An Experimental Study of The Jury Voting Model with Ambiguous Information*

Simona Fabrizi Steffen Lippert Addison Pan

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Abstract

This experimental study examines individual voting behaviour in a jury voting model with ambiguous information. Our experiment is twofold. We first replicate a variation of the Ellsberg three-color urn experiment to elicit each subject's attitude toward ambiguity. We then let subjects perform decision-tasks in which we vary the reliability of the information they receive and the voting rules by which group decisions are reached. Our analysis provides support for the existence of a strong link between an individual's attitude towards ambiguity and their voting behaviour in collective decision-making ambiguous settings.

1 Introduction

The jury voting model of Feddersen and Pesendorfer (1998), herein FP, suggests that informative voting is often not equilibrium behaviour, especially when the jury size gets large and the voting rule is unanimous. Out of all voting rules, unanimity gives individuals the strongest incentives to strategically vote against their private information (*strategic voting*). Such strategic voting is not

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contemplated by the Condorcet Jury Theorem: It establishes that collective decisions generated by majority (and *sincere*) voting have a higher probability of selecting the correct alternative than the decision made by a single expert, especially as the size of the group grows.

The reliability of the information provided to voters and how it impacts their belief formation and revision are key elements in determining the likelihood that a voter is pivotal and, conditional on pivotality, also whether the related posterior belief that a defendant is guilty surpasses the level of reasonable doubt. In spite of that, it is far from well-established how the incentives to vote against one's own information are affected both by the reliability of that information and by how subjective beliefs surrounding its quality are formed and revised.

Only a few studies exist, which attempt to depart from the canonical models of jury voting in which the reliability of the information provided to voters is precisely measured.

Keller, Sarin, and Sounderpandian (2007) show that ambiguity aversion persists in two-person group decisions. Similarly, Brunette, Cabantous, and Couture (2015) finds that individuals are less risk-averse and more ambiguity-averse in groups than in individual decision-settings. In contrast, Keck, Diecidue, and Budescu (2012) suggests that individuals in groups are likely to make ambiguity-neutral decisions.[1] Fabrizi and Pan (2017) provide theoretical insights for the voting behaviour's of ambiguity-averse jurors possessing ambiguous private information.

In this study, we break new ground by providing evidence that an individual's attitude towards ambiguity in a single person decision-setting is systematically related to that individual's behaviour in collective decision-making. We do so by testing how the presence of an ambiguous environment affects individual voting behaviour in juries. By doing so, we contribute to the study of collective decision-making, particularly in those more realistic scenarios where voters do not have access to information whose accuracy is precisely measured.

A Canonical Jury Voting Model Consider an illustrative example based on FP's set-up, of a jury of six members, $N = 6$, all sharing a common prior about the probability that the defendant is guilty or innocent, equal to $P(G) = P(I) = 0.5$. Before jurors simultaneously cast their votes to acquit (a) or convict (c), they get an independent private signal drawn from a common distribution.

[1] Instead, Pan, Fabrizi, and Lippert (2018) offers a characterization for when voters with non-congruent views are reluctant to vote against their private information.

The signal is either a guilty (g) or an innocent (i) one. Assume the correlation between their private signal and the true state of the defendant – that is the signal precision – to be 80%, so that $P(g|G) = P(i|I) = 0.8$. Another typical assumption in jury models is that jurors care equally about the quality of the verdict. If the jury reaches a correct verdict, the jurors' utility is normalized to zero, $U(A,I) = U(C,G) = 0$. However, jurors obtain a disutility when the jury reaches a wrong verdict. If the jury commits type I error, that is convicts an innocent defendant, jurors' disutility equals $U(C,I) = -q$; whereas if the jury commits type II error, that is acquits a guilty defendant, jurors' disutility equals $U(A,G) = -(1-q)$. In order to declare a defendant guilty, jurors must find that the evidence convinces them beyond a reasonable doubt. In practice, after the casting of votes, either a jury verdict of Acquittal (A) or Conviction (C) is determined by aggregating the individual votes and subject to the voting rule in place. That is, the voting rule identifies the minimum number of votes, k, out of the N votes, that are needed for a conviction to be reached. Assume a high level of reasonable doubt equal to $q = 0.9$ is required for casting a vote to convict. This implies that the ratio between the loss associated with committing type I errors as opposed to type II errors is ninefold.[2]

Absent any ambiguous information informative voting is the unique symmetric and responsive Nash equilibrium under the majority voting rule ($k = 4$).[3] Under the majority voting rule, (i) the probability of an individual juror casting a vote to convict when receiving an innocent signal is degenerate and equal to $\sigma(i)_{k=4} = 0$; and, conversely, (ii) the probability of an individual juror casting a vote to convict when receiving a guilty signal is equal to $\sigma(g)_{k=4} = 1$. However, subject to the unanimity voting rule ($k = 6$) any individual juror receiving an innocent signal no longer has a strict preference to vote to acquit: Upon receiving an innocent signal, any individual juror's equilibrium strategy is to randomize their vote to convict with positive probability, so that $\sigma(i)_{k=6} > 0$.

A Modified FP's Set-Up: Jury Voting Under Ambiguous Information We maintain all the assumptions of the illustrative example for a canonical jury model given above, except for one. In particular, we vary the standard set-up

[2]To better understand why type I errors are typically considered to be much more costly than type II errors, observe that when committing type I errors not only innocent defendants are found guilty, by mistake, but in addition the 'true' perpetrators - guilty persons - are still free as they 'escaped' from being convicted of their crimes.

[3]FP restrict attention to symmetric and responsive equilibria, that is equilibria in which voters with the same signal would choose the same strategy in terms of the probability of voting to convict; but voters would choose different strategies whether to vote to acquit or to convict upon receiving different signals.

by considering an ambiguous correlation between the private signal and the true state of the defendant. Specifically, we maintain that the signal precision is common to all jurors, but now follows an unknown distribution, varying between a minimum of 60% and a maximum of 80%, that is $P(g|G) = P(i|I) = [0.6, 0.8]$.[4] Next, we assume that jurors' attitudes towards ambiguity are consistent with one of the following expected utility models of decision-making: the Subjective Expected Utility (SEU) model and the expected utility model with multiple priors (Gilboa and Schmeidler, 1989) generalised by Hurwicz α-criteria (Hurwicz, 1951), with the $\alpha : (1-\alpha)$ weight mixture of Maxmin preference and Maxmax preference. Furthermore, we assume that the way in which rational jurors update their prior beliefs after receiving new information falls into either one of three main categories: the standard Bayesian updating, the Maximum Likelihood Updating (MLU) (Gilboa and Schmeidler, 1993) and the Full Bayesian Updating (FBU) (Pires, 2002).[5]

Canonical vs Ambiguous Decision-Making Environment We use the illustrative example of a canonical jury model described above to create a baseline for our experimental study. The goal of our experimental study is to explore departures from the individual voting behaviour predicted in a canonical jury model à la FP when voters are confronted with an ambiguous environment. To that end, in the remainder of this study we report about a two-stage experiment we conducted to test individual voting behaviour in a modified FP set-up, as just described above.

2 Experimental Design

Our main interest is in exploring voting behaviour in the ambiguous environment we described, and to relate their voting behaviour to their differing attitudes towards ambiguity.

This is not a trivial question to ask: How do individuals' attitudes toward ambiguity in single-person decisions translate in those individuals' behaviour when

[4]We have chosen to let the reliability of the signal vary downwards, with respect to the one jurors face in the absence of ambiguity. An alternative would be to let the ambiguous interval within which the 'true' precision lies within be centered around the (precise) level of that reliability in the FP's set-up, that is centered around $P(g|G) = P(i|I) = 0.8$, for instance, $P(g|G) = P(i|I) = [0.70, 0.90]$. Doing so, is left for further experimentation, for pure robustness checks of the results presented in this study.

[5]In our experiment, whenever subjects' updating behaviour would not conform to either of these categories, we will deem their behaviour as inconsistent.

confronted with an ambiguous game-theoretical voting situation? We are not the first to elicit subjects' attitudes toward ambiguity in an attempt to infer their behaviour in a group setting. For example, Kelsey and le Roux (2017) reports on a set of experiments to compare the effect of ambiguity as identified in single-person decisions on games involving two players. A voting scenario involves a situation in which an individual's decision (single vote) only partially determines the overall group decision (final verdict), as a function of the adopted voting rule. Since there is no established result in the literature that provides a clear link between an individual's attitude towards ambiguity and that individual's tendency to vote in accordance to their private and ambiguous signal in a voting scenario, the goal of our study is to fill this gap and provide novel insights in that direction.

For our experimentation, we implement *four within-subjects treatments*. All four treatments contain two stages of various decision tasks and one questionnaire about the subjects' social and personal characteristics. The first stage and the questionnaire are the same across all treatments. The differences across treatments are only featured by the set-ups of the second stage.

Specifically, in the first stage our design offers a variation of the Ellsberg three-color urn game à la Cohen, Gilboa, Jaffray, and Schmeidler (2000) aimed at identifying each subject's attitude towards ambiguity and their chosen updating rule when confronted with it.

In the second stage, the four treatments differ as follows. Two of the treatments consist of a voting environment à la FP, with a signal precision of $p = 0.8$, each subjected to either the 'M'-ajority voting rule (FP-M) or the 'U'-nanimity voting rule (FP-U). The remaining treatments, consider a modified voting environment with an 'A'-mbiguous signal precision, such that $P(g|G) = P(i|I) = [0.6, 0.8]$, each subjected to either the 'M'-ajority voting rule (A-M) or the unanimity voting rule (A-U).

Our experimental design allows us to introduce an ambiguous signal-state correlation to examine subjects' voting behaviour according to attitudes towards ambiguity and updating rules as revealed in the first stage of our experiment. Hence, two of the four treatments considered in the second stage not only replicate the jury model as found in FP, but, by doing so, also provide us with the necessary control group (baseline) for our data analysis of the additional two treatments, allowing for an alternative environment, namely those with an ambiguous information structure.

Stage 1 We computerize the experiment of Cohen et al. (2000) and conduct it with real cash prizes. Subjects are asked to place three consecutive bets on the colors of a randomly selected ball from a standard 3-color Ellsberg urn. Subjects are initially told that the urn contains 90 balls, of which 30 are white, and the remaining 60 are either black or yellow. The exact composition of the Ellsberg urn is then determined at random by the computer and not revealed to the subjects.[6] Next, the computer randomly selects a ball from that urn with replacement until a 'non-yellow' ball is selected. Subjects are not told about the color of the selected ball. Then subjects place Bets 1 and 2. Each bet has four alternatives. In Bet 1, subjects choose: (i) To bet on the color of the selected ball to be 'White'; (ii) To bet on the selected color of the ball to be 'Black'; (iii) To be 'Indifferent' between betting on the color of the selected ball to be 'White' or 'Black', leaving the computer to place a bet on their behalf by choosing to bet on either of these colors with equal probability; and, lastly, (iv) To choose 'Do Not Bet' on any specific color for the selected ball, thereby renouncing to the prospect of having a positive earning. In Bet 2, subjects choose: (i) To bet on the color of the selected ball to be 'White or Yellow'; (ii) To bet on the color of the selected ball to be 'Black or Yellow'; (iii) To be 'Indifferent' between betting on the color of the selected ball to fall under the option 'White or Yellow' or 'Black or Yellow', letting the computer choose among those options with equal probability; and, once again, (iv) To choose 'Do Not Bet', renouncing to the prospect of any positive earning. Therefore, Bets 1 and 2 are variants of the Ellsberg three-color urn experiment, in the sense that they are designed to have two more options than the two alternatives of the original Ellberg experiment, namely the 'Indifferent' and the 'Do Not Bet' options. Those additional options were added to allow for SEU or inconsistent subjects' preferences types, respectively. After Bet 2, subjects were told that the ball selected for Bets 1 and 2 was 'non-yellow' and that it was placed back into the urn. Next, the computer draws another ball, the color of which is once again not revealed to the subjects. Subjects then place Bet 3, consisting of the same options as in Bet 1.

For each of those bets, subjects could receive a NZD2.00 prize if placing a correct bet. Otherwise, subjects would receive no prize, that is if placing the wrong

[6]To generate ambiguity in the laboratory setting, we adopted the method of Stecher, Shields, and Dickhaut (2011) – so that, for instance, the true composition of the urn remains unavailable to both the subjects and the experimenters throughout the experiment. This has been shown to help to lower subjects' reluctance to engage in an ambiguous bet (Chow and Sarin, 2002). To induce ambiguity in the lab, we first generated 10,000 realisations of the relative proportion of black and yellow balls, and then selected one uniformly from these realisations and took it as the real proportion of black and yellow balls in the urn. By doing so, the randomly determined proportion of the black and yellow balls and the color of the selected ball for Bets 1 and 2 were not known to anyone for the duration of the experiment.

bet or if choosing not to bet. In any event, subjects receive no feedback on the outcome of their bets. Instead, subjects do receive payments according to the quality of their choices in Stages 1 and 2, but only at the very end of the experimental session they participated in.

Stage 2 To emulate the jury voting scenario, Stage 2 consists of one trial round and twenty subsequent rounds of decision-making between two alternatives. Specifically, at the beginning of each round, the computer randomly and independently selects one among two possible urns, a 'Blue' or a 'Red' one, with equal probability. Each urn contains 100 balls, either red or blue. The urn is said to be Red (Blue) if it predominantly contains Red (Blue) balls. Next, the computer randomly and independently assigns each subject to a group of other five subjects, tasked with guessing the right color of the urn selected for that round. Before each subject casts their vote about what they believe the color of the selected urn for that round to be, they receive a private information regarding the color of a randomly and independently drawn ball, with replacement, from that urn. For the ambiguous treatment only, before the computer randomly draws the ball for each subject, a graph of 10 bar charts is shown to all subjects. Each of the bar charts contains 10,000 realisations of 21 different proportions of the two colors, comprised between 60/40 and 80/20, that is any realisation of the percentage of the predominant balls of a given color in the set $P = \{0.60, 0.61, \ldots, 0.79, 0.80\}$.[7] Once subjects cast their vote, each vote gets next aggregated to form a specific group decision in accordance with the voting rule which applies to those subjects' treatment. The default for the group decision is set to be 'Blue' if that group falls short of meeting the minimum number of red votes for a 'Red' decision to be reached: For the (strict) majority voting rule the minimum number of red votes is four out of six; whereas for the unanimity voting rule that minimum number of red votes is six out of six.[8] No feedback regarding either the color of the selected urn, or other subjects' votes are provided during the experimental session. Only at the very end of the experimental session, subjects are revealed the quality of their decision in one randomly and independently selected round – out of the twenty rounds of decision-making they participated in – and are paid accordingly.

[7]These realisations are obtained in much the same way as the ones for Stage 1.

[8]Put differently, under the majority voting rule the group decision is 'Red' if four or more subjects in that group vote for red. Under the unanimity voting rule the group decision is 'Blue' if at least one of the subjects votes for blue.

Questionnaire Lastly, subjects are asked to complete a questionnaire after Stage 2. The questionnaire involves personality traits, locus of control and a few demographic questions. Answers in the questionnaire are only meant to be used as control variables in our empirical analysis of the experimental data. Subjects are informed that their answers to the questionnaire do not affect the payments they receive at the very end of the experimental sessions they participated in.

Payments Subjects are incentivised in taking part in the experiment and paying attention to their choices during the experiment as follows. They receive NZD10.00 as a show-up fee, NZD2.00 for each correctly placed bet, for a maximum of NZD6.00 attainable for choices made in Stage 1. Additionally, they receive NZD14.00 if their group decision in the randomly selected round out of the twenty rounds they were involved in is correct. Otherwise, they receive respectively (i) NZD13.00 or (ii) NZD5.00 if their group decision is incorrect in that randomly selected round. This can be either (i) because their choice is 'Blue' when the correct color of the selected urn is 'Red' (playing the same role as type II error, that is choosing to acquit the guilty), or (ii) it is 'Red' when the true color of the selected urn is 'Blue' instead (playing the same role as type I error, that is choosing to convict the innocent). The variation in the payments subjects receive following a wrong group decision relates to the gravity of that decision: It mirrors the same asymmetry that exists between the loss associated with type I and type II errors.[9] Hence, the maximum and minimum payments subjects can receive in an experimental session are NZD30.00 and NZD15.00, respectively.

3 Revealed Preferences and Updating Rules

Table 1 states all possible decisions from the first two bets and the possible corresponding revealed attitudes towards ambiguity. We identify each subject's decision regarding the bets from Stage 1 by acts of betting on d_W, d_B, $d_{W \cup Y}$ and $d_{B \cup Y}$, where W stands for 'W-hite', B stands for 'B-lack', '$W \cup Y$' stands for 'W-hite or Y-ellow', and '$B \cup Y$' stands for 'B-lack or Y-ellow'. So, for instance, think of a subject betting on d_W. If the color of the selected ball for that bet

[9] It is easy to derive that the loss in earnings when committing type I errors is equal to \$14-5=\$9; whereas the loss in earnings when committing type II errors is equal to \$14-13=\$1. Therefore, the relative importance between type I and type II errors is exactly 9:1, mirroring $q = 0.9$.

were indeed white, that subject would receive a prize of NZD2.00. Otherwise, if the color of the selected ball for that bet were not white, the subject would have placed a wrong bet and get no rewards.

If a subject were to select (i) 'White' in the first bet and 'White or Yellow' in the second bet, or (ii) 'Black' in the first bet and 'Black or Yellow' in the second bet, this would indicate the following alternative idiosyncratic preference patterns for that subject: (i) $d_W \succ d_B$ and $d_{W \cup Y} \succ d_{B \cup Y}$; or (ii) $d_W \prec d_B$ and $d_{W \cup Y} \prec d_{B \cup Y}$. Each of these two preference patterns satisfy the 'Sure-Thing Principle'. Thus, they are consistent with the SEU model and subjects exhibiting such preferences could be considered to be ambiguity neutral. If instead a subject's preference patterns were to exhibit a reversed preference ordering between the first and the second bet, that subject's preference towards ambiguity would likely satisfy – be consistent with – the multiple prior model. In particular, preference patterns consistent with the Hurwicz α-criteria, would allow subjects to have a whole range of intermediate attitudes with respect to ambiguity, rather than allowing only the extreme cases. Thus, if the revealed preference pattern were $d_W \succ d_B$ and $d_{W \cup Y} \prec d_{B \cup Y}$, it would indicate that subjects are likely to be ambiguity-averse, or equivalenty that their α satisfies the condition $\alpha > 1/2$. The opposite pattern $d_W \prec d_B$ and $d_{W \cup Y} \succ d_{B \cup Y}$ would suggest that subjects are likely to be ambiguity-loving, or equivalently that their α satisfies the condition $\alpha < 1/2$. Subjects who were to exhibit the pattern $(d_W \sim d_B, d_{W \cup Y} \sim d_{B \cup Y})$ would either have SEU preferences or adhere to the Hurwicz criteria, although with an $\alpha = 1/2$[10]. Other decisions, not easily associated with either of those preference patterns, and corresponding attitudes towards ambiguity, would then indicate some form of inconsistency.

Table 1: Revealed Preferences

	Bet 1			
	White	Black	Indifferent	Do Not Bet
Bet 2				
White or Yellow	SEU	$\alpha > 1/2$	inconsistent	inconsistent
Black or Yellow	$\alpha < 1/2$	SEU	inconsistent	inconsistent
Indifferent	inconsistent	inconsistent	SEU or $\alpha = 1/2$	inconsistent
Do Not bet	inconsistent	inconsistent	inconsistent	inconsistent

[10]There were only six subjects falling in this category.

Remember that, for bet 3, before placing their bet, subjects are told that the previously drawn ball for bets 1 and 2 was not yellow. This is done in order for subjects to make decisions for the third bet depending on their updating of their subjective prior beliefs. If any differences were to be observed in the decisions made by the different subjects, we could then reconcile those differences as resulting from varying updating rules subjects would adopt, depending on their attitudes towards ambiguity. For instance, subjects with SEU preferences would use the standard Bayesian updating rule. Therefore, for those subjects the preference ordering between the alternatives in bet 3 would not be altered from that expressed in bet 1. We could, for example, clearly identify the preference types of the subjects who were indifferent between betting on 'White' and 'Black'; or 'White or Yellow' and 'Black or Yellow'. Therefore, if those same subjects were to express choices in line with $d_W \sim d_B$ also in bet 3, they could be classified as belonging to the SEU type. For the remaining subjects who were also to exhibit consistent preferences, but with a preference pattern for the third bet such that $d_W \succ d_B$, we could conclude that their updating rule falls into the category of Full Bayesian Updating (FBU). The opposite pattern $d_W \prec d_B$ would indicate that the Maximum Likelihood Upating (MLU) were used instead. Any remaining cases, not falling in either of those categories, would then be labelled as 'others'.

Table 2 provides a summary of all the updating rules, including those that are inconsistent with any of the categories described above.

Table 2: Revealed Updating Rules

	Bet 3			
	White	Black	Indifferent	Do Not Bet
Bet 1, Bet 2				
White, White or Yellow	Bayes' Rule	others	others	others
Black, Black or Yellow	others	Bayes' Rule	others	others
White, Black or Yellow	FBU	MLU	others	others
Black, White or Yellow	FBU	MLU	others	others
Indifferent, Indifferent	FBU	MLU	Bayes' Rule	others

4 Experimental Data and Some Predictions

Our experiment was conducted between July and September 2017 at DECIDE (Laboratory for Business Decision Making) based at the University of Auckland.[11] [12] Subjects were recruited among students at the University of Auckland using ORSEE (Greiner, 2015). A total of 216 subjects participated in ten experimental sessions. Three sessions were conducted in each of the A-M and A-U treatments, and two sessions were conducted in each of the FP-M and FP-U treatments. All sessions were computerised, using z-Tree (Fishbacher, 2007). Preceding each stage, in each of these treatments, separate instructions were given to subjects by the experimenter as per our description in Section 3.[13] The subjects' total rewards from this experiment consisted of the earnings from Stage 1, Stage 2 and the show-up fee, as described in details in Section 3. This resulted in an average reward per subject of NZD26.00.

4.1 Descriptive Statistics

Below we reproduce some summaries for the descriptive statistics of our experiment.

Table 3 offers a summary of the individual and group decisions as well as their consequences in terms of type I and type II errors for the baseline treatments à la FP.

According to FP's framework, for the parameter values chosen for our experimental setting informative voting is not an equilibrium strategy under the unanimous voting rule whereas it is is under the majority voting rule. Previous experimental evidence has investigated group-decision making and tested Nash predictions for varying jury sizes and voting rules in the absence of ambiguity. These studies confirm the Nash prediction that unanimity voting rule underperforms against the majority voting rule, triggering (more) strategic voting, with subjects with blue (innocent) signals mixing between voting for blue

[11]The experiment was funded via the *University of Auckland Faculty Research Development Grant* titled 'Deliberation under Ambiguity' (awarded for the period 2015-2017 to Lippert & Fabrizi as co-PIs, and Ryan & Pfeiffer as AIs in the amount of NZD12,600.00).

[12]The ethical approval to conduct this research with human subjects was obtained from the University of Auckland Human Participants Ethics Committee on the 18th of June 2015 (with reference number 014565). This approval covers a period of three years, therefore elapsing on the 17th of June 2018.

[13]See supplementary material for detailed instructions given in each of the treatments listed in this study.

(acquit) and red (convict) more than they would do under the majority voting rule.[14] In practice though, and including in our baseline treatment, subject randomise their votes even when receiving a red signal.

Therefore, absent ambiguity and in line with existing studies, Table 3 highlights that subjects in our experiment are also more inclined to randomise their votes towards red (alias conviction) upon receiving a blue (innocent) signal when the unanimity voting rule is in place. This has implications for the occurrence of type I errors under the two alternative voting rules in place, across these baseline treatments.

Table 3: Experimental Realisations in the FP (Baseline) Treatments

$N = 6$	$k = 4$	$k = 6$
Number of individual decisions	600	720
Number of group decisions	100	120
All subjects		
Red votes with red signals	59.5%	68.5%
Red votes with blue signals	20.3%	24.4%
Ambiguity-averse subjects		
Red votes with red signals	53.3%	60.7%
Red votes with blue signals	0%	31.3%
SEU maximising subjects		
Red votes with red signals	69%	65.5%
Red votes with blue signals	34.2%	19%
Ambiguity-loving subjects		
Red votes with red signals	51.6%	75.4%
Red votes with blue signals	11%	30.4%
Wrong group outcomes	35%	45.8%
True jar 'Blue' (Type I error)	2%	0%
True jar 'Red' (Type II error)	66.7%	94.8%

Next, when looking at the experimental data generated in treatments with ambiguity, as highlighted in Table 4, it is possible to observe that conditional on

[14] Guarnaschelli, McKelvey, and Palfrey (2000), and Goeree and Yariv (2011).

the unanimity voting rule being in place, overall subjects upon receiving a blue (innocent) signal randomise considerably less when ambiguity exists as compared to when ambiguity is absent.

Additionally, subjects randomise their vote less against their information when receiving a red signal, but they do so more under majority voting than under unanimity in the baseline treatments. Under ambiguity this behaviour is reversed.

For instance, under the unanimity voting rule, overall subjects (i) vote for red when receiving red signals 68.5% of times absent ambiguity, but only 57.7% of times when ambiguity is present; and (ii) vote for red when receiving blue signals 24.4% and 17.9% of times, when ambiguity is absent or present, respectively.

These first remarks can be further broken down into different categories depending on idiosyncratic attitudes of subjects towards ambiguity.

Section 5 is devoted to assess whether any of those initial remarks can be confirmed when testing them using appropriate econometric models and controls, and what their statistical significance really is. But before getting into deeper econometric analyses of our experimental data, we would like to offer some experimental predictions for them, which could apply to the voting behaviour of ambiguity-averse types in particular.

Table 4: Experimental Realisations in the Ambiguity Treatments

$N = 6$	$k = 4$	$k = 6$
Number of individual decisions	1320	1680
Number of group decisions	220	280
All subjects		
Red votes with red signals	60.6%	57.7%
Red votes with blue signals	19.9%	17.9%
Ambiguity-averse subjects		
Red votes with red signals	62.3%	66.7%
Red votes with blue signals	20.3%	22.2%
SEU maximising subjects		
Red votes with red signals	72.9%	58.7%
Red votes with blue signals	16.1%	18.4%
Ambiguity-loving subjects		
Red votes with red signals	50.2%	45.8%
Red votes with blue signals	24.9%	13%
Wrong group outcomes	36.8%	52.5%
True jar 'Blue' (Type I error)	11%	0%
True jar 'Red' (Type II error)	66.7%	98.7%

4.2 Some Theoretical Predictions for Ambiguity-averse Voters

Next, and before getting into the econometric analyses of our experimental data, we provide some theoretical predictions based on Fabrizi and Pan (2017).

This study models jury voting under ambiguity with ambiguity-averse voters who use Full Bayesian Updating and MaxMin to choose their optimal strategies. It provides theoretical support for informative voting becoming an equilibrium strategy under the unanimous voting rule, in the presence of ambiguity when majority voting fails to sustain it an informative voting.

We reproduce here in particular the equilibrium behaviour predictions for the same parameters as those used in our experiment. These predictions are summarised in Table 5.

Table 5: Group Decision under Different Information Structures, given $n = 6$, $q = 0.9$

Signal Precision	Voting Rule	Informative Voting Condition	Informative Voting
$p = 0.8$	$k = 6$	$0.9961 < q \leq 0.9998$	No
	$k = 4$	$0.5 < q \leq 0.9412$	Yes
$p = [0.6, 0.8]$	$k = 6$	$0.8579 < q \leq 0.9253$	Yes
	$k = 4$	$0.5 < q \leq 0.7536$	No

Whether these theoretical predictions have any bearing on the behaviour we would observe in the real world, is entirely an empirical question. Our experiment represents a first step in that direction. In our laboratory setting, we can account for subjects who exhibit varying attitudes toward ambiguity, as well as revealed updating behaviours, when examining their voting choices. Furthermore, we control for the absence and presence of ambiguity in those voting scenarios, beyond varying the voting rule.

5 Analysis and Results

In the remainder of this section we provide results of our econometric analysis, focussing on estimating the determinants of the probability to vote for Red (alias of voting to convict) at the subject level.

We start by discussing results of a battery of Probit estimations that explain individual decisions to vote to convict for the ambiguity-averse subjects identified in our experiment, as summarised in Table 6 in the Appendix.[15] Our conjecture, based on Fabrizi and Pan (2017), is that the interaction between ambiguity and unanimity should decrease an ambiguity-averse subject's probability of voting to convict upon receiving a blue (innocent) signal. Indeed, Table 6 provides support for such conjecture. The coefficient for the combined marginal effect of adopting the unanimity rule when the signal precision is ambiguous is negative and highly statistically significant (at the 95% level). Holding everything else fixed, ambiguity-averse subjects are less likely to vote for red in later rounds. This is in spite of not receiving any feedback on their performance round by

[15]We are able to identify 480 observations falling in this category, based on their associated subjects' choices in Bets 1 and 2 that are consistent with exhibiting ambiguity-averse attitudes.

round. These results persist when controlling for various personality traits. It is worth mentioning that 'Openness to Experience' although strengthening the coefficient of the combined marginal effect of adopting the unanimity rule under ambiguity also reinforces the probability of voting for red following a red signal.

When repeating the analysis for the SEU-subjects,[16] the combined marginal effect of ambiguity and adopting the unanimity rule is not significant instead in explaining subject's voting behaviour as opposed to when voting in a non-ambiguous environment. Their behaviour is statistically not significantly different across those scenarios. These results are summarised in Table 7, which can also be found in the Appendix.

Lastly, when concentrating on the ambiguity-loving subjects,[17] we derive results summarised in Table 8, also found in the Appendix. Also for ambiguity-loving subjects the interaction between ambiguity and unanimity decreases their probability of voting to convict upon receiving a blue (innocent) signal. For the treatment with the unanimity voting rule in place, the coefficient for the combined marginal effect of having the unanimity voting rule in place when the signal precision is ambiguous is negative and highly statistically significant (at the 95% level), similarly to the case of ambiguity-averse subjects. And, as for ambiguity-averse subjects, this effect is also amplified over time (rounds).

In the Appendix, for completeness and robustness purposes we also provide results of a parallel set of linear estimations, for each of the three categories of ambiguity-averse, SEU, and ambiguity-loving subjects. The results of those estimations can be found in Tables 9-11. Their results are in line with those obtained using the Probit estimations discussed in Tables 6-8.

6 Final Remarks and Future Research

Our study sheds light on the link that appears to exist between an individual's sensitivity to ambiguity in single-person decisions and their behaviour in an ambiguous voting scenario. Whenever ambiguity affects choices at an individual level, ambiguity also matters in determining that individual's behaviour in a voting situation. Remarkably, both ambiguity-averse and ambiguity-loving

[16] We are able to identify 1,200 observations falling in this category, based on their associated subjects' choices in Bets 1 and 2 that are consistent with exhibiting SEU attitudes.

[17] We are able to identify 1,540 observations falling in this category, based on their associated subjects' choices in Bets 1 and 2 that are consistent with exhibiting ambiguity-loving attitudes.

attitudes translate in more cautious voting behaviour, that is in more reluctance to vote against the default, especially so under the unanimity voting rule. When thinking about a jury setting, such reluctance determines fewer instances of votes towards conviction (recall that blue is the default when voting either under the majority or the unanimity voting rule), reducing type I errors, but potentially exacerbating type II errors.

Our study is the first to attempt to link one's attitude towards ambiguity in single-person decisions to their behaviour in a voting situation, as a function of the voting rule in place. By stressing the strong link between ambiguity attitudes and voting behaviour under ambiguity, it also encourages further exploration of such a link, including via further theoretical modelling of voting behaviour in the presence of ambiguity. While our results are in line with some existing theoretical predictions for voting behaviour under ambiguity for ambiguity-averse voters,[18] theoretical models explaining voting behaviour in ambiguous scenarios for ambiguity-loving voters, or even better mixtures of ambiguity-averse, loving and neutral voters, do not yet exist. Such modelling would provide richer predictions upon which to base further experimental analyses of how ambiguity impacts collective decision-making.

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Table 6: Probit Estimations That Explain Red Individual Decisions, Ambiguity-averse Subjects

VARIABLES	(1) Red Vote	(2) Red Vote	(3) Red Vote	(4) Red Vote
Red Sample	1.172**	1.170**	1.350**	1.375***
	(0.560)	(0.562)	(0.526)	(0.513)
Unanimity Rule	1.679**	1.638**	1.788***	1.820***
	(0.684)	(0.673)	(0.589)	(0.685)
Red sample * Unanimity	-0.0753	-0.0735	-0.166	-0.203
	(0.631)	(0.633)	(0.611)	(0.594)
Ambiguity	1.570***	1.560***	1.608***	1.686***
	(0.583)	(0.575)	(0.492)	(0.569)
Ambiguity * Unanimity	-1.412**	-1.383**	-1.492***	-1.463**
	(0.674)	(0.664)	(0.517)	(0.642)
Round	-0.0204**	-0.0204**	-0.0214**	-0.0214**
	(0.00877)	(0.00879)	(0.00926)	(0.00944)
Locus of Control		-0.0606	0.0836	0.204
		(0.0840)	(0.211)	(0.240)
Extroversion			-0.108	-0.0316
			(0.183)	(0.235)
Agreeableness			0.195	0.233
			(0.158)	(0.210)
Contientiousness			0.225*	0.388
			(0.124)	(0.285)
Emotional Stability			-0.0785	-0.112
			(0.172)	(0.191)
Openness to Experience			0.381**	0.459*
			(0.176)	(0.272)
Overall Ability				-0.259
				(0.243)
Maths Ability				0.124
				(0.178)
Verbal Ability				-0.0348
				(0.156)
Motivation				-0.0779
				(0.191)
Constant	-2.201***	-1.870**	-5.892***	-8.102***
	(0.617)	(0.727)	(1.639)	(2.874)
Observations	480	480	480	480

Robust standard errors clustered at subject level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Probit Estimations That Explain Red Individual Decisions, SEU Maximising Subjects

VARIABLES	(1) Red Vote	(2) Red Vote	(3) Red Vote	(4) Red Vote
Red Sample	1.551***	1.572***	1.585***	1.578***
	(0.269)	(0.280)	(0.274)	(0.274)
Unanimity Rule	-0.368	-0.318	-0.255	-0.202
	(0.504)	(0.521)	(0.574)	(0.613)
Red sample * Unanimity	-0.284	-0.272	-0.295	-0.244
	(0.377)	(0.381)	(0.370)	(0.364)
Ambiguity	-0.236	-0.155	-0.183	-0.106
	(0.412)	(0.433)	(0.439)	(0.484)
Ambiguity * Unanimity	0.520	0.472	0.472	0.407
	(0.529)	(0.538)	(0.558)	(0.586)
Round	-0.0135*	-0.0139*	-0.0140*	-0.0142*
	(0.00802)	(0.00808)	(0.00817)	(0.00830)
Locus of Control		-0.199	-0.161	-0.154
		(0.127)	(0.136)	(0.143)
Extroversion			-0.0218	0.0444
			(0.116)	(0.109)
Agreeableness			0.0319	0.111
			(0.134)	(0.164)
Contientiousness			-0.0262	-0.107
			(0.153)	(0.156)
Emotional Stability			-0.105	-0.0760
			(0.141)	(0.147)
Openness to Experience			-0.00409	0.0998
			(0.144)	(0.140)
Overall Ability				-0.102
				(0.156)
Maths Ability				0.00612
				(0.128)
Verbal Ability				-0.125
				(0.121)
Motivation				0.224*
				(0.128)
Constant	-0.698*	0.319	0.668	-0.376
	(0.397)	(0.691)	(1.418)	(1.684)
Observations	1,200	1,200	1,200	1,200

Robust standard errors clustered at subject level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Probit Estimations That Explain Red Individual Decisions, Ambiguity-loving Subjects

VARIABLES	(1) Red Vote	(2) Red Vote	(3) Red Vote	(4) Red Vote
Red Sample	0.868***	0.870***	0.858***	0.903***
	(0.189)	(0.190)	(0.187)	(0.197)
Unanimity Rule	0.543	0.551	0.600	0.325
	(0.388)	(0.383)	(0.369)	(0.378)
Red sample * Unanimity	0.202	0.199	0.239	0.243
	(0.308)	(0.306)	(0.308)	(0.317)
Ambiguity	0.218	0.222	0.198	0.128
	(0.317)	(0.310)	(0.309)	(0.314)
Ambiguity * Unanimity	-0.907**	-0.911**	-0.936**	-0.724*
	(0.415)	(0.413)	(0.403)	(0.411)
Round	-0.0106*	-0.0106*	-0.0111*	-0.0111*
	(0.00579)	(0.00580)	(0.00585)	(0.00603)
Locus of Control		0.0143	-0.0249	-0.00909
		(0.0972)	(0.101)	(0.102)
Extroversion			-0.0449	0.0192
			(0.0825)	(0.0803)
Agreeableness			0.0894	0.0424
			(0.132)	(0.153)
Contientiousness			0.155	0.174
			(0.106)	(0.124)
Emotional Stability			-0.0920	-0.0768
			(0.133)	(0.130)
Openness to Experience			0.0732	0.138
			(0.121)	(0.135)
Overall Ability				-0.166
				(0.121)
Maths Ability				-0.0227
				(0.120)
Verbal Ability				-0.237**
				(0.102)
Motivation				-0.0148
				(0.105)
Constant	-0.877***	-0.956*	-1.707*	-2.200**
	(0.296)	(0.549)	(0.905)	(1.040)
Observations	1,540	1,540	1,540	1,540

Robust standard errors clustered at subject level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Linear Estimations That Explain Red Individual Decisions, Ambiguity-averse Subjects

VARIABLES	(1) Red Vote	(2) Red Vote	(3) Red Vote	(4) Red Vote
Red Sample	0.348**	0.348*	0.375**	0.377**
	(0.168)	(0.169)	(0.150)	(0.146)
Unanimity Rule	0.316**	0.304**	0.302**	0.331**
	(0.134)	(0.131)	(0.113)	(0.124)
Red sample * Unanimity	0.0641	0.0630	0.0441	0.0356
	(0.196)	(0.198)	(0.183)	(0.178)
Ambiguity	0.329***	0.325***	0.294***	0.344***
	(0.103)	(0.101)	(0.104)	(0.105)
Ambiguity * Unanimity	-0.271*	-0.262	-0.248*	-0.271*
	(0.157)	(0.155)	(0.121)	(0.134)
Round	-0.00686**	-0.00685**	-0.00689**	-0.00686**
	(0.00293)	(0.00293)	(0.00292)	(0.00294)
Locus of Control		-0.0192	0.0211	0.0615
		(0.0287)	(0.0717)	(0.0793)
Extroversion			-0.0314	-0.0132
			(0.0562)	(0.0640)
Agreeableness			0.0656	0.0733
			(0.0532)	(0.0698)
Contientiousness			0.0835**	0.127
			(0.0380)	(0.0761)
Emotional Stability			-0.0228	-0.0357
			(0.0576)	(0.0628)
Openness to Experience			0.111**	0.142
			(0.0523)	(0.0844)
Overall Ability				-0.0798
				(0.0618)
Maths Ability				0.0377
				(0.0504)
Verbal Ability				-0.0131
				(0.0459)
Motivation				-0.0288
				(0.0584)
Constant	-0.0171	0.0876	-1.152**	-1.815**
	(0.0859)	(0.177)	(0.516)	(0.780)
Observations	480	480	480	480
R-squared	0.219	0.220	0.268	0.278

Robust standard errors clustered at subject level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Linear Estimations That Explain Red Individual Decisions, SEU Maximising Subjects

VARIABLES	(1) Red Vote	(2) Red Vote	(3) Red Vote	(4) Red Vote
Red Sample	0.546***	0.548***	0.545***	0.536***
	(0.0792)	(0.0799)	(0.0816)	(0.0815)
Unanimity Rule	-0.106	-0.0927	-0.0775	-0.0577
	(0.146)	(0.147)	(0.168)	(0.180)
Red sample * Unanimity	-0.102	-0.100	-0.0994	-0.0928
	(0.116)	(0.115)	(0.116)	(0.115)
Ambiguity	-0.0668	-0.0448	-0.0495	-0.0242
	(0.125)	(0.129)	(0.134)	(0.147)
Ambiguity * Unanimity	0.151	0.141	0.138	0.122
	(0.162)	(0.161)	(0.169)	(0.175)
Round	-0.00421*	-0.00421*	-0.00420*	-0.00419*
	(0.00245)	(0.00245)	(0.00246)	(0.00247)
Locus of Control		-0.0616	-0.0504	-0.0486
		(0.0382)	(0.0415)	(0.0407)
Extroversion			-0.00693	0.0122
			(0.0353)	(0.0325)
Agreeableness			0.00620	0.0265
			(0.0400)	(0.0480)
Contientiousness			-0.00447	-0.0241
			(0.0462)	(0.0475)
Emotional Stability			-0.0312	-0.0218
			(0.0442)	(0.0465)
Openness to Experience			0.000814	0.0305
			(0.0441)	(0.0415)
Overall Ability				-0.0307
				(0.0467)
Maths Ability				0.00167
				(0.0369)
Verbal Ability				-0.0339
				(0.0355)
Motivation				0.0615
				(0.0383)
Constant	0.250**	0.568**	0.669	0.362
	(0.120)	(0.216)	(0.453)	(0.514)
Observations	1,200	1,200	1,200	1,200
R-squared	0.258	0.270	0.274	0.292

Robust standard errors clustered at subject level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Linear Estimations That Explain Red Individual Decisions, Ambiguity-loving Subjects

	(1)	(2)	(3)	(4)
VARIABLES	Red Vote	Red Vote	Red Vote	Red Vote
Red Sample	0.307***	0.308***	0.300***	0.304***
	(0.0663)	(0.0668)	(0.0653)	(0.0661)
Unanimity Rule	0.194	0.196	0.215*	0.125
	(0.120)	(0.119)	(0.114)	(0.117)
Red sample * Unanimity	0.0552	0.0541	0.0629	0.0618
	(0.103)	(0.104)	(0.102)	(0.103)
Ambiguity	0.0674	0.0684	0.0593	0.0341
	(0.102)	(0.100)	(0.0973)	(0.0947)
Ambiguity * Unanimity	-0.298**	-0.299**	-0.306**	-0.229*
	(0.136)	(0.135)	(0.130)	(0.132)
Round	-0.00349*	-0.00350*	-0.00348*	-0.00348*
	(0.00190)	(0.00190)	(0.00191)	(0.00191)
Locus of Control		0.00516	-0.00949	-0.00429
		(0.0316)	(0.0332)	(0.0332)
Extroversion			-0.0138	0.00347
			(0.0273)	(0.0264)
Agreeableness			0.0264	0.0112
			(0.0397)	(0.0451)
Contientiousness			0.0499	0.0516
			(0.0335)	(0.0364)
Emotional Stability			-0.0272	-0.0191
			(0.0424)	(0.0398)
Openness to Experience			0.0256	0.0461
			(0.0387)	(0.0415)
Overall Ability				-0.0504
				(0.0355)
Maths Ability				-0.00860
				(0.0359)
Verbal Ability				-0.0730**
				(0.0314)
Motivation				-0.00255
				(0.0319)
Constant	0.194**	0.166	-0.0739	-0.199
	(0.0851)	(0.173)	(0.276)	(0.322)
Observations	1,540	1,540	1,540	1,540
R-squared	0.157	0.157	0.177	0.207

Robust standard errors clustered at subject level in parentheses
*** p<0.01, ** p<0.05, * p<0.1