Online Appendix for *Career Concerns and the Dynamics of Electoral Accountability*

November 8, 2021

Appendix

A Senator Specific Variables and Descriptive Statistics

We incorporate various senator and race-specific characteristics, including `republican` (1 if senator is republican, 0 if democrat), `female` (1 if senator is female, 0 otherwise), `seniority` (number of years of service as a member of the Senate), `membership` (number of standing committees a senator is a member of during a congressional session), `com_leader` (1 if the senator held a leadership position in a senate committee, 0 otherwise), and `leader` (1 if the senator was minority or majority leader, 0 otherwise).[1]

To capture a measure of electoral preferences at the state level, we follow Canes-Wrone, Brady, and Cogan (2002) and compute the average vote spread for the period 2000-2012 between the Republican and Democrat candidates in the presidential election at a given state, `presrep.margin`, using data from Dave Leip's *Atlas of U.S. Presidential Elections*. To account for primary elections' characteristics of both incumbents and challengers we include `inc_contested` and `chall_contested` which take a value of 1 if the incumbent (challenger) won the primary election with a spread of less than 10%

We control for demographic characteristics at the state level including median household income (`income`), percent of a state's population older than 64 years old (`pop_64`), percent of a state's population with less than 9th grade of educational attainment (`educ_9th`), percent of a state's population that is black (`black`), and percent of a state's population that is hispanic (`hispanic`), all obtained from the 2000 Census' data. We also include two economic indicators that vary both across states and within electoral cycles. First, we collected data on state unemployment (`unemployment`) obtained from the Bureau of Labor Statistics. Second, we obtained a leading indicator of economic activity (`lead`) gathered monthly by the Federal Reserve of St. Louis.

Variable	**Levels**	**n**	%	$\sum$%
Party	Democrat	864	54.5	54.5
	Republican	720	45.5	100.0
	all	1584	100.0	
Membership	0	912	57.6	57.6
	1 or more	672	42.4	100.0
	all	1584	100.0	
Committee Leader	No	1308	82.6	82.6
	Yes	276	17.4	100.0
	all	1584	100.0	
Senate Leader	No	1500	94.7	94.7
	Yes	84	5.3	100.0
	all	1584	100.0	
Female	Male	1332	84.1	84.1
	Female	252	15.9	100.0
	all	1584	100.0	

Table A1: Summary Statistics: Incumbents' Characteristics

[1]The variables `seniority`, `membership`, `comleader`, and `leader` are constructed based on Stewart and Woon (2017).

Variable	n	Min	$\bar{x}$	$\tilde{x}$	Max	s	IQR
`pointlead`	1584	-41.30	19.17	18.19	78.26	15.08	18.87
`contributions` (1000 $)	1584	120.95	6636.86	5353.66	29525.84	4957.40	5423.85
`tv_ads` (1000 GRP's)	396	0.00	7.74	3.83	153.35	13.19	7.93
`tv_ads_challenger` (1000 GRP's)	283	0.00	5.41	2.30	93.63	10.20	5.10
`tv_ads_others` (1000 GRP's)	204	0.00	7.34	2.48	58.42	11.35	7.97
`tv_ads_others_challenger` (1000 GRP's)	199	0.00	8.03	2.86	149.99	15.68	7.31
`stance`	1584	-2.24	-0.09	-0.24	2.11	0.68	1.15
`seniority`	1584	1.00	12.45	9.00	45.00	9.90	12.00
`unemp`	1584	2.35	6.10	5.68	13.62	2.11	2.60
`lead_index`	1584	-5.80	1.29	1.38	6.15	1.26	1.34
`pop64`	1584	8.20	16.71	16.60	22.80	2.08	1.95
`educ_9th`	1584	3.20	6.89	5.95	11.70	2.30	3.55
`black`	1584	0.30	10.78	7.05	36.30	10.04	12.55
`hispanic`	1584	0.70	7.63	4.30	42.10	9.15	5.80
`presdem.margin`	1584	-0.26	0.01	-0.03	0.38	0.16	0.24

Table A2: Summary Statistics: States' Characteristics

We complement opinion data with the predicted `pointlead` obtained from three different sources. First, we use incumbent senators' approval rates (in 12% of monthly observations) listed by *Polling Report*, *Real Clear Politics* and *Pollster*. Second, remaining gaps are filled with prediction market data (in 11% of monthly observations) collected by Intrade in real-time.[2] Finally, we use national polls included in the *Roper* database that contain partisan congressional approval (in 7% of monthly observations). To include this information we extrapolate a linear fit between `pointlead`, as obtained from opinion data, and the alternative support measures. We control for Congress-session and monthly random effects.

To transform the raw prediction market data into monthly prices, we take the weighted average of collected prices for the stock that pays out if the incumbent senator wins on Election Day, where the weights are inversely proportional to the number of individual trades. Then, we use the transformation suggested by Rothschild (2015) to map monthly prices onto estimated vote shares as $share_t = \phi^{-1}(price_t)$, where $share_t$ is the estimated incumbent share in month t and ϕ denotes the normal density function. Approval data at the monthly level is constructed as the weighted average of incumbent approval (as a proportion of the total proportion of respondents that approved and disapproved the incumbent), where the weights are inversely proportional to the number of survey respondents. To transform congressional approval from national polls, first we collected individual information on whether survey respondents approved the job performed by the party of the incumbent in Congress. Then, we predict the probability that a voter in a given state and month supports the incumbent party's job in Congress by regressing individual binary Congressional job approval on state and date random effects.

Figure A1 shows the correlation between `pointlead`, as obtained from opinion data and the alternative support measures.

[2]Intrade sold contracts for some of the senate races in our sample during the years 2004, 2008, 2010, and 2012 that were worth $10 in the event the candidate won and $0 in the event the candidate lost.

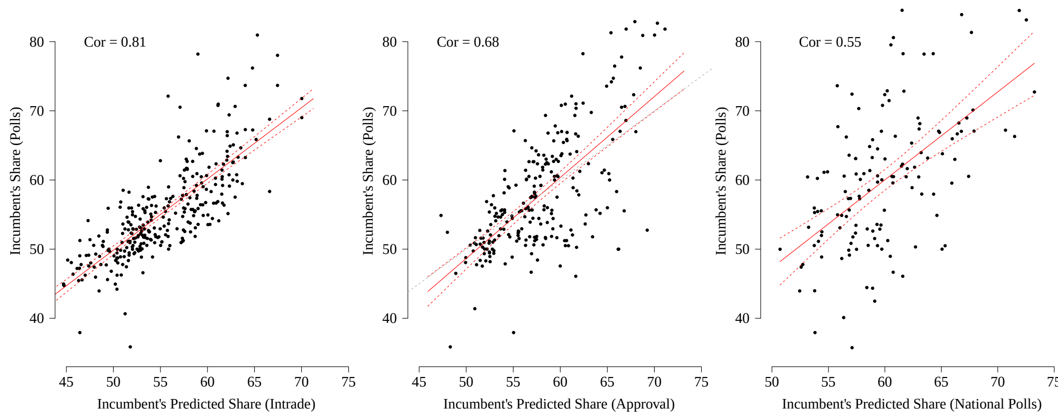


Figure A1: Predicted *vs* Observed Incumbent Share

B Estimation of Model Parameters

B.1 Estimation Procedure

In this section, we expand on our procedure to estimate the structural parameters ρ. As we explained in section 5, the difficulty in estimating ρ directly from the likelihood in (5.1) is that the conditional choice probability $Pr(y_{i,t}|p_{i,t};\rho_i,\psi)$ is not a known function of ρ_i. Instead, this is given by the optimal response of the politician with characteristics ρ_i in each state $(p_{i,t},\mu_{i,t})$, which result from the solution to

$$\max_{y_t}\left\{\underbrace{\lambda(x_t-\theta)^2-\gamma(e_t)^2+E\left[\overline{W}_{t-1}(p_{t-1})\;\middle|\;z_t\right]}_{h(z_t)}+\mu(y_t)\right\}, \tag{B1}$$

where $W_t(p_t,\mu_t)$ is the value from this problem, $\overline{W}_t(p_t)\equiv E_\mu\left[W_t(p_t,\mu_t)\right]$, and

$$E\left[\overline{W}_0(p_0)\;\middle|\;z_1\right]\equiv \Pr(1/2<p_0<\overline{p}\big|z_1)\omega+\Pr(p_0>\overline{p}\big|z_1)(\omega+\alpha).$$

Since the shocks $\{\mu_{it}(y)\}$ are i.i.d. TIEV random variables, we have

$$\Pr(y_{i,t}=y'|p_{i,t};\rho_i)=\frac{exp\left[h(p_{i,t},y';\rho_i)\right]}{\sum_{y\in Y}\exp\left[h(p_{i,t},y;\rho_i)\right]}$$

and

$$\overline{W}_{i,t}(p_{i,t})=\ln\left(\sum_{y\in Y}\exp\left[h(p_{i,t},y)\right]\right)+C,$$

where C is Euler's constant. For each trial parameter ρ_i. we obtain $h(p_{i,t},y;\rho_i)$ by solving the politician's problem recursively.

To relate senator's preference parameters to relevant observable attributes, while still allowing heterogeneity *conditional* on covariates, we model structural parameters as latent random variables drawn from distributions with parameters that are functions of senator characteristics, including party, gender, seniority, and leadership positions. This allows the preference estimates to be informed by both their effect on conditional choice probabilities and observable characteristics.

Specifically, we let $\phi_i \equiv \{\lambda_i, \omega_i, \alpha_i\}$, and fix $\lambda + \omega + \alpha = 1$, which is analogous to estimating normalized office payoffs ω/λ and α/λ. To satisfy the normalization, we assume that ϕ_i follows a Logistic Normal distribution, which effectively applies a logistic transformation to an underlying bivariate normal distribution, producing a distribution for $(\lambda_i, \omega_i, \alpha_i)$ over the 2-dimensional simplex. The underlying normals are assumed to have variances σ_ω^2 and σ_α^2 and means $\mathbf{Z}_i'\eta_\omega$ and $\mathbf{Z}_i'\eta_\alpha$, where $\mathbf{Z}_i$ are senators' characteristics, including: `republican`, `gender`, `leader`, `com_leader`, `seniority`, and `membership`. Denote the density of ϕ_i as $f_\phi(\cdot; (\mathbf{Z}_i'\eta_j, \sigma_j^2)_{j=\alpha,\omega})$. Ideal points θ_i have a normal distribution with mean zero, and variance σ_θ. Denote the density of θ_i as $f_\theta(\cdot; \sigma_\theta^2)$. The cost parameter γ_i follows a truncated normal distribution (truncated at zero) with mean $\mathbf{W}_i'\eta_\gamma$ and variance σ_γ^2, where $\mathbf{W}_i$ includes the vector of characteristics $\mathbf{Z}_i$ plus senator/race characteristics including: `income`, `pop_64`, `educ_9th`, `black`, `hispanic`, `unemployment`, `lead`, and total contributions (`contributions`). We denote the density of γ_i as $f_\gamma(\cdot; \mathbf{W}_{it}'\eta_\gamma, \sigma_\gamma^2)$.

Our estimation problem is then to choose $\{\phi_i, \theta_i, \gamma_i\}_{i=1}^N$ and $(\vec{\eta}, \vec{\sigma})$ to maximize the posterior distribution, which is proportional to:

$$\prod_{i=1}^{N}\prod_{t=1}^{T} Pr(y_{i,t}|p_{i,t}; \rho_i, \psi) f_\phi(\phi_i; (\mathbf{Z}_i'\eta_j, \sigma_j^2)_{j=\alpha,\omega}) f_\theta(\theta_i; \sigma_\theta^2) f_\gamma(\gamma_i; \mathbf{W}_{it}'\eta_\gamma, \sigma_\gamma^2)$$

To solve this problem, we combine a quasi-Newton gradient method (L-BFGS) with the value function obtained from the dynamic programming problem of each senator at each trial parameter. Because this algorithm must fully solve the senator's problem for each trial value of the parameters and then compute the gradients of the likelihood, it can be computationally costly relative to other alternatives proposed in the literature. In our case, this disadvantage is negligible as we compute the gradients required for optimization via a reverse-mode automatic differentiation algorithm (Carpenter, Hoffman, Brubaker, Lee, Li, and Betancourt (2015)), which is an extremely fast and efficient way to precisely compute exact derivatives.[3]

We measure uncertainty in the structural parameters' estimates – and other quantities of interest which are functions of these parameters – via a parametric bootstrap. That is, after obtaining parameter estimates, we draw 500 pseudo-samples from the estimated posterior density and re-estimate the parameters for each sample. We use the empirical distribution of these 500 estimates to compute confidence intervals and its sample variance as an estimator of the variance of the structural parameters.

[3]Usual optimization algorithms use finite differencing, which is a numerical approximation to gradient evaluations. This method turns out to be slow and imprecise for nonlinear and highly multidimensional functions such as the likelihood function we are dealing with in our problem.

B.2 Discretization

Our estimation approach requires that we discretize the variables measuring senators' advantage in polls and endogenous choices (policy position and TV advertisement). We use a grid of 15 categories for our measure of polls (`pointlead`), 30 categories for our measure of policy position (`position`), and three categories for our measure of TV advertisement (`tv-ads`). We partition each variable into equally-spaced bins and take the average value within bins as the representative value for each category. The bin size of the first and last categories is determined by the 5th and 95th percentiles of the variable distribution, which makes the discretization less sensitive to extreme outliers. We find that this binning captures the main features of the data well (for reference, see Figure B1 below, which plots continuous and discretized variables for two senators in the sample).

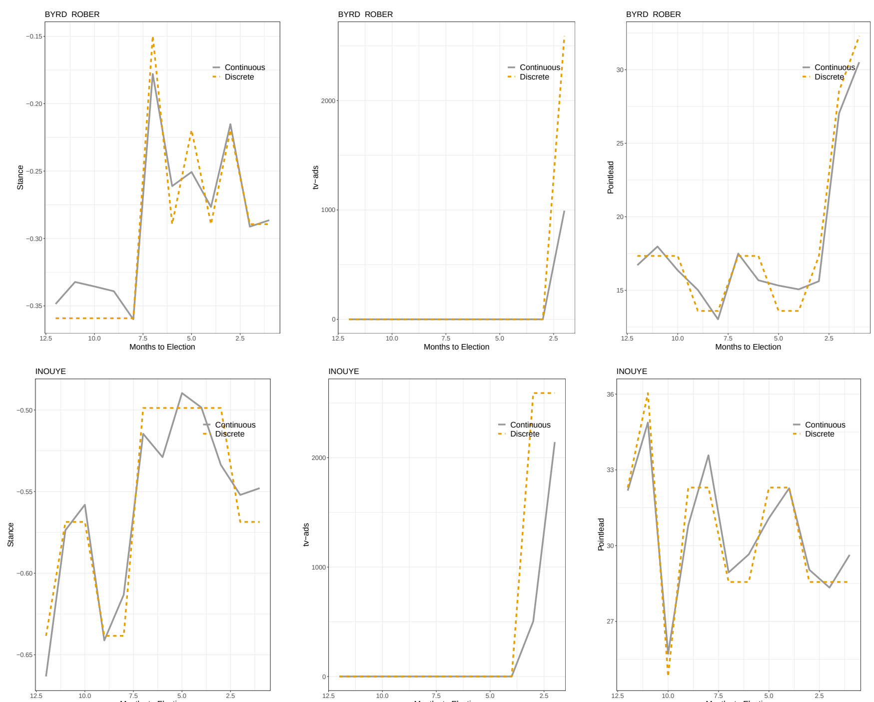


Figure B1: Actual observations and discretized values of polls, policy and TVads for senators Byrd (106th Congress) and Inouye (108th Congress).

The examples in the figure are representative of the results for all non-extreme senators, where the discretization entails only a minor loss of information. For the five most extreme senators in terms of policy position, the discretization induce a larger loss of information, as it fails to capture some of the variation in position taking for very extreme positions. As a robustness check, we recomputed our estimates further partitioning extreme positions and (separately) increasing spending categories to six. We find that the fit remains good with this finer partition, and that all the conclusions we emphasize in the paper remain unchanged.

C Additional Results

C.1 Structural Parameter Estimates

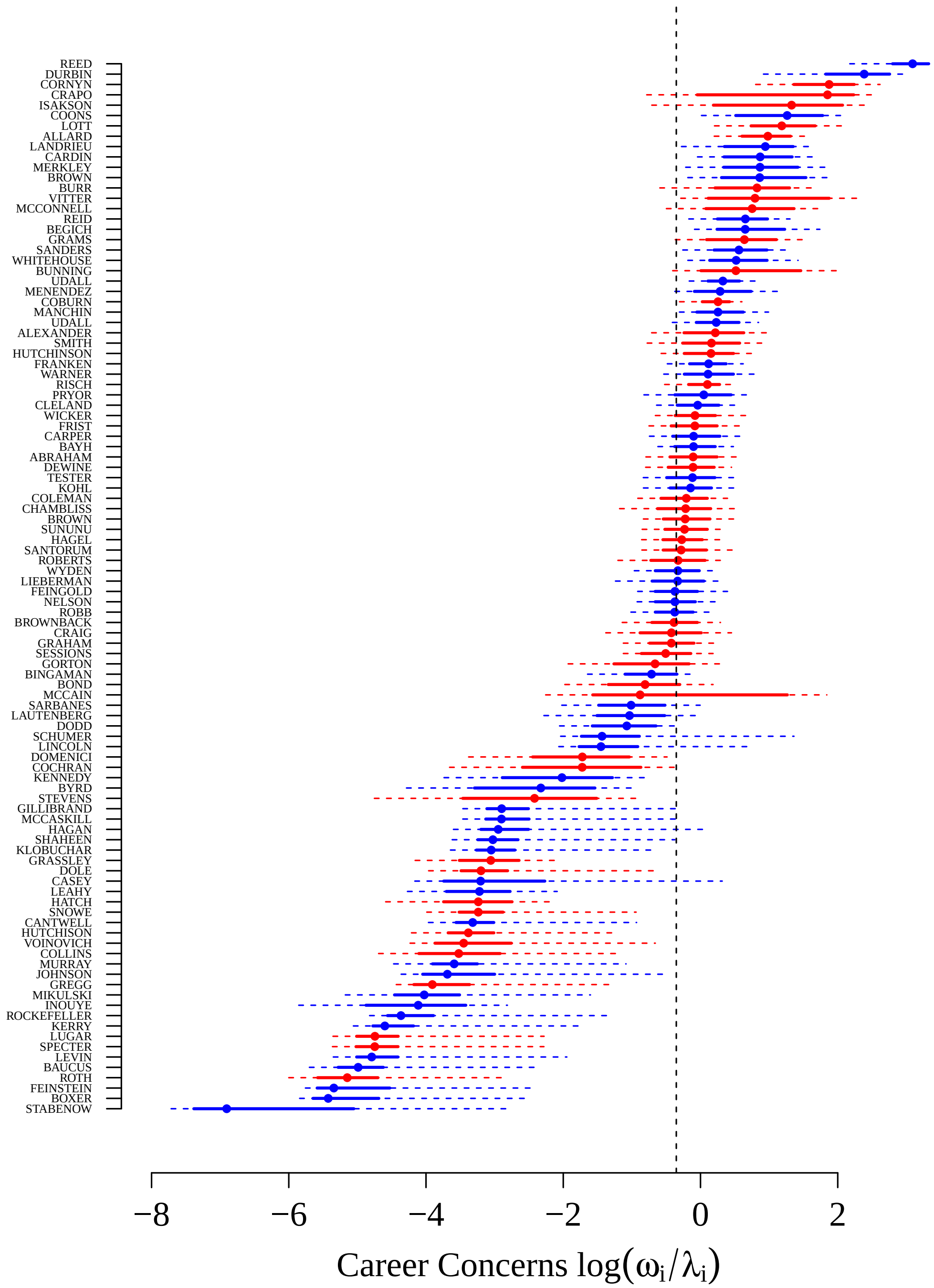


Figure C1: Value of Reelection (ω/λ). Solid thin (wide) lines represent 90% (80%) and bootstrap confidence intervals.

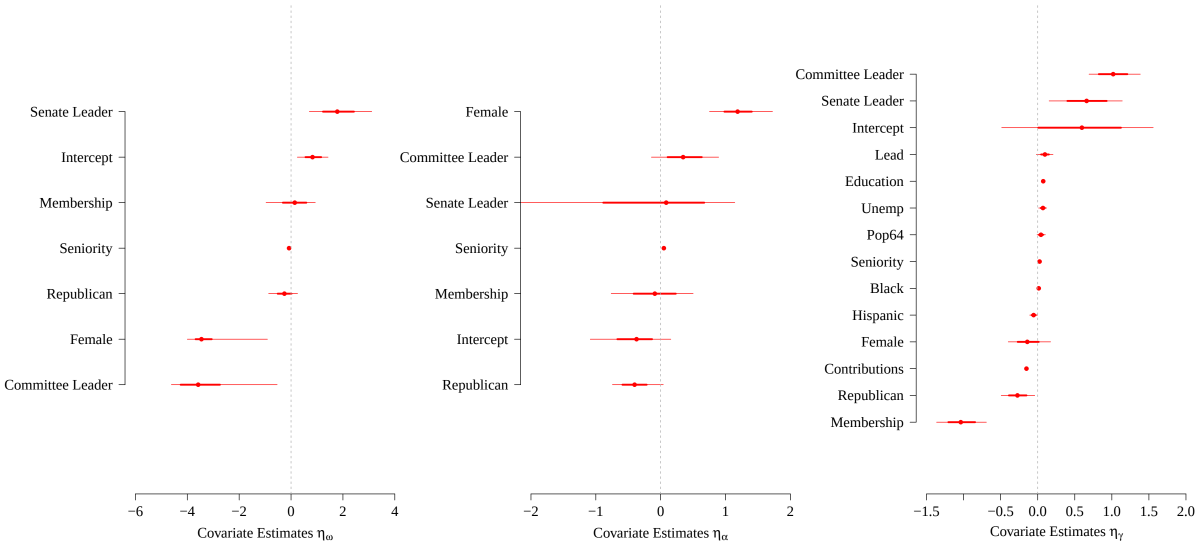


Figure C2: Estimates of the effect of covariates on Structural Parameters ω, α and γ $(\eta_\omega, \eta_\alpha, \eta_\gamma)$. Solid thin (wide) lines represent 90% (80%) and bootstrap confidence intervals.

C.1.1 Ideal Point Estimates

Because the impact of position-taking on electoral results varies depending on the senators' popularity and time to election, certain votes will be more congruent with their policy preferences than others. This implies that senators' votes on policy issues are not an unfiltered expression of ideological preferences, but rather strategic choices conditioned on the competitiveness of the race at the time of voting.[4] Our approach allows us to separate preferences from strategic position-taking.

Figure C3 presents our ideal point estimates for each senator in the sample, with 90% bootstrap confidence intervals.

[4]The available estimates of legislators' ideal policies (Poole and Rosenthal (1984), Clinton, Jackman, and Rivers (2004a)) are derived under the assumption that all votes in a legislators' voting records are sincere reflections of their preferences (see however Clinton and Meirowitz (2003), Iaryczower, Katz, and Saiegh (2013), Iaryczower, Katz, and Saiegh (2013) and Spenkuch, Montagnes, and Magleby (2018).

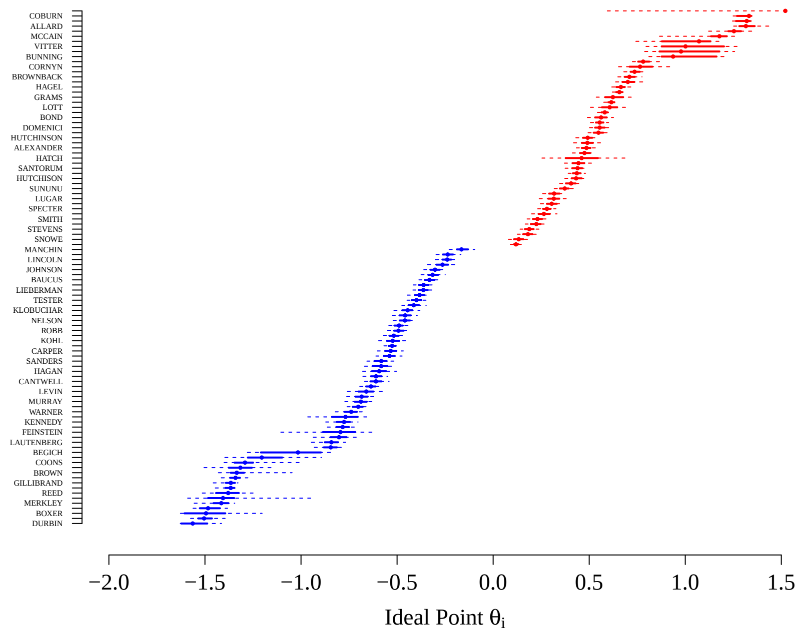


Figure C3: Ideal Point Estimates (Solid lines plot 90% bootstrap confidence intervals)

The distribution of ideal points obtained from our model is more heavily populated in the extremes of the political spectrum than the distribution of ideal points in the sincere voting framework (see Figure C4). The difference in the two sets of estimates indicates that while some senators are "pandering in" to more moderate voters, as the conventional wisdom indicates, others are "pandering out" to relatively more extreme voters. Overall, however, the differences between the strategic and sincere estimates in the US senate are relatively minor in this sample.

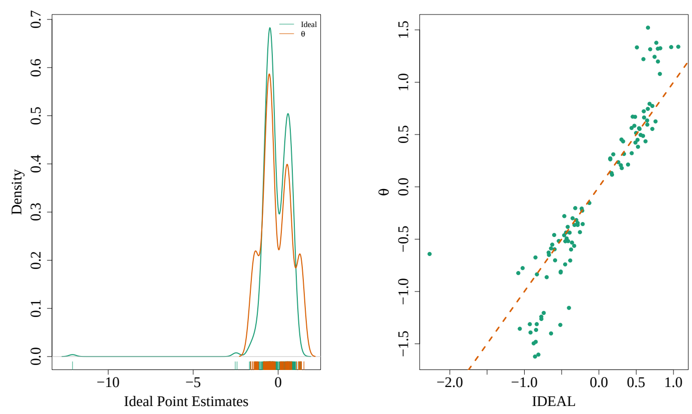


Figure C4: Ideal Point estimates (θ) vs sincere estimates (IDEAL)

C.2 Transition Function Estimates

	Dependent variable:				
	OLS	LDV	LDV	GFE	LDV(`partyvote`)
	(1)	(2)	(3)	(4)	(5)
$p_{i,t}$		0.818^{**}	0.764^{**}	0.759^{**}	0.763^{**}
		(0.022)	(0.024)	(0.029)	(0.026)
$(x_{i,t} - \xi)^2$	-6.369^{**}	-1.491^{**}	-2.133^{**}	-2.250^{**}	
	(2.299)	(0.493)	(0.812)	(0.519)	
$(x^p_{i,t} v - \xi)^2$					-8.086^{**}
					(2.688)
$\sqrt{e_{i,t}}$	0.028	0.018^{**}	0.021^{**}	0.014^{*}	0.024^{**}
	(0.017)	(0.007)	(0.007)	(0.006)	(0.008)
$\sqrt{e^{chall}_{i,t}}$	-0.137^{**}	-0.047^{**}	-0.049^{**}	-0.051^{**}	-0.046^{**}
	(0.022)	(0.009)	(0.010)	(0.007)	(0.010)
`seniority`			$0.064^{\dagger}$		$0.068^{\dagger}$
			(0.036)		(0.039)
`membership`			0.764		$1.379^{\dagger}$
			(0.753)		(0.831)
`com_leader`			−1.352		−1.562
			(1.029)		(0.991)
`leader`			−1.342		-2.002^{*}
			(0.842)		(0.957)
`female`			0.442		0.920
			(0.690)		(0.666)
`unemployment`			-0.416^{*}		−0.287
			(0.171)		(0.185)
`lead`			−0.316		−0.315
			(0.225)		(0.231)
`income`			−0.00000		0.00004
			(0.0001)		(0.00005)
`pop_64`			$0.262^{\dagger}$		0.339^{*}
			(0.143)		(0.135)
`educ_9th`			0.019		−0.034
			(0.119)		(0.140)
`black`			−0.029		−0.016
			(0.025)		(0.025)
`hispanic`			0.036		0.030
			(0.027)		(0.030)
`inc_contested`			−1.825		−0.166
			(1.133)		(1.884)
`chall_contested`			−0.732		−0.828
			(0.808)		(0.955)
`republican`			0.101	-2.488^{*}	1.084
			(1.554)	(1.203)	(1.432)
Observations	1,584	1,584	1,584	1,347	
Congress-Party FE	No	No	Yes	Yes	
Adjusted R^2	0.120	0.691	0.696	0.834	0.706
F Statistic	72.871^{**}	885.349^{**}	118.145^{**}	32.087^{**}	105.094^{**}

Note: $^{\dagger}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$.
Robust standard errors clustered at the senator-congress level in parentheses.

Table C1: Complete First Stage Results

	Dependent variable: $p_{i,t-1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$p_{i,t}$	0.787**	0.807**	0.813**	0.766**	0.759**	0.768**
	(0.023)	(0.022)	(0.024)	(0.029)	(0.029)	(0.031)
$(x_{i,t} - \xi)^2$	−1.739*	−1.555*	−1.906**	−1.984**	−2.250**	−1.923**
	(0.680)	(0.606)	(0.492)	(0.513)	(0.519)	(0.457)
$\sqrt{e_{i,t}}$	0.021**	0.009	0.017**	0.019**	0.014*	0.017**
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$\sqrt{e_{i,t}^{chall}}$	−0.048**	−0.042**	−0.045**	−0.053**	−0.051**	−0.043**
	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)
Observations	1,584	1,584	1,584	1,584	1,584	1,584
Congress-Party FE	Yes	Yes	Yes	Yes	Yes	Yes
Group FE	No	5	10	15	20	25
Adjusted R^2	0.694	0.761	0.805	0.823	0.834	0.849
F Statistic	212.167**	67.273**	49.125**	38.668**	32.087**	29.202**

Note: †*p<0.1;* **p<0.05;* ***p<0.01.*
Robust standard errors clustered at the senator-congress level in parentheses.

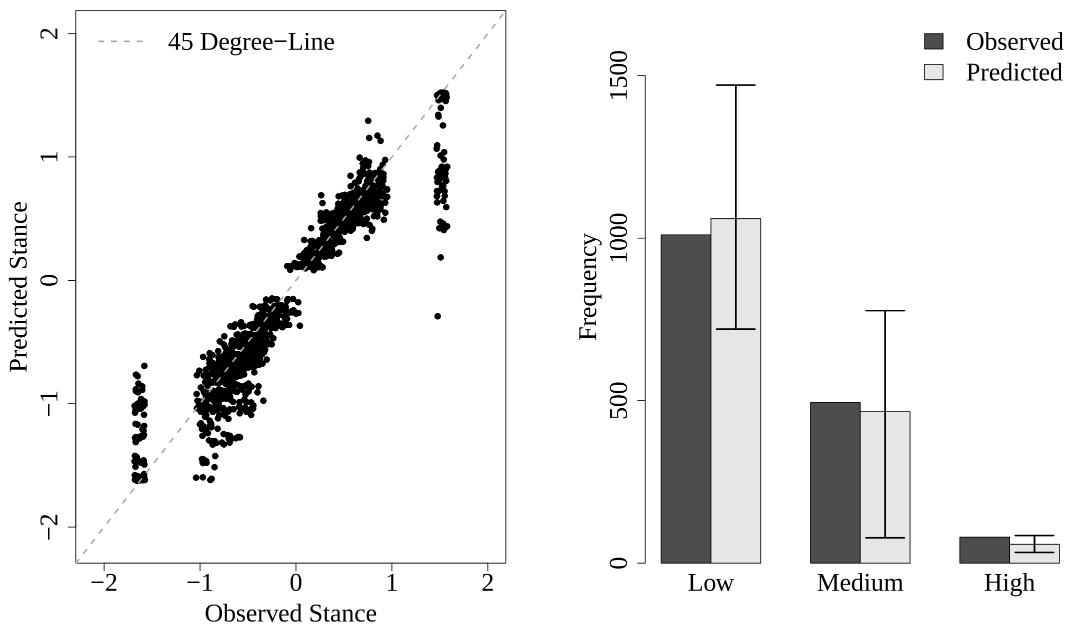
Table C2: First Stage OLS Results with Different Grouped Fixed-Effects

	Dependent variable: $p_{i,t-1}$		
	(1)	(2)	(3)
$p_{i,t}$	0.716**	0.764**	0.763**
	(0.026)	(0.024)	(0.024)
$x_{i,t}$	−2.055*		
	(1.043)		
$x_{i,t}^2$	$-1.195^{\dagger}$		
	(0.622)		
$x_{i,t} \times \xi$	23.399**		
	(3.769)		
$(x_{i,t} - \xi)^2$		−2.220**	−1.997*
		(0.810)	(0.838)
$\sqrt{e_{i,t}}$	0.024**	0.021**	
	(0.007)	(0.007)	
$\sqrt{e_{i,t}^{chall}}$	−0.046**	−0.050**	
	(0.010)	(0.010)	
$\log e_{i,t} + 1$			0.233**
			(0.082)
$\log e_{i,t}^{chall} + 1$			−0.601**
			(0.102)
$\xi_{i,t}$	−0.493		
	(3.111)		
$x_{i,t} \times \sqrt{e_{i,t}}$		−0.006	
		(0.006)	
Observations	1,584	1,584	1,584
Senator-State Controls	Yes	Yes	Yes
Congress-Party FE	Yes	Yes	Yes
Adjusted R^2	0.707	0.696	0.698
F Statistic	113.234**	114.448**	119.142**

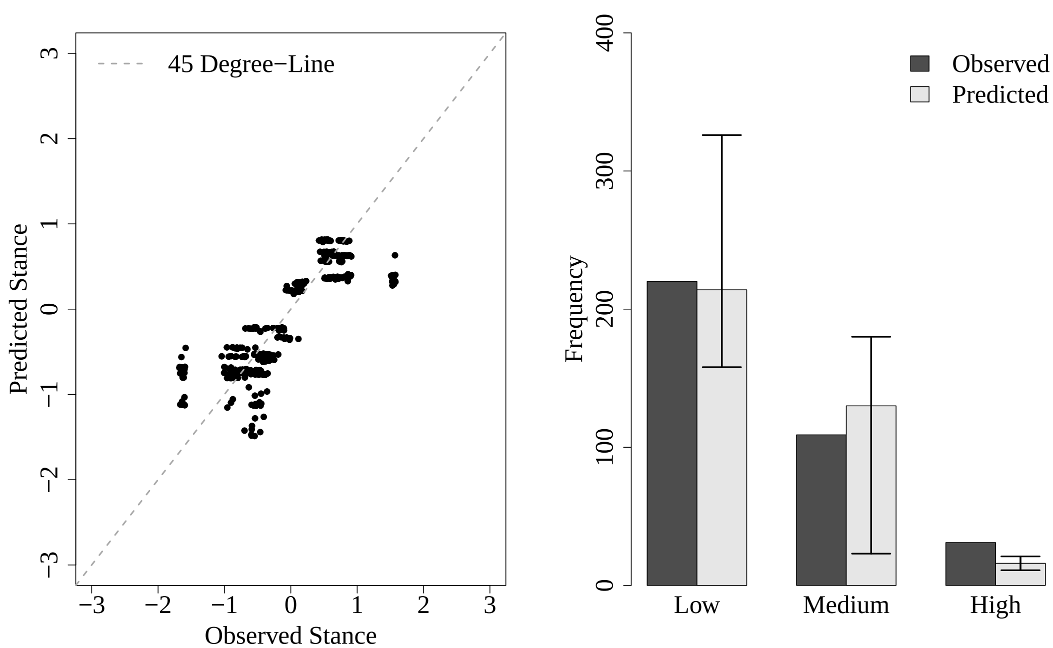
Note: †*p<0.1;* **p<0.05;* ***p<0.01.*
Robust standard errors clustered at the senator-congress level in parentheses.

Table C3: First Stage: Alternative Specifications

C.3 Goodness of Fit



In Sample



Out of Sample

Figure C5: Goodness of Fit, Within and Out of Sample

D Robustness

D.1 Strategic Challenger

In the paper we focused on the optimal dynamic behavior of the incumbent, fixing the challenger's spending at the levels we observe in the data. This simplified the presentation of the problem, and allowed us to focus on the core issue of electoral accountability. The cost of this simplification is that the model doesn't take into consideration the strategic responses of the challenger in states that are not observed in the data. This can potentially bias the parameter estimates.

To consider this possible concern, we extend the model to endogeneize the behavior of the challenger, and estimate the resulting dynamic game. As we show below, we find that the incumbent's parameter estimates of the benchmark model remain essentially unchanged.

We assume that the challenger gets an office payoff of one if she wins office and zero otherwise, and that spending e_t^c has a cost $\gamma^c(e_t^c)^2$ for the challenger. The incumbent's payoffs are as in the benchmark model. To avoid multiplicity of equilibria, we assume that in each stage politicians move sequentially, with the challenger moving first. In particular, we assume the following sequence:

1. At the beginning of each period t, incumbent and challenger observe p_t, which evolves according to eq. (5.2);
2. The challenger observes the shocks μ^c (which are i.i.d. TIEV and unobserved by the researcher), and chooses a level of TV ad buys e_t^c;
3. The incumbent then observes e_t^c and shocks μ and chooses (x_t, e_t).

Our solution concept is subgame perfect Nash equilibrium. We solve for the equilibrium of the game and associated conditional choice probabilities by backwards induction. We drop the subindex i for each incumbent for notational convenience. Suppose there are $t = T, \ldots, 1$ periods remaining to the election, and let $z_t^I \equiv (p_t, x_t, e_t, e_t^c)$. After observing (p_t, μ_t) and the challenger's ad expenditure e_t^c, the incumbent solves

$$\max_{y_t} \left\{ \underbrace{\lambda(x_t - \theta)^2 - \gamma(e_t)^2 + E\left[\overline{W}_{t-1}(p_{t-1}) \mid z_t^I\right]}_{h(z_t^I)} + \mu(y_t) \right\}, \tag{D1}$$

where $W_t(p_t, \mu_t, e_t^c)$ is the value from this problem, $\overline{W}_t(p_t) \equiv E_{\mu,\mu_t^c}\left[W_t(p_t, \mu_t, \tilde{e}_t^c(p_t, \mu_t^c))\right]$, and

$$E\left[\overline{W}_0(p_0) \mid z_1^I\right] \equiv \Pr(p_0 \in M | z_1^I)\omega + \Pr(p_0 \in H | z_1^I)(\omega + \alpha).$$

Since the shocks $\{\mu_t(y)\}$ are i.i.d. TIEV random variables, the incumbent's conditional choice probability is given by

$$\Pr(y_t = y' | p_t, e_t^c) = \frac{\exp\left[h(p_t, y', e_t^c)\right]}{\sum_{y \in Y} \exp\left[h(p_t, y, e_t^c)\right]}$$

Now consider the challenger. At the beginning of the period, the challenger observes (p_t, μ_t^c), and solves

$$\max_{e_t^c} \left\{ \underbrace{E_\mu \left[E \left[\overline{W}^c_{t-1}(p_{t-1}) \mid (p_t, e_t^c, \tilde{y}_t(p_t, \mu_t, e_t^c)) \right] \right] - \gamma(e_t^c)^2}_{h^c(p_t, e_t^c)} + \mu^c(e_t^c) \right\}, \tag{D2}$$

where $W_t^c(p_t, \mu_t^c)$ is the value from this problem, $\overline{W}^c_t(p_t) \equiv E_{\mu_t^c}\left[W_t^c(p_t, \mu_t^c)\right]$, and $E\left[\overline{W}^c_0(p_0) \mid p_1\right] \equiv \Pr(p_0 < 1/2 \big| p_1)$. From the TIEV distribution of the shocks, the challenger's conditional choice probability is given by

$$\Pr(e_t^c = e'^c | p_t) = \frac{\exp\left[h^c(p_t, e'^c)\right]}{\sum_{e^c \in \mathcal{E}} \exp\left[h^c(p_t, e^c)\right]}.$$

The structural parameters of the dynamic game include the vector of incumbent parameters ρ, as well as the challengers' cost of spending, $\gamma^{\mathbf{c}} \equiv \{\gamma_i^c\}_{i=1}^N$. We estimate these structural parameters by first solving for equilibrium strategies for every trial value of the parameters, and then search for the values that maximize the likelihood of the data.

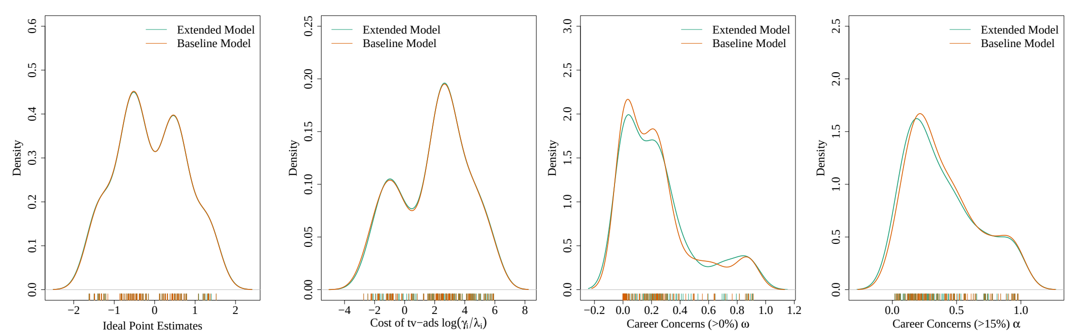


Figure D1: Parameter estimates in the Dynamic Game and Baseline Model

Figure D1 shows the distribution of the estimated structural parameters in the Baseline Model and in the Extended Model with endogenous challenger response. As the figures show, the two sets of estimates are remarkably similar. The new parameter in this model is the cost of spending for the challenger. Our estimates imply that incumbents enjoy a substantial cost advantage, which partly explains the fact that incumbents outspend challengers almost four to one (see Figure D2).

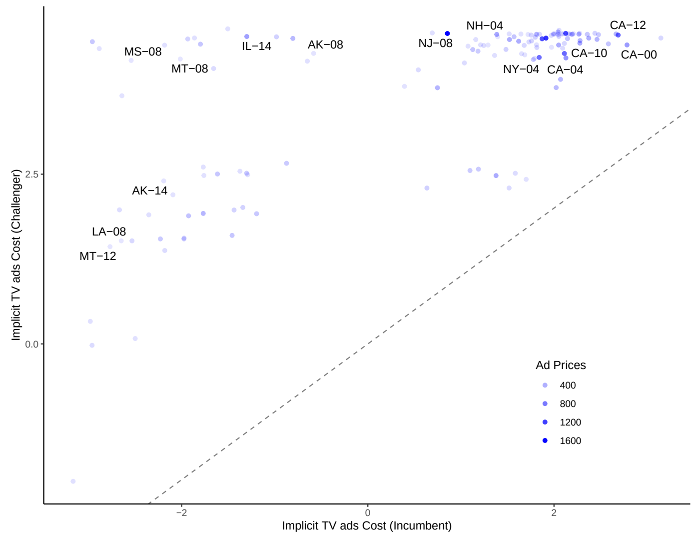


Figure D2: Implicit cost of TV ads for Incumbent and Challenger in the Extended Model with endogenous challenger response.

Figure D3 plots the aggregate *equilibrium* position-taking and TV ad buys by both the incumbent and challenger, as a function of the incumbent's electoral advantage. As the figure shows, the main results of the benchmark model are qualitatively unchanged. As in the baseline model, equilibrium electoral accountability and TV ad buys by the incumbent increase as the election gets closer, when the race is more competitive, and when the incumbent cares more about retaining office.

Quantitatively, the results are also largely similar to the benchmark. The exception is a moderately higher predicted level of electoral accountability and TV ad spending in close elections, in particular for senators in the top quartile of office motivation. These differences are not surprising. The simplification in the benchmark is to maintain the challenger at the observed level of TV ad spending in all states. When we allow the challenger to choose spending strategically, instead, she tends to spend more the more competitive the election is. This in turn prompts the incumbent to increase her effort in close elections (i.e., the game has strategic complementarities). From a quantitative point of view, however, these results show that introducing the challenger doesn't significantly change the conclusions from the benchmark model.

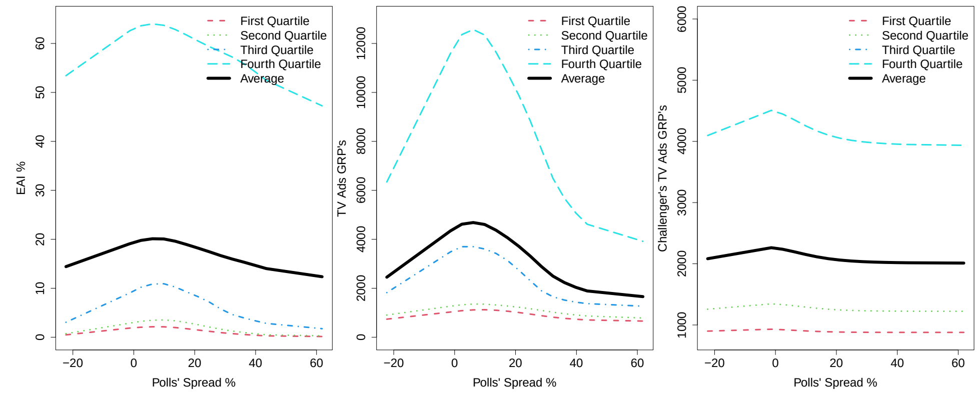


Figure D3: Equilibrium Position-Taking (EAI) and TV Advertising by Incumbent and Challenger, as a function of the incumbent's electoral advantage. Quartiles of the distribution of λ (policy) and λ/γ (ads).

Endogeneizing the challenger's response allows us to assess the extent to which advertising crowds-out electoral accountability. To do this, we quantify what policy choices senators would have made *in the absence* of advertising, and then compare electoral accountability in the counterfactual with the level of electoral accountability in the data.[5]

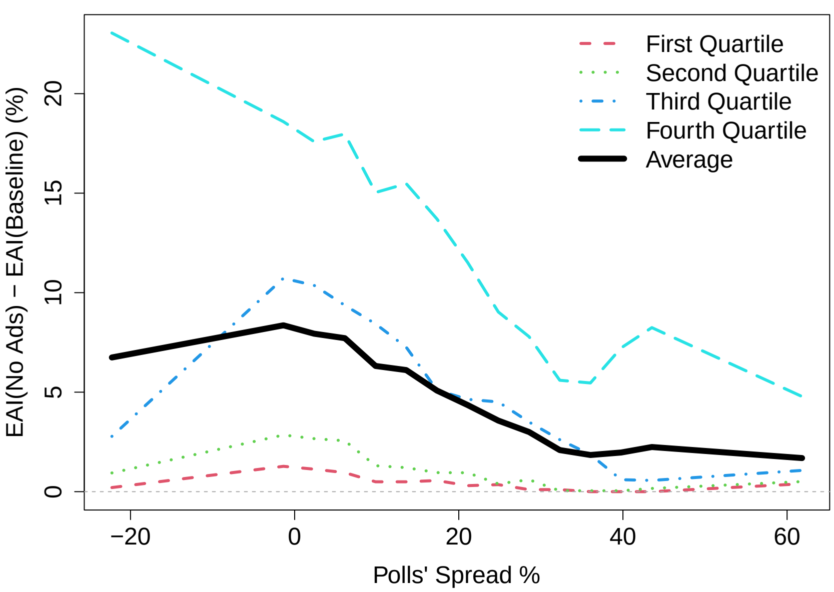


Figure D4: Counterfactual: Ban of Political Advertisements

Figure D4 presents the results. As the figure shows, banning advertisement would increase

[5] In a related exercise, Gordon and Hartmann (2013) estimate the effect of eliminating ads on vote shares in presidential elections. They show significant changes on electoral returns under no advertisement. Our policy counterfactual complements their results, capturing the effect of advertising on policy responsiveness.

electoral accountability in close elections by 9 p.p. for the average senator, and by about 20 p.p. for the senators in the top quartile of the distribution of office motivation (the magnitude of the gain decreases for larger advantages in the polls). We conclude that while advertising significantly crowds-out policy accountability (in particular in close elections, and for career-concerned politicians), it is only a contributing factor, and not the main force breaking the electoral connection between politicians and voters.

D.2 No Payoffs for Lopsided Wins ($\alpha = 0$)

In the paper, we assume that the politician gets an office payoff $\omega \geq 0$ if she wins the election, and an additional benefit $\alpha \geq 0$ from a large margin of victory. This formulation nests the model with $\alpha = 0$. The constrained model is rejected by the data for a large majority of senators in the sample. In fact, $\Pr(\alpha \geq 0.1) \geq 0.95$ for 78% of senators in our sample, and $\Pr(\alpha \geq 0.25) \geq 0.95$ for 34% of senators in our sample. In essence, in order to better explain the data, we need to increase the *marginal* return of "effort" (both ads and policy moderation) in non-close elections.

In this section, we present the main results of estimating the model assuming no extra payoffs from lopsided wins ($\alpha = 0$), and how these compare to the estimates of our benchmark specification. Figure D5 presents a comparison of the parameter estimates in the constrained model ($\alpha = 0$) and the baseline model.

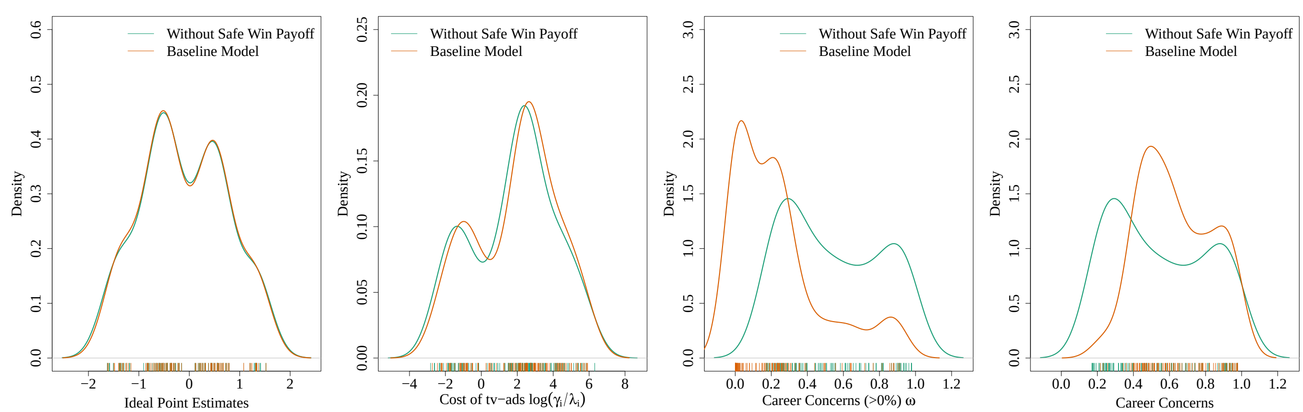


Figure D5: Comparison of Parameter Estimates in the Constrained Model ($\alpha = 0$) and the Baseline Model

As the first two panels show, the estimates of θ and γ are essentially unchanged when we set $\alpha = 0$. The third and fourth panel present the comparison of career concern estimates. The third panel plots the empirical distribution of our estimates for ω in both models. The right panel presents the empirical distribution of our estimates of total career concerns in the constrained model (ω) and in the benchmark model ($\omega + \alpha$). As the left panel shows, when we force α to zero, the model adjusts by increasing the value of ω for a large number of senators. Instead, the unconstrained model predicts a heightened responsiveness in lopsided elections for a non-negligible fraction of senators in our sample (right panel).

Figure D6 presents the aggregate policy functions in the constrained and the benchmark model. Unsurprisingly, in the constrained model, responsiveness in maximized in close elections, and decreases faster with higher advantages in the polls than in the unconstrained model. Both qualitatively and quantitatively, however, the conclusions of the paper remain essentially unchanged.

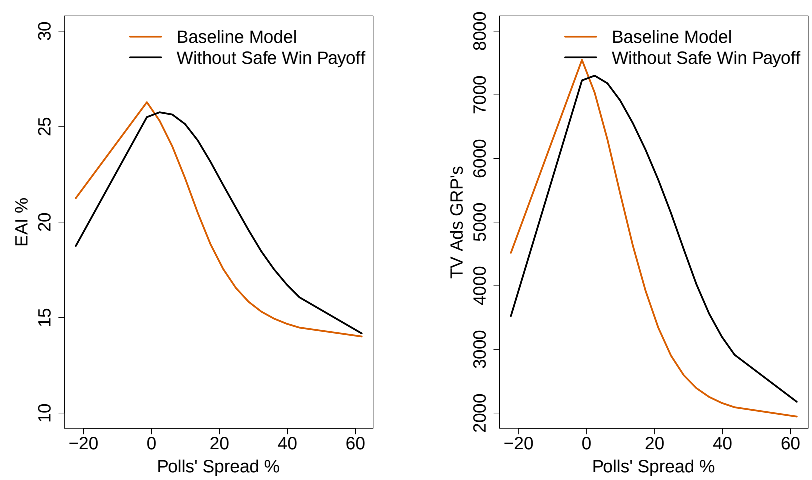


Figure D6: Comparison of Aggregate Policy Functions in the Constrained Model ($\alpha = 0$) and Baseline Model.

Finally, we evaluate the out-of-sample fit of the constrained model with respect to our baseline specification. We reestimate the parameters of the constrained model using only the first instance in which a senator runs for office in the sample, and use the resulting estimates to predict their behavior in the second or third run. This gives us a total of 360 observations to fit from 30 senators who run for office more than once. We find that the constrained model fits the data roughly as well as the unconstrained model, with a marginal improvement brought by the latter, in particular regarding advertising. This comparison being uninformative, we favor the agnostic approach of the unconstrained model. We reiterate, however, that the conclusions emphasized in the paper are robust to imposing the constraint that $\alpha = 0$ from the outset.

D.3 Threshold for Safe Wins

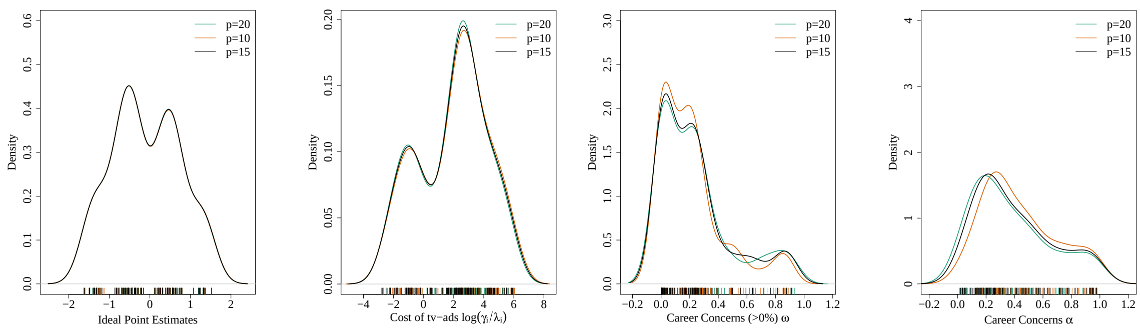


Figure D7: Career Concerns under Different Thresholds for Safe Wins

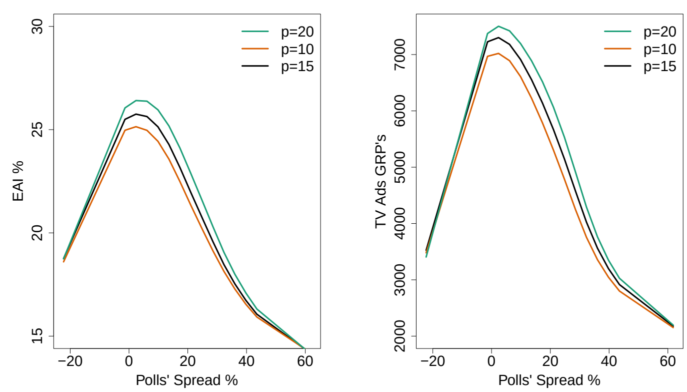


Figure D8: Aggregate (Mean) Policy Functions under Different Thresholds for Safe Wins

D.4 Instrumental Variables

As instruments for TV ads of a senator i, we use variation in TV ads in House races within i's state, as well as in TV ads from neighboring states. The idea is to use ads in races that face similar changes in ad costs, but that do not affect senator i's voter support directly. We then exploit a similar idea to instrument for policy positions. In particular, we instrument senator i's `position` with the position of the median House representative from the senator i's party and state. The exclusion restriction assumption is that changes in the position-taking of members of the House in the state of Senator i do not directly affect senator i's voter support. Instead, changes in the political environment that is common to both representatives and senator of the same state lead to similar policy responses by both types of legislators.

As additional instruments for policy positions we use economic conditions, measured by unemployment (`unemployment`) and leading indicators of economic activity (`lead`) in "neighboring" states. In the definition of neighbor, here we substitute geographical distances with distances in *ideological affinity*, as measured by cosponsorship relations. This builds on the idea that senators will tend to support the positions of like-minded senators, that are, in turn, a function of their own economic conditions, which are independent of variation in next period's voter support of the senator of interest.

	Dependent variable: $p_{i,t-1}$	
	OLS	IV
	(1)	(2)
$p_{i,t}$	0.764^{**}	0.722^{**}
	(0.024)	(0.034)
$(x_{i,t} - \xi)^2$	-2.133^{**}	-9.791^{**}
	(0.812)	(3.547)
$(x^p_{i,t} v - \xi)^2$	0.021^{**}	0.034^{**}
	(0.007)	(0.012)
$\sqrt{e_{i,t}}$	-0.049^{**}	-0.053^{**}
	(0.010)	(0.014)
Observations	1,584	1,416
Senator/District Covariates	Yes	Yes
Congress-Party FE	Yes	Yes
Adjusted R^2	0.696	0.653

Note: $^{\dagger}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$.
Robust standard errors clustered at the senator-congress level in parentheses.

Table D1: First Stage Results with IV

	Dependent variable:		
	$(x_{it} - \varepsilon_i)^2$	$\sqrt{e_{it}}$	$\sqrt{e^{chall}_{it}}$
	(1)	(2)	(3)
$p_{i,t}$	-0.002	-0.292^{**}	-0.307^{**}
	(0.001)	(0.061)	(0.055)
$\sqrt{e_{i,t}}^{house}$	0.0002	0.798^{**}	0.178^{*}
	(0.0004)	(0.071)	(0.069)
$\sqrt{e^{chall}_{i,t}}^{house}$	-0.00003	0.304^{**}	0.922^{**}
	(0.0005)	(0.061)	(0.062)
$\sqrt{e_{i,t}}^{neighbor}$	0.001	0.200^{**}	0.100
	(0.001)	(0.069)	(0.070)
$\sqrt{e^{chall}_{i,t}}^{neighbor}$	$-0.001^{\dagger}$	0.064	$-0.133^{\dagger}$
	(0.001)	(0.081)	(0.078)
$(x^{house}_{i,t} - \xi)^2$	0.200^{**}	5.886^{*}	2.763
	(0.042)	(2.892)	(2.348)
$\texttt{unemployment}^{cosp}$	-0.010	-2.798	-5.335^{*}
	(0.052)	(2.609)	(2.207)
$\texttt{lead}^{cosp}$	0.101^{**}	-1.114	2.749^{*}
	(0.030)	(2.044)	(1.389)
Senator-State Controls	Yes	Yes	Yes
Congress-Party FE	Yes	Yes	Yes
IV F-Tests	23.18^{**}	134.62^{**}	223.19^{**}
Observations	1,416	1,416	1,416
Adjusted R^2	0.413	0.740	0.764

Note: $^{\dagger}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$.
Robust standard errors clustered at the senator-congress level in parentheses.

Table D2: Instrument Relevance Results

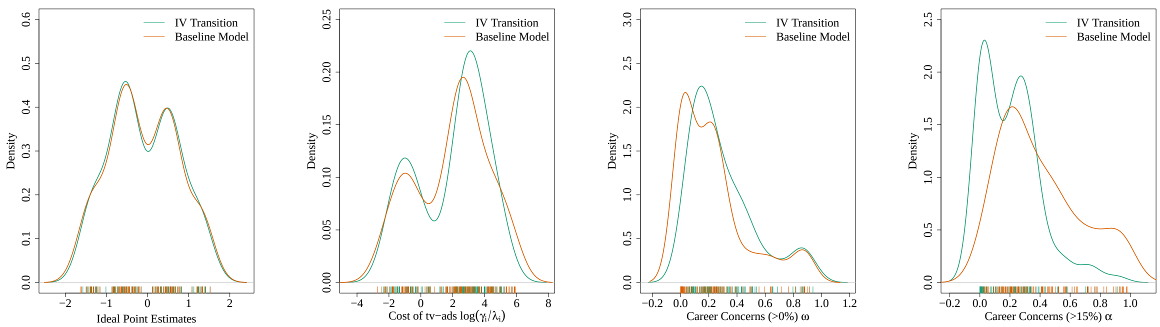


Figure D9: Structural Parameter Estimates in the Benchmark and IV estimates.

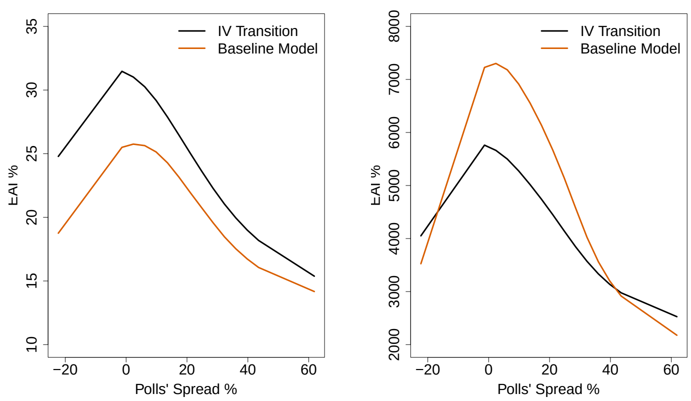


Figure D10: Aggregate (Mean) Policy Functions in the Benchmark and IV estimates.

D.5 Alternative Measures of Voter Ideology

In the benchmark specification of the transition function, we assume that the senators' policy positions affect voter support through deviations from mean voter preference, as measured by the republican presidential margin in each state. This is of course a simplified model, that might not fully capture the richness of the electoral environment. To evaluate this issue, in this section we explore the robustness of our benchmark specification using the survey-based estimates of the mean and standard deviation of state ideology obtained by Tausanovitch and Warshaw (2013).

We begin by estimating a transition function that incorporates both the mean ξ and standard deviation υ of voters' preferences in each district. Lower preference heterogeneity should make deviations from the mean of voter ideology more costly, and vice-versa. To capture this logic, we introduced an interaction of the standard deviation of voters' preferences υ with the distance of the policy position to the mean $(x_{i,t} - \xi)^2$. If this mechanism were relevant, we would expect a positive interaction term, indicating that larger variance in voters' preferences reduces the electoral cost of policy divergence. We find that the estimate for the interaction is positive (0.723) but not statistically different from zero (standard error of 0.625).

With these results in mind, we then reestimate the transition function using only the Tausanovitch and Warshaw (2013) mean voter preference measure, as in the specification we used in the paper. The results are presented in Table D3 below. When we compare these results (column 3) with the main specification in the paper, using presidential vote, we find very similar results. In particular, the point estimate of $(x_{i,t} - \xi)^2$ changes from -2.20 in the paper to -2.08 in the robustness check, and the standard deviation of the coefficient estimate changes from 0.83 to 0.74. Similarly, other coefficient estimates only show relatively small changes.

	Dependent variable: $p_{i,t-1}$			
	TW-OLS	TW-LDV	TW-LDV	Main Specification
	(1)	(2)	(3)	(3) in paper
$p_{i,t}$		0.817**	0.760**	0.764**
		(0.022)	(0.025)	(0.024)
$(x_{i,t} - \xi)^2$	−6.364**	−1.495**	−2.011**	−2.133**
	(2.463)	(0.501)	(0.731)	(0.812)
$\sqrt{e_{i,t}}$	0.023	0.017*	0.019**	0.021**
	(0.017)	(0.006)	(0.007)	(0.007)
$\sqrt{e_{i,t}^{chall}}$	−0.132**	−0.045**	−0.047**	−0.049**
	(0.022)	(0.009)	(0.009)	(0.010)
Observations	1,536	1,536	1,536	1,584
Senator-State Controls	No	No	Yes	
Congress-Party FE	No	No	Yes	
Adjusted R^2	0.116	0.692	0.699	0.699
F Statistic	68.268**	865.051**	115.753**	115.753**

Note: †p<0.1; *p<0.05; **p<0.01. Robust standard errors clustered at the senator-congress level in parentheses. The first three columns reproduce Columns 1-3 in Table 1 in the Paper using the Tausanovitch and Warshaw (2013) measure. Column 4 reproduces column 3 in the paper (our preferred specification), for comparison.

Table D3: Tausanovitch and Warshaw (2013) Measure: First Stage Results

We then re-estimate the structural parameters of the model using the Tausanovitch and Warshaw (2013) data, with the transition function specification in Table D3. Figure D11 presents the results. The figure plots the empirical distribution of our parameter estimates (for $\theta, \gamma, \omega, \alpha$) using the Tausanovitch and Warshaw (2013) measure and in our baseline model with presidential support. Our ideal point estimates and cost parameter estimates are essentially unchanged. Our career concern estimates are also similar, although here we do observe a non-negligible difference in point estimates of ω, α for some senators in our sample. In particular, the empirical distribution of ω and α in the robustness check puts more mass on moderately low values of ω and α relative to the larger mass on higher values in the main specification. In Figure D19, we show the effect of these changes on our aggregate policy functions. With some moderate differences in magnitudes, the results are consistent with all the conclusions we highlighted in the paper, including relatively low electoral accountability on average, and peak of electoral accountability in close elections on average.

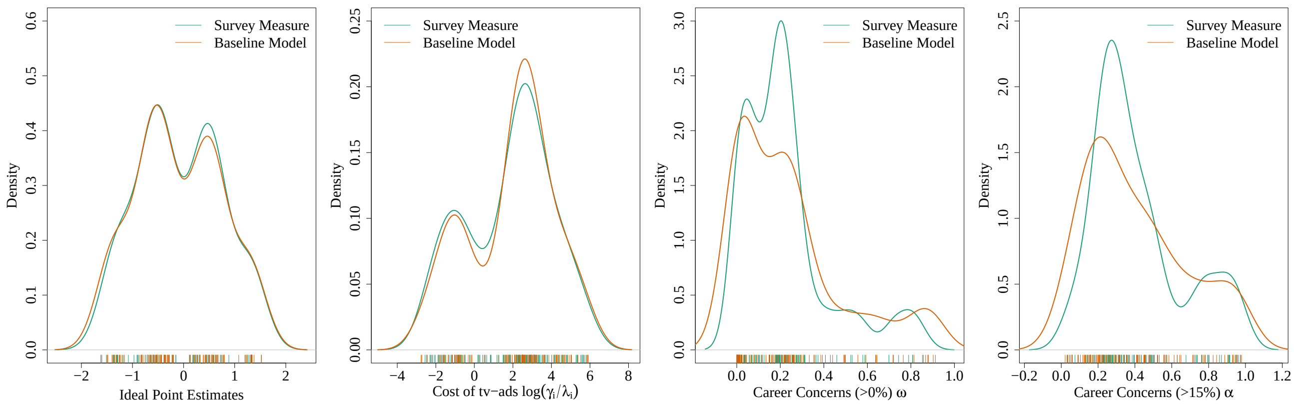


Figure D11: Comparison of Parameter Estimates using Tausanovitch and Warshaw (2013) Measure and Baseline Model.

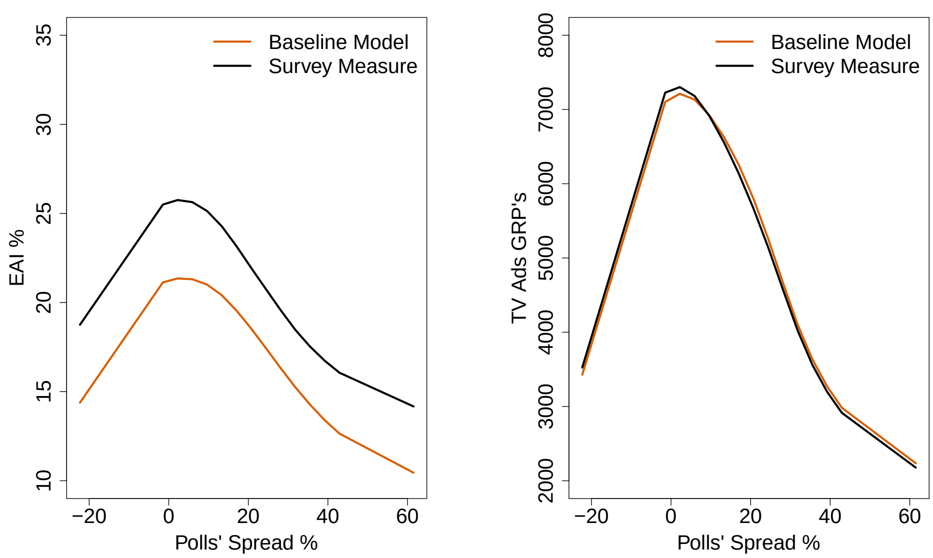


Figure D12: Comparison of Aggregate Policy Functions using Tausanovitch and Warshaw (2013) Measure and Baseline Model.

D.6 Measuring Policy Positions

To quantify senators' policy positions at each point in time, we use scaling techniques to obtain a one-dimensional measure capturing variability in senators' voting records. Specifically, we define senator i's `position` in month t as her "ideal point" estimate from a Bayesian Quadratic Normal model (Clinton, Jackman, and Rivers (2004b)). Unfortunately, in many instances (senator/month) there are just not enough votes in any given month to obtain precise estimates of individual senators' policy positions. Thus, attempting to measure policy positions by scaling roll calls in a single month results in highly variable point estimates with large standard errors, and missing data. To overcome this problem, we estimate policy positions using a twelve month rolling window of roll calls.

Figure D13 presents a crossplot of our measure of position-taking with a current-date-only measure of position-taking (point estimates only), restricting to periods in which there are at least fifty roll-call votes. As the figure shows, restricting to periods in which there is at least a minimally viable amount of information to obtain relatively precise estimates at the monthly level, the current-date-only measure is highly correlated with our original measure (correlation coefficient of 0.88).

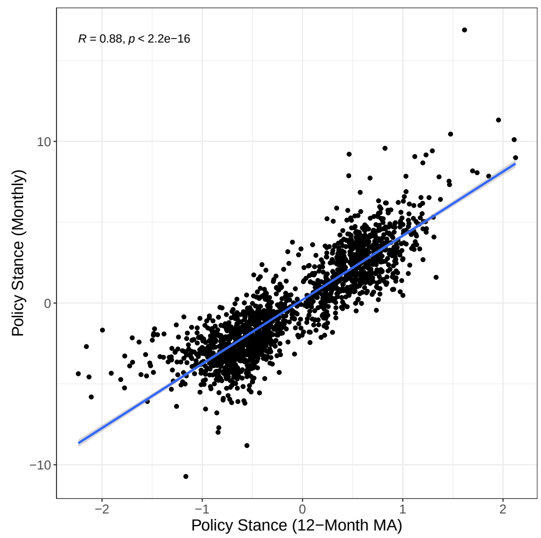


Figure D13: Benchmark measure of position-taking measure (x-axis), and monthly-data-only measure of position-taking (y-axis), whenever the latter can be computed (point estimates).

A possible concern is that our measurement strategy could artificially reduce our estimates of electoral accountability. To assess this possibility, we computed alternative measures of policy positions using alternative "windows" for estimation; i.e., we computed position estimates for any senator i in period t using only votes in the last three (3M) and the last six months (6M). As discussed above, including fewer roll calls in the analysis leads to more imprecise estimates. This can be seen in Figure D14, which plots the density of the standard errors of policy position's estimates with monthly data, as well as with three, six and twelve month roll call windows. As can be seen, monthly estimates have the largest standard errors, followed by 3M and 6M windows. Consistent with this, the correlation between our preferred measure and the 6M (point) estimates is 0.926, while the correlation between our preferred measure and the 3M (point) estimates drops to 0.71. The effect of reducing the window size is not limited to adding noise. In fact, as the scaling window gets smaller, we recover a significantly higher portion of extreme positions, which are very imprecisely estimated, due to the small number of roll-call votes available in smaller windows. When we remove the outliers due to imprecisely estimated positions, the correlations between the point estimates increase to 0.944 (6M) and 0.886 (3M).

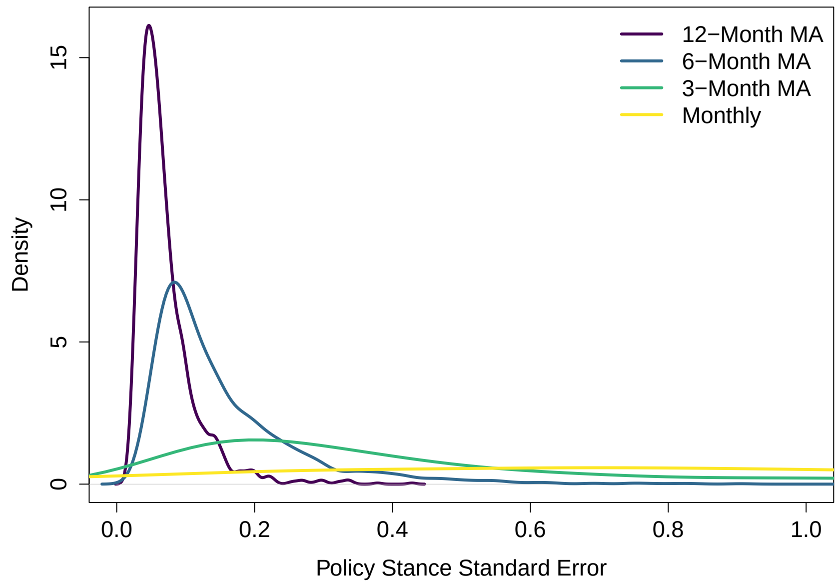


Figure D14: Density of the standard errors of policy position's estimates at the monthly level and for three, six and twelve month roll call windows.

To assess the potential effect of our measurement strategy on our estimates of electoral accountability, we re-estimate the full structural model with the 6M measure of position-taking, excluding outliers.[6] If our measurement strategy were to artificially reduce electoral accountability, reducing the scaling window would result in higher levels of electoral accountability. Figure D15 shows the predicted electoral accountability index and TV advertisement as a function of electoral advantage for our baseline specification and for the 6M model. As the figure illustrates, the aggregate policy functions are very similar using both measures of policy positions. In particular, we do not find politicians' responsiveness to be significantly higher for the smaller scaling window (in fact, it is slightly below the estimate for the benchmark model). We read this as reassuring evidence that our conclusion that electoral accountability is only moderate on average is robust to our joint scaling of votes.

[6]We do not estimate the structural parameters for the 3M measure, as we are left with fewer than 5 incumbent senators with non-missing data after removing extreme observations.

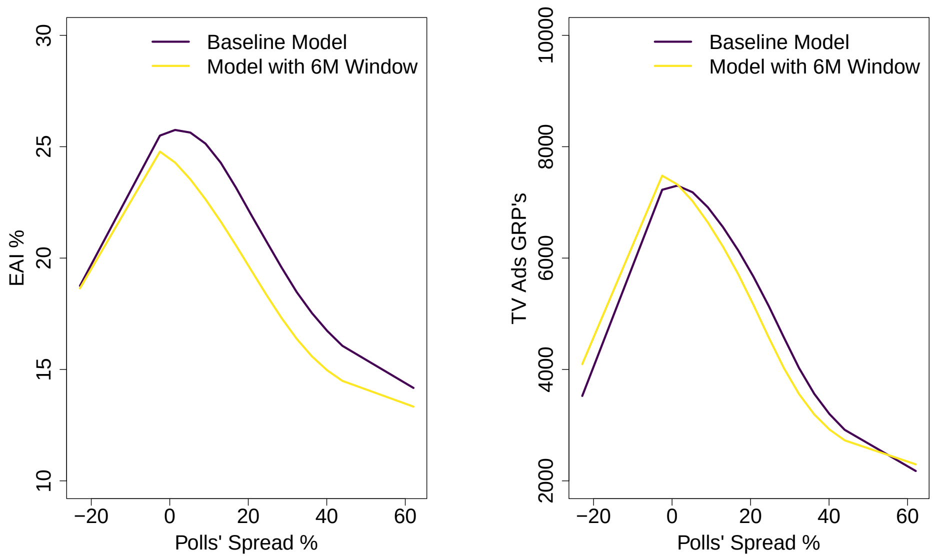


Figure D15: Electoral Accountability and TV Advertising for 12- and 6-Month Moving Averages

D.7 Measurement Error in TV advertising Costs

Available measures of TV advertisement costs can be imperfect due to high-frequency variation in prices or price discrimination by TV stations). Measurement error in the quantity of TV-ad buys would lead to attenuation bias in our transition function estimates (Table 6 in the paper); i.e., the estimated return of ads would be biased towards zero. To assess the consequences of measurement error on our structural parameter estimates and measures of electoral accountability, we re-estimate the model imputing a larger return of ads. In particular, we increase the coefficient of ads by 50% (1.5X) and by 100% (2X).

The result of this exercise for our parameter estimates is depicted in Figure D16. Ideal point estimates (θ) and cost parameters (γ) are essentially unchanged (see top row). However, we see that both the 1.5X and 2X experiments lead to a downward shift in the distribution of both the ω and α estimates. This suggests that if we had significant measurement error in TV ads, our career concern estimates would have an upward bias (legislators would be even more ideological than what we predict).

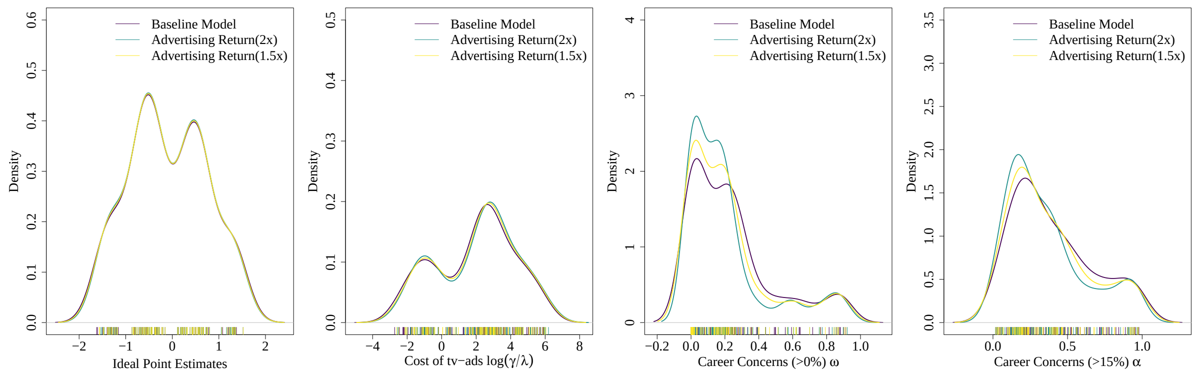


Figure D16: Comparison of Parameter Estimates with 1.5X return on ads, 2X return on ads, and Baseline Model

Figure D17 plots the aggregate policy functions computed from each set of estimates. As the figure shows, increasing the return of ads leads to a small reduction in the predicted level of policy and ad responsiveness. In other words, in the presence of measurement error, we would be moderately overestimating the extent of electoral accountability. This, if anything, would reinforce the main conclusions of the paper.

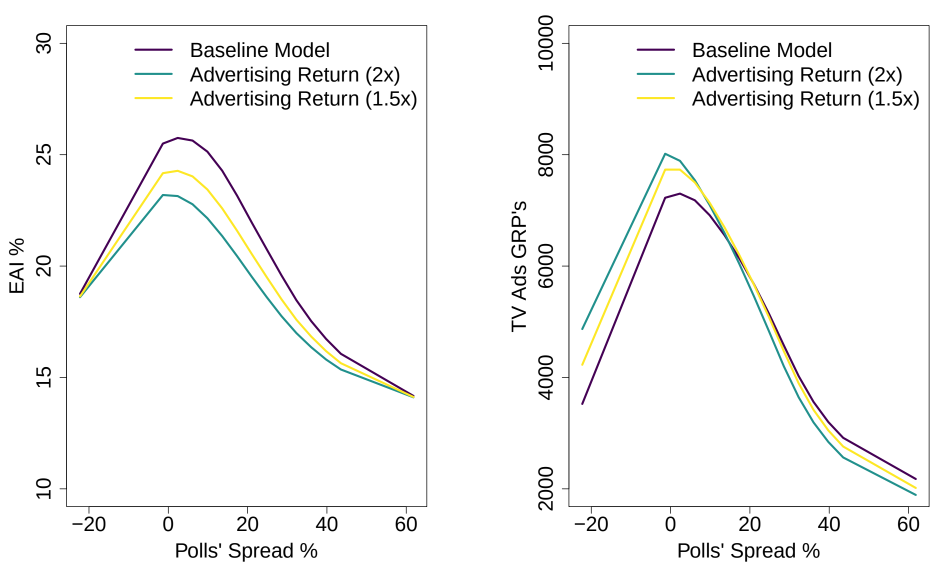


Figure D17: Comparison of Aggregate Policy Functions with 1.5X return on ads, 2X return on ads, and Baseline Model.

In the case that `tv-ads` are measured with an additive error (i.e., classical measurement error), a valid instrument for `tv-ads` will identify the true return of ads on voter support. In Section D.4 of this appendix, we use variation in TV ads in House races within a given state, as well as in TV ads from neighboring states. The IV results from Table D1 indicate an attenuation bias, with an IV estimate 1.7 times larger than the OLS estimate, which is in line with our simulations and our main conclusions regarding electoral accountability.

D.8 TV ads and Total Campaign Spending

In our empirical model, we focus on two instruments available to senators running for reelection: their voting record, and TV advertising. In practice, politicians have other instruments at their disposal (e.g., giving speeches, sending mailers, knocking on doors). It could then seem sensible to include total campaign expenditures as an aggregate measure of these electioneering activities.[7]

Doing this in this context is problematic for three reasons. First, total campaign expenditures include a surprisingly large number of expense items that do not directly influence voters (political consultant fees, surveys, food for campaign workers, database management, software support, legal and banking fees, supplies, etc). Second, even when we identify the electioneering activity itself, we would want to measure the quantity perceived by voters, not the cost for the campaign to influence that voter (price times quantity). In other words, we are not interested in the total expense associated with putting together a speech by the candidate, but the actual electioneering activity–the speech, and how many people watch that speech. Third, the expenditure data often doesn't allow us to identify the time in which the activity impacted voters, undermining our ability to focus on dynamics. In contrast, the advertising data (though imperfect) measures the quantity of an activity that we know is going directly to voters at a given time, and allows us to separate quantity from total cost.

These caveats being noted, we point out that total campaign expenditures are correlated with TV ad impressions, both across and within candidates. Table D4 presents the results of estimating a linear regression in which TV ad impressions are a function of total campaign spending (in real terms using the price of ads as a deflator), for both incumbent and challenger. Columns (1) and (3) present the unconditional estimates, while columns (2) and (4) present the estimates with Congress Session and Senator fixed effects. As the table shows, the coefficient estimates for total campaign spending are positive and statistically significant for both incumbent and challengers, with and without fixed effects.

For completeness, we recomputed our estimates using total campaign expenditures in lieu of TV ads. Figure D18 presents the distribution of the estimates of ideal points and career concerns (θ, ω, α) from our empirical model using total campaign spending instead of TV ads. The two sets of results produce similar estimates on the overall policy vs office tradeoffs, which are ultimately reflected in similar estimates of electoral accountability (more on this below). We note, however, that the estimates obtained using total campaign spending shift the distribution of ω estimates upwards, and the distribution of α estimates downwards, implying a relatively larger responsiveness in close than lopsided elections than the corresponding estimates with TV ads on average.

[7] Campaign expenditures are available from the Federal Election Commission, including item by item expenditures as entered by the campaign staff.

	Dependent variable:			
	TV Ads (Incumbent)		TV Ads (Challenger)	
	(1)	(2)	(3)	(4)
Total Campaign (Inc.)	0.802**	0.850**		
	0.078)	(0.084)		
Total Campaign (Chall.)			0.780**	0.877**
			(0.149)	(0.169)
Observations	1,584	1,584	1,584	1,584
Legislator-Congress FE	No	Yes	No	Yes
Adjusted R^2	0.464	0.422	0.346	0.296
F Statistic	1,370.450**	1,288.454**	836.817**	798.452**

Note: $^{\dagger}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$. *Robust standard errors clustered at the senator-congress level in parentheses.*

Table D4: Total Campaign Spending and TV Advertisement

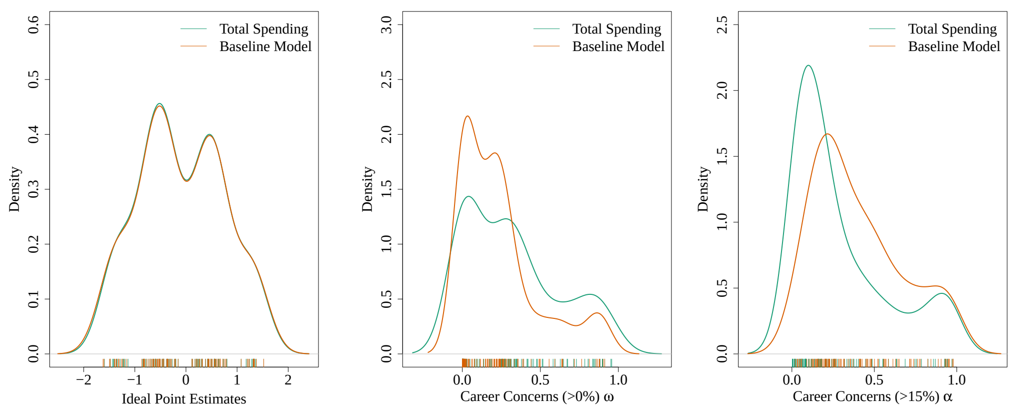


Figure D18: Comparison of Parameter Estimates for (θ, ω, α) using Total Campaign Spending and TV Ads (Baseline Model).

Figure D19 presents the comparison of aggregate policy functions for ads and electoral accountability using TV ads (Baseline Model) and Total Campaign Spending. To report comparable figures for TV ads and total Campaign Spending, we transform total campaign spending into impression equivalent units by dividing it by the average ad price in the state (this is imperfect of course, so the comparison should be taken with caution).

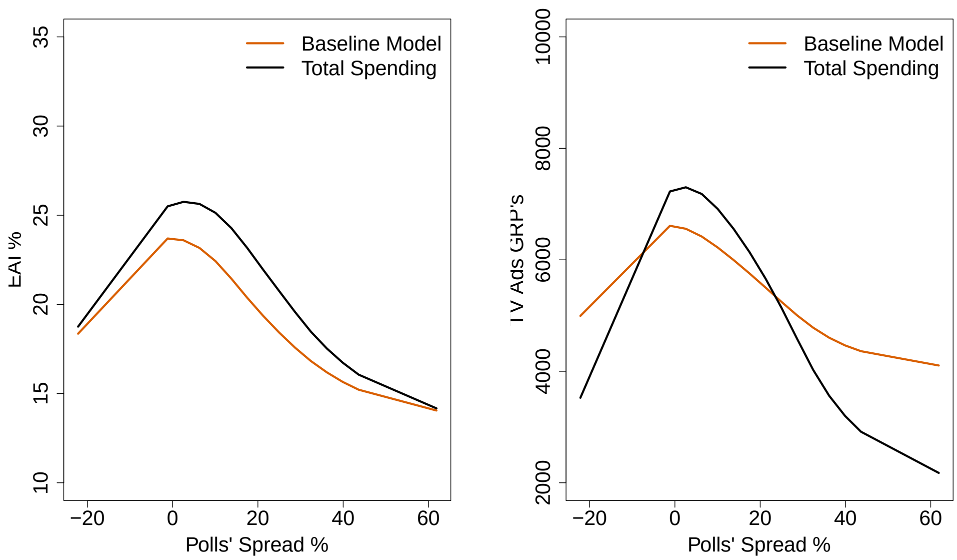


Figure D19: Comparison of Aggregate Policy Functions using Total Campaign Spending and TV Ads (Baseline Model). To report comparable figures for TV ads and total Campaign Spending, we transform total campaign spending into ad equivalent units by dividing it by the average ad price (this is presented only as a rough comparison).

Overall, we find similar patterns of responsiveness as a function of the advantage in the polls, with moderately lower levels of electoral accountability and – to the extent that this comparison is informative – a slightly larger average responsiveness of spending.

References

Canes-Wrone, B., D. W. Brady, and J. F. Cogan (2002): "Out of step, out of office: Electoral accountability and House members' voting," *American Political Science Review*, 96(1), 127–140.

Carpenter, B., M. D. Hoffman, M. Brubaker, D. Lee, P. Li, and M. Betancourt (2015): "The Stan Math Library: Reverse-Mode Automatic Differentiation in C++," *arXiv preprint arXiv:1509.07164*.

Clinton, J., S. Jackman, and D. Rivers (2004a): "The statistical analysis of roll call data," *American Political Science Review*, 98(02), 355–370.

Clinton, J. D., S. Jackman, and D. Rivers (2004b): "The Statistical Analysis of Roll Call Data," *American Political Science Review*, 55, 355–370.

Clinton, J. D., and A. Meirowitz (2003): "Integrating Voting Theory and Roll Call Analysis: A Framework," *Political Analysis*, 11, 381–396.

Iaryczower, M., G. Katz, and S. Saiegh (2013): "Voting in the Bicameral Congress: Large Majorities as a Signal of Quality," *The Journal of Law, Economics, & Organization*, 29(5), 957–991.

Poole, K., and H. Rosenthal (1984): "The Polarization of American Politics," *The Journal of Politics*, pp. 1061–1079.

Rothschild, D. (2015): "Combining forecasts for elections: Accurate, relevant, and timely," *International Journal of Forecasting*, 31(3), 952–964.

Spenkuch, J., P. Montagnes, and D. Magleby (2018): "Backward Induction in the Wild? Evidence from Sequential Voting in the US Senate," *American Economic Review*, 108(7), 1971–2013.

Stewart, C., and J. Woon (2017): "Congressional Committee Assignments, 103rd to 114th Congresses, 1993–2017:112th-115th," `http://http://web.mit.edu/17.251/www/data_page.html`.

Tausanovitch, C., and C. Warshaw (2013): "Measuring constituent policy preferences in congress, state legislatures, and cities," *The Journal of Politics*, 75(2), 330–342.