

On-line Appendix
Institution of Nomination and the Policy Ideology of
Primary Electorates
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Table A1: Number of validated voters by year, state, and election

State	2010		2012	
	General	Primary	General	Primary
AK	83	74	90	54
AL	361	289	444	230
AR	322	176	329	13
AZ	1,035	751	1,025	674
CA	3,629	2,891	3,243	2,292
CO	705	490	756	295
CT	518	272	370	131
DC	56	52	71	23
DE	148	70	162	55
FL	2,784	1,923	2,554	1,285
GA	1,056	640	1,131	192
HI	118	108	124	98
IA	417	214	470	104
ID	171	84	256	119
IL	1,573	1,048	1,339	701
IN	544	449	704	391
KS	380	246	490	242
KY	465	352	537	182
LA	390	292	444	NA
MA	693	399	683	250
MD	655	406	727	314
ME	245	180	294	96
MI	1,190	812	1,237	623
MN	653	347	757	245
MO	766	544	848	477
MS	212	42	276	135
MT	97	75	179	126
NC	897	448	1,132	758
ND	86	56	75	53
NE	89	51	409	243
NH	244	164	250	131
NJ	884	321	856	283
NM	294	150	300	153
NV	430	297	445	201
NY	1,733	633	1,702	180
OH	1,697	1,143	1,432	755
OK	353	247	415	162
OR	593	464	864	599
PA	1,735	1,240	1,472	740
RI	127	64	171	60
SC	387	271	581	5
SD	105	50	112	46
TN	537	405	708	325
TX	2,150	1,362	2,205	1,046
UT	211	107	353	141
VA	0	0	1,064	228
VT	56	29	107	9
WA	965	811	1,059	784
WI	742	488	850	412
WV	210	131	203	150
WY	63	46	97	55

Note: Cell counts are the number of validated general and primary voters from each year's CCES by state.

A Measurement approach

In this section, I describe my measurement approach for the MRP district estimates and in the section following present the details of its implementation. The basic intuition is to use opinion surveys to describe the political conservatism of primary election voters and general election voters in each district. Because sample sizes are often small, I use a hierarchical model to pool observations, allowing the data to indicate if the preferences of, say, Democratic primary voters in New York congressional districts are more similar to each other than they are to Democratic primary voters in West Virginia. The model allows observed correlation within New York to influence my estimate of the preferences of the New York Democratic primary electorates relative to the preferences of the West Virginia electorates. I summarize the political preferences of each electorate in each district to a single value on a liberal-conservative dimension so that I may characterize the relationship between the conservatism of congressional voting and the conservatism of primary and general electorates.

While we have opinion survey samples, moving from the sample to a population estimate has many challenges. The main problem in my case is small samples of primary voters in each district, but additional problems include measurement error in sampled preferences, differential survey non-response, and uncertainty about turnout. I apply the current best practices in response to each of these problems to best characterize the preferences of primary and general election voters in each district, and then provide tests of fit and validation.

A.1 Purpose of the hierarchical model and weights

I use the 2010 and 2012 Cooperative Congressional Election Studies (CCES) below. Even with sample sizes of around 55,000 respondents, dividing them among 435 congressional districts yields on average about 125 respondents per district per year. If primary turnout is 20 percent of the voting age population, this means around 25 total primary voters, which must then be divided into two party primaries.

Hierarchical models are a natural solution to the problem of small samples when covariates are available and/or observations nest in some natural way. They have been shown to have the lowest mean-square error for this kind of estimation (see, e.g., Jackman, 2009, ch. 7 for citations). In this case, my hierarchical approach models preferences as a function of individual covariates and nested geographies. I include the individual demographic characteristics of each respondent along with their turnout history in the primary and general election and their geographic location. Turnout is validated to administrative records with statewide voter files. The hierarchical model smooths across geographies, turnout, and respondents to provide best estimates for each electorate in each district. This in general shrinks estimates towards the grand mean across individuals and districts, reducing the influence of outlying values in small sample primary electorates. I estimate the model separately for each of three types of party of registration, Democrat, Republican, and Decline to State/other party. Formally, my model of individual preferences y_i within each party of registration with respondents nested within districts within states within Census regions,

$$\begin{aligned}
y_i &\sim N(\mu_i, \sigma_y^2) \\
\mu_i &= \beta' \mathbf{x}_i + \alpha'_{c(i)} \mathbf{t}_i + \delta_{c(i)} \\
\alpha_{c(i)} &\sim N(\alpha_{s(c)}, \Sigma_c) \\
\alpha_{s(c)} &\sim N(\bar{\alpha}, \Sigma_s) \\
\delta_{c(i)} &\sim N(\delta_{s(c)}, \sigma_c^2) \\
\delta_{s(c)} &\sim N(\delta_{r(s)}, \sigma_s^2) \\
\delta_{r(s)} &\sim N(0, \sigma_r^2)
\end{aligned} \tag{A1}$$

where y_i is a summary of the preferences of respondent i , μ_i is the expected value of y_i and σ_y^2 is the variance of the distribution of y_i . β is a vector of coefficients mapping individual characteristics \mathbf{x}_i to the expected value of y_i , $\alpha_{c(i)}$ is a vector of coefficients for congressional district $c(i)$ mapping a vector of turnout history \mathbf{t}_i (e.g., primary and general turnout) to the expected value of y_i , $c(i)$ is a function that returns the congressional district of respondent i , and $\delta_{c(i)}$ is an intercept shift for the expected value of y_i in congressional district $c(i)$. The hierarchical structure of the model proceeds in the following lines, with the congressional district turnout coefficients $\alpha_{c(i)}$ distributed multivariate normal with means specific to the state of that district through the function $s(c)$ and covariance matrix Σ_c . The state means for the turnout coefficients, $\alpha_{s(c)}$, are distributed multivariate normal with mean vector $\bar{\alpha}$ and covariance matrix Σ_s . Finally, each congressional district has an intercept shift $\delta_{c(i)}$ nested within states via a normal distribution with mean $\delta_{s(c)}$ and variance σ_c^2 , which are nested within regions with mean $\delta_{r(s)}$ and variance σ_s^2 . The region means are distributed normal with mean 0 and variance σ_r^2 .

In words, this hierarchical model allows the preferences of each respondent to vary with their party, individual characteristics such as age or race, their turnout history in primary and general elections, and the geography in which they reside. Their congressional district is related to their political preferences not only through an intercept shift, but also interacted with their turnout history, allowing primary and general election voters in each congressional district and of each party to have different coefficients relating turnout to their preferences. Each Democratic, Republican, and independent primary and general electorate in each congressional district has a different intercept for conservatism, holding constant individual demographics. I specify the effects in this way because turnout in congressional primaries may vary with the candidates on offer as well as the primary institution and local party dynamics, which vary by state and district.

To map the hierarchical model of the individual preferences of voters from each electorate in each congressional district, I apply the following procedure:

Note that in states with more open primary rules, I do not know in which primary the decline-to-state/other party registrants with a validated primary turnout record voted. Unlike turnout, party of registration is self-reported in the 2010 CCES such that, even in states without party of registration, I partition respondents by their self-report party of registration. I replicate this choices in the 2012 CCES. Thus in closed states I am likely better able to characterize the full primary electorate because of the required party registration.

Table A2: Procedure to estimate district-electorate preferences

1. Apply the estimated individual-level coefficients ($\hat{\beta}$ and $\hat{\alpha}_{c(i)}$) from the hierarchical models by party of registration along with the posterior mixed (random) effects ($\hat{\delta}_{c(i)}$) to each respondent. This creates the modeled conservatism for each respondent. For example, a Democratic registrant who voted only in the 2010 general election from New York's 22nd Congressional district would have predicted conservatism given her set of demographics and turnout history and the coefficients on age, gender, marital status, etc., plus the geography shift for Democratic general election voters in New York state, plus the geography shift for Democratic general election voters in New York's 22nd district.
2. Average the predicted conservatism of validated voters in the target election to each congressional district using the CCES post-stratification weights for those validated voters. For example, if the target electorate is general election voters in NY-22, take all of the survey respondents with validated vote in that election, Democrat, Republican, and other party, and calculate the weighted average of their predicted conservatism with CCES survey weights. This weighted average is my estimate of the conservatism of NY-22 2010 general election voters. To calculate the conservatism of NY-22 Democratic primary voters, calculate the weighted average only for those respondents with Democratic party of registration and with validated vote in the 2010 primary.

A.2 Connection to Multi-level Regression with Post-Stratification

The procedure in Table A2 above, using hierarchical models and post-stratification weights to aggregate to subnational geographies, is related to a line of recent work on estimating the policy opinions of subnational electorates using hierarchical models (e.g. Gelman and Little, 1997; Park, Gelman, and Bafumi, 2004; Lax and Phillips, 2009; Warshaw and Rodden, 2012). These methods, called multi-level regression with post-stratification (MRP), use post-stratification along with the hierarchical model to improve estimation. The hierarchical model helps improve the estimation of small-area quantities, essentially by shrinking small-area estimates towards larger areas in which they are nested. Post-stratification is a standard statistical adjustment for nonresponse bias in sample surveys. The combination of the two improves estimates of small-area opinion (e.g., Gelman and Little, 1997; Park, Gelman, and Bafumi, 2004; Lax and Phillips, 2009; Warshaw and Rodden, 2012).

However, I do not exactly follow MRP because I do not have Census targets for turnout in primary elections. Other research designs applying MRP create estimates based on known joint distributions of Census demographics at subnational levels.¹ The Census, however, does not provide joint distributions of demographics for primary electorates in each House district. What I have instead is the CCES data with post-stratification weights. The CCES weights post-stratify to the Census distributions (along with other known targets) in each state. In addition, I have the validated primary turnout for each respondent. I use the joint distribution of the CCES post-stratification

¹ Though, some applications also use external targets, such as religion, that are not included in the Census distribution, and others use the Census Current Population Survey product, which is subject to sampling error.

weights with the validated primary turnout as the target joint distribution for primary voters, just as MRP uses the Census joint distribution. My joint distribution is based upon the CCES sample, and so if it is not as high in quality as the Census estimates, my targets may be less effective at the post-stratification stage. Without clear benchmarks, it is hard to evaluate the procedure outside of the statistical theory that demonstrates that both hierarchical models and post-stratification improve the validity of survey estimates to corresponding population statistics. I present efforts below to validate the approach.

B Implementation

In this section I describe the data to which I apply the procedure described in Table A2 above, the details of the implementation, and provide efforts to validate the procedure.

B.1 Data sources

The data source to which I apply this model is the 2010 and 2012 CCES (Ansolabehere, 2010, 2012). Both surveys are a nationally representative sample of around 55,000 Americans with interviews before and after the 2010 midterm and 2012 presidential elections, stratified by state. The surveys asked standard sets of political questions about attitudes, preferences, and beliefs, and behaviors such as vote choice and turnout. The survey also validated turnout records by matching respondents to administrative records instead of relying only on self-reported turnout.

B.2 IRT model of conservatism

I describe in Section A above how to take individual-level measures of preferences and map them into best district estimates through a hierarchical model and stratification weights. In this section, I describe how I measure individual-level preferences. I aggregate responses to multiple policy questions into a single summary value of conservatism through an item-response theory (IRT) model. Aggregating across multiple responses mitigates measurement error and mimics the aggregation across roll call votes used to summarize roll call voting behavior in congress with NOMINATE.

To characterize the policy conservatism for each respondent to the 2010 and 2012 CCES, I estimate the grouped IRT model proposed by Lewis (2001) on respondent expressed preferences over a set of policy issues. Each CCES asked respondents how they would vote on a set of roll calls actually considered in the House and Senate, as well as other policy preferences not specific to any roll call vote. I identified 17 questions from each survey that serve as the items in the model. For 2012, the questions query preferences about abortion, the war in Iraq, environment vs jobs, the Ryan budget, the Middle Class Tax Cut, the Tax Hike Prevention Act, birth control exemption, Keystone pipeline, the Affordable Care Act, ending Don't Ask Don't Tell, the war in Afghanistan, gun control, climate change, immigration, gay marriage, affirmative action, and balancing the budget. For 2010, the questions query preferences about gun control, climate change, immigration, abortion, environment vs jobs, gay marriage, affirmative action, balancing the budget, the Stimulus, SCHIP, Carbon Tax, Affordable Care Act, Kagan nomination to the Supreme Court, Dodd Frank Act, ending Don't Ask Don't Tell, funding stem cell research, and the Troubled Asset Relief Program.

The Lewis (2001) model allows categorical, rather than binary responses, so I use all response categories available in the CCES on these questions. The model estimates group-specific intercept shifts and variances for the distributions of respondent ideal points. I group respondent ideal points by the intersection of three characteristics: their state of residence, their partisanship (coded three

ways, with leaners collapsed as partisans), and their primary turnout. Thus, for example, the model can estimate a different intercept and variance for the ideal points for respondents from New York who identify as Democrats and voted in the 2010 congressional primary relative to respondents from New York who identify as Democrats and did not vote in the primary.

The model estimates the item parameters and the group distributions. To calculate the ideology of each individual, I calculate the expected a posteriori ideal point for each respondent, conditional on their responses, the estimated item parameters, and their group membership (see Lewis, 2001, p. 279 for details). As with all ideal point models, the latent scale of ideology is only identified up to an affine transformation. I post-process the ideal points to have mean zero and unit variance for each survey.² My 2010 estimates correlate with the IRT estimates of Tausanovitch and Warshaw (2013) for 2010 CCES respondents at $r = 0.961$.

The ideology estimates correspond well to what one would think ideology should relate to. They correlate with partisanship and self-reported ideology, and they are superior predictors of vote choice than self-reported ideology: The R^2 of a linear model predicting Democratic House vote in 2010 with my estimate of ideology, partisanship, and state fixed effects is 0.87, compared to 0.85 with self-reported ideology (don't know respondents set to moderate). When both self-reported ideology and my measure are included in this model, the coefficient on self-reported ideology is 28 percent of its size without my measure of conservatism in the model, while the coefficient on my measure of conservatism is 88 percent of its original size. These same numbers for 2012 are R^2 of 0.78 versus 0.76, and coefficient ratios of 18 percent self-reported versus 96 percent my estimate.³ This suggests my estimate of conservatism is more closely related to vote choices than self-reported ideology, and so is more closely related to the preferences that motivate member behavior.

B.3 Procedure for district estimates

To estimate the conservatism of each primary and general electorate in each district, I implement the procedure in Table A2. I first estimate the hierarchical model of individual conservatism on the IRT results. In the hierarchical model, I use as individual characteristics in the model a standard set of variables used in political models: age, gender, race, marital status, church attendance, income ordinal and income missing, vote in the 2010 (2012) general, vote in the 2010 (2012 congressional) primary, and voted in both.⁴ I let the coefficients on the three turnout indicators vary by congressional district and state through random effects, and let the intercept term vary by congressional district, state, and region through random effects. I estimate the model separately for each of three types of party of registration, Democrat, Republican, and Decline to State/other party.⁵

In Table A3, I present the model R^2 from the individual hierarchical models. The models ex-

² Other estimation choices required for the ? EM implementation are number of quadrature points (for the approximation of group normal distributions), and convergence criteria. I use five quadrature points and iterate the EM algorithm until the maximum parameter change across all item and group parameters is less than $1e-5$.

³ Regression results available from the author on request.

⁴ I chose demographic variables based on the variables used by the CCES to construct its post-stratification survey weights. These are also a standard set of demographics used in studies of voting and turnout.

⁵ I estimate the hierarchical model using the R package `lme4` (R Development Core Team, 2015; Bates, Maechler, and Bolker, 2013). Coefficient estimates are consistent with other models of conservatism: males, the married, and the less secular are more conservative. I estimate primary voters are more conservative (liberal) in the Republican (Democratic) models.

plain a reasonable amount of variance in the individual scores within-party. Across-party variance explained is higher, at 0.60 in 2010 and 0.58 in 2012.⁶

Table A3: Hierarchical model fit

Year	Party	Model R ²
2010	Dem	0.19
2010	Rep	0.19
2010	DTS/Oth	0.21
2010	All	0.60
2012	Dem	0.22
2012	Rep	0.21
2012	DTS/Oth	0.21
2012	All	0.58

Note: Cell entries present the coefficients of determination for each mixed model by year and party of registration.

I next use the model estimates to calculate predicted values for each respondent in the survey. This replaces the respondent's IRT-estimated conservatism with the hierarchical model predicted conservatism. Then, for each electorate, I take the weighted average of the predicted preferences using the survey weights.⁷ This is similar to the final step of MRP, where opinion is imputed from the hierarchical model to the known Census targets. For example, to calculate the conservatism of the Republican primary electorate in the 7th district of Illinois, I average the predicted conservatism of all the respondents surveyed in IL-07 who are validated to have voted in the Republican primary, weighted by each survey weight. Note that the set of Republican primary voters includes both primary-only voters and primary voters who also voted in the general election. Likewise, my estimate of the general electorate includes the conservatism of general-only voters and general voters who also participated in the primary. This procedure provides an estimate of the preferences for each electorate that pools and smooths observations through the hierarchical model and stratifies to targets through the survey weights and validated turnout.

For states with open or not-fully-closed primary elections, I am uncertain in which primary each validated primary voter voted. To make estimates somewhat consistent across states, I use respondents' self-reported party of registration to construct estimates. That is, no matter the primary institution in place, Democratic primary electorate estimates are the weighted average of voters validated to have voted in the primary and who report being registered Democrats, and Republican primary electorate estimates are the weighted average of voter validated to have voted in the primary and who report being registered Republican. Clearly this choice induces measurement error in my estimates. To the extent this error might bias my estimate of the relationship, it seems more

⁶ Full coefficient estimates and estimates of variance of the mixed effect distributions are available from the author on request or from the replication archive.

⁷ Formally, if \hat{y}_i is the predicted conservatism for respondent i given i 's party, demographics, turnout history, and geography, then my estimate of the conservatism for electorate e in congressional district c is $\sum_{i \in e, c} w_i^{-1} \times \sum_{i \in e, c} \hat{y}_i w_i$, where w_i is the survey weight for respondent i and $i \in e, c$ evaluates to the set of respondents i validated to have voted in primary or general election e and residing in district c .

likely to do so in states with non-closed primaries, because I may be missing many non-Democrat and non-Republican registrants who actually participated in these primaries.⁸

B.4 How the model changes district estimates

To present intuition about how the hierarchical model estimates differ from the raw survey aggregates, I plot the district-electorate estimates against each other in Figures A1 and A2. Each figure compares the modeled versus raw district estimates for general electorates, Democratic primary electorates, and Republican primary electorates, separately for 2010 and 2012. The x-axis in each frame is the simple weighted mean respondent conservatism aggregated to each electorate in each congressional district.⁹ On the y-axis is the electorate conservatism estimated by the hierarchical model and the aggregation procedure of Table A2. Each circle is a district, and point size is proportional to the number of CCES respondents in that district matching that electorate characteristic (general voters or primary voters of that party of registration).

The figures highlight three key features of my procedure. First, when there is enough data, as in most of the districts in the two general election frames, the modeled estimates do not differ much from the raw estimates. In each frame, the dashed line is the 45 degree line indicating perfect correspondence, and in the general election frames the circles cluster around this line. Also apparent in the general election frames, but more so in the primary frames, is the slope being less than 1: hierarchical models shrink estimates towards the overall mean when there is not enough data. Because the primary electorates have smaller samples, it is apparent that the shrinkage (the attenuation of the slope) is larger for the primary district electorates.

The third key feature is the re-scaling of district estimates for outlying cases with small sample sizes. In each of the primary electorate frames, outlying cases along the x-axis, those with raw district estimates far away from most of the other primary electorates of that party, are brought towards the center of the distribution by the hierarchical procedure. For example, in the primary electorate frame for Republicans in 2010, one district electorate far to the left has a raw aggregated ideology of -0.8, or one standard deviation more liberal than average. This district is NY-07, and the CCES has one validated Republican primary voter in that district. The hierarchical model shrinks the district estimate to about 0.6, certainly on the liberal side of Republican primary electorates, but nowhere near as outlying as the raw estimate. Similar shrinkage is applied for other outlying raw estimates for both Democrat and Republican validated primary voters. This is exactly what the hierarchical model is supposed to do. This shrinkage lessens the leverage outlying cases have on parameter estimates and improves my statistical power to estimate the relationship between district primary preferences and member roll call behavior.

C Validation of measure and improvement over raw survey margins

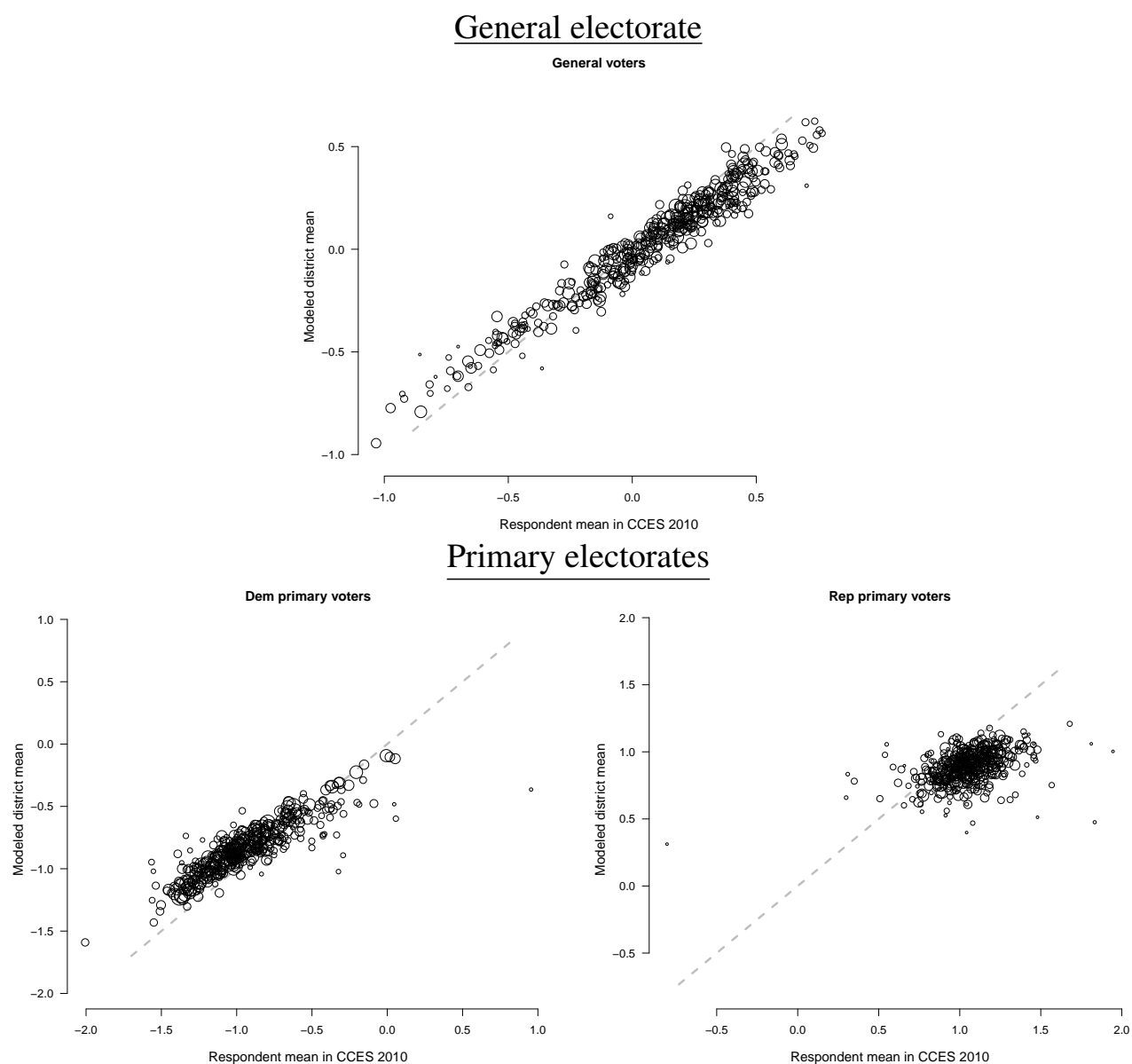
In this section, I present evidence on the validity of my estimates and then present some evidence of improvement through the hierarchical model over raw survey aggregates.

To demonstrate that my estimates of electorate conservatism in each district have reasonable face validity, I compare the estimated conservatism of general electorates to standard measures

⁸ In the two surveys, 18.8 percent (2010) and 19.7 percent (2012) of validated congressional primary voters reported being registered Decline-To-State or third party.

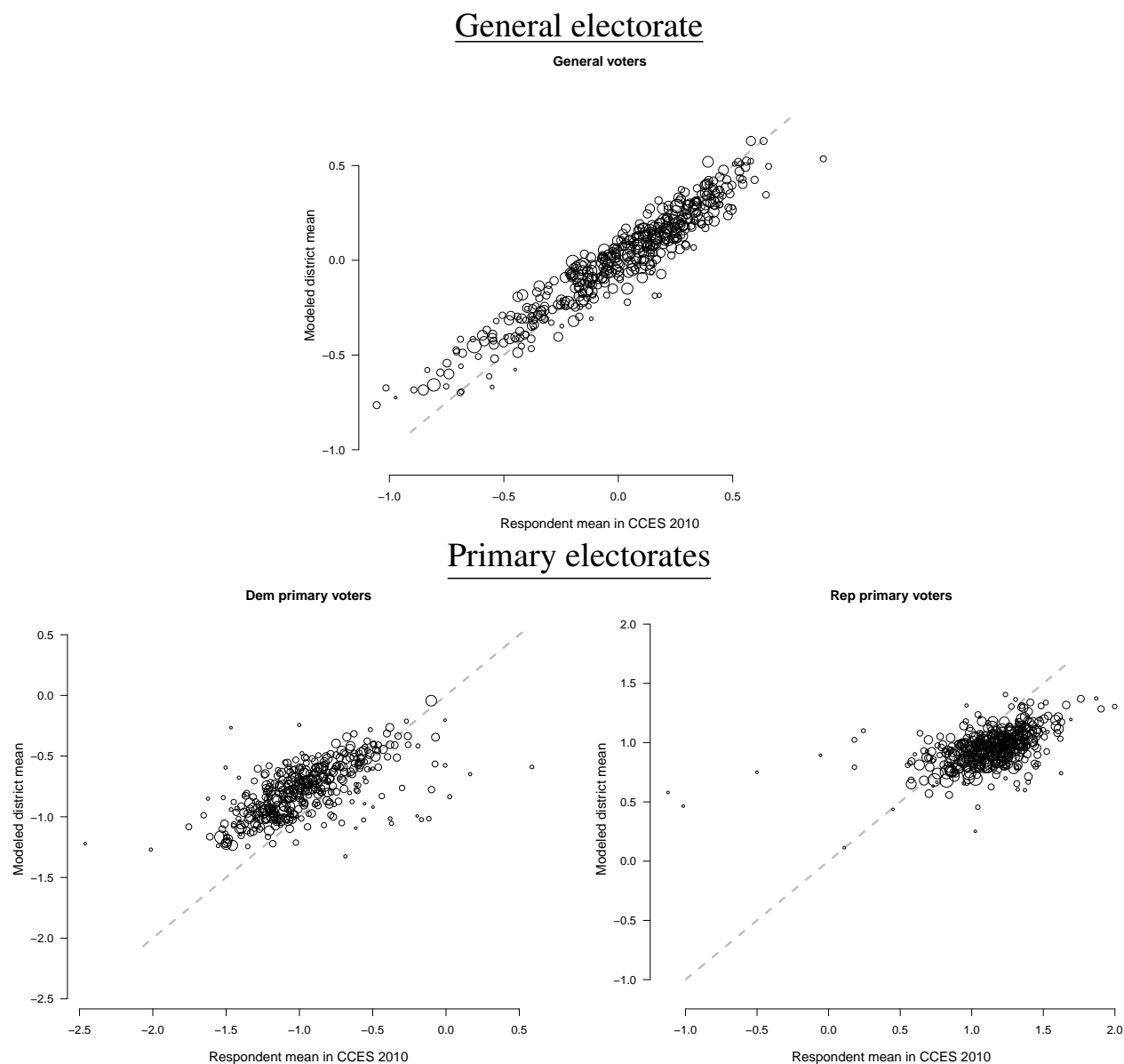
⁹ Formally, if y_i is the conservatism for respondent i , then my estimate of the conservatism for electorate e in congressional district c is $\sum_{i \in e, c} w_i^{-1} \times \sum_{i \in e, c} y_i w_i$, where w_i is the survey weight for respondent i and $i \in e, c$ evaluates to the set of respondents i validated to have voted in primary or general election e and residing in district c .

Figure A1: Hierarchical versus raw district estimates of electorates, 2010



Note: Each point is the estimated conservatism of a set of voters in one congressional district. The x-axis is the survey-weighted aggregate, the y-axis the result of the hierarchical estimation procedure. Point size proportional to the number of CCES respondents in that district-electorate.

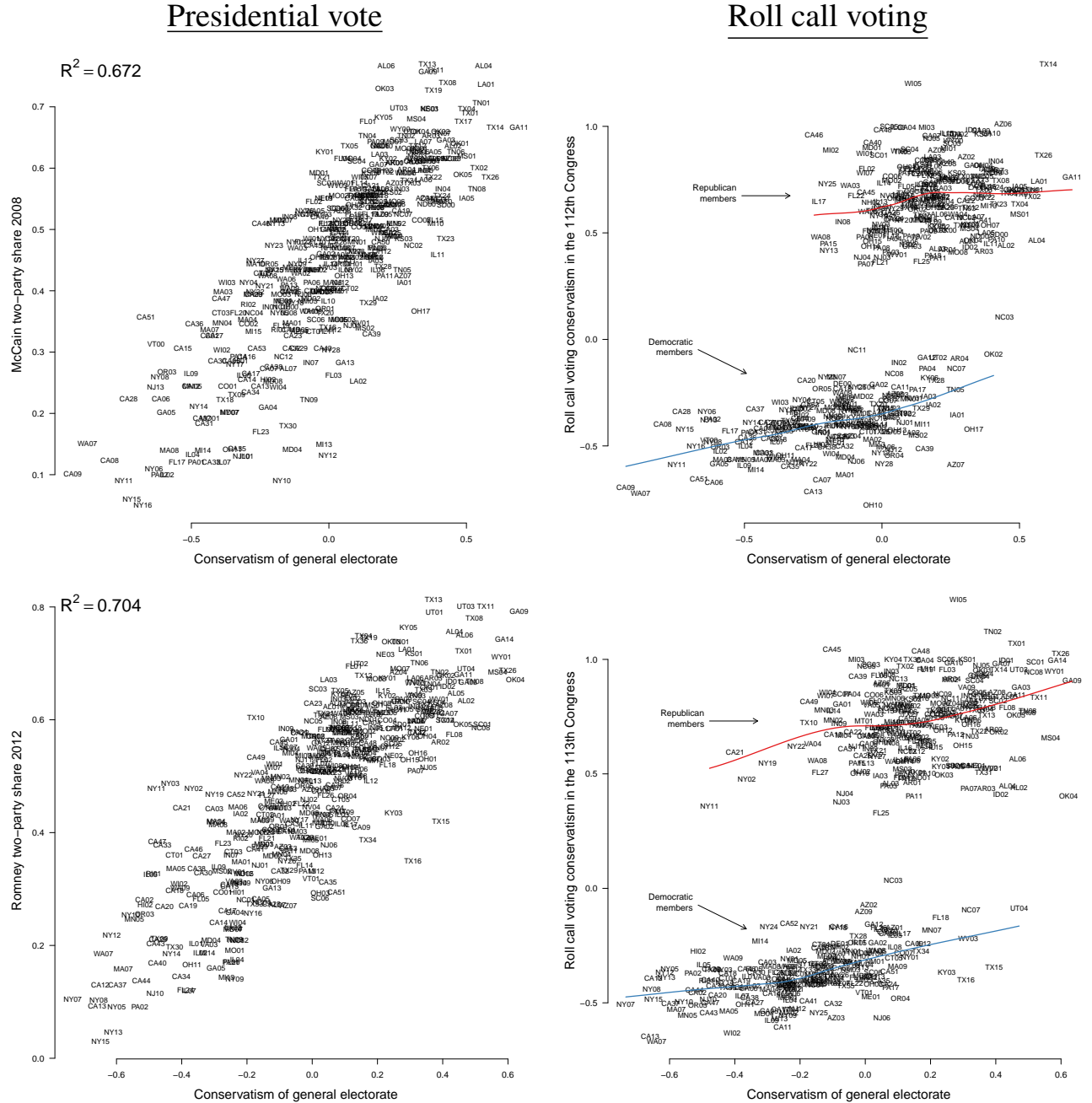
Figure A2: Hierarchical versus raw district estimates of electorates, 2012



Note: Each point is the estimated conservatism of a set of voters in one congressional district. The x-axis is the survey-weighted aggregate, the y-axis the result of the hierarchical estimation procedure. Point size proportional to the number of CCES respondents in that district-electorate.

of political preferences and representative behavior. Presidential vote is often used as a summary of the political preferences of a district. In the first column of Figure A3, I compare presidential vote share in 2008 and 2012 in the congressional district to my estimate of general election voter conservatism in that district and election. In the right column, I compare DW-NOMINATE score of the member of congress elected out of that district to the 112th (top frame) or 113th (bottom frame) House to the estimates of electorate conservatism in that election. Both frames suggest good validity to my estimates. Presidential vote share tracks electorate conservatism in a linear fashion with R^2 of 0.67 and 0.70, suggesting a good connection between my estimates of district conservatism and voting behavior in that district. The plot of member NOMINATE scores is common for modern congresses, with some responsiveness of Democrats to electorate conservatism, smaller responsiveness of Republicans to electorate conservatism, and a large intercept shift between Democratic and Republican members of the House. These plots suggest that my estimation procedure is capturing similar relationships as other measures of preferences used to measure the responsiveness of the House of Representatives (e.g., Ansolabehere, Snyder, Jr., and Stewart III, 2001; Clinton, 2006).

Figure A3: Face validity of hierarchical model estimates of district conservatism



Note: The x-axis in each frame is the estimated conservatism of the general electorate in each congressional district. The left column compares the estimates to 2008 and 2012 district presidential vote for the Republican. The right column compares the estimates to the roll call voting behavior of the House member in the following 112th and 113th Congresses summarized by DW-NOMINATE score.

C.1 Testing the two estimates against each other

Figure A3 presents face validity to the hierarchical estimates of district conservatism. To evaluate improvement in fit using the modeled estimates over the raw survey aggregates, I present six regression models in Table A4. The dependent variable is two-party Republican presidential vote share in the district (actual votes cast, not estimated from the CCES), with 2008 McCain vote matched to 2010 CCES districts (as there was no presidential election as a benchmark in 2010), and with 2012 Romney vote matched to 2012 CCES districts. For each year, I present three specifications, one with only modeled conservatism, one with only raw survey aggregated conservatism, and one with both terms. All models include state fixed effects to mimic my main analysis of member roll call voting behavior, which include state fixed effects.

Table A4: Relationship of raw and modeled district conservatism to actual votes

	2008	2008	2008	2012	2012	2012
Intercept	0.57*	0.51*	0.53*	0.54*	0.49*	0.50*
	(0.09)	(0.09)	(0.08)	(0.10)	(0.09)	(0.09)
Survey conservatism	0.35*		0.16*	0.39*		0.11*
	(0.02)		(0.03)	(0.02)		(0.03)
Modeled conservatism		0.43*	0.26*		0.51*	0.40*
		(0.02)	(0.04)		(0.02)	(0.04)
N	424	424	424	435	435	435
R ²	0.70	0.72	0.74	0.67	0.73	0.74
adj. R ²	0.66	0.68	0.70	0.63	0.70	0.71
Resid. sd	0.09	0.08	0.08	0.10	0.09	0.09

Standard errors in parentheses

* indicates significance at $p < 0.05$

Note: Dependent variable is Republican two-party presidential vote share in the district, with OLS coefficients and standard errors in parentheses. All models include state fixed effects. The 2008 Republican vote share is modeled with district conservatism estimates from the 2010 CCES, which may be one reason the coefficients are of smaller magnitude relative to 2012.

The results of Table A4 suggest the modeled estimates are closer to actual voting behavior than the raw survey aggregates. While the raw survey estimates do predict presidential vote share, with coefficients of 0.35 and 0.39 and adjusted R² of 0.66 and 0.63 (columns one and four), the modeled estimates do better – coefficients of 0.43 and 0.51, adjusted R² of 0.68 and 0.70 (columns two and five). When both estimates are included in the specification, the coefficient on the raw score is attenuated much more than the coefficient on the modeled score. The raw coefficients attenuate from 0.35 to 0.16 and 0.39 to 0.11 while the modeled coefficients attenuate from 0.43 to 0.26 and 0.51 to 0.40, respectively. Overall, the data suggest that modeled conservatism is a better predictor of actual presidential votes cast.

Note that the improvement of fit suggested in Table A4 is for the estimates of the preferences of the general electorates, which I noted in Figures A1 and A2 are less changed than estimates of primary electorates. Unfortunately, I do not possess an obvious national benchmark for primary

electorates along the lines of presidential vote share to validate. However, if we assume that the hierarchical procedure is doing more to alleviate measurement error for the primary electorates than for the general electorates, as is consistent with the smaller sample sizes, then the improvement of fit for general electorates presented in Table A4 would be a lower bound on the improvement of fit for primary electorates.

References

- Ansolabehere, Stephen. 2010. *Cooperative Congressional Election Study, 2010: Common Content*. [Computer File]. Cambridge, MA: Harvard University.
- Ansolabehere, Stephen. 2012. *Cooperative Congressional Election Study, 2012: Common Content*. [Computer File]. Cambridge, MA: Harvard University.
- Ansolabehere, Stephen, James M. Snyder, Jr., and Charles Stewart III. 2001. "Candidate Positioning in U.S. House Elections." *American Journal of Political Science* 45(1): 136–159.
- Bates, Douglas, Martin Maechler, and Ben Bolker. 2013. *lme4: Linear mixed-effects models using Eigen and syntax*.
- Clinton, Joshua D. 2006. "Representation in Congress: Constituents and Roll Calls in the 106th House." *Journal of Politics* 68(2): 397–409.
- Gelman, Andrew, and Thomas C. Little. 1997. "Poststratification into Many Categories Using Hierarchical Logistic Regression." *Survey Methodology* 23(2): 127–135.
- Jackman, Simon. 2009. *Bayesian Analysis for the Social Sciences*. West Sussex: John Wiley & Sons.
- Lax, Jeffrey R., and Justin H. Phillips. 2009. "How Should We Estimate Public Opinion in the States?" *American Journal of Political Science* 53(1): 107–121.
- Lewis, Jeffrey B. 2001. "Estimating Voter Preference Distributions from Individual-Level Voting Data." *Political Analysis* 9(3): 275–297.
- Park, David K., Andrew Gelman, and Joseph Bafumi. 2004. "Bayesian Multilevel Estimation with Poststratification: State-Level Estimates from National Polls." *Political Analysis* 12(4): 375–385.
- R Development Core Team. 2015. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing.
- Tausanovitch, Chris, and Christopher Warshaw. 2013. "Measuring Constituent Policy Preferences in Congress, State Legislatures, and Cities." *Journal of Politics* 75(2): 330–342.
- Warshaw, Christopher, and Jonathan Rodden. 2012. "How Should We Measure District-Level Opinion on Individual Issues?" *Journal of Politics* 74(1): 203–219.