Comments on: Decision-Making Under a Norm of Consensus: A Structural Analysis of Three-Judge Panels by Joshua Fischman

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Structural v. Reduced Form Econometrics

Corollary 7 *When $c_d = c_m = 0$, judges will vote in favor of their preferred outcomes, and will not be influenced by the other judges on the panel.*

Proof. When $c_d = c_m = 0$, disagreement is not costly, and hence all judges will vote in favor of their preferred outcomes. ■

Decision-Making Under a Norm of Consensus:
A Structural Analysis of Three-Judge Panels

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Abstract

This paper estimates a structural model of decision-making in judicial panels under a norm of consensus. Using data from asylum and sex discrimination cases in the courts of appeals, the model estimates ideology parameters for individual judges as well as a "cost" of dissent. I show that a positive cost of dissent for both the majority and the minority is necessary to reconcile the high rate of unanimity with the variation in individual judges' voting records. The parameter estimates of the structural model show that the dissent rate substantially understates the actual level of disagreement within panels and that consensus voting obscures the impact of ideology on case outcomes. A significantly positive cost of dissent for the majority also implies that judges will sometimes compromise to avoid a dissent by another judge, and hence, that case outcomes are not determined purely by majority rule. The methodology developed in this paper can also be used to derive more accurate estimates of judicial ideology that control for consensus voting.

Appellate courts in the United States, like many deliberative bodies, operate under an informal norm of consensus. Judges value unanimity, and will often compromise in order to reach agreement with their colleagues. Thus, each judge's vote in a case will be determined not only by that judge's own preferences, but also by the preferences of the other judges on the court. This interaction poses a significant challenge for the empirical analysis of decision-making in multimember courts: when only final votes are observable, the determinants of judicial behavior may be obscured by the unobservable influence of group deliberation (Howard 1968). This difficulty is compounded by the fact

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1

$$
\begin{aligned}
\Pr((P,P,P) \mid \alpha_1,\alpha_2,\alpha_3,c_d,c_m,\eta_t) = \\
&\sum_{\substack{i=1 \\ j,k\in S_t-\{i\}}}^{3} \Phi\left(\alpha_i-\eta_t+c_d\right)\Phi(\alpha_j-\eta_t)\Phi(\alpha_k-\eta_t) \\
&-\frac{1}{6}\sum_{\substack{i=1 \\ j,k\in S_t-\{i\}}}^{3} \left[\Phi\left(\alpha_i-\eta_t+c_d\right)-\Phi(\alpha_i-\eta_t)\right]\Psi^{-}(\alpha_j,\alpha_k) \\
&+\frac{1}{6}\sum_{\substack{i=1 \\ j,k\in S_t-\{i\}}}^{3} \left[\Phi\left(\alpha_i-\eta_t\right)+2\Phi\left(\alpha_i-\eta_t-c_d\right)\right]\Psi^{+}(\alpha_j,\alpha_k) \\
&-2\Phi(\alpha_1-\eta_t)\Phi(\alpha_2-\eta_t)\Phi(\alpha_3-\eta_t)
\end{aligned}
$$

Table 2: Estimates of Structural Parameters

	Asylum		Sex Discrimination	
Model Parameters				
c_d (Cost of dissent for minority judge)	1.71	(0.10)	3.21	(0.47)
c_m (Cost of dissent for majority judge)	1.36	(0.28)	0.00	
σ (Standard deviation of case cutoff)	0.44	(0.21)	2.75	(0.81)

The phenomenon to be explained

Sexual Discrimination Cases

Pro-Plaintiff votes	#Cases	Share of cases
3-0	366	37.5%
2-1	28	2.9%
1-2	41	4.2%
0-3	542	55.5%
Consensus:		**93.0%**

Asylum Cases

Pro-Asylum votes	#Cases	Share of cases
3-0	291	15.4%
2-1	45	2.4%
1-2	55	2.9%
0-3	1501	79.3%
Consensus:		**94.7%**

Understanding the model

- Consider a representative case before a 3-judge panel
- If: $p\%$ of judges would independently rule for plaintiff:
  - p^3 chance that plaintiff wins unanimously
  - $3p^2(1-p)$ chance that plaintiff wins a split decision
  - $3p(1-p)^2$ chance that plaintiff loses a split decision
  - $(1-p)^3$ chance that we lose unanimously
- Simple approach:
  Look for "excess consensus", relative to this baseline

Model Predictions and Data

Sex Discrimination Cases

Votes	Cases	Data	Model
3-0	366	37.5%	6.8%
2-1	28	2.9%	29.5%
1-2	41	4.2%	42.9%
0-3	542	55.5%	20.8%
Ave.		40.8%	40.8%
Consensus		93.0%	27.6%

Parameters:

- *p=40.8%*

Asylum Cases

Votes	Cases	Data	Model
3-0	291	15.4%	0.6%
2-1	45	2.4%	7.9%
1-2	55	2.9%	36.2%
0-3	1501	79.3%	55.3%
Ave.		17.9%	17.9%
Consensus		94.7%	55.9%

Parameters:

- *p=17.9%*

Model generates substantial "excess consensus"
$\Rightarrow$ Infer cost of dissent is high

Allowing for heterogeneity of cases

- There are both "easy" and "hard" cases:
  - $\alpha\%$ of cases have a $p\%$ chance of winning
  - $(1-\alpha)\%$ of cases have a $q\%$ chance of winning
- Implies data are a mixture of two distributions:
  - $\alpha p^3+(1-\alpha)q^3$ chance that plaintiff wins unanimously
  - $3[\alpha p^2(1-p)+(1-\alpha)q^2(1-q)]$ chance plaintiff wins a split decision
  - $3[\alpha p(1-p)^2+(1-\alpha)q(1-q)^2]$ chance plaintiff loses a split decision
  - $\alpha(1-p)^3+(1-\alpha)(1-q)^3$ chance plaintiff loses unanimously
  - And plaintiff wins $\alpha p+(1-\alpha)q$ of individual votes

Model Predictions and Data

Sex Discrimination Cases

Votes	Cases	Share	Prev. Model
3-0	366	37.5%	6.8%
2-1	28	2.9%	29.5%
1-2	41	4.2%	42.9%
0-3	542	55.5%	20.8%
Ave.		40.8%	40.8%
Consensus		93.0%	27.6%

Asylum Cases

Votes	Cases	Share	Prev. Model
3-0	291	15.4%	0.6%
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Ave.		17.9%	17.9%
Consensus		94.7%	55.9%

Model Predictions and Data

Sex Discrimination Cases

Votes	Cases	Share	Prev. Model	New Model
3-0	366	37.5%	6.8%	37.5%
2-1	28	2.9%	29.5%	2.9%
1-2	41	4.2%	42.9%	4.2%
0-3	542	55.5%	20.8%	55.5%
Ave.		40.8%	40.8%	40.8%
Consensus		93.0%	27.6%	93.0%

Parameters:

- α=40.3% of cases with p=97.6%
- $1-\alpha$=59.7% of cases with q=2.4%

Asylum Cases

Votes	Cases	Share	Prev. Model	New Model
3-0	291	15.4%	0.6%	15.4%
2-1	45	2.4%	7.9%	2.4%
1-2	55	2.9%	36.2%	2.9%
0-3	1501	79.3%	55.3%	79.3%
Ave.		17.9%	17.9%	17.9%
Consensus		94.7%	55.9%	94.7%

Parameters:

- α=17.8% of cases with p=95.2%
- $1-\alpha$=82.2% of cases with q=1.2%

Model now has three parameters to hit three unknowns

⇒Can never generate "excess consensus"

⇒There is no cost of dissent (or there is, but it is unidentified)

Solving the Identification Problem

- Estimating "excess consensus" requires either:
  - More restrictive model: Case quality: η~N(0,σ)
    - Reduce parameter set from (p,q,α) to (p,σ)
    - Normality => Eliminates fat tails
  - More variation: Exploit variation in composition of the panel
    - Case quality is randomly assigned across panels
    - And judges are randomly assigned to panels
- Within-judge between-panel variation is sufficient
  - An example:
    - Judge A voted for plaintiff in *a%* of past cases
    - Judge A voted for plaintiff in *b%* of past cases
    - Judge A voted for plaintiff in *c%* of past cases
  - If A-B-C are randomly constituted as a panel:
    - Unanimous vote expected in $abc+(1-a)(1-b)(1-c)\%$ of cases
    - More unanimous votes implies "excess consensus"
  - This inference requires no assumption about case quality

What if Preferences are Multi-Dimensional?

- Two-dimensional example:
  - 50% of cases involve international conventions: No preference heterogeneity on these cases
  - Judges vote independently

Pro-Asylum votes	Cases involving conventions	Regular cases	Average
Judge A	20%	40%	30%
Judge B	20%	60%	40%
Judge C	20%	80%	50%
If judges vote independently…			
Prob(ABC)	0.8%	19.2%	Data: (0.8+19.2)/2 = 10% Unidimensional model: 0.3*0.4*0.5= 6%
Prob(!A!B!C)	51.2%	4.8%	Data: (51.2+4.8)/2 = 27.5% Unidimensional model: 0.7*0.6*0.5 = 21%
Consensus	52%	24%	Data: 37.5% Unidimensional model: 27%

- Recall earlier intuition:
  - Ignoring case heterogeneity led us to (wrongly) infer "excess consensus"
  - Multi-dimensional preferences ↔ within-judge heterogeneity of cases
  - Again, we (wrongly) infer "excess consensus"