research (e.g., Peltzman 1984) often used demographic and economic data as proxies for policy preferences. Recent analyses have transitioned to survey-based measures of preferences, which are typically created by disaggregating respondents from national polls so that opinion percentages can be calculated for each state or district. To generate adequate subsample sizes, either many national surveys must be pooled over many years or very large surveys must be found. This severely restricts the type of preference measures that can be constructed and makes it difficult to gauge the relative influence of different groups. Studies that have examined responsiveness have therefore relied on general measures of preference aggregated across hundreds or even thousands of votes covering various types and issues. This approach has several limitations. First, responses are not directly matched with relevant roll call votes. Instead, an assumption is made that voters who hold liberal, moderate, or conservative opinions on one set of policies will do so on the set of roll call votes being analyzed. However, other research has shown that voters often hold ideologically "inconsistent" preferences across policy areas. Furthermore, without accurate measures as to how voters want specific roll calls to be cast, no common metric for opinion and votes exists, limiting inferences that can be drawn. A high correlation between roll call votes and the policy liberalness of a senator's same-party constituency reveals some sort of relationship, but it does not allow us to conclude whether same-party constituents are actually getting their senator to vote the way they want more often than the median voter or opposite-party constituents: "the inability to measure subconstituency preferences and voting behavior on a common scale prevents a definitive answer—we simply cannot see which constit-

uency is closer" to the legislator's revealed preferences (Clinton 2006, 407). Finally, most papers in this literature aggregate many different types of votes. To be sure, pooling types of votes has its advantages (e.g., idiosyncrasies across policy areas are averaged out). However, examining averages of opinion against averages of roll call votes means that the two cannot be directly compared, complicating analyses of representation (Bishin and Dennis 2002).

Supreme Court nominations are a particularly important area for adjudicating between median and nonmedian theories of representation. Kastellec et al. (2010) concluded that senators respond to state-level opinion in confirmation votes. This claim ties the Court, a potentially counter-majoritarian institution, to majority will. However, that study did not and could not explore to whom senators respond within states. If senators "overrespond" to subconstituencies, then earlier findings and conclusions on opinion effects are incomplete—and the majoritarian linkage is weakened. This shows the importance of studying subconstituency effects and of resolving the methodological difficulties of so doing.

Which subconstituencies in Supreme Court confirmation politics are likely to influence senators? One possibility is racial or ethnic groups. For example, public opinion among African Americans and Hispanics loomed large in the politics surrounding the respective nominations of Justice Thomas in 1992 and Justice Sotomayor in 2009 (Bishin 2009; Overby et al. 1992). In general, however, given the importance of partisanship in the Senate confirmation process (Epstein et al. 2006; Shipan 2008) and for the theoretical reasons discussed above, we would expect the views of partisan subconstituencies to play an important role in senators' voting decisions. Perhaps most importantly, primary elections allow challengers to attack incumbents who do not heed their partisan constituents' opinion. Indeed, Senate lore contains ominous warnings on this front. Despite being virtually unknown, Carol Moseley Braun defeated incumbent Senator Alan Dixon in the Illinois Democratic primary in 1992, principally campaigning against his vote to confirm Clarence Thomas a year earlier. Similarly, Senator Arlen Specter of Pennsylvania faced a strong primary challenge leading up to the 2010 election, with his vote against confirming Robert Bork in 1987 playing a large role in driving conservative support away from him (this challenge eventually led Specter to switch parties in 2009). More generally, Lee (2009) shows that much conflict in the modern Senate can be characterized as partisan fights and is not simply about ideology. This account would also support the argument that senators should be more mindful of their partisan constituents in high-stakes nomination fights. In-

deed, as we show below, public opinion on nominees is often polarized among partisans in the electorate, meaning that senators often face conflicting constituencies when they go to cast a vote on a nominee. Thus, we argue that in general, the partisan subconstituency is key for evaluating these sets of votes. Testing whether senators respond more to the median voter or their in-party median requires us to generate nominee-specific estimates of public support, broken down by partisan constituencies. In doing so we must overcome the methodological limitations outlined above. Specifically, we need to have measures of subconstituency policy preferences that relate directly to roll call votes on Supreme Court nominees and that are on the same scale.

DATA AND METHODS
Estimating opinion

To evaluate the role of subconstituency opinion on roll call voting on Supreme Court nominees, we estimate opinion by party for 11 recent nominees for which data exist (see the online supplemental appendix for more details): Rehnquist (for chief justice in 1986), Bork (1987), Souter (1990), Thomas (1991), Ginsburg (1993), Breyer (1994), Roberts (2005), Miers (2005), Alito (2005), Sotomayor (2009), and Kagan (2010). All were eventually confirmed except Bork (defeated in a floor vote) and Miers (nomination withdrawn before a vote). To generate the required measures of public opinion, we develop and employ a significant extension to multilevel regression and poststratification, or MRP, a technique originally developed in Gelman and Little (1997) and assessed by Lax and Phillips (2009, 2013) and Park, Gelman, and Bafumi (2006). It combines detailed national survey data and census data with multilevel modeling and poststratification to estimate public opinion at the subnational level. The extra information in these data allows for accurate estimates of state- or district-level opinion using a relatively small number of survey respondents—as few as contained in a single national poll. Standard MRP has two stages. First, individual survey response is modeled as a function of demographic and geographic predictors in the survey data. The state of the respondents is used to estimate state-level effects, which themselves are modeled using additional state-level predictors such as aggregate demographics. Those residents from a particular state yield information on how responses within that state vary from others after controlling for demographics. All individuals in the survey, no matter their location, yield information about demographic patterns that can be applied to all state estimates. The second stage is poststratification: the estimates for each demographic-geographic respondent type are weighted (poststratified) by

the percentages of each type in actual state populations, adding up to the percentage of respondents within each state who have a particular position.

The previous evaluations noted above demonstrated that MRP performs very well in generating accurate state-level estimates of public opinion. It consistently outperforms raw state breakdowns, even for large samples, and it yields results similar to those of actual state polls. A single national poll and simple demographic-geographic models (simpler than we use herein) suffice for MRP to produce highly accurate and reliable estimates. How does MRP accomplish this? Intuitively, it compensates for small within-state samples by using demographic and geographic correlations. There is much information within surveys that is typically thrown away; MRP makes use of it. Since we will incorporate uncertainty from our response models in our estimates of opinion and throughout the analysis, we can show that our results do not depend on assuming we have perfect models of response.

A "standard" use of MRP is sufficient to generate state-level estimates of opinion but cannot produce estimates of opinion by partisanship. The second stage of MRP involves poststratifying the estimates based on the Census Bureau's 5 Percent Public Use Microdata Sample's population frequencies, but these data do not include partisan identification. Thus, using standard MRP, one can estimate the level of support for, say, Samuel Alito among college-educated Hispanic males aged 18–29 in New Jersey, but one cannot estimate the level of support among Republican, Independent, or Democratic individuals of the same type. In general, using standard MRP to generate fine-grained estimates by variables not gathered by the Census Bureau (such as party or religion) is not possible directly. We have devised a method for doing so, producing three generally applicable extensions to MRP.

Using noncensus demographics with MRP

Full technical details of the procedure are given in the appendix, where we explain how all estimates are produced. Here we give the intuition behind the methods. Our approach involves using an additional stage of MRP to generate the necessary poststratification file from the census poststratification data and additional survey data. First, we collected data on individual survey responses about partisan identification (i.e., whether a respondent is a Democrat, a Republican, or an Independent) across multiple points in time spanning the years of the nominations in our data. We then model partisanship as a function of demographic and geographic variables. Specifically, we treat partisanship as a response variable and apply standard MRP to estimate the dis-

tribution of partisanship across the full set of "demographic-geographic types" (e.g., 4,800 for recent nominees). We then have an estimate of the proportion of Democrats, Independents, and Republicans among, say, college-educated Hispanic males aged 18–29 in New Jersey. This step splits the 4,800 types into a more expansive poststratification structure, with 14,400 (4,800 × 3) partisan-demographic-geographic types. The extra level of MRP provides us with an estimate of the information that would be readily estimated via standard MRP if the census data included partisan identification. We can now fit multilevel models of opinion on nominees and weight predicted responses by the full typology.

Incorporating uncertainty into MRP

It is sometimes suggested that when using generated regressors or other constructs measured with uncertainty, one should incorporate the uncertainty in these variables (Achen 1977). To be sure, it is not standard practice to incorporate uncertainty in regressors;[1] the degree to which it matters depends on the amount and correlates of the uncertainty, not the source (i.e., generating a regressor from prior analysis is not mathematically different from using any other data source that contains error). We go beyond existing work by accounting for uncertainty from multiple stages leading to our opinion estimates but also present "normal" results that take these estimates as given.

To do so, we make use of a method sometimes called propagated uncertainty or the method of composition (Treier and Jackman 2008). Rather than using analytical methods, we use empirical distributions to simulate uncertainty from each modeling stage (based on the variance-covariance matrix of a given multilevel model) and propagate it through the rest of the analysis. This yields uncertainty around all final estimates. Our estimates of subconstituency opinion have two sources of uncertainty. First, we estimate the distribution of partisanship across the census types using a model. As with any model, there will be uncertainty in the resulting coefficients. Using the variance-covariance matrix of the model, we draw 1,250 sets of coefficients, so that the empirical distribution of these captures the uncertainty estimated by the model. Each set is used to predict partisan type for our base demographic-geographic types, so that we now have 1,250 party poststratification sets. Thus, we have 1,250 estimates of the proportion of Democrats, In-

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1. Measures such as survey estimates, ideology scores, indices, and scales are usually measured with error that is ignored when these measures are used as independent variables.

dependents, and Republicans among college-educated Hispanic males in New Jersey aged 18–29.

We next model nominee support as a function of the nuanced demographic-geographic-partisanship categories that are now possible. We produce 1,250 random draws of the coefficients based on the model's variance-covariance matrix. Each set of coefficients is combined with one of the 1,250 poststratification sets, so that we now get 1,250 estimates of nominee support for each type of respondent, and therefore for each party constituency in each state. These estimates of opinion incorporate the uncertainty from the party-poststratification-creation stage and the nominee support stage. Finally, when we want to model roll call voting, we run a desired model for each of the 1,250 opinion sets. This new model also has uncertainty, of course, and we capture this by taking one simulated draw of coefficients from each run of each vote model given its variance-covariance matrix. If we did not do this, it would be as if only the opinion estimates had uncertainty, not the roll call models.[2] We now have 1,250 sets of estimates of the effects of opinion on roll call voting as well as our other predictors. We use these to form confidence intervals.

Each time we push the uncertainty from previous analyses into subsequent stages, until we wind up with a distribution of results for our main substantive analysis that reflects all underlying uncertainty from each stage of the process: we incorporate the uncertainty from our party identification model to create uncertainty for the poststratification weights, which then propagates into our models of nominee support to create uncertainty around opinion estimates. Finally, all uncertainty is propagated into the final roll call voting model.

Multinomial response

There is another complication that we set aside in the foregoing discussion, though it affects both MRP stages. In the party poststratification creation stage, we want to estimate the three-way party split (Democrat, Independent, or Republican). In the nominee support stage, we want to estimate the probability of supporting a nominee, opposing a nominee, and staying neutral (not having an opinion). It is difficult to implement MRP (or do any multilevel modeling) where the dependent variable is not dichotomous or continuous. It is theoretically possible to implement a fully

Bayesian approach, but it is computationally infeasible for a complicated problem such as the one at hand. Instead, we employ a two-step solution. We nest one dichotomous analysis inside another, so that the combination leads to the three-way division. For example, to estimate the percentage Democratic (D), Independent (I), and Republican (R), we first predict D versus I or R (these two lumped together so that one means D and zero means other) in a binary logistic regression. Then, we drop all Ds and take the remaining data to predict I (one) versus R (zero), conditional on not being a D. This nests the probability of I versus R within the probability of not being a D. Multiplying appropriately yields the percentage of each type. We refer to this as nested multinomial MRP.[3] To ensure that the ordering of these steps does not matter (we started with D vs. other), we repeat the entire process starting from the other side (starting with R vs. other). We then average the results from both orderings. For nominee support, we do similarly, predicting support versus other, and then making a conditional prediction of neutrality versus opposition, followed by starting from the other side and averaging. We can provide code for all the above extensions.

Visualizing subconstituency opinion

We begin our exploration of the opinion estimates in figure 1, which depicts kernel density plots of our estimates of support among opinion holders, broken down by Democrats, Independents, and Republicans, across states. Republican and then Democratic nominees are ordered by increasing state-level mean support. That is, the unit of analysis is states, broken down by each type of opinion (so each density plot summarizes 50 estimates of opinion). The dots under each distribution depict the mean of that respective distribution. Vertical dashed lines depict median state-level support. Note that support for nominees is always higher on average, and indeed very high in absolute terms, among constituents from the president's party. Figure 1 also reveals that polarization—defined as the difference between median Democratic and Republican opinion—varies significantly across nominees. Recent nominees Miers, Alito, Sotomayor, and Kagan generated large divisions of opinion, as did Bork. On the other hand, the nominations of Souter, Ginsburg, and Breyer generated little polarization and substantial overlap across constituencies. We observe the widest differences within party for the nomination of Rehnquist to

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2. Imagine if we had perfectly measured opinion so that opinion estimates did not vary. The 1,250 sets of roll call model coefficients would be identical, and we would therefore have empirical estimates of zero standard errors, despite uncertainty in each vote model. By drawing simulated coefficients from each vote model, we incorporate this vote model uncertainty.

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3. This can be less efficient than a full Bayesian approach in that we lose the gains from doing things in one step, such as assuming constant coefficients across stages as in ordered logit or assuming that other variances remain similar as in multinomial logit.
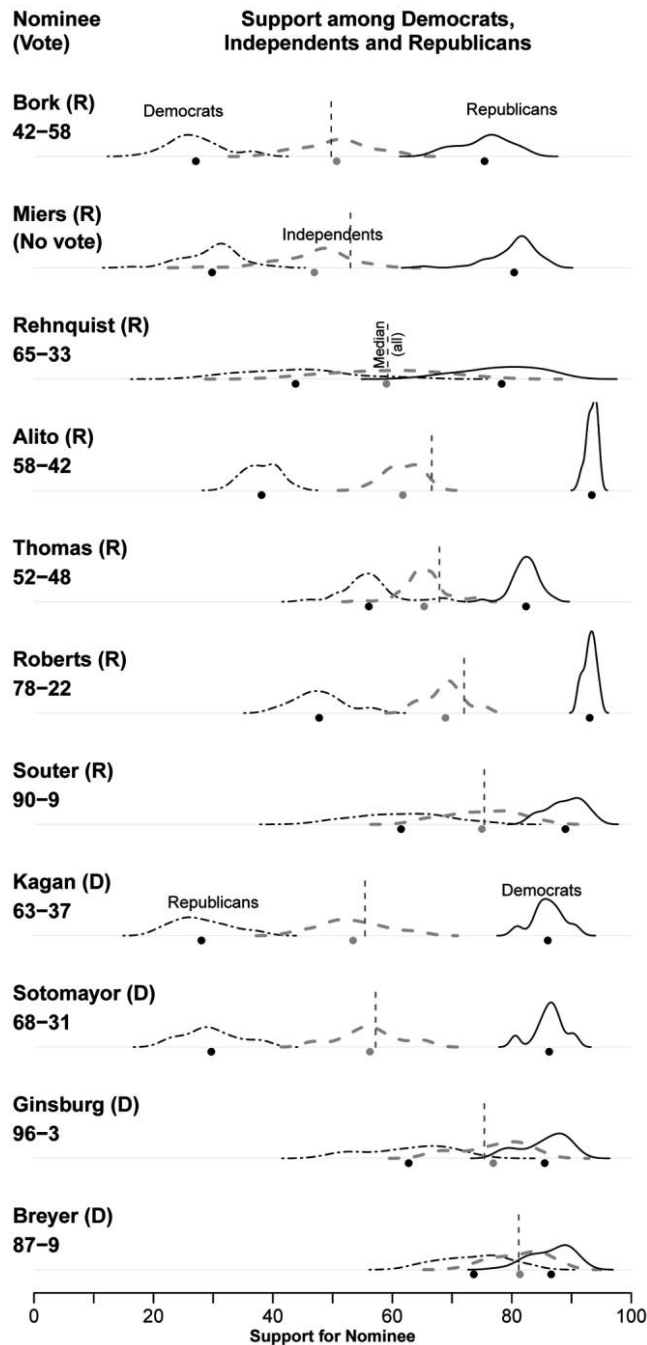
Figure 1. The distribution of nominee support among Democratic identifiers, Independents, and Republican identifiers. The graph depicts kernel density plots of our estimates of support among opinion holders. Nominees are ordered by increasing state-level mean support, except the four Democratic nominees (Kagan, Sotomayor, Ginsberg, and Breyer) appear last for clarity. The vertical dashed lines depict the median support across states. The dots under each distribution depict the mean of that distribution. The solid lines depict opinion among members of the president's party, the light dashed lines depict opinion among Independents, and the dark dashed lines depict opinion among members not of the president's party. Support is always higher, on average, among constituents from the president's party.

become chief justice. Figure SA-1 in the online supplemental appendix shows how opinion varies across both states and constituencies, as well as the degree of uncertainty in our opinion estimates. Taken together, these figures show that if senators respond differently to partisan constituencies, the effects on roll call voting can be quite consequential.

MODELS OF ROLL CALL VOTING

Excluding Miers and abstentions, a total of 991 confirmation votes were cast on 10 nominees, 71% to confirm the nominee. Our key tests evaluate how the probability of a confirmation vote changes as subconstituency opinion changes. Doing so requires careful accounting of not just nominee support by a particular group but also potentially the size of that group. To illustrate our measures, consider public opinion in Ohio on the confirmation of Justice Sotomayor. We limit the denominator to those with an opinion, which is 82.5% of Ohioans (this is from one particular sample and is used just to enable the example). Of those polled who held an opinion, 33.3% were Democrats, 83.8% of whom said confirm; 32.2% were Republicans, 23.6% of whom said confirm; and 34.6% were Independents, 50.6% of whom said confirm. Of all Ohio opinion holders, 53.0% supported confirmation. We measure supporters as the share of state opinion holders who support the nominee. A one-unit shift means that 1% of state opinion holders who fall in a particular category, such as constituents in a senator's party, switch from nonsupport to support. This shift is relative to the size of the state's opinion-holding population; what share of the party population this is depends on party size. That is, this unit shift flips a fixed share of the state opinion-holding population but an unfixed share of the party population (see the supplemental appendix).[4]

Predictors of roll call votes

Our main predictors are defined as follows:

- *Supporters out of all opinion holders*: the percentage of opinion holders that support the nominee.
- *Supporters in senator's party*: the percentage of opinion holders that share the party affiliation with the

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4. With partisan group size held constant, changes in the opinion variables reflect shifts of those with a particular partisan identification rather than increases in the size of that partisan subgroup as well as an opinion shift. One can set all this up differently, as long as one is careful about interpretation. One could change the meaning of a unit shift to be a percentage of a party group that shifts rather than a percentage of the entire opinion-holding population that shifts; results were similar for different ways of compartmentalizing opinion groups.

senator in question and support the nominee. We denote this category "IN" in the text for ease of presentation.

In some models, we add the following:

- *Supporters in opposition party*: the percentage of opinion holders who are in the opposite party and support the nominee. We denote this category OPP and distinguish them from independent supporters, whom we denote "IND." (We sometimes use "NOT IN" to describe all those not in the senator's party—i.e., combining IND and OPP.) In models that include OPP, there are six possible categories of opinion holder, summing to 100% (IN vs. IND vs. OPP × support vs. not). Otherwise, there are only four (IN vs. NOT IN × support vs. not).

We fix the partisan breakdown of the opinion holder population:

- *Percentage of opinion holders in the senator's party*
- *Percentage of opinion holders in the opposite party.*

On the basis of the existing literature, we include additional predictors as control variables, similarly to Epstein et al. (2006). These include nominee quality, ideological distance between a senator and a nominee or their locations (senator relative to president's party and nominee relative to senator's party), and whether the senator is of the same party as the nominating president. These studies show that senators are more likely to support nominees from a president of their party, more likely to support high-quality nominees, and less likely to support ideologically distant/extreme nominees. These measures are defined as follows:

- *Quality*: The degree to which a nominee is qualified to join the Court (according to newspaper editorials; Cameron, Cover, and Segal 1990). It ranges from zero to one (most qualified).
- *Ideological distance* between senator and nominee, or the *location* of one or both. For senators, we use DW-NOMINATE scores. For nominees, we employ the scores in Cameron and Park (2009). The authors use the past experience of each nominee (e.g., whether he or she served in Congress) to develop "nominate-scaled perception scores," placing nominees on the same scale as senators. For models using location rather than distance, we flip the senator location measure around its mean so that higher values indicate

greater distance from the ideological side of the president and nominee location around its mean so that higher values indicate greater distance from the senator's side ideologically (e.g., conservative for Republicans).
- *Senator in president's party*: Coded one if the senator is a copartisan of the president.

We estimate logit models in which the dependent variable is whether a senator voted to confirm or reject. In some models, we split opinion into two components: IN opinion versus NOT IN opinion. In other models, we break opinion down into three components: IN, IND, and OPP. Next, we vary the way in which we estimate the effect of senator and nominee ideology. In some models, we look only at the location of the senator, while in others we employ the distance between the senator and the nominee, and sometimes the location of both the nominee and the senator (depending on what is possible given inclusion of nominee fixed effects). (Distance models assume that senators become less inclined, ceteris paribus, to vote for a nominee as distance increases between them, whether toward one side or the other; location models allow for senators to respond to ideological position rather than distance, so that, say, a conservative senator can accept a "too" conservative nominee but not a "too" liberal one.) Next, in some models, we employ random effects to estimate varying intercepts for each nominee, while in others we employ fixed effects. The latter have the advantage of capturing unobserved heterogeneity across nominees (putting in a black box any reasons for such heterogeneity), but at the cost of removing substantive predictors that do not vary within nominees (quality and nominee ideology). Random effects allow us to include these predictors and provide efficiency gains from partial pooling, but at the cost of making a mild distributional assumption about nominee heterogeneity. Finally, some models use point estimates of nominee support; others incorporate the uncertainty of our opinion estimates into the model estimation. This allows us to gain a sense of how much the opinion estimate uncertainty influences our results (whether the uncertainty about opinion effects comes from the vote model uncertainty or the opinion estimates themselves).

Main results

The models split opinion in one of three ways: ".1" models split it one way (without breaking down by constituency, for a baseline), ".2" models split it two ways (pooling IND and OPP opinion together), and ".3" models split it three ways (IN support vs. IND support vs. OPP support).

Given these variations and the usage of different controls, there are 12 distinct models, each done once with normal point estimates (table 1) and once with full uncertainty (table 2). The former show standard errors and the latter confidence intervals, given that we use empirical distributions to calculate uncertainty (we show 90% confidence intervals, allowing for one-tailed 95% significance tests).

In both tables 1 and 2, the first row shows the extra impact of in-party opinion.[5] Looking across the models that include Supporters in senator's party, this coefficient is sizable, and there is strong statistical evidence of a large effect. (The results using point estimates of opinion show, as we would expect, slightly larger and more precise effects.) We conclude, with much confidence, that there is indeed a large "partisan constituency effect."

More concretely, in the .2 models, estimated differences between IN and NOT IN effects are .16, .12, .20, and .09 for the point estimate models and .15, .10, .19, and .08 for the full uncertainty models. On the basis of the simulations, we can calculate the probability that the effect difference between IN and NOT IN is statistically greater than zero. In the point prediction models, the probabilities of a positive difference in effect are .97, .98, .98, and .93 (similar to p-values between .03 and .07). For the full uncertainty models, these probabilities are .95, .95, .97, and .89 (similar to p-values between .03 and .11).

Table 3 summarizes and highlights these and other effects and differences, calculated using the simulation results and the full uncertainty models (e.g., the Difference between IN and NOT IN in table 3 is the equivalent of the first row in table 2).

To grasp the magnitude of the differential partisan effect, suppose that we flipped 1% of state opinion holders consisting of IN constituents from opposition to support while at the same time decreasing NOT IN support. Total support remains the same. This change means a likelihood of a yes vote that is up to five percentage points higher for a senator on the fence (the logit curve is steepest, with larger substantive effects, around 50%). This extra effect ranges from 2.5% to 4.8% across full uncertainty models.

Independents

Can we also distinguish the effects of IN opinion from IND, and/or the effects of IND from OPP party opinion, using the .3 models? Not really. The first two tables make it possible to see the difference in effect between IN and NOT IN opinion and between IN and OPP. Table 3 shows these more easily along with other full uncertainty estimates of effects and differences in effects. We note four things. First, the effect of IND itself is small and imprecisely estimated. Next, IN support is likely to have a larger effect than IND support. The difference between IN and IND opinion is positive and large, and the probability that in-party opinion is greater than independent opinion is about 80%–85% across models. Third, OPP support has a small and usually insignificant effect. Finally, we are not able to find clear evidence differentiating the effects of IND opinion from OPP opinion. Overall, we lack enough data relative to uncertainty to say much that is conclusive about IND comparisons in these three-way models, but we can still see that IN has a clearly larger effect than OPP and that it is likely that IN has a larger effect than IND.[6]

CONGRUENCE AND DEMOCRATIC PERFORMANCE

What is the bottom line for democratic representation given the partisan constituency effect? To answer this, we turn to a congruence analysis, measuring how often a senator's vote on a nominee matches what the median voter among opinion holders in his state wants, and how often these votes match the median voter within the senator's own party or opposition party. We present this information in the top part of figure 2 (with 95% confidence intervals depicted by the horizontal line around each estimate). We find congruence with the median voter of the entire state 75% of the time. This statistic, however, obscures a big difference in terms of partisan representation: majorities among opinion holders in the senator's own party will see their senator vote the way they want 87% of

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5. The key coefficient, Supporters in senator's party, captures the effect of raising IN support holding overall support constant. This means that calculating the total effect of adding IN support requires adding two coefficients (when IN support goes up, so does overall support, Supporters). The extra effect of a point of IN support is relative to the effect of adding a point of NOT IN support in .2 models or OPP support in .3 models. This is the same effect we would see if we simultaneously flipped one unit of opinion holders who are IN from yes to no and flipped one unit of opinion holders who are NOT IN or OPP from yes to no.

6. Other predictors perform as expected (note that when we control for in-party opinion and senator ideology, senators in the president's party are not more likely to approve a nominee than senators of the opposite party, ceteris paribus). To give a sense of relative effect magnitudes, in model 1.2, a two standard deviation swing in quality could lead to a swing of up to 44 percentage points in the chance of voting yes. Going from an Alito (who has a quality score of .81) to a Roberts (.97) increases the chance of a yes vote by up to 16 percentage points; going from an average nominee to Roberts increases it by up to 28 points. With respect to ideological distance, if Senator McCain had been on the fence for both Justices Ginsburg and Breyer, the additional ideological distance to the former would have reduced his chance of voting yes by up to 22 percentage points.

Table 1. Regression Results: Opinion Point Estimate Models

	Model 1.1	Model 1.2	Model 1.3	Model 2.1	Model 2.2	Model 2.3
Supporters in senator's party		.16*	.15		.12*	.12
		(.09)	(.09)		(.06)	(.06)
Supporters	.16	.10	.14	.14	.10	.09
	(.03)	(.04)	(.08)	(.03)	(.03)	(.04)
Supporters Independents			−.13			.02
			(.20)			(.10)
Percentage in senator's party	.03	−.06	−.13	.02	−.04	−.03
	(.03)	(.06)	(.13)	(.03)	(.04)	(.07)
Percentage in opposition party	−.03	−.03	−.11	−.03	−.03	−.02
	(.03)	(.03)	(.13)	(.03)	(.03)	(.07)
Senator-nominee ideological distance	−5.48	−5.51	−5.48	−5.59	−5.46	−5.47
	(.66)	(.67)	(.67)	(.66)	(.65)	(.65)
Senator ideology						
Nominee ideology						
Senator in president's party	1.99	−.33	−.25	1.61	−.02	−.04
	(.66)	(1.39)	(1.41)	(.60)	(.95)	(.96)
Quality	1.50	1.72	1.73			
	(1.08)	(1.10)	(1.11)			
Intercept	−9.05	−4.39	.98	−8.47	−5.18	−5.79
	(2.51)	(3.56)	(8.98)	(2.40)	(2.81)	(4.93)
Nominee fixed effects	No	No	No	Yes	Yes	Yes
Nominee random effects	Yes	Yes	Yes	No	No	No

	Model 3.1	Model 3.2	Model 3.3	Model 4.1	Model 4.2	Model 4.3
Supporters in senator's party		.20*	.20		.09*	.09
		(.11)	(.11)		(.06)	(.06)
Supporters	.15	.07	.07	.12	.09	.08
	(.03)	(.05)	(.09)	(.03)	(.04)	(.05)
Supporters Independents			−.00			.03
			(.21)			(.10)
Percentage in senator's party	.02	−.10	−.10	.01	−.03	−.02
	(.03)	(.07)	(.13)	(.03)	(.04)	(.07)
Percentage in opposition party	−.02	−.01	−.01	−.02	−.02	.00
	(.03)	(.03)	(.15)	(.03)	(.03)	(.07)
Senator-nominee ideological distance						
Senator ideology	−8.85	−8.82	−8.81	−8.63	−8.42	−8.43
	(1.06)	(1.07)	(1.07)	(1.00)	(1.00)	(1.00)
Nominee ideology	.80	2.22	2.20			
	(1.90)	(1.95)	(1.96)			
Senator in president's party	1.42	−.21	−.25	.47	−.65	−.69
	(1.84)	(1.96)	(1.96)	(.67)	(1.01)	(1.02)
Quality	1.82	2.04	2.03			
	(1.23)	(1.11)	(1.10)			
Intercept	−6.51	−1.41	−1.31	−6.14	−3.85	−5.07
	(2.83)	(3.95)	(9.40)	(2.46)	(2.88)	(4.98)
Nominee fixed effects	No	No	No	Yes	Yes	Yes
Nominee random effects	Yes	Yes	Yes	No	No	No

Note. The table presents logit models of roll call voting, treating our estimates of opinion as point predictions (i.e., measured with certainty). Standard errors are in parentheses. The models split opinion in one of three ways: ".1" models split it one way (without breaking down by constituency, for a baseline); ".2" models split it two ways (pooling independent and out-party opinion together); and ".3" models split it three ways (in-party support vs. independent support vs. out-party support). The model 1 set includes nominee random effects and uses senator-nominee distance. The model 2 set uses nominee fixed effects and senator-nominee distance. The model 3 set includes nominee random effects and uses senator and nominee location. The model 4 set uses nominee fixed effects and senator location. In each model, $N = 991$. The key rows are Supporters in senator's party; the key models are the .2 models. All are in bold.
* The key results for the key models, the difference between the effect of IN opinion compared to NOT IN opinion, are the shaded cells.

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Table 2. Regression Results: Full Uncertainty Models

	Model 1.1	Model 1.2	Model 1.3	Model 2.1	Model 2.2	Model 2.3
Supporters in senator's party		.15* (−.00, .29)	.14 (−.00, .31)		.10* (.00, .20)	.10 (.01, .20)
Supporters	.13 (.08, .18)	.07 (−.00, .15)	.10 (−.02, .23)	.11 (.06, .16)	.07 (.02, .13)	.07 (.00, .14)
Supporters Independent			−.11 (−.43, .23)			.01 (−.15, .17)
Percentage in senator's party	.02 (−.03, .07)	−.06 (−.15, .03)	−.12 (−.34, .10)	.01 (−.04, .06)	−.04 (−.11, .02)	−.04 (−.14, .07)
Percentage in opposition party	−.01 (−.07, .04)	−.01 (−.07, .04)	−.09 (−.31, .15)	−.01 (−.06, .03)	−.01 (−.06, .03)	−.01 (−.11, .09)
Senator-nominee ideological distance	−5.76 (−6.89, −4.63)	−5.76 (−6.91, −4.70)	−5.71 (−6.88, −4.61)	−5.78 (−6.95, −4.75)	−5.72 (−6.84, −4.65)	−5.74 (−6.80, −4.65)
Senator ideology						
Nominee ideology						
Senator in president's party	1.53 (.45, 2.67)	−.59 (−2.95, 1.85)	−.48 (−2.85, 1.91)	1.29 (.28, 2.30)	−.08 (−1.56, 1.48)	−.13 (−1.70, 1.39)
Quality	1.55 (−.32, 3.46)	1.75 (−.26, 3.57)	1.73 (−.24, 3.72)			
Intercept	−6.57 (−10.82, −2.21)	−2.59 (−8.38, 3.66)	2.05 (−13.36, 16.75)	−6.31 (−10.35, −2.23)	−3.65 (−8.44, 1.06)	−3.96 (−11.76, 3.58)
Nominee fixed effects	No	No	No	Yes	Yes	Yes
Nominee random effects	Yes	Yes	Yes	No	No	No

	Model 3.1	Model 3.2	Model 3.3	Model 4.1	Model 4.2	Model 4.3
Supporters in senator's party		.19* (.02, .40)	.19 (.02, .39)		.08* (−.02, .19)	.08 (−.02, .19)
Supporters	.11 (.06, .17)	.04 (−.06, .12)	.06 (−.09, .21)	.09 (.04, .14)	.06 (.00, .12)	.06 (−.02, .13)
Supporters Independent			−.07 (−.45, .31)			.02 (−.14, .18)
Percentage in senator's party	.00 (−.05, .06)	−.10 (−.22, .01)	−.13 (−.38, .10)	.00 (−.05, .05)	−.03 (−.11, .03)	−.03 (−.14, .08)
Percentage in opposition party	−.01 (−.06, .04)	−.01 (−.06, .05)	−.05 (−.31, .21)	−.01 (−.06, .04)	−.01 (−.06, .04)	.00 (−.11, .11)
Senator-nominee ideological distance						
Senator ideology	−9.37 (−11.10, −7.55)	−9.26 (−11.09, −7.49)	−9.37 (−11.18, −7.50)	−9.07 (−10.59, −7.41)	−8.83 (−10.39, −7.22)	−8.83 (−10.46, −7.20)
Nominee ideology	.94 (−2.34, 4.05)	2.18 (−.97, 5.19)	1.98 (−1.27, 5.33)			
Senator in president's party	.91 (−2.36, 4.10)	−.80 (−4.74, 2.84)	−.88 (−4.49, 2.90)	−.07 (−1.11, 1.08)	−1.01 (−2.75, .75)	−1.00 (−2.78, .67)
Quality	1.87 (−.30, 4.13)	2.08 (.07, 4.22)	2.08 (−.02, 4.11)			
Intercept	−3.84 (−9.18, 1.18)	.82 (−5.58, 7.57)	3.05 (−13.63, 20.44)	−3.86 (−8.21, .44)	−2.09 (−7.09, 2.82)	−2.90 (−10.50, 5.69)
Nominee fixed effects	No	No	No	Yes	Yes	Yes
Nominee random effects	Yes	Yes	Yes	No	No	No

Note. The table presents logit models of roll call voting where we incorporate the full uncertainty from each stage of our estimation. Numbers in parentheses are 90% confidence intervals, which allow for one-tailed 95% significance tests. The models split opinion in one of three ways: ".1" models split it one way (without breaking down by constituency, for a baseline); ".2" models split it two ways (pooling independent and out-party opinion together); and ".3" models split it three ways (in-party support vs. independent support vs. out-party support). The model 1 set includes nominee random effects and uses senator-nominee distance. The model 2 set uses nominee fixed effects and senator-nominee distance. The model 3 set includes nominee random effects and uses senator and nominee location. The model 4 set uses nominee fixed effects and senator location. In each model, $N = 991$. The key rows are Supporters in senator's party; the key models are the .2 models. All are in bold.
* The key results for the key models, the difference between the effect of IN opinion compared to NOT IN opinion, are the shaded cells.

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Table 3. Effects of Types of Opinion on Confirmation Vote Probability and Differences in Such Effects: Full Uncertainty Models
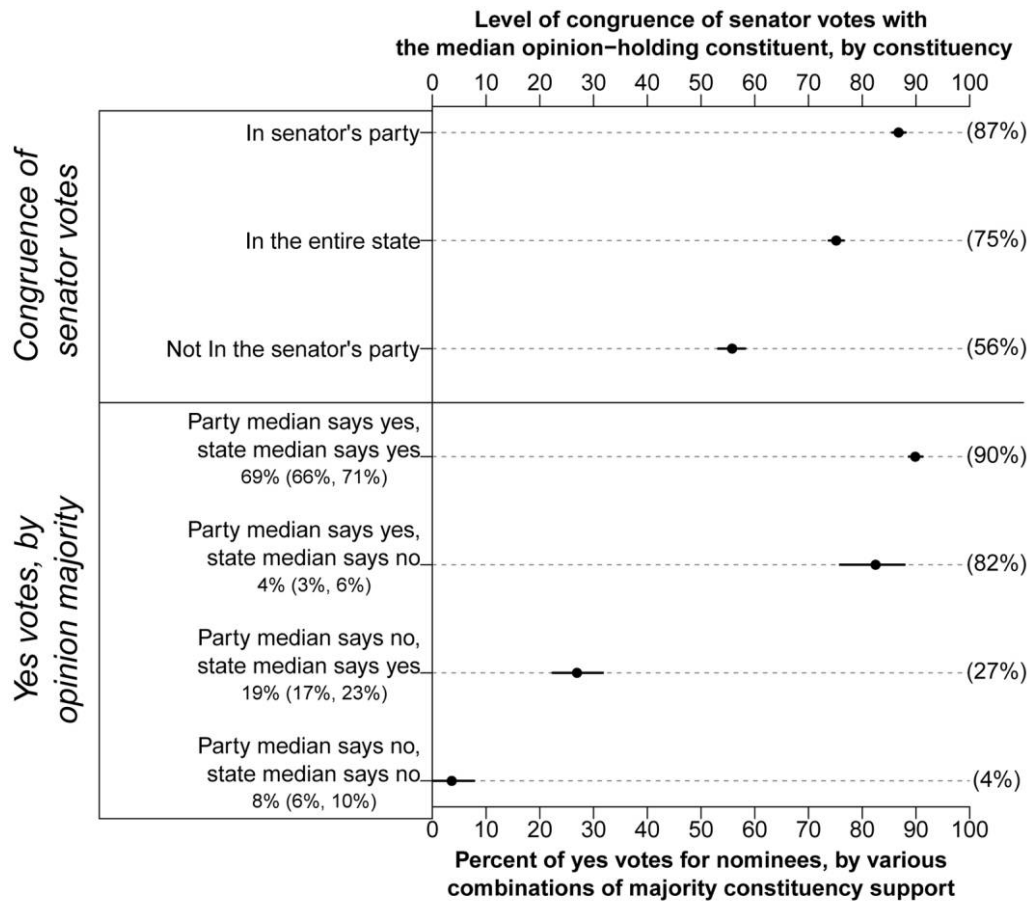
	Model 1.1	**Model 1.2**	Model 1.3	Model 2.1	**Model 2.2**	Model 2.3
Effect of all	.13 (.08, .18)			.11 (.06, .16)		
Effect of IN		.22* (.12, .32)	.25 (.10, .40)		.17* (.10, .26)	.17 (.09, .26)
Effect of NOT IN		.07 (−.00, .15)			.07 (.02, .13)	
Effect of IND			−.00 (−.25, .25)			.08 (−.04, .21)
Effect of OPP			.10 (−.02, .23)			.07 (.00, .14)
Difference between IN and NOT IN		.15* (−.00, .29)			.10* (.00, .20)	
Difference between IN and IND			.25 (−.12, .62)			.10 (−.08, .27)
Difference between IN and OPP			.14 (−.00, .31)			.10 (.01, .20)
Difference between IND and OPP			−.11 (−.43, .23)			.01 (−.15, .17)

	Model 3.1	**Model 3.2**	Model 3.3	Model 4.1	**Model 4.2**	Model 4.3
Effect of all	.11 (.06, .17)			.09 (.04, .14)		
Effect of IN		.23* (.11, .37)	.25 (.08, .44)		.14* (.05, .24)	.14 (.04, .24)
Effect of NOT IN		.04 (−.06, .12)			.06 (.00, .12)	
Effect of IND			−.00 (−.28, .26)			.08 (−.05, .21)
Effect of OPP			.06 (−.09, .21)			.06 (−.02, .13)
Difference between IN and NOT IN		.19* (.02, .40)			.08* (−.02, .19)	
Difference between IN and IND			.26 (−.15, .69)			.06 (−.12, .25)
Difference between IN and OPP			.19 (.02, .39)			.08 (−.02, .19)
Difference between IND and OPP			−.07 (−.45, .31)			.02 (−.14, .18)

Note. The table is based on the full uncertainty models presented in table 2 using our full set of simulations to calculate the levels of and confidence intervals around the key coefficients and differences in coefficients. The median estimate is shown with 90% confidence intervals in parentheses The key rows are Supporters in senator's part and Difference between IN and NOT IN (all in bold); the latter match the key rows in table 2. The key models are the .2 models.
* The key results for the key models are the shaded cells.

the time, whereas those in the opposing party will see their senator vote the way they want only 56% of the time.

When a senator's constituencies are in conflict, how does she weigh her competing constituencies? The second part of the graph depicts the percentage of yes votes for all the nominees, according to which constituencies favor confirmation. The percentages under the left-hand labels in this part of the graph depict the proportion of observations that fall into each category and the confidence intervals around that proportion. Finally, the two-by-two

**Level of congruence of senator votes with
the median opinion−holding constituent, by constituency**

Figure 2. Congruence in roll call voting on Supreme Court nominees, and percentage of yes votes by opinion majority across constituencies. In the top part of the graph, each point depicts the level of congruence with the median voter (among opinion holders) in the respective groups, while the numbers in parentheses denote the actual values. Horizontal lines depict 95% confidence intervals. The bottom part of the graph depicts the percentage of yes votes for all the nominees, according to which constituencies favor confirmation. The percentages under the labels in this part of the graph depict the proportion of observations that fall into each category, with the numbers of parentheses depicting 95% confidence intervals. Finally, the table below the graph depicts a 2 × 2 table of yes votes by state and party median opinion majorities.

Yes votes, by state median and party median opinion		
	State median says yes	State median says no
Party median says yes	90%	82%
Party median says no	27%	4%

table underneath the figure summarizes the breakdown of yes votes by state median and party median opinion. Flipping the support of the state median (i.e., moving across the columns) changes the voting far less than flipping the party median (i.e., moving down the rows). Both the state median and party median favor confirmation around 69% of the time. When this happens, a senator votes yes 90% of the time. The party median favors confirmation and the state median does not around 4% of the time; when this happens, the percentage of confirmation votes (82%) is a bit lower than when both constituencies agree. That is, flipping the median voter in the state but keeping the in-party

median voter as is slightly changes the chances of getting a yes vote. Conversely, the state median favors confirmation in opposition to the party median 19% of the time, and then a yes vote occurs only 27% of the time. Finally, in 8% of cases, neither median favors confirmation, and there are only 4% of yes votes when it happens. A nominee seeking a senator's vote would much rather have the median voter in the senator's party on her side than the median voter in the state.

Consider Justice Sotomayor: 34 voting senators faced conflicting constituencies (on the basis of point estimates). The five conflicted Democrats (Begich-AK, Conrad-ND,

Dorgan-ND, Johnson-SD, and Nelson-NE) all voted yes with their party median. Of the 29 conflicted Republican senators, all but nine sided with the party median against the state median by voting no (the nine: Martinez-FL [facing a large Hispanic constituency], Lugar-IN, Collins-ME, Snowe-ME, Bond-MO, Gregg-NH, Voinovich-OH, Alexander-TN, and Graham-NC).

More generally, suppose that the support of either the median voter or the party median voter perfectly predicted how a senator votes. Then, vote totals for each of the nominees would be as shown in figure 3. (We set aside uncertainty.) The fate of some nominees would not vary much if they moved to "median voter world" or "party median voter world." Judge Bork would not have become Justice Bork in either alternative scenario, and those nominees would also see little variation in their vote margins. On the other hand, Justices Alito, Rehnquist, Sotomayor, Kagan, and Roberts all show large gaps between the two scenarios. The voting on Justice Alito closely resembled that in party median voter world. Of the 10 nominees with votes, four show strong evidence of party influence, one is a tie (Roberts), and five are ambiguous given similarities between such worlds. Thomas is an outlier. Both scenarios show easy confirmation. Yet, he was narrowly confirmed. Miers of party median voter world would fall below the filibuster threshold, though she would have exceeded it with many votes to spare in median voter world. Kagan, Sotomayor, and Rehnquist were also possibly saved from the filibuster by the pull of the median
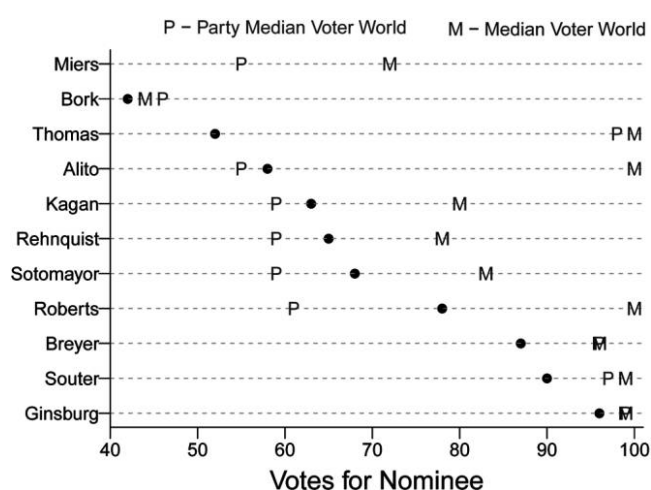

Figure 3. Votes for nominees in median voter world and in-party median voter world. Each point depicts the actual number of votes each nominee received. Compared to this are the number of votes each nominee would have received if the median voter in each state (among opinion holders) controlled the senator's vote as well as the number of votes that would have been received if the median voter in the senator's party controlled the senator's vote.

voter and the less than dispositive role of the party median. Note that the tendency to follow the party median, even where the outcome for the nominee is unchanged, drastically increases polarization in the confirmation process by increasing the no votes of the opposition party.

DISCUSSION AND CONCLUSION

Our fine-grained study of representation, focusing on votes by senators for or against the confirmation of Supreme Court nominees, reveals a somewhat distorted electoral connection. Confirmation politics is responsive to the public will, but not as previously thought. We find that senators weigh the opinions of their fellow partisans far more heavily, that they resolve the trade-off in representing their median constituent and median party constituent in favor of copartisans. This "partisan constituency effect" has significant substantive effects on voting behavior and can be troubling to normative democratic theory.

When party constituents have such strong influence, a distortion to median representation occurs on top of any distorting effects due to the copartisan electorate itself. That is, if senatorial candidates are chosen by more extreme electorates, that alone can mean that senators will not be perfectly representative. That they give extra attention to their in-party constituents even controlling for their own ideological preferences is then a particularly strong partisan distortion. Majority control over policy becomes far more difficult when the two parties do not converge toward the median, but instead represent influences of one extreme side or the other. Our results thus show how electoral incentives can polarize elites. Even in a relatively smooth distribution of opinion, partisan groupings that have disproportionate influence can lead to polarized voting behavior. A more optimistic reading of our results is that we still find responsiveness to mass opinion—even if it is unequal responsiveness.

More broadly, our results provide a new understanding of the factors that drive the roll call votes of senators. We show, for example, how important partisan opinion is relative to other forces, such as senator ideology and partisan loyalty. In median voter world, the electoral connection ties a representative back to his constituents strongly enough to make the median voter king (or queen). This seems a reasonable baseline for assessing democratic performance. If a representative gives extra weight to his fellow partisans back home, this implies a distortion of the electoral connection that ties a representative to his district or state, with policy pulled away from the median voter. Or, at least, the copartisan electoral connection would be undercutting the "regular" electoral connection. In this sense, our results pro-

vide more evidence for "leapfrog representation": replacing a representative from one party with one from the other results in voting behavior that jumps from one side of the median voter to the other (Bafumi and Herron 2010).

Further, our results refine our understanding of the relationship between the public and the Court. There is a persistent debate over the proper role of the Court in society and the degree to which we should be concerned that unelected life-appointed justices can block the majority will, as enacted through its elected representatives. One of the few external checks on this possible counter-majoritarianism is political control by the president and senators over who becomes a justice in the first place—a check that acts only preemptively, through the confirmation process. If the median voter controlled such nominations, fears of counter-majoritarianism would be ameliorated to some extent. However, if a senator's copartisans are given disproportionate attention, the democratic linkage between the Court and public is again called into question, and we have more reason to worry that the nomination and confirmation process might make the Court more counter-majoritarian rather than less.

Moreover, these worries may be compounded by the current era of partisan polarization in Supreme Court nomination politics. Cameron, Kastellec, and Park (2013) uncover two types of polarization. First, as is well known, the Senate has become increasingly polarized over the last 30 years or so. Second, as is less well known, nominees have become increasingly more polarized. Whereas responsiveness to the median voter by senators might counter the possibility of ideological polarization on the Court itself, partisan representation points in the opposite direction. This is especially true of justices confirmed during periods of unified government—as has been the case with the last six justices. Our results also emphasize the importance of Senate control. In median voter world, small partisan majorities in either direction would likely not constrain a president's choice of nominees, and the process need not be as divisive. But in party world, if the opposition party controls the Senate, a president might be far more constrained in the extent to which he can appoint an ideological ally or even a moderate. With the Republicans taking control of the Senate in 2015, should a justice retire in the coming two years, the prominence of party world would play a huge role in President Obama's calculation of what type of nominee would be confirmable.

Because we focused on a particular type of roll call vote, we must be tentative in making any claims about the generalizability of our results. Still, while Supreme Court confirmations are certainly special, we see no reason to believe that our findings would not also apply to high-profile votes

in the Senate, such as war resolutions, treaties, and major legislation. And, while extrapolating to the House requires more faith, the incentives that drive our results are also likely to apply to high-profile votes in that chamber. It is such votes, of course, that voters are most likely to be aware of, meaning that representatives will be most likely to weigh competing subconstituency pressures should they diverge. A worthy endeavor would be to extend our analysis to other important issue areas and see if our results hold. Similarly, the variation we find in responsiveness leads naturally to the question of what institutional and contextual factors predict when a representative will choose to side with one constituency over another. Our approach could easily be extended to study how variation in opinion interacts with factors such as proximity to elections and primary types in predicting responsiveness.[7]

To that end, we conclude by reiterating a methodological point. We have extended earlier work on generating model-based estimates of opinion from national polls—an extension that can be applied in many other areas of research in the future. Two-stage MRP will allow a researcher to estimate opinion within states or even potentially congressional districts, broken down by partisanship or many other factors, using data commonly available in surveys and the census. We hope that this extension of the standard MRP approach will point the way toward more nuanced analyses of public opinion and its effects on public policy and choice, and more fine-grained studies of legislative and policy-making behavior. Specifically, subgroup opinion estimates that are useful for the exploration of a wide variety of research questions should now be in reach. Besides breaking down opinion using information currently used in census weighting data, one can now estimate opinion by any categorization for which sufficient polling data are available (in the same polls or others). Finally, we also have incorporated multiple layers of uncertainty surrounding MRP estimates into our substantive analysis while comparing our findings to those based on the MRP point predictions. Collectively, these innovations should allow researchers to pursue more concrete answers to vital questions about the extent and quality of representation.

APPENDIX

Here, we provide technical details on how we generated our estimates and incorporated their uncertainty into our

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7. In the supplemental appendix, we discuss inconclusive evidence that senators give extra attention to their fellow partisan constituents when that group is larger than the other partisan group.

regressions of roll call voting. The first step was to estimate partisanship as a function of demographic and geographic predictors. We collected every Gallup poll in 1980, 1989–91 (there were fewer polls in 1990), 2000, 2005, and 2010 that asked party identification. The advantage is that Gallup's question wording did not change across these years: "In politics, as of today, do you consider yourself a Republican, a Democrat, or an Independent?" "Leaners" are coded as Independents, as are nonresponses (under 5%). We weight estimates from the two closest decennials if nominations do not fall on the exact decennial. We have Census Public Use Microdata Area (PUMA) data for 1980, 1990, and 2000. For 2009 nominees, we use 2009 Census American Community Survey data (the 2010 PUMA sample was never released).

Since the Census Bureau does not directly provide weights by party, which is necessary for the poststratification part of MRP, we need to estimate this more nuanced poststratification data. The first stage is to estimate the probability that each respondent in our surveys is one of three partisan categories: D, I, or R. Using a multilevel model, we then move from these individual responses to estimates of partisanship for each demographic-geographic type. Because partisanship comprises three categories, we employ what effectively is a multinomial or ordered logit, estimated using a two-stage nested procedure. While this is less efficient than doing so in a single multinomial stage, it allows us to build off of the MRP package (available on GitHub). The loss of efficiency increases confidence intervals around our results.

For each year, we code responses as a function of race and gender (males and females broken down into black, Hispanic, or white or other); one of four age groups (18–29, 30–44, 45–64, and 65+); one of four education groups (less than a high school education, high school graduate, some college, and college graduate); an interaction between age and education; state-level ideology (updated from Erikson, Wright, and McIver [1993]); and state.

In a given year, we first estimate the probability that a respondent is a Democrat against the probability that he is not (pooling Independents and Republicans). Then, conditional on not being a Democrat (excluding Democrats from the data), we estimate the probability of being a Republican against being an Independent. Formally, let $y(\cdot) = 1$ denote a positive response (Democrat 1 and other 0). For individual i ($i = 1, \ldots, n$), with indexes r, k, l, m, s, and p for race-gender combination, age category, education category, and state, respectively,

$$\Pr(y(\cdot) = 1) = \text{logit}^{-1}(\beta^0 + \alpha_{r[i]}^{\text{race,gender}} + \alpha_{k[i]}^{\text{age}} \\ + \alpha_{l[i]}^{\text{edu}} + \alpha_{k[i],l[i]}^{\text{age,edu}} + \alpha_{s[i]}^{\text{state}}).$$

(A1)

The grouped terms are random effects, modeled as a normal distribution with mean zero and endogenous variance, except for the state effect, which is relative to state ideology:

$$\alpha_r^{\text{race,gender}} \sim N(0, \sigma_{\text{race,gender}}^2) \quad \text{for } r = 1, \ldots, 6,$$

$$\alpha_k^{\text{age}} \sim N(0, \sigma_{\text{age}}^2) \quad \text{for } k = 1, \ldots, 4,$$

$$\alpha_{k,l}^{\text{age,edu}} \sim N(0, \sigma_{\text{age,edu}}^2) \quad \text{for } k = 1, \ldots, 4,$$

$$\alpha_l^{\text{edu}} \sim N(0, \sigma_{\text{edu}}^2) \quad \text{for } l = 1, \ldots, 4,$$

$$\alpha_s^{\text{state}} \sim N(\beta^{\text{ideo}} \cdot \text{relig}_s + \beta^{\text{ideo}} \cdot \text{ideo}_s, \sigma_{\text{state}}^2)$$

$$\text{for } s = 1, \ldots, 50.$$

(A2)

Next, we use the coefficients that result from these models to calculate predicted probabilities of being a particular partisan type for each demographic-geographic type. Let j denote a cell in our list of demographic-geographic types (4,800 demographic-geographic types, 96 within each state). For each cell j we have the population frequency derived from the census sample from the desired year. We then split each cell j into three parts. The results above allow us to make a prediction of each type of support, $(\hat{\theta}_j^{\text{DEM}}, \hat{\theta}_j^{\text{IND}}, \hat{\theta}_j^{\text{GOP}})$ based on the inverse logit given the relevant predictors and their estimated coefficients, as estimated in equation (A1). The first run, predicting Democrats against others, gives the probability of being a Democrat. The second run splits the remaining part of the cell into Republicans and Independents. Thus the probabilities will always sum to 100%. So the preexisting cell frequency is multiplied by partisan group share, as calculated above, to create a new set of frequencies, with three times the original number of cells, leading to 14,400 demographic-geographic-partisan types. Formally, N_j denotes the actual population frequency of a given cell j. A given cell j will be split into three cells, with frequencies $N_j\hat{\theta}_j^{\text{DEM}}$, $N_j\hat{\theta}_j^{\text{GOP}}$, and $N_j\hat{\theta}_j^{\text{IND}}$. Let q denote a cell in this new poststratification file (to distinguish it from j), specifying a demographic-geographic-partisan type, and let N_q denote its population frequency.

In terms of programming, the BLME package in R—which fits Bayesian linear and generalized linear mixed-effects models—uses point predictions for the variance parameters (the priors used in the BLME models were the default Wishart distribution). This requires the use of the SIM function in the ARM package to generate uncertainty estimates. It produces simulated samples of coefficients to empirically represent uncertainty. These then are each used to produce a set of party-poststratification weights. To confirm that starting with Democrats did not affect results, we redid the entire process, starting with the probability of being a Republican and then the conditional choice of otherwise being a Democrat

or Independent. Probabilities were similar. We averaged the results from the two starting points.

With these party-poststratification weights in hand, we can now turn to estimating public opinion on nominees among each partisan subconstituency in every state. Instead of modeling partisan identification, we now model nominee support. We first model explicit support for the nominee ($y_i^{\text{yes}} = 1$) against other responses ($y_i^{\text{yes}} = 0$ for an explicit negative response, "don't know," or "refused"). Then a nested model predicts an explicit negative response against don't know. We did the process again, but starting with the negative response and pooling the others, then averaging results from both starting points (just as we did above). The specification of the model is similar to that given above, except we now add a random effect for party, and we substitute state-level ideology for presidential vote (we found that state-level ideology is a better measure for capturing support for a liberal or conservative nominee; presidential vote is better at capturing partisan identification). For $i = 1, \ldots, n$,

$$
\Pr(y_i^{\text{yes}} = 1) = \text{logit}^{-1}(\beta^0 + \alpha_{r[i]}^{\text{race,gender}} + \alpha_{k[i]}^{\text{age}}
$$
$$
+ \alpha_{l[i]}^{\text{edu}} + \alpha_{k[i],l[i]}^{\text{age,edu}} + \alpha_{s[i]}^{\text{state}} + \alpha_{p[i]}^{\text{party}}). \tag{A3}
$$

For each nominee, we weight the cell frequencies on the basis of the two decennials nearest to the year of nomination. For example, Justice Breyer was nominated in 1994, so we let his demographic-geographic-partisan frequencies equal .6 × the 1990 frequencies + .4 × the 2000 frequencies. For some nominees we have race broken down into only two categories (black and white/other, denoted *wb* below), yielding 9,600 poststratification cells. For some, Hispanic is a separate category (denoted *wbh*), yielding 14,400 cells in total.[8]

We then use the results from the model in equation (A3) to make a prediction of pronominee support, $\hat{\theta}_q$, for each cell q. To get state-level estimates, we next poststratify, weighting the prediction by N_q^{adj}. Formally, let $\hat{\gamma}$ denote an estimate of nominee support at a given level of aggregation. For each state, we then calculate the estimated percentage who support the nominee, aggregating over each cell q in state s. Thus, $\hat{\gamma}_s = \sum_{q \in s} N_q \hat{\theta}_q / \sum_{q \in s} N_q$. This process yields estimates of explicit support for each nominee in each state. To obtain estimates for each partisan group in each state, we perform similar calculations, each time restricting the aggrega-

tion of probabilities in individual cells to a specific partisan subgroup. Let *qd* denote Democratic cells, *qr* denote Republican cells, and *qi* denote Independent cells:

$$
\hat{\gamma}_s^{\text{DEM}} = \frac{\sum_{q \in (s \cap qd)} N_q^{\text{adj}} \hat{\theta}_q}{\sum_{q \in (s \cap qd)} N_q^{\text{adj}}};
$$

$$
\hat{\gamma}_s^{\text{GOP}} = \frac{\sum_{q \in (s \cap qr)} N_q^{\text{adj}} \hat{\theta}_q}{\sum_{q \in (s \cap qr)} N_q^{\text{adj}}};
$$

$$
\hat{\gamma}_s^{\text{IND}} = \frac{\sum_{q \in (s \cap qi)} N_q^{\text{adj}} \hat{\theta}_q}{\sum_{q \in (s \cap q)} N_q^{\text{adj}}}.
$$

For each model, we generate 1,250 sets of simulated response model coefficients, so that the variation reflects an empirical distribution capturing uncertainty around the point prediction (median across sims) for the coefficients. For each of these, we then generate poststratifications, leading to 1,250 sets of ultimate estimates. We repeated the above flipping the nesting, and starting with explicit opposition to the nominee against the other two categories, then modeling support versus neutrality. Again, we get 1,250 sets of estimates. We averaged the estimates across the two ways of doing the nesting. Finally, for each of the 1,250 estimate sets, we run our roll call vote models. We then use the SIM function one last time to pull a single draw of coefficients from the model given the uncertainty in that model. We now have 1,250 sets of roll call vote model coefficients, the empirical distributions of which can be used to calculate confidence intervals. We reran the entire process a few times. Key results correlated across runs at .999, showing that 1,250 simulations are sufficient.

ACKNOWLEDGMENTS

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8. The poststratification files used are as follows (1980*wb*, e.g., means the 1980 poststratification file using only two race categories): for Bork and Rehnquist, a weighted average of 1980*wb* and 1990*wb*; for Thomas, Souter, Ginsburg, and Breyer, a weighted average of 1990*wb* and 2000*wb*; for Alito, Roberts, and Miers, 2005*wbh*; and for Sotomayor and Kagan, 2009*wbh*.

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Supplemental Appendix
to
"Polarizing the Electoral Connection: Partisan Representation in Supreme Court Confirmation Politics"

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In this appendix, we present some additional notes on our methods. We also include a supplemental table providing more information on the sample sizes in the nominee polls used. We comment on some additional analysis we did to see if our findings could be drawn out further. Finally, we present a series of figures showing estimates (with uncertainty) by state and party for all remaining nominees (highlighting Alito and Kagan as examples).

1. *Comprehensiveness of polls.* To produce estimates for as many nominees as possible, we searched the Roper Center's *iPoll* archive. These nominees are the only ones with sufficient polling data. For nominees who featured in only a handful of polls, we gathered every poll containing sufficient demographic and geographic information on individual respondents. For nominees with a large number of such polls, we only used the polls closest to their confirmation vote. For Thomas, we only retained polls taken after the Anita Hill allegations surfaced. This ensures as much as possible that our estimates tap state opinion as it stood at the time of the vote.

2. *Interpreting a unit shift.* A unit shift in our opinion measures flips a fixed share of the state population, but an unfixed share of the party population. One cannot scale to both at the same time. Consider Senator Voinovich in 2009 (R-OH). A unit shift in support consisting only of in-party opinion holders means that 1% of the total number of opinion holders in Ohio switch from no to yes, where the switchers consist only of Republicans. Support goes from 53.0% to 54.0% overall in Ohio, but only Republicans change, so this shift means that 3.1% ($= \frac{1}{32.2}$) of Republicans move from no to yes, increasing support among Republicans from 23.6% to 26.7%. Next, consider Senator Sherrod Brown (D-OH). Now, a unit shift in opinion holder support consisting only of Democrats still moves total support in Ohio from 53.0% to 54.0%, but this means that 3.0% ($= \frac{1}{33.3}$) of Democrats shifted from no to yes (83.8% becomes 86.8%). The unit shift in opinion holders correlates to a different size share within party because party sizes differ.

3. *Cell structure of data.* Technically, the MRP package in R converts this individual-level structure to an equivalent cell-level structure (of types) for the logistic regression, with counts of 1 and 0, and weights by cell. We use the more standard notation in the text.

4. Table SA-1 summarizes the number of respondents used in each of the nominee megapolls, as well as the number of polls used for each nominee.

5. *Do Senators behave differently depending on the extent of party control in their state?* We explored whether some senators showed more deference than others to their partisan constituents (their in-party median) or to the median of their state as a whole. Specifically, if the senator's party is dominant in their state, is the party median listened to over the state median. Following **?**, we started by defining a dominant party as one where it was larger than the independents and at least 5 percentage points larger in size than the opposing party. Then, where the senator's party was dominant, there were 46 votes where the senator faced a choice between what the two medians wanted, and 80% of the time the senator went with the party median. When the senator's party

Nominee	Number of observations	Number of polls
Alito	7,904	7
Bork	5,806	5
Breyer	1,524	1
Ginsburg	2,219	2
Kagan	8,207	8
Miers	1,008	1
Rehnquist	3,497	2
Roberts	7,191	8
Sotomayor	6,333	6
Souter	2,200	2
Thomas	3,540	4

Table SA-1: Summary of nominee polls

was not dominant, this dropped to 75%. However, the results were too dependent on the exact threshold chosen given the relatively small number of votes for us to form a clear conclusion. If the threshold for dominance were 10 percentage points in size, then these numbers were 77% and 76%. Or, if we compared the top half of the data to the bottom half, based on the two party split alone, the numbers were 76% and 75%. The most we can say is that it is possible that senators give extra attention to their fellow partisan constituents when that group is larger than the other partisan group. Sorting this out further would require an exploration of a much larger set of senate votes. This would be possible in future work with the MRP extensions we provide.

6. *Uncertainty around estimates.* In Figure SA-1, for each nominee, the top panels in the following figures depict the distribution of state-level opinion (among opinion holders) in each state, while the bottom panels are broken down by Democratic, Independent and Republican opinion. For each nominee, the states are ordered from lowest levels of state support to highest. The vertical lines connect the median estimate for each state (for the respective constituency). We also depict the uncertainty in the estimates: for each constituency and state, we plot the 95% confidence interval for each set of estimates (i.e the empirical distribution). To depict each distribution, we plot translucent dots such that the darker regions depict the center of the distribution and lighter region depicting the tails. For example, Republican support for Alito is more precisely estimated than the other subgroups for Alito and even than Democratic support for Kagan. For each nominee, the states are ordered from lowest levels of overall support to highest. There is substantial variance in opinion within the same constituency and across states. Variance across parties is even larger, with Democrats and Republicans far apart from each other in every state (for these nominees).
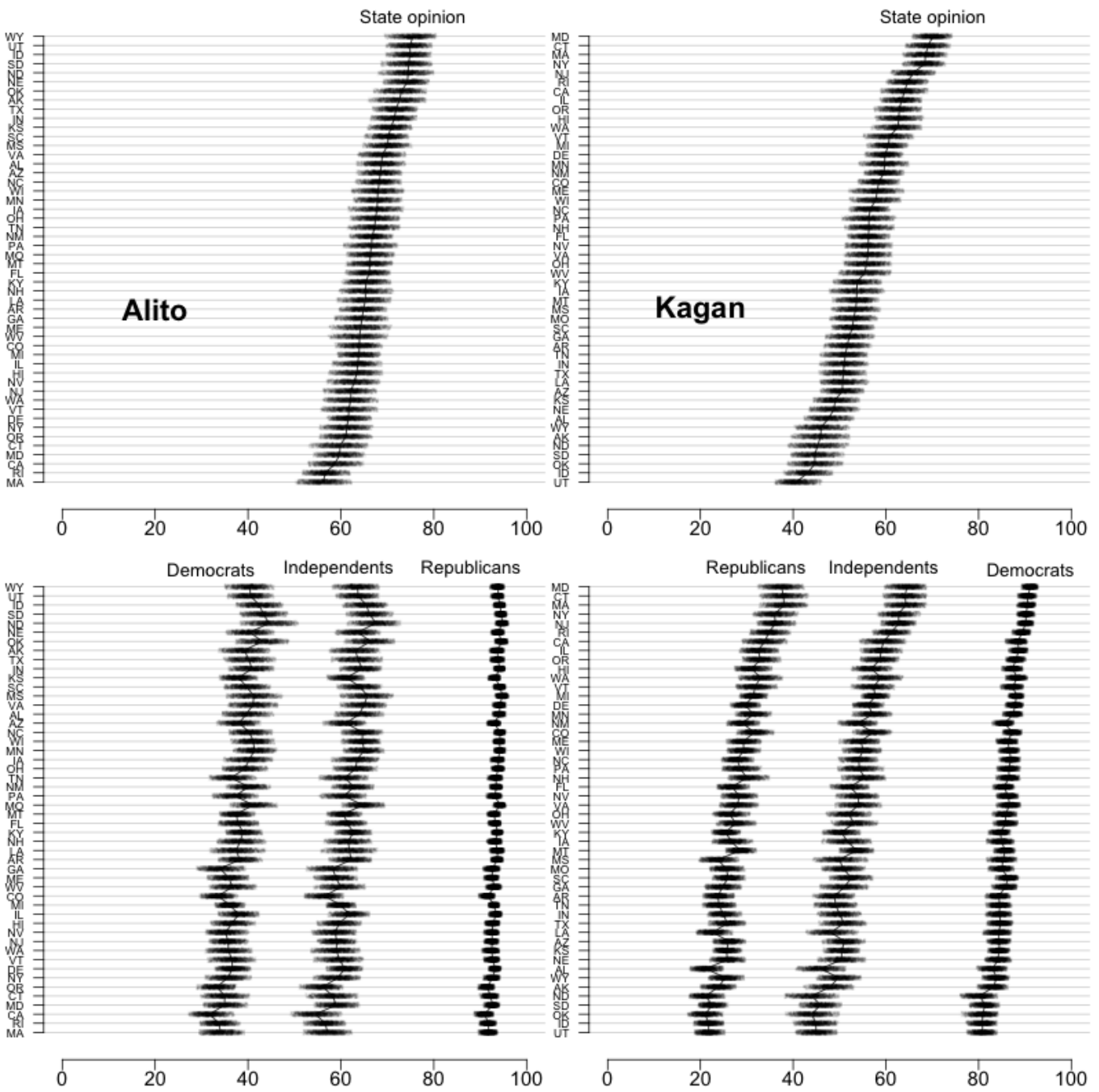
Figure SA-1: *Depicting estimates and uncertainty nominees by state and party.*

State opinion

Rehnquist

State opinion

Thomas

Democrats　Independents　Republicans

Democrats　Independents　Republicans

5

State opinion

Roberts

State opinion

Souter

Democrats Independents Republicans

Democrats Independents Republicans

6

State opinion

Sotomayor

Ginsburg

State opinion

Republicans   Independents   Democrats

Republicans   Independents   Democrats

State opinion

Breyer

Republicans   Independents   Democrats