Markov Chain Models of Small Group Deliberation

April 17, 2026

Abstract

This article develops a formal model of small group deliberation as a Markov chain process that yields exact outcome probabilities based on the group's initial state. Deliberation is modeled as a sequence of probabilistic transitions among vote configurations until the group reaches unanimity. The model builds on a well-established class of stochastic processes—absorbing Markov chains—to provide an empirically validated and practically useful representation of deliberation by juries. Closed-form solutions for binary verdicts and matrix-algebraic solutions for ordered verdicts quantify how deliberation dynamics translate initial juror preferences into collective outcomes. Validation against data from criminal jury deliberations shows that the model accurately predicts verdict probabilities under a wide range of conditions. Extensions to multi-option verdicts replicate classic experimental results on the influence of lesser-included offenses and decision rules. The framework offers a general, analytically tractable way to study small-group decision making and to estimate how procedural changes or trial errors alter verdict probabilities in criminal cases.

Small group deliberation is an iterative process in which decision-makers exchange arguments, scrutinize evidence, apply shared rules, and update their views as they move toward a collective conclusion (Gastil and Black 2007; Fishkin 2018). Deliberation is path-dependent and dynamic. Small group decisions depend on the options available, the procedures used by the group, and the preferences of its members (Niemeyer et al. 2024; Mendelberg, Karpowitz and Oliphant 2014). Outcomes are probabilistic. Factions may shift, compromises may emerge, and the group can converge on an option that was not initially the most popular choice (Luskin et al. 2022; Esterling, Fung and Lee 2021).

The dynamics of small-group deliberation are relevant in a variety of political settings that make decisions through deliberation (e.g., Myers and Mendelberg 2013; Gastil 2008). This article focuses on juries as a test case. For political scientists interested in deliberative decisions, juries are a relatively "pure" example of direct democracy in action. Jurors are randomly selected from representative cross-sectionss of American communities. Some may have prior jury experience, but they are typically strangers to one another. They are instructed to deliberate until they reach a unanimous verdict, but not told how to do so. There is no set agenda, other than selecting a foreperson, nor any formal procedural rules to follow. They make important decisions, including life-or-death decisions, and they do so on a large scale. Prior research on jury deliberation affords an opportunity to build on existing findings.

This article addresses a simple but consequential question: What verdict will a small group of jurors reach through deliberation? The article demonstrates that jury deliberation is effectively represented as a Markov chain process. Markov chain models are well established in the study of dynamic systems and have been widely applied to processes in which discrete states evolve probabilistically. Applied to jury deliberation, Markov chain models are useful for quantifying verdict probabilities, conditional on the initial state of jury deliberation.[1]

[1] Some may think that Arrow (1951) proved that it is impossible to predict how groups make choices, but Arrow's Impossibility Theorem concerns the nonexistence of a social-welfare function that aggregates individual preferences while satisfying several fairness axioms. Given Arrow's result, there no procedure that

The models can accommodate varying verdict options, nonlinear transition probabilities, and different jury sizes, yet are sufficiently structured to permit visualization and exact solutions.

Model predictions are compared to outcomes observed in prior research on jury deliberation to demonstrate validity in this domain.[2] A simple Markov chain model of deliberation effectively replicates outcomes observed when juries make binary choices, such as deciding whether a defendant is guilty or not guilty, or whether the sentence should be death or life imprisonment. The model also forecasts verdict probabilities when juries choose from ordered outcomes. For ordinal-level verdicts, validation data are limited, but the models enhance our understanding of how the range of options available to a small group affects its choice. By demonstrating that a standard stochastic modeling approach fits jury data, this article situates jury decision making within a broader class of well-understood deliberative systems.

The adapts and validates a classic model for the study of jury deliberation. The results contribute to our understanding of how deliberating groups reach consensus, a topic broadly relevant to political science. In addition, the research has useful practical applications for analyzing criminal trials and procedures. The model provides a transparent and empirically grounded way to infer verdict probabilities from juror preferences. This enables researchers to assess how trial procedures or evidentiary rulings affect probabilities of guilty verdicts, conviction on lesser offenses, or death sentences. It may support more objective assessment of criminal trials, advancing the promise of fair trials for all.

---

fairly aggregates juror preferences into a verdict. Our aim is a descriptive account of what juries do, not a normative prescription for what juries ought to do to minimize the risk of error, eliminate prejudice, inspire public confidence, or satisfy any other normative criterion. Whether a descriptive account fits observed data is an empirical question to be tested.

[2] There are other interesting aspects of deliberation, such how the foreperson is selected and how often jurors speak, but these aspects are not the focus of this article or the model developed herein.

I. Modeling Setup

This section defines the essential components of a model of jury deliberation, including basic features of criminal trials likely familiar to many readers. Like other models, it omits as many details as possible while faithfully depicting properties relevant to the study.

A. Structure of Criminal Jury Trial

The U.S. Constitution guarantees criminal defendants the right to trial by an impartial jury. When exercised, a jury is selected from a pool of qualified adults randomly summoned for jury duty. Jurors attend the trial, observe the defendant, hear arguments, and consider the evidence presented by both sides. When the trial is over, jurors are instructed to deliberate among themselves until they unanimously decide that the defendant is guilty (G) or not guilty (NG). When the jury reaches a verdict, the decision is announced, judgment is entered on the record, and the jury is dismissed.[3]

Criminal trial juries often have multiple verdict options, such as the ability to convict a defendant on lesser included offenses (LIOs). LIOs are crimes whose elements are a subset of the elements of a charged, greater offense (Hoffheimer 2004). For example, the levels of homicide turn on the defendant's culpability. First-degree murder (M1) requires premeditation. Second-degree murder (M2), a LIO of M1, is an unlawful killing with malice. Manslaughter (M3) is an LIO of both M1 and M2; it allows a jury to convict if the evidence proves the defendant was negligent, reckless, or voluntarily killed without adequate provocation. If the evidence proves premeditation for M1, it also establishes malice for M2 and negligence or recklessness for M3, but the defendant will only be convicted of M1. LIOs are mutually

[3] This paragraph describes American juries generally. There are exceptions and qualifications to these generalities owing to waiver, local practice, and unusual circumstances. A complete account of jury usage is beyond the scope of this article.

exclusive. If a defendant is convicted of a greater offense, the lesser offenses merge into it and the court enters judgment on the greater offense only.[4]

Understanding how juries deliberate LIOs may inform ongoing constitutional controversies surrounding their use in jury trials (Shellenberger and Strazzella 1995). In capital cases, the jury must be permitted to consider LIOs so that it is not forced into an all-or-nothing choice between capital guilt and acquittal (Hoffheimer 2005). Otherwise, instructions for considering LIOs vary by jurisdiction. Many jurisdictions require such instructions when the evidence warrants them, while others allow parties to decide whether to request them (Blair 1983).

B. Classic Markov Chains

Markov chains are a useful construct for depicting jury deliberation visually and for calculating the probabilities of G and NG verdicts given the jury's initial state. Markov chains are used to represent systems that move step-by-step among a set of possible states, where the chances of the next step depend only on the current state, not on how it got there (Ching and Ng 2006; Gagniuc 2017).

Visually, the system's possible states are represented as nodes. Arrows between nodes show how the system can transition from one state to another in one step. From a transient state, the system either (i) remains in the same state (a self-loop) or (ii) transitions to an adjacent node.

Some Markov chains have absorbing states. When the system reaches an absorbing state, it remains in that state and does not transition away from it. All non-absorbing states are

[4] LIOs are not the only example of ordered choices. Some juries have verdict options based on the defendant's mental fitness: NG, not guilty by reason of insanity, guilty but mentally ill, or G. While not perfectly linear, these options often have a severity ordering (Melville and Naimark 2002). Some juries decide whether the evidence supports sentencing enhancements, creating the equivalent of G, G+, and G++ verdicts (Bibas 2000). Death penalty juries may decide whether the defendant deserves life imprisonment with the possibility of parole, life without parole, or a death sentence (Wright Jr. 1990). In some countries, juries can render a "not proven" verdict (Hope et al. 2008).

transient states. In diagrams, the direction of arrows is important because the system may transition into an absorbing state but not away from it.

The Gambler's Ruin problem provides a classic illustration. In the standard Gambler's Ruin problem, a gambler starts with a certain amount of money and places bets until all the money is gone or the gambler has met a predetermined goal (Song and Song 2013). The system's state—the gambler's bankroll—increases by 1 with probability p (a win), and decreases by 1 with probability $1 - p$ (a loss). The state is bounded between endpoints, 0 ("ruin") and N ("goal"). In this classic example, there are $N+1$ possible states; 2 of the states are absorbing and $N - 1$ are transient. In subsequent sections, we solve for the gambler's probability of reaching N before hitting 0, given N and the gambler's initial bankroll.

The familiar framework is easily applied to a jury deliberating a binary verdict. In this case, the system's state represents the number of jurors in favor of a guilty verdict. When jurors deliberate a choice between G and NG, the state can be summarized by the number of G votes, 0, 1, 2 … N where N is the size of the jury. The two endpoints, 0 (unanimous NG verdict) and N (unanimous G verdict), are absorbing states and all other states are transient. Once deliberation hits an absorbing state, deliberation is effectively over; the remaining steps are formalities. With each step, the state of the jury's deliberation can increase by one, decrease by one, or stay the same.

C. Markov Chains with Ordered Outcomes

A Markov chain model of ordered outcomes builds on the familiar framework for binary outcomes. When trial outcomes are ordered, they can be ranked on a common, objective scale—e.g., NG < M2 < M1 by legal severity or punishment, regardless of who's voting.[5]

[5] Ordered preferences, by contrast, describe a particular juror's ranking of those outcomes, which need not increase (or decrease) along that legal scale. Given the evidence and proportionality norms, a juror might think M1 is too harsh and NG too lenient, making M2 the most preferred—even though NG < M2 < M1 is still the correct outcome order. The deliberation models discussed in this article use an ordered lattice of outcomes for transitions, yet allow voters whose preferences are not monotone in that order. Just a test to reference Note 1.

Let there be $K \geq 3$ ordinal verdict options. The state of deliberation is no longer a single number. Instead, the state is the count vector $x = (c_1, \ldots, c_K)$ with $c_r \in \{0, 1, \ldots, N\}$ and $\sum_{r=1}^{K} c_r = N$. This combinatorial expression represents the number of ways N jurors can be distributed with K verdict options.

$$S = \frac{(N + K - 1)!}{(K - 1)!N!} \tag{1}$$

The number of possible states grows quickly. If three jurors deliberate among three options, there are $\frac{5!}{2!3!} = 10$ possible initial states, already nontrivial to visualize. When a standard-size jury of 12 deliberates among three options, there are 91 possible initial states; with four options, there are 451 possible states.[6]

With K verdict options, there are K absorbing states because the jury can unanimously agree on any option. Every other state is transient; at least one more step is needed to reach a unanimous verdict. The number of transient states follows a simple formula: $T = S - K$.

With multiple options, moves are only between adjacent options. A juror may switch NG $\leftrightarrow$ M2 or M2 $\leftrightarrow$ M1, but not NG $\leftrightarrow$ M1 directly. As with deliberation between binary outcomes, the process continues until it reaches one of its K absorbing states.

The Markov chain is a relatively parsimonious construct. It depicts the state of deliberation, how it can change, and how it ends. It does not impose strong assumptions about jurors' reasons for preferring one verdict over another. Many things influence the starting point—trial evidence, defendant and victim characteristics, attorneys, among others—yet the antecedent causes of the starting point need not concern us here.[7] In this model, jury deliberation has a starting point and then proceeds from there until it concludes.

[6] The complexity presents no problem for modern computers, but it makes it impossible to depict complex chains visually or display complete transition matrices compactly. It also helps explain why existing studies report pre-deliberation vote counts for NG/G decisions, but not for NG/M2/M1 or NG/M3/M2/M1 decisions.

[7] In the Gambler's Ruin problem, there may be causal factors that explain how much money the gambler starts with, which indirectly influence the probability of reaching N before hitting 0, but once we account for the starting point, the antecedent causes do not affect the solution.

II. Defining Transition Probabilities

A transition probability matrix records the one-round probabilities for every "from" state to every "to" state. By convention, matrix rows sum to 1. Specifying this matrix lets us use linear algebra to compute absorption probabilities exactly, without simulating millions of deliberations.

A. Binary Verdict Choice

We start with the two-option case to define the approach we will extend to multiple verdicts. Let N be the jury size and index states by the current number of G votes, $i = 0, 1, \ldots, N$. The transition matrix $\boldsymbol{P} \in \mathbb{R}^{(N+1)\times(N+1)}$ records the one-round probabilities of moving from state i to state j.

The model's transition probabilities reflect our understanding of jurors and juries. The probabilities are not uniform across transient states. Stated in general form, probability of jurors on the dividing line between alternatives selecting the more punitive option in the next round of deliberation is a combination of internal and external influences.

$$m(G) = \underbrace{\omega_{\text{internal}}\,(.5)}_{\text{individual randomness}} + \underbrace{\omega_{\text{external}}\,(\tfrac{G-\delta}{N})}_{\text{systematic factors}} \tag{2}$$

The transition probabilities combine the personal, idiosyncratic reasons for juror votes with two external forces—*social influence* (larger factions pull more votes) and *leniency* (movement toward the more punitive option is slightly harder)—that influence jurors in deliberation.

If the jury has not reached a verdict, jurors are divided into NG and G factions. At any point, one member of each faction is closest to the NG/G cutting line. Jurors on the NG/G cutting line hover between two factions and are susceptible to changing their votes. In that moment, their personal vote is essentially a toss-up. In the $m(G)$ equation, this state amounts to a 0.5 probability of choosing the more punitive option. This part of the equation is analogous to the Gambler's probability of winning each bet. This is not to say that jurors are careless or decide cases randomly, but rather recognizes that jurors are autonomous agents with internal thoughts and motivations so numerous and varied they resemble pure noise (Kalven and Zeisel 1966; Devine 2012).

There is an element of randomness owing to the idiosyncrasies of those randomly selected for jury duty, but deliberating juries exhibit two regularities not present in a pure random walk. These are external factors that influence vote choice on the margin.

First, factions exert social influence. The larger the guilty faction, the more likely a swing juror will join it. The probability of voting for G increases linearly with G. The gravitational pull of the majority faction is a consistent and well documented feature of jury deliberation.

The second external factor influencing votes on the margin is the legal standard of proof used in criminal trials. The NG/G choice is tilted in the defendant's favor. In the literature, this tendency is known as the "leniency bias" (MacCoun and Kerr 1988; Kerr and MacCoun 2012). It is symbolized as δ in the $m(G)$ equation. This "bias" is not an inherent feature of juror psychology, but rather criminal law. Jurors are instructed to presume that the defendant is innocent and to require that the state prove guilt beyond a reasonable doubt.

We turn this single equation into three one-step transition probabilities via a simple symmetric transform. While the jury is divided, there are two jurors next to the cutting line, one from each faction, both with probability $m(G)$ of voting for a guilty verdict in the next round. This gives rise to the following transition probabilities:

$$p_i \;=\; m(G)^2, \qquad q_i \;=\; \big(1 - m(G)\big)^2, \qquad s_i \;=\; 1 - p_i - q_i. \tag{3}$$

Here, p_i is the probability of *gaining* one G vote, q_i the probability of *losing* one G vote, and s_i the probability of *staying* in place. For *absorption probabilities*, what matters is the ratio of p_i to q_i. Changing the self-loop mass s_i (e.g., making rounds longer or shorter) does not change the terminal probabilities; it only changes the expected time to reach a verdict.

To calculate specific transition probabilities from the general equation, we must specify the numeric values of N, δ, ω_{internal}, and ω_{external}. The value of N depends on jurisdiction and case type. In felony trials, $N = 12$; $N = 6$ in some misdemeanor trials.[8] In any case, N is constant during deliberation.

The leniency bias, δ, is well documented in the empirical literature. Prior research indicates that a 12-person jury that starts with a tie vote ($G = 6$) is more likely to acquit than to convict. Due to δ, the probability of conviction is approximately 50% when $G = 7$ which supports $\delta = 1$.

As for ω_{internal} and ω_{external}, their values are both set to 0.5, giving internal and external factors equal weight. The weights must sum to 1 and equal weights are a sensible default in the absence of other evidence (Armstrong 2001).[9]

For a jury deliberating a binary outcome, $m(G) = .25 + \frac{G-1}{2N})$. Three jurors deliberating a NG/G decision can be visually depicted with a simple Markov chain. Figure 1's transition probabilities derived from the $m(G)$ equation with $N = 3$.

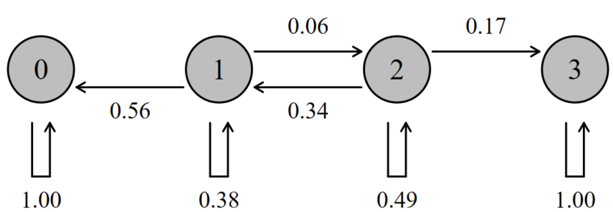

Figure 1: Markov Chain for a Three-Person jury Deliberating Binary Outcome

[8] Most trial juries have six or twelve members, but other jury sizes are used. Military courts-martial juries, for example, can have four, eight, or twelve members, depending on the severity of the offense. Some grand juries have 16 members. Virginia uses seven-person juries for misdemeanor trials.

[9] Equal weighting corresponds to the weight given to advice perceived as high quality. Bailey et al. (2023) report that the weight placed on others' advice is 32-48%, depending on perceived advice quality.

B. Ordered Verdict Choices

The two-option deliberation model extends naturally to multiple *ordered* verdicts.[10] When the jury has K options, juror verdict preferences fall along a continuum with K–1 cutpoints. Each cutpoint pits a faction that favors a more lenient outcome against a faction that favors a more punitive outcome. The deliberation is still a tug of war between two opposing factions, but now jurors who favor middle outcomes may switch sides, depending on the cutpoint.

Because verdicts are ordered, jurors may switch only between *adjacent* categories in one round. In the three-option example (NG < M2 < M1), a juror can switch NG $\leftrightarrow$ M2 or M2 $\leftrightarrow$ M1 in a round; a direct NG $\leftrightarrow$ M1 jump is not allowed.[11]

The probability of a juror on a cutting line voting for the more punitive outcome follows the $m(G)$ formula stated above, with one important adjustment. The leniency bias, δ, which favors the defendant in the NG/G decision, is set to 0 when the jury deliberation focuses on the level of offense rather than the determination of guilt. For example, when the jury is deliberating between M2/M1, the presumption of innocence does not favor one side over the other. Leniency is not a general trait of jurors; it is a presumption favoring NG specifically. If jurors unanimously agree that the defendant is guilty of murder, but are divided over premeditation, the presumption of innocence becomes a nonfactor.

With $K = 4$ ordered verdicts the state space becomes a tetrahedral lattice. The nodes are integer points (c_1, c_2, c_3, c_4) with a sum of N, corners are unanimities, and legal moves transfer one juror between adjacent options $r \leftrightarrow r{+}1$ along the edges of the pyramid-shaped lattice. As before, the state may move along right-angled edges; diagonal "shortcuts" are not possible. Locally, each interior node connects to up to six neighbors (two across each of

[10] Jury deliberation over multiple, mutually exclusive options that may be ranked by severity should be distinguished from deliberation over multiple charges against the same defendant (or cases with multiple defendants). When multiple charges are filed against a single defendant, the jury may find the defendant guilty on some, all, or none of the charges. Some of the charges may have LIOs, but they are separate charges.

[11] This constraint is evident on a Figure 3: the state cannot move diagonally in one step.

the three cuts). The same cut-based averaging defines the transition probabilities. Visually, the Markov chain with $K = 4$ is the 3D analogue of Figure 3.

C. Example Transition Probability Matrix

In the simple case of a three-person jury deliberating among three possible outcomes, the initial state may be any combination of NG, $M2$, and $M1$ where $NG + M2 + M1 = N$. The state space has 10 nodes: $K = 3$ absorbing unanimities and $T = 7$ transient compositions. This simple example fits on a page, but has no real analog in American courtrooms where the minimum jury size is six jurors.[12]

Consider a jury where NG, M2, and M1 each receive one vote. From this central transient state, the deliberation can transition to four distinct states in the next round, or it can remain in place. The transition probabilities are based on the probabilities of movement along each cutting line.

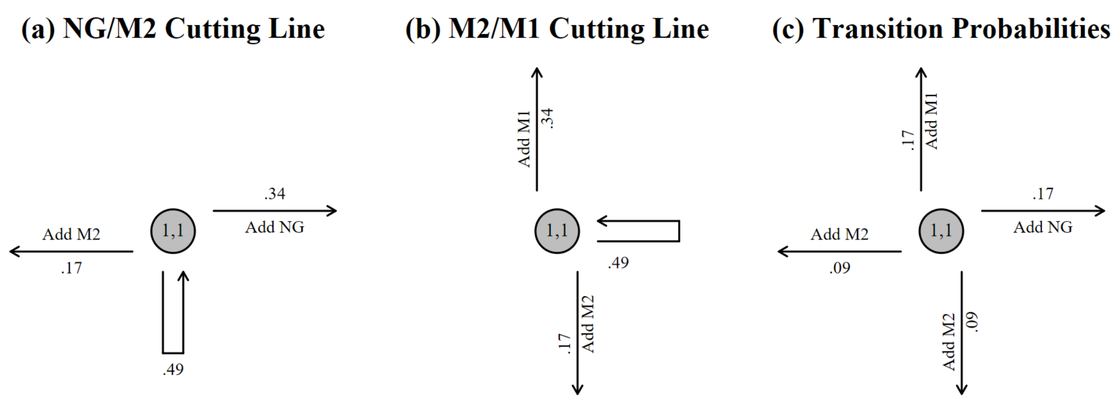

Figure 2: Transition Probabilities with Three Verdict Options

The NG/M2 cut line, depicted in Figure 2(a), pits one juror who favors NG against two who favor conviction. NG could gain a vote ($q_i = .34$), M2 could gain a vote ($p_i = .17$), or the deliberation could remain in the same state ($s_i = .49$). The M1 vote is not in play because the M2 vote is closer to the cutting line.

[12] In *Williams v. Florida*, 399 U.S. 78 (1970), the U.S. Supreme Court held that due process requires at least six jurors. Notwithstanding *Williams*, some military offenses are decided by courts-martial juries with four members.

The M2/M1 cut line, depicted in Figure 2(b), pits one juror who favors the most punitive outcome, M1, against two jurors who favor more lenient outcomes (either M2 or NG). If the next step is up or down, M2 could gain a vote ($q_i = .17$), M1 could gain a vote ($p_i = .34$), or vote tallies could remain unchanged ($s_i = .49$). In this direction, the NG vote is not in play.

Averaging across the $K - 1 = 2$ cuts assigns probability mass to the four adjacent neighbors reached by moving betweem NG↔M2 or M2↔M1, with the remainder assigned to the self-loop. This yields the transition probabilities from point (1,1) seen in Figure 2(c). (The s_i probability of .49 is omitted from the Figure 2 for simplicity.)

The resulting Markov chain is the nearest-neighbor walk on the simplex lattice. Figure 3 shows a triangle-shaped lattice of nodes with connecting arrows showing "legal" moves. Transition probabilities are displayed next to the node-to-node arrows.

Edge cases with constrained movement warrant some discussion. Edge cases occur when there are no votes for one option and jurors are divided between the other two choices. For example, if deliberation is at node $(1, 2)$ on Figure 3's diagonal edge, there is 1 vote for NG, 2 votes for M1, and no votes for M2. Because jurors cannot move directly between NG and M1 without passing through the intermediate M2 option, there are only three possibilities: the NG juror switches to M2 (state moves to the left), one M1 juror switches to M2 (state moves downward), or the state remains at $(1, 2)$.

On the left edge of Figure 3, the NG faction has lost all support and jurors are divided between M2 and M1. All jurors are on the punitive side of the cutting line between NG and M2, but there is still a .09 probability of NG gaining a vote due to the leniency bias and individual choice. On the bottom edge of Figure 3, there are 0 votes for M1 and jurors are divided between NG and M2 options. Here, all jurors are on the lenient side of the cutting line between M1 and M2. The probability of gaining an M1 vote is very low (.03). A non-existent M1 faction has no social influence and the leniency bias works against M1, but some internal factor may cause an M2 juror to switch their vote to M1.

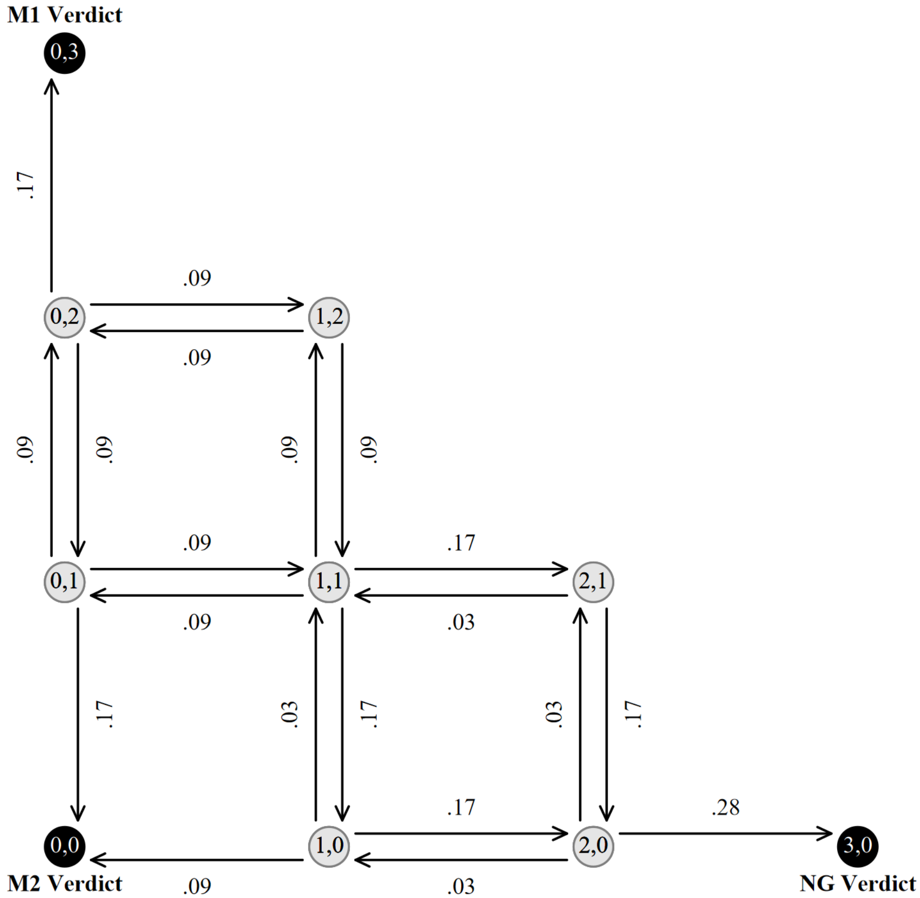

Figure 3: Two-Dimensional Markov Chain for a Three-Person Jury with Three Ordered Alternatives. Nodes are points $(NG, M1)$ with $M2 = N - NG - M1$; arrows show legal one-step moves between adjacent options. Edge labels display transition probabilities.

III. Obtaining Absorption Probabilities

This section explains how to compute the probability of arriving at an absorbing state given the system's initial state. It begins with the simple case of a pure random walk along a single chain, then treats the binary choice with nonuniform transition probabilities, and finally extends to multiple ordered outcomes.

A. Classic Gambler's Ruin

The Gambler's Ruin problem has a straightforward solution. On the line of nodes $\{0, 1, \ldots, N\}$ with absorbing endpoints $\{0, N\}$ and one fair step each round ($p = .5$), the probability of eventually hitting N before 0 when starting at i is $\frac{i}{N}$. So long as the transition probabilities are uniform across the chain, there is a relatively simple algebraic solution to the Gambler's Ruin problem.[13].

If jury deliberation were this simple, the probability of a guilty verdict would be equal to G_0/N (if $p = .5$) or an increasing exponential curve (concave if $p > .5$ and convex if $p < .5$). In practice, the probability of a guilty verdict is not a simple linear equation because the transition probabilities between transient states are not uniform.

B. Binary Jury Verdict

In jury deliberation, transition probabilities are *state-dependent*, not uniform. The simple solution to the Gambler's Ruin problem no longer applies. Instead, absorption probabilities are obtained via matrix algebra.[14] We begin by writing $\boldsymbol{P}$ in canonical block form by partitioning the matrix into four component blocks:

$$P = \begin{bmatrix} Q & R \\ 0 & I_K \end{bmatrix} \tag{4}$$

where

$\boldsymbol{Q}$ contains probabilities for moves *within* the transient set. These represent the "keep deliberating" steps.

$\boldsymbol{R}$ records probabilities of transitioning from transient state *directly* to an absorbing state in one round; these values are nonzero when the jury is *one vote away* from unanimity.

0 is a matrix of zeros that reflects the impossibility of transitioning from an absorbing state to a transient state.

---

[13] When $p \neq .5$, the gambler's probability of reaching N before hitting 0 is $\frac{1-(q/p)^i}{1-(q/p)^N}$ where $q = 1 - p$.

[14] One can also use matrix algebra to find the Gambler's Ruin probabilities, but those probabilities are simple equations.

$\boldsymbol{I}_k$ is a $K \times K$ identity matrix; once deliberation reaches an absorbing state, it will remain in that state in subsequent rounds.

The matrix of absorption probabilities from each transient state, $\boldsymbol{B}$, is obtained by multiplying the fundamental matrix, $(\boldsymbol{I}_T - \boldsymbol{Q})^{-1}$, by $\boldsymbol{R}$. This yields exact verdict probabilities from any initial transient state.

$$\boldsymbol{B} \;=\; (\boldsymbol{I}_T - \boldsymbol{Q})^{-1}\, \boldsymbol{R} \;\in\; \mathbb{R}^{T \times K} \tag{5}$$

where $\boldsymbol{B}i, j = \Pr(\text{absorb at verdict } j \mid \text{start at transient } i)$.

The fundamental matrix, $(\boldsymbol{I}_T - \boldsymbol{Q})^{-1}$, plays an important role in the solution. This matrix gives the expected number of visits to other transient states, starting from a transient state i, before it hits an absorbing state. By multiplying the expected number of visits to transient states by the corresponding probabilities of reaching final verdicts from those states, we obtain the probability of NG or G verdicts given the starting state i.

Because the jury's initial state may be unanimous, it is helpful to report outcome probabilities for *all* initial states. For complete results, simply stack the identity matrix for the absorbing rows, $\boldsymbol{I}_k$, beneath $\boldsymbol{B}$. The result yields verdict probabilities from every possible initial state of jury deliberation.

C. Ordered Outcomes Example

With more than two outcomes, there is no simple enquotedistance formula, even if the probabilities are uniform. Fortunately, the solution concept used to find the absorbing state probabilities for binary outcomes can be extended to the jury's deliberation with three or more ordered outcomes. Interpreting results requires careful attention to the ordering of states and outcomes.

Consider the simple case where $N = 3$ and $K = 3$. The verdict options are listed by ascending severity: NG < M2 < M1. To begin, we list all ten states with the *transients* *first*, then the three unanimity absorbers in order: $(0,1,2)$, $(0,2,1)$, $(1,0,2)$, $(1,1,1)$, $(1,2,0)$, $(2,0,1)$, $(2,1,0)$, $(3,0,0)$, $(0,3,0)$, $(0,0,3)$.

Using the cut-averaged, adjacent-move rule from the previous section, we generate the 10×10 transition matrix, $\boldsymbol{P}$ (rounded to 2 decimals). Here we adopt the *row-stochastic* convention (each row of $\boldsymbol{P}$ sums to 1. The block partition (vertical/horizontal lines) matches the absorbing-chain form $\boldsymbol{P} = \left[\begin{smallmatrix} Q & R \\ 0 & I_3 \end{smallmatrix}\right]$.

$$\boldsymbol{P} = \left[\begin{array}{ccccccc|ccc} .66 & .09 & .09 & 0 & 0 & 0 & 0 & 0 & 0 & .17 \\ .09 & .66 & 0 & .09 & 0 & 0 & 0 & 0 & .17 & 0 \\ .09 & 0 & .83 & .09 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & .09 & .09 & .49 & .17 & .17 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & .03 & .71 & 0 & .17 & 0 & .09 & 0 \\ 0 & 0 & 0 & .03 & 0 & .80 & .17 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & .03 & .03 & .66 & .28 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{array}\right].$$

To find $\boldsymbol{B}$, the probabilities of NG, M2, and M1 verdicts from the seven transient states, we multiply $(\boldsymbol{I}_T - \boldsymbol{Q})^{-1}$ by $\boldsymbol{R}$. The three values in row i of $\boldsymbol{B}$ are the probabilities of NG, M2, and M1 verdicts starting from transient state i.

$$\begin{bmatrix} .14 & .22 & .64 \\ .19 & .63 & .19 \\ .37 & .26 & .37 \\ .60 & .29 & .10 \\ .63 & .36 & .01 \\ .90 & .08 & .02 \\ .96 & .04 & .00 \end{bmatrix} = \begin{bmatrix} 3.74 & 1.12 & 2.18 & .63 & .42 & .61 & .52 \\ 1.12 & 3.39 & .98 & .84 & .56 & .81 & .68 \\ 2.18 & .98 & 7.52 & 1.62 & 1.08 & 1.57 & 1.32 \\ .63 & .84 & 1.62 & 2.62 & 1.74 & 2.52 & 2.13 \\ .08 & .10 & .19 & .31 & 3.86 & .60 & 2.23 \\ .11 & .14 & .28 & .45 & .60 & 5.86 & 3.23 \\ .02 & .02 & .04 & .07 & .39 & .57 & 3.42 \end{bmatrix} \cdot \begin{bmatrix} 0 & 0 & .17 \\ 0 & .17 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & .09 & 0 \\ 0 & 0 & 0 \\ .28 & 0 & 0 \end{bmatrix}$$

Proper substantive interpretation requires understanding the order of transient states. Consider the jury that starts with one vote for each possible verdict. The verdict probabilities from the $(1, 1, 1)$ state appear in the fourth row of $\boldsymbol{B}$: $(.60, .29, .10)$.

The fourth row of $(\boldsymbol{I}_T - \boldsymbol{Q})^{-1}$ gives the expected number of times the jury will visit each transient state before reaching an absorbing state. The sum of values in this row is the expected number of steps to reach a verdict from the initial state. From a $(1, 1, 1)$ start, the expected duration is 12.1 rounds. These values should be related to the duration of deliberation and the hung jury probability, but the terms of those relationships are not yet clear.

It is possible to obtain absorbing probabilities through Monte Carlo simulation, but an analytic solution is preferable to brute-force simulation. Naïve Monte Carlo can answer the same questions, but it is slower, noisy, and less transparent. Analytic absorption results give exact probabilities, run essentially instantly once the matrices are built, and scale gracefully with jury size. They are also easier to maintain: every quantity is a function of clearly defined states and transitions, not of simulation settings (e.g., seeds, draws, and burn-in).

An R package available on CRAN provides three core functions to construct the full one-step transition matrix, solve for the absorption probabilities in the ordered multi-verdict model, and calculate verdict probabilities given support for verdict options in the population from which jurors are selected. The implementation is designed to be fast, transparent, and easy to maintain; it avoids simulation and uses the standard absorbing-chain algebra.

IV. Validity of the Jury Deliberation Model

This section evaluates Markov chain models of jury deliberation against observational data to assess validity. Validation requires data that report, at minimum: the *starting state* of jury deliberation (pre-deliberation preferences) and the jury's *final verdict* (e.g., NG, a lesser, or the top count).

The model of binary choice can be validated using existing studies. A large empirical tradition examines the relationship between jurors' initial votes and final jury verdicts. The seminal work is Kalven and Zeisel (1966). The authors documented systematic relationships between jurors' pre-deliberation leanings and eventual verdicts, judge–jury agreement rates, and the influence of the initial majority.

Most empirical work on jurors and juries since publication of *The American Jury* focuses on binary verdicts (e.g., NG vs. G). We benefit from decades of accumulated research linking starting conditions to final verdicts under a rich variety of conditions (Devine 2012). Based on this research, we can estimate the observed relationship between votes and verdicts, accounting for factors like jury size and death penalty deliberation, from 2,303 jury deliberations (Devine et al. 2001; Edwards 2025). The empirical results provide a benchmark for evaluating model validity. Empirical analysis shows, not surprisingly, that the initial size of the guilty verdict faction is a strong predictor of the ultimate outcome. More surprisingly, six-person juries tend to be more lenient, controlling for the relative size of the guilty verdict faction, and the dynamics of death penalty deliberation are not significantly different than guilt deliberation (Edwards 2025, 2026 est.).

To assess validity, the initial conditions of 2,303 observed deliberations serve as starting points for simulated deliberation with Markov chain models.[15] We then analyze predicted outcomes with the equation previously applied to observed outcomes. As discussed above, the formal model yields closed-form verdict probabilities, but when applied to a finite sample, the predicted probabilities are estimated with standard errors. Figure 4 shows the Markov chain model's predicted probabilities against observed data points. The Markov chain model closely replicates the outcome of jury deliberation with binary verdicts, like NG/G and the life/death decision in capital sentencing.[16] The S-shaped curve relating the proportion of jurors in favor of a guilty verdict to the probability of a guilty verdict fits the observed results, including the observed leniency bias of juries.

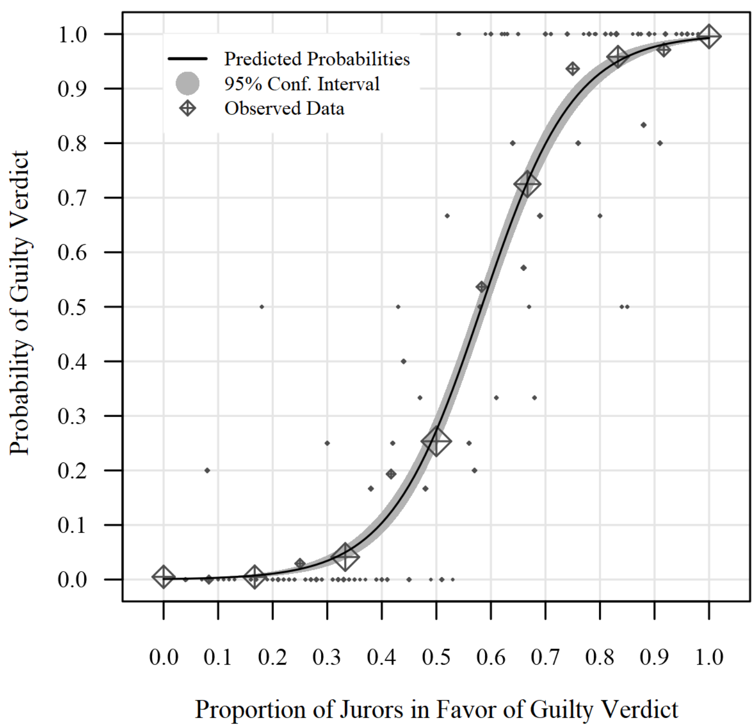

Figure 4: Comparison of Observed NG/G Verdicts and the Model's Predicted Probabilities

[15] I do not attempt to explain the starting points. This article does not address *why* some juries start with more guilty votes than others do. That is an important question, but it is beyond the scope of this article.

[16] Side-by-side comparisons using logistic regression analysis of observed and simulated verdicts appear in (Edwards 2026 est.). Coefficient differences are not significant.

Despite their prevalence and practical significance, jury trials with ordered outcomes are less studied and less well understood than trials with binary outcomes (Kerr 2017; Sandys and Dillehay 1995). Some studies explore the effect of alternative options on individual preferences. This research consistently shows that the choice set affects individual verdict preferences (Kelman, Rottenstreich and Tversky 1996; Lundrigan, Dhami and Mueller-Johnson 2018; Grofman 1985; Vidmar 1972; Hope et al. 2008). However, these studies focus on juror-level preferences without having subjects deliberate to a verdict. Koch and Devine (1999) analyzes the effect of lesser-included offenses (LIOs) on jury-level decisions, but unfortunately does not report participants' pre-deliberation preferences.

Hastie, Penrod and Pennington (1983) provides one opportunity to validate the Markov chain model's predicted verdict distributions with ordered options. The authors had mock jurors record their verdict preferences following a murder trial and then deliberate in groups of twelve to decide verdicts (pp. 196-197). Verdict options included not guilty (NG), manslaughter (M3), second-degree murder (M2), and first-degree murder (M1). The authors varied decision rules. For some juries, unanimity was required, while others were permitted to decide by 10-2, or 8-4 votes. Hastie, Penrod and Pennington (1983) does not specify starting state frequencies, but it does report the distribution of pre-deliberation juror preferences for each decision rule along with tallies of observed verdicts.

The initial vote distributions in the three experimental conditions reported by Hastie, Penrod and Pennington (1983) (undecided votes omitted) are used to generate probability distributions of all possible initial states for $N = 12$ and $K = 4$. We then weight each starting state's verdict probabilities by its initial-state probability. For jury deliberations under the 10-2 and 8-4 voting rules, the model's transition probability matrix is modified so that states with the requisite number of votes are absorbing states. The resulting verdict probabilities are multiplied by the number of observed deliberations in each study condition (omitting hung juries) to obtain the predicted verdicts in Table 1.

Table 1: Markov Chain Model Predicts Hastie et al.'s Observed Verdicts

	12-0 Rule				**10-2 Rule**				**8-4 Rule**			
	NG	M3	M2	M1	NG	M3	M2	M1	NG	M3	M2	M1
Juror Distribution	.14	.35	.28	.24	.09	.33	.26	.31	.13	.38	.29	.20
Observed Verdicts	0	7	13	0	0	5	13	5	0	8	13	1
Predicted Verdicts	.8	8.4	9.6	1.2	.3	7.1	12.4	3.2	.6	11.1	9.5	.7
	χ^2=3.44 P-value=.30				χ^2=2.01 P-value=.56				χ^2=2.82 P-value=.39			

Note: Juror vote distributions and observed verdicts from Hastie, Penrod and Pennington (1983, 196–197).

Chi-squared goodness-of-fit tests assess whether observed verdicts significantly deviate from the model's predicted frequencies. If the model captures the data-generating process, then the implied $\boldsymbol{B}$ is the limiting distribution of observed terminal frequencies, conditional on the starting state. Close agreement between observed verdict rates and $\boldsymbol{B}_{\cdot,c}$ across experimental conditions is strong evidence that the model captures both the direction and magnitude of deliberation dynamics. Based on the results, the model verdict could plausibly have generated the observed verdicts in each experimental condition. The observed data validate the Markov chain's capacity to predict verdict frequencies with multiple alternative verdicts and varying decision rules.

Hung jury rates offer another benchmark for model validation. The model supports predictions about the frequency of hung juries that can be tested against observational data. The expected number of rounds to absorption from transient states is equal to $(\boldsymbol{I}_T - \boldsymbol{Q})^{-1}\mathbf{1}$ where $\mathbf{1}$ is a $T \times 1$ vector of ones. The expected rounds to completion, which can be calculated, should be proportional to observed hung jury rates.[17] Unfortunately, the best available data on hung juries from Hannaford-Agor et al. (2006) do not allow additional validation tests.

[17] We can also compute verdict probabilities from starting states after H rounds of deliberation, representing a cut-off point where jurors are exhausted and the jury is hung. After H rounds of deliberation, $\boldsymbol{B}^{\leq H} = (\boldsymbol{I} - \boldsymbol{Q}^H)(\boldsymbol{I} - \boldsymbol{Q})\boldsymbol{R}$. Intuitively, verdict probabilities under the H round limit are the expected number of visits to transient states from starting states, multiplied by the probability of reaching final verdicts from each transient state.

The authors do not report hung jury rates by number of LIOs and those values cannot be recovered from the study datasets.[18]

V. Applications of Jury Deliberation Models

Effective models of small group deliberation over verdict options in criminal trials enable us to properly contextualize individual-level data about verdict preferences in a jury pool. This is useful for practitioners, researchers, and policymakers.

Models of jury deliberation may be usefully applied to evaluate the probability of a binary outcome. Given an estimate of verdict preferences in the population from which jurors are selected, one can estimate the probability that a jury will return a guilty verdict or, in capital sentencing, a death sentence. By comparing verdict probabilities under two different conditions, such as a legally fair trial and one marred by an error, one may estimate how much a trial error increased the probability of a guilty verdict or death sentence (Edwards 2024). The model allows the researcher to account for nonlinear deliberation effects and estimate the quantities of interest in criminal appeals and post-conviction proceedings (Edwards 2025). The researcher may estimate the harmfulness of a trial error or omission in terms of changed verdict probabilities, or the probability of a different outcome given newly discovered evidence. These estimates may help courts determine whether convictions and death sentences should stand or be overturned.

Models of jury deliberation are also useful for analyzing ordered alternatives. Given estimates of verdict preferences in the relevant population, one may obtain verdict probabilities. By comparing verdict probabilities across multiple conditions, we better understand the causal effects of trial variables when the outcome is not binary. To illustrate, we may build on prior research by Vidmar (1972), Grofman (1985), and Kelman, Rottenstreich and Tversky (1996) on the effect of limiting jurors' ability to consider LIOs.

[18] Some cases reported by Hannaford-Agor et al. (2006) featured LIOs, but respondents recorded first votes on the most serious charge only and did not provide more granular detail on initial vote distributions.

Vidmar's classic study demonstrated that jurors' assessment of a defendant's guilt is shaped by the verdict choices available. The finding is remarkable because it shows that non-evidentiary factors change jurors' assessment of guilt (Lundrigan, Dhami and Mueller-Johnson 2018; Simonson and Tversky 1992).[19] Based on Vidmar (1972)'s reported results, Grofman (1985) estimated the prevalence of all possible single-peaked preference profiles among subjects, allowing Grofman to extrapolate juror preferences under different verdict sets, holding case and juror characteristics constant. For this analysis, verdict options are labeled NG (not guilty), M3 (manslaughter), M2 (second-degree murder), and M1 (first-degree murder).

Kelman, Rottenstreich and Tversky (1996) had study participants read a description of an admitted killing and then choose their preferred verdict. The "upper group" was told M4 (involuntary manslaughter) was unavailable while the "lower group" was told M1 (murder with aggravating circumstances) was unavailable. Based on a logical ordering, those who prefer M4 would choose M3 as the next best option, while those who prefer M1 would choose M2 as the next best option; the ratio of M3:M2 votes should be greater in the upper group than in the lower group.[20] But the authors find the opposite pattern; eliminating the M4 option made M2 the winner while eliminating M1 made M3 the winner.

As interesting as their results are, Vidmar (1972), Grofman (1985), and Kelman, Rottenstreich and Tversky (1996) are unable to address the real outcome of interest: jury verdicts. With a model of jury deliberation, we are able to do that. To obtain verdict probabilities given preferences in the population from which jurors are selected, we multiply the probability distribution of possible starting states by the verdict probabilities that correspond to

[19] The result is more than an issue of the NG/M1 choice being affected by the seemingly irrelevant alternative of M2. Legal logic suggests the M2 option could decrease support for NG, but not M1. If a juror believes the defendant is guilty of M1 beyond a reasonable doubt, their assessment of M1 should not be affected by the M2 option because the M2 option does not change the quantum of evidence supporting M1. A juror who supports NG given two choices because the evidence does not prove M1 may think the same evidence proves M2 beyond a reasonable doubt.

[20] Assuming a set distribution of M4, M3, M2, and M1 preferences, the M3:M2 ratio in the upper group becomes (M4+M3):M2 while in the lower group it is M3:(M2+M1). The ratio would be greater in the upper group.

those starting states. The prior section showed how to obtain verdict probabilities for each possible starting state.

When twelve jurors have four verdict options, there are 455 possible starting conditions. Let $\boldsymbol{B}$ be the 455×4 matrix of absorption probabilities from those starting states. Verdict probabilities from starting points depend on what options jurors are permitted to consider during deliberation. Here, verdict options are a parameter of the deliberation model. For analytic purposes, we may alternately assume that deliberation is restricted to options jurors initially considered, or allow deliberation over the full set of verdict options, regardless of whether they initially evaluated those options.

To find the probability distribution of possible starting states, we assume that 12-person juries are selected at random from large jury pools with verdict preferences reported in prior works. The probability distribution follows standard statistical rules.[21] The assumption that jurors are randomly selected from a population may be relaxed to account for the selection effects of peremptory strikes by the prosecution and defense, but we incorporate these adjustments in order to complete Table 2 and Table 3.

The model of jury deliberation over ordered verdicts is also used to extend the Kelman et al. results through the deliberation process. Again, we have the opportunity to estimate verdict probabilities following restricted and unrestricted deliberation processes.

The Markov chain model of deliberation allows prior work by Vidmar, Grofman, and Kelman et al. to speak to the real outcome of interest in jury trials. A restricted deliberation process appears to intensify the reported effects of limiting verdict options initially considered by jurors. Notice, for example, that the M3/M2 ratios following deliberation point the same

[21] Under random selection, each juror is an independent draw from a population where the probability of preferring verdict k is θ_k (with $\sum_k \theta_k = 1$). The starting counts $X_0 = (X_1, \ldots, X_K)$ therefore follow the multinomial law:

$$\Pr(X_0 = x) = \frac{n!}{\prod_k x_k!} \prod_k \theta_k^{x_k}, \quad x_k \geq 0, \ \sum_k x_k = n.$$

(If jurors are chosen without replacement from a finite panel, the exact model is a multivariate hypergeometric distribution; for large panels the multinomial is an excellent approximation with mean $n\boldsymbol{\theta}$.)

Table 2: Estimating Deliberated Verdict Probabilities from Vidmar/Grofman Results

	Juror Preferences				**Restricted Deliberation**				**Unrestricted Deliberation**			
	NG	M3	M2	M1	NG	M3	M2	M1	NG	M3	M2	M1
(1)	54%	—	—	46%	.73	—	—	.27	.46	.17	.19	.17
(2)	16%	—	84%	—	.07	—	.93	—	.01	.05	.94	.00
(3)	8%	92%	—	—	.02	.98	—	—	.02	.98	.00	.00
(4)	16%	—	76%	8%	.07	—	.92	.01	.01	.05	.93	.01
(5)	8%	63%	—	29%	.02	.84	—	.14	.02	.75	.17	.05
(6)	8%	21%	71%	—	.01	.14	.85	—	.01	.14	.85	.00
(7)	8%	21%	63%	8%	.01	.14	.85	.01	.01	.14	.85	.01

Note: Juror preferences in conditions (1)-(7) are from Grofman (1985)'s analysis of Vidmar (1972)'s data.

Table 3: Estimating Deliberated Verdict Probabilities From Kelman et al. Results

	Juror Preferences				**Restricted Deliberation**				**Unrestricted Deliberation**			
	M4	M3	M2	M1	M4	M3	M2	M1	M4	M3	M2	M1
Upper Group	—	30%	57%	13%	—	.15	.83	.02	.00	.15	.83	.02
Lower Group	7%	55%	38%	—	.00	.72	.27	—	.00	.72	.27	.00

Note: Juror preferences in the upper and lower conditions are from Kelman, Rottenstreich and Tversky (1996, 296).

direction as the juror preferences reported in Table 3 but the differences are magnified. This is consistent with the view that deliberation produces consensus not by meeting in the middle but rather by holdouts joining the majority faction. Prior studies focused on individual-level changes may have understated the effect of decision alternatives on deliberated outcomes.

What happens when verdict options available in deliberation are unrestricted? The verdict preferred by a majority of jurors remains the most likely verdict in all configurations.[22] Verdict probabilities are strongly influenced by starting conditions, which may lead the jury to a verdict it would not have selected had it considered all options initially. Juries typically

[22] Grofman suggests that, given the M3 option, "juries drawn from Vidmar's subject population would almost always reach manslaughter as their unanimous verdict" Grofman (1985, 203). He reasons that M3 would receive a majority of votes in pairwise comparisons with all alternatives. The Condorcet winner is instead the M2 option, second-degree murder, as it is the first choice of 63% of respondents. Grofman's reference to "manslaughter" is likely a misreference. While Condorcet voting has logical appeal, juries are not required to make pairwise comparisons of all available options and the evidence suggests they do not.

reach consensus when all jurors join the faction with the initial majority, even if another verdict might win a pairwise vote. This is most clearly seen in rows (1) and (5) of Table 2, where jurors initially consider NG and M1, but not M2. Even though the majority of jurors prefer M2, the most likely verdict will be NG or M3 if the majority support those options initially due to their choice being restricted. In other words, an unrestricted deliberation process does not remedy a failure to consider all options initially.

Whether juries must consider LIOs, or may be allowed to consider them, ultimately raises normative and strategic issues beyond the scope of this article. But a model of jury deliberation informs the debate. The results in Table 2 and Table 3 would help the prosecution and defense decide whether consideration of LIOs serves their clients' best interests. The results would also enable an appellate court reviewing a trial to evaluate the effect of a mistaken LIO instruction and decide whether the mistake was harmful enough to warrant a new trial.

VI. Extensions and Future Work

This article focuses on how criminal trial juries deliberate after jurors have formed their initial verdict preferences. The transition probabilities defined above reflect the jury deliberation process. For other examples of small group deliberation, model parameters may be fine-tuned to reflect different presumptions, procedures, and intergroup dynamics. The Markov chain framework is modular: the state space (compositions of n across K ordered options) is fixed. What changes are the *norms* and *decision standards* encoded in the one–step tilts. We highlight several directions. Importantly, these refinements preserve the analytic solution via the same block-matrix machinery.

In other settings, the weight of external factors may be more or less than it is in jury deliberation. The group may conduct polls with secret ballots, or adopt other procedures to decrease $\omega_{external}$ and encourage group members to think independently. In other settings, such as a military courts-martial, greater group influence, $\omega_{external}$, may encourage individuals to conform to the majority view.[23]

In still other settings, the scales may not be tipped in one direction over the other. For example, in civil cases (preponderance, no leniency instruction) the majority verdict faction's social influence may be D/N where D is the number of votes for the defendant. In policy contexts with status–quo bias or risk aversion falling somewhere between a civil trial (no presumption for either side) and a criminal trial (strong presumption for the defendant), the amount of bias/presumption can be adjusted as appropriate for the setting.

The transition matrix for jurors applies an equal–weight rule to the per–cut transition probabilities. This is appropriate for unstructured jury deliberations that follow no particular agenda or procedural rules. When procedures privilege a particular order of decisions (e.g., "consider the lesser only after the greater"), it may be more appropriate to weight cut lines differently. If, for example, the jury must decide whether to convict before settling on a specific charge the NG/M3 cutting line may be weighted more heavily than other cutting lines. Data–driven choices for cut line weighting include *boundary–mass* weights $\lambda_r \propto c_r + c_{r+1}$ (cuts with more adjacent votes receive more attention) or *contact–mass* weights $\lambda_r \propto c_r\, c_{r+1}$ (more potential contact across the cut).

VII. Conclusion

This article has developed a general, analytically solvable model of jury deliberation that represents verdict formation as an absorbing Markov chain. The framework formalizes how individual preferences, social influence, and legal presumptions interact to determine collective outcomes. By capturing deliberation as a probabilistic process, the Markov chain model

[23] Settings where the majority faction has more or less influence should be contrasted with selection procedures that influence the starting point, but not the subsequent deliberation dynamics. For example, there are qualifications for serving on juries, along with exemptions and excuses, that make jury pools different from random samples of the jurisdiction's population. Many factors influence the jury's starting point and, consequently, verdict probabilities. This article demonstrates that the deliberation process is effectively represented as a Markov chain. Verdict probabilities depend on starting conditions, but not on how the group arrived at the starting point.

explains how juries with the same initial division can reach different verdicts and why small differences in the starting composition can lead to large differences in outcomes.

The model's predictions align closely with empirical evidence from thousands of observed jury deliberations, demonstrating that a relatively simple mathematical structure can replicate complex social dynamics. Comparison to observed deliberations demonstrates the scientific validity and practical utility of applying a well-established class of stochastic models to the specific context of jury decision-making. Extending the model to ordered verdicts provides new leverage for studying how the set of legally available options affects collective judgment—a question central to both legal doctrine and behavioral decision research. By doing so, it links the analysis of legal decision processes to the broader literature on dynamic systems and collective behavior. Establishing the model's validity through peer review is an important step toward its appropriate use in applied research aimed at estimating quantities of interest in appeals and post-conviction litigation.

Beyond the courtroom, the model offers a general method for analyzing small-group deliberation wherever individuals exchange reasons and converge on shared decisions. Its algebraic structure makes it easy to adapt to alternative settings, procedural rules, and normative assumptions. Future work can refine the model's transition parameters using empirical data, extend it to non-unanimous rules or multi-stage decisions, and explore its implications for evaluating the fairness of trials and other deliberative institutions.

References

Armstrong, J Scott. 2001. Combining Forecasts. In *Principles of Forecasting: A Handbook for Researchers and Practitioners.* Springer pp. 417–439.

Arrow, Kenneth J. 1951. *Social Choice and Individual Values.* John Wiley & Sons.

Bailey, Phoebe E., Tarren Leon, Natalie C. Ebner, Ahmed A. Moustafa and Gabrielle Weidemann. 2023. "A Meta-Analysis of the Weight of Advice in Decision-Making." *Current*

Psychology 42(28):24516–24541.

Bibas, Stephanos. 2000. "Judicial Fact-Finding and Sentence Enhancements in a World of Guilty Pleas." *Yale Law Journal* 110:1097.

Blair, Christen R. 1983. "Constitutional Limitations on the Lesser Included Offense Doctrine." *American Criminal Law Review* 21:445.

Ching, Wai-Ki and Michael K. Ng. 2006. *Markov Chains: Models, Algorithms and Applications*. Springer.

Devine, Dennis J. 2012. *Jury Decision Making: The State of the Science*. NYU Press.

Devine, Dennis J., Laura D. Clayton, Benjamin B. Dunford, Rasmy Seying and Jennifer Pryce. 2001. "Jury Decision Making: 45 Years of Empirical Research on Deliberating Groups." *Psychology, Public Policy, and Law* 7(3):622.

Edwards, Barry C. 2024. "A Scientific Framework for Analyzing the Harmfulness of Trial Errors." *UCLA Criminal Justice Law Review* 8:1.

Edwards, Barry C. 2025. "If the Jury Only Knew: The Effect of Omitted Mitigation Evidence on the Probability of a Death Sentence." *Virginia Journal of Social Policy & the Law* 32(1).

Edwards, Barry C. 2026 est. "Measuring Fairness." *Alabama Law Review* 70(3).

Esterling, Kevin M., Archon Fung and Taeku Lee. 2021. "When Deliberation Produces Persuasion Rather than Polarization: Measuring and Modeling Small Group Dynamics in a Field Experiment." *British Journal of Political Science* 51(2):666–684.

Fishkin, James S. 2018. *Democracy When the People Are Thinking: Revitalizing Our Politics Through Public Deliberation*. Oxford University Press.

Gagniuc, Paul A. 2017. *Markov Chains: From Theory to Implementation and Experimentation*. John Wiley & Sons.

Gastil, John. 2008. *Political Communication and Deliberation.* Sage.

Gastil, John and Laura Black. 2007. "Public Deliberation as the Organizing Principle of Political Communication Research." *Journal of Public Deliberation* 4(1).

Grofman, Bernard. 1985. "The Effect of Restricted and Unrestricted Verdict Options on Juror Choice." *Social Science Research* 14(3):195–204.

Hannaford-Agor, Paula L., Valerie P. Hans, Nicole L. Mott and G. Thomas Munsterman. 2006. "Evaluation of Hung Juries in Bronx County, New York, Los Angeles County, California, Maricopa County, Arizona, and Washington, DC, 2000-2001.".

Hastie, Reid, Steven D. Penrod and Nancy Pennington. 1983. *Inside the Jury.* Harvard University Press.

Hoffheimer, Michael H. 2004. "The Rise and Fall of Lesser Included Offenses." *Rutgers Law Journal* 36:351.

Hoffheimer, Michael H. 2005. "The Future of Constitutionally Required Lesser Included Offenses." *University of Pittsburg Law Review* 67:585.

Hope, Lorraine, Edith Greene, Amina Memon, Melanie Gavisk and Kate Houston. 2008. "A Third Verdict Option: Exploring the Impact of the Not Proven Verdict on Mock Juror Decision Making." *Law and Human Behavior* 32(3):241–252.

Kalven, Harry and Hans Zeisel. 1966. *The American Jury.* Little, Brown Boston.

Kelman, Mark, Yuval Rottenstreich and Amos Tversky. 1996. "Context-Dependence in Legal Decision Making." *The Journal of Legal Studies* 25(2):287–318.

Kerr, Norbert L. 2017. Suggested Do's and Don'ts for Future Jury Research: A Swan Song. In *The Psychology of Juries.* American Psychological Association pp. 257–285.

Kerr, Norbert L. and Robert J. MacCoun. 2012. "Is the Leniency Asymmetry Really Dead? Misinterpreting Asymmetry Effects in Criminal Jury Deliberation." *Group Processes & Intergroup Relations* 15(5):585–602.

Koch, Chantal Mees and Dennis J. Devine. 1999. "Effects of Reasonable Doubt Definition and Inclusion of a Lesser Charge on Jury Verdicts." *Law and Human Behavior* 23(6):653–674.

Lundrigan, Samantha, Mandeep K Dhami and Katrin Mueller-Johnson. 2018. "A Re-Examination of the Acquittal Biasing Effect of Offence Seriousness." *Psychiatry, Psychology and Law* 25(5):769–778.

Luskin, Robert C., Gaurav Sood, James S. Fishkin and Kyu S. Hahn. 2022. "Deliberative Distortions? Homogenization, Polarization, and Domination in Small Group Discussions." *British Journal of Political Science* 52(3):1205–1225.

MacCoun, Robert J. and Norbert L. Kerr. 1988. "Asymmetric Influence in Mock Jury Deliberation: Jurors' Bias for Leniency." *Journal of Personality and Social Psychology* 54(1):21.

Melville, John D. and David Naimark. 2002. "Punishing the Insane: The Verdict of Guilty but Mentally Ill." *Journal of the American Academy of Psychiatry and the Law Online* 30(4):553–555.

Mendelberg, Tali, Christopher F. Karpowitz and J. Baxter Oliphant. 2014. "Gender Inequality in Deliberation: Unpacking the Black Box of Interaction." *Perspectives on Politics* 12(1):18–44.

Myers, C. Daniel and Tali Mendelberg. 2013. Political Deliberation. In *The Oxford Handbook of Political Psychology, Second Edition.* Oxford University Press pp. 699—734.

Niemeyer, Simon, Francesco Veri, John S. Dryzek and André Bächtiger. 2024. "How Deliberation Happens: Enabling Deliberative Reason." *American Political Science Review* 118(1):345–362.

Sandys, Marla and C. Dillehay. 1995. "First-Ballot Votes, Predeliberation Dispositions, and Final Verdicts in Jury Trials." *Law and Human Behavior* 19(2):175–195.

Shellenberger, James A and James A Strazzella. 1995. "The Lesser Included Offense Doctrine and the Constitution: The Development of Due Process and Double Jeopardy Remedies." *Marquette Law Review* 79:1.

Simonson, Itamar and Amos Tversky. 1992. "Choice in Context: Tradeoff Contrast and Extremeness Aversion." *Journal of Marketing Research* 29(3):281–295.

Song, Seong Joo and Jong Woo Song. 2013. "A Note on the History of the Gamblers Ruin Problem." *CSAM (Communications for Statistical Applications and Methods)* 20(2):157–168.

Vidmar, Neil. 1972. "Effects of Decision Alternatives on the Verdicts and Social Perceptions of Simulated Jurors." *Journal of Personality and Social Psychology* 22(2):211.

Wright Jr., Julian H. 1990. "Life-Without-Parole: An Alternative to Death or Not Much of a Life at All." *Vand.erbilt Law Review* 43:529.