Predicting responsibility judgments from dispositional inferences and causal attributions

Antonia F. Langenhoff
University of California, Berkeley

Alex Wiegmann
University of Göttingen

Joseph Y. Halpern
Cornell University

Joshua B. Tenenbaum
Massachusetts Institute of Technology

Tobias Gerstenberg*
Stanford University

Abstract

How do people hold others responsible for their actions? In this paper, we test and extend a computational framework originally introduced by Gerstenberg et al. (2018) that assigns responsibility as a function of two factors: a dispositional inference that captures what we learn about a person's character from their action, and the causal role that the person's action played in bringing about the outcome. This framework has been shown to accurately capture how people assign responsibility to decision-makers in achievement contexts. Here, we focus on a more complex group setting in which political committee members vote on whether or not a policy should be passed. This setting allowed us to manipulate both dispositional inferences and causal attributions in graded ways, as well as directly test the model's key components by asking participants to judge how surprising and how important a committee member's vote was. Participants' answers to these questions in Experiment 1 accurately predicted the responsibility judgments of another group of participants in Experiment 2. In Experiment 3, we show that the model also predicts moral responsibility judgments and that, in the moral domain, dispositional inferences affect responsibility judgments more strongly than causal attributions.

Keywords: responsibility; causality; counterfactuals; pivotality; normality; voting; expectations.

*Corresponding author: Tobias Gerstenberg (gerstenberg@stanford.edu), 302 Jordan Hall, Stanford, CA, 94305.

Introduction

Shortly before the 2016 presidential election, Christopher Suprun, a Texas state elector for the Republican party, signaled that he would refuse to vote for Donald Trump, even if Trump won the popular vote in his state. Trump did indeed win the popular vote in Texas and on election day, as announced, Suprun voted for a different candidate. His decision caused turmoil among Republicans. Both Suprun's party colleagues and the voters vociferously proclaimed their anger in newspapers, blogs, and social networks. Despite Suprun's attempt, Trump won the electoral vote – and thus, the presidential election. Imagine that Hilary Clinton had become the next president of the United States. Certainly, Suprun's party colleagues would have held him responsible for contributing to Clinton's victory and Trump's loss in that case. But to what extent? Intuitively, Suprun would have been blamed more than a Democratic state elector who also voted against Trump. And suppose that Clinton's victory margin was only a couple of votes, as some projections had suggested before the election. Presumably Republicans would have blamed Suprun even more in this scenario.

Judgments of responsibility are ubiquitous in our everyday lives. When something goes wrong – for example, when our favored candidate lost an election – we want to know who is to blame. How exactly people assign responsibility has intrigued researchers in psychology (Alicke, 2000; Hilton, McClure, & Slugoski, 2005; Lagnado & Harvey, 2008; Shaver, 1985), philosophy (Hart & Honoré, 1959/1985) and the legal sciences (Moore, 2009) for decades. In this paper, we further develop and test a computational framework for responsibility judgments that was originally introduced by Gerstenberg et al. (2018).

The framework predicts that responsibility judgments are influenced by two key processes. Inspired by a rich literature in attribution theory (Ajzen, 1971; Fishbein & Ajzen, 1973; Heider, 1946; Weiner & Kukla, 1970), the first process is a *dispositional inference* that captures what we learn about a person's character from observing their action. The idea is that, in a given situation, we form an expectation about how another person will act, based on our knowledge about that person and the situation. The more the person's actual behavior diverts from our expectation, the more likely we are to infer that the person's action must have been determined by an unobserved aspect of her disposition. This dispositional inference, in turn, translates into a responsibility judgment: We hold another person responsible to the extent that we see her action as determined by her own dispositions, goals, or desires, rather than by determinants that are out of her control (e.g. Alicke, 2000; Uttich & Lombrozo, 2010).

In Suprun's case, his party affiliation and the outcome of the popular vote all spoke in favor of him voting for Trump. Given the gap between their expectations about how he would vote and Suprun's actual vote, the framework predicts that Republicans would assign a high level of blame to him for contributing to Trump's (hypothetical) loss. Critically, the framework predicts that Republicans would blame Suprun more than, for example, a Democratic state elector who also voted against Trump, but for whom voting for a candidate other than Trump was less surprising.

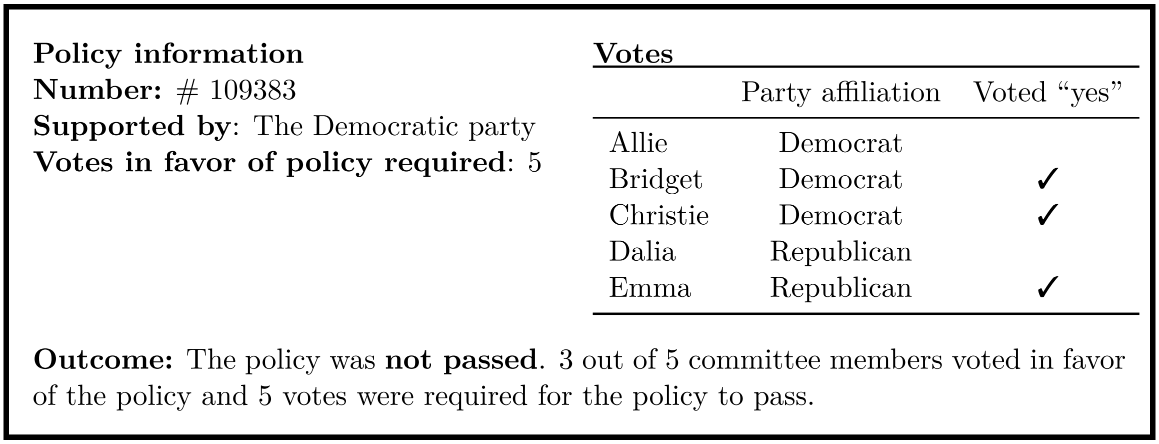
The second process is a *causal attribution* that determines what role the person's action played in bringing about the outcome. The framework predicts that a person is held more responsible for an outcome the closer their action was to having made a difference (see Chockler & Halpern, 2004). In the version of our hypothetical scenario above, in which Clinton and Trump were almost on a par and Clinton won the election by a margin of only a couple of votes, Suprun's vote for a different candidate was closer to having made a difference to the outcome than in a scenario in which the vast majority of electoral college members voted for candidates other than Trump. In the first case, had Suprun voted for Trump, he might have just tipped the balance in Trump's favor, while in the latter case, Trump would have lost the election even if Suprun had decided to vote for him. The framework predicts that Republicans would blame Suprun more in the close call compared to the clear loss.

Previously, Gerstenberg et al. (2018) tested the computational framework in a range of achievement contexts: participants were asked to attribute responsibility to goalkeepers trying to block penalties, game show contestants trying to win money, and gardeners trying to make flowers bloom. Overall, Gerstenberg et al.'s (2018) experiments showed a close match between the model's predictions and participants' actual responsibility judgments. Nevertheless, they left several questions unanswered. Here, we address three of them.

First, does the model pass a more direct test of its two key components: dispositional inferences and causal attributions? In previous tests of the framework, Gerstenberg et al. (2018) manipulated how expected an agent's action was, and whether the action made a difference to the outcome, to see how these factors affected responsibility judgments. While participants' responsibility judgments were consistent with the model's predictions, Gerstenberg et al. didn't test the components of their model directly. Here, we directly assess participants' dispositional inferences and causal attributions by asking them to evaluate a) how surprising an agent's action was and b) how important the action was for bringing about the outcome. We then investigate whether these judgments, in turn, predict responsibility judgments as postulated by the computational framework.

Second, do the framework's predictions hold in more complex causal settings? Gerstenberg et al.'s (2018) previous tests of the framework focused on situations in which a single agent brought about an outcome. However, several people often jointly contribute to an outcome, as in our hypothetical example where Clinton won the presidential election. In this scenario, Suprun was one among many electoral college members who voted for a candidate other than Trump, and thereby contributed to Clinton's victory. Gerstenberg and colleagues have investigated how people distribute responsibility in situations in which the contributions of several individuals combine to yield a group outcome (Allen, Jara-Ettinger, Gerstenberg, Kleiman-Weiner, & Tenenbaum, 2015; Gerstenberg & Lagnado, 2010; Koskuba, Gerstenberg, Gordon, Lagnado, & Schlottmann, 2018; Lagnado, Fenton, & Neil, 2013; Lagnado & Gerstenberg, 2015; Lagnado, Gerstenberg, & Zultan, 2013; Zultan, Gerstenberg, & Lagnado, 2012). Here, we connect this research on responsibility judgments in group settings with Gerstenberg et al.'s (2018) work by manipulating the causal structure of the situation, as well as action expectations in graded ways. To adequately explain responsibility judgments in these situations, we need a model of causal attribution that determines how important an individual's action was for bringing about the outcome, and a model of dispositional inferences that captures to what extent an action diverted from an expectation.

Third, we further test the framework by applying it to the moral domain. Questions of morality naturally elicit judgments of responsibility. Who is to blame for the car crash?



Policy information
Number: # 109383
Supported by: The Democratic party
Votes in favor of policy required: 5

Votes

	Party affiliation	Voted "yes"
Allie	Democrat	
Bridget	Democrat	✓
Christie	Democrat	✓
Dalia	Republican	
Emma	Republican	✓

Outcome: The policy was **not passed**. 3 out of 5 committee members voted in favor of the policy and 5 votes were required for the policy to pass.

Figure 1. Exemplary voting scenario.

Who is responsible for the workers who died during the factory fire? We propose that in situations like these, when more than a victory in a soccer game or the growth of a flower is at stake, the weights between dispositional inferences and causal attributions shift. Specifically, we predict that in the moral domain, inferences about a person's character become more important than causal attributions, reflecting the fundamental human motivation to determine the moral character of others (Uhlmann, Pizarro, & Diermeier, 2015).

In this paper, we report the results of three experiments, each of which tackles one of these open questions. Experiment 1 provided a direct test of how participants make dispositional inferences (by asking about how surprising a particular action was in a given situation) and causal attributions (by asking about how important an action was for the outcome). Experiment 2 asked participants to make responsibility judgments in a large variety of situations that manipulated action expectations and the causal structure in graded ways. Finally, Experiment 3 applied the framework to the moral domain by manipulating the moral valence of the outcome, as well as what question participants were asked to evaluate. Before describing each experiment in more detail, we provide an overview of our experimental paradigm, and explain the computational framework. Subsequently, we report our experimental results and relate them to the predictions of our computational framework. We conclude by discussing some remaining challenges.

Overview of the experimental paradigm

In our experiments, we presented participants with scenarios in which different political committees voted on whether or not a policy should be passed. For each scenario, participants saw how many votes in favor were required for the policy to pass, how each of the committee members voted, and what the outcome of the vote was. In Experiments 1 and 2, participants also saw each committee member's party affiliation and which party supported the policy: the Republican or the Democratic party.

Figure 1 shows a voting scenario similar to the ones used in Experiments 1 and 2. Policy #109383 was up for vote. There were five people on the committee: Allie, Bridget, Christie, Dalia and Emma. The policy was supported by the Democratic party. Five votes in favor of the policy were required in order for the policy to be passed. As it turned out, the Democrats Bridget and Christie, as well as the Republican Emma voted in favor of the policy, whereas Allie and Dalia voted against it. The policy was not passed since only three committee members voted in favor but all five votes were required for the policy to pass.

Experiment 3 did not include information about party affiliation. Instead, we told participants about the content of the policy that was up for vote. One group of participants made their judgments in a context where the content and the consequences of the policy were "morally neutral" (changing documents into a certain font) while another group made their judgments in a context where the content and the consequences of the vote were "morally negative"(introducing corporal punishment in schools).

We expected that a committee member's party affiliation in Experiments 1 and 2, and voting for the "morally appropriate" outcome in the morally negative context condition in Experiment 3 (i.e., voting against corporal punishment in schools) would affect participants' expectations about how a committee member would vote. By varying how the committee members actually voted, we manipulated the extent to which their votes were surprising. We predicted that the more surprising a vote was, the more likely our participants would be to infer that the vote must have been determined by the committee member's unique character or disposition (rather than by other factors such as allegiance to the party, or the overall quality of a particular policy).

In all three experiments, the committee members' causal contribution to the outcome was manipulated by varying the patterns of votes and the threshold of votes required for the policy to pass. We predicted that a vote would be seen as more important the closer it was to having made a difference to the outcome and the fewer causes had contributed to the outcome. We expand on these predictions below.

Model

We now discuss in more detail how we concretely implemented the two components of the computational framework – dispositional inferences and causal attributions – for the experiments reported here. For each component, we first briefly discuss the broader theoretical background, and then the specific model implementation.

Dispositional inferences

Background. How do we explain other people's behavior? Early attribution theorists suggested Bayesian inference as a normative framework for studying this question (Ajzen, 1971; Ajzen & Fishbein, 1975; Fischhoff & Beyth-Marom, 1983; Fishbein & Ajzen, 1973; Morris & Larrick, 1995; Trope, 1974; Trope & Burnstein, 1975). Within the Bayesian framework, behavioral attributions arise from a comparison between different hypotheses as explanations for a given action. Hypotheses are favored that have high prior probability and that explain the observed behavior well.

Generally, it has been shown that we consider both internal factors (such as a person's abilities, dispositions, goals, beliefs or desires) and external factors (such as the situation the person was in) as possible behavioral explanations. However, research in attribution theory has also revealed that when we try to make sense of others' behavior (as compared to our own behavior), we tend to emphasize dispositional or character-based explanations, and neglect the influence of situational and environmental factors (Jones & Harris, 1967;

Ross, Amabile, & Steinmetz, 1977). Moreover, in some domains, we may be generally more likely to make dispositional inferences than in others (Hursthouse, 1999; McIntyre, 2019). Recent work in moral psychology has shown that in the moral domain, we often tend to focus on those features of an action that are diagnostic about a person's character, rather than on its consequences or on whether a moral rule has been broken (Bartels & Pizarro, 2011; Bayles, 1982; Pizarro, Uhlmann, & Salovey, 2003; Uhlmann et al., 2015; Waldmann, Nagel, & Wiegmann, 2012). Based on these findings, researchers have argued that we are inherently motivated to determine the moral character of others (Uhlmann et al., 2015). We evaluate whether others are caring, fair, and trustworthy. Based on these evaluations, we decide whether to cooperate with or to avoid others in the future. When we assign responsibility to an individual in the moral domain, our inferences about that individual's character might play a relatively larger role than considerations about the individual's causal connection to the outcome.

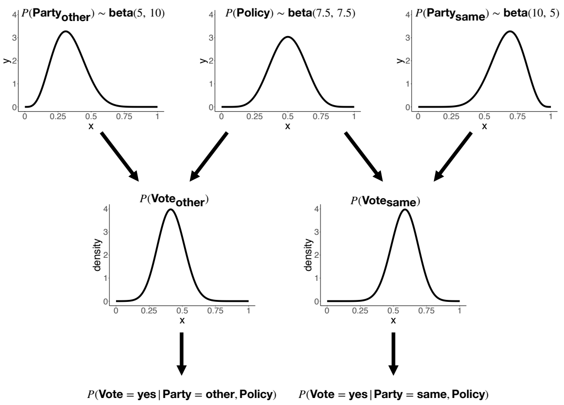
More recently, researchers have modeled behavioral attribution processes computationally (Baker, Jara-Ettinger, Saxe, & Tenenbaum, 2017; Baker, Saxe, & Tenenbaum, 2009; Jara-Ettinger, Gweon, Schulz, & Tenenbaum, 2016), building on earlier work in the Bayesian paradigm. Importantly, however, they point out that in order to computationally model how an observer attributes another person's action as caused by their abilities, dispositions or mental states, we first need to capture the observer's expectation about how an agent *should* act in a given situation. From this expectation about how an agent should act, the observer can then work backwards to infer the desires and beliefs that caused the agent's behavior using Bayes' rule (Baker et al., 2009). A general principle that determines how mental states cause actions and that has been much studied at the qualitative level is the *principle of rationality* (Dennett, 1987). It states that we take an "intentional stance" toward others and expect of them that they will act as rationally as possible to achieve their desires and goals, given their beliefs about the world (Baker et al., 2009). Empirical tests of models that represent human action understanding as Bayesian inverse planning based on this principle of rationality have shown a close match between model predictions and human data.

Implementation. As described in the previous section, a general idea underlying the computational framework of responsibility judgments is that, in a given situation, people draw inferences about a person's character from their action, and that these inferences, in turn, affect the extent to which a person is held responsible for an outcome. In this section, we outline how we formalized this idea in our model to generate specific predictions for our experimental paradigm. In our paradigm, the question is how much an observer learns about a committee member from how they voted in a given scenario, and how this inference affects the responsibility judgment.

We assume that there are three driving forces that affect a committee member's vote: 1) their belief about how strongly their party supports the policy, 2) their belief about the quality of the policy, and 3) their individual preference. An observer infers 1) and 2) based on how the committee members voted. A committee member's individual preference remains unobserved. We assume that a vote is attributed to a committee member's individual preference to the extent that it is surprising, given how the other committee members voted. We expect that a committee member will be held more responsible for the outcome if their vote was surprising and thus indicative of a strong individual preference.

$$
\begin{aligned}
\text{Party}_{\text{same}} &\sim \text{beta(a, b)}\\
\text{Party}_{\text{other}} &\sim \text{beta(b, a)}\\
\text{Policy} &\sim \text{beta}(\frac{a+b}{2}, \frac{a+b}{2})\\
\text{Vote}_{\text{same}} &= \frac{\text{Party}_{\text{same}} + \text{Policy}}{2}\\
\text{Vote}_{\text{other}} &= \frac{\text{Party}_{\text{other}} + \text{Policy}}{2}
\end{aligned}
$$

(a) Mathematical form


P(Party_other) ~ beta(5, 10)
P(Policy) ~ beta(7.5, 7.5)
P(Party_same) ~ beta(10, 5)
y
x
0
0.25
0.5
0.75
1
1
2
3
4
P(Vote_other)
P(Vote_same)
density
P(Vote = yes | Party = other, Policy)
P(Vote = yes | Party = same, Policy)

(b) Graphical representation

Figure 2. Generative voting model. When deciding how to vote, a voter takes into account his party affiliation (*same* or *other*), and the quality of the policy, weighing each factor equally. We fit a and b to the data with the constraint that $a > b$, reflecting the assumption that committee members affiliated with the party that supports the policy are *a priori* more likely to vote in favor of the policy than committee members from the other party. The diagram shows the shape of the prior distributions for $a = 10$, and $b = 5$. See Figure A1 for a sensitivity analysis of the parameter space, and Table C1 for detailed model predictions. *Note*: $\sim$ indicates "distributed as".

Specifically, we assume the generative voting model illustrated in Figure 2. Committee members who are affiliated with the party that is stated to support the policy start with a prior belief that their party supports the policy ($\text{Party}_{\text{same}}$), whereas committee members from the other party believe that their party doesn't support the policy ($\text{Party}_{\text{other}}$). A committee member votes by equally taking into account their belief about their party's support as well as their belief about the quality of the policy (Policy). We assume beliefs about the quality of a policy are initially unbiased – that is, policies are just as likely to be good or bad. We model these prior beliefs using beta distributions which have support between 0 and 1. We then assume that a committee member makes their choice about how to vote ($\text{Vote}_{\text{same}}$ or $\text{Vote}_{\text{other}}$) by equally weighting their belief about the party's support as well as the quality of the policy.

Our model performs Bayesian inference by conditioning on the observed evidence (the votes) to go from prior distributions over the party and party factors to posterior distributions over these factors (see Equation 1).

$$
\begin{aligned}
&p(\text{Party}_{\text{same}}, \text{Party}_{\text{other}}, \text{Policy}|\overrightarrow{\text{Votes}}) \propto\\
&p(\overrightarrow{\text{Votes}}|\text{Party}_{\text{same}}, \text{Party}_{\text{other}}, \text{Policy}) \cdot p(\text{Party}_{\text{same}}) \cdot p(\text{Party}_{\text{other}}) \cdot p(\text{Policy})
\end{aligned}
\tag{1}
$$

We assume that the vector of votes ($\overrightarrow{\text{Votes}}$) is generated from a binomial distribution with the probability of each vote determined by party membership and policy as shown in Figure 2. Based on the posteriors over $\text{Party}_{\text{same}}$, $\text{Party}_{\text{other}}$ and Policy, the model then forms an expectation about how the committee member of interest will vote.

For an example, consider committee member Allie in the voting scenario shown in Figure 1. Allie is a Democrat, and thus affiliated with the party that supports the policy. Accordingly, she is *a priori* more likely to vote for rather than against the policy. The model then updates this prior distribution based on how the other committee members voted. The two other Democrats, Bridget and Christie, voted for the policy, and one out of the two Republicans voted for the policy. Based on this evidence, the model now believes Allie is even more likely than before to vote in favor of the policy.

We define the extent to which a committee member's vote is surprising as the difference between the actual vote (coding a vote against the policy as 0 and a vote for the policy as 1) and the expected vote (where we use the mean of the posterior over the committee member's vote ($\text{Vote}_{\text{same}}$ or $\text{Vote}_{\text{other}}$ depending on the committee member's party) as our measure of expectation; see Figure 2). Given that an observer would have expected Allie to vote for the policy, her actual vote against the policy is surprising. The inference that Allie's vote must have been affected by her individual preference (since it's not well-explained by how the others voted) is then predicted to lead to an increased judgment of responsibility.

We implemented the dispositional inference model in `R` (R Core Team, 2019) using the `greta` package (Golding, 2018). We modelled the prior distributions over Party and Policy as beta distributions, and the likelihood function for the pattern of votes as a binomial distribution, as shown in Figure 2. `greta` uses Markov-chain Monte Carlo (MCMC) inference to approximate the posterior distribution. The code implementing this model is available on the project's github repository: `https://github.com/cicl-stanford/voting_responsibility`

Causal attributions

Background. We now turn to the second key process in the computational framework: A causal attribution of the person's role in bringing about the outcome. One way of capturing whether a person's action is causally connected to an outcome is to run a counterfactual simulation and ask whether the outcome would have been different without the person's action (Lewis, 1973). This test of causation works well in situations that involve a single agent: Is Martin responsible for the bottle being smashed? Yes, because had Martin not dropped the bottle, the bottle would not have smashed.

However, this simple counterfactual analysis does not suffice in general as a model of responsibility. Consider again the voting scenario in Figure 1. All five of the committee members had to vote in favor for the policy to pass but only three committee members did, so the policy did not pass. Intuitively, Allie and Dalia are each somewhat responsible for the policy not passing, because both of them voted against the policy. However, their individual actions did not make a difference to the outcome because the outcome was causally *overdetermined*: Even if Allie had voted in favor of the policy, it would still have failed since five votes in total were required for the policy to pass.

Halpern and Pearl (2005) introduce a solution to this problem. They define a person's action as a cause of an outcome if the outcome would have depended on the action *under certain contingencies*. Their definition identifies Allie and Dalia as causes even in this case of overdetermination. Building on Halpern and Pearl's (2005) definition of causality, Chockler and Halpern (2004) developed a model of responsibility that makes graded predictions. The degree of responsibility that an action bears for an outcome is defined in terms of the minimal number of changes that would have to be made to make the outcome counterfactually dependent on the person's action. The fewer changes are necessary to move from the actual situation to a situation in which the outcome counterfactually depends on the person's action, the more responsibility is assigned to that person. Gerstenberg and colleagues called this notion the person's *pivotality* for the outcome (for an overview, see Lagnado, Fenton, & Neil, 2013). In a range of experiments (Gerstenberg & Goodman, 2012; Gerstenberg & Lagnado, 2010; Lagnado, Gerstenberg, & Zultan, 2013; Zultan et al., 2012), they showed that a person's pivotality is a significant predictor for how much responsibility people assign to that person for a group outcome.

In our computational model of responsibility, we consider an individual's pivotality as one component of the causal attribution process. However, we believe that when assigning responsibility to individuals in a voting setting in which the causal contribution of each individual that voted in line with the outcome of the vote is identical, people take an additional factor into account when evaluating the causal contribution of a particular individual to the group outcome; namely, the number of causes that contributed to the outcome. Different lines of research suggest that people assign more responsibility to an action for an outcome if fewer causes contributed to the outcome (Darley & Latané, 1968; Latané, 1981; White, 2014). To see how this notion differs from that of pivotality, consider the well-known "diffusion of responsibility" phenomenon: In situations where multiple people would be capable of helping another person in an emergency, people often have a reduced sense of responsibility (Darley & Latané, 1968).[1] In such a situation, each "bystander" is pivotal – if they intervened, the victim would be helped, but nevertheless individuals have a reduced sense of responsibility as the number of people who could help increases. Based on this finding, we predict that in addition to a person's pivotality, people take into account how many causes were involved in bringing about the outcome when evaluating an person's causal contribution to an outcome and, as a consequence of that, their responsibility.

Implementation. We define the pivotality of a person's action A for an outcome E in a particular scenario S as

$$\mathit{Pivotality}(A, S, E) = \frac{1}{C+1}, \tag{2}$$

where C is the minimal number of changes that are required to make A pivotal for E in S describes the causal structure of the situation and what actually happened. In our voting scenarios, S describes the number of votes needed for a policy to be passed (the threshold) and how each committee member voted. In the voting scenarios that we consider, C simply represents the number of other voters who would have needed to vote differently in order for the person under consideration to become pivotal. For example, Allie's pivotality in our example above is $\frac{1}{2}$ ($\frac{1}{1+1}$), since one vote needs to be changed to make Allie's vote pivotal (Dalia would have needed to vote in favor of the policy, rather than against it).

In addition to how close a person's action was to making a difference to the outcome (as measured by pivotality), we also predict that the number of causes that contributed to the outcome affects how important an individual contribution is perceived. The more causes

[1] Note, however, that a recent study of real-life bystander intervention found that in most actual public conflicts, at least one person did something to help the victim. (Philpot, Liebst, Levine, Bernasco, & Lindegaard, 2019).

there are that have contributed to an outcome, the less important each individual cause is perceived to be. In our voting setting, this means that the more committee members voted in line with the outcome of the vote, the less important each vote is perceived to be.

Overall, we predict that both *pivotality* and *the number of causes* affect participants' causal attributions. We assume that both factors affect causal attributions in an additive way (with *number of causes* being a negative predictor).

$$\textit{Causal attribution} = \beta_1 \cdot \textit{Pivotality} + \beta_2 \cdot \textit{Number of causes}, \tag{3}$$

whereby β_1 and β_2 determine how much emphasis is put on pivotality and the number of causes when making causal attributions.

Bringing it together: The computational model

We predict that judgments of responsibility are sensitive to what the observer learned about the person from their action ('dispositional inference'), and how important the person's action was perceived for the outcome ('causal attribution'). For simplicity, we assume that both factors of the model combine additively to affect judgments of responsibility.

$$\textit{Responsibility} = \alpha \cdot \textit{Dispositional inference} + \beta \cdot \textit{Causal attribution} \tag{4}$$

In the remainder of this paper, we report the results of three empirical studies, designed to answer three outstanding questions: Can the model components be directly assessed by asking people to judge dispositional inferences and causal contributions directly (Experiment 1)? Does the model capture how people assign responsibility in group contexts with more complex causal settings (Experiment 2)? And finally, can the model be applied to the moral domain, where judgments of responsibility play a central role (Experiment 3)?

Experiment 1: Testing dispositional inferences and causal attributions directly

In Experiment 1, participants' task was to judge to what extent the vote of a politician who voted in a committee on whether a new policy should be passed was 1) surprising and 2) important for the outcome. With these test questions, we aimed to directly assess the two main components of our computational model.

We predicted that participants' judgments of how surprising the vote of an individual committee member was would increase the greater the difference was between the mean of the posterior distribution of how the committee member was expected to vote (based on his party membership and on how the other committee members voted) and how the committee member actually voted. Further, we predicted that judgments of how important an individual vote was would increase 1) the closer the vote was to having been pivotal for the outcome, and 2) the fewer the number of committee members whose votes contributed to the outcome.

Methods

Participants. 40 participants (M_{age} = 35, SD_{age} = 11, 10 female) were recruited via Amazon Mechanical Turk. Participation was restricted to workers based in the US with a prior approval rate greater than 95% (see Mason & Suri, 2012, for details about how Amazon Mechanical Turk works).

Design. Experiment 1 included 27 voting scenarios. Each scenario featured a different political committee comprised of five members.[2] Between scenarios, we manipulated how each committee member voted, how many votes in favor of the policy were required for the policy to pass (1–5), the outcome of the vote (passed / did not pass), which political party supported the policy (Democrats / Republicans) and the party affiliation of each committee member. Figure 1 shows one scenario. For each scenario, we assessed importance and surprise judgments for one out of the five committee members. We selected 27 scenarios that elicit a range of predictions from our surprise and importance model.[3]

Procedure

The experiment was programmed in *Qualtrics*. After receiving instructions, participants answered a set of comprehension check questions. Participants were redirected to the beginning of the survey in case they didn't correctly answer all of the comprehension check questions. Participants were then presented with the 27 voting scenarios in randomized order. For each scenario, participants were asked to judge the extent to which they considered one of the committee members' votes 1) important and 2) surprising. For example, when the committee member John had been described as having voted in favor of the policy and the policy passed, participants were asked: 1) "How important was John's vote for the policy passing?" and 2) "How surprising was John's vote?". Participants responded using continuous sliders whose endpoints were labeled with "not important at all" (0) and "very important" (100), as well as "not surprising at all" (0) and "very surprising" (100). On average, it took participants 13.67 minutes ($SD = 9.29$) to complete the experiment.[4]

Results

We first describe participants' judgments for a selection of cases in detail, and then report their overall judgments.

Detailed analysis of a selection of scenarios. Figure 3 shows the results of four of the voting scenarios. The figure shows participants' mean judgments together with the predictions of the surprise and importance model described above. In all four scenarios, the policy was passed because the number of votes in favor met or exceeded the threshold (T).

We take a look at surprise judgments first. In all four scenarios, the committee member for whom ratings were assessed (the "focus person", indicated by the arrow in Figure 3) voted in favor of the policy. In Scenario 1 and 2, the focus person was affiliated with the party that supported the policy, whereas in Scenario 3 and 4, the focus person was affiliated with the other party. We see that in general, participants were more surprised when a person voted in favor of a policy despite being from the opposite party.

However, surprise judgments were not solely determined by whether a person's vote was consistent with their party affiliation. Participants were more surprised about the

[2] Note that unlike the example in Figure 1, we used only male first names for the politicians within our actual experiments, in order to eliminate possible gender effects.

[3] See Table B1 in the Appendix for a full list of the scenarios.

[4] All materials including data, experiments, and analysis scripts are available here: `https://github.com/cicl-stanford/voting_responsibility`

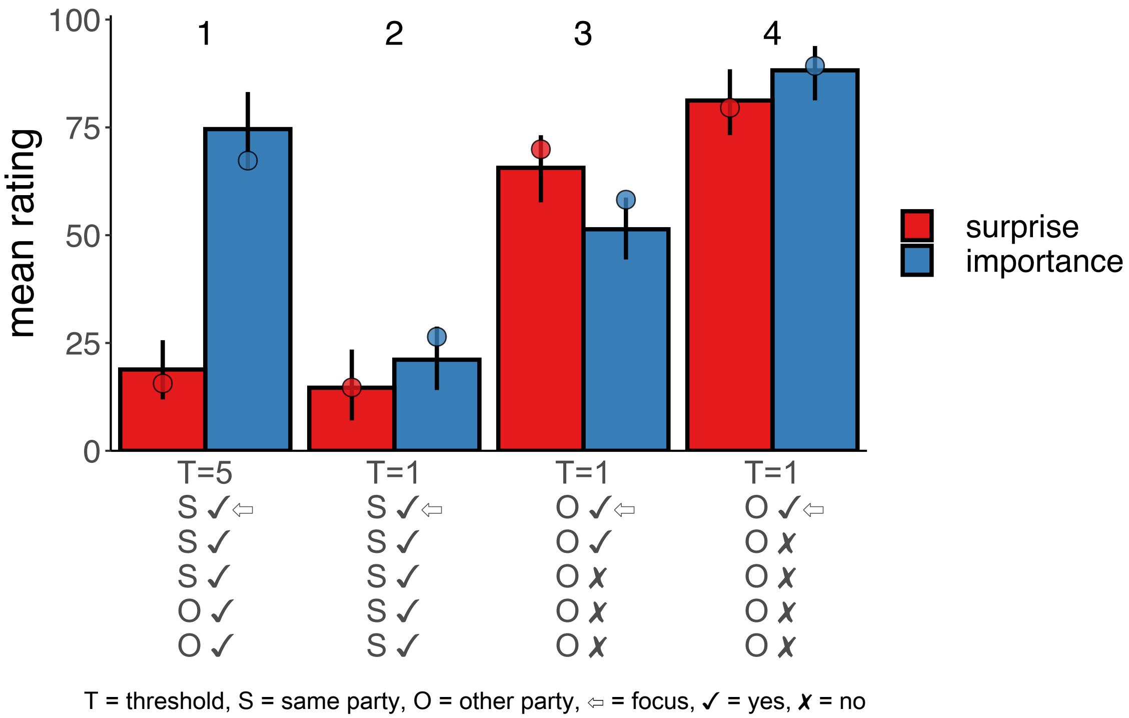
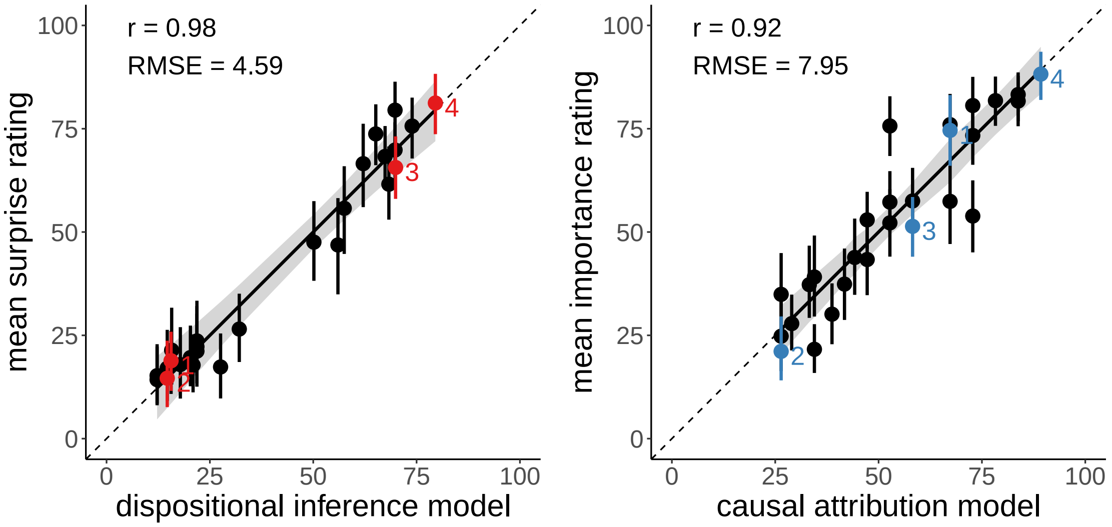


Figure 3. **Experiment 1**: Importance and surprise judgments for Scenarios 1–4. Bars indicate mean judgments, error bars indicate bootstrapped 95% confidence intervals, and points indicate model predictions. The text on the x-axis shows what happened in each scenario. For example, in Scenario 3, the threshold T for the vote to pass was 1, the focus person (indicated by the arrow) was from the other party (O) that doesn't support the policy, and voted in favor of the policy. All other four committee members were also from the other party. One of them voted in favor, and three voted against the policy.

person's vote in Scenario 4 than in Scenario 3 (9.63 [7.83, 11.36]).[5] The model accurately captures this difference. As detailed above, the model assumes that a person's voting decision is determined not only by their party membership but also by the quality of the policy. While we cannot observe a policy's quality directly, we can infer the quality by looking at how other committee members voted. While in Scenario 4 all others voted against the policy, in Scenario 3, one of the other committee members also voted in favor of the policy. Participants were sensitive to this subtle difference in their surprise judgments, and the model explains how this difference arises.

We now consider participants' importance judgments. In Scenarios 1 and 4, the focus person's vote is pivotal. In both scenarios, had the focus person voted against the policy, the policy would not have passed. In Scenarios 2 and 3, the outcome is overdetermined. However, whereas in Scenario 2, all other committee members would have needed to vote differently in order for the focus person to become pivotal for the outcome, in Scenario 3, the focus person is only "one step away" from being pivotal. The focus person would have been

[5] For any statistical claim, we report the mean of the posterior distribution together with the 95% highest-density interval (HDI). Here, for example, the posterior over the difference between Scenario 4 and 3 has a mean of 9.63, and the 95% HDI ranges from 7.83 to 11.36. All Bayesian models were written in Stan (Carpenter et al., 2017) and accessed with the `brms` package (Bürkner, 2017) in `R` (R Core Team, 2019).



(a) Surprise judgments (b) Importance judgments

Figure 4. **Experiment 1**: Surprise and importance judgments. Data points show mean judgments. The colored data points correspond to the four scenarios shown in Figure 3. The gray ribbon shows the 95% highest-density interval (HDI) for the model fit. The error bars indicate bootstrapped 95% confidence intervals. *Note*: r = Pearson moment correlation, RMSE = root mean squared error.

pivotal if the second committee member had also voted against the policy. As predicted, participants judged the focus person's vote as more important the closer it was to being pivotal for the outcome. Participants' importance judgments are greater in Scenarios 1 and 4 than in Scenario 3 (20.05 [15.02, 25.15]), and greater in Scenario 3 than in Scenario 2 (31.79 [26.76, 36.83]).

However, if pivotality was the only factor that influenced people's judgments of importance, then varying the threshold while keeping pivotality fixed should not make a difference. That is, we should expect no difference in importance judgments between Scenario 1 and 4 since in both scenarios, the focus person's vote was pivotal for the outcome. However, participants considered the person's vote more important in Scenario 4 than in Scenario 1 (21.96 [16.89, 27.93]). This shows that participants' importance judgments are not solely determined by how close a person's vote was to having been pivotal for the outcome, but that it also matters how many causes contributed to the outcome. In Scenario 4, there was only a single cause for the policy passing – the focus member's vote. In contrast, in Scenario 1, there were five causes for the policy passing – all of the committee members' votes were required. A vote is seen as more important when it is the only cause versus just one of several causes. Our model of causal attribution which considers both pivotality and number of causes adequately captures the pattern of importance judgments.

Overall results and model comparison. Figure 4 shows scatter plots of the model's predictions and participants' mean surprise and importance ratings for all 27 scenarios. We fitted the model to individual participants' responses by specifying a Bayesian linear mixed effects model with random intercepts and slopes for each predictor.

Our *dispositional inference model* captures participants' average surprise judgments very well with $r = .98$ and RMSE = 4.59 (Figure 4a). A model that considers only whether the committee member voted in line with his party affiliation also correlates well with participants' judgments $r = .95$ and RMSE = 7.66. We compared the models using approximate leave-one-out crossvalidation as model selection criterion (PSIS-LOO; cf. Vehtari, Gelman, & Gabry, 2017). According to this criterion, the Bayesian surprise model performs better than the model that considers only party affiliation (difference in expected log predictive density (elpd) = 38.4, with a standard error of 16.1).[6]

Figure 4b shows that the *causal attribution model* accounts well for participants' mean importance judgments with $r = .92$ and RMSE = 7.95. Remember that our causal attribution model considers both the extent to which a person's action was pivotal for the outcome, as well as the number of causes that contributed to the outcome. This model compares favorably with lesioned models that only consider a subset of the predictors, such as just pivotality ($r = .88$ and RMSE = 10.06; elpd = 37.4, standard error = 8.8) or just the number of causes that contributed to the outcome ($r = .54$ and RMSE = 17.54; elpd = 233.3, standard error = 23.7).

Discussion

In this experiment, we presented participants with a number of different voting scenarios that manipulated how many votes were required for a particular policy to pass, the political affiliation of the committee members, how each committee member voted, and whether the policy passed (see Figure 1). The results show that the extent to which participants found a committee member's vote to be surprising and important for the outcome was systematically affected by this information. To explain participants' surprise judgments, we developed a dispositional inference model that forms an expectation about how a committee member would vote based on the committee members' party affiliations as well as how they voted. This model captures participants' surprise judgments well, and better than a model that only considers a committee member's party affiliation.

Participants' judgments about how important a committee member's vote was for the outcome are well-explained by our causal attribution model. This model considers both how close a person's vote was to being pivotal for the outcome, as well as how many other committee members voted alike. A vote is seen as more important the closer it was to being pivotal (i.e., when the outcome of the overall vote would have been different had the committee member voted differently) and the fewer causes contributed to the outcome.

Experiment 2: Responsibility judgments in voting scenarios

In Experiment 1, we experimentally manipulated the extent to which a vote was surprising and its importance for the outcome, and assessed how these manipulations affected participants' dispositional inferences and their causal attributions. Since the computational framework predicts that dispositional and causal inferences combine additively to yield responsibility judgments, the extent to which committee members in our voting scenarios are considered responsible for the outcome of the vote should be influenced by the same

[6] As a rule of thumb, a model is considered superior when the difference in expected log predictive density is greater than twice the standard error of that difference (for details, see Vehtari et al., 2017).

experimental manipulations in exactly the same way: The more surprising a vote was, the more responsible a committee member should be held for the outcome of the vote. Further, voters should be judged more responsible the closer their vote was to having been pivotal and the fewer committee members voted in line with the outcome of the vote. To test these predictions, we presented participants in Experiment 2 with voting scenarios like those in Experiment 1, and asked them to what extent different committee members were *responsible* for the outcome of the vote.

Experiment 2 included 24 of the 27 voting scenarios used in Experiment 1, as well as 146 additional ones. Including the voting scenarios from Experiment 1 in the current experiment allowed us to not only look at the extent to which our experimental *manipulations* of surprise and importance affected responsibility judgments, but also to predict the responsibility judgments in Experiment 2 based on participants' surprise and importance judgments in Experiment 1 for this selection of scenarios.

Methods

Participants. 208 participants ($M_{age} = 36$, $SD_{age} = 14$, 86 female) were recruited via Amazon Mechanical Turk using Psiturk (Gureckis et al., 2016). Participation was again restricted to workers based in the US with a prior approval rate greater than 95%.

Design. In Experiment 2, we manipulated the size of the committee ($N = 3$ vs. $N = 5$), the political affiliations of the committee members (M_{p_i}), how each committee member voted (v_i), and the threshold for the policy to be passed (T). We aimed to test as many possible combinations of these different factors as possible. In principle, there would have been $2^3 \times 2^3 \times 3 + \times 2^5 \times 2^5 \times 5 = 5312$ different possible scenarios, taking into account the political affiliations, pattern of votes, and the different thresholds for committees of size 3 and 5. However, since the votes are being cast simultaneously, there are many scenarios that are symmetrical for our purposes. For example, if all of the committee members were Democrats, and two voted for the policy while one voted against it, we don't care which of the three voted against the policy. Taking into account these symmetries reduces the number of scenarios to 340.

We further reduced the number of scenarios by removing all scenarios for which the pattern of votes was unusual. A scenario is unusual if a majority of the committee voted against their political affiliation. For example, consider a scenario in which the policy is supported by the Democrats but all committee member are Republicans. Here, we removed all the scenarios in which more than 2 of the Republicans voted in favor of the policy. Removing all unusual scenarios reduces the number of scenarios to 170 (30 scenarios for committees of size 3, and 140 scenarios for committees of size 5).

We split the 170 scenarios into 10 different conditions with 17 scenarios each. Each condition included 3 scenarios with $N_{committee} = 3$, and 14 scenarios with $N_{committee} = 5$.

Procedure

Participants were randomly assigned to one of 10 conditions. After receiving instructions, each participant made responsibility judgments for a set of 17 scenarios. Participants judged to what extent a particular committee member was responsible for the policy passing or not passing. Participants made their judgments on sliding scales ranging from “not at all responsible” (0) to “very much responsible” (100).

Participants assigned responsibility to committee members whose vote was in line with the outcome. Depending on the scenario, participants were either asked to make one or two judgments. When all committee members whose vote was in line with the outcome shared the same party affiliation, participants made only one judgment. When two of the committee members whose vote was in line with the outcome came from different political parties, then participants were asked to judge the responsibility for one of the Democrats and one of the Republicans. Out of the set of 170 scenarios, there were 90 scenarios in which participants were asked to make a single judgment, and 80 scenarios in which they made responsibility judgments for two committee members. Thus, we have a total of 250 data points.

In our example scenario depicted in Figure 1, two voters voted in line with the outcome of the vote (policy not passed): Allie and Dalia. In this case, since Allie and Dalia came from different political parties, we assessed responsibility judgments for both of them. Thus, in this scenario, participants made two ratings; one for Allie (Democrat) and one for Dalia (Republican). On average, it took participants 6.61 minutes ($SD = 7.03$) to complete the experiment.

Results

We first discuss a selection of cases individually before examining the data on a higher level of aggregation to see whether, and to what extent, participants’ responsibility judgments were influenced by dispositional inferences and causal attributions.

Detailed analysis of a selection of cases. Figure 5 shows participants’ judgments for 24 of the 170 scenarios. These 24 scenarios are the ones that were also used in Experiment 1. The figure shows participants’ mean responsibility judgments in addition to the mean surprise and importance judgments from Experiment 1, as well as the predictions of a model that uses participants’ surprise and importance judgments from Experiment 1 to predict participants responsibility judgments in the current experiment. For example, in the first scenario, the threshold for the policy passing was one ($T = 1$), and all the committee members were from the party other than the one that supported the policy (O). The policy passed because one of the committee members voted in favor of the policy. We see that in this case, participants in Experiment 1 considered the committee member’s action very surprising, and also judged that the vote was very important. Here, in Experiment 2, participants judged the responsibility of the committee member to be very high and the model correctly predicts a high responsibility judgment in this case.

In Scenario 24, the threshold was 5, but all committee members voted against the policy. Two members were affiliated with the party that supported the policy, and three were affiliated with the other party. Participants in Experiment 1 found it somewhat surprising that the focus person didn’t vote for the policy even though he was from the party that supported the policy. Note, however, that they found this less surprising than what the focus person did in Scenario 1 (who also voted against the party affiliation). In Scenario 1, all other committee members voted against the policy, and the focus member was the only one voting in favor. However, in Scenario 24, all of the committee members voted against the policy, thus making the action of the focus member less surprising.

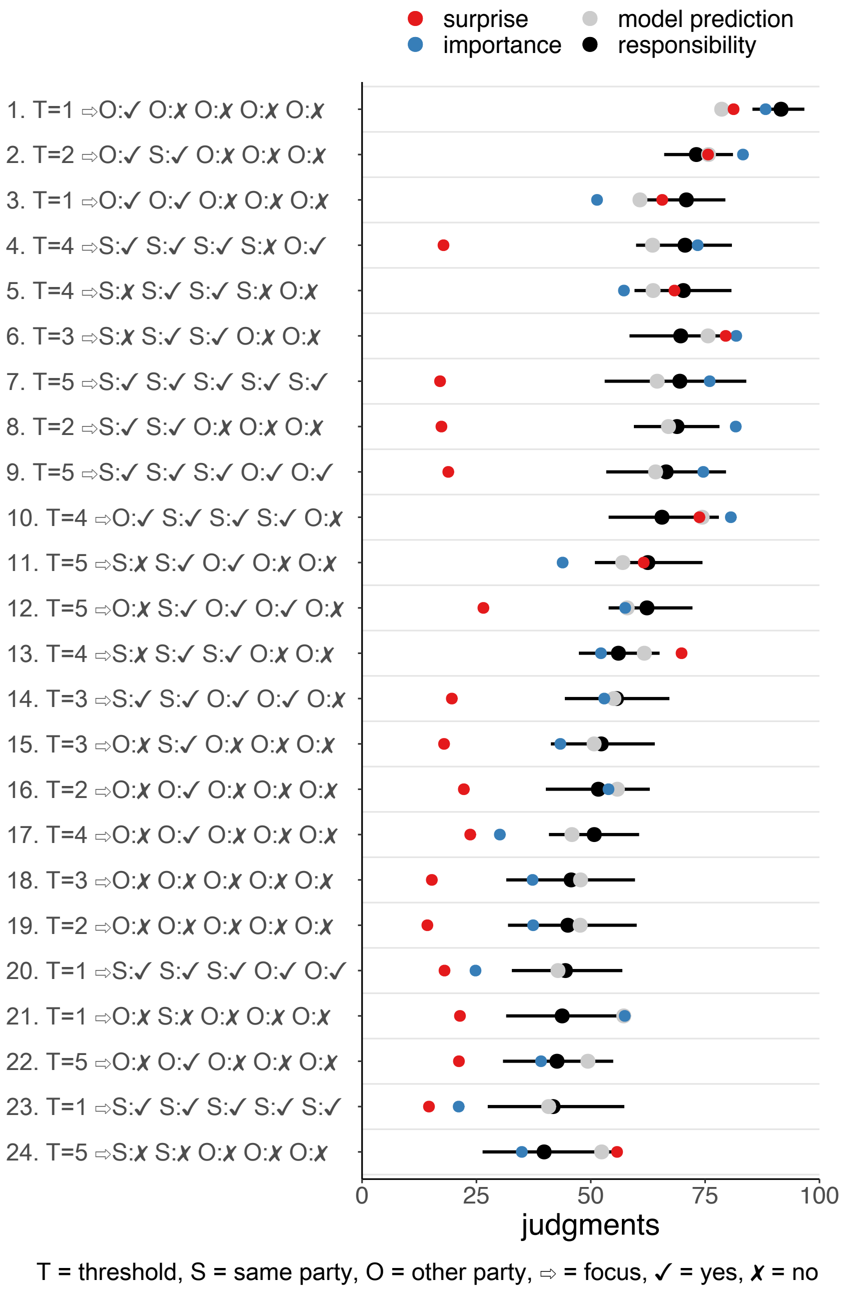


Figure 5. Mean responsibility judgments (black dots) together with the mean surprise (red dots) and importance (blue dots) judgments based on Experiment 1, as well as the model prediction (gray dots) that combines surprise and importance judgments. We numbered the cases here in decreasing order of participants' mean responsibility judgments. *Note:* The error bars indicate bootstrapped 95% confidence intervals.

Participants in Experiment 1 judged that the focus person's action was not particularly important in Scenario 24. His vote is far from being pivotal (all of the other four votes would have needed to change), and it's only one among five causes of the outcome. Participants in Experiment 2 judged that the focus person in Scenario 24 was not very responsible for the outcome. Again, the model captures this case quite well, although it predicts a slightly higher judgment than what people say.

To derive the model predictions for the 24 scenarios used in both Experiment 1 and 2, we used participants' mean surprise and importance judgments from Experiment 1 as predictors in a Bayesian linear mixed effects model of participants' responsibility judgments in Experiment 2, with both random intercepts and slopes. The model accounts well for the responsibility judgments across the 24 scenarios, as shown in Figure 5 with $r = .86$ and RMSE = 6.59. The 95% HDI of the posterior for the surprise predictor ($\beta_{\text{surprise}} = 0.14$ [0.01, 0.26]) and the importance predictor ($\beta_{\text{importance}} = 0.43$ [0.27, 0.57]) both exclude 0. Figure 6a shows a scatter plot of the model predictions and participants' responsibility judgments.

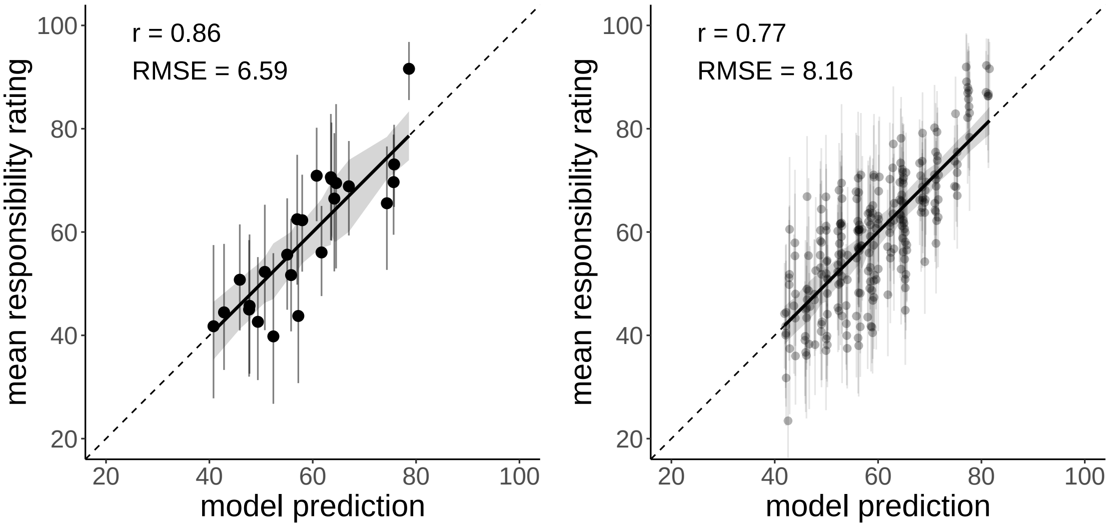
Using the surprise and importance models that were fitted to participants' judgments in Experiment 1 as predictors yields a similar fit to participants' responsibility judgments, with $r = .85$ and RMSE = 6.76 (posterior estimates for the surprise ($\beta_{\text{surprise}} = 0.20$, 95% HDI [0.08, 0.32]) and importance predictor ($\beta_{\text{importance}} = 0.41$ [0.27, 0.55]). The close correspondence between the predicted responsibility judgments based on participants' empirical surprise and importance judgments and the surprise and importance model was to be expected, given the high correlation between the models' predictions and participants' judgments in Experiment 1 (see Figure 4).

Overall, we see that participants' responsibility judgments in this selection of 24 scenarios were both affected by how surprising a committee member's vote was, and how important the vote was for the outcome. We now consider how well the model captures participants' responsibility judgments across the whole range of scenarios, and also compare the full model to lesioned models that consider only surprise, or only importance.

Overall results and model comparison. In order to apply the model to the full set of cases, we took the predictor that is relevant for the dispositional inference component of the model (i.e., the surprise model) and those that are relevant for the causal attribution component (i.e., pivotality and the number of causes). We then computed a Bayesian mixed effects model with random intercepts and slopes to predict participants' responsibility judgments (see Table 1). Figure 6b shows a scatter plot of the model predictions and participants' responsibility judgments for the full set of 170 scenarios (with 250 judgments). Overall, the model predicts participants' responsibility judgments well with $r = .77$ and RMSE = 8.16. Table 1 shows the estimates of the different predictors. As can be seen, none of the predictors' 95% HDIs overlap with 0.

To investigate further whether the different components of the model are needed to adequately capture participants' responsibility judgments, we constructed two lesioned models: one that considers only the dispositional inference part (i.e., using only `surprise` as a predictor), and one that considers only the causal attribution part (i.e., using only `pivotality` and `n_causes` as predictors).

The model that considers only surprise as a predictor performs markedly worse, with $r = .29$ and RMSE = 12.36. A model that considers only pivotality and the number of causes performs relatively well, with $r = .76$ and RMSE = 8.37. Comparing models with approximate leave-one-out crossvalidation as the model-selection criterion shows that a model that includes `surprise` as a predictor performs better than a model that considers only `pivotality` and `n_causes` as predictors (difference in expected log predictive density



(a) Model predictions for a *selection of cases* based on participants' surprise and importance judgments in Experiment 1.

(b) Model predictions for the *full set of cases* based on considering surprise, pivotality, and the number of causes as predictors.

Figure 6. **Experiment 2**: Scatter plot between model predictions (x-axis) and mean responsibility judgments (y-axis). The gray ribbon indicates the 95% HDI for the regression line. The error bars indicate bootstrapped 95% confidence intervals. (*Note*: r = Pearson moment correlation, RMSE = root mean squared error.)

(elpd) = 89.4, with a standard error of 16.1). A model that, in addition to the predictors discussed here, also considers whether the outcome was positive or negative (i.e., whether the policy passed), does an even better job at predicting participants' responsibility judgments with r = .81 and RMSE = 7.60 (difference in elpd = 70.7, with a standard error of 14.6, compared to the model without the `outcome` predictor). Participants assigned more responsibility when the outcome was positive (i.e., when a committee member voted in favor of a policy) than when the outcome was negative (and a committee member voted against a policy).

Table 1
Estimates of the mean, standard error, and 95% HDIs of the different predictors in the Bayesian mixed effects model. Note: `n_causes` *= number of causes.*

`responsibility ~ 1 + surprise + pivotality + n_causes + (1 + surprise + pivotality + n_causes | participant)`

term	estimate	std.error	lower 95% HDI	upper 95% HDI
intercept	59.94	3.25	54.70	65.22
surprise	21.68	4.57	14.17	29.23
pivotality	13.52	1.82	10.47	16.53
n__causes	-5.72	0.50	-6.55	-4.90

Discussion

In this experiment, we asked participants to make responsibility judgments about individual committee members for a large set of voting scenarios. Our computational framework captured participants' judgments well. While previous work showed that the model accounts well for responsibility judgments about individual decision-makers in achievement contexts (Gerstenberg et al., 2018), the results of this experiment show that the model also does a good job of accounting for responsibility judgments about individuals in group settings. Furthermore, while the responsibility judgments obtained in previous work were consistent with the key processes that the model postulates (dispositional inference and causal attribution), the results of Experiments 1 and 2 together provide a much stronger test of this proposal. Participants' surprise and importance judgments in Experiment 1 predict the responsibility judgments of different participants in Experiment 2.

The results further showed that while both components of the model are important, participants' responsibility judgments were most strongly influenced by the causal attribution aspect of our framework which expresses how important a person's action was for bringing about the outcome. However, as we discussed earlier, the extent to which dispositional inferences play a role for responsibility judgments might differ between domains. In Experiment 3, we test the idea that in the moral domain, the most relevant component may shift from causal attributions to dispositional inferences.

In addition to the factors that our model considers, we also found that participants' responsibility judgments were affected by whether the outcome was positive (i.e., the policy was passed) or negative (i.e., the policy was not passed). This effect was not predicted by our model, but could in principle be accommodated by it. Right now, our model assumes that committee members are just as likely to vote for or against a policy. It is possible, however, that people consider it generally more likely that committee members will vote against a policy rather than in its favor; that is, that the prior distribution over the policy is skewed toward voting "no". It is well known that people often prefer to "do nothing" when they have the choice between acting and not acting (see, e.g., Ritov & Baron, 1992); it seems plausible that they expect others to behave in the same way. In our voting setting, this means that participants might have assumed that committee members vote "yes" only if they really agree with the policy, while voting "no" is compatible both with being against the policy and with having no strong opinion.

Experiment 3: Responsibility judgments in moral contexts

Gerstenberg et al. (2018) previously tested the computational framework in achievement contexts, where the outcome critically depended on an individual's skill. Achievement contexts naturally elicit judgments of responsibility, as one can witness in any sports bar. However, judgments of responsibility are also particularly relevant in the moral domain. The computational framework is not restricted to specific contexts or a specific domain. When people assign responsibility to an individual for an outcome in the moral domain, the framework predicts that their judgments should be affected by dispositional inferences on the one hand, and causal attributions on the other hand, just like in achievement contexts.

However, research in moral psychology has shown that when people make moral judgments, they often assign more weight to those features of a behavior that seem most informative of character (Bartels & Pizarro, 2011; Bayles, 1982; Cushman, 2008; Gerstenberg, Lagnado, & Kareev, 2010; Pizarro et al., 2003; Schächtele, Gerstenberg, & Lagnado, 2011; Uhlmann et al., 2015; Waldmann et al., 2012). Against this background, we hypothesized that when people make responsibility judgments in the moral domain, the relative weights they assign to dispositional inferences versus causal attributions may shift.

We tested this prediction by manipulating the moral valence of the policy that the committees in Experiment 3 voted on. Whereas in our previous experiments, participants simply read that the committee voted on a policy with a certain identification number, participants in the current experiment were informed about the content and the consequences of the policy. One group of participants assigned responsibility in a "morally neutral context", in which the committee members voted on a policy to change the font of all government documents to *Arial*. A second group of participants assigned responsibility in a "morally negative context". Here, the policy was a request to reintroduce corporal punishment, such as spanking or paddling, in schools. We predicted that causal attributions would affect participants' responsibility judgments in both conditions, but that they would play a smaller role in the morally negative condition than in the morally neutral condition. We made this prediction because we assumed that the committee member's immoral vote in the morally negative condition would be more surprising for participants than the committee member's vote in favor of a certain font in the morally neutral condition, and thus that the impact of dispositional inferences in the morally negative condition would be larger.

Importantly, however, in the moral domain, people are not concerned only with determining whether or to what extent a person is responsible for an outcome (Knobe, 2010). They are also motivated to determine whether the person's action was generally right or wrong (Haidt, 2001) and if so, whether the person should be punished her for her wrongdoing (Cushman, 2008; Darley, 2009). Whereas the causal role that a person's action played for bringing about the outcome is critical for judgments of responsibility, judgments of moral wrongness are tied more closely to the action itself (Cushman, 2008; Teigen & Brun, 2011). This suggests that when evaluating to what extent it was morally wrong that a particular committee member voted in favor of children being spanked and paddled at school, the answer should neither depend on the causal structure of the scenario nor on how the other committee members voted.

To test how dispositional inferences and causal attributions affect judgments about the moral wrongness of an action, Experiment 3 included a third condition. In this condition, the policy was also a request to reintroduce corporal punishment in schools. However, instead of asking for responsibility judgments, we asked participants for the extent to which they considered the votes of particular committee members morally wrong. We predicted that when people evaluate the extent to which an individual's action was morally wrong, their judgment should be largely unaffected by our experimental manipulations of causal importance.

To sum up, our key predictions in Experiment 3 were that, first, for judgments of responsibility, the importance of causal attribution would be smaller in the morally negative than in the morally neutral context condition. Second, we predicted that for judgments of moral wrongness, the causal attribution component of the model would not matter.

Methods

Participants. 314 participants were recruited via the UK-based internet-platform *Prolific*. Inclusion criteria were English as native language and an approval rate not lower than 90%. Experiment 3 involved an attention check and a manipulation-check question. Participants who answered either of these questions incorrectly were removed from the analysis, leaving 236 participants (159 female, 74 male, 3 unspecified, $M_{\text{age}} = 31$, $SD_{\text{age}} = 9$).

Design. As in Experiment 1 and 2, we presented participants in Experiment 3 with scenarios in which a political committee voted on whether or not a motion should be passed. As before, we manipulated how each committee member voted and how many votes in favor of the policy were required for the policy to pass (1–5). Based on different combinations of these factors, we constructed five different voting scenarios whose structure is illustrated in Figure 7. To keep the scenarios somewhat more simple, the size of the committee (5 members) and the outcome of the vote (policy passed) were held constant in this experiment. In addition, the focus person, for whom we assessed responsibility or moral wrongness ratings, was always described as having voted in favor of the policy. Like in Experiments 1 and 2, the focus person's causal contribution to the outcome varied based on how the remaining committee members voted. For example, in Scenario 2 in Figure 7, the threshold for the policy to pass is 1. Since, in addition to the focus person, one other committee member ended up voting in favor of the policy, in this scenario, the focus person's pivotality is 0.5 and the outcome of the vote has two causes.

In our previous experiments, we manipulated participants' expectations about how a committee member would vote by giving them information about the committee members' party affiliation and about which party supported the policy. In the current experiment, participants did not receive any information about party affiliation and party support. Instead, we manipulated participants' expectations about how a committee member would vote via information about the moral context of the vote: We specified the moral valence of the policy, so that participants made their judgments in either a "morally neutral" or a "morally negative" context. In addition, we varied the test question. Instead of asking for responsibility judgments, one group of participants was asked to evaluate the extent to which they considered a particular committee member's action morally wrong. Thus, Experiment 3 had three conditions: *neutral* (morally neutral context, responsibility judgments), *moral* (morally negative context, responsibility judgments) and *wrongness* (morally negative context, moral wrongness judgments).

Procedure

Experiment 3 was programmed in *Unipark*, a German online survey platform. Participants were randomly allocated to one of three conditions. After receiving instructions, they were presented with all five voting scenarios in randomized order. After each scenario, participants made responsibility or moral wrongness judgments, depending on the condition, for those members that had been described as having voted in favor of the motion (1–5 judgments, depending on the scenario). For example, participants in the morally neutral context condition read "To what extent is Dallas responsible for the font of all government documents being changed to Arial", participants in the morally negative context condition read “To what extent is Dallas responsible for corporal punishment being introduced in schools” and participants in the moral wrongness condition read “To what extent is it morally wrong that Dallas voted in favor of introducing corporal punishment in schools?”. Participants did the rating using a slider ranging from “not at all responsible” or “not at all morally wrong” (0) to “very much responsible” or “very much morally wrong” (100) with an invisible starting point.

After having completed all five scenarios, participants answered a manipulation-check question that assessed whether the context manipulation was successful. Participants in the morally neutral context condition were asked “How do you morally judge voting in favor of changing government documents into Arial”. Participants in the morally negative context condition and the moral wrongness condition were asked “How do you morally judge voting in favor of introducing corporal punishment in schools?” They could choose between the answer options “bad”, “good” and “neutral”. At the end of the survey, participants responded to an attention check question and reported their demographics.[7] On average, it took participants 5.63 minutes ($SD = 2.52$) to complete this experiment.

Results

Figure 7 shows participants’ mean responsibility judgments across the five different scenarios separately for the *neutral* and *moral* condition, and their moral wrongness judgments in the *wrongness* condition. Qualitatively, we can see that in the *neutral* condition, participants’ responsibility judgments differentiate more between the different scenarios than in the *moral* condition. In the wrongness condition, participants’ judgments were very high and didn’t vary between the scenarios. Overall, responsibility judgments were higher in the moral condition ($M = 78.42, SD = 28.53$) than in the neutral condition ($M = 66.11, SD = 31.69$), and wrongness judgments were even higher ($M = 88.60, SD = 20.37$).

To test our prediction that the different experimental conditions would affect the extent to which the causal attribution component of the model matters, we computed a Bayesian mixed effects model with the two predictors that capture the causal attribution part of the model (`pivotality` and `n_causes`), as well as `condition` and its interactions with the other predictors. Because we had only five observations for each participant, we included only random intercepts and no random slopes.

Table 2 summarizes the regression results. As predicted, the extent to which causal attributions affect participants’ judgments differed between conditions. In particular, what role pivotality played in participants’ judgments differed between conditions. To further explore what role causal attributions played in the different conditions, we ran separate Bayesian regressions for each condition with `pivotality` and

[7] As expected, the majority of participants (91%) in the morally neutral context condition considered changing the font of government documents into Arial as neutral and the majority of participants (74% in *moral* and 79% in *wrongness*) in the morally negative context conditions judged introducing corporal punishment in schools as bad. However, there were also a number of participants in the morally neutral context condition who indicated that they considered changing the font of government documents into Arial as bad or good (8 participants), and a number of participants in the morally negative context conditions who indicated that they considered introducing corporal punishment as neutral or good (25 participants in *moral* and 12 participants in *wrongness*). These participants were excluded from subsequent analyses.

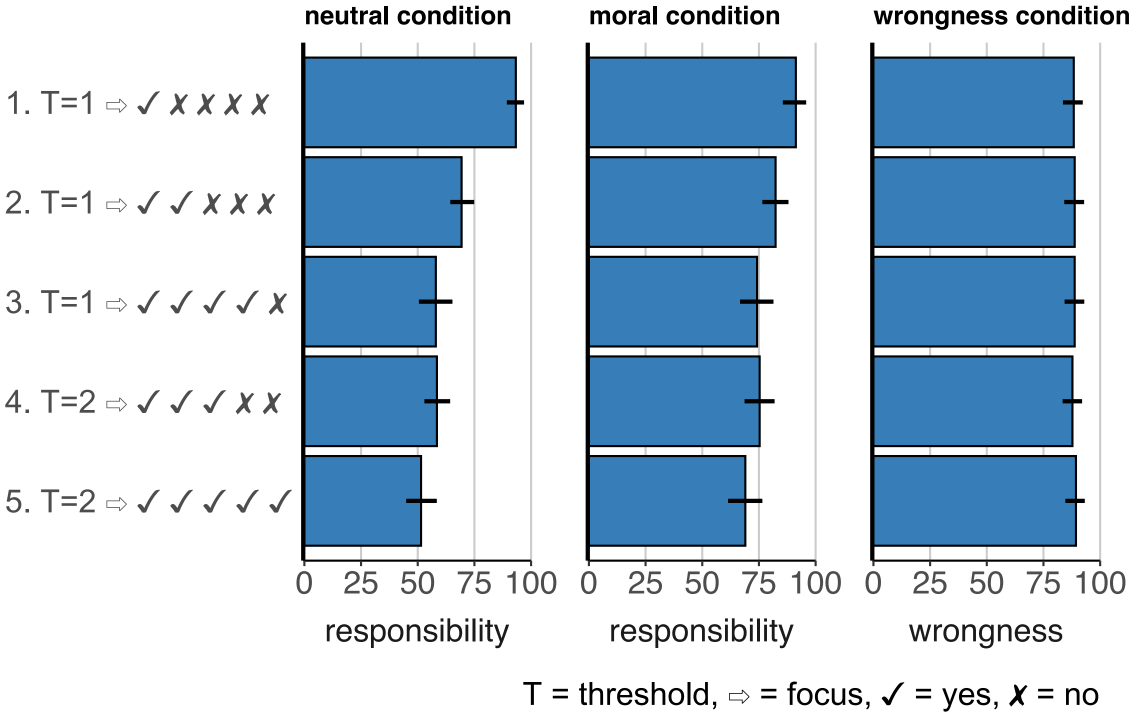


Figure 7. Experiment 3: Participants' mean responsibility ratings in the *neutral* and *moral* condition, as well as their mean wrongness ratings in the wrongness condition. *Note*: The error bars indicate bootstrapped 95% confidence intervals.

`n_causes` as predictors, and random intercepts for participants. In the neutral condition, the estimates for the `pivotality` and `n_causes` predictor were 38.45 $[22.63, 54.09]$ and -2.78 $[-5.87, 0.30]$, respectively. In the moral condition, they were 8.90 $[-5.85, 23.12]$

Table 2

Estimates of the mean, standard error, and 95% HDIs of the different predictors in the Bayesian mixed effects model. Note: `n_causes` *= number of causes.*

```
responsibility ∼ 1 + (pivotality + n_causes) * condition + (1 |
participant)
```

term	estimate	std.error	lower 95% HDI	upper 95% HDI
intercept	55.03	7.14	43.51	66.81
pivotality	38.83	6.33	28.41	49.11
n_causes	-2.71	1.22	-4.70	-0.69
$\text{condition}_{\text{moral}}$	30.29	10.40	12.93	46.96
$\text{condition}_{\text{wrongness}}$	33.57	10.05	16.84	49.96
$\text{pivotality:condition}_{\text{moral}}$	-29.86	9.26	-44.92	-14.52
$\text{pivotality:condition}_{\text{wrongness}}$	-39.06	8.88	-53.64	-24.35
$\text{n\_causes:condition}_{\text{moral}}$	-1.00	1.79	-3.89	1.91
$\text{n\_causes:condition}_{\text{wrongness}}$	2.87	1.72	0.05	5.72

and -3.71 $[-6.44, -1.01]$. Finally, in the wrongness condition, the estimates were -0.10 $[-4.45, 4.16]$ and 0.17 $[-0.69, 1.03]$. Consistent with our hypothesis, pivotality had a less strong effect on participants' responsibility judgments in the moral condition than in the neutral condition. Further, it did not seem to affect participants' wrongness judgments at all in the wrongness condition.

Discussion

In this experiment, we applied the computational framework to the moral domain. We used a similar setup as in Experiments 1 and 2, with individuals in a group voting for an outcome. However, instead of manipulating voting expectations via information about the committee members' party affiliation, we manipulated information about the moral content and the consequences of the policy, as well as the question that participants were asked to evaluate. We hypothesized that in a morally negative context, judgments of responsibility would be less sensitive to the causal role that a person's action had for bringing about the outcome, and more strongly affected by what dispositional inference is licensed based on observing the action. We further hypothesized that judgments of moral wrongness would not be at all affected by the causal role of the person.

Our experimental manipulation of pivotality was a good predictor of participants' responsibility judgments both the *neutral* and *moral* condition, but pivotality affected judgments less in the *moral* condition. While we did not assess dispositional inferences about the committee member's directly, this result is in line with our idea that in the moral domain, the weights that people put on the two components of the computational model shift so that the influence of causal attributions decreases and dispositional inferences play a larger role (cf. Uhlmann et al., 2015). In other words, it seems that participants in the *moral* condition learned something much more important about the focus committee member; namely, that the focus member is "immoral" or "a bad person".

In the *wrongness* condition, pivotality did not predict the extent to which participants considered the focus committee member's action morally wrong. This is in line with previous work (Cushman, 2008; Darley, 2009; Teigen & Brun, 2011) and common intuition: When making a judgment about the extent to which a person's action was morally wrong, we should make that decision independently of what other people did in that situation. Thus, while people might often try to excuse their behavior by pointing out that other people behaved equally badly, our results indicate that this might not be the most efficient strategy (Falk & Szech, 2013; Green, 1991).

General Discussion

In this paper, we further developed and extended a computational framework of responsibility judgments, originally introduced by Gerstenberg et al. (2018). This framework predicts that people assign responsibility based on two cognitive processes: dispositional inference and causal attribution. Here, we tested the framework in a voting setting in which multiple members of a political committee voted on whether or not a policy should be passed. This setting allowed us to quantitatively manipulate information relevant to the two key components of the model, and systematically investigate how each component affects people's responsibility judgments. Specifically, we manipulated the causal structure of the situation (by having committees of different size and different thresholds of how many votes were required for a policy to pass), the political affiliation of the committee members (i.e., whether a committee member was affiliated with the party that supported the policy), how each committee member voted, whether the policy was passed, and the moral context of the vote (*neutral* or *moral*).

These factors, in turn, affect the predictions of our model. Specifically, the party affiliations, voting pattern, and the moral context of the vote affect the extent to which a particular committee member's vote is *surprising*. For example, an individual committee member's vote is particularly surprising in a situation in which they voted "yes" even though their party didn't support the policy, and all of the other committee members voted against the policy. The threshold which determines how many votes are required for a policy to pass and the voting pattern affect how *important* an individual committee member's vote was for the outcome. For example, an individual "yes" vote was particularly important when the threshold to pass was 1 and none of the other committee members voted in favor of the policy.

Within our framework, we map surprise and importance onto the two key cognitive processes: surprise is linked to *dispositional inference* because a surprised observer will update her beliefs about the person – she has learned something about the person that she didn't know before. And importance is linked to *causal attribution* as it expresses an assessment of the structure of the situation and the causal role that a person's action played in bringing about the outcome.

Experiment 1 directly tested the model's key components by assessing participants' judgments of surprise and importance. As predicted, the extent to which participants considered the vote of an individual committee member surprising was affected by the committee member's party affiliation and by how the other committee members voted. In addition, the factors that we captured with our causal attribution model predicted importance ratings: votes were judged more important if they were closer to being pivotal and if fewer causes contributed to the outcome.

In Experiment 2, we showed that for the subset of voting situations that were used in both Experiment 1 and 2, participants' surprise and importance judgments from Experiment 1 predicted participants' responsibility judgments in Experiment 2. In addition, our responsibility model accounted well for the overall set of patterns that were employed in this large-scale experiment: Participants held committee members more responsible for the outcome when their vote was more surprising, when they were closer to being pivotal, and when fewer causes contributed to the outcome of the vote. It turned out that in addition, the outcome of the vote also affected participants' responsibility judgments. This was not predicted by our account; however, it could in principle be accommodated in our model by assuming that committee members are generally more likely to vote against rather than in favor of a policy (cf. Ritov & Baron, 1992).

In Experiment 3, we applied the computational framework to the moral domain. We showed that, as in previous experiments, participants who made responsibility judgments in a morally negative context considered both what they learned about a committee member as a person, as well as how much the committee member contributed to the outcome of the vote in their responsibility judgments. However, the impact of the causal attribution component was smaller in the morally negative condition than in the the morally neutral condition.

We also showed that when participants made judgments about the moral wrongness of a committee member's action, the causal contribution of the committee member's action to the outcome did not play a role. Thus, across the three conditions of Experiment 3 (*neutral* to *moral* to *wrongness*), we showed that the weight people put on the causal contribution factor decreased. These results are consistent with recent proposals in the moral psychology literature that, for questions of moral concern, people predominantly focus on information that is indicative of a person's character or disposition (Bartels & Pizarro, 2011; Bayles, 1982; Cushman, 2008; Gerstenberg et al., 2010; Pizarro et al., 2003; Schächtele et al., 2011; Uhlmann et al., 2015; Waldmann et al., 2012).

The work presented here makes three main contributions toward a comprehensive computational framework of responsibility judgments: First, we developed specific computational implementations for the dispositional inference and causal attribution components of our framework. While prior work had only indirectly tested how these components relate to responsibility judgments (Gerstenberg et al., 2018), we provide a more direct test here. We show that our computational models of dispositional inference and causal attribution accurately predict participants' surprise and importance judgments in Experiment 1, respectively, and that these two components are critical for capturing participants' responsibility judgments in Experiment 2.

Second, this work connects prior research on how expectations and dispositional inferences affect responsibility judgments to individual decision makers with research that has looked at how responsibility is attributed to individuals in group contexts (Gerstenberg & Lagnado, 2010; Koskuba et al., 2018; Lagnado, Fenton, & Neil, 2013; Lagnado & Gerstenberg, 2015; Zultan et al., 2012). The voting paradigm allowed us to manipulate prior expectations in a natural way, and the results showed that these expectations influenced responsibility judgments. Further, the paradigm featured complex causal settings with expectations manipulated in graded ways, and thus provided a challenging test bed for our computational model.

Third, we show that our framework can be applied to the moral domain as well; our results suggest that people's responsibility judgments in moral contexts are affected by dispositional inferences and causal attributions, just like in other settings. Beyond this more general contribution, the successful application of the framework to the moral domain has important practical implications. For example, a currently much debated topic is how we can design artificial intelligence that behaves responsibly in critical situations (Friedenberg & Halpern, 2019; Halpern & Kleiman-Weiner, 2018; Himmelreich, 2019; Mao & Gratch, 2006; Wallach & Allen, 2008). How do we want a self-driving car to behave when it has the option to either hit a child on a bike that suddenly turned into its lane or to avoid the child by swerving into an oncoming lane, hitting into another car on this lane and injuring its passengers (Awad et al., 2018; Rahwan et al., 2019)? To answer questions like this one, we need to work toward a prescriptive model for how responsibility should be assigned. Formalizing notions of how people actually assign responsibility in a variety of moral contexts is an important first step toward this goal.

Future directions: dispositional inference

The evidence presented here and by Gerstenberg et al. (2018) shows that dispositional inferences are a key component underlying responsibility judgments. However, more research is needed to better understand exactly how dispositional inferences affect responsibility judgments. We will discuss three questions that future work should address in more detail: First, what is the role of prior expectations? Second, how do action expectations map onto responsibility judgments? And third, how can different mental states be incorporated into the framework?

The role of prior expectations. A central idea in the computational framework of responsibility judgments is that people compare their expectation about how an agent *should* act with the agent's actual behavior. But where do people's initial expectations about how one ought to behave come from? There are at least two different sources: Prior expectations can be informed by what *any reasonable person* would do in that situation, or by what the *specific person* under consideration is likely to do (cf. Sytsma, Livengood, & Rose, 2012). In our introductory example, given the angry reactions that Suprun's decision not to vote for Trump triggered in many Republicans, it seems that they expected him to vote the way that any "reasonable Republican" would vote in that situation. However, imagine that Suprun's friends and family members know him as a strong character, willing to make unconventional decisions if that means he can stay true to his principles. For them, his decision might have been less surprising, because they compared Suprun's behavior to what they believed he would do, given his earlier behavior.

In the experiments reported here, participants did not have any specific background information about the committee members. However, in Experiments 1 and 2, participants knew the committee members' party affiliation, and participants in the morally negative context condition in Experiment 3 knew what the "morally right" voting decision was (voting against corporal punishment in schools). This information affected participants' expectations about how a committee member would vote. In future work, it would be interesting to compare more specifically between expectations resulting from more general versus person-specific standards of comparisons and investigate how they may influence people's responsibility judgments differently.

From action expectations to responsibility judgments. In our voting setting, we were able to go directly from action expectations (and whether or not they were violated) to responsibility judgments: Our model predicts that the more surprising a committee member's vote, the stronger the dispositional inference about that committee member and thus the higher the level of responsibility that is assigned to the committee member for the outcome of the vote.

It is important to note, however, that in other settings, this direct mapping may not be feasible. In achievement contexts, for example, actors are sometimes given more responsibility for unexpected actions (Brewer, 1977; Fincham & Jaspars, 1983; Malle, Monroe, & Guglielmo, 2014; Petrocelli, Percy, Sherman, & Tormala, 2011), and sometimes for expected actions (Johnson & Rips, 2015). Gerstenberg et al. (2018) showed that violating expectations in itself does not result in more (or less) responsibility, but that dispositional inferences *mediate* the relationship between action expectations and responsibility judgments. Unexpected actions can lead to different dispositional inferences – and thus, differentially affect judgments of responsibility – depending on the context in which they are made. As a goalie in soccer, for example, saving an unexpected shot is diagnostic for skill and good future performance. Thus, the computational framework predicts that, in this context, unexpected actions will yield more responsibility or credit. In contrast, in contexts where unexpected actions are indicative of poor decision-making – for example, when a contestant in a game show bets on the color with the lower probability in a two-colored spinner – the framework predicts that unexpected actions will be assigned less credit.

In our voting paradigm, a direct mapping from action expectations to responsibility judgments was feasible; in other settings, action expectations may affect responsibility judgments differently. Future studies should test our framework in even more diverse settings and investigate exactly how action expectations affect responsibility judgments via dispositional inferences.

Modeling mental states. Responsibility is a rich and multifaceted concept (cf. Hart, 2008). There are many different factors that influence the way in which people assign responsibility. One group of "inputs" to responsibility judgments that has received particular attention are the agent's mental states (see Young & Tsoi, 2013, for a review). For example, it has been shown that when assigning responsibility, people take into account whether agents intended the consequences of their actions (Cushman, Knobe, & Sinnott-Armstrong, 2008; Shultz & Wright, 1985), whether the consequences were realized in the intended way (Alicke, Rose, & Bloom, 2012; Gerstenberg et al., 2010; Guglielmo & Malle, 2010; Pizarro et al., 2003; Schächtele et al., 2011), and whether they were able to foresee the consequences of their actions (Lagnado & Channon, 2008; Markman & Tetlock, 2000; Young & Saxe, 2009).

Several models of how mental states affect responsibility judgments have been put forward. For example, Malle, Guglielmo, and Monroe's (2014) *Path Model of Blame* predicts that once an observer has established whether an agent has caused an outcome, considerations about the agent's intention lead the observer to two different information-processing paths to blame: If the agent is found to have caused the outcome intentionally, the observer considers his reasons for acting. In contrast, if the outcome was unintentional, the observer considers the agent's obligation and capacity to prevent the harmful outcome from occurring (see also Monroe & Malle, 2017). While empirical tests of the Path Model have yielded convincing results, the model's predictions are purely qualitative; as most other theories of responsibility judgments, it leaves unanswered the question of how *much* responsibility people assign to an individual for an outcome in a given situation.

So far, mental states have not been explicitly incorporated into the computational framework presented here. For example, in our voting experiments, it is taken for granted that the committee members cast their votes intentionally. Explicitly modeling mental states within the computational framework is an important next step. We believe that an agent's mental state should affect the framework's dispositional inference component. Specifically, an agent's mental state should affect the expectations that an observer develops about how the agent will act, and thus the extent to which the observer draws an inference about the agent's character. For example, when someone knowingly votes in favor of a policy that has morally negative consequences, this licenses a stronger inference about that person's character than when someone voted without actually knowing what these consequences would be. As mentioned earlier, researchers have recently begun to model how people infer mental states from actions computationally (Baker et al., 2017, 2009; Jara-Ettinger et al., 2016). This work is a good starting point for modeling mental states within the computational framework of responsibility judgments presented here.

Future directions: Causal attribution

In this paper, we have extended the simple model of causal contribution used in Gerstenberg et al. (2018) by implementing a graded notion of pivotality, as well as by incorporating the number of causes that contributed to the outcome as an additional subcomponent of the causal attribution process.

However, the model of causal attributions employed here is still a fairly simple one. Currently, we assume that the observer has no uncertainty about the agent's pivotality and the number of causes that contributed to the outcome, and that both factors influence causal attributions in a linear additive way. In many situations, however, observers are unsure about what actually happened, and need to infer each agent's causal contribution. Similar to our model of dispositional inference, future work should explore an inferential model for making causal attributions that draws on and extends the notions of pivotality and number of causes that we employed in our model.

We know from other work in causal cognition that causal attributions can be quite nuanced (e.g., Alicke, Mandel, Hilton, Gerstenberg, & Lagnado, 2015; Allen et al., 2015; Einhorn & Hogarth, 1986; Gerstenberg, Peterson, Goodman, Lagnado, & Tenenbaum, 2017; Lombrozo, 2010; White, 2014; Wolff, 2007). In what follows, we briefly discuss two factors that have been shown to affect causal attributions and that future work on the computational framework for responsibility attributions will need to take into account: The extent to which the cause is spatiotemporally connected to the outcome, and the causal function that determines how the individual actions are integrated to yield the group outcome.

Physical processes. As established earlier, the computational framework for responsibility judgments is based on counterfactual theories of causation (Lewis, 1973), which capture causation by determining whether the candidate cause made a difference to the outcome. However, in philosophy, there is a second major theoretical framework for thinking about causation besides counterfactual theories: so-called *process theories of causation*. Process theories establish causal relationships by analyzing whether there was a physical connection that linked the candidate cause and the effect. Empirical work has shown that in some situations, participants' causal judgments are predominantly influenced by information about physical connections (Dowe, 2000; Lombrozo, 2010; Walsh & Sloman, 2011; Wolff, 2007), whereas in others, participants use counterfactual analyses to infer causation (Gerstenberg, Goodman, Lagnado, & Tenenbaum, 2012, 2014, 2015; Gerstenberg et al., 2017).

So far, the computational framework's focus on counterfactual analyses has proven successful at capturing people's causal attributions. However, our scenario didn't manipulate information about physical connections. In our voting scenarios, a committee member's causal contribution to the outcome of the vote depends only on how the other committee members voted. In real life, however, we are often confronted with situations in which the individual physical connections of different group members to an outcome differ. Based on previous research (Dowe, 2000; Iliev, Sachdeva, & Medin, 2012; Lombrozo, 2010; Walsh & Sloman, 2011; Wolff, 2007), it seems plausible that people would integrate such information into their responsibility judgments. Hence, future research on the computational framework should look at situations in which the extent to which the individual causes are physically connected to a joint outcome differ quantitatively.

Causal integration functions. Another aspect that has been shown to affect judgments of causation and of responsibility is the way in which individual contributions combine to determine a group outcome (Allen et al., 2015; Gerstenberg & Lagnado, 2010; Lagnado, Gerstenberg, & Zultan, 2013; Waldmann, 2007; Zultan et al., 2012). For example, are the individual contributions added together, so each cause contributes something to the overall outcome (addition)? Do all causes need to surpass a certain threshold (conjunction)? Or is one cause sufficient for bringing about the outcome (disjunction)?

In our experiments, we varied the way in which the individual votes combined to yield the outcome of the vote to some extent by varying the threshold of votes required for the policy to pass. For example, a voting situation in which the threshold was five represents a conjunctive situation, while a situation in which only one committee member had to vote in favor of the policy for the policy to pass represents a disjunctive situation. As reported above, the way in which our participants assigned responsibility indicates that they were sensitive to these variations. In future work, it would be interesting to more specifically manipulate different causal functions. For example, one could create situations in which the individual committee members differ in how much power they have to influence the outcome of the vote and look at how this affects responsibility judgments.

Conclusion

Deciding whether and to what extent someone is responsible for an outcome is something we do every day. In this paper, we tested and extended a computational framework Gerstenberg et al. (2018) that postulates two key processes in responsibility judgments: dispositional inferences and causal attributions. We have shown that the framework's predictions hold when its two key components are assessed directly, when the framework is employed in more complex causal settings, and when it is tested in the moral domain. In doing so, we have provided further evidence that the computational framework for responsibility attribution is applicable as a unified tool for obtaining quantitative predictions about how people assign responsibility to others in a variety of contexts.

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Appendix A
Sensitivity analysis of Bayesian surprise model

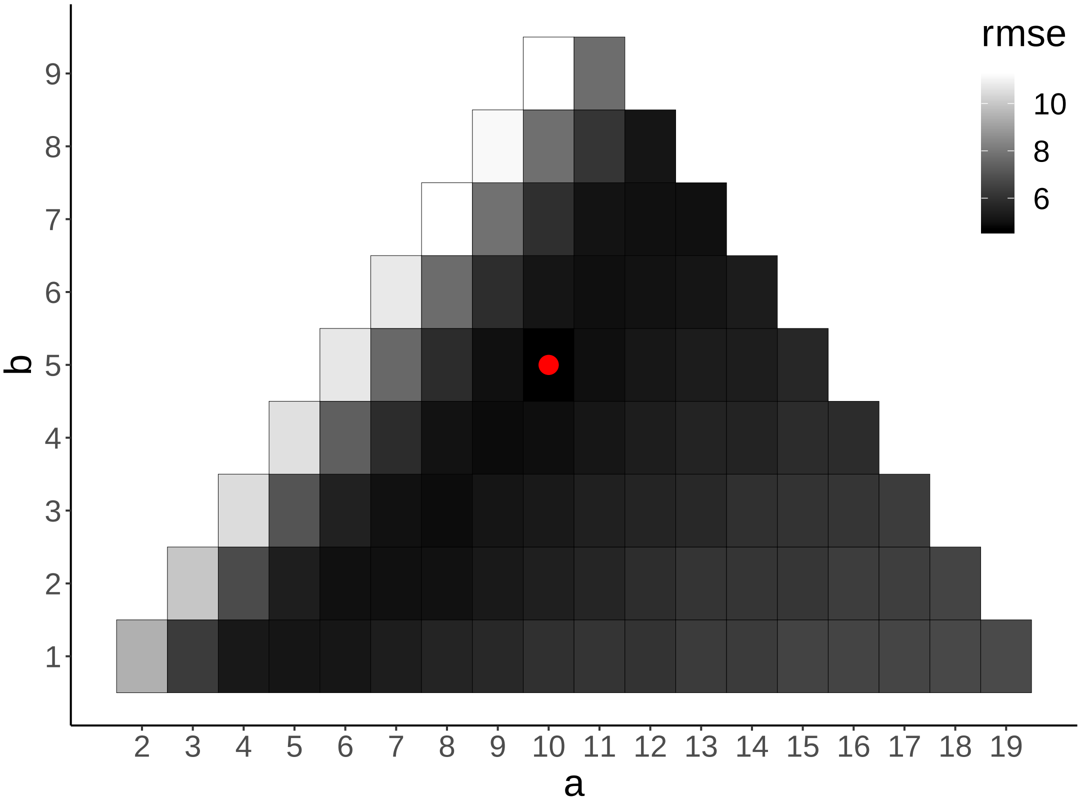

Figure A1. Sensitivity analysis of the Bayesian surprise model. The tile plot shows the root mean squared error between model predictions and participants' mean surprise judgments for the scenarios presented in Experiment 1 as a function of the two parameters a and b that were fitted to the data (see Figure 2). The red dot indicates the best fitting set of parameters: $a = 10$ and $b = 5$.

Appendix B
Scenarios presented in Experiment 1

Table B1
List of 27 scenarios presented in Experiment 1.

		party					vote						
scenario	person	p1	p2	p3	p4	p5	v1	v2	v3	v4	v5	threshold	outcome
1	1	1	1	1	0	0	1	1	1	1	1	5	1
2	1	1	1	1	1	1	1	1	1	1	1	1	1
3	1	0	0	0	0	0	1	1	0	0	0	1	1
4	1	0	0	0	0	0	1	0	0	0	0	1	1
5	1	1	1	1	1	1	1	1	1	1	1	5	1
6	2	1	1	0	0	0	1	0	1	0	0	5	0
7	2	0	0	0	0	0	1	0	0	0	0	5	0
8	3	1	1	1	0	0	1	1	0	0	0	4	0
9	1	1	1	1	0	0	1	1	1	1	1	1	1
10	3	1	1	1	0	0	1	1	0	0	0	3	0
11	2	1	0	0	0	0	0	0	0	0	0	1	0
12	1	1	1	0	0	0	1	1	0	0	0	2	1
13	1	1	1	1	1	0	1	1	1	0	1	4	1
14	4	1	0	0	0	0	1	1	1	0	0	5	0
15	1	0	0	0	0	0	0	0	0	0	0	2	0
16	2	1	0	0	0	0	1	1	0	0	0	2	1
17	4	1	1	1	0	0	1	1	1	1	0	4	1
18	1	1	1	0	0	0	0	0	0	0	0	5	0
19	1	0	0	0	0	0	0	0	0	0	0	3	0
20	1	1	1	0	0	0	1	1	1	1	0	3	1
21	2	0	0	0	0	0	1	0	0	0	0	4	0
22	2	0	0	0	0	0	1	0	0	0	0	2	0
23	2	1	0	0	0	0	1	0	0	0	0	3	0
24	3	1	1	1	1	0	1	1	0	0	0	4	0
25	5	1	0	0	0	0	0	1	1	1	1	1	1
26	5	1	1	0	0	0	0	0	1	1	1	2	1
27	5	0	0	0	0	0	1	1	1	1	1	2	1

Note: person: indicates which person's action in the committee participants were asked to judge; party: 1 = affiliated with the party that supports the policy, 0 = opposite party; vote: 1 = yes, 0 = no; threshold: number of votes required in favor in order for the policy to pass; outcome: 1 = policy passed, 0 = policy didn't pass.

Appendix C
Surprise model predictions

Table C1

Predictions of the Bayesian surprise model. same = committee members who are affiliated with the party that supports the policy, other = committee members from the other party, n = number of people in the committee, yes = number of people who voted yes, party = mean of the party posterior, vote = mean of the vote posterior, surprise = predicted surprise associated with a 'yes' vote, policy = mean of the policy posterior. For example, in Scenario 18, the committee had two members affiliated with the party that supported the policy and two members from the other party (in addition to the fifth committee member whose action we are evaluating). One of the committee members affiliated with the party that supported the policy voted yes, and one of the committee members from the other party voted yes. The posterior indicates that the remaining committee member will vote 'yes' with probability .58 if he is affiliated with the party that supported the policy, and probability .42 if he is from the other party. The surprise column indicates how surprised an observer would be with a 'yes' vote. The surprise predictions were fitted to the data with a Bayesian linear mixed effects model yielding the following parameters for the fixed intercept $= -76.41$ *and slope* $= 244.60$. *(*Note*: Model predictions are based on the model in which* $a = 10$, *and* $b = 5$*; see Figure 2 for details of the model.)*

	same					other					
scenario	n	yes	party	vote	surprise	n	yes	party	vote	surprise	policy
1	0	0	0.67	0.57	28.78	2	0	0.31	0.39	72.88	0.47
2	0	0	0.66	0.59	24.67	2	1	0.34	0.42	64.43	0.51
4	0	0	0.66	0.55	33.36	4	0	0.29	0.36	79.55	0.44
5	0	0	0.67	0.58	27.31	4	1	0.32	0.40	69.92	0.49
6	0	0	0.66	0.59	24.70	4	2	0.34	0.43	63.64	0.51
9	1	0	0.65	0.56	32.10	1	0	0.33	0.39	71.64	0.46
11	1	1	0.68	0.59	24.08	1	0	0.32	0.41	67.87	0.50
12	1	1	0.68	0.60	20.63	1	1	0.35	0.44	59.95	0.53
13	1	0	0.65	0.55	34.28	3	0	0.31	0.38	76.02	0.45
14	1	0	0.65	0.56	30.61	3	1	0.32	0.40	70.94	0.47
17	1	1	0.68	0.57	27.59	3	0	0.30	0.39	73.92	0.47
18	1	1	0.68	0.59	23.48	3	1	0.32	0.41	67.11	0.50
19	1	1	0.67	0.60	20.29	3	2	0.35	0.44	59.67	0.53
22	2	1	0.66	0.58	26.37	0	0	0.33	0.42	66.61	0.50
23	2	2	0.69	0.61	19.77	0	0	0.34	0.43	62.40	0.52
24	2	0	0.64	0.54	36.10	2	0	0.31	0.38	76.44	0.44
27	2	1	0.66	0.57	29.43	2	0	0.30	0.39	73.36	0.47
28	2	1	0.66	0.58	26.28	2	1	0.34	0.42	65.67	0.50
30	2	2	0.69	0.60	21.99	2	0	0.31	0.41	68.40	0.50
31	2	2	0.69	0.61	18.15	2	1	0.34	0.43	61.86	0.53
32	2	2	0.69	0.62	15.61	2	2	0.36	0.46	55.81	0.56
35	3	1	0.65	0.55	32.99	1	0	0.33	0.39	71.78	0.46

	same					other					
scenario	n	yes	party	vote	surprise	n	yes	party	vote	surprise	policy
37	3	2	0.68	0.59	24.40	1	0	0.33	0.41	67.02	0.50
38	3	2	0.67	0.60	20.93	1	1	0.36	0.44	59.77	0.53
39	3	3	0.70	0.61	18.41	1	0	0.32	0.42	65.13	0.53
40	3	3	0.70	0.63	14.58	1	1	0.35	0.46	56.87	0.56
43	4	2	0.65	0.57	28.09	0	0	0.34	0.41	67.05	0.49
44	4	3	0.69	0.60	20.75	0	0	0.34	0.43	63.15	0.52
45	4	4	0.71	0.63	14.68	0	0	0.34	0.44	60.01	0.55

Appendix D
Scenarios presented in Experiment 2

Table D1

List of 30 scenarios with three committee members in Experiment 2. Note that if there was a member from each party that supported the outcome, participants were asked to assign responsibility to each member on separate sliders.

	party			vote				
scenario	p1	p2	p3	v1	v2	v3	threshold	outcome
1	0	0	0	0	0	0	1	0
2	0	0	0	1	0	0	1	1
3	1	0	0	0	0	0	1	0
4	1	0	0	1	0	0	1	1
5	1	0	0	1	1	0	1	1
6	1	1	0	1	0	0	1	1
7	1	1	0	1	1	0	1	1
8	1	1	0	1	1	1	1	1
9	1	1	1	1	1	0	1	1
10	1	1	1	1	1	1	1	1
11	0	0	0	0	0	0	2	0
12	0	0	0	1	0	0	2	0
13	1	0	0	0	0	0	2	0
14	1	0	0	1	0	0	2	0
15	1	0	0	1	1	0	2	1
16	1	1	0	1	0	0	2	0
17	1	1	0	1	1	0	2	1
18	1	1	0	1	1	1	2	1
19	1	1	1	1	1	0	2	1
20	1	1	1	1	1	1	2	1
21	0	0	0	0	0	0	3	0
22	0	0	0	1	0	0	3	0
23	1	0	0	0	0	0	3	0
24	1	0	0	1	0	0	3	0
25	1	0	0	1	1	0	3	0
26	1	1	0	1	0	0	3	0
27	1	1	0	1	1	0	3	0
28	1	1	0	1	1	1	3	1
29	1	1	1	1	1	0	3	0
30	1	1	1	1	1	1	3	1

Note: party: 1 = affiliated with the party that supports the policy, 0 = opposite party; vote: 1 = yes, 0 = no; threshold: number of votes required in favor in order for the policy to pass; outcome: 1 = policy passed, 0 = policy didn't pass.

Table D2

List of 140 scenarios with five committee members in Experiment 2. Note that if there was a member from each party that supported the outcome, participants were asked to assign responsibility to each member on separate sliders.

	party					vote						
scenario	p1	p2	p3	p4	p5	v1	v2	v3	v4	v5	threshold	outcome
31	0	0	0	0	0	0	0	0	0	0	1	0
32	0	0	0	0	0	1	0	0	0	0	1	1
33	0	0	0	0	0	1	1	0	0	0	1	1
34	1	0	0	0	0	0	0	0	0	0	1	0
35	1	0	0	0	0	1	0	0	0	0	1	1
36	1	0	0	0	0	0	1	0	0	0	1	1
37	1	0	0	0	0	1	1	0	0	0	1	1
38	1	0	0	0	0	1	1	1	0	0	1	1
39	1	1	0	0	0	0	0	0	0	0	1	0
40	1	1	0	0	0	1	0	0	0	0	1	1
41	1	1	0	0	0	1	1	0	0	0	1	1
42	1	1	0	0	0	1	0	1	0	0	1	1
43	1	1	0	0	0	1	1	1	0	0	1	1
44	1	1	0	0	0	1	1	1	1	0	1	1
45	1	1	1	0	0	1	0	0	0	0	1	1
46	1	1	1	0	0	1	1	0	0	0	1	1
47	1	1	1	0	0	1	1	1	0	0	1	1
48	1	1	1	0	0	1	1	0	1	0	1	1
49	1	1	1	0	0	1	1	1	1	0	1	1
50	1	1	1	0	0	1	1	1	1	1	1	1
51	1	1	1	1	0	1	1	0	0	0	1	1
52	1	1	1	1	0	1	1	1	0	0	1	1
53	1	1	1	1	0	1	1	1	1	0	1	1
54	1	1	1	1	0	1	1	1	0	1	1	1
55	1	1	1	1	0	1	1	1	1	1	1	1
56	1	1	1	1	1	1	1	1	0	0	1	1
57	1	1	1	1	1	1	1	1	1	0	1	1
58	1	1	1	1	1	1	1	1	1	1	1	1
59	0	0	0	0	0	0	0	0	0	0	2	0
60	0	0	0	0	0	1	0	0	0	0	2	0
61	0	0	0	0	0	1	1	0	0	0	2	1
62	1	0	0	0	0	0	0	0	0	0	2	0
63	1	0	0	0	0	1	0	0	0	0	2	0
64	1	0	0	0	0	0	1	0	0	0	2	0
65	1	0	0	0	0	1	1	0	0	0	2	1
66	1	0	0	0	0	1	1	1	0	0	2	1
67	1	1	0	0	0	0	0	0	0	0	2	0

	party					vote						
scenario	p1	p2	p3	p4	p5	v1	v2	v3	v4	v5	threshold	outcome
68	1	1	0	0	0	1	0	0	0	0	2	0
69	1	1	0	0	0	1	1	0	0	0	2	1
70	1	1	0	0	0	1	0	1	0	0	2	1
71	1	1	0	0	0	1	1	1	0	0	2	1
72	1	1	0	0	0	1	1	1	1	0	2	1
73	1	1	1	0	0	1	0	0	0	0	2	0
74	1	1	1	0	0	1	1	0	0	0	2	1
75	1	1	1	0	0	1	1	1	0	0	2	1
76	1	1	1	0	0	1	1	0	1	0	2	1
77	1	1	1	0	0	1	1	1	1	0	2	1
78	1	1	1	0	0	1	1	1	1	1	2	1
79	1	1	1	1	0	1	1	0	0	0	2	1
80	1	1	1	1	0	1	1	1	0	0	2	1
81	1	1	1	1	0	1	1	1	1	0	2	1
82	1	1	1	1	0	1	1	1	0	1	2	1
83	1	1	1	1	0	1	1	1	1	1	2	1
84	1	1	1	1	1	1	1	1	0	0	2	1
85	1	1	1	1	1	1	1	1	1	0	2	1
86	1	1	1	1	1	1	1	1	1	1	2	1
87	0	0	0	0	0	0	0	0	0	0	3	0
88	0	0	0	0	0	1	0	0	0	0	3	0
89	0	0	0	0	0	1	1	0	0	0	3	0
90	1	0	0	0	0	0	0	0	0	0	3	0
91	1	0	0	0	0	1	0	0	0	0	3	0
92	1	0	0	0	0	0	1	0	0	0	3	0
93	1	0	0	0	0	1	1	0	0	0	3	0
94	1	0	0	0	0	1	1	1	0	0	3	1
95	1	1	0	0	0	0	0	0	0	0	3	0
96	1	1	0	0	0	1	0	0	0	0	3	0
97	1	1	0	0	0	1	1	0	0	0	3	0
98	1	1	0	0	0	1	0	1	0	0	3	0
99	1	1	0	0	0	1	1	1	0	0	3	1
100	1	1	0	0	0	1	1	1	1	0	3	1
101	1	1	1	0	0	1	0	0	0	0	3	0
102	1	1	1	0	0	1	1	0	0	0	3	0
103	1	1	1	0	0	1	1	1	0	0	3	1
104	1	1	1	0	0	1	1	0	1	0	3	1
105	1	1	1	0	0	1	1	1	1	0	3	1
106	1	1	1	0	0	1	1	1	1	1	3	1
107	1	1	1	1	0	1	1	0	0	0	3	0

	party					vote						
scenario	p1	p2	p3	p4	p5	v1	v2	v3	v4	v5	threshold	outcome
108	1	1	1	1	0	1	1	1	0	0	3	1
109	1	1	1	1	0	1	1	1	1	0	3	1
110	1	1	1	1	0	1	1	1	0	1	3	1
111	1	1	1	1	0	1	1	1	1	1	3	1
112	1	1	1	1	1	1	1	1	0	0	3	1
113	1	1	1	1	1	1	1	1	1	0	3	1
114	1	1	1	1	1	1	1	1	1	1	3	1
115	0	0	0	0	0	0	0	0	0	0	4	0
116	0	0	0	0	0	1	0	0	0	0	4	0
117	0	0	0	0	0	1	1	0	0	0	4	0
118	1	0	0	0	0	0	0	0	0	0	4	0
119	1	0	0	0	0	1	0	0	0	0	4	0
120	1	0	0	0	0	0	1	0	0	0	4	0
121	1	0	0	0	0	1	1	0	0	0	4	0
122	1	0	0	0	0	1	1	1	0	0	4	0
123	1	1	0	0	0	0	0	0	0	0	4	0
124	1	1	0	0	0	1	0	0	0	0	4	0
125	1	1	0	0	0	1	1	0	0	0	4	0
126	1	1	0	0	0	1	0	1	0	0	4	0
127	1	1	0	0	0	1	1	1	0	0	4	0
128	1	1	0	0	0	1	1	1	1	0	4	1
129	1	1	1	0	0	1	0	0	0	0	4	0
130	1	1	1	0	0	1	1	0	0	0	4	0
131	1	1	1	0	0	1	1	1	0	0	4	0
132	1	1	1	0	0	1	1	0	1	0	4	0
133	1	1	1	0	0	1	1	1	1	0	4	1
134	1	1	1	0	0	1	1	1	1	1	4	1
135	1	1	1	1	0	1	1	0	0	0	4	0
136	1	1	1	1	0	1	1	1	0	0	4	0
137	1	1	1	1	0	1	1	1	1	0	4	1
138	1	1	1	1	0	1	1	1	0	1	4	1
139	1	1	1	1	0	1	1	1	1	1	4	1
140	1	1	1	1	1	1	1	1	0	0	4	0
141	1	1	1	1	1	1	1	1	1	0	4	1
142	1	1	1	1	1	1	1	1	1	1	4	1
143	0	0	0	0	0	0	0	0	0	0	5	0
144	0	0	0	0	0	1	0	0	0	0	5	0
145	0	0	0	0	0	1	1	0	0	0	5	0
146	1	0	0	0	0	0	0	0	0	0	5	0
147	1	0	0	0	0	1	0	0	0	0	5	0

	party					vote						
scenario	p1	p2	p3	p4	p5	v1	v2	v3	v4	v5	threshold	outcome
148	1	0	0	0	0	0	1	0	0	0	5	0
149	1	0	0	0	0	1	1	0	0	0	5	0
150	1	0	0	0	0	1	1	1	0	0	5	0
151	1	1	0	0	0	0	0	0	0	0	5	0
152	1	1	0	0	0	1	0	0	0	0	5	0
153	1	1	0	0	0	1	1	0	0	0	5	0
154	1	1	0	0	0	1	0	1	0	0	5	0
155	1	1	0	0	0	1	1	1	0	0	5	0
156	1	1	0	0	0	1	1	1	1	0	5	0
157	1	1	1	0	0	1	0	0	0	0	5	0
158	1	1	1	0	0	1	1	0	0	0	5	0
159	1	1	1	0	0	1	1	1	0	0	5	0
160	1	1	1	0	0	1	1	0	1	0	5	0
161	1	1	1	0	0	1	1	1	1	0	5	0
162	1	1	1	0	0	1	1	1	1	1	5	1
163	1	1	1	1	0	1	1	0	0	0	5	0
164	1	1	1	1	0	1	1	1	0	0	5	0
165	1	1	1	1	0	1	1	1	1	0	5	0
166	1	1	1	1	0	1	1	1	0	1	5	0
167	1	1	1	1	0	1	1	1	1	1	5	1
168	1	1	1	1	1	1	1	1	0	0	5	0
169	1	1	1	1	1	1	1	1	1	0	5	0
170	1	1	1	1	1	1	1	1	1	1	5	1

Note: party: 1 = affiliated with the party that supports the policy, 0 = opposite party; vote: 1 = yes, 0 = no; threshold: number of votes required in favor in order for the policy to pass; outcome: 1 = policy passed, 0 = policy didn't pass.

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