Are Legislators Informed by Like-Minded Experts? Testing the Preference-Distance Hypothesis Using Observational Data*

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Abstract

Theoretical expectations regarding the legislative influence of outside agents, such as lobbyists, agency officials or policy experts, often depend on the *relationship* between legislators' and agents' preferences. Legislators and non-elected outside agents evaluate the merits of policies using distinct criteria and considerations, however, so a test of any preference-distance hypothesis must accommodate distinct preference dimensions for each type of actor. We develop a measurement method that flexibly estimates the policy preferences for a class of outside agents – witnesses in committee hearings – defined on a policy analytic dimension that can be orthogonal to legislators' preferences as measured by roll call voting. Using our witness preference estimates, we find that legislators in the U.S. Congress heavily condition their questioning in Medicare hearings on preference distance in a way consistent with cheap talk informational models of strategic lobbying, showing that legislators tend to consult with like-minded experts in committee hearings.

Keywords: Lobbying, Policy Preferences, Information, U.S. Congress, Committee Hearings, Medicare

Understanding the interactions between legislators and external agents is important in the scholarship of lobbying and interbranch relations. In particular, studying the relationship between legislators and unelected outside agents, such as lobbyists, experts and agency officials, sheds light on a legislature’s capacity to seek external policy-relevant information, and helps to identify the external actors that influence the policy-making process.

In many strategic theoretical models of legislative lobbying, the interaction between lobbyist and legislator depends on the proximity of their *preferences* regarding policies. For example, Austen-Smith (1992, 1993) characterizes lobbying as a “cheap talk” game in which a lobbyist typically is more informative to a legislator the more similar their preferences, a result that is consistent with the canonical view that lobbyists tend to influence allies (Bauer, Pool, and Dexter, 1963; Hall and Deardorff, 2006). The idea that lobbying can be characterized as cheap talk is not uncontested (e.g., Calvert, 1985; Lohmann, 1995; Potters and van Winden, 1992), so empirically testing the preference-distance hypothesis can illuminate the nature of the strategic environment in which lobbying occurs.¹

An empirical test of such propositions requires a strategy for measuring the preferences of each type of actor. Recently, several studies have developed measurement strategies that place the preferences of legislators and outside agents on a one-dimensional common space (Barberá, 2015; Battista, Peress, and Richman, 2021; Bonica, 2013; Crosson, Furnas, and Lornez, 2020; McKay, 2008; Shor, Berry, and McCarty, 2010). Non-elected agents are often policy experts with their own goals and incentives, however, and so may have policy preferences defined on a dimension that is different from that of elected legislators (Esterling, 2004). In that case, an *a priori* assumption that reduces preferences of different

¹The cheap talk preference-distance hypothesis has been tested in lab experimental settings where the experimenter assigns preferences (e.g., Battaglini, Lai, Lim, and Wang, 2019; Blume, Lai, and Lim, 2020; Cai and Wang, 2006; Crawford, 1998; Dickhaut, McCabe, and Mukherji, 1995; Lai, Lim, and Wang, 2015), but it has never been tested using observational data for lobbying in settings where preferences must be estimated.

groups of political actors to a single dimension will be inappropriate (Jessee, 2016).

In this paper, we argue that it is necessary to allow flexibility in measuring the policy preferences of both elected and non-elected agents when testing hypotheses about the interactions between legislators and outside agents within committee hearings. We present a new measurement method to place policy preferences on a two-dimensional common space, one dimension for legislators and the other for the witnesses who are invited to testify at hearings. In our application that examines Medicare² hearings, we recover a preference dimension for witnesses that is orthogonal to legislators’ roll-call preference dimension. Using text analysis of witnesses’ testimony, we demonstrate that the expert witnesses’ preferences at these hearings map onto a policy analytic health care “cost-quality” dimension that is orthogonal to legislator preferences as measured by DW-Nominate scores.

We show that the posterior witness preference estimates that we recover in our flexible model have better construct validity than preference estimates that constrain all actors’ preferences to a single dimension, in that only our unconstrained preference estimates have a clear correspondence with institutional theories of strategic information transmission. This empirical test demonstrates a use case and the validity of our measurement method, and it contributes to research on lobbying as it presents the first evidence using observational data to support established theories that legislators tend to seek information from agents whose preference is closer to theirs than those with preferences distant from theirs (e.g., Austen-Smith, 1992; Bauer et al., 1963).

Preferences and Information-Seeking Questions in Committee Hearings

We test hypotheses from theoretical lobbying models in the context of U.S. congressional committee hearings. In committee hearings, legislators publicly pose statements and questions regarding the hearing topic to outside agents such as lobbyists and policy

²Medicare is the primary social health insurance program in the U.S.

specialists, who in this context are referred to as “witnesses,” and who typically have both preferences and expertise on the given policy topic (Esterling, 2004). While legislators use hearings for many different purposes (Huitt, 1958), we focus specifically on the relationship between preference distance and the propensity for committee members to direct *information-seeking* questions to witnesses within a hearing. Our primary outcome of interest is the count of legislators’ *falsifiable sentences*, or statements that engage the witness in informational, epistemic discourse (Esterling, 2011). Esterling (2007) demonstrates that information-seeking falsifiable questioning is consistent with policy-making “workhorse” behavior, in contrast to non-falsifiable opinion or anecdotal questioning that is consistent with grandstanding “showhorse” behavior (Park, 2021).

Using this key outcome, we test whether members of Congress condition their falsifiable (information-seeking) questioning of witnesses on the similarity of policy preferences within the legislator-witness dyad, as a test of the widely-recognized “cheap talk” preference-distance hypothesis proposed in Austen-Smith (1992, 1993). The core result in cheap talk models of strategic information transmission, established in Crawford and Sobel (1982), is that messages should be more informative to a receiver, and hence more valuable, the closer the preferences of the receiver (the legislator) and sender (the witness). In the context of hearings, under cheap talk assumptions one should expect to see a legislator posing fewer information-seeking questions to witnesses, the farther their distance in the legislatively-relevant preference space.

Hypothesis 1a. The *closer* the preferences between a witness and a legislator, the more informational questions the legislator will direct to the witness.

In contrast, observing that witnesses with more distant preferences are *more* informative would disconfirm a cheap talk environment and instead would be consistent with alternative game structures such as costly signaling or lobbying with verification (e.g., Calvert, 1985; Diermeier and Feddersen, 2000; Lohmann, 1995; Potters and van Winden, 1992).

Hypothesis 1b. The *farther* the preferences between a witness and a legislator, the more informational questions the legislator will direct to the witness.

Of course, if members do not systematically use hearings to gather information (Huitt, 1958) then the null hypothesis could be true and both of these alternatives could be false.³

Next we note that if information does matter, we additionally expect that the dependence of falsifiable questions on preference distance under either Hypothesis 1a or 1b should be especially apparent among witnesses that have research-based expertise, when there is stronger policy information asymmetry between members and witnesses (Austen-Smith, 1993), but less apparent for non-experts.⁴

Hypothesis 2. The dependence of falsifiable questions on preference distance should be greatest among witnesses that have research-based expertise.

³Scholars may dispute whether *either* cheap talk or costly signaling models apply to lobbying in committee hearings. For example, some might argue that the presence of multiple senders or receivers in hearings creates different expectations (but see Battaglini et al., 2019; Lai et al., 2015, who show cheap talk expectations hold in such settings). We emphasize that scientifically, *our hypothesis test is predicated on the assumption that both alternatives (1a and 1b) are false*, and hence the correct skepticism is already built into the statistical test. And note too that identification in the statistical model does not depend on the motivation underlying the preference-distance hypothesis; as we explain in more detail below, the only assumption needed for recovering witness preferences is the generic assumption that preferences matter *in any way* for committee interactions.

⁴This expectation occurs under the assumption that witnesses' information acquisition is exogenous to the hearing (c.f. Diermeier and Feddersen, 2000). This assumption is plausible in that committees tend to call witnesses because of their existing expertise on the topic (Esterling, 2004), rather than because of a possibility that an invitation to testify would lead them to do additional (costly) research.

Finally, we note that any relationship between preference-distance and legislators’ falsifiable statements may not only be driven by the members’ information-seeking incentives but also can be a result of their non-strategic and non-informational incentives. For example, through homophily legislators might be attracted to witnesses who are sociologically similar irrespective of any informational considerations (Bauer et al., 1963). Alternatively, legislators may wish to grandstand by “grilling” witnesses with whom they disagree (Park, 2021). If either of these non-informational incentives are in play, then we may observe that not only legislators’ falsifiable sentences but also their non-falsifiable *opinion* and *anecdotal* sentences – those questions and statements that do not engage in policy epistemic discourse (Esterling, 2007) – will have a relationship with preference-distance and in a similar direction. Testing whether preference-distance matters for non-epistemic sentences in this way enables us to evaluate whether any observed preference dependence is primarily sociological or primarily informational. If preferences matter for all three types of sentences, that implies that the underlying mechanism is a sociological one; if they matter only for falsifiable sentences that implies that the legislators’ information-seeking incentives are the driving force for the relationship. Thus, comparing the preference-distance test across the three question types can serve as a placebo test to isolate the information-seeking effect in the naturalistic setting of committee hearings.

Hypothesis 3. Preference distance should matter for falsifiable sentences but not for opinion and anecdotal sentences.

Defining and Measuring Preferences in Hearings

To test these preference-distance hypotheses using data from a real-world legislature, the analyst must have a strategy to infer preferences for both legislators and outside agents. Congress scholars have long relied on legislators’ roll call voting to infer preferences for legislators using scaling methods such as IDEAL or DW-NOMINATE (Clinton, Jackman, and

Rivers 2004b; Poole and Rosenthal 1997). Roll-call scaling is of no help however in measuring the preferences of outside agents, such as lobbyists, policy experts and administrative officials, because they do not vote on legislation. Several alternative approaches exist to measure outside agents' preferences, all of which rely on an assumption that the preferences of both legislators and outside agents can be characterized by a single dimension. For example, Bonica (2013) estimates common space ideology scores from contribution-giving patterns; Barberá (2015) estimates the same from Twitter follower data; Crosson et al. (2020) and McKay (2008) use group-level preferences as if they were roll call votes to estimate groups' public positions.⁵

However, there is no *a priori* reason to measure the policy preferences of outside agents using the same dimension that measures legislator preferences. Fundamentally, the utility function each type of actor uses to evaluate policies is very different. Legislators' preferences tend to be defined over the implications of a legislative action on their reelection prospects, and hence preference measures inferred from roll calls are informed by partisanship or left-right ideology (Tausanovitch and Warshaw, 2017), which are the dominant heuristics that governs electoral politics (Hinich and Munger, 1994).

In contrast, outside agents are not elected, so they are not pressured by constituents, party officials or donors. Further, witnesses in committee hearings are often invited based on their expertise on the hearing's topic (Esterling, 2004). As Tetlock (1986) demonstrates, policy experts generally have elaborate policy knowledge and cognitive integrative complexity regarding many dimensions that govern policy considerations. As a result, they tend to evaluate policies in terms of analytical considerations regarding the placement of a trade-off along a possibility frontier, rather than relying on ideology as a heuristic, which in turn defines a second preference dimension.⁶

⁵The third approach does not measure preferences of individuals in organizations.

⁶To use a concrete example, if a restaurant patron is not a dietitian, they might choose between red wine and mineral water based on how it tastes with the meal. But if they

For example, in our application we focus on expert testimony regarding Medicare policy, which is an example of a complex policy where expert preferences are unlikely to be rigidly constrained by a single underlying, fixed left-right ideology dimension. To give a sense of substantive expertise required for health care hearings, a small number of the hearings include headline-grabbing topics such as coverage of prescription drugs, comprehensive health financing reform, and the solvency of the Medicare trust fund. But the majority of the topics were less visible, more technical issues such as prospective payment systems for health providers, competition and managed care, billing fraud, medical savings accounts, risk adjustment, coverage information for beneficiaries, prevention and disease management, telemedicine, long term care, billing relations between the VA and Medicare, and demonstrations involving military retirees and the Federal Employee Health Benefits Program.

Policy experts typically do not evaluate policies regarding these topics using a partisan or ideological heuristic. Instead, they understand that changes to Medicare, as a health coverage plan, generally imply moves along a cost-quality possibility frontier. Both liberal and conservative experts would prefer quality care at lower costs, since lower costs imply both a reduction in government spending and improvement in access to health care. As a result, the policy preferences of these outside agents typically cannot be determined by their own partisan or left-right ideology. Instead, experts will evaluate the merits of policy proposals, and form their preferences over proposals, based on their analytical understanding of the impact of the proposal on their specific policy-relevant commitments.

are a dietitian they might choose between red wine and mineral water based on expert-informed views of whether red wine is protective or harmful to health. In this way, a non-expert and an expert have different considerations that form their preferences over the same object, and hence preferences in this context are two-dimensional. At the same time, non-dietitians who prefer red wine will have preferences that are closer to dietitians who believe red wine is protective.

At the same time, the policy views of experts can matter for legislators. For example, program costs might be more relevant to conservative legislators and quality might be more relevant to liberals.

Thus, it is critical to properly locate the outside agents' preferences in the correct preference space to accurately test theoretical arguments regarding the interactions between these actors. The primary advantages of our proposed measurement method are twofold. First, statistically, our method helps to reduce measurement error that can occur when a two-dimensional space is artificially reduced to a single dimension. For example, in an extreme case where the preference dimensions of the outside agents and legislators are orthogonal, the one-dimensional measurement strategy would erroneously measure agent preferences with what are essentially random numbers, while our measurement conveys meaningful variations across agents reflected in the two-dimensional space. This measurement error in turn would bias parameter estimates to zero and produce false negatives when testing institutional hypotheses. Second, substantively, our method extracts additional information about the nature of the dimension that structures policy preferences among the outside agents, which is often of interest in itself.

The scholarship on ideology and preferences has certainly benefited from the methodological advances in single-dimensional measurements of political agents' latent preferences, given their simplicity and wide applicability. The trade-off in informational loss and potential measurement errors has received relatively less attention, however ([Jessee, 2016](#)). Our study highlights this understudied aspect of preference measurement strategies by relaxing the single-dimension constraint, and showcases what we might have missed under these simpler representations of the empirical world.

Statistical Model

We propose a statistical model that flexibly estimates witnesses' policy preferences in order to test our preference-distance hypotheses using data from hearings. Our model includes both a *measurement strategy* to recover outside agents' preferences, and an *identification strategy* to show that we are able to recover the parameters for our hypothesis tests. Our model requires three types of data: 1) DW-Nominate scores to measure legislator preferences, 2) data that construct a common space ideology measure such as survey responses or CF scores from Bonica (2013) in order to create a bridge between legislators' roll call preferences and witnesses' policy preferences, and 3) the count of legislators' questions or statements directed to each witnesses within a committee hearing.

Label legislators' policy-relevant preferences regarding legislation as L_l and agents' policy-relevant preferences regarding the same legislation as L_a . Within a given hearing, each legislator (indexed by j) directs some number of each type of question to each witness as an outside agent (indexed by i). In this context, the outcome O_{ij}^m is the count of sentences of type $m \in \{falsifiable, opinion, anecdotal\}$ within the ij^{th} member-witness dyad. We model the dyadic count outcomes as a function of the preference distance between legislator and agent using the equation set,

$$O_{ij}^m \sim \text{OverdispersedPoisson}(\widetilde{\lambda}_{ij}^m) \quad (1a)$$

$$\ln \widetilde{\lambda}_{ij}^m = \lambda_{ij}^m = \beta_0^m + \beta_1^m d(L_{l_j}, L_{a_i}) + \beta_2^m R_i + \beta_3^m d(L_{l_j}, L_{a_i}) R_i + \boldsymbol{\eta}_{ij}^m$$

$$L_{l_j} \sim \text{Normal}(\mu_{l_j}, \sigma^{L_l}) \quad (1b)$$

$$\mu_{l_j} = \alpha_0 + \alpha_1 \psi_{l_j}$$

$$L_{a_i} \sim \text{Normal}(\mu_{a_i}, \sigma^{L_a}) \quad (1c)$$

$$\mu_{a_i} = (\alpha_0 + \alpha_2) + (\alpha_1 + \alpha_3) \psi_{a_i}.$$

Here each count outcome is modeled in equation 1a with an overdispersed Poisson stochastic process with parameter $\widetilde{\lambda}_{ij}^m$.⁷ The term $d(L_{l_j}, L_{a_i})$ is a preference-distance function that

⁷As Skrondal and Rabe-Hesketh (2007) and Harrison (2014) show, the dyad-level random effects we include accommodate the added variance in overdispersed counts.

measures the distance in preferences between the j^{th} committee member and the i^{th} witness; we implement the distance function in two alternative ways, using a squared or linear distance, $d(L_{l_j}, L_{a_i}) = (L_{l_j} - L_{a_i})^2$ or $d(L_{l_j}, L_{a_i}) = |L_{l_j} - L_{a_i}|$. To complete the outcome model, R is an observed indicator variable that equals one if the witness comes from an organization that specializes in policy research, and equals zero otherwise.⁸ The parameter β_1^m tests the preference-distance hypothesis among witnesses that are not from research-based organizations and β_3^m tests whether preference distance matters differently for witnesses from research-based organizations. β_0^m and β_2^m are constants. Finally, $\boldsymbol{\eta}_{ij}^m$ collects the remaining parameters, covariates and random effects relevant to the dyad.

Equations 1b and 1c are the *bridging* equations that establish the functional relationship between legislator preferences L_l and agent preferences L_a . ψ is a bridging parameter used for identifying the model. Consider each of L_l , L_a and ψ in turn.

Congress scholars routinely take legislators' L_l preferences as indicated by their observed roll-call votes, and hence recovered correctly through well-established scaling procedures such as IDEAL (Clinton, Jackman, and Rivers, 2004a) or DW-NOMINATE (Poole and Rosenthal, 1991). Roll-call votes indicate legislators' office-induced or operational preferences (Burden, Caldeira, and Groseclose, 2000; Rhode, 1991), preferences which summarize the full vector of relevant influences on each legislator including party, constituency, interest group and donor pressure along with her personal beliefs. Furthermore, the roll-call revealed preferences capture the public reputation that members of Congress cultivate for electoral purposes (Cox and Poole, 2002; Dougan and Munger, 1989; Poole and Rosenthal, 1997). For these reasons it is legislators' operational preferences measured in roll-call vote scaling that are relevant to most institutional tests (Burden et al. 2000; but see Clinton 2012) rather than legislators' underlying personal ideology.⁹

⁸Research organizations are universities, foundations and non-partisan think tanks.

⁹Supplementary Materials (SM) section A.5 shows that members' survey-based personal ideology scores and their roll-call voting scores are correlated but not identical.

The next statistical task is to measure outside agents’ preferences in a comparable legislative policy preference space L_a in order to establish the distance $d(L_{l_j}, L_{a_i})$ between legislator and agent. Since agents are not legislators, their occupation neither requires nor enables them to vote on legislation, and so roll-call preferences do not and indeed cannot exist for them. In addition, while legislators vote on many bills, we typically only observe individual agents take a position on a single bill before the committee, if they take any position at all, and often witnesses’ support or opposition is to technical provisions in the legislation. As a result, the legislatively-relevant preferences L_a that govern interaction in a hearing are missing data for all outside agents.

To impute the missing agent preferences, one can exploit a data source that establishes a common space ψ for legislator and agent preferences, such as their left-right ideology, and then use the *bridging functions* 1b and 1c to map the common preference space ψ to both legislator preferences L_l and agent preferences L_a (Jessee, 2016; Shor et al., 2010). If the parameters of both bridging functions are identified, the analyst can then use the estimated parameters in the bridging function 1c and the common space measure $\widehat{\psi_{a_i}}$ to impute the missing agent preferences – that is, to measure each L_{a_i} .

This bridging strategy takes it as a reasonable *a priori* supposition that an individual’s own left-right ideology will be related to their preferences over legislation, both for legislators and for agents. Since the common space preference score ψ is a scale that measures the individual’s left-right ideology, it must be estimated. In the application we use survey items and an IRT model to measure ψ . Other possible bridging data sources include Bonica (2013) estimates of common space ideology scores from contribution-giving patterns and Barberá (2015) estimates from Twitter follower data. We use Bonica’s CF scores to replicate the results we find using the survey data in the SM (section A.9). However, we report the results from the survey items in the main text since the survey was core to our study design, and since the survey items are designed and validated to measure ideology and load on a single dimension, while the construct validity of these other common space

measures is less clear (Tausanovitch and Warshaw, 2017).

Since we take L_l as observed via roll call scaling and take ψ as estimated using the survey items that measure legislators’ left-right ideology, the parameters α_0 and α_1 in equation 1b are identified as in ordinary regression and provide a mapping from the common space ideology scale ψ to the legislators’ roll-call preference space L_l . We follow convention and use DW-NOMINATE scores to measure L_l , and hence the relationship between ψ and L_l is a simple linear regression.

Next consider the bridge to agent preferences in equation 1c. The parameter α_2 allows the agent preference dimension to have a different intercept, which we call a “shift,” relative to the legislator mapping recovered in equation 1b. Likewise the parameter α_3 allows the agent preference dimension to have a different slope, which call a “rotation.” This flexibly places the preferences of legislators and agents in a two-dimensional space. In the special case where α_2 and α_3 are both equal to zero, then L_a and L_l describe the same line, leaving only a single dimension to describe both legislator and agent preferences as a special case. In the case where $\alpha_3 = -\alpha_1$ (and if the error terms in equations 1b and 1c are independent), then L_a is orthogonal to both L_l and to ψ ; in any other case L_a and L_l are correlated in two dimensions by their common relationship with ψ . Since L_a is missing for all agents, however, the $\alpha_a = [\alpha_2, \alpha_3]'$ parameters are not identified in equation 1c, which is the fundamental problem of bridging (see Jessee, 2016, 1110, equation 2). Thus, one needs an identification strategy in order to make progress.

Two Competing Identification Strategies

We consider two approaches to identification.

Single Equation Constrained-Regression. To solve this identification problem, Jessee (2016) proposes a regression-based approach that assumes the agents and legislators share identical parameters in the bridging functions (e.g., as in Crosson et al., 2020). Under

this approach, one imputes the missing agent preferences by setting the unidentified parameters in equation 1c to zero ($[\alpha_2, \alpha_3]' \equiv \mathbf{0}$), and setting $\sigma^{L_a} = \sigma^{L_l}$ and the implied covariance $\sigma^{L_a, L_l} = 0$. $\widehat{L}_{a_i}$ can then be imputed using the point estimates from the legislator bridging equation 1b ($[\widehat{\alpha}_0, \widehat{\alpha}_1]'$) along with the estimates for agents' common space preferences ($\widehat{\psi}_{a_i}$) and the linearity assumption for the mapping from equation 1c.

This solution imposes the *unidimensional assumption* that legislator and agent preferences have an identical functional relationship to ψ , which is the special case of identical lines. Conceptually, since this identification strategy relies exclusively on the parameters that map from ψ to L_l , the imputation under this constraint is the counterfactual of what agents' preferences would have been, if they instead had been legislators.

Unconstrained Simultaneous Equations Model for Flexibly Estimating Witness Policy Preferences. Jessee (2016) advanced the preference measurement literature by demonstrating the fundamental problem of bridging across different types of actors. We build on these insights to offer a flexible solution to this identification problem by leveraging legislators' observed question-asking behavior, using the jointly-estimated simultaneous equations model of equation set 1. Supplementary Materials (SM) section A.1 gives a formal proof of the flexible model's identification and SM section A.2 gives a computational proof of identification.

In the formal proof, we show that the model contains enough information to estimate an agent preference scale that can shift and rotate relative to the legislator preference scale, but only when the outcome equation is paired with the bridging equations in the set of simultaneous equations in equations 1a, 1b and 1c. That is, β_1^m , α_2 and α_3 , along with L_{a_i} for every i , are each identified but only in the simultaneous equations (the remaining parameters are identified under normal regression assumptions). Given this system of equations, we show an additional data requirement that there must be at least two committee members directing questions to at least two agents.¹⁰

¹⁰It is common for identification to have such minimum data requirements. For example,

Our proof for identification relies on several results. First, we prove that a unique β_1 is recovered from the system of equations without reference to the L_{a_i} , α_2 or α_3 parameters, provided there are at least two witnesses and two legislators for a minimum of four dyads and the equations are estimated simultaneously. To show this, we demonstrate that when we meet the data requirements, we can rewrite equation 1a as a single equation with β_1 as a single unknown and hence recoverable only from the data. Second, we show that the shift and rotation parameters, α_2 and α_3 , are each unique within the system of equations given β_1 and terms that are identified in the data; and since we can recover β_1 from the data, then we also can recover the shift and rotation parameters. Finally, we show that each L_{a_i} is also unique given β_1 . Thus the system of equations is identified. We emphasize that the identification strategy does not depend on restrictive priors in the statistical model.

The model has a counter-intuition that we are using legislators' patterns of question-asking in committee hearings to infer witnesses' preferences *and* to test the preference-distance hypothesis, which on the surface seems circular. Equation 9 of the proof demonstrates, however, that the parameter that tests the preference-distance hypothesis, β_1 , is recovered only with reference to the preferences of at least two different legislators and the expected count of questions these legislators pose to at least two different witnesses, but does not require knowledge of witnesses' preferences L_a . The legislator preferences and question counts are known from the data and hence the model has no circularity.¹¹

The identification proof demonstrates that the sign of β_1 is not relevant for identification. It makes no difference to the model if the question rates increase or decrease as preferences become more distant, and indeed the model enables a test between the two

parameters of a line require at least two observations.

¹¹Equation 9 is identified using data from multiple dyads, but are expectations or constants and hence do not imply stochastic dependence across observations in the data. Spatial dependence across dyads is a statistical issue unrelated to identification.

competing expectations in hypothesis 1a and 1b. Likewise, identification does not depend on the underlying motivation for the preference-distance hypothesis; it is irrelevant if one believes signaling is or is not the underlying mechanism driving the pattern of questions. However, if $\beta_1 = 0$, that is, if preference distance has no relevance to behavior in the committee hearings, then the model results in a divide by zero error and is not identified. In practice, in the unlikely case that the estimated $\hat{\beta}_1$ is exactly and identically zero, the model will fail to converge and return no results. Fortunately the model is identified even when the null hypothesis is accepted; only in the very special case of a point estimate of (machine precision) zero is the model not identified.

Geometrically, estimating the parameters in equation 1c allows the posterior agent preference dimension L_a to change basis away from L_l by accommodating a rotation. We define as *constrained-regression* agent preferences the L_a^0 that are imputed from the unidimensional constraint that sets $\alpha_2 = \alpha_3 = 0$, and the flexible, *unconstrained* preferences L_a^1 are imputed from the simultaneous equations model that estimates α_2 and α_3 . The rotation that results from α_3 (which is a regression coefficient) can be described by the angle θ (measured in radians) governing the direction of the relationship through a Cartesian coordinate space, and one can retrieve θ post-estimation via the cosine rule and the vectors of constrained and unconstrained preferences (Binmore and Davies, 2001, 18),

$$\theta = \cos^{-1} \frac{\langle \mathbf{L}_a^0, \mathbf{L}_a^1 \rangle}{\|\mathbf{L}_a^0\| \|\mathbf{L}_a^1\|}. \quad (2)$$

Setting aside any shift between the two lines, the angle $\theta = 0$ is the parallel case; $\theta = \pi/2$ is orthogonal; and $0 < \theta < \pi/2$ is oblique.¹² The constrained-regression method forces the rotation to always and often implausibly equal the parallel case with $\theta \equiv 0$.

¹²An obtuse rotation is also possible. Below we show how to optionally impose soft constraints on the model priors if there are substantive reasons to ensure a posterior rotation does not exceed the orthogonal direction.

Application to Medicare Hearings

We use the model in equation set 1 to test for the relationship between preference distance and questioning in congressional committee hearings on the Medicare program. To select the sample, we randomly drew 29 hearings from the universe of all hearings on the Medicare program (Campbell, 2003; Patashnik and Zelizer, 2001) that were held between 2000 and 2003 across 12 different congressional committees and subcommittees.

Behavioral Outcomes (O_{ij}^m). Esterling (2007) creates rules to code sentences in transcripts of committee hearings into the three mutually-exclusive sentence types: falsifiable, opinion and anecdotal (see the SM section A.3 for details). We measure outcomes by counting the number of each of these three types of sentences that legislators make within each legislator-witness dyad. That is, we concatenated each legislator’s statements directed to each witness, and then counted the number of occurrences of each type of sentence. Table 1 shows the descriptives for the 669 dyads in the sample. In all, across all of the 29 hearings there are 67 witnesses and 87 committee members.¹³

Table 1: Member-Lobbyist Dyadic Outcome Data

	Mean	SD	N
Falsifiable Count	1.2	3.1	669
Opinion Count	0.5	1.6	669
Anecdotal Count	0.4	1.7	669

Note in Table 1 that under our coding, at these hearings members are most likely to make falsifiable inquiries. Most members ask zero questions to most witnesses, and so these counts have low means and high standard deviations. We accommodate this over dispersion in the count variables in the statistical model by including dyad-level random

¹³In the sample we exclude all committee members who do not speak to any of the witnesses at the given hearing and so are likely not to have been present.

effects (Harrison, 2014; Skrondal and Rabe-Hesketh, 2007).

Legislator Preferences (L_l). We use first dimension DW-NOMINATE scores (Lewis, Poole, Rosenthal, Boche, Rudkin, and Sonnet, 2018; Poole and Rosenthal, 1991) from the 108th Congress to measure legislators’ roll call preferences L_l .¹⁴ In our sample of 87 legislators, these scores range from -0.83 to 0.73 with the mean at 0.17 ($sd = 0.439$).

Research-based Organization Indicator (R). The model allows the intercept and the effect of distance to differ between research-based organizations (witnesses from universities, foundations and non-partisan think tanks) and non-research organizations. Under this coding, 37 percent of the sample is research-based.

Common Space Ideology Measures (ψ). To estimate a personal ideology scale ψ that is the core component of the bridging equation, we administered a survey containing a battery of ideology items to the witnesses who appeared at the hearings in the data set, and to *former members of Congress*, who are not in the hearings sample. That is, we use survey responses from former members of Congress who did not attend the sampled hearings rather than the committee members from the sampled hearings, most of whom at the time of the data collection were current incumbents. Since former members’ DW-NOMINATE scores are in the same roll-call preference space L_l as the committee members in the sample, it is not necessary to use the same legislators in the bridging component as in the outcome component of the model; it is the same preference dimension for both.

Administering the survey to former members rather than current members is preferable for two reasons. First, while in office many members have a policy not to respond to

¹⁴Available on voteview.com. The results should be similar using roll-call scales from Bailey (2007) or Clinton et al. (2004a) (see Carroll, Lewis, Lo, Poole, and Rosenthal, 2009). Since we focus on Medicare, we show in SM section A.4 that restricting the scaling to include only health care roll call votes would yield identical results.

academic surveys, and even those who respond would likely assign staff to complete and return the survey which would introduce measurement error in the measure of personal ideology ψ . Former members are either retirees or they are employed where it is unlikely that staff support would fill out surveys relevant to their past legislative work.¹⁵ Second, like the witnesses, former members are typically private citizens, not elected officials, and so former members are more likely to fill out the responses based on their own, personal ideology rather than on an office-induced preference that is conditioned by pressure from constituents, party, donors or groups. This in turn would undermine bridging equation 1b, which is a mapping from legislators' personal ideology ψ to their office-induced preference L_l . We describe the sample of former members in SM section A.5.

To measure the common space scale ψ we administered the following survey items to both a set of former members of Congress and to the witnesses in the sample. These questions are validated to measure each individual's left-right ideology.¹⁶

- **[Markets]** The protection of consumer interests is best insured by a vigorous competition among sellers rather than by federal government regulation on behalf of consumers.
- **[Companies]** There is too much power concentrated in the hands of a few large companies for the good of the country.
- **[HelpPoor]** One of the most important roles of government is to help those who cannot help themselves, such as the poor, the disadvantaged, and the unemployed.
- **[Access]** All Americans should have access to quality medical care regardless of ability to pay.
- **[Incomes]** The differences in income among occupations should be reduced.

¹⁵Further, many of the responses had handwritten notes and comments from the responding former member him or herself.

¹⁶These questions come from the study [Heinz, Laumann, Nelson, and Salisbury \(1999\)](#), response sheet P, items a, d, e, i, n. each measured on a five point scale (strongly agree = 1 to strongly disagree = 5). In the sample, these items load on a single factor (the first eigenvalue 2.12, the second 0.37). Only the *Markets* indicator loads negatively.

The labels in square brackets were not included in the survey question wording. The descriptives of the survey responses are in table 2.

Table 2: Ideology Indicator Descriptives for Former Members and Witnesses

	Mean	SD	N
Markets	2.9	1.3	142
Companies	2.9	1.2	139
HelpPoor	1.7	0.7	144
Access	1.7	0.8	144
Incomes	3.4	1.3	142
FMC DWNominate	-0.1	0.3	77

We estimate ψ via an IRT model; SM section A.6 shows the full model and we suppress the IRT model in equations 1b and 1c to simplify the presentation.

To complete the bridging data set, we merged in the most recent DW-NOMINATE scores for each former member, that is, the score from the Congress just prior to the member separating from the institution. In this rectangular dataset, we have responses to the ideology survey questions from both former members and the witnesses, but the first dimension DW-NOMINATE scores are missing for every witness.

Statistical Model and Estimation. We estimate both the single equation “constrained-regression” model and the flexible “simultaneous equations” model using Bayesian MCMC estimation. The details are in SM section A.6. We include random effects for the legislator, the witness, and the dyad in both models.

To complete each Bayesian model, we set the priors for the discrimination parameters in the ψ IRT model as distributed Uniform(0, 10) in order to ensure the correct (known) direction labeling in the factor model (and constraining the parameter for the Markets item to be negative). The σ_{L_i} prior is Uniform(0,100). ψ and each η have a standard normal prior. All other priors are unrestricted, normally distributed with mean zero and standard deviation 1,000. Other than setting the direction of the discrimination

parameters in the IRT model, identification of the model does not depend on the priors.

Simulation. We conducted a computational simulation to demonstrate identification for the simultaneous equations model and show that the model recovers benchmark parameters and replicates the data well under posterior predictive checks. The results are presented in SM section A.2. The simulation serves as an additional proof of identification, confirming the analytical proof, in that model convergence and the recovery of unique and correct benchmark parameter estimates in an MCMC model are sufficient to demonstrate both theoretical and empirical model identification (Jackman, 2000).

Results

We first discuss the results that use the constrained-regression approach that restricts agent and legislator preferences to a single dimension, that is, relying on $\widehat{L}_a^0$ to test the preference-distance hypothesis. We then discuss results from our proposed model that relaxes this constraint and uses instead the preference estimates $\widehat{L}_a^1$ from the flexible simultaneous equations model.¹⁷

Results from the Constrained-Regression Model. In the constrained-regression identification strategy, agent preferences in equation 1c are imputed using ψ and the bridging parameters estimated in equation 1b, and by setting $\alpha_2 = \alpha_3 = 0$. Overall, the results across the specifications show that none of the outcome hypotheses appear to be confirmed using this measurement strategy – seeming to imply that committee members do not condition their interactions on distance in the preference space, where “distance” is with respect to the constrained-regression estimates for agent preferences $\widehat{L}_a^0$. Under

¹⁷In SM section A.7, we report results across all model specifications, Widely Applicable Information Criterion (WAIC) values (Vehtari, Gelman, and Gabry, 2017), and posterior predictive checks.

this unidimensional assumption, the effects are estimated as small and not significant, and exhibit considerable variability across specifications.

Figure 1: Relationship between preference distance and count outcomes, using the constrained-regression approach (the absolute value of legislators' roll-call preferences L_l minus agents' regression-based preference estimates L_a^0), indicating a lack of construct validity under the unidimensional assumption. Confidence bands indicate 95 percent conditional credible intervals. $N_{dyads} = 669$, $N_{witnesses} = 67$, $N_{members} = 87$.

We present the results of the simplest of these models in figure 1, the absolute value distance function with no party covariate in the bridging equation. Here we set the random effects to their sample means. In this figure, the columns correspond to falsifiable, opinion and anecdotal questions, respectively, and the rows correspond to witnesses who represent research-focused (top) and non-research (bottom) organizations. The dark line in each frame indicates the conditional point estimate for each subgroup and each outcome, and the light shaded areas indicate 95 percent conditional credibility intervals. Note that when placing the unidimensional constraint on preferences, the analyst would need to conclude that the preference-distance hypotheses developed from strategic information transmission (as well as sociological homophily) are false under this implementation – that is, using

this method, there appears to be no significant relationship between preference distance and the count of any of the three types of sentences, for each type of witness.

Results from the Flexible Simultaneous Equations Model. In the flexible simultaneous equations model, the witness-specific bridging parameters α_2 and α_3 are identified, which permits a flexible shift and rotation of the witness preference space L_a^1 away from the legislator roll-call preference space L_l . The results show a remarkable robustness in the outcome equation parameters across all of the specifications, where the coefficients testing the hypotheses are large, statistically significant, and stable across specifications. In addition, the WAIC statistics show lower values compared to the constrained-regression models, indicating the added complexity from the unconstrained parameters improves expected out of sample prediction (Vehtari et al., 2017). SM section A.7 reports the full set of results across multiple specifications for the model.

First consider the relationship between the estimated witness preferences from the simultaneous equations model, which yields unconstrained estimates for the preferences L_a^1 , and those estimated for the constrained-regression case L_a^0 . Figure 2 plots the relationship. In this figure, each circle represents a witness; the blue dots indicate witnesses who come from Democrat constituency groups, the red from Republican (see the SM section A.7.2 for coding rules). The size of the circle is proportional to the variance of the posterior preference estimate. As figure 2 demonstrates, the rotation is virtually orthogonal ($\theta = \frac{\pi}{2.47}$), in direct contrast to the assumption motivating the constrained-regression approach that the two preference spaces are unidimensional. If the true agent preference space is orthogonal to legislators’ roll-call preference space, then clearly adding the unidimensional constraint is inappropriate, and the result is similar to “measuring” agents’ preferences using the equivalent of a random number generator. Note as well, though, that the (red dot) agents we coded as in the Republican constituency tend to locate in the top-right quadrant, that is, on the conservative sides of both dimensions, which shows

the relative orientation of both scales is correct.

Figure 2: The relationship between agents’ constrained-regression preference estimates L_a^0 and unconstrained, structural equation model preference estimates L_a^1 . Blue dots indicate classified as in the Democratic party constituency, and red dots Republican. Note the estimated rotation is almost fully orthogonal.

SM section A.7 shows that the precision of structural parameter estimates as well as the imputed agent preferences are higher in the flexible model relative to the constrained model, and posterior predictive checks of the outcome data (Gabry, Simpson, Vehtari, Betancourt, and Gelman, 2019) lend strong support to the flexible model.

To contrast the two estimation approaches, figure 3 shows the results of the outcome equation parameter estimates for the flexible simultaneous equations model, and is the same set up as figure 1 above. These results are from a model with a soft constraint on the priors that prevents the rotation θ from exceeding the orthogonal case, although the results from the unconstrained case where in some specifications the angle of rotation is mildly obtuse yield nearly identical results (see SM section A.7). Here one can see that, in contrast to the results in figure 1, there is a clear negative relationship between preference

Effects of Preference Distance - Flexible Model

Figure 3: Relationship between preference distance and count outcomes, using the simultaneous equation model estimates (the absolute value of legislators’ roll-call preferences L_l minus agents’ posterior preference estimates $\widehat{L}_a^1$), indicating good construct validity in contrast to the constrained results of the previous figure. Confidence bands indicate 95 percent conditional credible intervals. $N_{dyads} = 669$, $N_{witnesses} = 67$, $N_{members} = 87$.

distance and the number of sentences a witness attracts in the committee hearings. The most obvious and striking result is that committee members condition all questions, no matter the type, on preference distance. This pattern specifically for falsifiable statements is consistent with Hypothesis 1a but is inconsistent with Hypothesis 1b.

Recall there are two possible reasons that preferences might matter within the hearing. First, members might simply have a sociological aversion to interacting with witnesses who are dissimilar (Bauer et al., 1963). This is a common phenomenon in social interactions since people are typically more comfortable interacting with those who share similar attitudes and traits. Second, members might tend to direct questions to witnesses whose statements are most informative in sense of cheap talk models of strategic information transmission (Austen-Smith, 1992, 1993). The results do not directly adjudicate between these two possibilities. That said, there is some suggestive evidence from comparisons

across the frames of figure 3 that the members are engaging in information seeking in the hearings. First note that members condition their falsifiable sentences on the type of organization, consistent with Hypothesis 2. This pattern is consistent with information-seeking behavior in that there is a greater informational asymmetry between legislators and witnesses from research organizations (Crawford and Sobel, 1982) and the asymmetry prompts a greater responsiveness to preference distance under the assumption that information acquisition is exogenous.

Second, note that members are more responsive to preference distance for falsifiable sentences than they are for opinion- and anecdotal-related sentences, and that is true for both types of groups. This pattern supports Hypothesis 3. These latter contrasts serve as a type of placebo test of information theory, showing the preferences matter most for falsifiable and epistemic discourse at the hearings.

Replication Using CF Scores. In SM section A.9, we report the results of a replication for figures 1 and 3, but using the CF scores of Bonica (2013) in place of our survey items to measure the ideological common space ψ . The results replicate exactly, except with slightly higher uncertainty estimates given the inherent measurement error present in the CF score point estimates. The results demonstrate that one can use off-the-shelf CF scores in place of a validated survey to recover witness preferences using our approach. That the results are nearly identical is no surprise given that the common space measure is only used for identification in the model and plays no substantive role. The SM also demonstrates, however, that using the CF scores directly as preference measures leads to null results identical to figure 1, which also is no surprise given these are unidimensional preference measures.

Describing the Posterior Preference Dimension. Since the witness preference dimension that we recover is orthogonal to their personal ideology, it is important to understand the scale and why it makes substantive sense for the witnesses' policy preferences

to be structured in this way.¹⁸ In general, as Tetlock (1986) notes, policy experts tend to view policies through an analytical lens, rather than through ideology as a heuristic; policy experts are more likely to understand the real-world impacts of policy interventions as well as the trade offs involved and so condition their preferences on this knowledge. To give an example, on the topic of managed care, the witnesses that were the most extreme on each side of the estimated witness preference dimension $\widehat{L}_a$ were both academics. The witness closest to liberals was a professor of public health who testified about the importance of providing better coverage through the Medicare+Choice program. The one closest to conservatives was a professor of health economics who testified about the need to harness market incentives in managed care to promote cost savings.

That ideology does not structure witnesses’ preferences over a complex policy such as Medicare should therefore be no surprise. The nature of the dimension that underwrites witnesses’ policy preferences over Medicare policy is of substantive interest, and our approach is able to identify this preference dimension. We use text analysis to systematically understand the content of the witness preference dimension. To do this, we conduct a word frequency analysis of the written testimony¹⁹ separately for witnesses who have a high preference score L_a^1 and those with a low preference score, stratified by topic.²⁰ The resulting word clouds are in figure 4. Notice that the witnesses that are in closer proximity to conservatives focus more on costs, premiums and coverage, and those closer to liberals focus more on care, plan requirements and beneficiaries.

¹⁸In SM section A.7, we rule out possible alternative descriptions of the scale, such as if the scale had measured only policy expertise or topical interests.

¹⁹We stemmed, removed stop words, and removed common words such as Medicare, physician, plan, etc.; see SM section A.8 for more detail on the text analysis.

²⁰We use Congressional Research Service topic classifications to assign hearings to topics. We must stratify by topic because, while the dimension is not confounded by topic, the word distributions will by necessity be topic-specific.

revealed by legislators’ behavior within the contextually-situated interaction of a committee hearing. We demonstrate how to estimate agents’ preferences using an equation set, pairing an outcome equation with bridging equations in a system of equations that identifies the agent preference shift and rotation parameters. In contrast, the constrained-regression approach imputes the missing agent preferences using the assumption that agents’ preferences are confined to the legislative roll-call preference space. Conceptually the constrained preferences are unlikely to match the preferences as they were operative in the interaction that is embedded within an institution, and statistically the constraint introduces measurement error in the behavioral hypothesis tests.

The fundamental problem of recovering the preferences of outside agents applies to nearly all legislatures, and indeed much cross-institutional research, in any application where the researcher seeks to model the interaction between actors that come from different institutions (Jessee, 2016). We show that outside agent preferences can be recovered from text data publicly available at hearings combined with a survey that only needs to contain five questions to construct the common space; we also show the results replicate using off-the-shelf common space estimates from Bonica (2013). The flexible simultaneous equation method thus should generalize to other institutional interactions and can be used to explore comparative statics in other settings in future research.

Data Availability Statement. The replication materials can be found at: [blinded]

Supplementary Material. Supplementary material are attached.

Competing Interests. The authors declare no competing interests.

Research with Human Subjects. The human subjects protocol for this study was approved by [blinded]

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Supplementary Material for

Are Legislators Informed by Like-Minded Experts? Testing the
Preference-Distance Hypothesis Using Observational Data

November 3, 2022

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A Supplementary Material

This SM provides technical detail that space limitations do not allow in the main text. Throughout the SM, to reduce clutter in the figures, we refer to the simultaneous equations model as the “flexible” model, and contrast it with the “constrained” model that reduces all preferences to a single dimension.

A.1 Formal Proof of Identification

Because agent preferences are missing for all agents, we must have an identification strategy to impute the missing data. To show the identification strategy for our flexible model, without loss of generality we simplify the problem by setting $m = 1$, and ignore quantities that are either observed or identified by the structure of the data: $\{R, \beta_2, \beta_3, \boldsymbol{\eta}\}$, and set $\sigma^{L_a} = \sigma^{L_i}$ and assume the implied covariance is zero.

First consider what happens if one tries to impute an agent’s preference based on a single dyad ($i = 1, j = 1$), where we only observe legislator preference L_{l_1} and outcome O_{11} . To see if the preference estimate L_{a_1} that we recover from equation set 1 is unique from information in this single dyad, assume a quadratic distance function, take the logged expectation of the outcome equation 1a, and then rearrange as

$$\frac{\lambda_{11} - \beta_0}{\beta_1} = L_{a_1}^2 - 2L_{a_1}L_{l_1} + L_{l_1}^2. \quad (3)$$

Setting $L_{l_1} = 0$ shows

$$L_{a_1} = \pm \sqrt{\frac{\lambda_{11} - \beta_0}{\beta_1}} \quad (4)$$

which is not unique.²¹

Now add a second legislator with preference L_{l_2} to create a second dyad ($i = 1, j = 2$). Dividing the expectation of the outcome equation of the first dyad by that of the second

²¹This interim result requires $\beta_1 \neq 0$ and $\lambda_{11} > \beta_0$. Note that $\lambda_{ij} = \ln E(O_{ij}) = \ln O_{ij}$.

dyad and taking logs yields:

$$\ln \frac{E(O_{11})}{E(O_{12})} = \lambda_{11} - \lambda_{12} = \beta_1 [(L_{l_1}^2 - L_{l_2}^2) - 2L_{a_1}(L_{l_1} - L_{l_2})]. \quad (5)$$

Solving for L_{a_i} shows the result is unique,

$$L_{a_1} = \left[\frac{L_{l_1} + L_{l_2}}{2} - \frac{\lambda_{11} - \lambda_{12}}{2\beta_1(L_{l_1} - L_{l_2})} \right]. \quad (6)$$

Equation 6 shows that a pair of legislators is required for L_{a_1} to be unique, and the witness preference L_{a_1} can be recovered by the observed questioning behavior of two legislators at the hearing (λ_{11} and λ_{12}) and the legislators' preferences (L_{l_1} and L_{l_2}). This is only an interim result, however; each L_{a_i} can be recovered only if we can show β_1 is itself identified in the system of equations, which we turn to next.

While the solution for L_{a_1} is unique given β_1 and the data, we know from bridging equation 1c that the dimension that defines $E(L_a)$ must be able to shift and rotate from L_l via the parameters α_2 and α_3 , and hence L_a is also defined by the bridging equation 1c. $\widehat{\psi_{a_1}}$ is recovered from the IRT model and α_0 and α_1 are recovered from regression equation 1b. Hence, each of the quantities $\{\psi, \alpha_0, \alpha_1, L_l, \lambda\}$ is identified with the data. Setting the right hand side of equation 6 equal to the right hand side of equation 1c yields one equation but three unknowns: $\beta_1, \alpha_2, \alpha_3$. And so the model is still not identified with only two dyads.

Next, add a second second witness that receives questions from the same two legislators to create two more dyads, $(i = 2, j = 1)$ and $(i = 2, j = 2)$ with question rates λ_{21} and λ_{22} . To simplify the expression without loss of generality, set $\psi_{a_2} = 0$. Adding the second dyad adds one additional equation in the form of equation 6 but adds no new parameters under our simplifications. Using this equation pair and equation 1c we solve for both α_2

and α_3 , each as a reduced form function of β_1 and the quantities identified in the data:

$$\left[\frac{L_{l_1} + L_{l_2}}{2} - \frac{\lambda_{21} - \lambda_{22}}{2\beta_1(L_{l_1} - L_{l_2})} \right] - \alpha_0 = \alpha_2, \quad (7a)$$

$$\frac{(\lambda_{21} - \lambda_{22}) - (\lambda_{11} - \lambda_{12})}{-2\beta_1(L_{l_1} - L_{l_2})(\psi_{a_1})} - \alpha_1 = \alpha_3. \quad (7b)$$

Thus when adding a second witness, the unknowns α_2 and α_3 are each a function of identified quantities and β_1 , so knowing β_1 means we also learn α_2 and α_3 . In addition, recall that 6 shows if we know β_1 we also learn each L_{a_i} . Fortunately, β_1 can be recovered from the outcome equation 1a without relying on L_{a_i} , α_2 or α_3 because $(L_{l_i} - L_{a_i})^2$ is itself implicitly a nonlinear function only of the quantities that are identified with the data and β_1 . To show this, write the logged expectation of the outcome equation using the first dyad ($i = 1, j = 1$)

$$\lambda_{11} = \beta_0 + \beta_1(L_{l_1}^2 - 2L_{a_1}L_{l_1} + L_{a_1}^2), \quad (8)$$

then plug the results of equations 7a and 7b into 1c, and then substitute that expanded term for the expectation of L_{a_1} into equation 8, which yields

$$\lambda_{11} = \beta_0^* + \beta_1 \left[L_{l_1}^2 - L_{l_1}L_{l_2} + \frac{(L_{l_1} + L_{l_2})^2}{4} \right] + \frac{1}{\beta_1} \left[\frac{(\lambda_{11} - \lambda_{22})^2}{4(L_{l_1} - L_{l_2})^2} \right] \quad (9)$$

where β_0^* includes all terms that are constant.²² Equation 9 is a function only of quantities identified in the data and β_1 , and hence is one equation with one unknown.²³ Equation 9 can be rewritten as a quadratic function by subtracting λ_{11} from both sides and multi-

²² β_0 itself is recovered as a regression parameter in the statistical model.

²³The quantities on the right-hand side of equation 9 are expectations or constants, and hence do not imply stochastic dependence across observations in the data. Spatial dependence across dyads is a statistical issue unrelated to identification.

plying through by β_1 , and hence there are up to two real number solutions for β_1 .²⁴ As a final step, one can use a principled decision rule to select among the possible solutions, such as choosing the solution that maximizes the probability of observing O_{11} in equation 1. Hence, β_1 can be recovered from the data, and as we show above, the remaining parameters can be recovered given β_1 . As a result, the simultaneous equations model is identified provided the minimum data requirements are met.

A.2 Simulation to Demonstrate Model Identification

Here we offer a simulation to demonstrate identification of our flexible simultaneous equations model that allows agent preferences to shift and rotate relative to legislator preferences (e.g., measured in DW-NOMINATE), and to evaluate the bias and efficiency properties of the flexible simultaneous equations model when compared to the constrained-regression model that does not permit shifts or rotation. The simulation examines identification, bias and efficiency for the model structural parameters (that is, the model coefficients) as well as for the ideal point estimates of agents, under both approaches.

As we describe in the text, the flexible simultaneous equations model is composed of two submodels, a bridging component and an outcome component. We reproduce the system here as equations 11 and 10, except for transparency in the simulation we use a normal stochastic component rather than a Poisson. Note that the identification in the text does not depend in any way on non-linearities in the stochastic component of the outcome equation, so this simplification is of no consequence for the demonstration.

²⁴Estimation only considers real number solutions, so any non-real solutions for β_1 can be ignored. Identification fails in the unlikely case when there are only non-real solutions, but this would be a failure of empirical identification, not theoretical identification.

Outcome Equation

$$\left. \begin{aligned} O_k &\sim \text{Normal}(\mu_k, 1) \\ \mu_k &= \beta_0 + \beta_1 d(L_{l_j}, L_{a_i}) + \boldsymbol{\eta}_k + \epsilon_k \end{aligned} \right\} K_{i-1} \leq k \leq K_i, \text{ where } K_i - K_{i-1} = N_i, \quad (10)$$

Bridging Equation

$$L_{l_j} = \alpha_0 + \alpha_1 \psi_{l_j} + \epsilon_j^{L_l}, \quad (11a)$$

$$L_{a_i} = (\alpha_0 + \alpha_2) + (\alpha_1 + \alpha_3) \psi_{a_i} + \epsilon_i^{L_a} \quad (11b)$$

where i indexes agents, j indexes legislators, and k indexes legislator-agent dyads.

For simplicity in the simulation, we set $\alpha_0 = \beta_0 = 0$ and $\boldsymbol{\eta}_k = \mathbf{0}$ for all i, j, k in the data generating process and omit all random effects and coefficients from the simulation's statistical model, which are not relevant for considerations of identification. In the bridging equation 11a we set the legislator-specific transformation parameter $\alpha_1 = 1$, which is the parameter that governs the relationship between the common space ideology scale ψ and preferences L_l among legislators. To generate agent preferences, the simulation considers three cases: parallel preference dimensions for agent and legislator ($\theta = 0$), an oblique rotation ($\theta = \frac{\pi}{4}$) and an orthogonal rotation ($\theta = \frac{\pi}{2}$). The agent-specific transformation parameter α_3 in equation 11b governs rotation in the relationship between ψ and agent preferences L_a . To implement the three cases, we vary the amount of rotation by setting $\alpha_3 = 0$ for the parallel case, $\alpha_3 = -0.5$ for the oblique case, and $\alpha_3 = -1$ for the orthogonal case. In all cases we set the shift parameter $\alpha_2 = 0.5$ in order to show α_2 and α_3 are separately identified.

There are $N_l = 500$ legislators that are used for bridging and $N_a = 500$ agents. We draw the $N_l + N_a$ observations of the ideology common space ψ from a standard normal distribution. We set the standard deviation σ_l of $\epsilon_j^{L_l}$ to 0.25 and draw the N_l observations of L_l from equation 11a assuming a normal distribution for each $\epsilon_j^{L_l}$. Likewise we set the standard deviation σ_a of $\epsilon_j^{L_a}$ to 0.25 and draw the N_a observations of L_a from equation 11b assuming a normal distribution for each $\epsilon_j^{L_a}$.

For the outcome equation 10, we set $\beta_1 = 1$; k indexes dyads with N_i committee

members per agent (that is, each agent is nested within N_i dyads). In the simulation we set N_i constant across agents and vary the cluster size to be 3, 5, 7, and 10 to explore the effect of cluster size and the sampling variability in committee member locations on the precision of agent ideal point estimation. We draw the N_i observations for O_k by drawing each committee member’s preferences L_{l_j} from a standard normal distribution, computing the distance $d(L_{l_j}, L_{a_i})$ using the committee member’s L_{l_j} and the “true” (unobserved) agent preference L_{a_i} and the parameters in equation 10, and setting the normally-distributed ϵ_k to each have standard deviation $\sigma_k = 0.25$. After creating the outcomes, we set each of the “observed” agent preferences L_a^{obs} to missing and retain the “true” agent preferences L_{a_i} as the benchmarks for posterior predictive checks (Gelman, Meng, and Stern, 1996).

A.2.1 Estimation

We estimate the model in `OpenBUGS` using Bayesian MCMC methods (Spiegelhalter, Thomas, Best, and Gilks, 1996). We run the model until the posterior distribution of the structural estimates are stationary, and then sample from the posterior distribution to create marginal distributions of each parameter of interest. These models converge almost instantly and show excellent mixing. For each model, we use a 10k burn in period, and then sampled 10k iterations saving each 10 for 3 chains (3000 replicates from the posterior).

A.2.2 Simulation Results

We estimate two versions of the model for each rotation (parallel, oblique and orthogonal), one version for the model based on the constrained-regression approach that estimates the bridge and outcome equations separately, and one for the flexible structural equations model that estimates the bridge and outcome equations jointly.

The simulation shows that the simultaneous equations model recovers unique, unbiased

estimates for all of the structural parameters in the model but the constrained-regression approach does not. In addition, the simulation explores the conditions for bias and efficiency for the estimation of agent ideal points by examining whether the model is able to recover unbiased estimates of the “true” benchmark agent ideal-point preferences that generated the simulated data. We use posterior predictive checks (Gabry et al., 2019; Gelman et al., 1996) to demonstrate the consequences for estimation and for the imputation of agent ideal points and structural parameters in cases where the agent preference dimension is rotated away from the roll call-based legislative preference dimension, comparing results from the flexible simultaneous equations model with results derived from the constrained-regression approach.

Structural Parameters. First consider the results for the structural parameter estimates for the three rotation cases for the basic case of 10 unbiased committee members. We begin by noting that in all three cases, in the flexible model the bridging equation intercept and rotation parameters for agent preferences L_a are recovered exactly: The estimates for the bridging model intercept $\widehat{\alpha}_2$ are precisely centered at 0.5 for each of the three cases (SE 0.01); the estimates for the rotation parameters $\widehat{\alpha}_3$ are precisely zero for the parallel case, -0.5 for the oblique case, and 1.0 for the orthogonal case (all with SE 0.01). Of course the α_2 and α_3 parameters are not identified for the constrained-regression model so there is nothing to report for that case.

Next consider the structural parameters in the outcome model, shown in figure 5. These parameters are identified for both the constrained and flexible models. To save space in the figure, we call the simultaneous equations model the “flexible” model – that is, the full model without the unidimensional constraint. The benchmark target value for each parameter is shown by a horizontal line. The estimates are shown in a color that matches the color of the corresponding target line. To get a sense of the variability in the parameter estimates, we estimate a modification of the model with 10 committee

Structural Parameters: Constrained vs. Flexible Model

Figure 5: Simulation results for the structural parameter estimates with 10 unbiased committee members, for three example rotations. To reduce clutter, we label the simultaneous equations model as the “flexible” model, that is the full information and unconstrained model described in the main text. Notice that the flexible structural equations model results remain unbiased and efficient across rotations, while the constrained-regression estimates increase in bias and inefficiency with the degree of rotation.

members that allows 10 independent estimates of each parameter within each run.

We jitter the placement of the parameter estimates on the horizontal axis in figure 5 so that the estimates can be seen distinctly. The variation in the vertical direction indicates the amount of uncertainty across replicates of the estimates. Note that the flexible model retrieves unbiased point estimates for each parameter and with extremely low uncertainty. In contrast, the degree of bias in the constrained regression estimates increases with the degree of rotation. The parallel rotation case matches the unidimensional preference space assumptions that motivate the constrained-regression model, and in this case, the constrained model returns reasonable estimates for β_1 , but with about 10 times the uncertainty of the flexible model. In addition, the regression model underestimates the intercept β_0 and inflates the standard error of the regression for the outcome equation σ_k by a factor of four. For the orthogonal case, the regression approach underestimates the estimate for β_1 by a factor of four as well, which is a direct result of measurement error in the estimate for $\widehat{L}_a$ that occurs under a rotation.

Posterior Predictive Checks. Following the advice of Gelman and his coauthors (2019; 1996), we make use of posterior predictive checks to verify the model estimates for $\widehat{L}_a^{obs}$ track the “true” agent preferences L_a . Equation 12 writes out the posterior distribution of the agent preference estimates decomposed into conditional distributions, and this equation shows how the missing data parameters $z = f(L_a^{obs})$ and the structural parameters in the outcome equation β are mutually informative (Tanner and Wong, 1987) when generating the predicted data,

$$p(L_a^{obs}, \alpha, \beta | \psi, L_l) = \int_Z p(L_a^{obs} | \alpha, \beta, \psi, L_l) p(\alpha) p(\beta | z) p(z) dz, \quad (12)$$

where $z \in Z$. In effect, L_a appears on both the left- and the right-hand side of the model, so equation 12 must marginalize over the missing data distribution for z to estimate β , which in turn updates L_a^{obs} . In contrast, to conduct a hypothesis test for the outcome

equations, the constrained-regression approach constructs the z function using expected values for agent preferences L_a^{obs} under the constraints $\alpha_2 \equiv 0$ and $\alpha_3 \equiv 0$. To the extent the constraint is false, the result will be measurement error in the estimates of L_a^{obs} and this will be visible in the posterior predictive checks.

Figure 6 plots a random draw of 100 simulated densities of $\widehat{L}_a^{obs}$ against the true density that generated the data L_a for each of the three rotation cases, and for each of the two models. The flexible model simulates the underlying agent preferences exactly, although with a slight decrease in precision as the degree of rotation increases. In contrast, the constrained regression model is unable to recover the densities for the true agent preferences, with the degree of departure increasing as the rotation increases. Figure 7 shows the expected values of $\widehat{L}_{a_i}^{obs}$ averaged across the full set of simulations plotted against the corresponding true agent preference, along with descriptive statistics for the correlation and mean squared error. The flexible model recovers efficient and unbiased estimates in all three rotation cases, although with a doubling of the MSE when going from the parallel to the orthogonal case. The constrained regression model shows both inefficiency and bias across all three cases, seen in the MSE and correlation statistics; for example, the MSE of the parallel (best case) constrained regression is 60 times that of the flexible model. The scatter plot indicates that in the orthogonal case, the estimates of the constrained regression model have no correspondence with the true data; instead, the estimates are like a random draw.

Robustness Checks. To assess whether the model results in the flexible model is dependent on the number of committee members per agent, and if the location of the committee members matter, we re-estimated the flexible model with 7, 5, and 3 committee members instead of 10 in the main results. We also estimate a model with three committee members that are only drawn from the right hand (“conservative”) end of the legislative preference space L_l to assess whether bias in the location of members relative

Figure 6: Posterior predictive check with 10 unbiased committee members: empirical densities of the outcome distributions. To save clutter we label the simultaneous equations model as the “flexible” model. Dark curve indicates the true distribution while the light curves are representative draws of fake data for each model and each degree of rotation. The flexible model simulates the outcome data across the rotations, with a slight decrease in efficiency as the rotation increases. The constrained-regression model fails to simulate the outcome data as the degree of rotation increases, and is always less efficient than the flexible model.

Figure 7: Posterior predictive check 10 unbiased committee members: scatter plots of point estimates for agent preferences versus true, for each model and each degree of rotation. To save clutter we label the simultaneous equations model as the “flexible” model. The correlation coefficient ρ indicates the flexible model predicts the outcome data across the rotations, with a slight decrease in efficiency as the rotation increases, while the constrained-regression model fails to predict the outcome data as the degree of rotation increases. The mean square error (MSE) indicates the flexible model is more efficient in each case.

to the location of agents affect the results. These models return nearly identical results. The structural parameters remain identified and unbiased, but the efficiency of estimates decreases by a factor of 10 (MSE of 0.001 with 10 committee members versus of 0.01 with five members).

Summary of Identification. To summarize, the previous SM section gives a formal mathematical proof of identification in the simultaneous equations, subject to data requirements that there must at minimum be two agents nested in two dyads. The simulation is an empirical proof of identification, and demonstrates that our proposed model exactly and uniquely recovers the target benchmarks for every model parameter, that is, all of the equation structural parameters as well as the parameters imputing the missing agent preferences. That the flexible model reliably converges in all cases is an additional proof of the model’s empirical identification, which is a sufficient demonstration of theoretical identification (that is, theoretical models can fail to be empirically identified but empirically identified models must be theoretically identified). Thus the simulation confirms the theoretical identification strategy that we give in the previous section.

A.3 Coding of the Hearings Transcripts

In the application, we develop a set of hypotheses regarding the different types of statements that legislators make within committee hearings. To collect the outcome data regarding the types of sentences stated in committee hearings, a research assistant and one of the authors hand coded the sentences (questions and statements) that legislators direct to specific witnesses at the sampled committee hearings, as recorded in committee hearing prints, making use of the hearings transcript coding rules in [Esterling \(2007\)](#). The coding rules contain 20 separate codes to mutually exclusively and exhaustively classify the types of statements and questions committee members ask of witnesses at the hearing. In addition to a set of “miscellaneous” statements, we follow the procedures in [Esterling](#)

(2007) to organize these codes under the labels “falsifiable,” “opinion,” and “anecdotal” sentences.

Falsifiable sentences contain analytical policy information and are stated in a form that could be made into an operational research statement. Unlike opinion sentences, they are asserted as positive effects of a program or factual descriptions of the real world. Unlike anecdotal sentences, they are asserted as general and systematic, rather than local or personal. Examples of falsifiable sentences include:

- Verifiable factual statement. “Cataracts is one of the most significant causes for decreased vision.”
- Description of how a program, policy, or organization operates at a general level. “From 1966 and until the mid-1990s, claims billing errors by hospitals across the country were handled through normal external audit process[es].”
- Causal implication or argument about the effect of a current policy or program. “The SMI Trust Fund, which in balance on an annual basis, shows a rate of growth of costs which is clearly unsustainable.”
- The hypothetical future effects of a proposal. “If Medicaid payments to managed care plans... are set below market rates to achieve savings, the participation of mainstream plans could be compromised.”
- Description of past actions in the policy process and intents of political actors. “Congress intended for payment reform to neither increase nor decrease overall Medicare payments to physicians.”

Opinion sentences are normative or non-falsifiable statements, or statements that are explicitly qualified as the author’s own belief or opinion. In all cases, these statements are not asserted as “true” or empirically demonstrable. Examples include:

- A policy position. “Medicare beneficiaries should be provided with a range of health plan choices, and those choices should be accompanied by incentives to select the more cost effective alternatives.”
- A policy recommendation. “Delinking public health care programs from public cash assistance programs is good public policy.”
- A normative argument (fairness, ideology). “No reason has been shown why the pharmaceutical industry should be singled out from others that freely negotiate the prices of their products with the DVA and the other departments and agencies of the Federal Government.”
- The speaker’s belief, feeling, or desire. “The proposed 16 percent reduction in the conversion factor results from a misinterpretation by HCFA of the mandate for budget neutrality contained in OBRA-89, as well as from inappropriate and demeaning assumptions about anticipated physician behavior in response to payment reform.”
- A rhetorical question or political advice. “The Congress may want to create a process to adjust future conversion factors based on actual billing experience.”

Anecdotal sentences reference only the speaker’s immediate experience, or the immediate experience of the witness’s organization with a policy or program, or only make reference to local conditions such as conditions within a specific congressional district. Examples include:

- A person’s or organization’s particular experience in a program. “In December our accountant received a list of more than 10,000 alleged billing errors during those five years.”
- Likely effects from program or an alternative generalized from personal experience. “Dr. Russell Snow, an eye, ear, nose, and throat doctor from Caldwell, Idaho, says

his colleagues are so frightened by federal enforcement provisions that many more are [going to drop Medicare patients].”

- Information about a congressional district or locality. “In my State, the hospitals that are okay are the ones that are doing cardiac.”
- Statements about length of personal experience with a policy area
- Quote from well-known figure, adage, what “other people” are saying

Reliability tests for coding. A research assistant independently recoded a testbed random sample of sentences stated in Medicare committee hearings ($N = 578$) for an inter-coder reliability test, and one of the authors re-coded a second random sample ($N = 711$) one year after completing the first round of coding to conduct an intra-coder reliability test. The Cohen’s Kappa reliability statistic for the intercoder reliability test is 0.57 with a 71 percent agreement rate (32 percent expected, $p < 0.0001$), and the intra-coder reliability is 0.79 with an 85 percent agreement rate (30.5 percent expected, $p < 0.0001$). While there are no established thresholds for reliability, a kappa statistic in the range of 0.75 to 0.80 is widely considered excellent agreement beyond chance, and 0.40 to 0.75 fair to good agreement beyond chance (Nuendorf, 2002, 143). All member sentences in the hearing transcripts sampled for this project were double-coded by both the research assistant and the principal investigator, with the latter resolving disagreements.

A.4 Are Health Care Roll Calls Different?

The topics of the 29 sampled hearings include headline grabbing issues such as prescription drug benefits, comprehensive health financing reform, and the solvency of the Medicare trust fund, and also less visible issues such as prospective payment systems for health providers, competition and managed care, billing fraud, medical savings accounts, risk adjustment, coverage information for beneficiaries, prevention and disease management, telemedicine, long term care, billing relations between the VA and Medicare, and

demonstrations involving military retirees and the Federal Employee Health Benefits Program. The results of the main paper demonstrate that the preference space for health care witnesses across these topics is along a quality-cost dimension, a dimension that rotates orthogonally to the legislator roll-call preference space recovered in first dimension DW-NOMINATE scores.

The DW-NOMINATE procedure uses a cross section of roll calls, and it is reasonable to wonder if legislators’ roll-call preferences estimated from the subset of health care roll calls also would rotate away from DW-NOMINATE scores. To evaluate this, we extracted the subset of health-specific roll calls taken in the House in the 106th, 107th and 108th congresses (corresponding to the time period of the present study) by identifying all bills listed on [Lewis et al. \(2018\)](#) with “Social Welfare” in the Clausen Code, and then among those we searched the CRS policy topic codes for health-related topics. To enable convergence we dropped all votes where there was more than 90 percent agreement in the chamber, along with a handful of other votes that empirically prevented convergence.²⁵ This yielded 62 health-specific votes across the three congresses. We developed a model that is similar in structure to the equation set 1b but substituting the roll calls for the survey items to estimate the common space ψ .

In this model, the standardized size of α_1 in predicting the first dimension DW-NOMINATE scores from the health-only roll calls is 0.93, which indicates that a scale recovered from health-care votes is nearly an exact prediction of their scores based on all votes. Further, since DW-NOMINATE scores are observed for all members, we are able to estimate the rotation parameter for members who are in the data set (i.e., those who attended the sampled health care hearings) and found that this rotation parameter tests to zero. So the assumption that preferences estimated from the full set of roll calls, such as those in DW-NOMINATE, are appropriate for estimating legislative preferences in this study.

²⁵Roll call votes are not validated as items useful for scaling, and it is not unusual to find empirical convergence problems in such data.

A.5 Details of the Former Members of Congress Survey

In the fall of 2005 one of the authors mailed paper surveys to 199 former members of the U.S. Congress (FMC). The survey contained a consent cover letter and a second page containing only the five questions designed to measure personal ideology. Among those who received surveys, 77 former members returned a completed survey (11 were returned as undeliverable) for a 39 percent response rate. Among the former members, 51 were Democrats, 26 Republicans; 18 served in the Senate. The most liberal (minimum) DW-NOMINATE score is -0.85 and the most conservative (maximum) is 0.69. This gives good coverage of the DW-NOMINATE dimension. By comparison, in the 109th House, the most liberal member scored -0.743 and the most conservative, 0.998, with only 8 members exceeding 0.69.

We use the former members' responses to the survey items (described in the main text) and an IRT model to estimate their personal left-right ideological ideal point ψ . Figure 8 illustrates the relationships between the personal ideology space ψ , party identification, and the roll call preference space DW-NOMINATE among the set of former members in the sample (in a figure similar to [Shor and McCarty, 2011, 535](#)). In this figure, Republicans are indicated with filled circles, Democrats with empty circles, the pooled relationship between ψ and DW-NOMINATE is indicated by the solid black line, and the relationships adjusted for party are indicated by dashed lines. In the left hand panel, we include only an intercept shift for party, while the right hand panel we also include a term interacting party with ψ .

If one ignores the party classification there is a clear linear relationship between ψ and DW-NOMINATE. If one considers party, the members' common space preferences ψ remain unimodal but the roll call preferences separate into a bimodal distribution. Further, if one allows the full interaction of the right hand panel, it appears that among Republican members, personal ideology has no relationship with roll call voting, while ideology matters for Democrats. One could conclude that ideology does not matter for Republicans,

Figure 8: The relationship between personal ideology ψ and roll call preferences L_l among former members of Congress. $N = 77$. The solid line is the unconditional regression while the dashed lines account for differences by party.

although there is no suggestion in the Congress literature that would support this asymmetric relationship, and the full interaction is likely an over fit to the sample. Given the possible importance of political party, in all statistical models we report we evaluate the robustness of the imputation of L_a to both including and excluding party as a covariate in the bridging equation (equation 1b) and 1c.

A.6 Implementation of the Statistical Model and Estimation

The flexible statistical model is composed of two submodels that are estimated jointly, and linked by the common parameter L_{a_i} . Submodel *A* is a measurement model that places former members and witnesses into a personal common ideology space ψ and bridges these scores into the two-dimensional legislative preference space L_l and L_a . Submodel *B* contains the outcome equations of substantive interest. Here we set out the full flexible model, and then implement the constrained-regression approach (Jessee, 2016) as a set of restrictions on the flexible model. We estimate the flexible model in a Bayesian framework with likelihood:

Likelihood for Submodel A (Bridging Equations):

$$\left. \begin{aligned} Markets_i &\sim \text{OrderedLogit}(-1 \times \psi_i) \\ Companies_i &\sim \text{OrderedLogit}(\gamma_{11}\psi_i) \\ HelpPoor_i &\sim \text{OrderedLogit}(\gamma_{12}\psi_i) \\ Access_i &\sim \text{OrderedLogit}(\gamma_{13}\psi_i) \\ Incomes_i &\sim \text{OrderedLogit}(\gamma_{14}\psi_i) \\ L_{(a,l)_i} &\sim \text{Normal}(\mu_{0i}, \sigma_L) \\ \mu_{0i} &= \alpha_0 + \alpha_1\psi_i \\ &\quad + \alpha_2 Agent_i + \alpha_3 \psi_i Agent_i + \alpha_4 \mathbf{X} \end{aligned} \right\} 1 \leq i \leq N_1$$

Likelihood for Submodel B (Outcome Equation):

$$\left. \begin{aligned} Distance_k &= |L_{l_j} - L_{a_i}| \text{ or } (L_{l_j} - L_{a_i})^2 \\ Falsifiable_k &\sim \text{OverdispersedPoisson}(\lambda_{1k}) \\ \ln \lambda_{1k} &= \beta_{10} + \beta_{11} Distance_k + \beta_{12} ResOrg_k + \\ &\quad \beta_{13}(ResOrg_k \times Distance_k) + \eta_{1k} + \eta_{2j} + \eta_{3i} \\ Opinion_k &\sim \text{OverdispersedPoisson}(\lambda_{2k}) \\ \ln \lambda_{2k} &= \beta_{20} + \beta_{21} Distance_k + \beta_{22} ResOrg_k + \\ &\quad \beta_{23}(ResOrg_k \times Distance_k) + \gamma_1 \eta_{1k} + \eta_{2j} + \eta_{3i} \\ Anecdote_k &\sim \text{OverdispersedPoisson}(\lambda_{3k}) \\ \ln \lambda_{3k} &= \beta_{30} + \beta_{31} Distance_k + \beta_{32} ResOrg_k + \\ &\quad \beta_{33}(ResOrg_k \times Distance_k) + \gamma_2 \eta_{1k} + \eta_{2j} + \eta_{3i}. \end{aligned} \right\} 1 \leq k \leq N_2$$

where i indexes N_1 former members and witnesses (combined), k indexes N_2 legislator-witness dyads that occur across all of the committee hearings in the sample, L_{a_i} is imputed for each witness in the k th dyad, and j indexes legislators.²⁶

Submodel A is the measurement model that places the witnesses who appeared at the congressional committee hearings into the legislative preference space. The equation set in submodel A imputes witnesses' preference scores L_{a_i} by first placing witnesses into a *survey response* ideology space defined by the set of ideological attitude survey questions,

²⁶Specifically, legislators are indexed as congress-committee-legislator, so Henry Waxman has separate indexes as a member of the Subcommittee on Health in the 106 and 107 Congresses, and yet another as a member of the Subcommittee on Government, Information and Technology in the 106th Congress. The legislator random effects η_{2j} are estimated over these indexes.

a space denoted in the likelihood by ψ , via the estimated difficulty parameters (factor coefficients) γ_{11} to γ_{14} and the ordered probit threshold parameters.²⁷ Submodel A then identifies the transformation from ψ to the legislative roll call space L_l (DW-NOMINATE) with the linear transformation given by α_0 and α_1 , and optional covariates $\mathbf{X}$, while the posterior agent preferences L_a from the flexible model also depend on the α_2 and α_3 structural parameters, the *Agent* indicator (1 if witness, 0 if former member of Congress), and the interaction between *Agent* and ψ .

The outcome equations are contained in submodel *B*. Each within-dyad question type count is modeled as over dispersed Poisson-distributed, conditional on the within-dyad distance in legislative preference space, allowing separate β parameters for dyads that have a witness from a *Research organization* ($= 1$) such as a university or think tank, and for dyads where the witness is not from a research organization ($= 0$). Distances can be measured in any way; here we show two possible distance measures, the absolute linear distance or quadratic distance.

The outcome equations are estimated simultaneously as seemingly unrelated regressions, and they share a common legislator-specific random effect η_2 that captures the committee member’s propensity to ask questions and make statements of all types to witnesses; a witness-specific random effect η_3 that captures the witness’s propensity to attract questions and comments from legislators; and a dyad-specific random effect, η_1 , that captures omitted variables that govern the dyadic interaction. These three random effects capture any omitted legislator-, witness-, or dyad-specific covariates. In particular, the random effects account for any structural features of the committee process, such as if the majority party has the ability to schedule witnesses that are more favorable to majority committee members. The dyad-level random effect also accounts for over dispersion

²⁷For identification we constrain the difficulty parameter for the *Markets* survey item to be negative one; the negative sign is because this item has an opposite ideological direction from the other items.

that comes from added variance in the count data (Skrondal and Rabe-Hesketh, 2007).

To complete the Bayesian model, we set the priors for the λ parameters as distributed Uniform(0, 10) in order to ensure the known direction labeling in the factor model. The σ_L prior is Uniform(0,100). ψ and each η have a standard normal prior. All other priors are unrestricted, normally distributed with mean zero and standard deviation 1000. Other than setting the correct direction labels for the items in the IRT model, the model in no way depends on the priors for identification (see above for the formal proof).

In order to evaluate the robustness of each modeling approach, we estimate the model under slightly different specifications to accommodate differing specifications in the literature. First, we vary the distance measure by using either an absolute value distance function or a quadratic distance function. The institutions literature typically assumes a quadratic distance but this is only to preserve differentiability when the preferences coincide and is not theoretically or empirically required. Second, we also estimate the models with and without an indicator for political party in the bridging imputation equation. One can include arbitrary covariates $\mathbf{X}$ in the imputation equation, provided one has measures of the covariates for both former members and for witnesses. Given the possible importance of political party as a covariate in this imputation, including a party covariate requires a classification of witnesses into Democratic and Republican interest group constituencies that we describe below. Finally, we estimate the simultaneous equations model without any constraint on the degree of rotation, and one with a soft constraint that constrains $\alpha_1 + \alpha_3 \geq 0$. This constraint prevents the angle of rotation from exceeding $\frac{\pi}{2}$, that is, to prevent an obtuse rotation that is implausible in this setting.

The flexible simultaneous equations model estimates both A and B submodels simultaneously, so the bridging submodel and the outcomes submodel jointly inform the posterior distribution over each L_a^1 . The constrained-regression approach estimates the two models separately and so the outcome equations do not update the preferences of agents, yielding agent preference estimates L_a^0 that are derived under the assumption that legislator and

agent preferences are constrained to a single dimension. We report all results as well as Bayesian model averages in the SM section A.7 below to demonstrate the presence or absence of variability across specifications, and we also report WAIC information statistics (Vehtari et al., 2017) for model comparison. Overall, we find there is considerable fluctuation in the outcome equation parameter estimates under the constrained-regression approach across these specifications, but considerable stability when using the flexible simultaneous equations model.

Estimation. We estimate the model in `OpenBUGS` using Bayesian MCMC methods (Spiegelhalter et al., 1996). We run the model until the posterior distribution of the structural estimates are stationary, and then sample 3,000 replicates from the posterior distribution to create marginal distributions of each parameter of interest. For each model, we use a 100k burn in period, and then sampled 300k iterations saving each 300 for 3 chains.

A.7 Results

In this section we describe the full sets of model results that are summarized in the paper. We first describe the measurement model that recovers the ideology common space ψ , and then the constrained-regression results, and then the flexible structural equations model results.

A.7.1 Measurement Model

Here we describe the results of the model that measures personal ideological preferences ψ , the common space ideology measure that appears in the bridging equations. Table 3 shows the results of the measurement model using only the data from the former members' sample (i.e., for now not using the responses from witnesses). The measurement model is able to test the convergent validity of the indicators we use to estimate ψ , which is indi-

cated by large and statistically significant discrimination parameters (factor coefficients) λ ; these are reported in the first two columns of results in table 3 and clearly indicate convergent validity. The measurement model results shown in table 5 show the discrimination parameters from the pooled (witness plus former member) sample. Comparing the discrimination parameter results across these two tables, one can see that the parameters are equivalent in the pooled and unpooled case. This equivalence shows that the responses to these items is invariant across the two groups and so serve as good measures of a common space (Jessee, 2016).

The next two sets of columns in table 3 regress the personal ideology scale ψ on former members' roll-call vote first dimension DW-NOMINATE scores (Lewis et al., 2018) in order to construct the bridge that we use in the constrained-regression approach. The middle columns regress former members' DW-NOMINATE scores on their ideology (ψ) and a set of covariates which test whether there are organizational or employment-based characteristics that would affect the bridging transformation among members. Here we include covariates for party identification, whether the former member was a senator, the member's tenure in office, and whether the former member returned the survey from the DC area (likely indicating a lobbyist versus a true retiree). Note that only party identification is significantly different from zero. The fixed effect of party is large, 0.47, and the posterior is far to the right of zero.

The final set of columns in table 3 re-estimates the bridging model among the former members but excluding covariates. Including the party covariate reduces the mapping coefficient α_1 point estimate from 0.26 to 0.11. That party is a statistically significant predictor of legislators' roll-call scores is no surprise. Party plays a central role in organizing congressional politics. The literature on Congress leaves it as an open question whether it is theoretically sensible to include this covariate in the bridging model (Krehbiel, 2000); instead of taking a side, we estimate all models below including and excluding the party variable.

Table 3: Bridge Equation Posterior Results (former members only)

	ψ Model Only		with Covariates		without Covariates	
	Mean	SE	Mean	SE	Mean	SE
Bridge Equation						
Ideology (ψ)			0.11	0.03	0.26	0.03
DC Area			-0.01	0.04		
Chamber			-0.02	0.07		
Tenure			-0.00	0.02		
Party			0.47	0.05		
Constant			-0.21	0.03	-0.05	0.04
Sigma			0.15	0.01	0.20	0.02
Ideology Factor Loadings						
Markets	1		1		1	
Companies	1.63	0.42	1.60	0.41	1.61	0.37
Help Poor	2.86	0.89	2.65	0.76	2.53	0.67
Access	2.33	0.54	2.51	0.58	2.51	0.52
Incomes	1.83	0.44	1.86	0.44	1.75	0.38

Posterior structural parameter estimates for the bridge equation (only equation 1b), modeling DW-NOMINATE roll-call preference scores for the former member (FMC) subsample ($N = 87$). Note that party is the only covariate other than ideology that predicts roll-call preferences. Comparing factor loadings with those in table 5 shows the items load identically on the ideology factor across member and witness subsamples.

A.7.2 Imputing Party Preferences of Witnesses

To use party as a covariate in the bridging equation, we need the party identification of both legislator and agent. Unfortunately, we do not have party identification for the witnesses in the sample; in addition, the vast majority of groups in the sample do not make campaign contributions and so contribution data cannot help either. To impute this missing data, we use a data-driven approach to classify witnesses by party where we regress estimates for witness’s personal ideology ψ on a classification for the type of organizations that the witness works for.²⁸ In this descriptive regression, we examine which employer types have witnesses that are statistically different on ψ compared to

²⁸This regression is on the full sample of 165 witnesses who returned surveys as a part of the larger project, not just the ones in the sample of hearings.

those who work at the baseline category of for-profit trade associations, organizations that are firmly in the Republican constituency. In this analysis, we find that professional associations, corporations, law firms, partisan think tanks, and industry coalitions are statistically similar to for-profit trade associations, while labor unions, universities, non-profit NGOs, state and federal agencies, not-for-profit trade associations, nonpartisan think tanks, and hospitals are statistically more liberal. Witnesses in the first set we label as in the Republican constituency, and the latter set in the Democratic constituency.

A.7.3 Results for the Constrained-Regression Models

In this section we report the full set of results for the sentence count outcome equations from the constrained-regression approach to bridging, which constrains agent preferences to the legislative roll call preference space under an assumption that these always coincide within a single dimension.

To estimate the models in table 4 we first extract the expected values of the witness preferences $\widehat{L}_{a_i}^0$ based on the regression results reported in the second and third columns of table 3 and witnesses' estimated ideology score $\widehat{\psi}_{a_i}$, relying on the linear assumptions of the regression, and then we use these estimates to construct the distance measures between $\widehat{L}_{a_i}^0$ and L_{l_j} within each dyad. We then jointly regress each question count on distance, the research organization indicator, the interaction between distance and research organization, and a constant, using an overdispersed Poisson likelihood for each count type. These three outcome models are estimated jointly and each equation includes random effects for witness, legislator and dyad (not shown). Table 4 reports the results that 1) include or exclude the party covariate in the bridging equation, and 2) use the absolute value or quadratic function to measure distance. Note that in each specification, distance is not statistically related to any of the question counts. The tables also indicate the Widely Applicable Information Criterion (WAIC) value (Vehtari et al., 2017) is lowest for the linear specification with party covariate, indicating that this specification is the

best fit to out of sample predictions.

A.7.4 Constrained-Regression Results that Combine the Two-Step Model into One Step

One might reasonably wonder if the main difference between the results we observe from the “two-step” regression procedure (above) and simultaneous equations model (below) is simply due to the intervening step; that is, the constrained-regression approach has a second stage while the simultaneous equations model has only one, and so perhaps the differences are due only to the procedure. To evaluate this, we re-estimate the regression approach for the simulation data in a one-step procedure making use of the `cut` function available in `OpenBUGS`, which allows the model to update the structural parameters in the outcome equations based on estimates for the agent preferences, but does not simultaneously update the agent preferences based on posteriors for the structural parameters.

This one-step method returns estimates that are exactly identical to those returned by the two-step method. In the paper we focus on the latter since the two-step method is the current practice in the bridging literature.

A.7.5 Results for the Flexible Simultaneous Equations Model

We report in tables 5 and 6 the results from the flexible simultaneous equations model, which employs the rotated posterior preference measures for witnesses in the outcome equation distance functions. In contrast to the constrained-regression approach, the flexible model estimates the bridge equation model and the outcome models jointly and hence uses the full information in both models for identification and to improve estimation.

Table 5 reports the results of the model that includes a soft constraint $\alpha_1 + \alpha_3 \geq 0$, which prevents the rotation of the witness preferences from achieving an obtuse rotation, which is theoretically implausible and would likely reflect an over fit to the sample. There are many things to note in this table. First, note that the factor loadings for ψ are stable across the specifications and are indistinguishable from the factor loadings that resulted

Table 4: Constrained-Regression Model Results

	Linear Distance				Quadratic Distance			
	with Party		without Party		with Party		without Party	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Outcome Equations								
Falsifiable Statement Count								
Distance	-0.15	0.37	0.47	0.44	-0.57	0.40	0.50	0.45
ResearchOrg	0.72	0.41	0.48	0.41	0.44	0.34	0.30	0.38
Interaction	-1.07	0.64	-0.46	0.65	-0.73	0.73	-0.25	0.70
Constant	-1.61	0.27	-1.84	0.30	-1.51	0.25	-1.75	0.26
Opinion Statement Count								
Distance	-0.94	0.59	-0.13	0.66	-1.47	0.66	-0.22	0.67
ResearchOrg	0.15	0.57	-0.20	0.57	-0.14	0.45	-0.36	0.50
Interaction	-1.57	1.09	-0.54	1.06	-1.60	1.26	-0.53	1.16
Constant	-2.91	0.39	-3.25	0.41	-2.92	0.34	-3.22	0.35
Anecdotal Statement Count								
Distance	-0.17	0.87	0.88	0.90	-1.07	0.93	0.49	0.89
ResearchOrg	0.70	0.78	0.19	0.78	-0.18	0.61	-0.56	0.65
Interaction	-5.42	1.70	-3.37	1.57	-6.00	2.09	-2.85	1.70
Constant	-4.79	0.61	-5.12	0.59	-4.57	0.51	-4.82	0.49
Dyad-Specific Random Effect								
Falsifiable Equation	1		1		1		1	
Opinion Equation	1.74	0.12	1.77	0.12	1.74	0.12	1.76	0.12
Anecdotal Equation	2.62	0.22	2.58	0.21	2.61	0.21	2.56	0.20
WAIC								
Falsifiable Model	994.81		1030.19		1061.32		1075.97	
Opinion Model	553.72		575.16		631.25		596.23	
Anecdotal Model	454.97		544.29		584.25		577.75	

Structural parameter estimates for the constrained-regression model that imputes agent preferences based on the unidimensional assumption, comparing results with two distance functions and with and without covariates. $N_{dyads} = 669$, $N_{witnesses} = 67$, $N_{members} = 87$. Notice the effect estimate for distance for both types of witnesses is indistinguishable from zero, and the point estimates vary widely across specifications, suggesting measurement error in the agent preferences under this approach.

Table 5: Flexible Simultaneous Equations Model Posteriors with Soft Constraint

	Linear Distance				Quadratic Distance			
	with Party Mean	SD	without Party Mean	SD	with Party Mean	SD	without Party Mean	SD
Bridge Equation								
Ideology (ψ)	0.07	0.03	0.21	0.03	0.07	0.03	0.22	0.03
Agent	-0.08	0.05	-0.13	0.07	-0.06	0.05	-0.12	0.06
Ideology X Agent	-0.05	0.03	-0.18	0.04	-0.05	0.03	-0.18	0.04
Party	0.45	0.05			0.44	0.05		
Constant	-0.21	0.03	-0.07	0.04	-0.21	0.03	-0.07	0.03
Sigma	0.19	0.02	0.25	0.03	0.19	0.02	0.23	0.02
Ideology Factor Loadings								
Markets	1		1		1		1	
Companies	1.61	0.33	1.60	0.31	1.59	0.32	1.59	0.31
Help Poor	2.13	0.52	2.14	0.48	2.13	0.53	2.10	0.46
Access	1.94	0.41	1.97	0.39	1.94	0.42	1.98	0.39
Incomes	1.63	0.35	1.56	0.30	1.63	0.35	1.56	0.31
Outcome Equations								
Falsifiable Statement Count								
Distance	-1.87	0.67	-2.07	0.76	-2.55	0.82	-2.56	0.92
ResearchOrg	1.02	0.46	1.16	0.47	0.67	0.36	0.78	0.39
Interaction	-2.26	0.96	-2.54	1.01	-2.36	1.31	-2.88	1.38
Constant	-0.88	0.35	-0.80	0.38	-1.10	0.27	-1.08	0.31
Opinion Statement Count								
Distance	-2.94	0.87	-2.54	1.12	-3.44	1.06	-2.94	1.26
ResearchOrg	0.59	0.62	0.97	0.66	0.27	0.47	0.49	0.52
Interaction	-3.08	1.55	-4.02	1.62	-4.74	2.41	-5.79	2.60
Constant	-2.02	0.46	-2.15	0.55	-2.45	0.36	-2.53	0.43
Anecdotal Statement Count								
Distance	-0.72	1.10	-0.23	1.40	-0.92	1.26	-0.31	1.39
ResearchOrg	2.39	0.93	2.88	1.00	1.20	0.69	1.53	0.76
Interaction	-13.43	3.31	-14.67	3.31	-24.15	6.99	-25.93	7.07
Constant	-4.33	0.62	-4.53	0.74	-4.45	0.51	-4.53	0.58
Dyad-Specific Random Effect								
Falsifiable Equation	1		1		1		1	
Opinion Equation	1.66	0.12	1.65	0.12	1.66	0.12	1.66	0.12
Anecdotal Equation	2.54	0.22	2.51	0.22	2.55	0.23	2.50	0.22
WAIC								
Falsifiable Model	964.93		956.34		962.03		956.93	
Opinion Model	538.13		541.88		543.99		543.30	
Anecdotal Model	425.47		421.17		424.08		420.08	

Parameter estimates for the flexible simultaneous equations model that allows agent preferences to shift and rotate away from the roll-call space, with soft constraint on the rotation, with two distance functions and with and without covariates. $N_{dyads} = 669$, $N_{witnesses} = 67$, $N_{members} = 87$. Notice that distance is strongly related to outcomes across specifications.

in the measurement model that only includes former members. This indicates that the ideology survey measures have high convergent validity and measure a common space.

Second, note that the model is able to estimate agent-specific bridging parameters (attached to the *Agent* and *Ideology* $\times$ *Agent* rows) that govern the degree of shift and rotation of the witness preference space away from the roll-call preference space. Each of these indicates an approximate orthogonal rotation. Third, note that the hypotheses based on cheap talk information theory regarding preference distance, research organization, and their interaction are largely confirmed. And these results are quite stable across the four specifications. That the results are significant in this table but not in the constrained-regression approach strongly suggests that the constrained-regression approach generates preference scores for witnesses that are measured with error.

Table 6 shows the same results but without the soft constraint, that is, permitting the rotation of witness preferences to an obtuse angle. Note that even with this extreme rotation the results are nearly identical to those from the previous model, and also stable across specifications.

For comparison between the constrained-regression and the simultaneous equations models, figure 9 presents a dot chart that represents the structural parameter estimates for the outcome equations in the case of the linear distance function. The dots represent the parameter estimate where in each cluster, the top dot indicates the party variable is included in the bridge equation, the middle dot is the specification that excludes party, and the lower dot is the Bayesian model average (McElreath, 2016, 203-4). Note that in the constrained-regression case, the parameter estimates are small, not significant, and show variability across specifications. In contrast, in the flexible model, the results are large, significant, and remarkably similar across specifications. This contrast strongly suggests the presence of measurement error from using the constrained preference estimates for witnesses in the distance function (Kukush, Schneeweis, and Wolf, 2004), and as we show in the main text, in the regression case the analyst would mistakenly be led to accept the

Table 6: Flexible Simultaneous Equations Model Posteriors without Soft Constraint

	Linear Distance				Quadratic Distance			
	with Party Mean	SD	without Party Mean	SD	with Party Mean	SD	without Party Mean	SD
Bridge Equation								
Ideology (ψ)	0.09	0.03	0.24	0.03	0.10	0.02	0.24	0.03
Agent	-0.09	0.06	-0.14	0.07	-0.07	0.06	-0.12	0.06
Ideology X Agent	-0.33	0.07	-0.27	0.07	-0.29	0.06	-0.27	0.06
Party	0.48	0.05			0.45	0.05		
Constant	-0.22	0.03	-0.07	0.03	-0.21	0.03	-0.07	0.03
Sigma	0.16	0.02	0.24	0.03	0.15	0.02	0.22	0.03
Ideology Factor Loadings								
Markets	1		1		1		1	
Companies	1.59	0.32	1.60	0.30	1.55	0.30	1.59	0.30
Help Poor	1.95	0.45	2.13	0.47	2.02	0.46	2.10	0.45
Access	1.96	0.41	2.03	0.40	2.04	0.42	2.01	0.39
Incomes	1.68	0.34	1.60	0.31	1.63	0.32	1.58	0.30
Outcome Equations								
Falsifiable Statement Count								
Distance	-1.86	0.59	-1.76	0.99	-2.57	0.78	-2.62	0.88
ResearchOrg	0.97	0.47	1.26	0.52	0.65	0.38	0.75	0.39
Interaction	-2.08	0.94	-2.76	1.13	-2.31	1.28	-2.72	1.38
Constant	-0.87	0.34	-0.95	0.46	-1.08	0.28	-1.07	0.29
Opinion Statement Count								
Distance	-2.40	0.85	-2.03	1.47	-3.13	1.09	-2.99	1.21
ResearchOrg	0.75	0.63	1.17	0.77	0.33	0.50	0.46	0.51
Interaction	-3.56	1.48	-4.46	1.87	-5.22	2.31	-5.71	2.53
Constant	-2.19	0.47	-2.40	0.71	-2.47	0.38	-2.51	0.41
Anecdotal Statement Count								
Distance	-0.73	1.11	0.20	1.78	-1.31	1.34	-0.44	1.36
ResearchOrg	2.41	0.95	3.15	1.12	1.15	0.74	1.45	0.74
Interaction	-14.00	3.14	-15.40	3.37	-26.17	7.22	-26.13	7.01
Constant	-4.33	0.66	-4.78	0.90	-4.39	0.55	-4.49	0.56
Dyad-Specific Random Effect								
Falsifiable Equation	1		1		1		1	
Opinion Equation	1.66	0.12	1.66	0.12	1.66	0.12	1.66	0.12
Anecdotal Equation	2.55	0.23	2.51	0.23	2.59	0.22	2.50	0.22
WAIC								
Falsifiable Model	965.10		958.67		964.94		958.12	
Opinion Model	546.49		545.27		547.00		543.17	
Anecdotal Model	428.63		427.78		424.81		421.49	

Parameter estimates for the flexible model that allows the agent preference space to shift and rotate away from the roll-call preference space, without soft constraint on the rotation, comparing results with two distance functions and with and without covariates. $N_{dyads} = 669$, $N_{witnesses} = 67$, $N_{members} = 87$. The results are similar to soft-constrained results of the previous table.

Figure 9: Coefficient estimates from the constrained-regression model (left) and the flexible simultaneous equations model (right). Notice that the regression model returns small, unstable and insignificant estimates, which is characteristic of measurement error. The simultaneous equations model returns large and significant results across specifications.

null institutional hypotheses.

A.7.6 Agent Preference Estimates and Posterior Model Checks

In this section we compare the estimates of agent preferences (and their precision) between the constrained-regression approach to bridging and the flexible simultaneous equations model that estimates agent preferences based on observed behavior of members in committees. The constrained model assumes that agents' and legislators' preference spaces coincide, while the flexible structural equations model allows the agent preference space to be distinct. We examine the effect of including and relaxing this constraint on agent preference estimates. The specifications of each model are those described above, with a

linear distance function and no covariates in the bridging equation.

Figure 10 shows a histogram of the change in the standard deviation of each witness’s preference estimate, where the standard deviation of the preferences from the constrained-regression model is subtracted from the standard deviation of the posteriors from the flexible simultaneous equations model, so negative changes indicate that the unconstrained preference is estimated more precisely. While the degree of change in precision varies, the histogram indicates that the flexible, unconstrained preferences are estimated typically with more precision than the constrained.

Figure 10: Agents’ preferences tend to be estimated with greater precision in the flexible simultaneous equations model than in the constrained-regression model.

Next, we report the results of posterior predictive checks (Gabry et al., 2019) for the flexible simultaneous equations model, to verify that the model can reproduce the observed distributions of the outcome data. We draw 3,000 replicates of the three outcome variables – the counts of falsifiable, opinion and anecdotal statements and questions that members direct to witnesses – derived from the posterior estimates of each model. This creates $3,000 \times 3$ “fake data” replication data sets.

As we describe in the paper, the vast majority of witnesses receive zero questions so the median for each outcome is zero; by comparison, the 9,000 replicated data sets also all have median zero. Because it is such an easy target, the median is not a good test for

Figure 11: Posterior predictive check for the flexible simultaneous equations model: actual and fake outcome data, showing a good replication of the data.

this reproducibility of the original data. We report the means and standard deviations for the true and fake data in table 7, and these also very closely match. In this table, the fake data results are the averages of the means and standard deviations across all 3,000 replicates. Finally, figure 11 shows the histograms of the true data (in dark colors) and for comparison we show the histogram of a single replicate fake data set (in light colors) for each of the outcomes. (The other replicates are very similar.) Overall, the flexible model does a good job replicating the original data based on the posterior parameter estimates, matching not only the means and standard deviations but also the pronounced skewness of the outcome data.

Considering confounds for the witness preference space. Given that the posterior preferences for witnesses rotate away from a well-defined and familiar roll-call preference

Table 7: Flexible Model Posterior Predictive Check Tests

Outcome	Mean	SD
Falisfiable:TrueData	1.16	3.15
Falisfiable:FakeData	1.16	3.12
Opinion:TrueData	0.46	1.59
Opinion:FakeData	0.38	1.75
Anecdotal:TrueData	0.38	1.72
Anecdotal:FakeData	0.46	1.59

space, it is a reasonable question to ask if the agent posterior parameters $\widehat{L}_a^1$ measure a preference space, as opposed to a confounding space such as a degree of technical expertise or topic or some other dimension. For example, it is possible that legislators at one end of the ideological spectrum value expertise more than the other and the agent space is simply an expertise space. However, we examine the correlation between a wide variety of measures of the witness' technical expertise (such as the presence of data tables and figures and the number of cites to academic research in the testimony) and the posterior witness preferences and there is none.

Figure 12: Distribution of agent preferences across selected topics using estimates of L_{ai}^1 from the simultaneous equations model, showing preferences are unrelated to topics.

Perhaps another confound is topic, where perhaps liberals ask more questions to wit-

nesses from one topic area and conservatives from another. To test this we organized the hearings by topic and find no differences in the distributions of witness preference locations across topics. This is illustrated in figure 12, where the large center dot is the average of witness preferences for the topic and the smaller dots are the individual estimates, for topics where there are six or more witnesses. Note that the averages closely cluster around the center and show little variability, while the individuals vary significantly around the average for all topics.

A.8 Text Analysis Details

The latent, agent-specific preference scale we recover in the application is orthogonal to the preference scale of legislators that is recovered using roll-call votes. In the paper we describe the text analysis procedure where we analyze the testimony of witnesses who score either high or low on the agent preference scale to describe the content of the preference dimension.

To conduct the text analysis, we grouped the hearings by topic, and identified the witnesses who had the highest and lowest posterior preference scores L_a^1 for the following set of topics: managed care, regulatory impacts, physician payments, disease management, and prescription drug coverage, and we pooled the testimony for those with high values together and those with low values together. We stratified by topic in order to ensure comparability across the two sets of documents and since word frequencies are governed by the content of documents. We made use of the text analysis tools recommended in [Silge and Robinson \(2017\)](#).²⁹ We stemmed and removed common English language stop words, and then we deleted health-care specific stop words that were common to both sets of documents and hence did not distinguish between documents that score high and low on the witness preference dimension. These words are “medicare,” “health,” “program,” “managed,” “patient,” “physician,” and “plan.”

²⁹Available at <https://www.tidytextmining.com/>.

A.9 Replication using Bonica CF Scores

As we explain above, identification of the flexible model requires a measure for a personal ideological space ψ that is a common preference space shared by both agents and legislators. We use this common space to map between personal ideological preferences and individuals’ policy preferences and is necessary for the model’s identification. Our application to Medicare hearings was designed to measure this common ideological space using standard survey items, which is the most preferred method as the survey items have been validated to measure personal ideology. Sending out surveys to legislators and witnesses is time consuming and costly, however. In this section we demonstrate that one can achieve nearly identical results using the existing measures of ideological common space developed by Bonica (2013), called CF scores, which enables researchers to use off-the-shelf data to estimate flexible policy preferences for witnesses at any set of hearings on any topic.

We accessed the Bonica CF scores at <https://data.stanford.edu/dime>. For the former members of Congress we used the recipient CF scores for the member’s final year in office, finding exact matches using the member’s ICPSR number. For the witnesses, we first extracted all individuals in the contributor database that had the matching last name, and either the matching first name or initial or initials. We then manually examined the matches for each individual to match using other attributes such as the witness’s employer or location. This manual matching could yield one of three results for each witness. If the search yielded a unique exact match on all attributes we record the witness CF contributor score. If the search yielded no matches or only matches that lack identifying attributes (such as if there were many “smith, tom” entries but none with a matching employer) then we do not record a CF score for that witness. Finally, if the search yielded several exact matches (such as if there were separate entries for “esterling, kevin” and “esterling, kevinm” both employed at UCR) then we took the weighted average of the corresponding CF scores, where the weights were determined by the number of contributions supporting each score, so if the first entry had 3 contributions

and the second had 133 contributions, the corresponding weights would be (3/136) and 133/136). We do not provide the worksheets for the matches in the replication material since these contain the Bonica identification numbers, but we can make the worksheets available on request with IRB approval.

These matching procedures produced CF scores for all but one of the former members of Congress, and 33 out of 67 witnesses. If an analyst wished to rely exclusively on CF scores for the common space, then the estimation sample would need to be limited to witnesses who have matching CF scores. However, the present application was designed around a survey-based approach to measuring the common space and so the survey responses determined the estimation sample. To keep the remaining 34 witnesses and one member who did not have a matching CF score, we use the survey common space measure to impute the missing witness CF scores. The survey items and the CF scores load uniquely on a single factor and hence this imputation is simply using one ideology common space (the survey measure) to impute scores on another ideology common space (the CF scores), using a standard bridging model, so the imputation is straightforward.

Figure 13 shows the results in which we replicate the model underlying figure 3 of the main text, but relying only on the Bonica CF scores as the common space. The results are essentially identical to those we find using survey items.

Figure 14 shows the results in which we replicate the model underlying figure 4 of the main text, using the flexible model, but again relying only on the Bonica CF scores as the common space. The results are very nearly identical, with the exception that the Bonica replication results have slightly higher standard errors and WAIC scores, which reflects the methodological issue that the Bonica CF score point estimates have measurement error while the scores in our preferred model are IRT scores that are latent scales. Thus the preferred results here are based on our survey rather than CF scores, but we are able to show here that one gets essentially the same results either way. We note that the similarity of results across the two different common space measures is no surprise

Figure 13: Replication of Figure 3 results from the constrained-regression model but using Bonica CF scores for the common space measure. The results are essentially identical to those using survey items to measure the common space.

since the common space measure is only used for identification in the model and does not directly play a substantive role. Thus, an analyst could rely on Bonica CF scores for the common space measure and not administer a survey in order to implement our model.

Finally, we re-estimated the constrained model using the exact setup as in Figure 1 of the main text, but instead using CF scores for both the committee members (those who participated in the hearings) and the witnesses. The results under this replication are essentially identical to those found in Figure 1 so we omit the results here. This null result too is no surprise since substituting CF scores for DW-NOMINATE scores does not change the model in any way other than changing the scale of the distance measure, which has no econometric impact, and since CF scores rely on the same unidimensional structure as DW-NOMINATE scores.

Measuring Preference Distance - Flexible + CF Scores

Figure 14: Replication of Figure 4 results from the flexible model but using Bonica CF scores for the common space measure. The results are exactly similar except the standard errors and the model WAIC scores are a bit larger because of the measurement error in the Bonica CF score point estimates relative to the survey-based IRT model.

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