ELECTORAL COMPETITION UNDER POLICY COMPLEXITY AND POLITICAL SOPHISTICATION: A COMPUTER MODEL

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Abstract

This dissertation poses questions about the attainability of representative democracy while contemplating the fact that voters lack the intellectual capacity to make the decisions that maximise their own utilities. The potential for voters to vote incorrectly depends on their so called political sophistication, on the complexity of the issue being addressed at an electoral campaign and the complexity of the candidates' proposals. The outcomes of interest are the convergence of political parties, the proportion of incorrect voters, the level of competition between parties and the general welfare of the voters. A model with two parties and stochastic voters who do not have perfect information is developed, with assumptions justified, and then analysed. The removal of parties' complete information makes the model analytically intractable. Therefore, agent-based modelling is used to study the desired dynamics. Given that there are no optimal strategies for parties, the experiments simulate parties with varying desiderata. Taking advantage of the computational affordances of agent-based modelling, settings with third parties were also studied. Results show that, as previously suspected by political sophistication scholars, the political sophistication of voters have an effect on the likelihood of incorrect voting, the likelihood of incorrect outcomes, the level of party polarisation, and the degree of party competition.

Keywords: Electoral Competition, Formal Model, Correct Voting, Political Sophistication, Agent-Based Modelling

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Chapter 1

Introduction

Government in countries far and near are now unrecognisable from the forms they embodied only a hundred years ago. Most societies today recognise in their constitutions their people's right to have a say in their national government. Many civilians are proud to live in democracies, and some of them go through great pains to defend them from perceived threats to take their vote away. Meanwhile, during the same transformative century, the bureaucratic state has grown to new heights, becoming involved in complex matters all in the name of people who are not even aware of such operations, and even if they were, would not be able to grasp large parts of the endeavour.

In regards to the demands of political knowledge, normative theories of democracy differ in strictness (Somin, 2006). Still, it is no surprise that many have expressed their disapproval of the democratic system or of the democratic voter. Their claim says that if the electorate has trouble knowing what it wants, whatever signal they sent to the political elites can be damaging; therefore, representative democracies cannot function without a minimum amount of political sophistication from their citizens (Rapeli, 2018). To protect its voice and make use of the ballot, an effective citizen shows interest in politics and stays informed about it (Berelson et al., 1954).

Perhaps a representative democracy is asking too much from the average citizen who has to respond to other more immediate demands of modernity. Year after year, government policies are growing in provisions and become more specific in their implementation. Representative democracy expects voters to stay abreast of the activity of a vast bureaucracy while also being able to predict what coalition parties might form should they cast a vote in their favour. They must be able to understand every policy proposal, determine if it is morally correct, judge it by its technical feasibility and then assess whether the cost-benefit trade-off is a fair deal for a treasury that deals with non-trivial quantities. It is no surprise then that democracies are paying a hefty price to serve their citizenry while also remaining largely unresponsive (Adam et al., 2019). Policy complexity is increasingly unmanageable for the common voter. Figure 1.1 shows that the number of proposals political candidates make in an electoral campaign has been increasing steadily every year.

Schumpeter (2013) argued that electoral systems are pointless in their attempt to address the principal-agent problem of the electorate and its representatives. For voters to be capable of enacting political accountability, they require not only more information than what they have but also

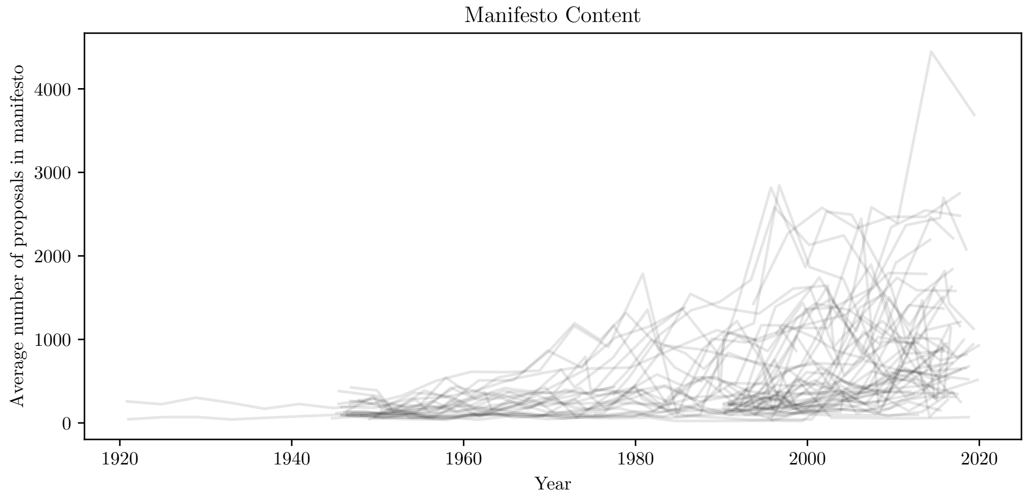

Figure 1.1: The mean size of manifesto over time, it is calculated by counting the number of proposals of every candidate and then obtaining the average. Each line is a country. Data obtained from the Manifesto Project.

more thought than what they have to spare. If such premonition were true, then there is strong justification for a pessimistic view of democracy (Pierce, 2015).

This dissertation poses questions about the attainability of representative democracy while contemplating the fact that voters lack the intellectual capacity to make the decisions that maximise their utilities. The potential for voters to vote incorrectly depends on their so-called political sophistication, on the complexity of the salient issues in the electoral campaign and the complexity of the candidates' proposals. The outcomes of interest are the convergence of political parties, the proportion of incorrect voters, the level of competition between parties and the general welfare of the voters.

A model with two parties and stochastic voters who do not have perfect information is developed, with assumptions justified, and then analysed. The withdrawal of parties' complete information makes the model analytically intractable. Therefore, this study proceeds to use agent-based modelling to observe the desired dynamics directly. Given that there are no optimal strategies for parties, the experiments simulate parties with varying desiderata. Taking advantage of the computational affordances of agent-based modelling, settings with third parties were also studied.

Results show that, as previously suspected by political sophistication scholars, the political sophistication of voters affect the likelihood of incorrect voting, the likelihood of incorrect outcomes, the level of party polarisation, and the degree of party competition.

Chapter 2

Literature Review

2.1 Electoral Competition

Suffrage has been perhaps the most recognisable feature from the breed of representative democracies that emerged in the 17th century. Just as most economists expect market systems to produce efficient prices for private goods, most political scientists expect electoral competition to encourage political candidates to tune their platforms to fulfil the public requirements of the franchise, the demand side. One of the first scholars to apply economic theory to the study of the behaviour of parties and voters in electoral competition was Anthony Downs. He posited that politicians, just as voters, are rational and economic actors that act for their selfish ends: “parties formulate policies to win elections, rather than win elections to formulate policies” (Downs, 1957).

The approach came at a time where political science, as an academic field, was dominated by behavioural studies (Ansolabehere, 2009). The introduction of a spatial model of voting forked a branch now known as political economy and has been it’s “theoretical workhorse” ever since (Cox, 2001). Such a framework allows political scientists to draw political outcomes from population characteristics in a given institutional setting. For example, Duverger predicted that first-past-the-post systems would produce two dominant parties, while proportional systems tend to a larger number of parties(1954). Political scientists have been positioning voters along an ideological left-to-right spectrum has since the early days of the French First Republic (Heywood, 2017), but only since Down’s application of Hotelling’s Location Model and Black’s single-peakedness assumption have they applied this framework to produce positive claims (Black, 1948; Hotelling, 1929). Converse showed empirically that the preferences of real voters in different issues present correlations in bundles, thus allowing modellers to describe policy-based competition in spatial dimensions (1964). More recently, Benoit and Laver found that two and sometimes three independent dimensions are enough to capture preference information (2006).

A central prediction derived from spatial theory is the median voter theorem: provided that there are only two vote share maximising candidates, voters always vote, have no incentive to misconstrue their single-peaked preferences, the median voter’s preference dictates the outcome of a majority rule voting system. Scholars rely on the theorem as a mean to explain why politicians will tend to adopt similar platforms and why radical candidates or parties will seldom get elected.

Although there is evidence to support this prediction, there are also contradicting episodes (Fujiwara, 2015; Holcombe, 1980; Lee et al., 2004).

The divergence of political parties has been an object of study for multiple generations of political scientists, each of which has offered their unique explanation for why candidates diverge. The valence theory accommodates a dictating median voter with divergence. Candidates who expect to be at a disadvantage for non-policy reasons are motivated to move away from the median in order to avoid losing out in valence terms against an advantaged candidate (Ansolabehere & Snyder, 2000; Wittman, 2005). Another possibility is that parties diverge because they operate under the assumption that there is a threat of a third party entering the competition. If they position themselves at equidistant points around the mean, the third party will not find an opportunity to steal the deciding vote (Palfrey, 1984). Alternatively, it is possible that parties are not merely vote-share optimisers and have preferences beyond holding political office. Politicians usually are experienced professionals capable of receiving higher wages than those offered in the civil service, so they are likely to be motivated by non-pecuniary factors, which is the explanation behind the Besley and Coate (1997) citizen-candidate model. Far from having exhausted all the literature behind political divergence, a final element to consider is the fact that parties in electoral competitions are rarely atomic, meaning that they are groups of individuals who, even though they might have the same goal for the group, have perverse individual incentives (Snyder Jr, 1994).

All of the models mentioned above are deterministic voting models because candidates are fully confident of the vote distribution for any position they and their competitors take. On the other hand, probabilistic voting models mean that candidates operate under uncertainty and strategise accordingly (Coughlin, 1992). Calvert (2013) contended that probabilistic voting models are realistic, for candidates are never truly capable of predicting the response of the electorate perfectly. Whether these models continue to predict party convergence will depend on the assumptions they permit. Just like with purely policy-oriented deterministic models, a stochastic model can explain divergence if it assumes that there are valence issues in place and if that voter error across different parties is correlated (**adamsPolicyDivergenceMulticandidate**; Nixon et al., 1996).

The results obtained from rational choice are more paradoxical than complete. Utility maximising voters should not take the time to vote, nor should they invest time to stay on top of public affairs. Most voters are not going to cast a meaningful vote; they are too far from the median to be pivotal. Added up with the fact that the difference in utility between the two candidates might not be larger than the cost of travelling to the polling centre, there is no incentive to cast a vote (Ledyard, 1984). Following this line of reasoning further, Downs realised that the payoffs from actively learning about policies are insignificant, so it pays to be politically ignorant. Furthermore, Caplan posits that it might not even be rational to be rational, as people might not accrue any benefits from updating their beliefs after receiving new information (2001).

2.2 Bounded Rationality Framework

In order to study the decision making of actors placed in electoral competition, be them voters or parties, researchers have had to dig deeper than merely describing optimal decision functions. Herbert Simon argued that understanding behaviour through the lens of comprehensive rationality is futile. The rational choice framework is unable to predict social outcomes because it assumes too much about the goals of actors, who might have multiple ones, and might not even be well-aware of them nor of the nature of their trade-offs (Simon, 1985). With the introduction of the bounded rationality framework, Simon proposed a novel approach where actors continue to be driven by the pursuit of their goals, but despite that, they are constrained by their access to accurate information and by their cognitive and emotional architectures.

The bounded rationality framework recognises that individuals have to dedicate time and effort in order to find the optimal decision, unlike rational choice framework which assumes that players are fully informed and have the time and capacity to find the best responses. In reality, even if players had the means to obtain all the required information in order to optimise their strategic situations, they might not even have the memory capacity to store all the information nor the cognitive facilities to produce the correct calculations from the data. For these reasons, models of electoral competition should leave behind unrealistic expectations of best responding players.

2.3 Correct Voting

Provided that the bounded rationality framework is accurate in representing human behaviour, it is safe to assume that voters do not always make the decisions that maximise their utility. They are no longer assumed to be perfectly rational, and they are prone to making mistakes. What follows is a review of the multiple and parallel branches of literature that cover the causes and consequences of a non-optimal voter.

Should a voter submit a vote for the candidate she would have chosen with complete awareness of the consequences that follow from that choice and all other alternatives, she has voted correctly (Dahl, 1989). Voters are capable of voting incorrectly, especially if they lack political knowledge or political sophistication (**lauCorrectVotingThirtythree2014**; Gilens, 2001; Sokhey & McClurg, 2012). Lau and Redlawsk (1997) utilised a mock election which manipulated the available knowledge of experiment subjects whom the researchers asked to vote. They showed that voters are more likely to choose correctly if there are relatively fewer candidates or when the candidates are more distinct.

Political sophistication can be hard to define. Luskin (1987) offered a definition which involves the number of beliefs and attitudes a person holds, the range in topics these cognitions span over, and the associations this person has between them. However, for all intents and purposes, it is by and large referred to as the effective use of political knowledge. Scholars will often conflate political sophistication with political knowledge and refer to them as the same feature (Fiske et al., 1983; Larkin et al., 1980). Still, several studies indicate that testing a person's accrued knowledge is the best way to determine whether she is politically sophisticated (Carpini & Keeter, 1993). Luskin (1990) did not find that informational variables such as exposure to political information in media or level of education explained levels of political sophistication. This finding is compatible with the concept above of rational irrationality. Instead, it was motivational factors such as occupation and intrinsic interest that showed higher correlations. Nevertheless, there remains those who dispute the validity of sophistication measurements because it relies on surveys containing questions that can be too sparse or carried out by pollsters biased in determining the level of a respondent's knowledge (Rapeli, 2018). Regardless, such methods have been used continuously and determined that affluent and educated middle-aged men tend to display higher degrees of political knowledge (Carpini & Keeter, 1996; Fraile, 2011; Rapeli, 2013).

Voters may not acquire information with the sole purpose of voting; they could be doing so for non-pecuniary motivations instead and derive pleasure from participating in political discussions (Aldashev, 2010; Somin, 2006). The electoral context is also used by scientists to explain a voter's acquisition of political information. Seyd (2020) looks at the longevity of the incumbent, which if long enough, can give voters the capacity to attribute blame. He also pays special attention to the contrast between the running candidates, given that a relatively large difference would incentivise voters to acquire political knowledge.

The effects of political sophistication and information, or lack thereof, are not understudied. While it can be clear that more information will lead to better choices for voters and institutions (Lau & Redlawsk, 1997) presumably because voters have a better chance at identifying those candidates that share their views (Visser et al., 2007). Althaus (1998) determined that if the public had perfect knowledge about politics, then the electoral outcomes would be different 20% of the time. By analysing survey data, Bartels (1996) has also concluded that the uninformed vote was causing distortions in collective preferences.

2.4 Agent-Based Models

Advances in software technology have allowed social scientists to simulate the behaviour of their objects of study through agent-based models (ABM). ABMs consist of independent agents, or players, interacting with each other in a computer simulation that reproduces their environment, often consisting of time and space (Holland & Miller, 1991). Unlike with mathematical modelling, ABM use is not solely focused on finding the equilibrium of a model, but rather, it attempts to describe the dynamics of a system.

Agents are constrained in memory and cognition, just like real humans are. Modellers endow ABM with algorithms based on research on human behaviour (Kim et al., 2010). This realistic mapping of strategic players offers researchers the opportunity to aggregate outcomes from the micro to the macro, while also generating data that can they can unpack in the other direction. The lack of analytic tractability and the quick expansion of model parameter space is offset by the potential to link multiple domains and permit more considerable heterogeneity in agents

Political scientists have used ABMs to produce time series depicting electoral competition (Fowler & Smirnov, 2005; Laver, 2005; Smirnov & Fowler, 2007), to model incompletely informed parties searching for better platforms (Kollman et al., 1992), to explain the likelihood of incumbent victory in complex electoral landscapes (Wichowsky, 2012), to test the influence of opinion variation in a constitutional amendment process (Whicker & Strickland, 1990), among other things.

Chapter 3

Model Definition

This chapter presents a general model of electoral competition with heterogeneous sophisticated voters.

Elections are held at every time period t to select a policy for an issue with natural complexity $q \in \mathbb{Q}^+$. This natural complexity remains constant through periods. There are $c \in \{A, B\}$ candidates that, for every election at each time period, propose a policy with ideological preference $p_t^c \in \mathbb{Q}$ and with complexity q_t^c to address the issue.

There are $i \in \{1, 2, \ldots, n\}$ voters with heterogeneous and exogenous ideology preferences $p_i \in \mathbb{Q}$ and political sophistication $s_i \in \mathbb{Q}^+$. Given that the ideology of voters can expand infinitely in both directions, it is fair to say that the probability density of a voter's ideal point approaches 0 as it goes further to the extremes. Therefore, the policy preferences of voters are i.i.d. and drawn from a normal distribution with mean 0 and standard deviation σ. The political sophistication of voters are i.i.d. and drawn from a gamma distribution with mean and standard deviation σ. The support for the shape of the sophistication distribution comes from the assumption that only a tiny minority in society have large amounts of political sophistication.

Voters cast their vote according to a loss function

$$l_{it}(c) = \sqrt{\lambda(p_i - p_t^c)^2 + (1 - \lambda)(q - q_t^c)^2}$$

where $\lambda \in [0, 1]$ is a parameter known by all players that mixes the utility voters give to candidates proposing policies with ideological positions that match their preference and the utility they give to candidates proposing policies with complexity that matches the issue. Note that the loss function is essentially a distance function in a Euclidean space with ideology in one dimension and complexity in the other. Voters tend to be risk averse, which is the reason behind the quadratic form behind their loss function. This is a common assumption done both in analytical and computational models (de Marchi, 2005; Schofield & Sened, 2006).

Given that voters are constrained by their political sophistication, they can have mistaken beliefs over what the issue complexity q, their preference p_i, and candidate policy proposal (p_t^c, q_t^c) really are. Their beliefs are marked by a tilde and are specified by adding a noise term ϵ. Therefore, the belief of voter i of its own preferences is

$$\tilde{p}_i = p_i + \epsilon_i^P$$

where ϵ_i^P and ϵ_i^Q (the noise term in $\tilde{q}_i$) are independently drawn from an uniform distribution with range $[-\gamma_i, \gamma_i]$. γ_i is the difference between the voter's political sophistication and the issue's natural complexity:

$$\gamma_i = \begin{cases} 0 & for\ s_i \geq q \\ q - s_i & for\ s_i < q \end{cases}.$$

Beliefs $\tilde{p}_{it}^c$ and $\tilde{q}_{it}^c$ are similar, except their noise bounds are defined by γ_{it}^c which compares the voter's political sophistication to the candidate's policy complexity rather than to the issue's complexity:

$$\gamma_{i,t}^c = \begin{cases} 0 & for\ s_i \geq q_t^c \\ q_t^c - s_i & for\ s_i < q_t^c \end{cases}.$$

Given the voters beliefs, their decision function is actually defined by

$$\omega_{it}(c) = \sqrt{\lambda(\tilde{p}_i - \tilde{p}_{it}^c)^2 + (1-\lambda)(\tilde{q}_i - \tilde{q}_{it}^c)^2}. \tag{3.1}$$

Voters try to minimise their decision function ω. Candidates care about maximising their vote share. The candidate with the highest vote share becomes elected.

Chapter 4

Solution Concept

4.1 Nash Equilibria

Finding the Nash Equilibria of the model defined in chapter 3 using mathematical analysis is as follows. Candidates have to choose a p_t^c and q_t^c so that they maximise their probability of having more votes than the other candidate. Therefore, they maximise π_t^c formally defined as

$$\pi_t^c = \sum_i Pr(\omega_{it}^c \leq \omega_{it}^{-c}). \tag{4.1}$$

Equation 3.1 can be understood as the sum of two parts. The first one being the requirement for candidate proposals to be close to the voter's ideological positions, and the second one being the requirements for candidates to submit proposals with a complexity that matches the complexity of the issue at hand. From here onward, they are respectively referred to as the ideology and complexity factors.

Assuming that the complexity factor was non-existent and therefore all error terms ϵ are equal to 0, the parties' proposals converge to the median voter in p. This strategy profile where both parties proposals have $p^c = p_m$ and $q^c = q$, where p_m is the preference of the median voter, is a Nash Equilibria if both parties have no profitable deviation.

$$\begin{aligned}
\omega_{it} &= \sqrt{\lambda(\tilde{p}_i - \tilde{p}_m)^2 + (1-\lambda)(\tilde{q}_i - \tilde{q}_{it}^c)^2} && (4.2)\\
&= \sqrt{\lambda(p_i + \epsilon_i^P - (p_m + \epsilon_{it}^{cP}))^2 + (1-\lambda)(q + \epsilon_i^Q - (q + \epsilon_{it}^{cQ}))^2}. && (4.3)
\end{aligned}$$

Noise terms ϵ have two possible values. The first being 0 in the case that voter's political sophistication is larger than the compared complexity and the second one being a value drawn from a uniform distribution which parties can expect to converge to their mean when iterating over a large number of voters. Given that the bounds of the uniform distribution are opposite numbers, this mean is 0. Therefore $E[\epsilon] = 0$ and it follows that

$$\pi_t^c = \sum_i Pr(\sqrt{\lambda(p_i + E[\epsilon_i^P] - (p_m + E[\epsilon_{it}^{cP}]))^2 + (1-\lambda)(q + E[\epsilon_i^Q] - (q + E[\epsilon_{it}^{cQ}]))^2} \leq \omega^{-c}) \tag{4.4}$$

$$= \sum_i Pr(\sqrt{\lambda(p_i - p_m)^2} \leq \omega^{-c}). \tag{4.5}$$

To confirm whether this is a Nash Equilibria, we evaluate policy changes along the p and q dimensions both independently and simultaneously.

If a candidate moves p in any direction by δ, then it is a best response if

$$\sqrt{\lambda(p_i - (p_m + \delta))^2} \leq \sqrt{\lambda} \tag{4.6}$$

which because of the Median Voter Theorem we know that the optimal policy for a candidate is the one that is equal to the median voter's preference [1]. It follows that no value of δ will make the left side of the inequality smaller than the right side.

If a candidate moves q in any direction by δ then the ϵ_i^c also changes but it is also expected to be 0. It is a best response if

$$\sqrt{\lambda(p_i - p_m)^2 + (1-\lambda)(q - (q + \delta))^2} \leq \sqrt{\lambda(p_i - p_m)^2} \tag{4.7}$$

$$\sqrt{\lambda(p_i - p_m)^2 + (1-\lambda)\delta^2} \leq \sqrt{\lambda(p_i - p_m)^2}, \tag{4.8}$$

which can never happen as long as $\lambda < 1$.

So far it has been shown that there is no profitable deviation for a candidate when making changes either in p or q. The remaining case is when the candidate simultaneously changes p by δ_p and q by δ_q. This is a best response if

$$\sqrt{\lambda(p_i - p_m - \delta_p)^2 + (1-\lambda)\delta_q^2} \leq \sqrt{\lambda(p_i - p_m)^2}$$

which is only true if

$$\lambda((p_i - p_m)^2 - (p_i - p_m - \delta_p)^2) \geq (1-\lambda)\delta_q^2 \tag{4.9}$$

$$\delta_p(p_i - p_m) \geq \frac{\lambda\delta_p^2 + (1-\lambda)\delta_q^2}{2\lambda}. \tag{4.10}$$

Let f be the function for candidates to optimize

$$f(\delta_p, \delta_q) = \frac{\lambda\delta_p^2 + (1-\lambda)\delta_q^2}{2\lambda\delta_p}$$

[1] Appendix A.1 shows why this cannot be demonstrated using $E[p_i - p_m] = 0$.

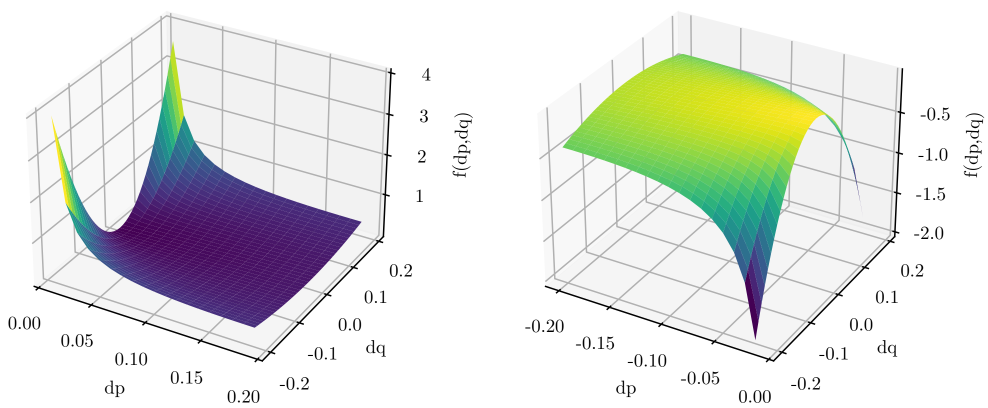

Figure 4.1: $f(\delta_p, \delta_q)$ surface plot. On the left $\delta_p > 0$ and on the right $\delta_p < 0$.

therefore following equation 4.10 and considering that δ_p can be have either a negative or positive value, the optimality constraint is conditional:

$$\begin{cases} \delta_p > 0 & \Rightarrow p_i - p_m \geq f(\delta_p, \delta_q) \\ \delta_p < 0 & \Rightarrow p_i - p_m \leq f(\delta_p, \delta_q) \end{cases}.$$

Assuming that δ_p is negative and that $\lambda = 0.5$, the first-order condition of

$$f(\delta_p, \delta_q)$$

to obtain its maximum values is

$$2\delta_p - \delta_p^2 - \delta_q^2 + \frac{2\delta_q}{\delta_p} = 0$$

which shows that there exists multiple profitable deviations for candidates [2]. This is visible in figure 4.1 shows the surface plot of f over δ_p and δ_q where there exists a flat area at the bottom of the surface where $\delta_p < 0$ and at the top of the surface where $\delta_p > 0$. All of the points in flat areas are equal in payoff, therefore there is no unique Nash Equilibria and they are all weak.

4.2 Agent-Based Modelling

4.2.1 Analytical Tractability

The conclusions arrived at employing mathematical analysis are not enough to derive the insights this paper looks to discuss. In order to answer the questions of the paper more concretely, this

[2] Appendix A.2 includes the partial derivatives of f.

paper further analyses the model with the use agent-based modelling, which relieves the modeller from concerns of over specifying the model and making it analytically intractable. The computer simulations of the rigorous specification of voter and candidate behaviour also provides the researcher with the capacity to inspect otherwise unobservable features of the system. Hence, by shifting from classical analysis to computational modelling, the model is permitted to expand in complexity. Additionally, computational models provide researchers with the tools to inspect the state of the model at any point of the game.

As shown above, for parties to choose the pair $\{p^c, q^c\}$ that optimises equation 4.1 they must know the ideological preference of the median voter p_m and the natural complexity of the issue q. Parties are often involved with lobbyists and think-tanks who provide an information subsidy for them; therefore, it is reasonable to assume that parties have higher levels of political sophistication than voters. However, it is also true that these external organisations are biased with their agendas; hence, the model assumes that parties cannot completely trust them to know q. Likewise, the median voter is also not immediately recognised because of the changes in individual opinions of the voters between electoral cycles. The model's median voter does not change between periods but it is not essential to the argument of this paper that parties are aware of the fact.

Therefore, besides information in the game being imperfect for unsophisticated voters, the model is now also one of incomplete information where parties do not know the ideological preferences with political sophistication of all voters, and the true complexity of the issue. Every time period, the parties are signalled with the vote share, policy proposals $\{p^c, q^c\}$ of both parties in the previous election, and the preferences and sophistication of the voters that supported them on the previous election, which they use to estimate the relevant parameters. Therefore, candidates study the probability function $Pr_t(q|\Pi^c, P^c, Q^c, \Pi^{c-1}, V^c, P^{c-1}, Q^{c-1})$ in order to obtain q where $\Pi^c = \{\pi_x^c \ \forall \ x \in [0, t)\}$, $P^c = \{p_x^c \ \forall \ x \in [0, t)\}$, $Q^c = \{q_x^c \ \forall \ x \in [0, t)\}$ and V^c is the set of all voters that voted for candidate c in the previous election.

4.2.2 Model Extensions

Optimising equation 4.1 is now deemed to be analytically intractable. There is no provable best response strategy, so the agent-based model assumes that candidates make use of informal decision heuristics, which is more fitting to what is observable in practice: players have different styles and it is not often that they all share the same style (MacGregor et al., 2006).

These decision heuristics, albeit non-optimal, are the representation of the underlying preferences of the parties that implement them. Laver (2005) identifies three common values that candidates can concern themselves with: party vote share, party policy position and the positions of their current supporters. While in practice, parties can have preferences that are linear combinations of these three common values, the parties defined in the model will only have one of these as a priority. As done by Laver and Sergenti (2011) and previously by Laver alone, this paper also implements the strategies that best approximate these party objectives. The code, implemented in NetLogo, for the following strategies are available in Appendix A.3.

Parties that only care about maximising vote share are called hunters. As long as their vote share in the previous period is larger than the vote share in the time period immediately before, they change their position by a predetermined amount δ in a given direction. If their vote share has decreased, they will change direction randomly and continue in that direction as long as their vote share grows. The adaptive learning literature often showcases this strategy (Nowak & Sigmund, 1993); however, given its greedy and naive nature, it cannot be considered to be a near-optimal solution. A more sophisticated algorithm would record the position in which it was most successful or execute more complex calculations derived from formal analysis. Even so, the hunter algorithm is simple enough to implement in a computational model and does reasonably well in finding p_m and q even though it does not require considerable computer resources.

Aggregator parties are those who only care about representing the preferences of their supporters. Every election, they will run with a proposal situated at the centroid of all their supporters in the previous election. Accordingly, the result of this algorithm is a more representative party that responds to the preferences of their supporter. The assumption that parties have knowledge of the preferences of their supporters can be validated by the parties with more democratic internal procedures.

Finally, sticker parties are those that care solely about their ideological preferences. Their positions in ideology and complexity remain fixed through the periods. They should be the worst performing type of party, as they do not in any way care about responding to the number of voters that represent them. Models with only sticker parties are static and can serve as a benchmark against which the rest of the decision heuristics can compare.

Since it is much less taxing to analyse models with larger numbers of parties computationally than formally, the agent-based model can afford to include scenarios where there are more than two parties. Because this paper's model is essentially a spatial model in one dimension, and because of limited computation resources available, analysing more than three parties is out of the scope of this study. With competitions of more than two parties, the possibility of strategic voting becomes available to voters. Once again attributing to the computational constraints and the analytical complexity, the model specification does not permit voters to misrepresent their believed preferences and they only vote sincerely.

4.2.3 Outcomes of Interest

At any given period, there are variables that indicate what determined inputs produce specific outcomes, under the assumption of correct voting dependant on political sophistication. These variables measure the specific properties of the model states, which this study uses accordingly to answer its questions of interest.

The first indicators pertain to the positions of the parties and are useful to determine whether parties converge to similar positions. When there are only two candidates, the distance between the complexity and the distance between the ideological positions of their policy proposals is recorded. Under three party games, the mean party eccentricity replaces the measure of the distance between parties. A party's eccentricity is its Euclidean distance from the voter with mean policy preferences and mean sophistication.

Competition among parties can be measured by calculating the effective number of parties (ENP) (Laakso & Taagepera, 1979). It is derived by adding up the squares of the votes each party receives and using this number to divide the square of total votes:

$$ENP = \frac{n^2}{\sum_c (\pi_c n)^2}.$$

Should the ENP equal the actual number of parties, it can be said that the model is at a state where there is perfect competition, that is, voter support is evenly distributed among parties.

Given a candidate that has captured the largest vote share, the mean loss is the average of the loss functions of all the voters, and it serves as a mark of the general contentment. It is especially relevant when comparing against the mean precise loss, which is the average of the loss functions of all the voters have if they have perfect knowledge. The difference between the mean loss and mean precise loss can serve as a display of the cost of incorrect voting.

The size of the proportion of voters who vote incorrectly is recorded, provided that incorrect voting is the primary occurrence of interest of the model. A voter votes incorrectly if they cast a vote for a party that is not the one that minimises their loss function.

4.3 Experiment Design

4.3.1 Run Parametrisations

The computational experiment consists of simulating the model and recording the observable outcomes. This section discusses the methodological issues that arise when estimating the quantities of interest from obtained data and how it is that they can be relied upon with confidence.

As with all experiments, the objective of a computational experiment is to vary one or more input parameters while holding everything else constant. The basic unit of analysis is a run, defined as an execution of the model for a determined vector of input parameters.

For the model presented in this paper, there are five input parameters: q, λ, θ, party strategy and the number of parties. θ is a parameter used to scale sophistication in the calculation of γ:

$$\gamma_i = \begin{cases} 0 & for\ \theta s_i \geq q \\ q - \theta s_i & for\ \theta s_i < q \end{cases}.$$

θ also applies to the calculation of $\gamma_{i,t}^c$.

Ideally, the experiment executes runs for every possible combination of input parameters to obtain a perfect sample of parametrizations. Unfortunately, this is not possible in this study given that q, λ and θ are in $\mathbb{R}$. These parameters in continuous space can be replaced by discrete sets of evenly spaced values that are within the range of the parameters. For example, the experiment could use $\{0, 0.1, 0.2, \ldots, 1\}$ to investigate λ and θ. Assuming that we also obtain a set of 40 discrete values for q and considering that there are two possible values for the number of parties and three values for party strategies, the combination of the input parameters produces 29040 vectors, each of which to be run.

It is important to note that the selected points are arbitrary. For example, there is no specific reason for having chosen 11 points within the range of λ; it could have been 5 or 30 points. Given that the model is non-linear and complex [3], there is also no reason to believe that the selected input parameters will produce a complete picture of the possible outcomes.

What this paper does instead is set-up the experiment so that it uses Monte Carlo parametrisations. Accordingly, it randomly samples, from uniform distributions, precise parameter values for each model run. Therefore, all points within the range of the input space have equal chances of being run.

4.3.2 Markov Processes

The number of periods, or iterations, executed in a run is determined by the characteristics of the process that generates the data. For this reason, all run repetitions are characterised as time-homogeneous Markov Chains. The outcomes from a given iteration in a run are the realisations of a state space. That is, the vector of outcomes y_t is an element of state space Y_t, which is the collection of all possible outcome combinations. The distribution vector π_t represents the probability distribution over Y_t. If $\pi_t(Y_t) = 1$ the process is said to be deterministic, otherwise it is probabilistic or stochastic. A Markov process is a stochastic process where the probability of any future outcome depends only on the current outcome:

$$P_{ij}^{t,t+1} = Pr(X_{t+1} = j | X_t = i, X_{t-1} = i_{t-1}, \dots, X_0 = i_0) = Pr(X_{t+1} = j | X_t = i).$$

If $P_{ij}^{t,t+1}$ is constant across time, it is said to be a time-homogeneous Markov Chain.

The evolution of state space distribution π over t will depend on the transition probability matrix, which is the collection of all the one-step transition probabilities among all possible states. Vector π will converge to a π_∞ in all time-homogeneous Markov Chains, where $\lim_{t\to\infty} \pi_t = \pi_\infty$. Once a process has reached π_∞ it is said to have entered steady state.

All time-homogeneous Markov processes tend towards at least one steady state. If regardless of initial state space distribution π_0, the process converges on a unique π_∞ then this process is called ergodic. Given that all stochastic time-homogeneous Markov processes with finite state spaces are ergodic (Ljungqvist & Sargent, 2018), all runs executed by this study can be assumed to eventually enter steady and run-unique spaces.

The computational model can be interpreted as a stochastic time-homogeneous Markov Chain with a finite space because it meets the requirements. Given an input vector, the state of the model x_t can be described by party proposals $\{p_t^c, q_t^c\}$ and it is finite given that the model is hosted by a computer. All of the outcomes of interest can be calculated by using x_t alone. Furthermore, provided only the listed party strategies described above are in play, the future positions of the candidates do not depend on states earlier than x_t. Finally, the probability of a given x_t depends on the transition probabilities, which are a function of the run inputs and the model assumptions.

[3] γ is not continuous and the outcomes of the model depend on the interaction of parties.

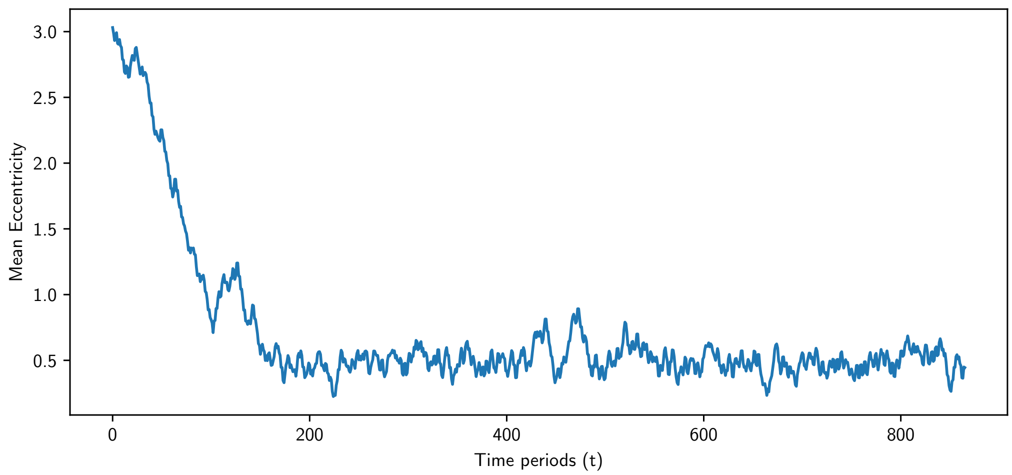

Figure 4.2: Mean eccentricity results from an example run with 2 hunter parties. The process stabilises around time period 170.

4.3.3 Outcome Estimates

Having recognised that the model is ergodic and prone to reaching a steady state. Process outcomes obtained before π has reached a steady state cannot be considered indicative of model behaviour given that they are only transitioning. Different repetitions of a run will transition across different non-steady states. Hence, only the outcomes from steady states will be recorded and used for analysis, meaning that all the information from transition states is discarded. The stochastic model shall not converge into a single state as a deterministic model would but, rather, it will cycle across multiple states, which is evident when observing any outcome of interest. Outcomes y_t are calculated from state variables x_t therefore if the state stabilises, so do the outcomes. Figure 4.2 shows an observed outcome in a single run repetition and how it reaches steady state after about 150 iterations.

The determination of the minimum amount of periods required for the process to stabilise has been done visually. Extreme parametrizations were trialled and their resulting plots inspected. Runs where all parties are stickers start in steady state, but the rest of configurations take approximately 300 cycles to reach steady state.

The random components in the model require the experiment to execute multiple repetitions for every run. Each repetition uses a different random seed so that the outcomes are different, even with the same input parameters. Therefore, the estimates of the outcomes are the means of the sampled outcomes from each repetition once it has reached steady state. The number of repetitions is determined by diagnostic methods such as power tests and standard error to standard deviation ratios.

Chapter 5

Results

5.1 Description

The experiment executed a total of 120000 runs. For each of the six combinations of party number and party strategies, there were 50 configurations or input parametrisations. Each configuration was repeated 400 times. Sticker runs only were set-up and the outcomes calculated, but processes with all-aggregator or all-hunter parties were made to run 300 iterations in order to guarantee burn-in. Overall, generating the data required 40 hours of computing on a 1.5GhZ processor running Windows 10.

The model is simulated in a space with dimensions of 40x40. The mean for the distribution of q_i, and the standard deviations σ are all equal to 3. The mean of the p_i distribution is equal to 0. Figure 5.1 shows the NetLogo representation of the model.

The summary statistics for the outcomes of interest is in Appendix B.1. Raincloud visualisations of the outcomes by the number of parties and candidate strategies are also available in Appendix B.2. Note that the sticker and hunter distributions for any given outcome are practically indistinguishable, practically stating that the proposals candidates make in all-hunter games are as good as random. This disappointing result is likely due to the state space distribution π being close to a perfect uniform distribution, and therefore the number of possible states in a stabilised all-hunter model is large [1].

Diagnostic tests were performed to ensure that the number of repetitions was high enough to be able to rely on the estimates of the outcomes of interest. To verify that enough observations have been collected so that a t-test rejects the null hypothesis of the outcomes being zero. Appendix B.3 contains the table with the p-values of the t-test for every parametrization; it supports the claim that 400 repetitions per run are enough to rely on the mean estimates of the outcomes. There are no analytical expectations for any of the outcomes; hence, there are no other available one-sample t-tests to perform. In order to ensure that the same level of precision is maintained across different

[1] To be clear, the state space distribution does not give equal chances to all states. A party at a given position cannot immediately jump to a coordinate too far away. However, the state space distribution is attributing equal chances to all the possible transitions.

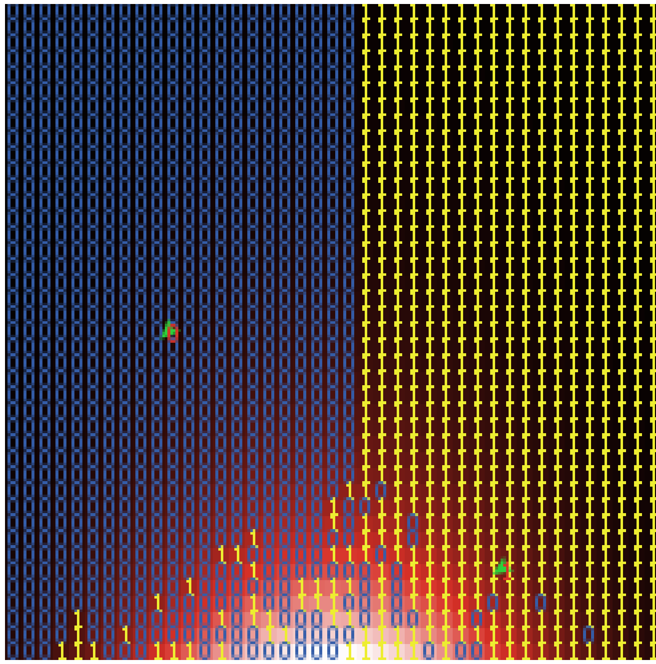

Figure 5.1: Capture of a NetLogo view of the model. It is a 40x40 Euclidean space. The strength of the colour red in the background indicates the relative density of voters at a given point, white being the strongest. The green arrows are the positions of the candidates. For example, candidate 0 is proposing a policy with ideology in position -10 and complexity 20. The blue and yellow numbers mark the vote cast by the voters in those points.

variables of the same run and the same variables of different runs, the standard error of every outcome is normalised by dividing it by its standard deviation to obtain a comparable ratio. Appendix B.4 contains the table of the standard error to standard deviation ratios and shows that the level of precision is equal for all the variables in all the runs and that they are all about 5% of their standard deviation.

The following subsections discuss the effects of a given input on the many outcomes under study. Regression coefficients are done using ordinary least squares except when the dependent variable is a ratio, which requires maximum likelihood estimation. Unless a difference is mentioned, all models are specified according to the following equation:

$$Y = \alpha + \beta_q q + \beta_\lambda \lambda + \beta_\theta \theta + \beta_{parties} X_{parties} + \beta_{agg} X_{agg} + \beta_{hunter} X_{hunter}.$$

where $X_{parties}$ is a dummy indicating the run simulated a three-party election, X_{agg} a dummy for all-aggregator runs and X_{hunter} a dummy for all-hunter runs. Specifications can vary by including interaction terms or specifying quadratic relations. The observations for the regression can be sub-sampled if the discussion involves only a specified party strategy or a fixed number of parties.

5.2 Correct Voting

	Dependent variable: % Incorrect Voters		
	(1)	(2)	(3)
q	0.029***	0.076***	0.076***
	(0.001)	(0.005)	(0.005)
λ	0.286***	-0.612***	-0.757***
	(0.044)	(0.197)	(0.213)
θ	-0.583***	-0.535***	-0.639***
	(0.041)	(0.043)	(0.117)
X_{agg}	-0.058*	-0.058*	0.070
	(0.030)	(0.030)	(0.055)
X_{hunter}	0.008	0.008	0.008
	(0.030)	(0.030)	(0.030)
$X_{parties}$	0.590***	0.491***	0.491***
	(0.025)	(0.049)	(0.049)
q^2		-0.001***	-0.001***
		(0.000)	(0.000)
λq		0.015***	0.014***
		(0.004)	(0.004)
$qX_{parties}$		0.005**	0.005**
		(0.002)	(0.002)
λq^2		0.593***	0.562***
		(0.130)	(0.131)
λ^2		0.500***	0.479***
		(0.173)	(0.173)
θX_{agg}			-0.244***
			(0.088)
λX_{agg}			0.318*
			(0.181)
LL null	-1658.097		
Log Likelihood	-861.184	-786.628	-781.198
Note:		*p<0.1; **p<0.05; ***p<0.01	

Table 5.1

Incorrect voters are those that chose a candidate that were not the ones that minimised their loss function because they had the wrong beliefs about the ideological position of the proposals of these candidates. Furthermore, it is also possible that those who voted correctly are unsophisticated; it just happens so that their draw from the uniform distributions over the range of believed candidate positions was beneficial. Therefore, the percentage of incorrect voters is smaller than the proportion of voters who lack the sophistication to make the correct choice.

According to the logistic regression models displayed in table 5.1, all the inputs have significant effects on the percentage of incorrect voters. Aggregator settings are prone to lowering the percentage of incorrect voters simply because aggregator parties try to represent those voters who are low in sophistication so they will tend to make less complicated proposals than when randomising positions such as the stickers do.

The introduction of a third party to a two setting configuration, while keeping the rest of the inputs constant, is expected to increase the percentage of incorrect voters. Not because a new competing party demands higher sophistication from the voters, but simply because, given the same lack of political sophistication and, consequently, maintaining a uniform distribution over the available candidates, there are higher chances of voting incorrectly.

As expected, q has a significant and positive correlation with the percentage of incorrect voters. Higher levels of issue complexity will make larger proportions of the population unable to determine the precise positions of the candidates and the level of complexity of the issue. The inverse applies for θ, which is a scaling parameter for voter political sophistication. Which explanatory variable is more influential is hard to say. The regression coefficient of q is much smaller, but it is also a parameter with a wider range, whereas θ is a scaling unit parameter. Moreover, when θ is 0 voters have no political sophistication and will vote incorrectly half of the time, thus the coefficient of θ allows comparing the potential outcome of the dependent values against a setting where the election of voters is uniformly random.

In all-aggregator competitions, parties will end up in positions that are in the centre of their supporters. Given that no voter can support two parties simultaneously if all the population votes correctly then the voters will be cleanly split by a line in the euclidean space. Whether this line is vertical or horizontal is determined by λ. If $\lambda = 1$ then voters care only about the ideology of proposals, and therefore the line will divide voters in ideological left and right groups. When $\lambda = 0$, voters ignore ideology and focus solely on whether the proposals have complexity that matches the issue's complexity, therefore, the line will be horizontal, and a party will have much lower complexity than the other. This is the reason why the regression coefficient of λ is positive: When parties split the vote horizontally (the dividing line is vertical), they will have similarly complicated policies whereas when the split is vertical, then one party will be significantly less complicated than the other thus aiding voters in their decision making. Hence, moving λ from 0 to 1 reduces the percentage of incorrect voters. This effect does not hold when the parties are not aggregators, as is evident in appendix B.5, which shows results from the same models in but with hunter and sticker data. In those models, λ ceases to be a significant determinant.

It is not a surprise that the percentage of correct outcomes for a given input configuration is strongly correlated with the percentage of incorrect voters. Each of these instances recorded an amount called the total incorrect cost, the difference in total loss of all voters and the total loss of all voters should the correct candidate been elected. On average, input configurations had seven incorrect outcomes out of 400 repetitions, each of which provides an observation of a total incorrect cost. While the total incorrect cost was always positive, meaning that voters are better off by voting correctly, the variation was too large to be explained by such a limited sample.

A more accessible value to estimate is the cost of incorrect voting as a percentage of mean precise loss without discarding those episodes in which the precise and incorrect outcomes were the same. Firstly, the cost of incorrect voting is derived from the difference between the mean voter loss and the mean voter precise loss. This difference is divided by the cost of mean voter precise loss which produces the desired ratio. Provided that the episodes where the outcomes were correct are still counted, this ratio will be biased towards 1. Regardless, the indicator can still illustrate the cost of having incorrect voters across all electoral cycles. Logistic regression on this variable does not show any promising explanations, only that, controlling for other factors, a unit increase of q is expected to increase the cost of incorrect voting by 0.29 percentage points. The complete table showing these results can be found in Appendix B.6.

5.3 Party Convergence

	Dependent variable: q distance
	(1)
Intercept	-29.982***
	(10.399)
p distance	7.874***
	(1.983)
p distance^2	-0.382***
	(0.093)
Observations	50
R^2	0.283
Adjusted R^2	0.252
Residual Std. Error	2.278(df = 47)
F Statistic	9.272*** (df = 2.0; 47.0)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.2

The position of a candidate is a function of its strategy, among other things. However, given that the position of hunters does not present any significant difference to the ones of the stickers, they do not provide any useful information from which insights on party polarisation could be derived. Therefore, this subsection only discusses the positional outcomes of aggregator parties.

In two-party settings, aggregators show a much lower level of polarization than the benchmarks provided by the hunters and stickers, their distances in p and q are narrower. As shown in table 5.2, a linear regression on distances in q with distances in p as an explanatory variable and specified with a quadratic term shows a significant result with p-values below 0.001. However, the coefficient of determination of this model remains below 0.3 so the explanation of the variation in the distance will rely on other variables.

Note that aggregators are not expected to converge given that they relocate to the centroids of their supporters. Therefore, if there are levels of distance in p that are relatively low or relatively high, it must be because a large proportion of voters is voting incorrectly, thus making the centroid of parties closer than would be if voters voted correctly. Accordingly, both party distance variables respond significantly to θ and q, as shown in table 5.3.

Input θ regulates the level of sophistication of voters, low levels of which will increase the chances that both parties stand closer to each other. On the other hand, higher levels of sophistication have marginal returns. As defined by γ, once the sophistication is higher than the natural complexity of the issue, it does not make any difference if it grows any further. This explains why a regression on distance in p shows a significant fit with a quadratic specification for q. This is not the case with θ, which has a strictly linear relationship with distances in p.

The appropriate indicator for a three-party configuration is the mean eccentricity of parties. Nevertheless, aggregators do not produce any significantly different results from any other strategy when competing in three-party elections. Such distinction occurs only in two-party settings. Aggregators split the votes between themselves and position in the middle of each. Consequently, they are more likely to sit at more extreme positions if the number of parties increases. What the results show is than in three-party settings, the eccentricity of parties is as good as when party positions are allocated randomly.

Just as with the party position distances, both q and θ have an influence on the eccentricity of aggregators in 2 parties, q in a much minor degree. However, λ has the opposite effect it has on the party distance in p than it has on eccentricity. When $\lambda = 1$, voters only care about policy ideology, even though their capacity to correctly identify political positions continues to be disturbed by their political sophistication, or lack thereof. Parties will propose symmetric policies equidistant to the mean. If $\lambda = 0$, voters only care about the complexity of the issue and the proposals, so the voters split vertically. θ regulates the distance among these two; hence the term for the interaction of θ and λ is also significant.

5.4 Electoral Competition

The ENP will depend on the number of parties participating in the run. Therefore, the effective number of parties outcome is normalised by being divided by the number of parties, and so, competition can be compared across runs with a different number of parties. The regression on normalised ENP, including interactions between party numbers, aggregator dummies and other inputs has a coefficient of determination of 0.89. In the same model, and although not immediately evident by looking at the violin plots included in the appendix B.2, the regression coefficient of the aggregators' dummy presents a slight effect on competition compared to stickers and hunters.

Figure 5.2 shows the predicted values of ENP according to different inputs. The relationship of q with ENP is always quadratic, and the curve flattens at high levels of q. However, the difference of a third party on ENP is larger on aggregators than on non-aggregators. Furthermore, for each configuration of party numbers, the differences in ENP of aggregators and non-aggregators go from positive to negative as q grows. Regardless of the number of parties or their strategies, Larger levels of q correspond to larger proportions of people randomising their vote, essentially eroding the

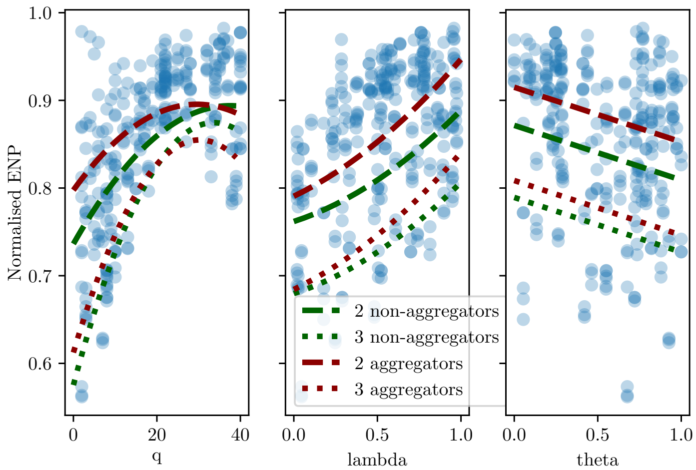

Figure 5.2: Fitted lines on normalised ENP by input variable.

	Aggregators		Hunters	
	p distance	q distance	p distance	q distance
Intercept	7.289***	6.413***	13.532***	13.938***
	(0.808)	(1.233)	(0.188)	(0.239)
q	-0.067***	0.314***	-0.001	-0.001
	(0.011)	(0.083)	(0.005)	(0.006)
λ	3.862***	-4.867***	0.198	-0.372
	(1.210)	(0.832)	(0.205)	(0.261)
θ	13.440***	7.494**	-0.188	0.148
	(2.181)	(3.660)	(0.197)	(0.249)
$\lambda\theta$	-4.374**			
	(1.865)			
θ^2	-7.302***	-6.417*		
	(1.950)	(3.470)		
q^2		-0.005**		
		(0.002)		
Observations	50	50	50	50
R^2	0.753	0.659	0.037	0.048
Adjusted R^2	0.725	0.620	-0.026	-0.014
Residual Std. Error	0.904(df = 44)	1.623(df = 44)	0.411(df = 46)	0.522(df = 46)
F Statistic	26.823*** (df = 5.0; 44.0)	17.023*** (df = 5.0; 44.0)	0.583 (df = 3.0; 46.0)	0.775 (df = 3.0; 46.0)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5.3

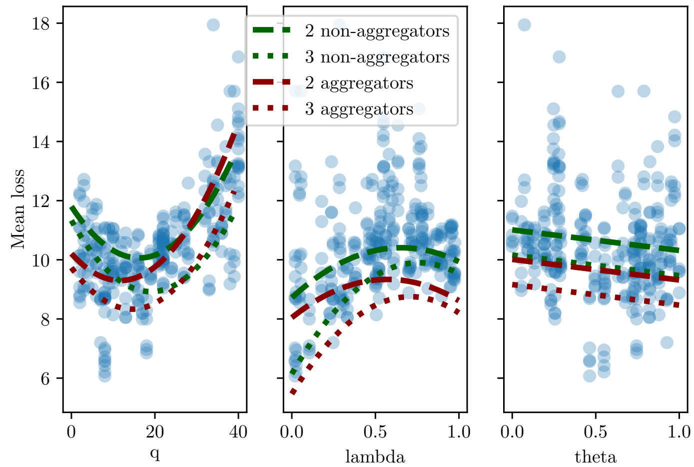

Figure 5.3: Fitted lines on mean voter loss by input variable.

advantages any party has due to being closer to a larger mass of voters. θ, due to regulating the political sophistication of voters, has the opposite effect.

There is higher competition when $\lambda = 1$, and voters only care about ideology. Ideological preferences have a normal distribution; therefore, the division of voters among parties around the mean can be similar as long as they are equally distant from the mean. This is not the case when $\lambda = 0$ and voters only care about policies matching the complexity of the issue due to the fact that the political sophistication of voters has a gamma distribution which is not symmetrical. The difference between the lines of the aggregators and non-aggregators in the λ figure reflects the fact that aggregator configurations tend to be more competitive.

5.5 Voter Satisfaction

If voters had perfect knowledge, their mean loss would depend on the distance between them and the elected party. A high mean loss would mean that the winning party is far from the mean and because the other parties cannot be closer to the mean, then it follows that the parties would be polarised. However, the model assumes voters have imperfect knowledge, and so they sometimes vote for a party other than the closest one. It is possible that there is little polarisation so the conclusions derived in perfect knowledge do not hold. If the mean loss is high, it indicates that the incorrect voting is high enough to allow parties to venture far apart from the median voter's ideal point.

Whether voters vote perfectly depends on their political sophistication and the complexity of the issue, therefore, q and θ make sense as determinants for voter mean loss. Figure 5.3 displays the prediction of mean loss as specific inputs change. q has roughly any effect when the levels are low because most voters are likely to be voting correctly. Notice that the θ prediction lines are close to flat, implying that political sophistication could have a lesser effect on mean loss than q.

The number of parties and the party strategies have a higher effect than voter sophistication. Three aggregator configurations will always have a party near the median, whether voters have perfect information or not. Given that this party tends to win, the mean loss is often lower in three aggregator configurations. The winning party is more likely to distance itself from the mean by removing a third party rather than by changing into all-sticker or all-hunter configuration. Aggregator party configurations are better at finding the median voter than the randomly allocated stickers and hunters, but not more than three parties are better than two parties.

The relationship between λ and mean voter loss is analytically straightforward. When voters only pay attention to the p axis, voter loss is always going to be heterogeneous because each voter has their preference on p. Such is not the case with the q axis given that voters only care about the complexity of the issue in which case the mean loss is going to be homogeneous and with the possibility of being 0. For this reason, as λ increases, so does the mean voter loss. This relationship is apparent in the left panel of figure 5.4, where $q = 0$ so there is perfect knowledge and therefore precise voting. As λ grows, the mean loss of different parties converges to the same point because regardless of the number of parties, both configurations will have the same distances between q and the complexity of parties. The right panel shows the same effect only when $q = 40$, at which point no voter has perfect knowledge of the relevant positions. When more parties are involved in the competition, there are fewer chances of selecting the correct candidate, the one that is closest to q; hence, the mean loss does not converge when $\lambda = 1$.

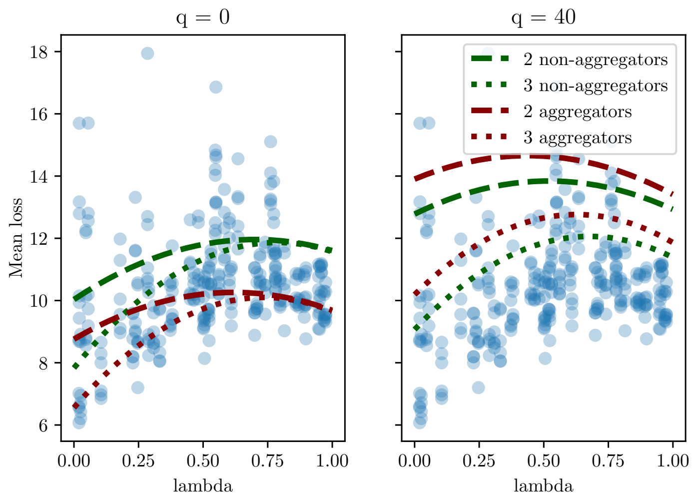

Figure 5.4: Comparison of fitted lines of λ on mean voter loss. The left pane shows the fitted line when $q = 0$ and the right pane shows $q = 40$.

Chapter 6

Discussion

Even if it was possible to measure incorrect voting in the real world effectively, the likelihood the model approximates real population quantities is extremely low. For one, the data generated from the hunter strategies was disappointing in what it revealed. Perhaps with more computational resources and fewer sacrifices in the length of the runs, the agent-based model would have produced enough data to estimate the hunter outcomes more precisely. Secondly, as Luskin (1990) identified, voters are likely aware of their shortcomings and therefore utilise an assortment of non-spatial decision heuristics they find to be effective in shortcutting processes that demand additional time and information. Finally, the strategies of the parties in the experiment does not resemble the strategy of parties in the real world, and they most likely command varying levels of information and decision-making processes. Conceivably, parties are capable of anticipating that voters are not sophisticated enough to make decisions on a given issue thus shifting away from intellectually demanding messages and focusing on sound bites or actively obfuscating their communications in a similar way to what Shepsle conceptualised as strategic political ambiguity 1972[1].

This is not to say that analysing the model can serve no purpose. Provided that assumptions of the model are correct, both the analytical and data analysis show that political sophistication can influence on electoral outcomes. The analysis of best responses for the initial model proved that there is no unique Nash Equilibria and that they are all weak. A modification on the available knowledge to candidates was introduced before the computational simulation, and then the data provided evidence that political sophistication, policy complexity and voter preferences for addressing complex issues with a fitting solution can have an influence on the amount of correct voting and consequently the polarisation of parties, the degree of electoral competitiveness and welfare of voters.

According to Lau et al. (2014) where they conducted an empirical study across elections in thirty-three countries, political sophistication has a positive effect on correct voting, and the number of parties is found to be the most substantial institutional-level variable to affect correct voting. These findings agree with the results in the computational experiment, but they cannot be directly

[1]US Republican Candidate for president in 2012, Mitt Romney, has been captured in video admitting that discussing policy at a high level in front of a national audience is not a sensible strategy (https://www.youtube.com/watch?v=LkPBNi7D1hA).

compared given that the agent-based model measured correct voting across a population whereas Lau et al. do it on the individual level.

As mentioned in the preceding chapter, not only those who vote incorrectly lack political sophistication. It is also feasible for someone who has zero political information to select the candidate that best represents him by mere chance. Therefore, any evidence of incorrect voting being a consistent feature of a voter population should reveal a larger scarceness of political sophistication.

According to the model, the noise in the beliefs of the unsophisticated voters is drawn from a random distribution. If the noise is large enough, or if the candidates are close enough, then the voters are essentially voting at random. Perhaps this could explain the strength, or lack thereof, of a voter's preference of one candidate over another. As further research, it would be interesting to explore the ways political sophistication drives the undecided vote that consistently features in electoral polls.

The scope of the paper did not permit the student author to investigate further extensions of the model thoroughly. A robustness check of the findings to start with is varying the population parameters, namely the sophistication and political ideology means and their variances. As shown by Laver and Sergenti (2011), integrating sub-populations can reproduce local minima present in the real world and expose the shortcomings of the greedy algorithms some parties use to make decisions. Furthermore, supplementary research should reveal the belief formation processes of parties, which would allow the model to reduce the search space when analysing possible party beliefs of population means or issue complexity, given the signals from previous electoral cycles. Such signals could also be intermediated by additional players such as private media companies who have incentives to distort party beliefs given their profit-making nature. It would also be interesting to endogenise the political sophistication of voters according to their income, education, available time, contentment with the status quo, electoral polarization or any other credible motivation for an individual to improve their ability to determine the real meaning and implications of a policy proposal.

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Appendix A

Chapter 4 Appendix

A.1 Expected $p_i - p_m$

Because the distribution of voter preferences is normal, it is symmetric and the mean is equal to the median. Therefore, parties should be able to expect that, over a large number of voters, $p_i - p_m$ will add up to 0.

Equation 4.5 should therefore be able to be further rearranged to

$$\pi_t^c = \sum_i Pr(\sqrt{\lambda E[p_i - p_m]^2} \leq \omega^{-c}) \tag{A.1}$$

$$= \sum_i Pr(\sqrt{\lambda} \leq \omega^{-c}) \tag{A.2}$$

which seems to show that if $q_c = q$ then ω cannot be further downsized than when $p_c = p_m$, agreeing with the Median Voter Theorem. However, if the expectation operator is used in equation 4.6, the following result is obtained:

$$\sqrt{\lambda\delta^2} \leq \sqrt{\lambda} \tag{A.3}$$

which, if it was the case that $\delta < 1$, would show that there would be a profitable deviation for candidates from submitting a policy proposal at the point of the median voter.

A.2 Partial derivatives of $f(\delta_p, \delta_q)$

$$\frac{\partial f}{\partial \delta_p} = 2\delta_p - (\delta_p^2 + \delta_q^2)$$

$$\frac{\partial f}{\partial \delta_q} = \frac{2\delta_q}{\delta_p}$$

A.3 NetLogo Strategies

This code was modified from a copy Michael J. Laver from NYU shared with me.

```
to hunt
  ifelse (c-my-size > c-old-my-size) [jump 1] [set heading heading + 90 + random-float 180 jump 1]
      ;;hunter makes a move of size 1 in same direction as previous move if this increased party sup
      ;;NB the NetLogo command FORWARD is limited to a maximum of a unit move per tick
      ;;JUMP is needed for larger than unit moves
      ;;else reverses direction and makes a move of size 1 in on a heading chosen from the 180 degre
  set c-old-my-size c-my-size
      ;;remember party size for next cycle - note that "go" calls "update-support" BEFORE asking hun
end

to aggregate
   if (c-my-size > 0)
   [
     set xcor (sum [p-votes * pxcor] of patches with [p-closest-party = myself] / c-my-size)
     set ycor (sum [p-votes * pycor] of patches with [p-closest-party = myself] / c-my-size)
   ]
end
```

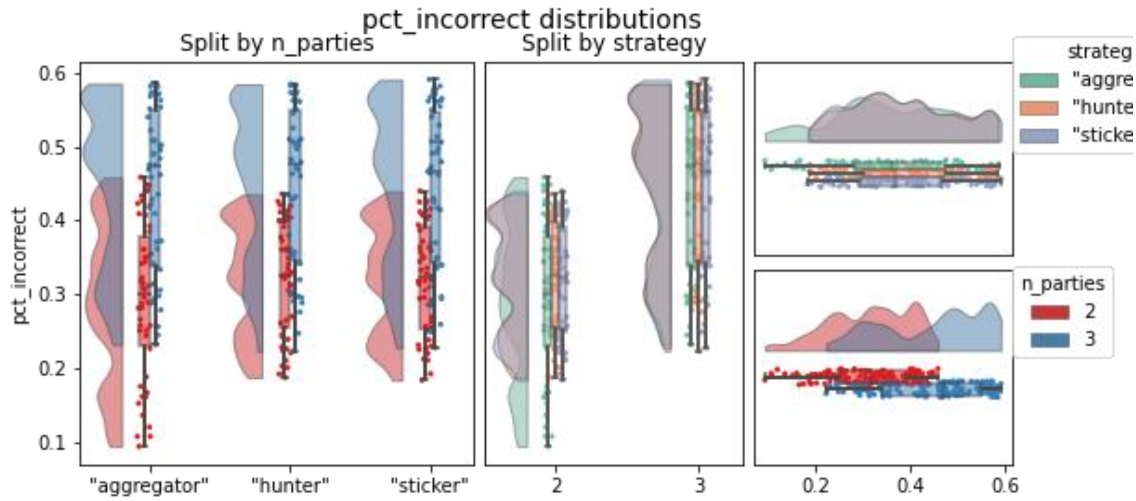
Appendix B

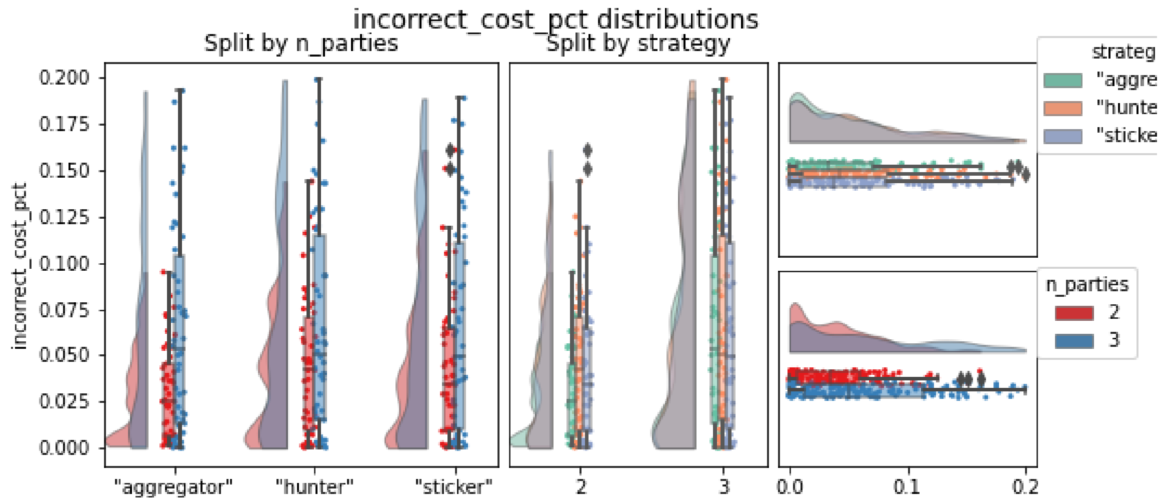
Chapter 5 Appendix

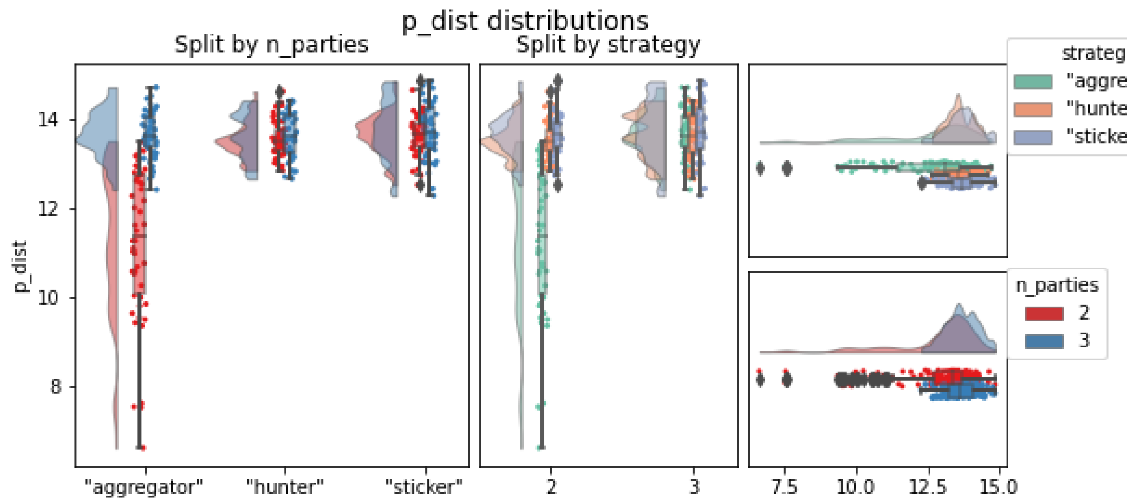
B.1 Result Data Description

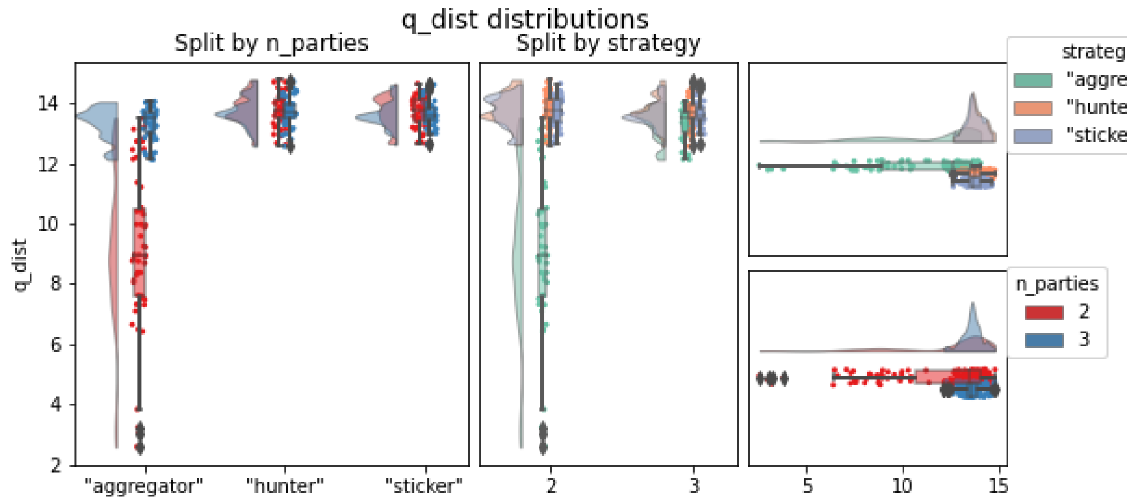
	enp	mean_loss	eccentricity	p_dist	q_dist	pct_incorrect	incorrect_cost_pct
count	300.000000	300.000000	300.000000	300.000000	300.000000	300.000000	300.000000
mean	2.125699	10.464886	1.779250	13.236461	12.886673	0.378827	0.051253
std	0.412360	1.724665	0.221460	1.222744	2.052289	0.118503	0.049074
min	1.374159	6.071504	0.871779	6.638287	2.587285	0.094322	0.000000
25%	1.811162	9.499124	1.832757	13.033867	12.985260	0.293122	0.008750
50%	1.946767	10.299093	1.863139	13.523543	13.554901	0.363003	0.039000
75%	2.545415	11.144890	1.884571	13.923917	13.899887	0.471447	0.075250
max	2.859627	17.941651	1.946060	14.833971	14.786883	0.590865	0.199000

B.2 Rainclouds

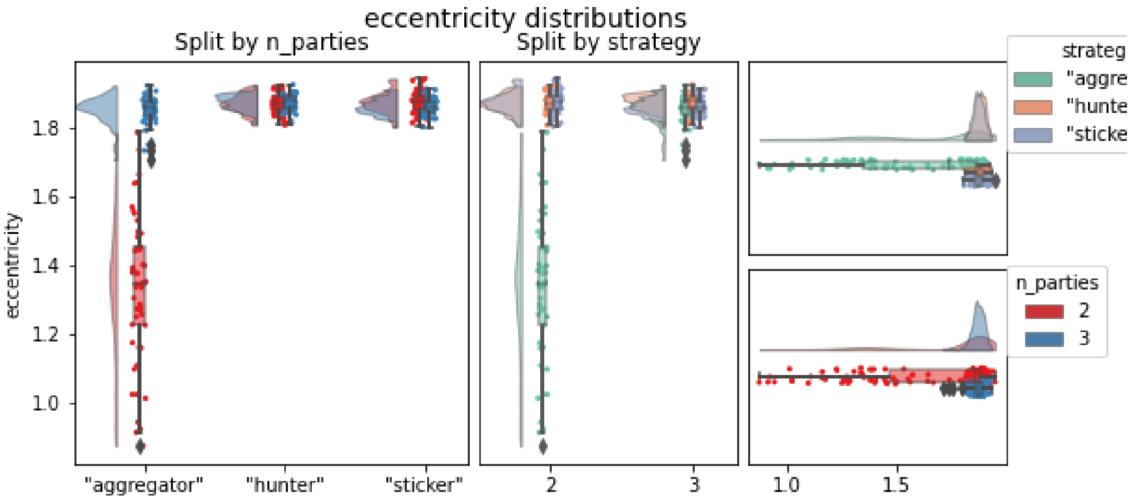

pct_incorrect distributions
Split by n_parties
Split by strategy
pct_incorrect
"aggregator"
"hunter"
"sticker"
strateg
"aggre
"hunte
"sticke
n_parties
2
3


incorrect_cost_pct distributions
Split by n_parties
Split by strategy
incorrect_cost_pct
"aggregator"
"hunter"
"sticker"
strateg
"aggre
"hunte
"sticke
n_parties
2
3

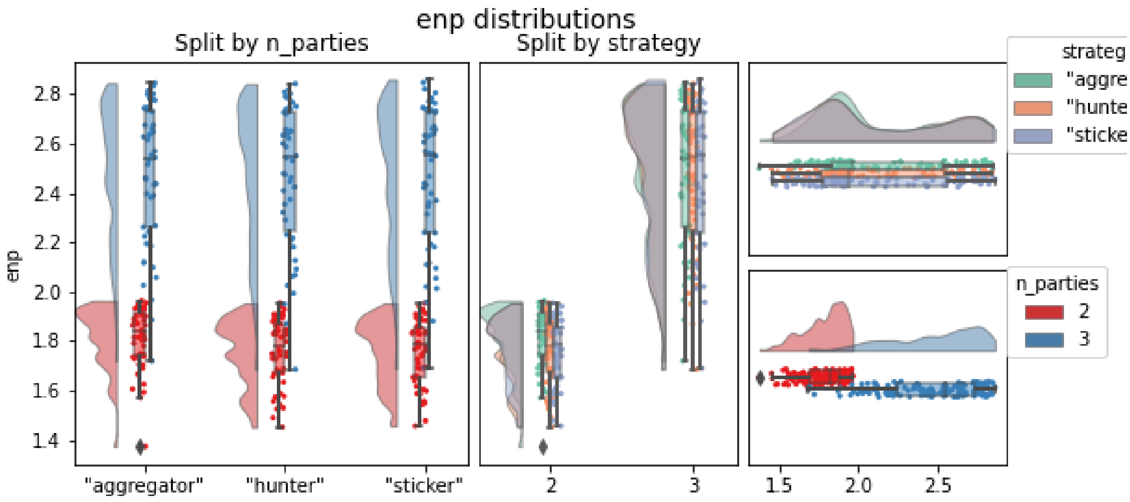

p_dist distributions
Split by n_parties
Split by strategy
p_dist
"aggregator"
"hunter"
"sticker"
strateg
"aggre
"hunte
"sticke
n_parties
2
3

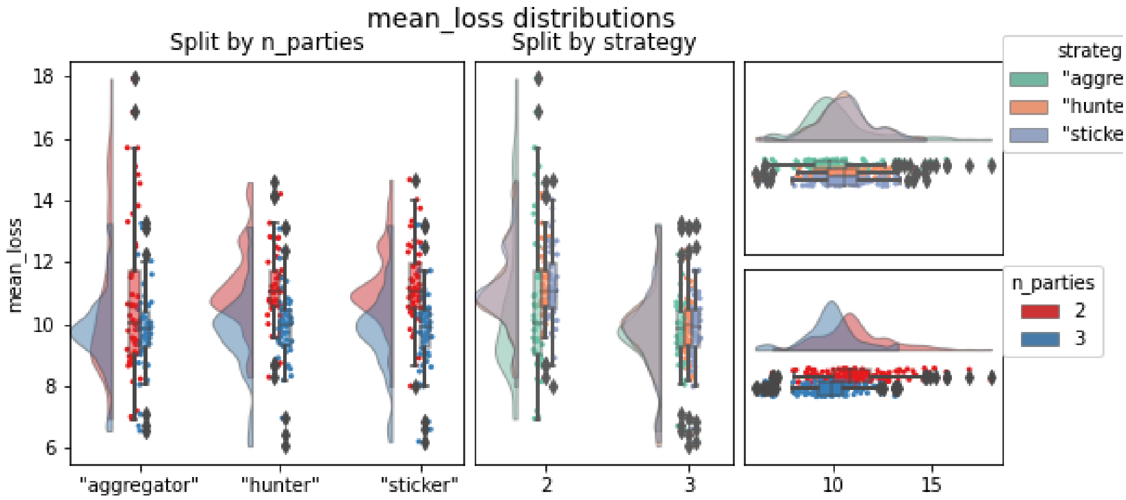


q_dist distributions
Split by n_parties
Split by strategy
q_dist
"aggregator"
"hunter"
"sticker"
strateg
"aggre
"hunte
"sticke
n_parties
2
3



eccentricity distributions
Split by n_parties
Split by strategy
eccentricity
"aggregator"
"hunter"
"sticker"
strateg
"aggre
"hunte
"sticke
n_parties
2
3


enp distributions
Split by n_parties
Split by strategy
enp
"aggregator"
"hunter"
"sticker"
strateg
"aggre
"hunte
"sticke
n_parties
2
3


mean_loss distributions
Split by n_parties
Split by strategy
mean_loss
"aggregator"
"hunter"
"sticker"
strateg
"aggre
"hunte
"sticke
n_parties
2
3

B.4 Standard Error / Standard Deviation

q	kappa	lambd	strategy	n_parties	enp	mean_loss	eccentricity	p_dist	q_dist	pc
2	0.676816	0.046096	”aggregator”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
			”hunter”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
			”sticker”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
	0.731994	0.950714	”aggregator”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
			”hunter”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
			”sticker”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
3	0.054363	0.178896	”aggregator”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
			”hunter”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
			”sticker”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
	0.420538	0.481681	”aggregator”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
			”hunter”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
			”sticker”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
4	0.765460	0.946963	”aggregator”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
			”hunter”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
			”sticker”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
5	0.735397	0.814584	”aggregator”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
			”hunter”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
			”sticker”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
6	0.263315	0.740050	”aggregator”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
			”hunter”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
			”sticker”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
	0.891531	0.897714	”aggregator”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
			”hunter”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
			”sticker”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
7	0.926335	0.247062	”aggregator”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
			”hunter”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	
			”sticker”	2	0.050063	0.050063	0.050063	0.050063	0.050063	
				3	0.050063	0.050063	0.050063	0.050063	0.050063	

B.5 Aggregator Incorrect Voting

	Dependent variable: % Incorrect Voters		
	(1)	(2)	(3)
q	0.028***	0.073***	0.074***
	(0.001)	(0.007)	(0.007)
λ	0.334***	-0.388	-0.481*
	(0.053)	(0.241)	(0.261)
θ	-0.505***	-0.466***	-0.586***
	(0.050)	(0.053)	(0.139)
$X_{parties}$	0.548***	0.411***	0.411***
	(0.030)	(0.060)	(0.060)
q^2		-0.001***	-0.001***
		(0.000)	(0.000)
λq		0.009**	0.009*
		(0.005)	(0.005)
$qX_{parties}$		0.007***	0.007***
		(0.003)	(0.003)
λq^2		0.666***	0.647***
		(0.155)	(0.156)
λ^2		0.418**	0.403*
		(0.211)	(0.212)
θX_{agg}			0.000***
			(0.000)
$\lambda\theta$			0.207
			(0.221)
LL Null	-1028.648		
Log Likelihood	-552.835	-507.353	-506.917
Note:			*p<0.1; **p<0.05; ***p<0.01

Table B.1: This is a regression on non-aggregator data only. Therefore $n = 200$.

B.6 Incorrect Cost %

	Dep. Variable:		% Incorrect Cost			
	Method:		dydx			
X	**dy/dx**	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
q	0.0029	0.001	2.339	0.019	0.000	0.005
lambd	0.0453	0.052	0.872	0.383	-0.057	0.147
kappa	-0.0646	0.043	-1.494	0.135	-0.149	0.020
aggregator	-0.0071	0.031	-0.228	0.819	-0.068	0.054
hunter	0.0009	0.030	0.031	0.976	-0.058	0.059
nparties3	0.0255	0.026	0.984	0.325	-0.025	0.076