

Words Get in the Way: The Effect of Deliberation in Collective Decision-Making*

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Abstract

We estimate a model of strategic voting with incomplete information in which committee members – judges in the US courts of appeals – have the opportunity to communicate before casting their votes. The model is characterized by multiple equilibria, and partial identification of model parameters. We obtain confidence regions for these parameters using a two-step estimation procedure that allows flexibly for characteristics of the alternatives and the individuals. To quantify the effects of deliberation on outcomes, we compare the probability of mistakes in the court with deliberation with a counterfactual of no pre-vote communication. We find that for most configurations of the court in the confidence set, in the best case scenario deliberation produces a small potential gain in the effectiveness of the court, and in the worst case it leads to large potential losses.

Keywords: partial identification, deliberation, communication equilibrium, voting

JEL codes: D72, C35, D82

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1 Introduction

Deliberation is an integral part of collective decision-making. Instances of voting in legislatures, courts, boards of directors, shareholder meetings, and academic committees are generally preceded by some form of communication among members, ranging from free to fully structured, and from public to private or segmented.

Does talking affect what people actually do? While a rosy picture of deliberation as an open-minded exchange of ideas suggests that it influences behavior, many real-world examples show that formal instances of deliberation can become hollow, with speeches being allowed but unheard (think of legislators' speeches in the chambers of Congress).¹ Even more, deliberation can possibly be counterproductive to the interests of some committee members, steering collective outcomes in the direction that more influential committee members would prefer. The question then is: does deliberation allow committee members to overcome their initial differences of opinion and points of views and increase the efficiency of decision-making? Or is it detrimental to effective decision-making?

How much deliberation can achieve in any given situation will naturally depend on the characteristics of the individuals making the decision and the choice situation. When the committee members have common goals, they should have incentives to exchange information truthfully, and act on it cohesively (Coughlan (2000), Goeree and Yariv (2011)). When instead committee members disagree, it will generally be harder to have them truthfully report their information to others. How much they will do so depends on how informative their private information is relative to the prior beliefs and biases of other committee members, and on their expectations about how others will communicate.

Our goal in this paper is to quantify the effect of deliberation on collective choices. To do this we structurally estimate a model of voting with deliberation. This approach allows us to disentangle committee members' preferences, information, and strategic considerations, and ultimately, to compare equilibrium outcomes under deliberation with a counterfactual scenario in which pre-vote communication is precluded.

We focus on decisions of the U.S. courts of appeals on criminal cases. The appellate court setting is attractive for this analysis for three reasons. First, appellate courts make decisions on issues in which there is an underlying common value component; a correct decision under the law, even if this can be arbitrarily hard to grasp given limited information. This environment allows us to evaluate the effect of deliberation on the efficiency of collective

¹Even in these cases deliberation might be important for outcomes, although here the relevant communication might involve private messages among groups of legislators.

outcomes. Second, courts of appeals are small committees, composed of only three judges. This allows us to capture relevant strategic considerations in a relatively simple environment. Third, within each circuit, judges are assigned to panels and cases on an effectively random basis. The random assignment norm minimizes the impact of “case selection”, whereby appellants are more likely to pursue cases in courts composed of more sympathetic judges.

We consider a simple decision-making model, tailored to the application. Three judges decide whether to uphold or overturn the decision of the lower court by simple majority vote. Whether the decision should be overturned or not is unobservable, for both the econometrician and the judges. Judges only observe a private signal, the precision of which is individual specific, and differ in the payoff of incorrectly overturning and upholding a decision of the lower court. The bias and the precision of judges’ private information is allowed to vary with characteristics of the case and the individual. To allow flexible communication, we consider communication equilibria (Forges (1986), Myerson (1986)), following Gerardi and Yariv (2007).

Because the incentive for any individual member to convey her information truthfully depends on her expectations about how others will communicate, any natural model of deliberation will have a large multiplicity of equilibria. Since this is also the case in our setting, the conventional maximum likelihood approach does not apply without an equilibrium selection mechanism. Instead, we base our estimation and inference solely on equilibrium conditions. These equilibrium conditions do not point identify the structural parameters characterizing judges’ biases and quality of information. For this reason, we obtain confidence regions for these parameters using a two-step estimation procedure that allows flexibly for characteristics of the alternatives and the individuals.

Our main result is a measure of the effect of deliberation in collective decision-making: how much do outcomes differ *because of* deliberation? To do this, we compare the equilibrium probability of error with deliberation with the probability of error that would have occurred in the absence of deliberation for the same court and case characteristics.

The comparison leads to mostly discouraging results for the prospects of deliberation. For most comparable points in the confidence set, in the best case deliberation produces a small gain in the effectiveness of the court, and in the worst case it leads to large losses. Consider for instance courts with the most competent judges. The minimum equilibrium error probability with deliberation is less than 5 pp lower than the corresponding error probability without deliberation. Yet at the same time, the maximum equilibrium error probability with deliberation is more than 25 pp higher than the corresponding error probability without deliberation. Especially, if we restrict attention to courts with small preference diversity

and highly competent judges, the latter number becomes as high as 60 pp.

The previous comparison is completely agnostic about the determinants of equilibrium selection in future play. If, instead, we restrict attention to equilibria *consistent* with the observed data, the prospects for deliberation are rather bleak. As in the case of all equilibria, the maximum equilibrium probability of error with deliberation generally vastly exceeds the corresponding figure maximum without deliberation. In addition, for a large number of points in the CS, the minimum equilibrium probability of error with deliberation across equilibria consistent with the data is *higher* than the minimum probability of error without deliberation. For 20% of the points in the confidence set, for instance, the minimum equilibrium probability of error without deliberation is below 1%. The corresponding figure for equilibria consistent with the data is 23%. Furthermore, for more than eighty percent of all comparable points in the confidence set, *all* equilibria with deliberation are worse than all equilibria without deliberation. Thus, although in the best case scenario deliberation *can* potentially reduce mistakes vis a vis the benchmark of no deliberation, in the selection of equilibria that is consistent with the data these potential gains are not realized. Instead, communication on average leads to large losses in the effectiveness of the court.

Surprisingly, the more unfavorable results for deliberation obtain when judges are highly competent (i.e., when judges' private signals are very precise). This is because the maximum equilibrium probability of error with deliberation actually increases with the competence of judges in the court, independently of the direction and level of their bias. The reason for this result is that judges' best responses in the game with deliberation are very sensitive to their expectations about how other individuals will communicate. And since judges care directly about the content of each others' messages, the effect of these beliefs is larger the more valuable is the information held by other members of the court.

In addition to speaking of the effect of deliberation on outcomes, our results also provide a new explanation for the large proportion of cases decided unanimously in the US court of appeals. This feature is commonly interpreted in the literature to suggest that judges are either like-minded from the outset, or have an intrinsic desire to compromise (see Fischman (2007) and references therein). Our results suggest an alternative interpretation. They suggest that competent judges with heterogeneous preferences can often agree after deliberating. Thus, a high rate of unanimous decisions does not imply either agreement *ex ante*, or a desire to put forward a "unified" stance in each case. Instead, it can be a consequence of communication among competent individuals with heterogeneous preferences.

2 Related literature

The structural estimation of voting models with incomplete information is a relatively recent endeavor in empirical economics. This paper extends several recent papers examining voting behavior in committees with incomplete information and common values (Iaryczower and Shum, (2012b, 2012a); Iaryczower, Lewis, and Shum (2011)).² In those papers committee members are assumed to vote without deliberating prior to the vote. This paper takes the analysis one step further, by allowing explicitly for communication among judges. As we show below, this extension is far from a trivial one, as the deliberation stage introduces multiple equilibria, rendering the conventional estimation approach inapplicable.

In terms of estimation and inference, this paper draws upon recent-developed tools from the econometric literature on partial identification (eg. Chernozhukov, Hong, and Tamer (2007), Beresteanu, Molchanov, and Molinari (2011)). A closely-related paper is Kawai and Watanabe (forthcoming), who study the partial identification of a strategic voting model using aggregate vote share data from Japanese municipalities.

Our basic model of collective decision-making builds on Feddersen and Pesendorfer (1998), allowing for heterogeneous biases and quality of information (all of which are public information). To this we add deliberation as in Gerardi and Yariv (2007), considering communication equilibria.³ This is an attractive model of voting with deliberation because the set of outcomes induced by communication equilibria coincides with the set of outcomes induced by sequential equilibria of any cheap talk extension of the underlying voting game.

Coughlan (2000), and Austen-Smith and Feddersen, (2005, 2006) introduce an alternative approach in this context, extending the voting game with one round of *public* deliberation. In essence, both papers allow committee members to carry out a straw poll prior to the vote (in the case of Austen-Smith and Feddersen (2005, 2006), this includes a third message, e.g. abstention). Coughlan (2000) shows that if committee members are sufficiently homogeneous, there is an equilibrium in which individuals vote sincerely in the straw poll, making all private information public. Austen-Smith and Feddersen, (2005, 2006) show that a similar result holds for a committee of size three when biases also are private information

²Iaryczower, Katz, and Saiegh (2012) uses a similar approach to study information transmission among chambers in the U.S. Congress. For structural estimation of models of voting with private values and complete information see Poole and Rosenthal (1985, 1991), Heckman and Snyder (1997), Londregan (1999), Clinton, Jackman, and Rivers (2004) – for the US Congress– and Martin and Quinn, (2002, 2007) – for the US Supreme Court. Degan and Merlo (2009), De Paula and Merlo (2009), and Henry and Mourifie (forthcoming) consider nonparametric testing and identification of the ideological voting model.

³Our model therefore is a particular case of Gerardi and Yariv (2007). In this paper, Gerardi and Yariv focus on a comparison of the set of communication equilibria across different voting rules. They show that every outcome that can be implemented with a non-unanimous voting rule r can also be implemented in communication equilibria with a non-unanimous rule r' .

if committee members are moderate enough, and provide a comparison of equilibria with partial revelation of information under simple majority and unanimity.⁴

While we are not aware of other papers analyzing deliberation with field data in a setting similar to the one considered here, some recent papers have analyzed deliberation in laboratory experiments. Guarnaschelli, McKelvey, and Palfrey (2000), using the straw poll setting of Coughlan (2000), show that subjects do typically reveal their signal (above 90% of subjects do so), but that contrary to the theoretical predictions, individuals' private information has a significant effect on their final vote. Goeree and Yariv (2011) show that when individuals can communicate freely, they typically disclose their private information truthfully and use public information effectively (as in Austen-Smith and Feddersen (2005) bias is private information, so individuals are identical *ex ante*).⁵

Finally, equilibria of voting with deliberation can lead to *panel effects* in voting. For papers studying panel effects in the courts of appeals see Fischman (2007), Kestellec (2011, 2013), and Boyd, Epstein, and Martin (2010).

3 The Model

We consider a model of voting in a small committee, tailored to cases from the US appellate courts. We allow for pre-vote deliberation amongst the judges – that is, for judges to discuss the case with each other, and potentially to reveal their private information to each other. Our model is based on Feddersen and Pesendorfer (1998) and Gerardi and Yariv (2007).

There are three judges, $i = 1, 2, 3$. Judge i votes to uphold ($v_i = 0$) or overturn ($v_i = 1$) the decision of the lower court. The decision of the court, $v \in \{0, 1\}$ is that of the majority of its members; i.e. overturns ($v = \psi(\vec{v}) = 1$) if and only if $\sum_i v_i \geq 2$.

We assume that the goal of judge i is that the decision of the court follows her own best understanding of how the law applies to the particulars of the case. There is room for conflict and interpretation because whether the decision of the lower court should be overturned ($\omega = 1$) or upheld ($\omega = 0$) according to the law is itself unobservable. Instead, each judge i only observes a private signal $t_i \in \{0, 1\}$ that is imperfectly correlated with the truth; i.e., $\Pr(t_i = k | \omega = k) = q_i > 1/2$ for $k = 0, 1$. The parameter q_i captures the informativeness of

⁴The complication in the analysis comes from the fact that players condition on being pivotal both at the voting and the deliberation stage. For other models of deliberation, see Li, Rosen, and Suen (2001), Doraszelski, Gerardi, and Squintani (2003), Meirowitz (2006), and Landa and Meirowitz (2009), Lizzeri and Yariv (2011).

⁵For other experimental results on deliberation, see McCubbins and Rodriguez (2006) and Dickson, Hafer, and Landa (2008).

i 's signals.⁶ The judges' signals are independent from each other conditional on ω .

Judge i suffers a cost $\pi_i \in (0, 1)$ when the court incorrectly overturns the lower court ($v = 1$ when $\omega = 0$) and of $(1 - \pi_i)$ when it incorrectly upholds the lower court ($v = 0$ when $\omega = 1$).⁷ The payoffs of $v = \omega = 0$ and $v = \omega = 1$ are normalized to zero. Thus given information \mathcal{I} , judge i votes to overturn if and only if $\Pr^i(\omega = 1|\mathcal{I}) \geq \pi_i$, or, equivalently, if and only if $\Pr^i(\mathcal{I}|\omega = 1)/\Pr^i(\mathcal{I}|\omega = 0) \geq \frac{\pi_i}{1-\pi_i} \frac{1-\rho}{\rho}$, where $\rho \equiv \Pr(\omega = 1)$ denotes justices' common prior probability that the decision of the lower court should be overturned.⁸ For convenience, we let $\theta \equiv (\rho, \vec{q})$.

In the absence of deliberation, this setting describes a voting game G . As in Gerardi and Yariv (2007), we model deliberation by considering equilibria of an extended game in which judges exchange messages *after* observing their signals and *before* voting. In particular, we consider a cheap talk extension of the voting game that relies on a fictional mediator, who helps the judges communicate. In this augmented game, judges report their signals \vec{t} to the mediator, who then selects the vote profile \vec{v} with probability $\mu(\vec{v}|\vec{t})$, and informs each judge of her own vote. The judges then vote. A *communication equilibrium* is a sequential equilibrium of this cheap talk extension in which judges (i) convey their private information truthfully to the mediator, and (ii) follow the mediator's recommendations' in their voting decisions (we describe the equilibrium conditions formally below). A powerful rationale for focusing on the set of communication equilibria, M , is that the set of outcomes induced by communication equilibria coincides with the set of outcomes induced by sequential equilibria of *any* cheap talk extension of G (see Gerardi and Yariv (2007)).

We can now define communication equilibria more formally. As we described above, in a *communication equilibrium* judges (i) convey their private information truthfully to the mediator, and (ii) follow the mediator's recommendations' in their voting decisions. These define two sets of incentive compatibility conditions, which we call the "deliberation stage" and "voting stage" constraints respectively.

⁶ Assuming $q_i > 1/2$ is without loss of generality, because if $q_i < 1/2$ we can redefine the signal as $1 - t_i$. The assumption that the signal quality does not depend on ω is made only for simplicity.

⁷ Thus, $\pi_i < 1/2$ reflects a bias towards upholding (or towards the Petitioner), while $\pi_i > 1/2$ reflects a bias towards overturning (or towards the Respondent). These preconceptions can reflect a variety of factors inducing a non-neutral approach to this case, such as ingrained theoretical arguments about the law, personal experiences, or ideological considerations.

⁸ Note that since ω is assumed to be unobservable, there is always information that would make any two justices disagree about a case. Moreover, if sufficiently biased, two justices can disagree almost always. In particular, with $\pi \approx 0$ (or $\pi \approx 1$), justice i is almost always ideological. On the other hand, when $\pi = 1/2$ for all i , the setting boils down to an unbiased, pure common values model.

Voting Stage. At the voting stage, private information has already been disclosed to the mediator. Still the equilibrium probability distributions $\mu(\cdot|\vec{t})$ over vote profiles \vec{v} must be such that each judge i wants to follow the mediator's recommendation v_i . Hence we need that for all $i = 1, 2, 3$, for all $v_i \in \{0, 1\}$, and for all $t_i \in \{0, 1\}$,

$$\sum_{t_{-i}} p(t_{-i}|t_i; \theta) \sum_{v_{-i}} [u_i(\psi(v_i, v_{-i}), \vec{t}) - u_i(\psi(1 - v_i, v_{-i}), \vec{t})] \mu(\vec{v}|\vec{t}) \geq 0, \quad (3.1)$$

where as usual $t_{-i} \equiv (t_j, t_k)$ and $v_{-i} \equiv (v_j, v_k)$ for $j, k \neq i$. Here $p(t_{-i}|t_i; \theta)$ denotes the conditional probability mass function of t_{-i} given t_i , and $u_i(\psi(\vec{v}), \vec{t})$ denotes the utility of judge i when the decision is $\psi(\vec{v})$ and the signal profile is \vec{t} . Note that $u_i(\psi(v_i, v_{-i}), \vec{t}) - u_i(\psi(1 - v_i, v_{-i}), \vec{t}) = 0$ whenever $v_{-i} \notin P_i \equiv \{(v_j, v_k) : v_j \neq v_k\}$. Then (3.1) is equivalent to (3.2) (for $v_i = 1$) and (3.3) (for $v_i = 0$) for $i = 1, 2, 3$ and for all $t_i \in \{0, 1\}$:

$$\sum_{t_{-i}} p(t_{-i}|t_i; \theta) [p_\omega(1|\vec{t}; \theta) - \pi_i] \sum_{v_{-i} \in P_i} \mu(1, v_{-i}|\vec{t}) \geq 0 \quad (3.2)$$

and

$$\sum_{t_{-i}} p(t_{-i}|t_i; \theta) [\pi_i - p_\omega(1|\vec{t}; \theta)] \sum_{v_{-i} \in P_i} \mu(0, v_{-i}|\vec{t}) \geq 0, \quad (3.3)$$

where $p_\omega(\omega|\vec{t}; \theta)$ denotes conditional probability mass function of ω given \vec{t} . There are therefore 12 such equilibrium conditions at the voting stage. For interpretation, note that the conditions (3.2) can be written as

$$\sum_{t_{-i}} [\Pr(\omega = 1|t_{-i}, t_i; (q, \rho)) - \pi_i] \sum_{v_{-i} \in P_i} \mu((1, v_{-i})|(t_i, t_{-i})) \Pr(t_{-i}|t_i; (q, \rho)) \geq 0,$$

which provided $\sum_{t_{-i}} \sum_{v_{-i} \in P_i} \mu((1, v_{-i})|(t_i, t_{-i})) \Pr(t_{-i}|t_i; (q, \rho)) > 0$, can be written as

$$\Pr(\omega = 1|v_i = 1, t_i, Piv^i; (\vec{q}, \rho, \mu)) \geq \pi_i.$$

That is, conditional on her vote v_i , signal t_i , and conditional on Piv^i , the event that i is pivotal in the decision (given μ), i prefers to overturn the decision of the lower court. Similarly conditions (3.3) boil down to $\Pr(\omega = 1|v_i = 0, t_i, Piv^i; (\vec{q}, \rho, \mu)) \leq \pi_i$.

Deliberation Stage. At the deliberation stage, communication equilibria require that judges are willing to truthfully disclose their private information to the mediator, anticipating the outcomes induced by the equilibrium probability distributions $\mu(\cdot|\vec{t})$ over vote profiles \vec{v} . This includes ruling out deviations at the deliberation stage that are profitable

when followed up by further deviations at the voting stage. To consider this possibility we define the four “disobeying” strategies:

$$\begin{aligned}\tau_1(v_i) = v_i &: && \text{always obey} \\ \tau_2(v_i) = 1 - v_i &: && \text{always disobey} \\ \tau_3(v_i) = 1 &: && \text{always overturn} \\ \tau_4(v_i) = 0 &: && \text{always uphold}\end{aligned}$$

We require that for all $i = 1, 2, 3$, all $t_i \in \{0, 1\}$, and $\tau_j(\cdot)$, $j = 1, 2, 3, 4$:

$$\sum_{t_{-i}} p(t_{-i}|t_i; \theta) \sum_v [u_i(\psi(\vec{v}), \vec{t})\mu(\vec{v}|t_i, t_{-i}) - u_i(\psi(\tau_j(v_i), v_{-i}), \vec{t})\mu(\vec{v}|1 - t_i, t_{-i})] \geq 0 \quad (3.4)$$

There are therefore 24 such equilibrium conditions at the deliberation stage.

For any given $(\theta, \vec{\pi})$, the conditions (3.2), (3.3), and (3.4) characterize the set of communication equilibria $M(\theta, \vec{\pi})$; i.e.,

$$M(\theta, \vec{\pi}) = \{\mu \in \mathcal{M} : (\theta, \vec{\pi}, \mu) \text{ satisfies (3.2), (3.3) and (3.4)}\}, \quad (3.5)$$

where \mathcal{M} is the set of all possible values that μ can take, and it can be conveniently thought of as the set of 8×8 dimensional matrices whose elements lie in $[0, 1]$ and each row sums to one. Note that $M(\theta, \vec{\pi})$ is convex, as it is defined by linear inequality constraints on μ .

Remark 3.1 (Robust Communication Equilibria). Note that for given v_i , the vote profiles in which the *other* judges vote unanimously to overturn or uphold do not enter the incentive compatibility conditions at the voting stage. Thus, without any additional refinement, the set of communication equilibria includes strategy profiles in which some members of the court vote against their preferred alternative only because their vote cannot influence the decision of the court. These include not only strategy profiles μ that put positive probability only on unanimous votes, but also profiles in which i votes against her preferred alternative only because *conditional* on her signal and her vote recommendation she is sure – believes with probability one – that her vote is not decisive. Consider the example in Table 1.

The strategy profile in Table 1 is a communication equilibrium for $\rho = 0.1$, and $\pi_i = 0.3, q_i = 0.6$ for $i = 1, 2, 3$. However, judge 1 votes to overturn with positive probability even if $\Pr(\omega = 1|\vec{t}) < \pi$ for all \vec{t} . This in spite of the fact that non-unanimous vote profiles are played with positive probability. However, *conditional* on $t_1 = 0$ (columns 5 to 8) and $v_1 = 1$ (rows 1 to 4), judge 1 believes that either $\vec{v} = (1, 0, 0)$ or $\vec{v} = (1, 1, 1)$ are played. As a result, her vote is not decisive in equilibrium, and 1 is willing to vote to overturn. The same is true in this example conditional on $t_1 = 1$. A similar logic holds for judges 2 and 3.

		Signal Profile							
		(1,0,0)	(1,0,1)	(1,1,0)	(1,1,1)	(0,0,0)	(0,0,1)	(0,1,0)	(0,1,1)
Vote Profile	(1,0,0)	0.000	0.033	0.000	0.015	0.005	0.000	0.077	0.000
	(1,0,1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1,1,0)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1,1,1)	0.119	0.282	0.132	0.274	0.216	0.118	0.202	0.132
	(0,0,0)	0.855	0.657	0.859	0.689	0.623	0.850	0.688	0.858
	(0,0,1)	0.000	0.000	0.000	0.000	0.131	0.000	0.000	0.000
	(0,1,0)	0.026	0.027	0.010	0.022	0.025	0.031	0.033	0.009
	(0,1,1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Pr(v=1 t)	0.119	0.282	0.132	0.274	0.216	0.118	0.202	0.132
	Pr(v=0 t)	0.881	0.718	0.868	0.726	0.784	0.882	0.798	0.868
	Pr(w=1 t)	0.069	0.143	0.143	0.273	0.032	0.069	0.069	0.143

Table 1: A Non-Robust Communication Equilibrium for $\rho = 0.1$ and $\pi_i = 0.3, q_i = 0.6$ for $i = 1, 2, 3$.

Because these equilibria are not robust to small perturbations in individuals' beliefs about how others will behave, we rule them out. To do this, we require that each individual best responds to beliefs that are consistent with small trembles (occurring with probability η) on equilibrium play (so that all vote profiles have positive probability after any signal profile). Formally, in all equilibrium conditions (at both the voting and deliberation stage) we substitute $\Pr(\vec{v}|\vec{t})$ in place of $\mu(\vec{v}|\vec{t})$, where for any \vec{t} and \vec{v} ,

$$\Pr(\vec{v}|\vec{t}) = \sum_{\hat{v}:\hat{v}_i=v_i} \mu(\hat{v}|\vec{t}) \prod_{j \neq i} (1 - \eta)^{\hat{v}_j=v_j} \eta^{\hat{v}_j \neq v_j}$$

The η we use in the empirical section is 0.000001. To evaluate the robustness of our results, we replicate the analysis using two larger values of η : 0.001 and 0.01. This relaxes significantly the consistency of equilibrium beliefs with equilibrium strategies. The results, presented in Figure 10 in the appendix, show that our findings are qualitatively unchanged.

4 Data

The data are drawn together from two sources. The main source is the United States Courts of Appeals Data Base (Songer (2008)). This provides detailed information about a substantial sample of cases considered by courts of appeals between 1925 and 1996, including characteristics of the cases, the judges hearing the case, and their votes. Among the roughly 16,000 cases in the full database, we restrict our attention to criminal cases, which make up around 25% of the total. The case and judge-specific variables which we use in our analysis are summarized in Table 5 in the Appendix. Additional information for judges involved

in these decisions was obtained from the Multi-User Data Base on the Attributes of U.S. Appeals Court Judges (Zuk, Barrow, and Gryski (2009)).

Since we are modeling the voting behavior on appellate panels, we distinguish between judges' votes for *upholding* ($v = 0$) versus *overturning* ($v = 1$) the decision of a lower court.⁹ Thus, given the majority voting rule, among the eight possible vote profiles, there are four which lead to an outcome of upholding the lower court's decision – $(0, 0, 0)$, $(1, 0, 0)$, $(0, 1, 0)$, $(0, 0, 1)$ – and four leading to overturning – $(1, 1, 1)$, $(1, 1, 0)$, $(1, 0, 1)$ and $(0, 1, 1)$.

For each case, we include a dummy variable (“FedLaw”) for whether the case is prosecuted under federal (rather than state) law, as well as dummy variables for the crime in each case. These crime categories are based on the nature of the criminal offense in the case, and do not exhaust the set of possible crimes, but instead constitute “common” issues, bundling a relatively large number of cases within each label. Thus “Aggravated” contains murder, aggravated assault, and rape cases. “White Collar” crimes include tax fraud, and violations of business regulations, etc. “Theft” includes robbery, burglary, auto theft, and larceny. The “Narcotics” category encompasses all drug-related offenses.

In addition to the nature of the crime, we also include information about the major legal issue under consideration in the appeal. In particular, we distinguish issues of Jury Instruction, Sentencing, Admissibility and Sufficiency of evidence from other legal issues.

We also include three variables which describe the makeup of the judicial panel deciding each case: an indicator for whether the panel is a Republican majority (“Rep. Majority”), whether the panel contains at least one woman (“Woman on panel”), and whether there is a majority of Harvard and/or Yale Law School graduates on the panel (“Harvard-Yale Majority”). This latter variable is included to capture possible “club effects” in voting behavior; the previous literature has pointed out how graduates from similar program may share common judicial views, and vote as a bloc.

Finally, we include four judge-specific covariates. “Republican” indicates a judge's affiliation to the Republican Party. “Yearsexp” measures the number of years that a judge has served on the court of appeals, at the time that he/she decides a particular case (this variable varies both across judges and across cases). “Judexp” and “Polexp” measure the number of years of, respectively, judicial and political experience which a judge had prior to his/her appointment to the appellate court.

Judges are assigned to cases on an effectively random basis. The particular assignment pro-

⁹Courts of appeal in the US do not determine the guilt or innocence of the accused, but only assess whether or not errors have been committed at trial. Their decisions are based on the record of the case established by the trial court, and do not consider additional evidence or hear witnesses.

cedures vary from circuit to circuit, with some circuits using explicitly random assignments (via random number generators) and others incorporating additional factors as dictated by practical considerations (e.g., availability). This semi-random nature of panel assignment means that the parties in each case have little influence over the particular makeup of the panel which hears their case; this minimizes “case selection” problems which may otherwise confound the interpretation of the estimation results.¹⁰

5 Econometric Model

5.1 Partial identification of model parameters

The immediate goal of the estimation is to recover the signal/state distribution parameters, θ , and the judges’ preference vector $\vec{\pi}$. The information used to recover these parameters is the distribution of the voting profiles, $p_v(\vec{v})$, which can be identified from the data. Here we define the *sharp identified set* for the model parameters.¹¹ The sharp identified set of $\{\theta, \vec{\pi}\}$ is the set of parameters that can rationalize $p_v(\vec{v})$ under some equilibrium selection mechanism λ – a mixing distribution over $\mu \in M(\theta, \vec{\pi})$. In other words, the sharp identified set \mathcal{A}_0 is the set of $(\theta, \vec{\pi}) \in \Theta \times [0, 1]^3$ such that there exists a λ that satisfies

$$p_v(\vec{v}) = \int_{\mu \in M(\theta, \vec{\pi})} \lambda(\mu) \sum_{\vec{t}} \mu(\vec{v}|\vec{t}) p(\vec{t}; \theta) d\lambda. \quad (5.1)$$

However, because the set $M(\theta, \vec{\pi})$ of communication equilibria is convex, whenever there exists a mixture λ satisfying (5.1) there exists a single equilibrium $\mu \in M(\theta, \vec{\pi})$ such that $p_v(\vec{v}) = \sum_{\vec{t}} \mu(\vec{v}|\vec{t}) p(\vec{t}; \theta)$.¹² Thus \mathcal{A}_0 boils down to

$$\mathcal{A}_0 = \{(\theta, \vec{\pi}) \in \Theta \times [0, 1]^3 : \exists \mu \in M(\theta, \vec{\pi}) \text{ s.t. } p_v(\vec{v}) = \sum_{\vec{t}} \mu(\vec{v}|\vec{t}) p(\vec{t}; \theta)\}. \quad (5.2)$$

¹⁰See Iaryczower and Shum’s (2012b) study of US Supreme Court voting behavior for a more extended discussion and assessment of case selection.

¹¹The sharpness of the identified set is in the sense of Berry and Tamer (2006), Galichon and Henry (2011), Beresteanu, Molchanov, and Molinari (2011). However, our estimation approach differs quite substantially from those papers.

¹²This fact implies an observational equivalence between a unique communication equilibrium being played in the data, versus a mixture of such equilibria. Sweeting (2009) and De Paula and Tang (2012) discuss the non-observational equivalence between mixture of equilibria and a unique mixed strategy equilibria in coordination games. One difference is that communication equilibria induce correlated actions, whereas mixed-strategy equilibria induce independent actions.

We will also introduce the following set \mathcal{B}_0 :

$$\mathcal{B}_0 = \{(\theta, \vec{\pi}, \mu) \in \mathcal{B} : \mu \in M(\theta, \vec{\pi}) \text{ and } p_v(\vec{v}) = \sum_{\vec{t}} \mu(\vec{v}|\vec{t})p(\vec{t}; \theta)\}, \quad (5.3)$$

where $\mathcal{B} = \Theta \times [0, 1]^3 \times \mathcal{M}$ and \mathcal{M} is the set of $\mu - 64 \times 64$ dimensional matrices, the elements of which are positive and each row sums to 1. The set \mathcal{B}_0 is the sharp identified set of $\{(\theta, \vec{\pi}, \mu)\}$, where μ is the true mixture voting assignment probability. The identified set \mathcal{A}_0 can be considered as the projection of \mathcal{B}_0 onto its first $d_\theta + 3$ dimensions, corresponding to the parameters $(\theta, \vec{\pi})$.

Identification in a Symmetric Model: Intuition. Before proceeding on to the estimation of the identified set, we provide some intuition for the identification of the model parameters by analyzing a stripped-down model in which the three judges are symmetric, in the sense that they have identical preferences and quality of information. That is, the bias parameters are identical across judges ($\pi_1 = \pi_2 = \pi_3 = \pi$) and so are the signal accuracies ($q_1 = q_2 = q_3 = q$). In this simple model, there are only three parameters (ρ, q, π) .

In Figure 1 we show the pairs (π, q) in the identified set for four different vote profile vectors and given values of the common prior ρ . The figure on the upper left panel plots the identified set for $\rho = 0.5$, and a uniform distribution of vote profiles, i.e., $p_v(\vec{v}) = 1/8$ for all \vec{v} . Because of the symmetry of the vote profile and the characteristics of the individuals, the identified set is also symmetric. Moreover, the set of biases π in the identified set for each value of q is increasing in q . Thus, low ability judges must be moderate if they are to be consistent with the “data”, but high ability judges can be very biased towards either upholding or overturning and still play a mixture of equilibria consistent with the data.

The figure on the top right plots the pairs (π, q) in the identified set for the uniform distribution over vote profiles and $\rho = 0.1$. In this case the public information incorporated in the prior is very favorable towards upholding the decision of the lower court. As a result, only judges that are very biased towards *overturning* can vote in a way consistent with the uniform distribution of the voting profile. The figures in the lower panel return to $\rho = 0.5$, but consider non-uniform distributions of vote profiles. In the lower-left figure only unanimous votes have positive probability, and the probability of overturning is $p_v(1, 1, 1) = 0.9$, while $p_v(0, 0, 0) = 0.1$. As in the first figure, low ability judges must be moderate if they are to be consistent with the “data”, but high ability judges must be biased towards overturning, and increasingly so the higher the information precision. The same result holds in the lower right figure, where also overturning is more likely, but only non-unanimous votes have positive probability. In this case, however, more moderate judges are consistent with

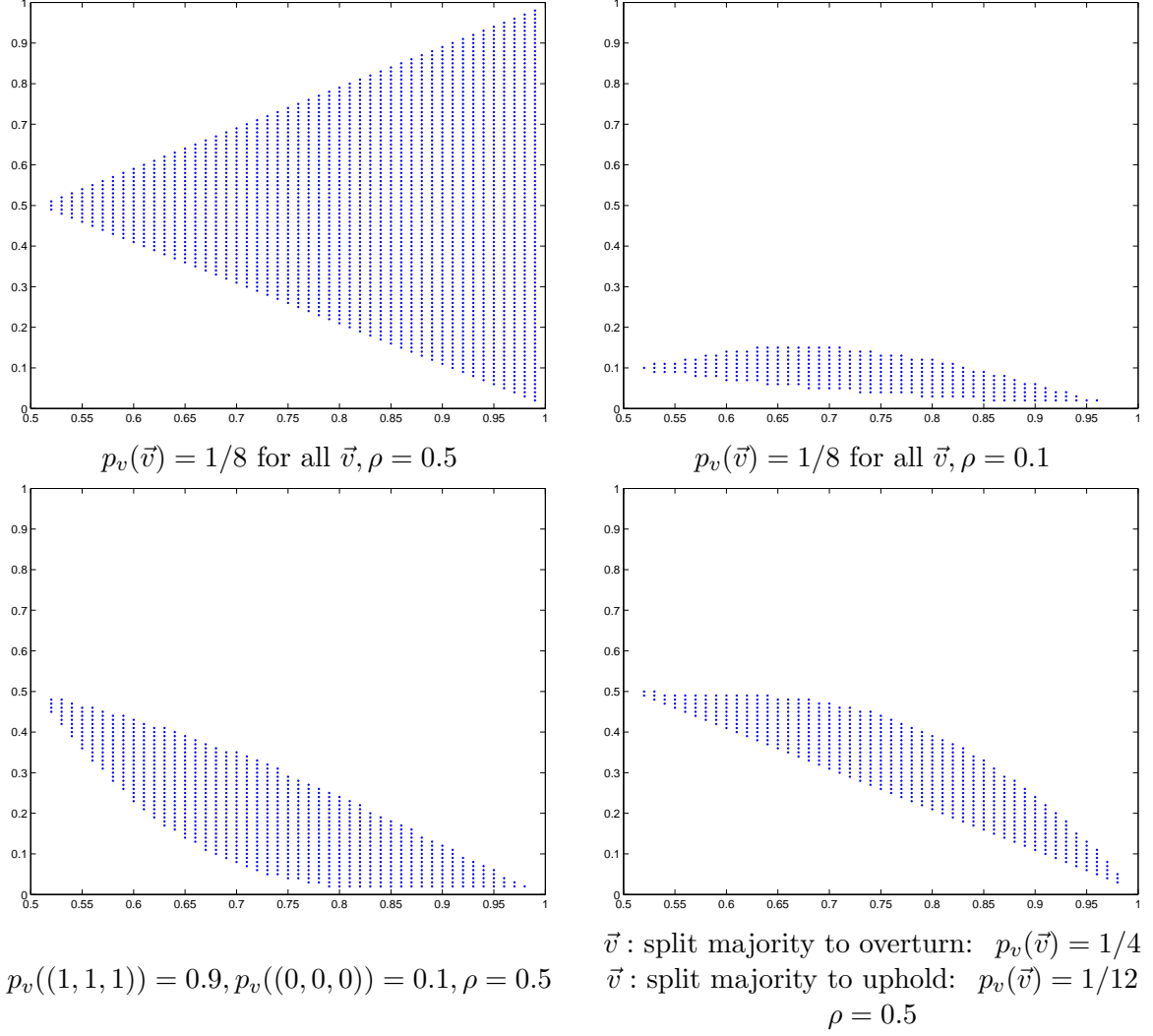


Figure 1: Identification of Second-Stage Parameters: A Simplified Model: $q_i = q$ for all i , $\pi_i = \pi$ for all i . X-axis: q (probability of correct signal); Y-axis: π (judges' bias parameter)

the data for any given level of q .

5.2 Estimation

To study the estimation of the identified set, we define the criterion function

$$Q(\theta, \vec{\pi}; W) = \min_{\mu \in M(\theta, \vec{\pi})} Q(\theta, \vec{\pi}, \mu; W) \text{ where} \\ Q(\theta, \vec{\pi}, \mu, W) = (\vec{p}_v - P_t(\theta)\vec{\mu})' W (\vec{p}_v - P_t(\theta)\vec{\mu}), \quad (5.4)$$

and where $\vec{p}_v = (p_v(111), p_v(110), p_v(101), p_v(100), p_v(010), p_v(001), p_v(000))'$, $\vec{\mu}$ is a 64-vector whose $8k + 1$ 'th to $8k + 8$ 'th coordinates are the $(k + 1)$ 'th row of $\mu(\vec{v}|\vec{t})$ for $k = 0, \dots, 7$, $P_t(\theta) = p(\vec{t}, \theta)' \otimes [I_7 | 0_7]$ and W is a positive definite weighting matrix specified later.

The profile of vote probabilities $p_v(\vec{v})$ is unknown, but can be estimated by the empirical frequencies of the vote profiles:

$$\hat{p}_v(\vec{v}) = \frac{1}{n} \sum_{l=1}^n 1(V_l = \vec{v}), \quad (5.5)$$

where V_l is the observed voting profile for case l and n is the sample size. Assuming that the cases are i.i.d., by the law of large numbers, $\hat{p}_v(\vec{v}) \rightarrow_p p_v(\vec{v})$ for all $\vec{v} \in \mathcal{V}$, where $\mathcal{V} = \{111, 110, 101, 100, 011, 010, 001\}$. One can define a sample analogue estimator for \mathcal{A}_0 :

$$\hat{\mathcal{A}}_n = \{(\theta, \vec{\pi}) \in \Theta \times [0, 1]^3 : Q_n(\theta, \vec{\pi}, W_n) = \min_{(\theta, \vec{\pi}) \in \Theta \times [0, 1]^3} Q_n(\theta, \vec{\pi}, W_n)\}, \quad (5.6)$$

where W_n is an estimator of W and Q_n is defined like Q except with \vec{p}_v replaced by its sample analogue $\hat{\vec{p}}_v$.

The following theorem establishes the consistency of $\hat{\mathcal{A}}_n$ with respect to the Hausdorff distance:

$$d_H(\hat{\mathcal{A}}_n, \mathcal{A}_0) = \max \left\{ \sup_{(\theta, \vec{\pi}) \in \hat{\mathcal{A}}_n} \inf_{(\theta^*, \vec{\pi}^*) \in \mathcal{A}_0} \|(\theta, \vec{\pi}) - (\theta^*, \vec{\pi}^*)\|, \sup_{(\theta^*, \vec{\pi}^*) \in \mathcal{A}_0} \inf_{(\theta, \vec{\pi}) \in \hat{\mathcal{A}}_n} \|(\theta, \vec{\pi}) - (\theta^*, \vec{\pi}^*)\| \right\}. \quad (5.7)$$

In general partially identified models, the sample analogue estimators for the identified sets typically are not consistent with respect to the Hausdorff distance. See e.g. Chernozhukov, Hong, and Tamer (2007). Our problem has a special structure that guarantees consistency under mild conditions.

Theorem 1. Suppose that $W_n \rightarrow_p W$ for some finite positive definite matrix W and Θ is compact. Also suppose that $\text{cl}(\text{int}(\mathcal{B}) \cap \mathcal{B}_0) = \mathcal{B}_0$.¹³ Then, $d_H(\hat{\mathcal{A}}_n, \mathcal{A}_0) \rightarrow_p 0$ as the sample size n goes to infinity.

Proof. Because $p(\vec{t}, \theta) = p(\vec{t}|w = 1; \theta)\rho + p(\vec{t}|w = 0; \theta)(1 - \rho)$ is continuously differentiable in θ , Theorem 2.1 of Shi and Shum (2012) applies and shows that $d_H(\hat{\mathcal{B}}, \mathcal{B}_0) \rightarrow_p 0$, where

$$\hat{\mathcal{B}}_n = \{(\theta, \vec{\pi}, \vec{\mu}) \in \mathcal{B} : Q_n(\theta, \vec{\pi}, \mu; W_n) = \min_{(\theta, \vec{\pi}) \in \Theta \times [0, 1]^3} Q_n(\theta, \vec{\pi}, W_n)\}, \quad (5.8)$$

where $Q_n(\theta, \vec{\pi}, \mu; W_n)$ is defined like $Q(\theta, \vec{\pi}, \mu; W)$ but with \vec{p} and W replaced by $\hat{\vec{p}}$ and W_n . Because $\hat{\mathcal{A}}_n$ and \mathcal{A}_0 are the projections of $\hat{\mathcal{B}}_n$ and \mathcal{B}_0 onto their first $d_\theta + 3$ dimension, respectively, we have $d_H(\hat{\mathcal{A}}_n, \mathcal{A}_0) \rightarrow_p 0$. \square

5.3 Confidence Set

Next, we discuss statistical inference in partially identified models based on confidence sets which cover either the true parameter, or the identified set with a prespecified probability. Following the literature, we construct a confidence set by inverting a test for the null hypothesis $H_0 : (\theta, \vec{\pi}) \in \mathcal{A}_0$ for each fixed $(\theta, \vec{\pi})$. To be specific, we collect all the $(\theta, \vec{\pi})$ such that there is one $\mu \in M(\theta, \vec{\pi})$ at which the H_0 is accepted. The collection of all those $(\theta, \vec{\pi})$ forms a confidence set.¹⁴

Next, we define the test statistic used in the test which we will invert. Standard application of the central limit theorem gives us $\sqrt{n}(\hat{\vec{p}}_v - \vec{p}_v) \rightarrow_d N(0, \Sigma)$, where Σ denote the variance matrix of $(1(V_l = 111), 1(V_l = 110), 1(V_l = 101), 1(V_l = 100), 1(V_l = 011), 1(V_l = 010), 1(V_l = 001))'$. Let $\hat{\Sigma}_n$ be the sample analogue estimator of Σ . Then the law of large number implies $\hat{\Sigma}_n \rightarrow_p \Sigma$.

Accordingly, we define the following test statistic:

$$T_n(\theta, \vec{\pi}) = nQ_n(\theta, \vec{\pi}; \hat{\Sigma}_n^{-1}). \quad (5.9)$$

By definition, $T_n(\theta, \vec{\pi}) \leq nQ_n(\theta, \vec{\pi}, \mu; \hat{\Sigma}_n^{-1})$ for any $(\theta, \vec{\pi}, \mu) \in \mathcal{B}_0$. Using standard argu-

¹³This is a weak assumption that is satisfied if each point in \mathcal{B}_0 is either in the interior of \mathcal{B} or is a limit point of a sequence in the interior of \mathcal{B} . Unlike seemingly similar assumptions in the literature, it does not require the identified set \mathcal{B}_0 to have nonempty interior. In this paper, numerical calculation of the identified sets for different values of \vec{p}_v shows that this assumption holds.

¹⁴This inferential method differs from the approach of Pakes, Porter, Ho, and Ishii (2009), which is based on moment inequalities derived from agents' best-response correspondences. While this approach has proved useful in several applications with games of complete information, in the context of our incomplete information environment we have not been able to derive moment inequalities based on best-response behavior.

ments, we can show that for any $(\theta, \vec{\pi}, \mu) \in \mathcal{B}_0$, $nQ_n(\theta, \vec{\pi}, \mu, \hat{\Sigma}_n^{-1}) \rightarrow_d \chi^2(7)$. Thus, a test of significance level $\alpha \in (0, 1)$ can use the $1 - \alpha$ quantile of $\chi^2(7)$ as critical value. The confidence set for $(\theta, \vec{\pi})$ is defined as

$$CS_n(1 - \alpha) = \{(\theta, \vec{\pi}) \in \Theta \times [0, 1]^3 : T_n(\theta, \vec{\pi}) \leq \chi_{7, \alpha}^2\}, \quad (5.10)$$

where $\chi_{7, \alpha}^2$ is the $1 - \alpha$ quantile of $\chi^2(7)$.

Theorem 2. *Suppose Σ is invertible. Then*

- (a) $\liminf_{n \rightarrow \infty} \inf_{(\theta, \vec{\pi}) \in \mathcal{A}_0} \Pr((\theta, \vec{\pi}) \in CS_n(1 - \alpha)) \geq 1 - \alpha$; and
- (b) $\liminf_{n \rightarrow \infty} \Pr(\mathcal{A}_0 \subseteq CS_n(1 - \alpha)) \geq 1 - \alpha$.

Proof. (a) For any sequence $\{(\theta_n, \vec{\pi}_n) \in \mathcal{A}_0\}_{n=1}^\infty$, there exists $\{\mu_n \in M(\theta_n, \vec{\pi}_n)\}_{n=1}^\infty$ such that $\vec{p}_v = P_t(\theta_n) \vec{\mu}_n$. Thus, $nQ_n(\theta_n, \vec{\pi}_n, \mu_n; \hat{\Sigma}_n^{-1}) = n(\hat{\vec{p}}_v - \vec{p}_v)' \hat{\Sigma}_n^{-1} (\hat{\vec{p}}_v - \vec{p}_v) \rightarrow_d \chi^2(7)$. Thus

$$\begin{aligned} \Pr((\theta_n, \vec{\pi}_n) \in CS_n(1 - \alpha)) &= \Pr(T_n(\theta_n, \vec{\pi}_n) \leq \chi_{7, \alpha}^2) \\ &\geq \Pr(nQ_n(\theta_n, \vec{\pi}_n, \mu_n; \hat{\Sigma}_n^{-1}) \leq \chi_{7, \alpha}^2) \\ &\rightarrow \Pr(\chi^2(7) \leq \chi_{7, \alpha}^2) = 1 - \alpha. \end{aligned} \quad (5.11)$$

This implies part (a).

(b) Part (b) holds because

$$\begin{aligned} \Pr(\mathcal{A}_0 \subseteq CS_n(1 - \alpha)) &= \Pr\left(\sup_{(\theta, \vec{\pi}) \in \mathcal{A}_0} T_n(\theta, \vec{\pi}) \leq \chi_{7, \alpha}^2\right) \\ &\geq \Pr\left(\sup_{(\theta, \vec{\pi}, \mu) \in \mathcal{B}_0} nQ_n(\theta, \vec{\pi}, \mu; \hat{\Sigma}_n^{-1}) \leq \chi_{7, \alpha}^2\right) \\ &= \Pr(n(\hat{\vec{p}}_v - \vec{p}_v)' \hat{\Sigma}_n^{-1} (\hat{\vec{p}}_v - \vec{p}_v) \leq \chi_{7, \alpha}^2) \\ &\rightarrow \Pr(\chi^2(7) \leq \chi_{7, \alpha}^2) = 1 - \alpha, \end{aligned} \quad (5.12)$$

where the second equality holds because for all $(\theta, \vec{\pi}, \mu) \in \mathcal{B}_0$, $\vec{p}_v = P_t(\theta) \vec{\mu}$. \square

Remark 5.1. Part (a) shows that CS_n covers the true value of $(\theta, \vec{\pi})$ with asymptotic probability no smaller than $1 - \alpha$. Interestingly, it is also a confidence set that covers \mathcal{A}_0 with asymptotic probability no smaller than $1 - \alpha$, as shown in part (b).¹⁵ The intuition for this phenomenon is that the random components of $T_n(\theta, \vec{\pi}, \mu)$ – which are just the empirical frequencies of the vote probabilities $\hat{\vec{p}}$ – do not depend on the model parameters (θ, π) . Because of this, the second-stage confidence sets for (θ, π) are obtained by the random elements in $\hat{\vec{p}}$, by a (loosely-speaking) partially-identified analog of the Delta method. In contrast, in

¹⁵ Imbens and Manski (2004) initiated a sizable literature regarding these two types of confidence sets.

typical moment inequality models, the random sample moment functions depend explicitly on the model parameters.

Remark 5.2. Because the confidence set CS_n above is based on the asymptotic critical value for $nQ_n(\theta, \vec{\pi}, \mu; \hat{\Sigma}_n^{-1})$, which is weakly bigger than $T_n(\theta, \vec{\pi})$, it may over-cover asymptotically; that is, it may be larger than necessary. Tighter and nonconservative confidence sets can be constructed by directly approximating the distribution of $T_n(\theta, \vec{\pi})$ using the methods developed in Bugni, Canay, and Shi (2011) and Kitamura and Stoye (2011).¹⁶ The disadvantage of doing this is two-fold: (i) the critical value will need to be simulated and will depend on θ and $\vec{\pi}$ and (ii) a tuning parameter will need to be introduced to reflect the slackness of the inequality constraints. In addition, in our data, we find that the confidence set CS_n is not much larger than the estimated set $\hat{\mathcal{A}}_n$, suggesting that not much can be gained by adopting the more complicated methods.

The confidence set can be computed in the following steps:

(1) for each $(\theta, \vec{\pi})$, compute $T_n(\theta, \vec{\pi}) = nQ_n(\theta, \vec{\pi}; \hat{\Sigma}_n^{-1})$ by solving the quadratic programming problem:

$$Q_n(\theta, \vec{\pi}; W_n) = \min_{\vec{\mu} \in [0,1]^{64}} (\vec{p}_v - P_t(\theta)\vec{\mu})' W (\vec{p}_v - P_t(\theta)\vec{\mu})' \\ \text{s.t. (3.2), (3.3), (3.4), and } \sum_{j=k+1}^{k+8} \vec{\mu}_j = 1, \quad k = 0, \dots, 7. \quad (5.13)$$

(2) repeat step (1) for many grid points of $(\theta, \vec{\pi}) \in \Theta \times [0, 1]^3$, and

(3) collect the points in step (2) that satisfy $T_n(\theta, \vec{\pi}) \leq \chi_{7,\alpha}^2$ and the points form $CS_n(1-\alpha)$.

For all the results in this paper, we use a value of $\alpha = 0.05$.

5.4 Handling Covariates – Two-step Estimation

Here we describe a two-step estimation approach for this model, which resembles the two-step procedure in Iaryczower and Shum (2012b). This is a simple and effective way to deal with a large number of covariates. Throughout, we let X_t denote the set of covariates associated with case t , including the characteristics of the judges who are hearing case t .

¹⁶ See Wolak (1989) for the case where the inequality constraints are linear in the structural parameters θ .

In the first step, we estimate a flexible “reduced-form” model for the vote probabilities $p_v(\vec{v}|X)$.¹⁷ Specifically, we parameterize the probabilities of the eight feasible vote profiles using an 8-choice multinomial logit model. Letting i index the eight vote profiles, we have

$$\begin{aligned} p_v(v_i|X; \beta) &= \frac{\exp(X_i' \beta_i)}{1 + \sum_{i'=1}^7 \exp(X_{i'}' \beta_{i'})}, \quad i = 1, \dots, 7; \\ p_v(v_8|X; \beta) &= \frac{1}{1 + \sum_{i'=1}^7 \exp(X_{i'}' \beta_{i'})}, \end{aligned} \quad (5.14)$$

where v_1, \dots, v_7 are the 7 elements in \mathcal{V} and $v_8 = 1 - \sum_{i=1}^7 v_i$.¹⁸ Because the labeling of the three judges is arbitrary, it makes sense to impose an *exchangeability* requirement on our model of vote probabilities. In particular, the conditional probability of a vote profile (v_1, v_2, v_3) given case characteristics X and judge covariates (Z_1, Z_2, Z_3) should be invariant to permutations of the ordering of the three judges; i.e., the vote probability $P(v_1, v_2, v_3|X, Z_1, Z_2, Z_3)$ should be exchangeable in (v_1, Z_1) , (v_2, Z_2) and (v_3, Z_3) , for all X . These exchangeability conditions imply restrictions on the coefficients on (X, Z_1, Z_2, Z_3) in the logit choice probabilities.¹⁹

Given the first-stage parameter estimates $\hat{\beta} = (\hat{\beta}_1, \dots, \hat{\beta}_7)'$, we obtain estimated vote probabilities $\hat{p} = (p(v_1|X; \hat{\beta}), \dots, p(v_7|X; \hat{\beta}))'$. In the second stage, we use the estimated voting probability vector \hat{p} to estimate the identified set of the model parameters $(\theta, \vec{\pi})$ using arguments from the previous section. This estimation procedure allows the underlying model parameters $(\theta, \vec{\pi})$ to depend quite flexibly on X . The voting assignment μ is allowed to depend on X arbitrarily, $\mu(\vec{v}|\vec{t}, X)$.

Both the estimation and the inference procedure described in the previous section can be used for each fixed value of $X = x$ in exactly the same way, only with $\hat{p}_v(\vec{v})$, $\hat{\vec{p}}_v$, $p_v(\vec{v})$ and \vec{p}_v replaced by $p_v(\vec{v}|x, \hat{\beta})$, $\vec{p}_v(x, \hat{\beta})$, $p_v(\vec{v}|x, \beta)$ and $\vec{p}_v(x, \beta)$, $(\theta, \vec{\pi}, \mu)$ replaced by $(\theta(x), \vec{\pi}(x), \mu(\cdot|\cdot; x))$ and $\hat{\Sigma}_n$ replaced by $\hat{\Sigma}_n(x) = (\partial \vec{p}_v(x, \hat{\beta}) / \partial \beta') \hat{\Sigma}_\beta (\partial \vec{p}_v(x, \hat{\beta}) / \partial \beta)$, where $\hat{\Sigma}_\beta$ is a consistent estimator of the asymptotic variance of $\sqrt{n}(\hat{\beta} - \beta)$, which can be obtained from the first stage. The consistency and the coverage probability theory go through as

¹⁷This approach is commonplace in recent empirical applications of auction and dynamic game models (see for example Ryan (2012), and Cantillon and Pesendorfer (2006)).

¹⁸By using a parametrization of the conditional vote probabilities $P(v|X)$ that is continuous in X , we are also implicitly assuming that the equilibrium selection process is also continuous in X . Note that such an assumption is not needed if we estimate $P(v|X)$ nonparametrically and impose no smoothness of these probabilities in X .

¹⁹In particular, symmetry implies the following constraints: (i) $\beta_{1,111} = \beta_{2,111} = \beta_{3,111}$, (ii) $\beta_{1,011} = \beta_{2,101} = \beta_{3,110}$, (iii) $\beta_{1,100} = \beta_{2,010} = \beta_{3,001}$, (iv) $\beta_{2,011} = \beta_{3,011} = \beta_{1,101} = \beta_{3,101} = \beta_{1,110} = \beta_{2,110}$, (v) $\beta_{2,100} = \beta_{3,100} = \beta_{1,010} = \beta_{3,010} = \beta_{1,001} = \beta_{2,001}$, (vi) $\gamma_{011} = \gamma_{110} = \gamma_{101}$, and (vii) $\gamma_{001} = \gamma_{100} = \gamma_{010}$. See also Menzel (2011) for a related discussion about the importance of exchangeability restrictions in Bayesian inference of partially identified models.

long as $\hat{\beta}$ is consistent and asymptotically normal and $(\partial \vec{p}_v(x, \beta) / \partial \beta') \Sigma_\beta (\partial \vec{p}_v(x, \beta) / \partial \beta)$ is invertible, where Σ_β is the asymptotic variance of $\sqrt{n}(\hat{\beta} - \beta)$. This assumption holds automatically in the logit case described above as long as Σ_β is invertible.

6 Results

6.1 First-Stage Estimates

The results from the first-stage estimation are given in Table 2. Since these are “reduced-form” vote probabilities, these coefficients should not be interpreted in any causal manner, but rather summarizing the correlation patterns in the data.

Nevertheless, some interesting patterns emerge. First, vote outcomes differ significantly depending on the type of crime considered in each case (cases involving *aggravated assault*, *white collar* crimes and *theft* are significantly less likely to be overturned in a divided decision than other cases) and in response to differences in legal issues (cases involving problems with *jury instruction* or *sentencing* in the lower courts are on average less likely to be overturned in a divided decision, while cases involving issues of *sufficiency* and *admissibility* of evidence are less likely to be overturned in unanimous decisions).

Vote outcomes also change with the partisan composition of the court. A republican judge is less likely to be in the majority of a divided decision to overturn (less so in *assault* and *white collar* cases) and more likely to be in the majority of a divided decision to uphold the decision of the lower court. At the same time, cases considered by courts composed of a majority of republican judges on average have a significantly higher probability of being overturned in both unanimous and divided decisions. The first result indicates that this is due to the voting behavior of the democrat judge when facing a republican majority.

Finally, vote outcomes also differ based on judges’ judicial and political experience. Judges with more judicial and political experience, or with more years of experience in the court, are less likely to be in the majority of a divided decision to overturn. Neither having a female judge on the panel, or a majority of graduates from Harvard or Yale Law schools (a possible *club* effect) are significantly related to vote outcomes.

6.2 Second-Stage Estimates: Preferences and Information

In the second stage of the estimation, we use the estimated voting probability vector $\hat{p} = p(\vec{v}|X; \hat{\beta})$ to estimate the identified set of the model parameters $(\theta, \vec{\pi})$.

	$v = (v(i), v(k), v(m))$					
	$v = (1, 1, 1)$		$v = (1, 0, 1)$		$v = (0, 1, 0)$	
	Coef.	St.Err.	Coef.	St.Err.	Coef.	St.Err.
FedLaw	-0.124	0.132	-1.001	0.235	-0.304	0.274
Aggravated	-0.216	0.271	-1.261	0.519	0.552	0.560
White Collar	-0.400	0.232	-0.740	0.439	0.449	0.510
Theft	0.024	0.242	-1.371	0.563	1.404	0.510
Narcotics	-0.295	0.244	-0.594	0.474	0.049	0.593
Rep. Majority	0.329	0.179	1.320	0.445	-0.560	0.379
Female	0.043	0.166	0.198	0.346	0.141	0.326
Harvard-Yale Majority	-0.124	0.119	-0.275	0.277	-0.138	0.245
Jury Instruction	-0.120	0.118	-0.906	0.360	0.246	0.216
Sentencing	-0.326	0.130	-0.919	0.384	-0.056	0.267
Admissibility	-0.345	0.100	-0.317	0.229	0.407	0.190
Sufficiency	-0.557	0.116	-0.421	0.277	-0.249	0.226
J(i) Republican	-0.195	0.118	-1.951	0.347	0.641	0.327
J(i) Years of Experience	-0.003	0.004	-0.028	0.010	0.005	0.009
J(i) Prior Judicial Experience	-0.001	0.004	-0.046	0.012	-0.006	0.010
J(i) Prior Political Experience	0.006	0.007	-0.041	0.022	0.034	0.015
J(i) Rep * Assault	-0.021	0.163	0.920	0.464	0.054	0.399
J(i) Rep * WhtCol	0.106	0.138	0.844	0.447	-0.217	0.371
J(i) Rep * Theft	-0.166	0.158	-0.079	0.577	-0.952	0.456
J(i) Rep * Nrtcs	-0.053	0.141	0.419	0.483	-0.088	0.426
J(k) Republican	-0.195	0.118	-0.969	0.363	-0.313	0.431
J(k) Years of Experience	-0.003	0.004	-0.019	0.014	0.014	0.012
J(k) Prior Judicial Experience	-0.001	0.004	-0.004	0.014	-0.027	0.015
J(k) Prior Political Experience	0.006	0.007	-0.047	0.033	-0.036	0.030
J(k) Rep * Assault	-0.021	0.163	0.738	0.611	-0.108	0.587
J(k) Rep * WhtCol	0.106	0.138	0.470	0.582	0.539	0.536
J(k) Rep * Theft	-0.166	0.158	1.752	0.694	-1.451	0.846
J(k) Rep * Nrtcs	-0.053	0.141	0.434	0.618	-0.328	0.630
J(m) Republican	-0.195	0.118	-1.951	0.347	0.641	0.327
J(m) Years of Experience	-0.003	0.004	-0.028	0.010	0.005	0.009
J(m) Prior Judicial Experience	-0.001	0.004	-0.046	0.012	-0.006	0.010
J(m) Prior Political Experience	0.006	0.007	-0.041	0.022	0.034	0.015
J(m) Rep * Assault	-0.021	0.163	0.920	0.464	0.054	0.399
J(m) Rep * WhtCol	0.106	0.138	0.844	0.447	-0.217	0.371
J(m) Rep * Theft	-0.166	0.158	-0.079	0.577	-0.952	0.456
J(m) Rep * Nrtcs	-0.053	0.141	0.419	0.483	-0.088	0.426
Constant	-0.439	0.217	-0.891	0.252	-4.504	0.522

Table 2: First-stage estimates, from a multinomial logit model (baseline vote profile (0,0,0))

To present the results, we fix benchmark case and judge characteristics, and later on introduce comparative statics from this benchmark. For our benchmark case we consider a white collar crime prosecuted under federal law, in which the major legal issue for appeal is admissibility of evidence. Judges 1 and 2 are Republican, and judge 3 is a Democrat (so that the majority of the court is Republican). All three judges are male, and at most one of the judges has a law degree from Harvard or Yale.

The three benchmark judges differ in their years of court experience, as well as prior judicial and political experience. See Table 6 in the Appendix for the full benchmark specification.

6.2.1 The Symmetric (ρ, q, π) Model

We begin by analyzing the symmetric model introduced in Section 5.1. In the symmetric model, the bias parameters and signal accuracies are assumed to be identical across judges. As a result, the model has only three parameters (ρ, q, π) .

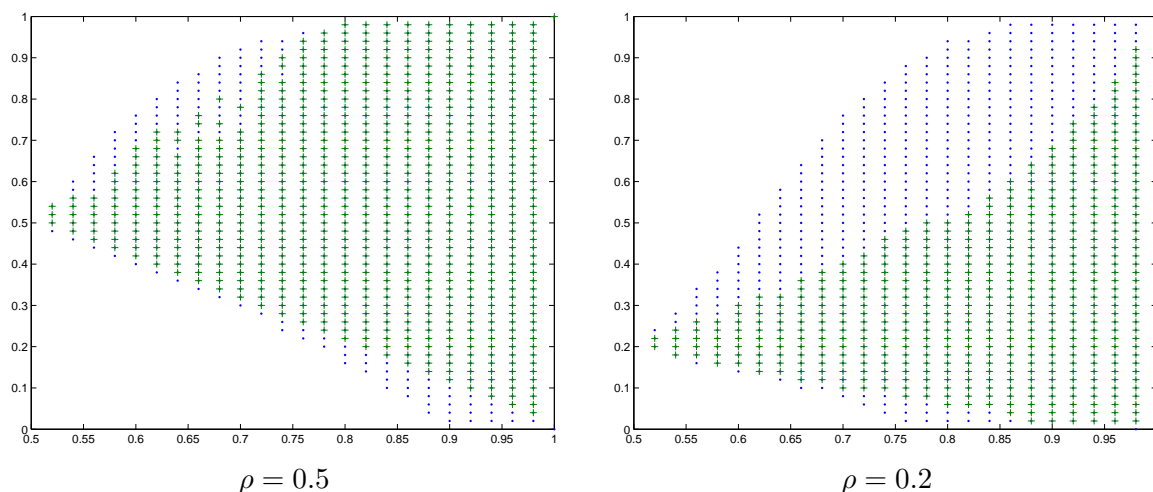


Figure 2: 95% Confidence set, for symmetric justices model. X-axis: q (probability of correct signal); Y-axis: π (judges' bias parameter). Computed at benchmark values of covariates (predicted vote profile probabilities are $\hat{p}_v(111) = 0.212$; $\hat{p}_v(101) = 0.019$; $\hat{p}_v(110) = 0.008$; $\hat{p}_v(011) = 0.009$; $\hat{p}_v(100) = 0.019$; $\hat{p}_v(010) = 0.014$; $\hat{p}_v(001) = 0.019$; $\hat{p}_v(000) = 0.700$). Green dots: estimates of identified set (using Eq. (5.8)). Blue dots: 95% confidence set.

The left panel in Figure 2 plots the pairs (π, q) in the identified set for $\rho = 0.5$. Because the distribution of vote profiles is asymmetric in favor of upholding the decision of the lower court, the identified set for $\rho = 0.5$ is asymmetric towards larger values of π (particularly for low competence levels, q), indicating a preference towards upholding the decision of the lower courts. But while the distribution of vote profiles is highly asymmetric in favor of

upholding, the identified set for $\rho = 0.5$ is only mildly asymmetric, and not qualitatively different than the set we obtained for the uniform distribution over vote profiles in section 5.1. Moreover, as in that case, the range of biases π that are consistent with the data for a given value of q is increasing in q . Thus, low ability judges must be moderate if they are to be consistent with the data, but high ability judges can be heavily biased towards upholding or overturning and still play a mixture of equilibria consistent with the data.²⁰

To evaluate the range of possible equilibrium outcomes under deliberation, we compute the probability that the court reaches an incorrect decision for every point $(\theta, \vec{\pi})$ in the confidence set. Because of the multiplicity of equilibria, for each such point $(\theta, \vec{\pi})$ there is a set of communication equilibria $M(\theta, \vec{\pi})$, with each $\mu \in M(\theta, \vec{\pi})$ being associated with a certain probability of error

$$\varepsilon(\mu, (\theta, \vec{\pi})) = (1 - \rho)\varepsilon_I(\mu, (\theta, \vec{\pi})) + \rho\varepsilon_{II}(\mu, (\theta, \vec{\pi})).$$

Here $\varepsilon_I(\mu, (\theta, \vec{\pi})) = \Pr(v = 1 | \omega = 0) = \sum_{\vec{t}} \sum_{\vec{v}: v=1} \mu(\vec{v} | \vec{t}) p(\vec{t} | \omega = 0)$ denotes the type-I error (overturn when should not) in the equilibrium μ , given $(\theta, \vec{\pi})$, and $\varepsilon_{II}(\mu, (\theta, \vec{\pi})) = \Pr(v = 0 | \omega = 1) = \sum_{\vec{t}} \sum_{\vec{v}: v=1} \mu(\vec{v} | \vec{t}) p(\vec{t} | \omega = 1)$ is the type-II error (fail to overturn when it should) in the equilibrium μ , given $(\theta, \vec{\pi})$. Note that both the type-I error and the type-II error are functions of the model parameters $\mu, \theta, \vec{\pi}$, and inference on them amounts to projecting the confidence set of the model parameters onto the range of these functions.

We consider two objects of interest, in order to address two conceptually distinct questions. First is the maximum and minimum error probabilities across all possible equilibria, for all parameter values in the confidence set. For each point in the confidence set, define

$$\bar{\varepsilon}(\theta, \vec{\pi}) \equiv \max_{\mu \in M(\theta, \vec{\pi})} \varepsilon(\mu, (\theta, \vec{\pi})), \text{ and } \underline{\varepsilon}(\theta, \vec{\pi}) \equiv \min_{\mu \in M(\theta, \vec{\pi})} \varepsilon(\mu, (\theta, \vec{\pi})).$$

Second is the maximum and minimum error probabilities across equilibria that are consistent with the observed data \vec{p}_v . For each point $(\theta, \vec{\pi})$ in the confidence set, and data \vec{p}_v , we define

$$\bar{\varepsilon}^*(\theta, \vec{\pi}, p_v) = \max_{\mu \in M(\theta, \vec{\pi})} \left\{ \varepsilon(\mu, (\theta, \vec{\pi})) \quad \text{s.t.} \quad p_v(\vec{v}) = \sum_{\vec{t}} \mu(\vec{v} | \vec{t}) p(\vec{t}; \theta) \right\}$$

²⁰The right panel of Figure 2 plots the pairs (π, q) in the identified set for $\rho = 0.2$, which is approximately the sample probability that a case is overturned for the benchmark specification. In this case the public information incorporated in the prior favors upholding the decision of the lower court. As a result, when private signals are not too informative, only judges that are relatively biased towards *upholding* can vote in a way consistent with the data. However, as with $\rho = 0.5$, high ability judges can have relatively extreme preferences for overturning or upholding and still play a mixture of equilibria consistent with the data.

and similarly for $\underline{\varepsilon}^*(\theta, \vec{\pi}, p_v)$.²¹

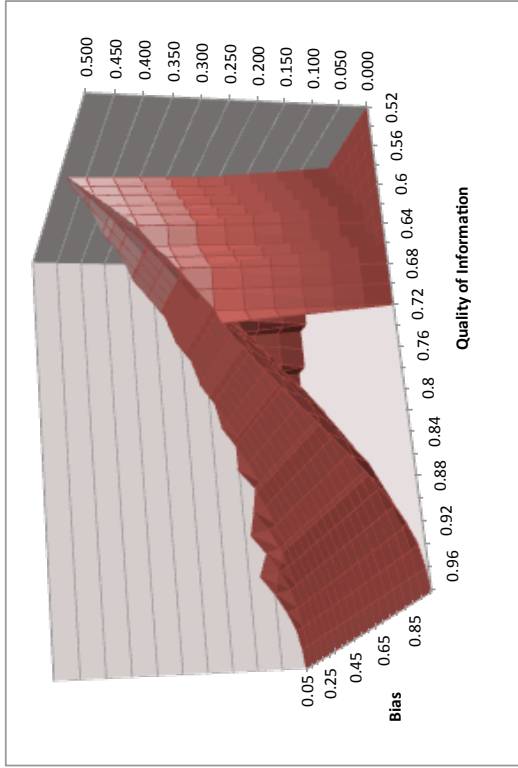
The first object gives us the safest bounds on what *could* happen, for any equilibrium selection rule, including both mixtures of equilibria that are consistent with the observed data and others that are not. The second objects tells us what *did* happen in our data.

The upper left and lower left panels of Figure 3 present the minimum and maximum equilibrium errors across all equilibria in the symmetric (q, π, ρ) model. The figures plot $\bar{\varepsilon}(\theta, \vec{\pi})$ and $\underline{\varepsilon}(\theta, \vec{\pi})$ for all combinations of q and π in the confidence set, fixing $\rho = 0.5$. Consider first $\underline{\varepsilon}(\theta, \vec{\pi})$ in the upper-left panel. For low quality of information, as we saw, only moderate judges are consistent with the data (Figure 2). With higher quality of information, the set of biases consistent with the data expands, so that courts with significant heterogeneity are consistent with the data. Nevertheless, the minimum error $\underline{\varepsilon}(\theta, \vec{\pi})$ falls with the competence of the court, and goes to zero as $q \rightarrow 1$, even when judges have extreme biases.

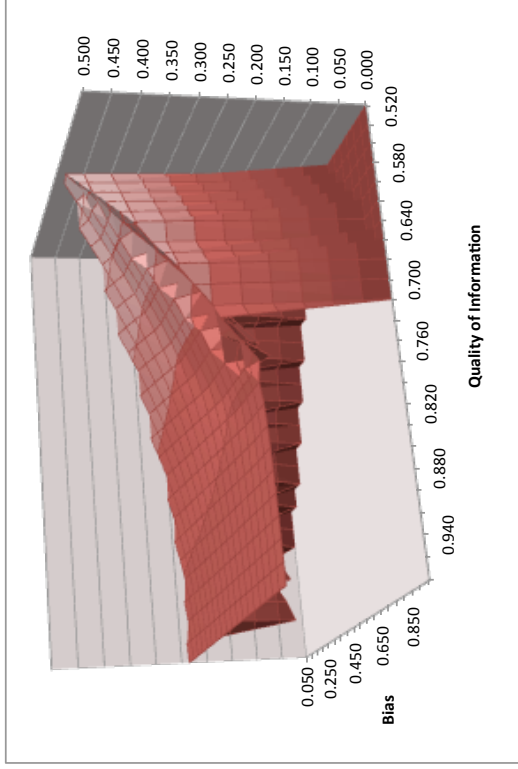
The bottom-left panel presents the upper bound of the equilibrium probability of error $\bar{\varepsilon}(\rho, q, \pi)$ for points in the confidence set. This *worst case* measure illustrates the flip side of deliberation: the maximum equilibrium error with communication actually increases with the precision of judges' private information, and goes to one for $q \rightarrow 1$, independently of the direction and level of justices' bias. Thus, courts composed of highly competent judges can produce wrong decisions very frequently after deliberating. As we argue below, the reason for this inefficiency is that best responses in a game with deliberation are very sensitive to agents' expectations of how other individuals will communicate. And because judges care directly about the content of each others' messages, the effect of these beliefs is larger the more valuable is the information held by other members of the court.

The upper right and lower right panels of Figure 3 plot the minimum and maximum probability of error for equilibria consistent with the data, $\bar{\varepsilon}^*(\theta, \vec{\pi}, p_v)$ and $\underline{\varepsilon}^*(\theta, \vec{\pi}, p_v)$. Specifically, the figures show the maximum and minimum error probability in equilibria matching voting profile distributions that are in the 95% confidence set of the "true" voting profile distribution. Thus, while the figures on the left panel provide the bounds of the 95% confidence interval of the potential error probability, the figures on the right panel plot the 95% confidence interval of the true error probability.

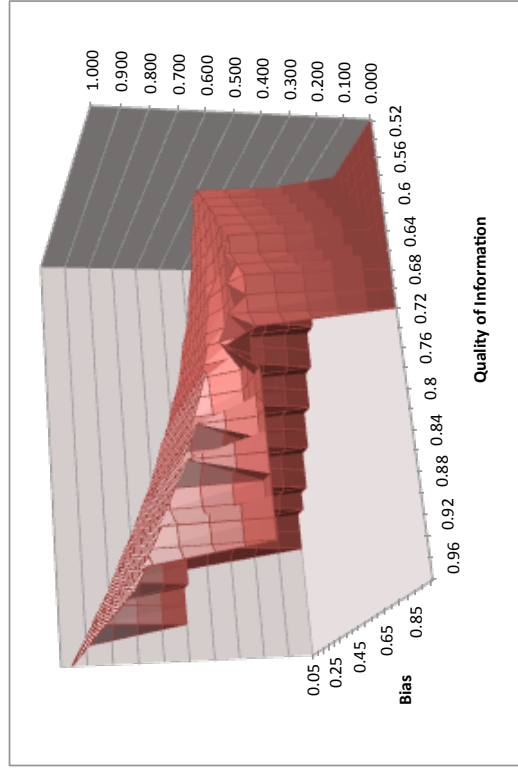
²¹Because $M(\theta, \vec{\pi})$ is a convex set and the constraint $p_v(\vec{v}) = \sum_{\vec{t}} \mu(\vec{v}|\vec{t})p(\vec{t};\theta)$ is linear in μ , μ can be replaced with a linear combination of elements in $M(\theta, \vec{\pi})$ without affecting the value of $\bar{\varepsilon}^*(\theta, \vec{\pi}, p_v)$ or $\underline{\varepsilon}^*(\theta, \vec{\pi}, p_v)$. Therefore, when considering equilibria consistent with the data, we are not assuming that the same equilibrium is played in every case."



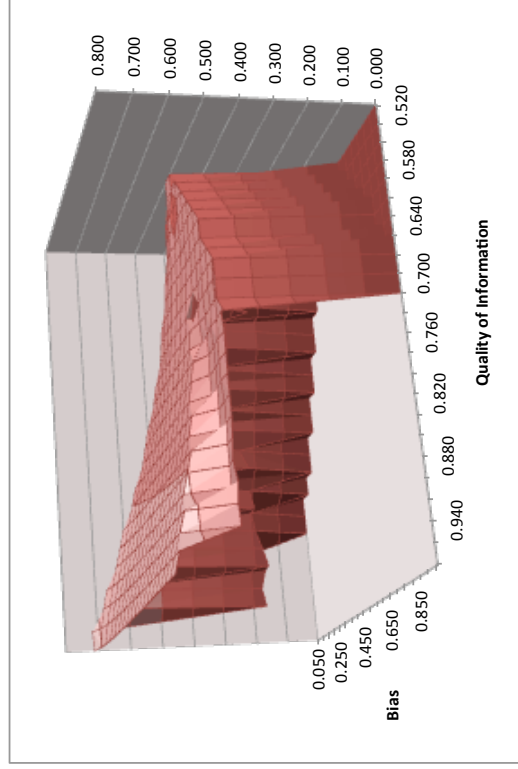
Min. Error $\varepsilon(\rho, q, \pi)$ - All Equilibria



Min. Error $\varepsilon^*(\theta, \vec{\pi}, p_v(\vec{v}))$ - Eq. Consistent w/ Data



Max. Error $\bar{\varepsilon}(\rho, q, \pi)$ - All Equilibria



Max. Error $\bar{\varepsilon}^*(\theta, \vec{\pi}, p_v(\vec{v}))$ - Eq. Consistent w/ Data

Figure 3: Symmetric Model. Minimum and Maximum Equilibrium Probability of Errors with Deliberation for $\rho = 0.5$, across all equilibria, and across equilibria consistent with the data. Axis represent Quality of Information and Judges' Bias.

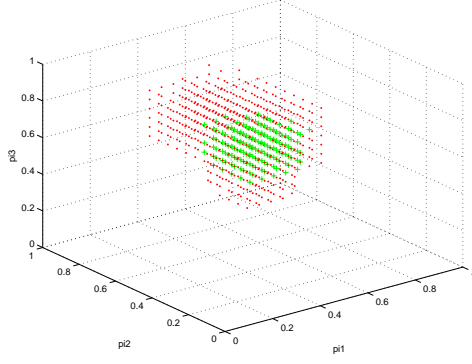
Although the results are qualitatively similar to the unconstrained max and min error probabilities, the upper and lower bounds of the equilibrium errors tighten significantly. In particular, the lower bound of $\underline{\varepsilon}^*(\theta, \vec{\pi}, p_v)$ in the confidence set, which is attained for high levels of q , increases from close to zero in the unconstrained case to about 25% for equilibria consistent with the data. It follows that if we focus on mixtures of equilibria that are consistent with the data, then for any possible configuration of bias and competence in the confidence set the court chooses incorrectly at least one fourth of the time. Thus, although in the best case scenario deliberation *can* reduce mistakes to almost zero when courts are competent, these potential gains are far from being realized given the selection of equilibria that is consistent with the data.

6.2.2 Heterogeneous Preferences: The $(\rho, q, \vec{\pi})$ Model

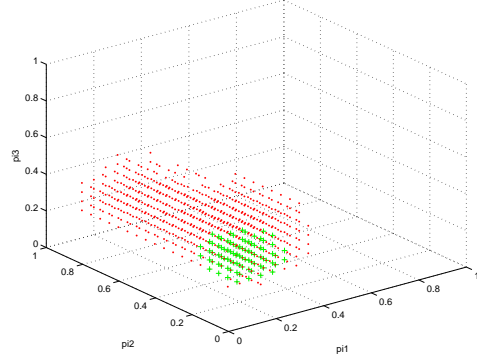
The previous model suppressed heterogeneity in preferences. However, it is possible that this heterogeneity is precisely what leads to better outcomes, raising the level of deliberation by bringing together different points of view. We now extend the analysis to allow for heterogeneous preferences. Here each judge i is allowed an idiosyncratic bias π_i . The model is then characterized by a vector $(\rho, q, \pi_1, \pi_2, \pi_3)$. Figure 4 plots the set of $\vec{\pi}$ in the confidence set for different values of the prior, ρ , and precision of private information, q .

The results for the confidence set with heterogeneous preferences extend naturally the results of Figure 2 for the symmetric model: while low competence judges must be homogeneous and relatively moderate in order to be consistent with the data, competent judges can be highly *heterogeneous* and still generate a distribution of vote profiles consistent with the data. This result is interesting because it implies that deliberation can allow high ability judges to surpass initial differences of opinion. A distinctive feature of decisions in the courts of appeals is the large proportion of cases decided unanimously. This fact is commonly interpreted in the literature as indicating that either judges were like-minded from the outset, or that they have an intrinsic desire to compromise (see for example Fischman (2007)). Our results suggest an alternative interpretation. High unanimity rates do not imply common interests at an ex ante stage. Instead, deliberation among competent judges can generate the high frequency of unanimous votes observed in the data, without requiring auxiliary motives such as the desire of judges to compromise, or to put forward a “unified” stance in each case.

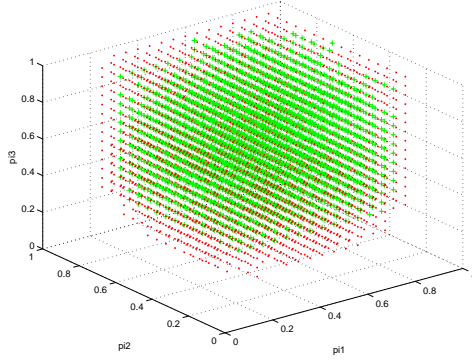
As in the case of the symmetric (ρ, q, π) model, we can also compute here the maximum and minimum error probabilities across all equilibria, $\bar{\varepsilon}(\theta, \vec{\pi})$ and $\underline{\varepsilon}(\theta, \vec{\pi})$ and across equilibria consistent with the data, $\bar{\varepsilon}^*(\theta, \vec{\pi}, p_v)$ and $\underline{\varepsilon}^*(\theta, \vec{\pi}, p_v)$ for each point in the confidence set.



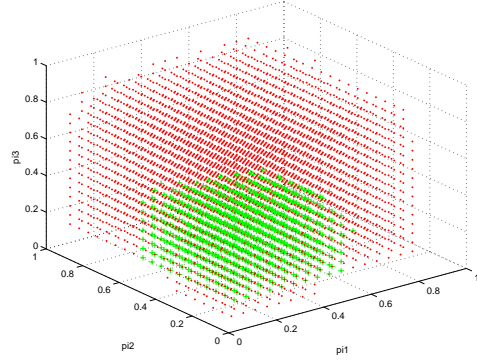
$$q = 0.60, \rho = 0.50,$$



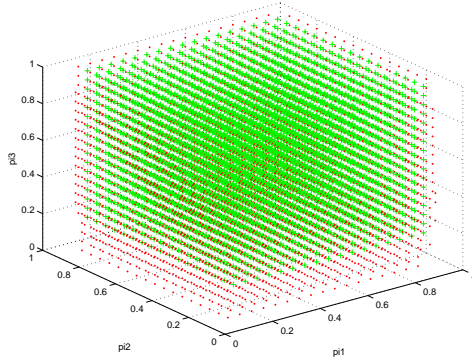
$$q = 0.60, \rho = 0.20$$



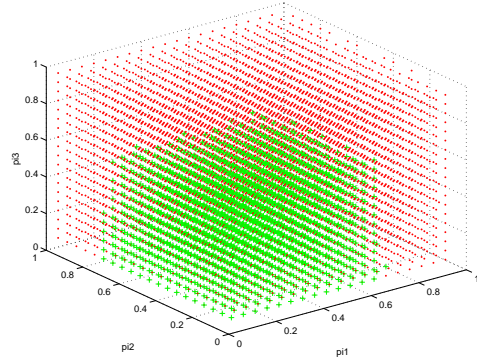
$$q = 0.76, \rho = 0.50,$$



$$q = 0.76, \rho = 0.20$$



$$q = 0.90, \rho = 0.50,$$



$$q = 0.90, \rho = 0.20$$

Figure 4: Hyperplanes of confidence set, for heterogeneous preferences model. (π_1, π_2, π_3) on (x, y, z) -axis. Green dots: estimates of identified set (using Eq. (5.8)). Red dots: 95% confidence set.

To reduce the dimensionality of the problem, we introduce a measure of *polarization* of the court,

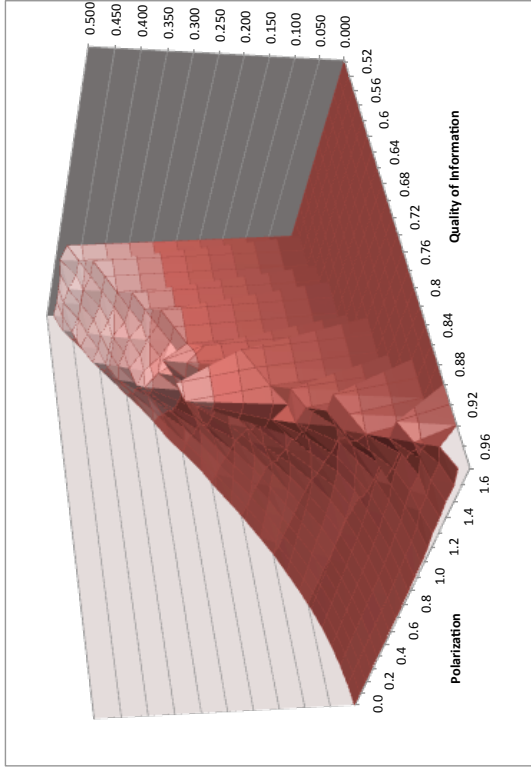
$$P = \sum_{i \in N} \sum_{j \neq i} (\pi_i - \pi_j)^2.$$

Polarization increases as judges' bias parameters are farther apart from one another, reaching a theoretical maximum of two, and decreases as judges' preferences are closer to each other's, reaching a minimum of zero when all judges have the same preferences.

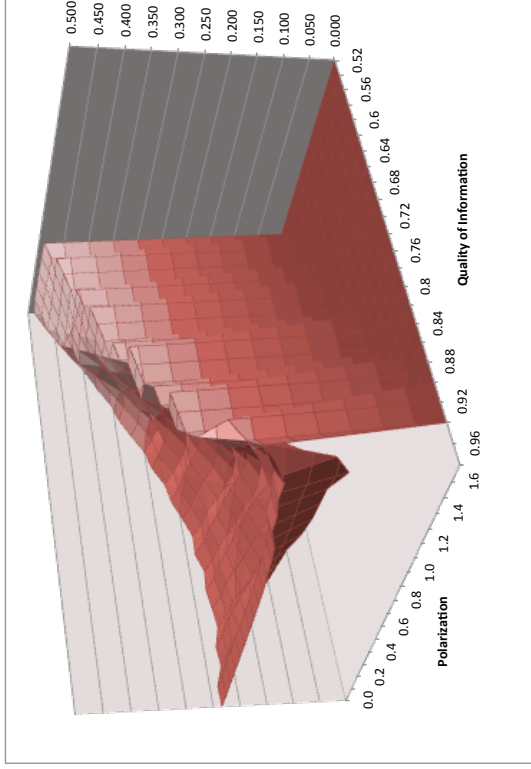
The upper-left and lower-left panels of Figure 5 present the minimum and maximum equilibrium errors across all equilibria in the heterogeneous model. The figures plot $\bar{\varepsilon}(\theta, \vec{\pi})$ and $\underline{\varepsilon}(\theta, \vec{\pi})$ for all combinations of competence (q) and polarization (P) consistent with points $(\theta, \vec{\pi})$ in the confidence set, for $\rho = 0.5$.

The results in the generalized model are a natural extension of the results for the symmetric model. For low q , only very homogeneous courts, composed entirely of moderate judges, are consistent with the data. These courts are highly inaccurate, even after pooling information, and correspondingly make wrong decisions very often (about half of the time in the limit as $q \rightarrow 1/2$). As ability increases, however, more polarized courts can be consistent with the data. These more polarized, but more able courts are capable of producing decisions that have few errors. In fact, the minimum equilibrium error probability (in the top-left panel) decreases with q , and goes to zero as $q \rightarrow 1$, even when judges are very *heterogeneous*. On the other hand, more able courts are also capable of producing wrong decisions very frequently. The bottom-left panel presents the maximum equilibrium probability of error $\bar{\varepsilon}(\rho, q, \pi)$ for points in the confidence set. As in the symmetric model, the maximum equilibrium error with communication is attained when the precision of judges' private information is large (and goes to above 90% for $q \rightarrow 1$).

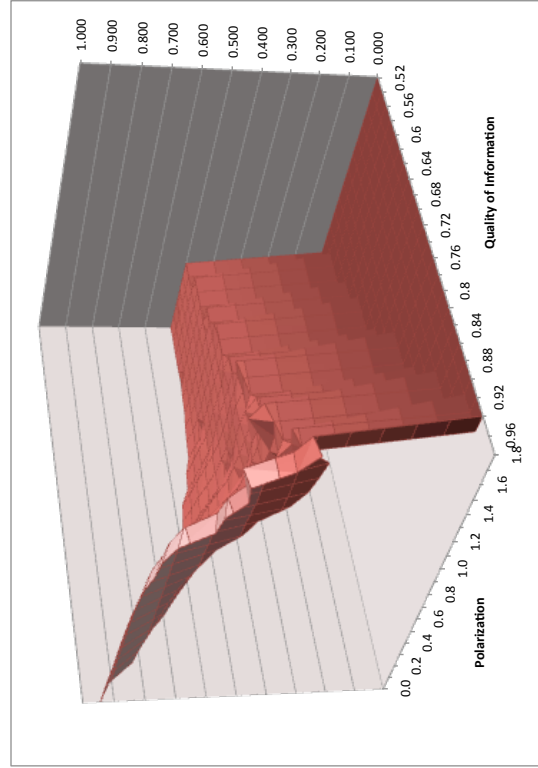
The fact that courts composed of competent judges can produce such frequent errors after deliberating shows the fragility of outcomes to the multiple beliefs that judges can have in equilibrium about how other judges will share, interpret and use information. To see this in more detail, consider the “bad” equilibrium presented in Table 3. In the model, judges' beliefs about how others will communicate are built into the equilibrium strategy $\mu(\cdot | \vec{t})$. Table 3 presents a particularly inefficient equilibrium for $q = 0.98$ and $\vec{\pi} = (0.20, 0.95, 0.50)$. Here the court overturns almost always when it should uphold, and upholds when it should overturn. This requires judges to go against their own private information.



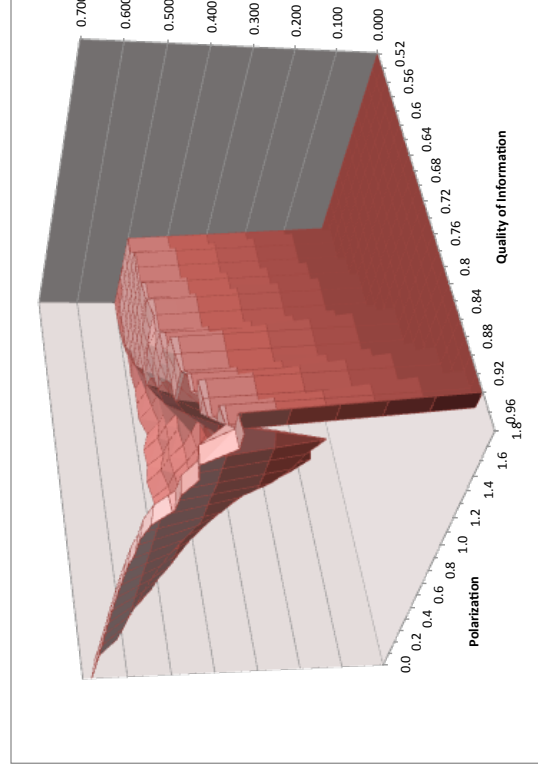
Min. Error $\underline{\varepsilon}(\rho, q, \pi)$ - All Equilibria



Min. Error $\underline{\varepsilon}^*(\theta, \vec{\pi}, p_v(\vec{v}))$ - Eq. Consistent w/ Data



Max. Error $\bar{\varepsilon}(\rho, q, \pi)$ - All Equilibria



Max. Error $\bar{\varepsilon}^*(\theta, \vec{\pi}, p_v(\vec{v}))$ - Eq. Consistent w/ Data

Figure 5: Minimum and Maximum Equilibrium Probability of Errors with Deliberation for $\rho = 0.5$, across all equilibria, and across equilibria consistent with the data. Axis represent Quality of Information and Degree of Polarization.

		Signal Profile							
		(1,0,0)	(1,0,1)	(1,1,0)	(1,1,1)	(0,0,0)	(0,0,1)	(0,1,0)	(0,1,1)
Vote Profile	(1,0,0)	0.00000	0.00000	0.00000	0.00000	0.00016	0.00005	0.00020	0.00014
	(1,0,1)	0.00000	0.00000	0.00268	0.00115	0.00001	0.00001	0.00222	0.00196
	(1,1,0)	0.00000	0.00000	0.00001	0.00081	0.00000	0.00000	0.00000	0.00000
	(1,1,1)	0.99957	0.00000	0.00017	0.04062	0.95890	0.99964	0.99736	0.00105
	(0,0,0)	0.00000	0.99696	0.99699	0.95629	0.04067	0.00002	0.00005	0.99683
	(0,0,1)	0.00006	0.00000	0.00000	0.00000	0.00018	0.00001	0.00014	0.00000
	(0,1,0)	0.00037	0.00000	0.00000	0.00000	0.00008	0.00028	0.00003	0.00000
	(0,1,1)	0.00000	0.00304	0.00015	0.00112	0.00000	0.00000	0.00000	0.00001
	Pr(overturn)	0.99957	0.00304	0.00301	0.04370	0.95891	0.99964	0.99958	0.00302
	Pr(uphold)	0.00043	0.99696	0.99699	0.95630	0.04109	0.00036	0.00042	0.99698
	Pr(w=1)	0.02000	0.98000	0.98000	0.99999	0.00001	0.02000	0.02000	0.98000

$$q = 0.98, \vec{\pi} = (0.20, 0.95, 0.50)$$

Table 3: An Example of a Communication Equilibrium in which highly competent judges make mistakes with high probability after deliberating.

To understand why this is possible, consider the problem of judge 1 after receiving a signal $t_1 = 1$. In equilibrium, judge 1 votes to uphold ($v_i = 0$) with positive probability. Given μ , this is indeed a best response to her *post-deliberation* beliefs about whether the decision of the lower court should be overturned. Because $t_1 = 1$, judge 1 can exclude (put probability zero on) the last four columns in the table. Similarly, because $v_1 = 0$, judge 1 can similarly exclude the first four rows in the table. Moreover, because judge 1 is not pivotal when both of the other judges vote to uphold (row 5) or when both of the other judges vote to overturn (row 8), these events are not payoff relevant. We are thus left with rows 6 and 7 and columns 1 to 4. But given this, judge 1 is almost sure that $\vec{t} = (1, 0, 0)$; i.e., that the two other judges received information favoring upholding the decision of the lower court. These two signals overwhelm her own information, and, given $q \approx 1$, also her prior belief and bias. As a result, judge 1 is willing to vote to uphold the decision of the lower court, against her private information. A similar logic holds for judges 2 and 3.²²

The general point that this example illustrates is that deliberation across rational actors opens a wide array of beliefs that are consistent with equilibrium behavior. With common values, this allows committee members to form inferences about the information disseminated across the committee that can sustain wildly inefficient outcomes.

²²As Table 3 illustrates, implementing bad outcomes might require equilibria that seem in some sense fragile. These equilibria, however, are robust to perturbations of beliefs around equilibrium play in the sense of remark 3.1. In particular, we require that each individual best-responds to beliefs that are consistent with small trembles (occurring with probability $\eta = 0.000001$) on equilibrium play. Increasing the value of η (relaxing further the consistency of equilibrium beliefs with equilibrium strategies) eliminates some of these fragile equilibria, but does not change the nature of the results (see Figure 12 in the Appendix).

The previous results are relevant as a measure of the range of outcomes that could be realized for any equilibrium selection, including both mixtures of equilibria that are consistent with the observed data, and others that are not. The upper right and lower right panels of Figure 5 plot the minimum and maximum probability of error for equilibria consistent with the data, $\bar{\varepsilon}^*(\theta, \vec{\pi}, p_v)$ and $\underline{\varepsilon}^*(\theta, \vec{\pi}, p_v)$.

As in the symmetric model, the error bounds in equilibria consistent with the data are qualitatively similar to the corresponding bounds across all equilibria. There is, however, a significant difference in the levels. This is shown in Figure 6, which plots the percentiles for maximum and minimum errors for all equilibria, and equilibria consistent with the data, across all points in the 95% confidence set. Note that while $\underline{\varepsilon}^*(\theta, \vec{\pi}, p_v(\vec{v})) \leq 30\%$ for 85% of the points in the CS, on the other hand $\underline{\varepsilon}^*(\theta, \vec{\pi}, p_v(\vec{v})) \geq 9\%$ for 90% of the points in the CS, and $\underline{\varepsilon}^*(\theta, \vec{\pi}, p_v(\vec{v})) \geq 20\%$ for 80% of the points in the CS. As we argued in the context of the symmetric model, although in the best case scenario deliberation *can* reduce mistakes to almost zero when courts are competent, these potential gains are far from being realized given the selection of equilibria that is consistent with the data.

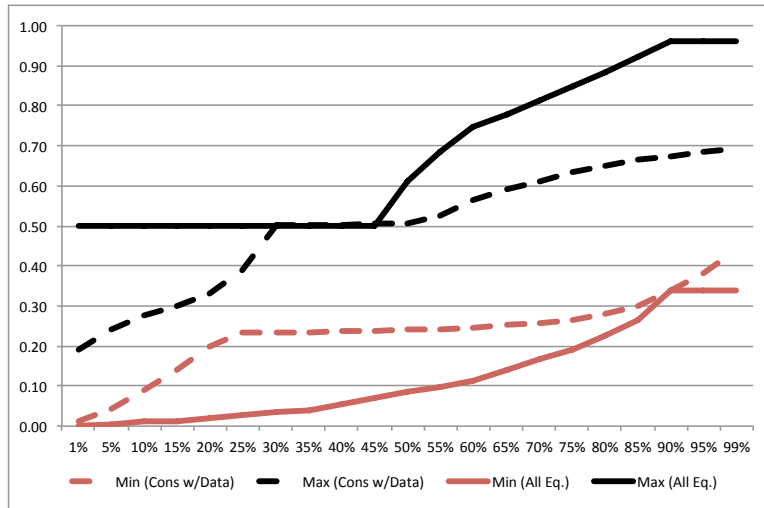


Figure 6: Solid (dashed) lines plot the percentiles for maximum and minimum errors for all equilibria (equilibria consistent with the data) across all points in the 95% confidence set.

Comparative Statics. In the discussion above, we have focused on the benchmark case and court characteristics. It should be clear, however, that both the confidence set and the set of equilibrium outcomes for each point in the confidence set are functions of the observable characteristics that enter the first stage multinomial logit model. Thus, proceeding as above, we can quantify the changes in types and outcomes associated with alternative

configurations of the cases under consideration or the judges integrating the court.

To illustrate this, we evaluate the effect of switching judge 2’s party from Republican to Democrat, keeping all else equal. Changing from the benchmark “RRD” partisan configuration of the court to the alternative “RDD” partisan configuration has two noticeable effect on the predicted probability of different vote outcomes. First, each vote profile overturning the decision of the lower court has a lower probability under a democratic-controlled court than under a republican-controlled court. In particular, $\hat{p}_v(000)$ changes from 0.677 to 0.636, and $\hat{p}_v(111)$ from 0.223 to 0.234. Second, democratic-controlled courts tend to generate more divided decisions than republican-controlled courts. Relative to republican-controlled courts, democratic-controlled courts put a relatively large probability on divided decisions overturning the decision of the lower court (now $\hat{p}_v(101) = 0.030$, $\hat{p}_v(110) = 0.035$, and $\hat{p}_v(011) = 0.027$, while $\hat{p}_v(100) = 0.015$, $\hat{p}_v(010) = 0.011$, and $\hat{p}_v(001) = 0.011$).

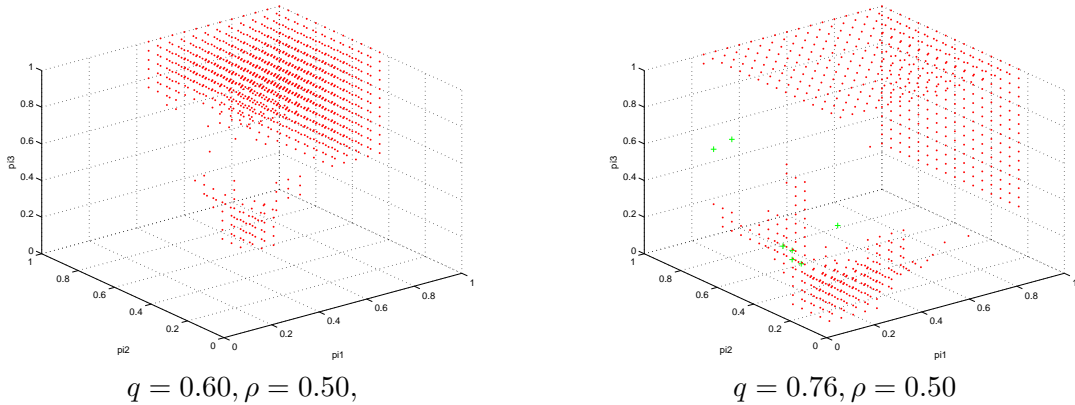


Figure 7: Difference in 95% Confidence Set from switching judge 2 from Republican to Democrat (RRD to RDD). Red crosses: in confidence set for RDD but not RRD specification; green dots: in confidence set for RRD but not RDD specification.

Figure 7 illustrates the change in the confidence set, for two given levels of q , and $\rho = 1/2$. The figure shows that the RDD partisan configuration induces a larger confidence set, with more biased types now being consistent with the data for any given q . Because RDD allows more extreme types and eliminates few moderate types, the set of feasible outcomes with a democratic majority tends to be broader than with a republican majority, generating larger maximum errors and smaller minimum errors for given parameters.

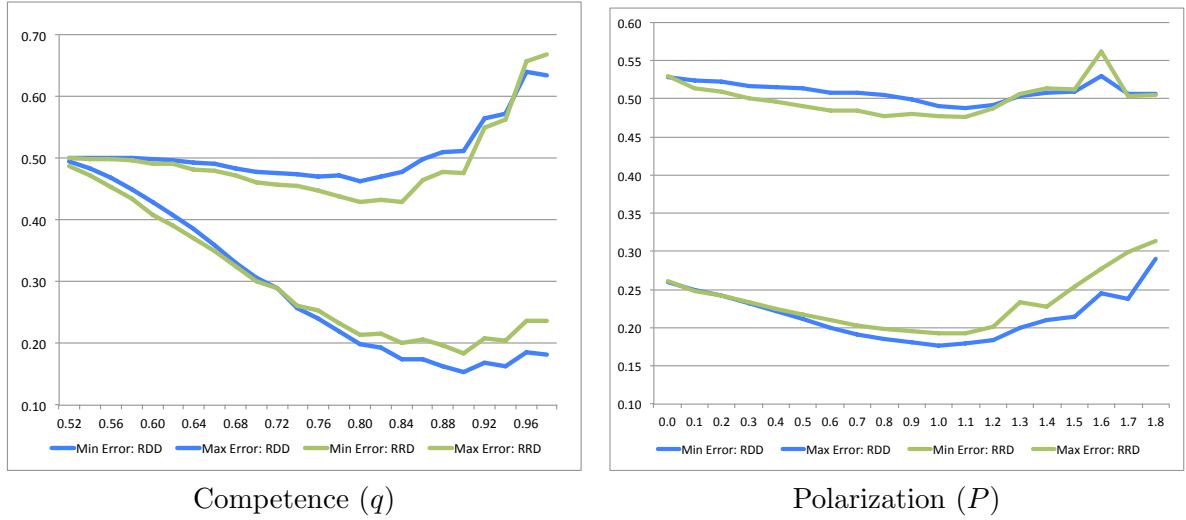


Figure 8: Min and Max Error Probability in Equilibria consistent with data for RRD (green) and RDD (blue) specifications, with $\rho = 0.5$. As a function of Competence and Polarization.

In particular, as shown in Figure 8, the democratic controlled courts generate larger maximum errors than the republican controlled courts for homogeneous courts and intermediate levels of competence, and smaller minimum errors for high levels of competence and heterogeneous courts.

6.3 The Impact of Deliberation

Having described the outcomes attained in equilibria with deliberation, our next goal is to quantify the effect of deliberation: how much do outcomes differ *because of* deliberation?

To do this, we compare equilibrium outcomes with deliberation with the outcomes that would have arisen in a counterfactual scenario in which judges are not able to talk with one another before voting. As before, in terms of outcomes, we focus on the probability of mistakes in the decisions of the court. We then compare the equilibrium probability of error with deliberation with the corresponding equilibrium probability of error that would have occurred in the absence of deliberation for the same court and case characteristics.

Specifically, for each point $(\theta, \vec{\pi})$ in the identified set we compare the maximum and minimum error probabilities across all equilibria, $\bar{\varepsilon}(\theta, \vec{\pi})$ and $\underline{\varepsilon}(\theta, \vec{\pi})$, and across equilibria consistent with the data, $\bar{\varepsilon}^*(\theta, \vec{\pi}, p_v)$ and $\underline{\varepsilon}^*(\theta, \vec{\pi}, p_v)$, with the corresponding maximum and minimum error probabilities in responsive Bayesian Nash equilibria (BNE) of the voting game *without* communication, $\bar{\varepsilon}^{ND}(\theta, \vec{\pi})$ and $\underline{\varepsilon}^{ND}(\theta, \vec{\pi})$. To carry out this comparison, we solve for all responsive BNE of the non-deliberation game, for all parameter points in the

confidence set.²³

Figure 9 plots, for various values of judges’ information precision q , the maximum and minimum equilibrium errors with and without deliberation as a function of the degree of polarization in the court. The figures on the left panel show the maximum and minimum error probability across all communication equilibria, and the figures on the right panel show the maximum and minimum error probability in equilibria matching voting profile distributions that are in the 95% confidence set of the “true” voting profile distribution.

All Equilibria. We consider first unconstrained outcomes, across all equilibria. The figure on the top left panel shows the results for an intermediate level of competence, $q = 0.76$. Two facts are apparent from the figure. First, although both the game with deliberation and the game without deliberation have multiple equilibria, these two kinds of multiplicity are qualitatively different. While the multiplicity of equilibria in voting without deliberation has relatively minor consequences for the effectiveness of the court, the multiplicity of equilibria with deliberation can lead to wildly different outcomes. Second, the figure shows that while the equilibrium error bounds in the game with deliberation are relatively insensitive to the level of polarization in the court, the equilibrium errors without deliberation increase rapidly with the degree of polarization. Thus, in heterogeneous courts, the best outcome with deliberation leads to large gains vis a vis the best outcomes without deliberation. When courts are relatively homogeneous, instead, equilibrium errors without deliberation are already close to the best outcomes achievable with deliberation, so that the possible gain attributable to deliberation is relatively small. Furthermore, the worst outcomes with deliberation imply very large losses with respect to *all* equilibrium outcomes without deliberation.

The middle and bottom left panels (for $q = 0.8$ and $q = 0.9$) show a somewhat different story. For these higher levels of competence in the court, the probability of error without deliberation is close to the best outcomes with deliberation for all levels of polarization of the court (for all bias configurations in the confidence set). Thus deliberation only allows for a minimal gain in achieving a smaller probability of error, but significantly increases the maximum equilibrium probability of error.²⁴

In fact, it is these latter results, and not those in the top figure, which are most representative of outcomes across all parameters in the confidence set. Whenever there exists a responsive

²³Characterizing responsive equilibria in the non-deliberation game is an algebra-intensive, but simple task. We discuss this further in Section 8.

²⁴In fact, the worst outcomes with deliberation can and in general are worse than the errors in non-responsive equilibria with communication (50% given $\rho = 1/2$).

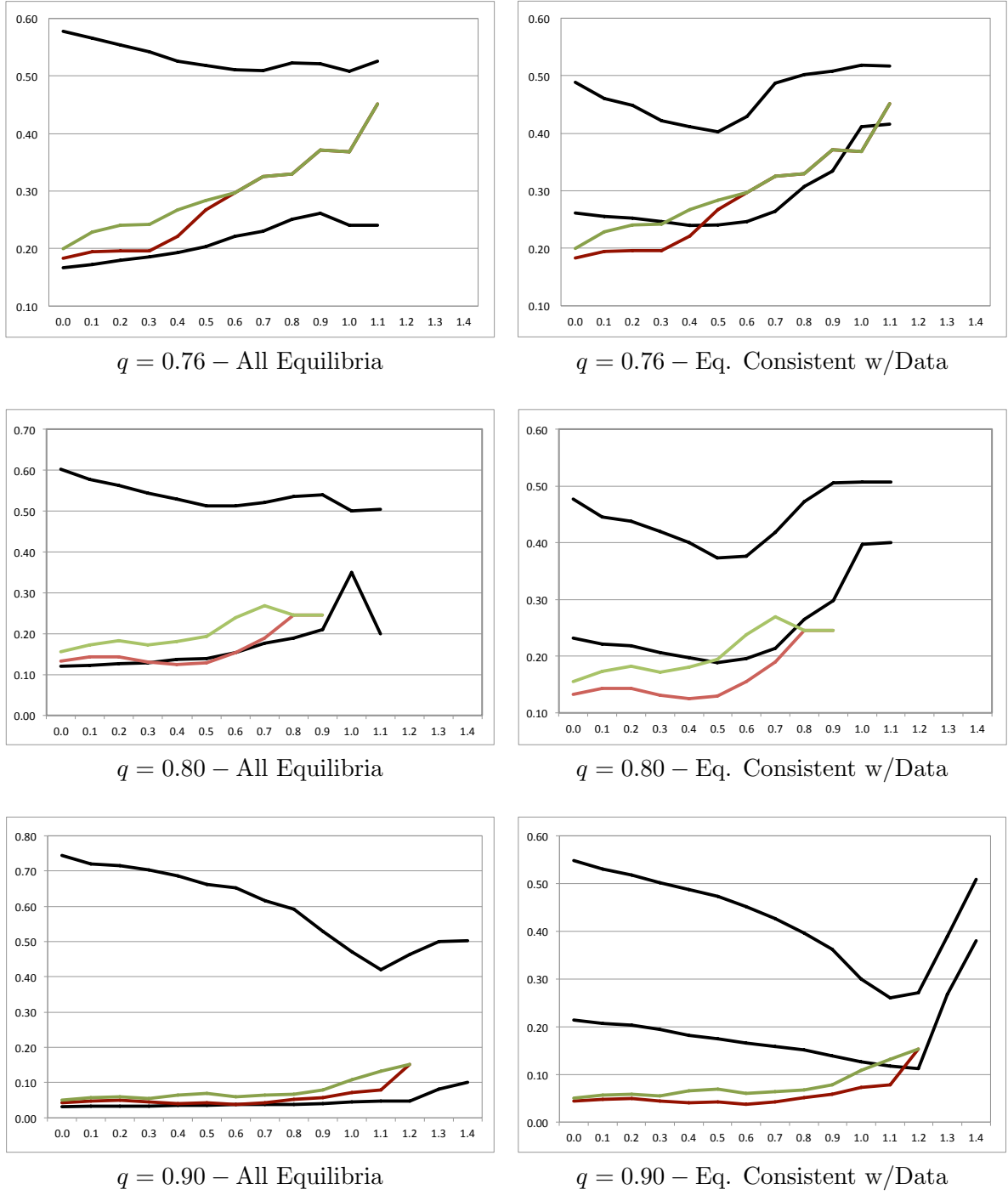


Figure 9: Probability of mistakes with and without deliberation for each point $(\theta, \vec{\pi})$ in the confidence set, with $\rho = 0.5$, across all equilibria (left), and across only equilibria consistent with the data (right). Y-axis is the probability of error, and X-axis is the degree of Polarization in the court. Black lines plot the min. and max. equilibrium errors with deliberation; red and green lines plot the min. and max. errors without deliberation.

equilibrium in the game without deliberation, deliberation typically only produces a small potential gain in the effectiveness of the court in the best case scenario, but can lead to large losses in the worst case. Across the confidence set, for courts with more competent judges ($q \geq 0.8$), the minimum equilibrium error probability with deliberation is less than 5 pp lower than the corresponding error probability without deliberation. Yet at the same time, the maximum equilibrium error probability with deliberation is more than 25 pp higher than the corresponding error probability without deliberation. Especially, if we restrict attention to courts with small degrees of polarization (polarization ≤ 0.3) and very competent judges ($q = 0.9$), the latter number becomes as high as 60 pp.

It should be noted, however, that deliberation does have an unambiguously positive effect on outcomes, in that it expands the set of court characteristics for which the decisions of the court can be responsive to information. Indeed, in slightly over one fourth of the court configurations for which there is a communication equilibrium that is consistent with the data, the game without deliberation has no responsive equilibria.

Equilibria Consistent with the Data. The figures on the right panel show the results for equilibria consistent with the data. As we described in Section 6.2, the constraint that equilibria are to be consistent with the data leads to a substantially narrower range of outcomes. Moreover, the minimum and maximum errors in equilibria consistent with the data are more responsive to the degree of polarization of the court.

The comparison with the equilibrium errors of the voting game without deliberation leads to striking results. As in the case of all equilibria, the maximum equilibrium probability of error with deliberation generally vastly exceeds the corresponding figure maximum without deliberation. In addition, for a large number of points in the CS, the minimum equilibrium probability of error with deliberation across equilibria consistent with the data is *higher* than the minimum probability of error without deliberation. This is illustrated in Figure 10, which plots the percentiles for maximum and minimum errors for equilibria with deliberation and without deliberation across all comparable points in the 95% confidence set (for all points in the CS for which there exists a responsive equilibrium without deliberation).

For 20% of the points in the confidence set, the minimum equilibrium probability of error without deliberation is below 1%. The corresponding figure for equilibria consistent with the data is 23%. Similarly, while for 70% of the points in the confidence set, the minimum equilibrium probability of error without deliberation is still below 14%, it reaches 25% for equilibria consistent with the data. Furthermore, for more than eighty percent of all comparable points in the confidence set, *all* equilibria with deliberation are worse than all

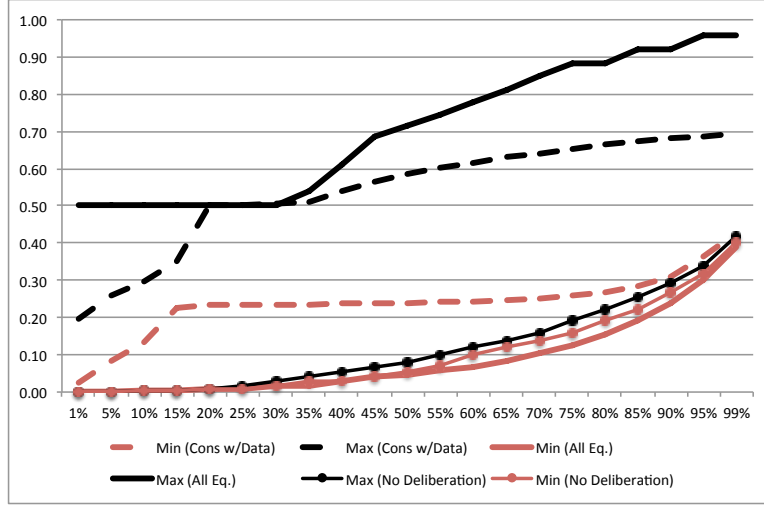


Figure 10: Percentiles for maximum and minimum errors for equilibria with deliberation and without deliberation across all comparable points in the 95% confidence set.

equilibria without deliberation. Thus, although in the best case scenario deliberation *can* potentially reduce mistakes vis a vis the benchmark of no deliberation, in the selection of equilibria that is consistent with the data these potential gains are not being realized. Instead, communication among judges on average leads to a large loss in the effectiveness of the court.

Welfare. The results so far are agnostic about equilibrium selection, and highlight the potential for deliberation to increase the errors in decision-making. It could be argued, however, that equilibria that maximize judges' aggregate welfare constitute a focal point, both in the game with deliberation and in the game without deliberation. If this were the case, deliberation could in fact improve welfare, and would certainly do so if we don't restrict to equilibria consistent with the data.

In order to quantify this potential gain, we adopt a utilitarian approach, and compare social welfare in the equilibria that maximize the sum of judges' payoffs with and without deliberation, for all equilibria and for equilibria consistent with the data. For a given point $(\theta, \vec{\pi})$ in the confidence set, and given a communication equilibrium μ , judge i 's expected utility is minus the expected cost of type I and type II errors,

$$U_i(\mu; (\theta, \vec{\pi})) = -[\rho \varepsilon_{II}(\mu; (\theta, \vec{\pi}))(1 - \pi_i) + (1 - \rho) \varepsilon_I(\mu; (\theta, \vec{\pi}))\pi_i].$$

Therefore, the equilibrium that maximizes judges' total welfare, $\mu^*(\theta, \vec{\pi})$, is the $\mu \in M(\theta, \vec{\pi})$

that maximizes $\mathcal{U}(\theta, \vec{\pi}, \mu) \equiv \sum_i U_i(\mu; (\theta, \vec{\pi}))$. A similar definition applies for non-deliberation equilibria, giving $\sigma^*(\theta, \vec{\pi})$. For equilibria consistent with the data, the equilibrium that maximizes judges' total welfare, $\tilde{\mu}(\theta, \vec{\pi})$, is

$$\tilde{\mu}(\theta, \vec{\pi}) = \arg \max_{\mu \in M(\theta, \vec{\pi})} \left\{ \mathcal{U}(\theta, \vec{\pi}, \mu) \quad \text{s.t.} \quad p_v(\vec{v}) = \sum_{\vec{t}} \mu(\vec{v}|\vec{t}) p(\vec{t}; \theta) \right\}$$

The left panel of Figure 11 plots the maximum aggregate welfare for points in the confidence set across all equilibria of the game with deliberation, $\mathcal{U}^D(\theta, \vec{\pi}) \equiv \mathcal{U}(\mu^*(\theta, \vec{\pi}); (\theta, \vec{\pi}))$, and in the game without deliberation, $\mathcal{U}^N(\theta, \vec{\pi}) \equiv \mathcal{U}(\sigma^*(\theta, \vec{\pi}); (\theta, \vec{\pi}))$. The difference is plotted for various levels of competence q , as a function of the degree of polarization in the court. The right panel provides a similar comparison restricting to the maximum aggregate welfare across equilibria consistent with the data, $\tilde{\mathcal{U}}^D(\theta, \vec{\pi}) \equiv \mathcal{U}(\tilde{\mu}(\theta, \vec{\pi}); (\theta, \vec{\pi}))$.

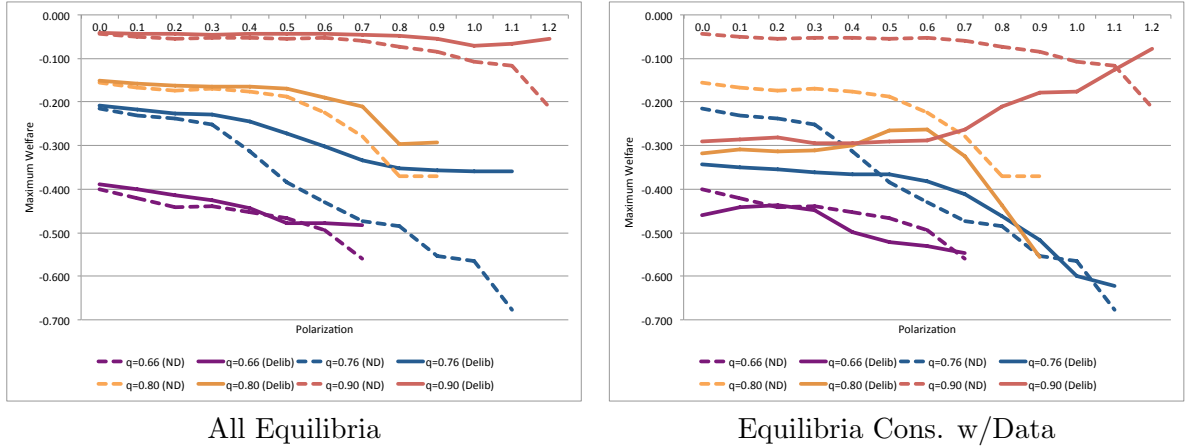


Figure 11: Maximum Equilibrium Welfare under Deliberation and No-Deliberation. Solid lines denote outcomes with deliberation, for $\rho = 0.5$. Dashed lines denote outcomes with no deliberation.

The plot of the unconstrained maximum welfare with deliberation $\mathcal{U}^D(\theta, \vec{\pi})$ and without $\mathcal{U}^N(\theta, \vec{\pi})$ shows that deliberation can induce a relatively large gain in welfare when the court is heterogeneous. The gains in welfare however, are not uniform across feasible configurations of the court. In fact, deliberation leads to no welfare improvement in 70% of all comparable parameter configurations in the confidence set. The comparison of $\mathcal{U}^N(\theta, \vec{\pi})$ with the maximum welfare across equilibria consistent with the data, $\tilde{\mathcal{U}}^D(\theta, \vec{\pi})$ shows a markedly different result. In fact, for most of the parameter configurations represented in the figure, deliberation induces a loss in the maximal aggregate welfare. This loss is particularly severe if judges are highly competent (if q is large).

7 Conclusion

Deliberation is ubiquitous in collective decision-making. This is well understood. What is less clear is whether talking can have an effect on what people actually do. In this paper, we quantify the effect of deliberation on collective choices. To do this we structurally estimate a model of voting with deliberation. This approach allows us to disentangle committee members' preferences, information, and strategic considerations, and ultimately, to compare equilibrium outcomes under deliberation with a counterfactual scenario in which pre-vote communication is precluded.

Because the incentive for any individual member to convey her information truthfully to others depends on her expectations about how others will communicate, any natural model of deliberation will have a large multiplicity of equilibria. In our setting, this implies that the structural parameters characterizing judges' biases and quality of information are only partially identified. For this reason, we obtain confidence regions for these parameters using a two-step estimation procedure that allows flexibly for characteristics of the alternatives and the individuals.

To quantify the effect of deliberation on outcomes we compare the equilibrium probability of error with deliberation with the probability of error that would have occurred in the absence of deliberation for the same court and case characteristics. The comparison leads to discouraging results for the prospects of deliberation. When we compare across all potential outcomes, in the best case deliberation produces a small gain in the effectiveness of the court, and in the worst case it leads to large losses. When we restrict to equilibria that are consistent with the observed data, the comparison is bleaker still. In fact, for a large range of comparable points in the confidence set, *all* equilibria with deliberation are worse than all equilibria without deliberation. Thus, although in the best case scenario deliberation *can* potentially reduce mistakes vis a vis the benchmark of no deliberation, in equilibria consistent with the data these potential gains are not realized. Instead, communication among judges on average leads to large losses in the effectiveness of the court: words *do* indeed get in the way of effective decision-making.

In spite of the progress made, much work remains ahead in order to fully understand the effect of deliberation on collective decision-making. A potentially rich area for progress is in the intersection of data availability and the specification of the model describing the environment and the nature of strategic interactions. In the absence of knowledge of a particular sequence in which committee members communicate prior to a vote, the theoretical approach of Gerardi and Yariv (2007) is very attractive. This is because the set of outcomes induced by communication equilibria coincides with the set of outcomes in-

duced by sequential equilibria of any possible communication sequence. Given knowledge of a particular communication protocol, however, equilibrium analysis yields more precise predictions. This, in turn, would allow us to obtain a narrower identified set of the parameters of interest. Furthermore, in this context we could potentially use not only vote outcomes, but also the messages exchanged among committee members, or the duration of deliberation, as data, further reducing uncertainty about parameters. It follows from this discussion that while the difficulties in identifying suitable applications are not minor, the potential rewards are far reaching.

Our empirical approach can also be more immediately extended to evaluate the effect of deliberation on outcomes across different issues and decision-making environments.

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8 Appendix: Responsive Equilibria without Deliberation

In Section 6.3 we compare the equilibrium probability of error in voting with deliberation with the corresponding equilibrium probability of error that would have occurred in the absence of deliberation for the same court and case characteristics. Specifically, for each point $(\theta, \vec{\pi})$ in the confidence set we compare the maximum and minimum error probabilities across all equilibria, $\bar{\varepsilon}(\theta, \vec{\pi})$ and $\underline{\varepsilon}(\theta, \vec{\pi})$, and across equilibria consistent with the data, $\bar{\varepsilon}^*(\theta, \vec{\pi}, p_v)$ and $\underline{\varepsilon}^*(\theta, \vec{\pi}, p_v)$, with the corresponding maximum and minimum error probabilities in responsive Bayesian Nash equilibria (BNE) of the voting game *without* communication, $\bar{\varepsilon}^{ND}(\theta, \vec{\pi})$ and $\underline{\varepsilon}^{ND}(\theta, \vec{\pi})$. To carry out this comparison, we solve for all responsive BNE of the non-deliberation game, for all parameter points in the confidence set.

In the game without deliberation, the strategy of player i is a mapping $\sigma_i : \{0, 1\} \rightarrow [0, 1]$, where $\sigma_i(s_i)$ denotes the probability of voting to overturn given signal s_i . It is easy to show that $\sigma_i(s_i) > 0$ (< 0) only if $\Pr(\omega = 1 | s_i, Piv^i) \geq \pi_i$ ($\leq \pi_i$), or

$$\frac{\Pr(s_i | \omega = 1) \Pr(Piv^i | \omega = 1)}{\Pr(s_i | \omega = 0) \Pr(Piv^i | \omega = 1)} \geq \frac{\pi_i}{1 - \pi_i} \frac{1 - \rho}{\rho} \quad (8.1)$$

Let $\alpha_{i\omega} \equiv \Pr(v_i = 1 | \omega)$ denote the conditional probability that i votes to overturn in state ω , and note that $\alpha_{i1} = q_i \sigma_i(1) + (1 - q_i) \sigma_i(0)$, and $\alpha_{i0} = (1 - q_i) \sigma_i(1) + q_i \sigma_i(0)$. Substituting in (8.1), we have that $\sigma_i(s_i) > 0$ only if (for $j, k \neq i$)

$$\frac{\Pr(s_i | \omega = 1)}{\Pr(s_i | \omega = 0)} \left[\frac{\alpha_{j1}(1 - \alpha_{k1}) + \alpha_{k1}(1 - \alpha_{j1})}{\alpha_{j0}(1 - \alpha_{k0}) + \alpha_{k0}(1 - \alpha_{j0})} \right] \geq \frac{\pi_i}{1 - \pi_i} \frac{1 - \rho}{\rho} \quad (8.2)$$

Under certain conditions (when the court is sufficiently homogeneous) there is an equilibrium in which all judges vote *informatively*; i.e., $\sigma_i(1) = 1, \sigma_i(0) = 0$ for all $i \in N$. Note that with informative voting $\alpha_{i1} = q_i$, and $\alpha_{i0} = (1 - q_i)$. Then informative voting is a best response for each i iff

$$\frac{\rho(1 - q_i)}{\rho(1 - q_i) + (1 - \rho)q_i} \leq \pi_i \leq \frac{\rho q_i}{\rho q_i + (1 - \rho)(1 - q_i)}$$

In general, other responsive equilibria are possible. With binary signals and a symmetric environment ($q_i = q$ and $\pi_i = \pi \forall i \in N$), the literature has focused on symmetric responsive BNE. Here of course the restriction has no bite. Still, there is a relatively “small” class of equilibrium candidates for any given parameter value. The exhaustive list is presented in Table 4.

Eq. Class	Judge i		Judge j		Judge ℓ		Non-Generic
	$\sigma_1(1)$	$\sigma_1(0)$	$\sigma_2(1)$	$\sigma_2(0)$	$\sigma_3(1)$	$\sigma_3(0)$	
<u>Pure Strategies:</u>							
(EQ1.a)	1	0	1	0	1	0	
(EQ1.b)	1	0	1	0	1	1	
(EQ1.c)	1	0	1	0	0	0	
<u>All judges mix:</u>							
(EQ2)	σ_1	0	σ_2	0	σ_3	0	
(EQ3)	1	σ_1	1	σ_2	1	σ_3	
(EQ4)	σ_1	0	σ_2	0	1	σ_3	
(EQ5)	σ_1	0	1	σ_2	1	σ_3	
<u>Two judges mix:</u>							
(EQ6.a)	σ_1	0	σ_2	0	1	1	
(EQ6.b)	σ_1	0	σ_2	0	0	0	X
(EQ6.c)	σ_1	0	σ_2	0	1	0	
(EQ7.a)	1	σ_1	1	σ_2	1	1	X
(EQ7.b)	1	σ_1	1	σ_2	0	0	
(EQ7.c)	1	σ_1	1	σ_2	1	0	
(EQ8.a)	σ_1	0	1	σ_2	1	1	X
(EQ8.b)	σ_1	0	1	σ_2	0	0	X
(EQ8.c)	σ_1	0	1	σ_2	1	0	

Table 4: We indicate by σ_j in column $\sigma_j(s)$ that $\sigma_j(s) \in (0, 1)$

Characterizing responsive equilibria in the non-deliberation game is a laborious but simple task. We illustrate the main logic in case (8.c) in Table 4; i.e., $\sigma_i(1) \in (0, 1)$, $\sigma_j(0) \in (0, 1)$, $\sigma_i(0) = 0$, $\sigma_j(1) = 1$, and $\sigma_k(1) = 1$, $\sigma_k(0) = 0$. (The analysis of the other cases is similar; full details are available upon request). Note that here $\alpha_{10} = (1 - q_1)\sigma_1(1)$, $\alpha_{11} = q_1\sigma_1(1)$, $\alpha_{20} = (1 - q_2) + q_2\sigma_2(0)$, $\alpha_{21} = q_2 + (1 - q_2)\sigma_2(0)$, $\alpha_{30} = 0$, and $\alpha_{31} = 1$.

In equilibrium, $i = 1$ has to be indifferent between upholding and overturning after $s_1 = 1$. Then if it exists, $\sigma_2^*(0)$ is given by the value of $\sigma_2(0) \in [0, 1]$ that solves (8.2) with equality for $i = 1$ and $s_i = 1$, or

$$\sigma_2^*(0) = \frac{[q_1(1 - \pi_1)\rho - (1 - q_1)\pi_1(1 - \rho)][(1 - q_2)q_3 + q_2(1 - q_3)]}{(2q_3 - 1)[q_1(1 - \pi_1)\rho(1 - q_2) + (1 - q_1)\pi_1(1 - \rho)q_2]},$$

which in turn implies $\alpha_{20}^* = (1 - q_2) + q_2\sigma_2^*(0)$ and $\alpha_{21}^* = q_2 + (1 - q_2)\sigma_2^*(0)$. Similarly, in equilibrium, $i = 2$ has to be indifferent between upholding and overturning after $s_2 = 0$. Then when it exists, $\sigma_1^*(1)$ is given by the value of $\sigma_1(1) \in [0, 1]$ that solves (8.2) with equality for $i = 2$ and $s_2 = 0$, or

$$\sigma_1^*(1) = \frac{(1 - q_2)q_3(1 - \pi_2)\rho - q_2(1 - q_3)\pi_2(1 - \rho)}{(2q_3 - 1)[(1 - q_2)q_1(1 - \pi_2)\rho + q_2(1 - q_1)\pi_2(1 - \rho)]},$$

which implies $\alpha_{10}^* = (1 - q_1)\sigma_1^*(1)$ and $\alpha_{11}^* = q_1\sigma_1^*(1)$. Finally, in equilibrium $i = 3$ has to have incentives to vote informatively. This means that

$$\underbrace{\frac{1 - q_3}{q_3}}_{s_3=1} \leq \frac{\alpha_{21}^*(1 - \alpha_{11}^*) + \alpha_{11}^*(1 - \alpha_{21}^*)}{\alpha_{20}^*(1 - \alpha_{10}^*) + \alpha_{10}^*(1 - \alpha_{20}^*)} \cdot \frac{1 - \pi_3}{\pi_3} \cdot \frac{\rho}{1 - \rho} \leq \underbrace{\frac{q_3}{1 - q_3}}_{s_3=0}$$

We can then evaluate numerically, for each point $(\rho, \vec{q}, \vec{\pi})$ in the confidence set, if the conditions for this to be an equilibrium are satisfied. As before, the error associated with this equilibrium σ is $\varepsilon^{ND}(\sigma, \theta) = (1 - \rho)\Pr(v = 1|\omega = 0; \sigma, \theta) + \rho\Pr(v = 0|\omega = 1; \sigma, \theta)$, where given majority rule and independent mixing, for $k, \ell \neq j$

$$\Pr(v = 1|\omega, \sigma, \theta) = \sum_{j=1}^3 \alpha_{k\omega} \alpha_{\ell\omega} (1 - \alpha_{j\omega}) + \alpha_{1\omega} \alpha_{2\omega} \alpha_{3\omega}$$

9 Appendix: Additional Figures and Tables

Variable:		Mean	Std.Dev.
<i>Case characteristics:</i>			
FedLaw	=1 if case prosecuted under federal law	0.8169	0.3868
Aggravated	=1 if crime is aggravated assault/murder	0.1221	0.3274
White Collar	=1 if white collar crime	0.2038	0.4029
Theft	=1 if crime is theft	0.1418	0.3489
Narcotics	=1 if drug-related crime	0.2062	0.4047
Rep. Majority	=1 if ≥ 2 republicans on panel	0.4454	0.4971
Female	=1 if ≥ 1 female judge on panel	0.0829	0.2758
Harv-Yale Majority	=1 if ≥ 2 Harvard/Yale grads on panel	0.1809	0.3850
Jury instruction	=1 if main legal issue is jury instruction	0.1970	0.3978
Sentencing	=1 if main legal issue is sentencing	0.1628	0.3692
Admissibility	=1 if main legal issue is admissibility of evidence	0.3474	0.4762
Sufficiency	=1 if main legal issue is sufficiency of evidence	0.2543	0.4355
# cases:		3244	
<i>Judge characteristics:</i>			
Republican	=1 if judge is republican	0.5392	0.4989
Yearsexp	Years of appeals court experience	7.1893	7.8409
Judexp	Years of prior judicial experience	1.9197	3.7628
Polexp	Years of prior political experience	6.8547	7.0750
#judges:		523	
<i>Vote Outcomes:</i>			
Unanimous to Overturn		21.4%	
Divided to Overturn		2.6%	
Divided to Uphold		3.8%	
Unanimous to Uphold		72.2%	

Table 5: Summary statistics of data variables

Table 6: Benchmark specification

<i>Estimated Vote Probabilities $p_v(\vec{v} X)$:</i>			
$\hat{p}_v(111)$	=0.223	$\hat{p}_v(000)$	=0.677
$\hat{p}_v(101)$	=0.020	$\hat{p}_v(010)$	=0.015
$\hat{p}_v(110)$	=0.013	$\hat{p}_v(001)$	=0.018
$\hat{p}_v(100)$	=0.025	$\hat{p}_v(011)$	=0.010

Case characteristics:

FedLaw	=1	Jury instruction	=0
Narcotics	=0	Sentencing	=0
Aggravated	=0	Admissibility	=1
White Collar	=1	Sufficiency	=0
Theft	=0	Rep. Majority	=1
Female Judge	=0	Harvard-Yale Majority	=0

Judge characteristics:

	Judge 1	Judge 2	Judge 3
Republican	1	1	0
Yearsexp	7.19	0	7.19
Judexp	1.92	0	1.92
Polexp	0	6.85	6.85

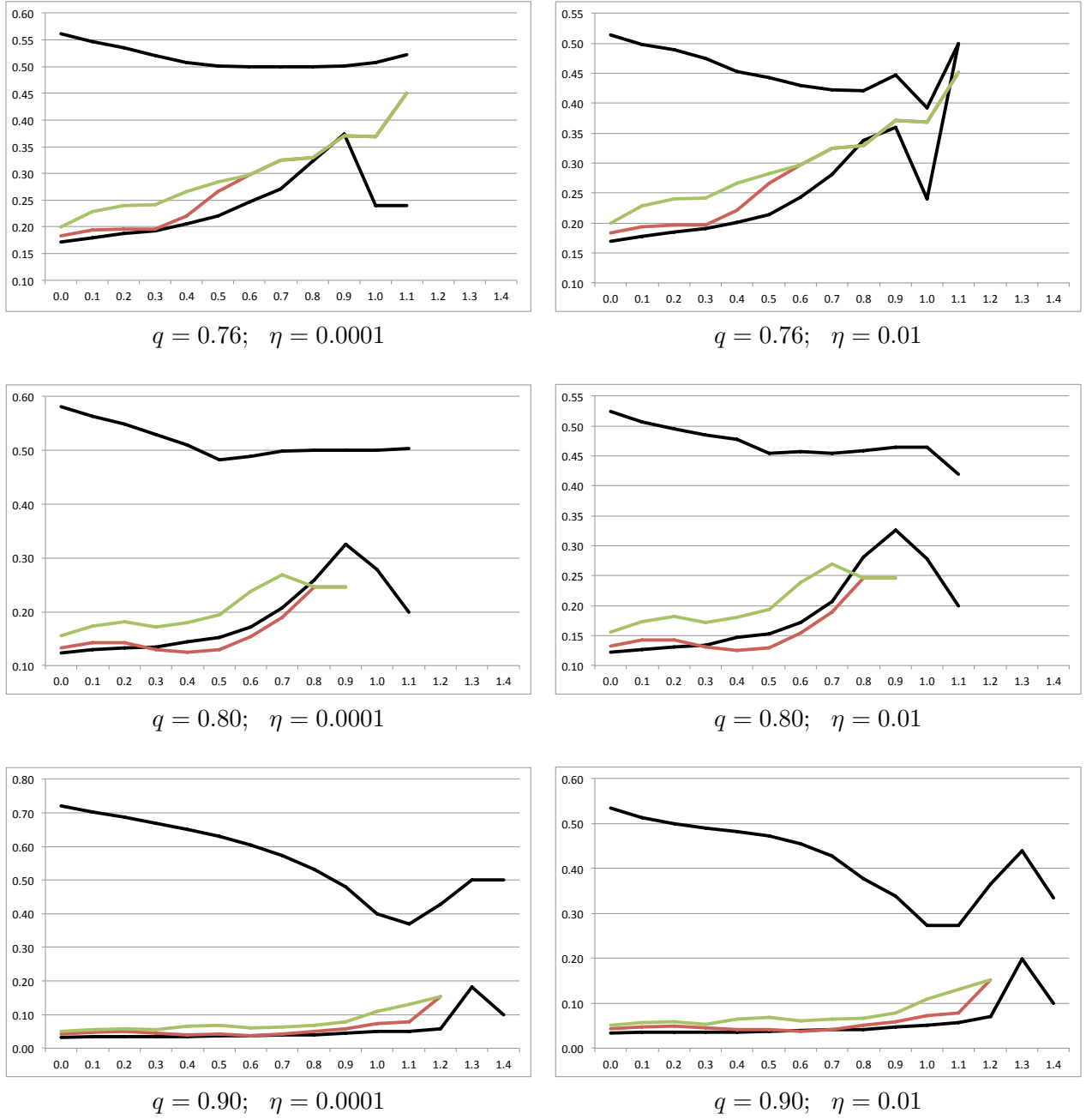


Figure 12: Probability of Mistakes with and without Deliberation, with $\rho = 0.5$. Larger Noise in Beliefs Consistent with Equilibrium: $\eta = 0.0001$ (left) and $\eta = 0.01$ (right). Main Specification has $\eta = 0.000001$. Y-axis is the probability of error, and X-axis is the degree of Polarization.