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Essays in Public Economics and Political Economy

Utilising Empirical Methods for Public Policy

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Submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy (Economics)

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Dedication

To Laura Beaton and Sally Jones, the two most inspiring people I have ever known.

Also to the memory of my father, whose broad intellectual curiosity I inherited.

Acknowledgements

I would like to thank my supervisors, David Byrne, Marc Chan, Timothy Moore and Eik Swee; as well as my committee chair, Kalvinder Shields.

I would also like to thank Paul Frijters, John DeNew, Victoria Baranov, Jan Kabatek, Ross Hickey, Nicholas Gruen, Marco Faravelli, Anthony Heyes, Reshad Ahsan, Leslie Martin, Kevin Staub, Svetlana Danilkina, Todd Morris, David Delacretaz, Ellen Muir, Ingrid Burford, Boon Han Koh, my partner Laura Beaton, and my family and friends for their feedback and support.

I would like to express my gratitude for the Jim Perkins Travelling Scholarship which gave me the opportunity to write my third chapter in London.

Declaration

This thesis comprises only my original work towards the Doctor of Philosophy (Economics) except where indicated in the preface. Due acknowledgement has been made in the text to all other material used. This thesis is fewer than the maximum word limit in length, exclusive of tables, maps, bibliographies and appendices. All errors are my own.

Preface

This thesis comprises research which is entirely my own, except for chapter 4 which was written in collaboration with Paul Frijters. This chapter is included in this thesis with the agreement of Prof. Frijters and, following the guidelines of the University of Melbourne, the majority is my own work. This research is supported by an Australian Government Research Training Program (RTP) Scholarship. I declare that I have no relevant or material financial interests that relate to the research described in this paper.

Abstract

Chapter 1 provides an introduction to this thesis. It is primarily an examination of how empirical methods in economics can be used for political and public economic analysis. The ultimate goal of this thesis is to propose methods from empirical economics that could be useful for the analysis and practice of public policy.

Chapter 2 uses a novel Australian dataset to show the effect of cross-sectional weather shocks on voting behaviour in the 2016 Australian federal Senate election. I spatially link every ballot cast at the polling place level to climate data and Census demographic data. I find evidence that cold temperature shocks affect voting at the intensive margin, causing people to commit more errors on the ballot paper. I also document heterogeneous effects of temperature on voting mistakes, with cold shocks having greater effects on citizens born overseas and citizens without tertiary education. I show that my findings are consistent with existing evidence that cold weather increases the cost of performing cognitive tasks.

Chapter 3 is a descriptive analysis of voter preferences in the 2016 Australian Senate election. It uses the rank ordered logit model (also called the exploded logit or the Plackett–Luce model) to recover choice parameters of Australian voters in a federal Senate election. When voters convey their preference rankings over political parties in an election they select on numerous characteristics, including policy. By using the rank ordered logit model to include voters' six most preferred choices, I observe a distinctly different set of policy preferences than when only first preferences are considered. This is due to the large amount of policy variation in lower order rankings. Following the communicative voting literature I hypothesise that voters have different motivations governing higher and lower voter rankings. Specifically, first preferences appear to be instrumental, in that most first preferences go to parties with a high probability of being elected. Lower rankings are hypothesised to expressive, conveying the expressive policy preferences of voters. I conduct Hausman tests on regressions with

the higher rankings removed to show support for this hypothesis. This paper aims to give an indication of the kinds of issues that voters select on as well as explore specific voting behaviours. In this way, this paper considers whether ranked voting outcomes could be used by public policy makers to determine which issues matter to the public and which are less important.

Chapter 4 uses wellbeing and income tax data from the United States to show that an individual's life satisfaction varies due to changes in the amount of taxes paid per household in their ZIP code, net of the effect of own income. Specifically, when others in the highest income tax bracket pay more income tax, it has a positive effect on own wellbeing. Conversely, when others in the lowest income tax bracket pay more income tax, it has a negative effect on own wellbeing. These findings hold irrespective of an individual's own level of income and hence the own income tax bill, indicating that the life satisfaction effect of income tax on a particular income group is not determined by membership of that group. We rely on an instrumental variables approach to identify our effect, using simulated state level marginal income tax rates to instrument for the amount of taxes paid. We use marginal tax rate data from the NBER TAXSIM model to achieve this.

Chapter 5 concludes and summarises this thesis.

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Chapter 1

Introduction

There is a pressing need in public policy to make effective use of the massive amounts of data being generated by economic, social, and political interaction. The field of economics has developed numerous methods for understanding and interpreting these data. This dissertation is an examination of how empirical methods in economics can be used for political and public economic analysis, specifically with the aim to use these approaches in the delivery of public policy.

Chapter 2 examines the use of geospatial microdata, which are being created by public and private institutions, to better understand institutional design. Geospatial data have massive potential to give insights into the effects of both anthropogenic and natural shocks to human institutions. This chapter looks chiefly at the effect of weather shocks on public choice. It uses data from the 2016 Australian election to show the effect of cold shocks on voting mistakes. By spatially linking weather data to polling places it is possible to show, by relying on the exogeneity of weather shocks for identification, that cold shocks increase the prevalence of voting errors during the election. This chapter contributes to the overall thesis by showing how spatial data can uncover insights into individual behaviour which are impossible to observe at the macro level. It provides a framework for which spatial shocks can be observed and their effect on public institutions, in this case a public choice

mechanism, can be quantified and analysed.

Chapter 3 looks at how electoral data can be used to guide public policy. Although electoral data have the obvious use of determining the outcome of elections, there is also valuable information that can be gleaned from voting microdata. Specifically, when voters are asked to rank their most preferred political parties this can reveal which kinds of policies or public issues are important to them. These data have the potential to relay important information about individual policy preferences that is impossible to extract from electoral data where voters convey only their most preferred option. The chapter uses electoral data from Australia's 2016 Senate election. In Australian elections, individual voters are asked to rank their six most preferred political parties. This creates a complex voter profile for each individual. The voting data are then linked to data from the Australian Election Study, which provides information about the policy stances of different parties. By doing this it is possible to observe which policy stances correlate with more preferred voter outcomes. By using the rank ordered logit model to recover choice parameters relating to specific policies, it is possible to show which policies can rationalise observed voting patterns. In this way, the chapter proposes ways in which ranked voting outcomes could be used by public policy makers to determine which issues really matter to the public at the time of an election.

Chapter 4 utilises wellbeing data from the Gallup Poll in the US and shows how this can be used to analyse and guide public policy. Self reported measures of wellbeing are already being used extensively in public policy around the world (see chapter 4 for a discussion of this), and this chapter contributes to the growing literature which analyses this. It links wellbeing data from the US Gallup Daily Poll, collected between 2008 and 2015, to income tax data from the Internal Revenue Service. By employing an instrumental variables approach, utilising simulated marginal tax rate data from the NBER TAXSIM model, the paper finds that own wellbeing is directly affected by variation in other group's income tax. This highlights the ways in which self reported wellbeing measures can be used to meaningfully guide and evaluate public policy beyond conventional measures of consumption and

productive output.

There is huge potential for empirical economics methods to by used in public policy analysis and practice. This thesis puts forward several ways in which this can be done, with a focus on applied microeconomic methods.

Chapter 2

The Winter of Our Discontent: Cold Effects on Voting Mistakes in an Australian Election

2.1 Introduction

This paper observes voting mistakes at the individual level which are the result of weather shocks. In order for preference aggregation mechanisms, such as elections, to function properly they rely on both the individual's willingness to participate and for the mechanism to be designed such that individuals have no incentive to lie or misrepresent their preferences. This means that electoral outcomes can be undermined if voter turnout is low, or if individuals are not correctly incentivised to reveal their preferences when they vote. Although there are issues related to the design of the electoral mechanism which may relate to these two conditions, the focus of this paper is the external factors which relate to conveying preferences. It has long been established in the political economy and political science literature that weather shocks, such as rain, adversely affect voter turnout (Fujiwara et al., 2016; Artés, 2014; Shachar and Nalebuff, 1999; Eisinga et al., 2012; Gomez et al., 2007). It is conjectured

that this is because individuals perceive the increased cost of voting in the rain as lower than their payoff from voting, removing their individual incentive to participate. In Australia and elsewhere, this has been tackled by the introduction of compulsory voting. However, this justification for compelling voters to the ballot box relies on the assumption that they will correctly convey their preferences once there.

There is a gap in this literature which is driven by data constraints. Because we rarely observe individual level outcomes we can often observe easily what drives decisions before individual steps into voting booth (e.g. turnout) but cannot observe how they behave when they cast their vote. This paper fills that gap by using individual level voting data to provide evidence that variation in voting costs, driven by weather shocks, adversely affects voting behaviour when in the ballot booth. Specifically, a cold temperature shock on election day induces more voting mistakes on average. This suggests that although compulsory voting limits the effect of variables, such as weather, on voter turnout, there is still an effect at the intensive margin and ultimately on election outcomes.

I make use of a change to the Australian election system in 2016 which enables the reproduction of a de-identified copy of every Australian ballot. Every ballot cast in the 2016 Australian Senate election is observed at the polling place (PP) level. I then spatially link this electoral data to historical climate data, as well as weather data from the time of the election, and to demographic data obtained from the 2016 Australian Census. With these data I observe those votes which were filled out incorrectly but, due to special vote saving provisions enacted before the election, were still counted in the final result. These are specifically those voters who did not correctly follow the instructions on the ballot. My primary finding is that cold temperature shocks, defined as a deviation below historical average temperatures, increase the number of mistakes made on the ballot. I also document heterogeneous effects of cold shocks, with a larger effect on citizens born overseas and those without tertiary education.

Australia is an ideal environment to study the effect of weather in this way as its vast

geographic area ensures a large amount of weather variation. As well as this, compulsory voting has the effect of ensuring that Australia has a high turnout rate. In the 2016 election, voter turnout was 91% and historically turnout has been consistently higher than 90% since 1925 (AEC, 2016b). This limits the effect of weather on voting behaviour at the extensive margin, i.e. voter turnout. This means that any effects of weather on voting behaviour will not be driven by turnout, but rather by voting behaviour when the vote is cast. Without evidence of how weather affects voting in the ballot booth, it is impossible to quantify the total effect of weather on voting. I provide evidence that weather has sizeable effects on voting at the intensive margin and quantify the magnitude of this effect.

My paper contributes to the political economy literature focussing on elections and weather effects. It also contributes to literature considering the effects of compulsory voting. I also draw on evidence from the affective and social neuroscience literature to show that my result is consistent with an increase in cognitive costs associated with cold temperature shocks. The heterogeneous effects of weather shocks support this hypothesis, showing that those citizens who are making more mistakes are the ones more likely to face higher cognitive costs. These are, specifically, citizens born overseas who are more likely to be unfamiliar with Australia's voting rules and have a lower competency with English, and citizens without tertiary level education.

The paper is structured as follows, **Section 2** identifies my location within and contribution to the existing literature. **Section 3** introduces the reader to the Australian Senate electoral mechanism as well as the changes that occurred in 2016. **Section 4** describes the sources of the data and how the dataset was constructed. **Section 5** discusses the empirical approach of this paper. **Section 6** discusses the key results. **Section 7** explores heterogeneous effects of temperature on voting behaviour. **Section 8** conducts robustness checks and **Section 9** concludes.

2.2 Literature

The primary area of literature related to this paper covers the effects of weather on voter turnout. With respect to the effects of temperature on voting at the extensive margin, results indicate different effects of heat versus cold on voting behaviour. Van Assche et al. (2017) consider temperature and voting in Presidential elections in the US from 1960 to 2016. They find that increases in temperature lead to increases in voter turnout. Conversely, Wuffle et al. (2012) find that in colder states in the USA there is higher turnout. Moreover, Matsusaka and Palda (1999) find that temperature does little to explain voter turnout. One clear result from these findings is that heat and cold may not have symmetric effects on voter behaviour. This assertion is supported by the psychology literature. Taylor et al. (2016) document the dissimilar effects of heat and cold on cognition and human behaviour. Therefore, clearly contextualising the climate and season is vital to correctly interpreting the effect of temperature on behaviour. Due to the fact that my paper studies an election which occurred during the middle of winter in Australia, my analyses are informative about the effect of cold weather on voter behaviour but have little to say about the effect of heat.

A well documented relationship is that between rainfall and voter turnout. Much of the evidence suggests that rainfall will decrease turnout (Fujiwara et al., 2016; Artés, 2014; Shachar and Nalebuff, 1999; Eisinga et al., 2012; Gomez et al., 2007), although there is also some evidence to suggest that rainfall has no effect on turnout (Knack, 1994; Persson et al., 2014). The mechanism for this has been posited as rainfall increases the cost of turnout which leads to lower equilibrium participation in elections. Rainfall has also been used in several papers as an instrumental variable for turnout, with first stage regression providing further evidence that it has a negative effect on turnout (Arnold and Freier, 2016; Hansford and Gomez, 2010; Lind, 2014; Lo Prete et al., 2014). My paper also tests for the effect of rainfall at the intensive margin, concluding that there is no effect on voter behaviour.

Other relevant areas are those which look at the effect of compulsory voting on the quality

of information aggregation. Krishna and Morgan (2012) contest that there is an implicit trade-off in moving from voluntary to compulsory voting in that heterogeneous information costs mean that the amount of preference information will increase, but that the quality of the information will decrease. I show a similar result, except that my heterogeneous costs could be considered cognitive susceptibility to weather rather than informational. (Borgers, 2004) also makes the argument that compulsory voting with majority rule leads to turnout which is too high and many who vote should abstain in equilibrium.

My contribution to this literature is to show evidence that weather effects can change voting outcomes at the intensive margin. To understand the underlying mechanics defining this relationship, I also draw on the psychology literature to show that the findings are consistent with the effect of cold on individual's ability to perform cognitive tasks. Taylor et al. (2016) look at the effect of environment on tasks that require mental effort. These include memory tasks (verbal, spatial, working), attention tasks and executive function tasks (reasoning, problem solving). They find that there are varied effects of cold stress, however cold stress tends to have a negative impact on cognitive function. Patil et al. (1995) find that 3°C cold water immersion for 3 minutes increased alertness but that short term memory deteriorated. Shurtleff et al. (1994) find that 4°C for 30 minutes reduced matching accuracy in subjects. Mäkinen et al. (2006) find that 10°C over 10 days increased response time and decreased accuracy and efficiency of tasks in subjects. Wuffle et al. (2012) highlight the importance of considering deviation from means. They point out that adaptability to weather necessitates this approach to capture meaningful short run effects. This is the primary justification for using weather shocks in the empirical approach of this paper.

I also directly contribute to the literature on Australian elections. Leigh (2005) considers the economic determinants of partisan choice in Australian elections, showing that certain demographics correlate highly with ideological preferences. I contribute to this by further showing that certain demographics respond to short-run weather shocks differently as well. Hellwig and McAllister (2016) consider the effect of macroeconomic trends in Australian

elections and political perceptions. They show that economic indicators do not make voters more or less likely to vote for incumbents. I contribute to this literature by showing that short run shocks need to be accounted for as well as long run shocks.

2.3 Background

2.3.1 Australian Federal Government Elections

The Australian electoral system is excellently suited to this analysis for several reasons. Firstly, voting is compulsory and voter turnout is extremely high. This limits the effect of weather on voter turnout and ensures the effects we observe are at the intensive margin. Secondly, the Australian electoral system is complicated; both in terms of how voters fill out ballots and how those votes then map to elected candidates. This is especially true of Senate elections. The first point means that I am able to observe significant effects of weather shocks on how well voters fill out their ballots. The second point means that it is highly unlikely that individuals are voting strategically in the traditional sense, i.e. they are not misrepresenting their preference rankings in order to improve the probability of their most preferred candidates getting elected.

The federal Australian parliament is the legislative body of Australia. It consists of two houses and the Queen, who is represented in Australia by the Governor-General. The upper house is known as the Senate. It represents the six Australian states and two territories and is modelled after the United States' Senate. At the time of the 2016 federal election the states were represented by twelve Senators each and the territories by two each; a total of 76 Senators. The lower house, the House of Representatives, represents 150 electorates of approximately 150,000 people each. The Australian Government, the executive body of Australia, is formed by whichever party achieves a majority in the House of Representatives, following the Westminster system.

Voting in Australian federal elections has been compulsory for all citizens since 1925.

Failure to vote, or provide sufficient reason for not voting, will result in a $20 fine. Failure to pay this fine can result in court summons and gaol time. Members of the Senate and the House of Representatives are elected through a different, but similar, electoral mechanism.

The House of Representatives is elected at the electorate level by an instant-runoff voting rule. This consists of voters nominating their most preferred to least preferred candidates in order on their ballot. The most preferred candidate is indicated with a "1" and the next most preferred with a "2" and so on. When the votes are counted, candidates with the fewest votes are iteratively eliminated until a single candidate has a clear majority and is elected. Because the focus of this paper is on the Senate I will concentrate more thoroughly on the Senate voting rule and how this rule was changed for the 2016 federal election.

In Senate elections, multiple Senators representing a single state are elected from a single vote. Owing to the need to elect multiple Senators simultaneously the Australian Senate uses the Single Transferable Vote (STV) system to elect its members. This is similar to the instant-runoff system of the House of Representatives, in that voters number their most preferred candidates, but there are two major differences. The first difference is candidates do not need a clear majority but rather a quota of votes to be elected. The quota is determined by the number of senators to be elected as follows:

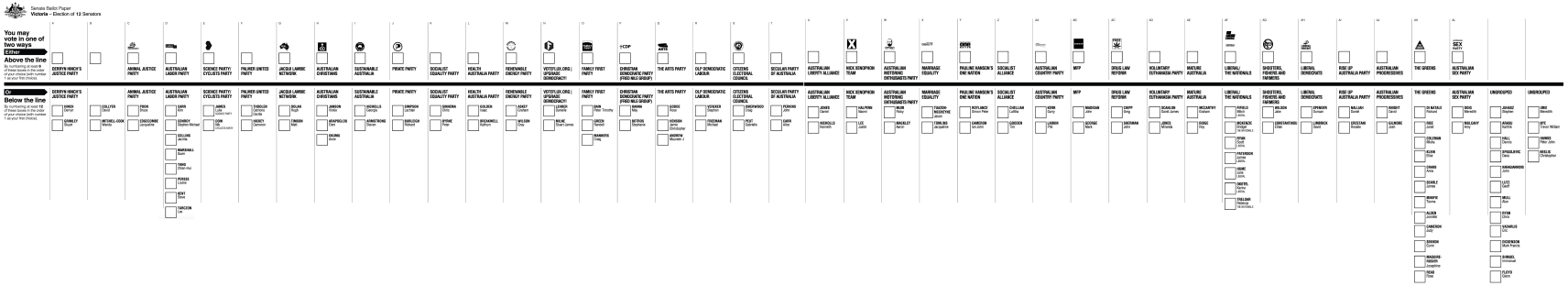
$$\text{Quota} = \left\lfloor \frac{\text{Number of Valid Ballots}}{\text{Number of Senate Vacancies} + 1} \right\rfloor + 1$$

As an example, the quota for Victoria in the 2016 election was 269,250 votes.

The second major difference is that the Senate allows for two, mutually exclusive, options when casting a vote. Voters may either convey their preferences over the political parties contesting the election **or** convey their preferences over the individual candidates who are subsets of the parties. The ballot is formatted so that the political party options are across the top of the ballot and then there is a thick black line on the ballot with the candidates below. It is important to note that candidates fall directly below the party to which they belong. Figure 2.1, below, is a reproduction of the Victorian Senate Ballot from 2016. The

Ballot itself is not intended to be legible, but rather to convey the fact that casting a valid vote is already a cognitively complex task due to the larghe number of possoible options. This makes voting in this context especially susceptible to shocks which raise the costs of voting.

Figure 2.1: Victorian 2016 Senate Ballot



The existence of the thick black line has led to the terms voting "above the line" (ATL) to indicate voting for parties and voting "below the line" (BTL) to indicate voting for candidates. From the 1984 to the 2013 federal elections a vote could be cast in one of two ways. Voting below the line required full preferential voting which meant that voters had to number all candidates in preferred order. It is worth noting that in 2013 some ballots had upwards of 100 candidates on them. Otherwise voters could place a single "1" above the line to nominate their most preferred party. This was known as a group voting ticket which essentially deferred a vote to the nominated party to fill out that individual's ballot paper as they saw fit. The Australian Electoral Commission (AEC) reported that in the 2013 federal election over 96% of all valid votes were cast above the line. Concerns that this system was unrepresentative and being manipulated by political parties led to a reform of the Senate voting system for the 2016 federal election.

2.3.2 2016 New Senate Voting Rules

The 2016 change to the Senate voting rule abolished the group voting ticket above the line and full preferential voting below the line. The new system is called "Optional Preferential Voting." Voters now have the option to **either** number "1" to "6" above the line **or** number 1-12 below the line. In this system, above the line voting is now essentially shorthand for below the line voting in that preferences flow to candidates below the line in ticketed order. Due to the large scale of these state-level elections, as well as the election-by-quota system, by-elections cannot be held if there is a casual vacancy. As a result, a record of all ballots are retained to do an effective recount if a Senator resigns, dies, or is disqualified. It is from this retained record that the data are constructed.

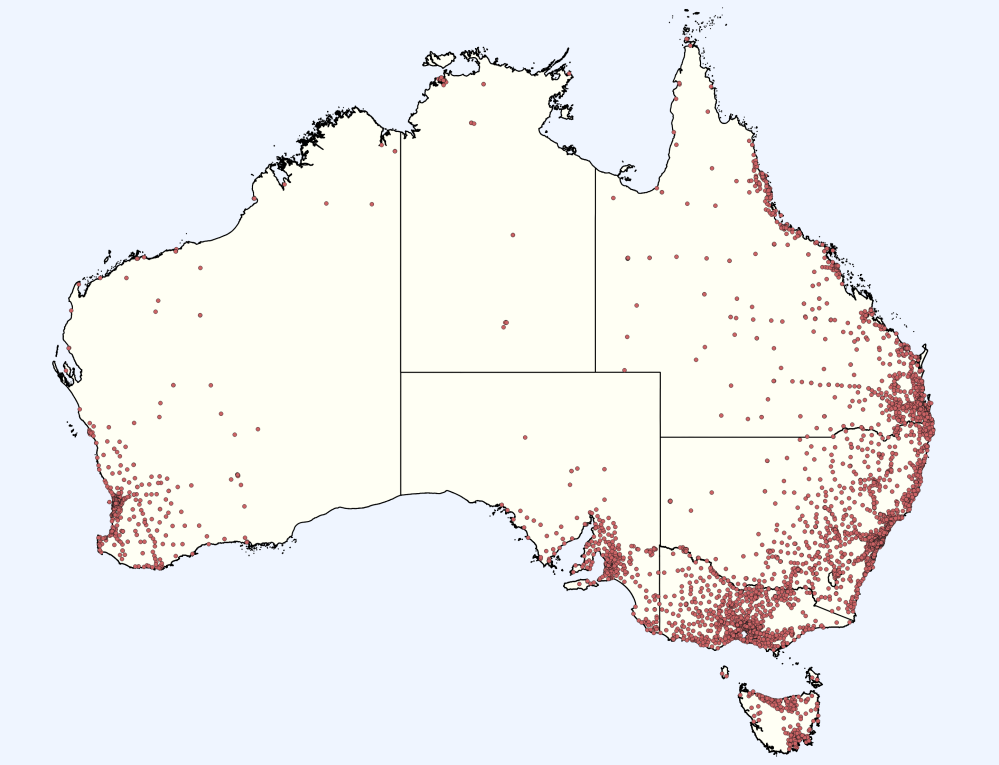
2.4 Data

2.4.1 Election Data

Individual level voting data is obtained from the Australian Electoral Commission.[1] I utilise the electoral dataset to observe the voters who made mistakes on the ballot. I observe voters at the polling place level and all of the 150 Australian electorates are in my sample. An electorate typically has around 150,000 citizens with approximately 100,000 registered voters. According to the AEC, 14,406,706 votes were cast in the 2016 Australian federal election. I remove the votes that cannot be spatially tagged (discussed in section 2.8.2) and take a 10% random sample of all votes cast, 1,383,892 votes in total. Taking this sample is due to the computational constraints of cleaning the large dataset. I then exclude votes that were cast before election day as well as polling places farther than 30km away from weather stations, which is around 900 polling places. Section 2.8.2 discusses this in more detail and tests for possible selection effects of excluding these data. Polling places are typically in primary and high schools, churches and community centres. Figure 2.2 shows the distribution of polling places around Australia. Polling places are clustered around urban areas and it is clear from this figure that there is a large enough spread in the latitude and longitude of polling places that there will be sufficient variation in our weather data to identify a weather effect.

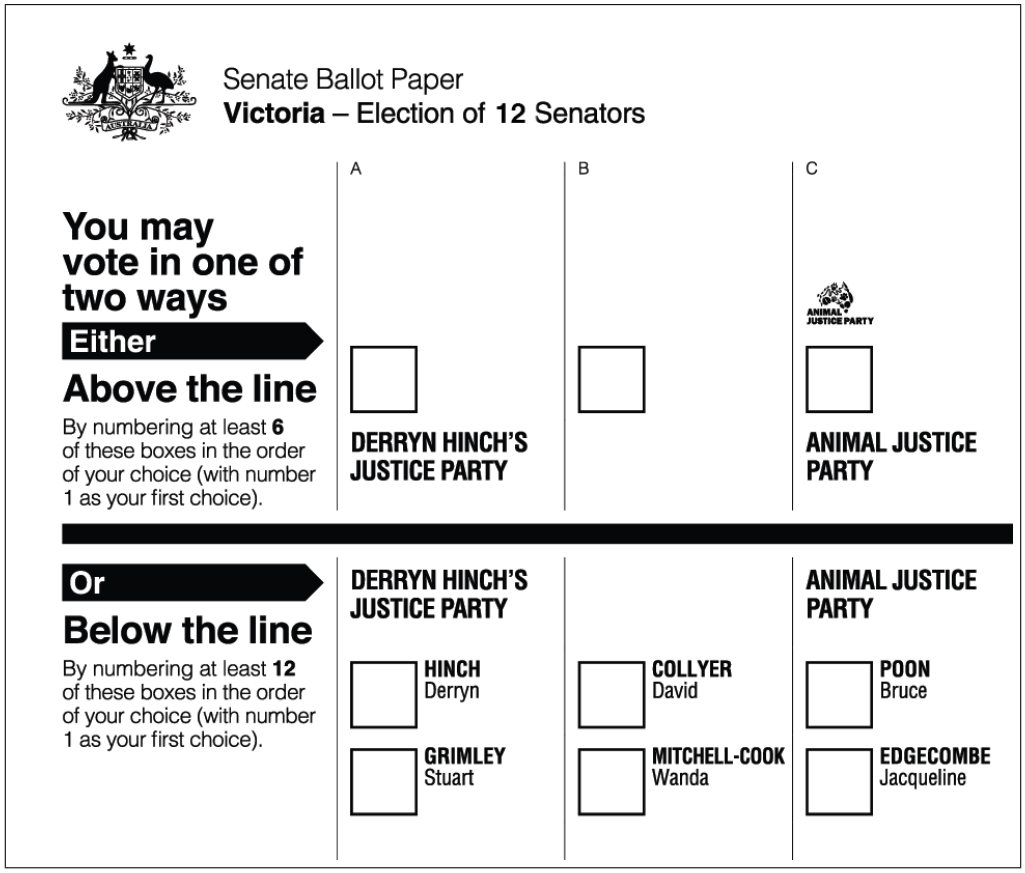
[1] Copyright Commonwealth of Australia (Australian Electoral Commission) 2017

Figure 2.2: Distribution of Polling Places



In the election data there are three ways individuals can make voting mistakes. Each of these mistakes explicitly contravenes the instructions on the ballot, see figure 2.3 below for a reproduction of the ballot instructions. The first kind of mistake is generated by voters who place **fewer** than 6 preferences above the line. This violates the explicit instructions on the ballot to number "at least" 6 preferences above the line. The second kind of mistake is generated by voters who place **fewer** than 12 preferences below the line. This violates the explicit instructions on the ballot to number "at least" 12 preferences below. The third is generated by voters who vote **both** above and below the line. This contravenes the instructions to either vote above or below the line. This comprises 6.7% of votes in my sample.

Figure 2.3: Ballot Instructions



Note: Image of Sample Ballot Obtained From Wikipedia Commons

It is worth noting that 7% of all votes cast were not counted in the final result for other reasons, such as the the ballot being blank or identifying. These votes are not included in this study as they are only identifiable at the electorate level and therefore cannot be reliably linked to accurate weather data. The following figures demonstrate what the mistakes which are considered in this paper would look like as they appear on the ballot:

Figure 2.4: Example of Voting Mistakes: Above the Line

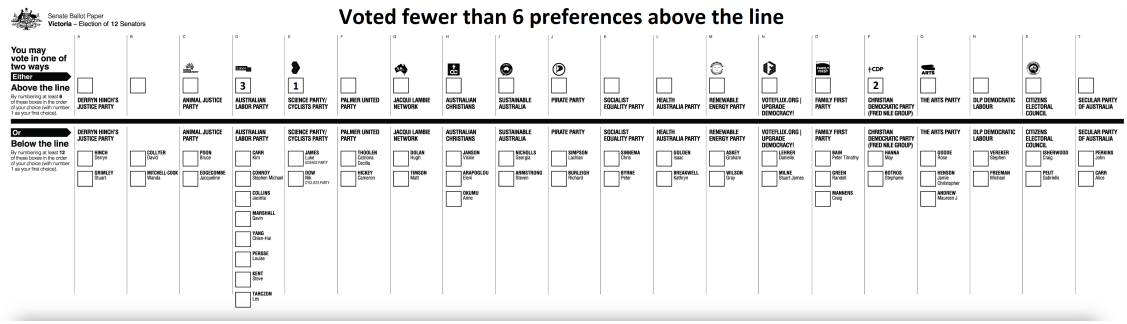
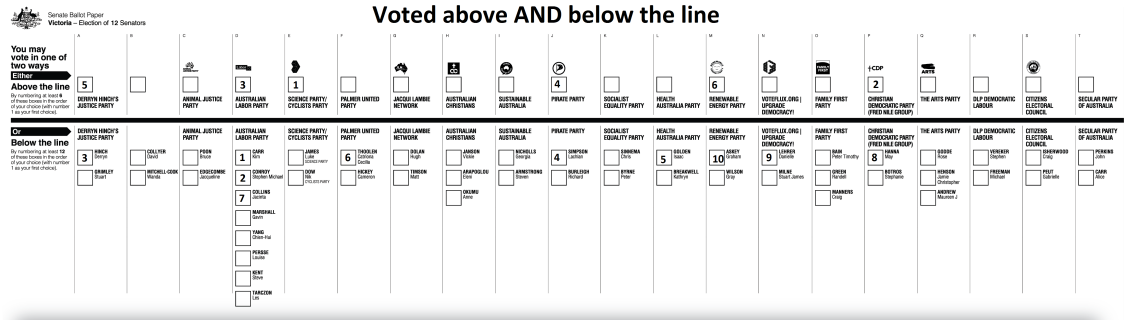


Figure 2.5: Example of Voting Mistakes: Above and Below the Line



2.4.2 Weather Data

The election that I am considering took place on 2nd July 2016, which is mid-winter in Australia. My weather data are obtained from the Australian Bureau of Meteorology[2] and contain both detailed data from the time of the election as well as historical data. For the day of the election, I observe half hourly measurements from 8am - 6pm which come from 370 Weather stations around Australia. My variables of interest are: Temperature (°C), Precipitation (mm), Humidity (%), Wind speed (km/h), Air pressure (hPa), and Daily solar exposure (MJ/m^2) which is used as an approximation for cloud cover. See figure 2.9 in the appendix to see the spatial distribution of weather stations as well as the cross sectional variation in minimum temperature on election day.

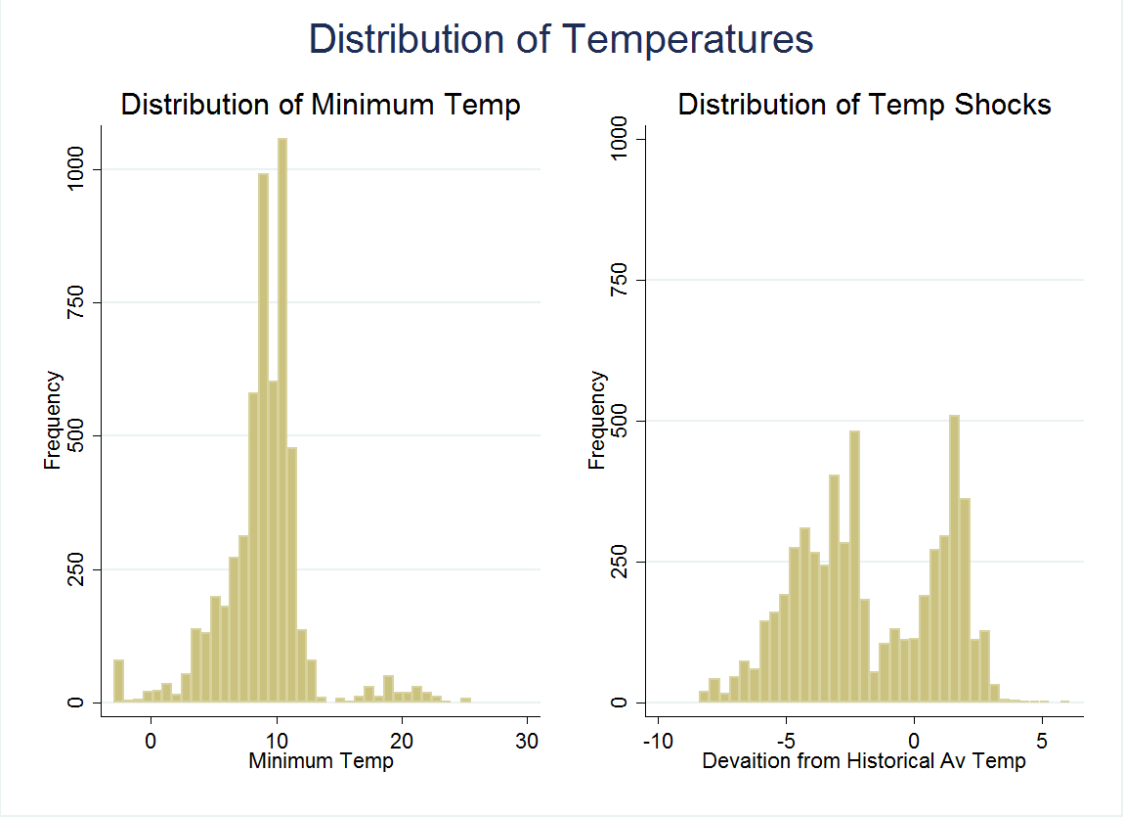
I also observe historical weather data for the 2008 - 2015 period at three hour intervals. I

[2]Copyright Commonwealth of Australia, Bureau of Meteorology 2017

use these observations to create historical climate variables for the day of the election. These are constructed by taking 9am - 6pm the average temperature, precipitation etc for all days within the range of one week either side of July 2nd for those years.

Finally, weather observations are linked to polling places by taking inverse weighted distance observations of the three closest stations to each polling place, following the approach of Feddersen et al. (2012). I exclude polling places where the closest weather station is more than 30 km away. I test the sensitivity of my results to this specification in the robustness section. Figure 2.6 shows the distribution of absolute minimum temperature and temperature shocks. From the figure it is clear that the election was a cold day compared to historical averages.

Figure 2.6: Distribution of Temperature and Temperature Shocks



2.4.3 Census Data

Voter demographics are taken from the Australian Bureau of Statistics[3] (ABS) 2016 Census. I observe voter demographics at the ABS Statistical Area Level 1 (SA1) Level. The 61,695 SA1 blocks have, on average, 400 people and range from 200 to 800 people in size. I match SA1 areas to their nearest polling place and take average demographics. This assumes that on average people vote at nearest polling place to where they live.

The key variables I control for are: share of polling place that is female, share of polling place with tertiary education, share of polling place born overseas, share of polling place unemployed, median age of polling place in years, and median total household weekly income of polling place in AUD.

2.4.4 Summary Statistics

Table 2.1 contains the summary statistics for my data. The first thing to note is that there is a large variation in the distribution of people per polling place. To ensure that this is not driving the results, table 2.23 in the appendix contains the main results but include weights for the number of people per polling place. Although this marginally reduces the point estimate, it does not greatly change the main result. On average, 8% of the votes cast at each polling place are mistakes and polling places are, on average, 10 km from their nearest weather station.

[3]Copyright Commonwealth of Australia, Australian Bureau of Statistics 2017

Table 2.1: Summary Statistics at the Polling Place level

Variable	Mean	Std. Dev.	Min.	Max.	N
Election Data					
Persons per Polling Place (PP)	168.16	168.63	1	3230	6136
Incorrect Votes (% of PP)	7.86	5.41	0	100	6133
Weather & Climate					
Distance of weather station to PP (km)	10.26	6.77	0.13	29.99	6136
Temperature Shock (°C)	-1.74	2.79	-8.35	23.43	6136
Min Temperature (°C)	9.05	3.47	-2.9	27.22	6136
Max Temperature (°C)	16.87	3.48	-0.72	33.2	6136
Mean Temperature (°C)	14.22	3.11	-1.44	30.18	6136
Max Precipitation (mm)	0.35	0.88	0	27.83	6136
Mean Humidity (%)	61.49	13.6	18.17	99	6136
Mean Solar Exposure (MJ/m$ˆ2$)	10.29	2.96	0.01	20.43	6136
Mean Wind Speed (km/h)	12.38	5.19	0.16	39.98	6136
Mean Air Pressure (hPa)	795.55	275.2	0	1030.78	6136
Historical Average Min Temp 2008-2015	10.79	3.39	-2.17	25.73	6136
Historical Average Max Temp 2008-2015	15.67	3.57	-0.17	30.87	6136
Historical Average Mean Temp 2008-2015	13.44	3.42	-1.07	28.06	6136
Historical Average Precipitation 2008-2015	1.87	1.04	0	10.42	6136
Historical Average Humudity 2008-2015	67.05	7.37	10.83	90.78	6136
Historical Average Solar Exposure 2008-2015	8.89	2.49	0.01	19.98	6136
Historical Average Wind Speed 2008-2015	13.89	3.85	0.98	29.21	6136
Historical Average Air Pressure 2008-2015	792	273.71	0	1023.83	6136
Demographics					
Female share of PP	0.5	0.03	0.15	0.6	6136
Tertiary Educated share of PP	0.39	0.09	0	0.68	6136
Born Overseas share of PP	0.32	0.15	0.02	1	6136
Unemployed share of PP	0.07	0.03	0	0.43	6136
Median Age of PP	39.56	6.34	14	67.33	6136
Median HH Weekly Income (AUD)	1471.06	467.36	0	3850.27	6136

2.5 Empirical Approach

2.5.1 Main Specification

I draw on econometric methods adapted form the new climate literature to identify my effects. Dell et al. (2014) & Hsiang (2016) give a good review of the literature. I create a

weather shock variable as the deviation of the realised weather variable from its historical average level. Identification relies on the exogeneity of cross-sectional weather variation. I estimate the model,

$$Y_{ij} = \alpha_j + \beta_1 \mathrm{D}_{ij}^{\mathrm{T}} + \gamma \Gamma_{ij} + \delta \mathbf{X}_{ij} + \epsilon_{ij} \tag{2.1}$$

where,

$$\mathrm{D}_{ij}^{\mathrm{T}} = \mathrm{T}_{ij} - \overline{\mathrm{T}}_{ij} \tag{2.2}$$

In this specification $Y_{ij} \in [0, 100]$ is the share of polling place i in electorate j who voted incorrectly. T_{ij} is the minimum temperature (°C) during the election (from 8am - 6pm). $\overline{\mathrm{T}}_{ij}$ is the 2008-2015 average temperature (°C) for a week either side of that day (also 8am - 6pm). For the purposes of this paper, $\overline{\mathrm{T}}_{ij}$ will be referred to as "climate" in that it captures the averages of our weather variables over a 7 year period. It should be noted that this is only a very short run view of climate.

In this way, $\mathrm{D}_{ij}^{\mathrm{T}}$ is the realised minimum temperature deviation from the historical minimum temperature. Γ_{ij} is a matrix of other weather variables as deviations from historical averages which include: Precipitation (mm), Humidity (%), Wind speed (km/h), Daily solar exposure (MJ/m^2) and Air pressure (hPa). X_{ij} is a matrix of demographic covariates, α_j are electorate level fixed effects, and ϵ_{ij} is the idiosyncratic error term.

In my model standard errors are clustered at the electorate level. Although I do not weight the data for my main results, I check that the use of analytic weights does not greatly change my results (see table 2.23 in the appendix). Electorate level fixed effects control for House of Representatives specific effects, such as campaigning, area specific and state specific effects.

I use a linear specification despite the fact that the outcome variable is bounded between 0 and 1. This is because estimation with a non-linear model yields similar point estimates

when marginal effects are estimated at the means of the variables of interest. I discuss this and estimate the main results using a fractional logit regression model in table 2.13 of the robustness section.

2.5.2 Alternative Specification

A potential issue with my constructed deviation variable is that there are now two underlying data generating processes being captured in the single variable. To see if the climate effect is driving my results I use the following specification to separate the climate effect from the weather shock effect. I use a similar approach to that of Dell et al. (2009) who consider cross sectional temperature shocks and income at sub-national level and Dell et al. (2012) who examine temperature shocks and economic growth. I estimate the following model,

$$Y_{ij} = \alpha_j + \beta_1 \mathrm{T}_{ij} + \beta_2 \overline{\mathrm{T}}_{ij} + \gamma \mathbf{Z}_{ij} + \delta \mathbf{X}_{ij} + \epsilon_{ij} \tag{2.3}$$

Where Z_{ij} is a matrix of other weather variables and their historical averages. This specification is primarily to show that the results found using the model from equation (1) are not being driven by $\overline{\mathrm{T}}_{ij}$. All heterogeneous effects and robustness tests are conducted on the specification in equation (1).

Alternative Specification: Interpreting Coefficients

By including both the temperature on the day and historical averages for this time period, my model captures the effect of weather shocks as well as climate effects. This can be seen if the model is rewritten as,

$$Y_{ij} = \alpha_j + \beta_1 (\mathrm{T}_{ij} - \overline{\mathrm{T}}_{ij}) + (\beta_1 + \beta_2) \overline{\mathrm{T}}_{ij} + ... + \delta \mathbf{X}_{ij} + \epsilon_{ij} \tag{2.4}$$

In this case, β_1 can be interpreted as a weather shock, or the deviation of the realised temperature on the day from historical mean, and the effect of average historical weather,

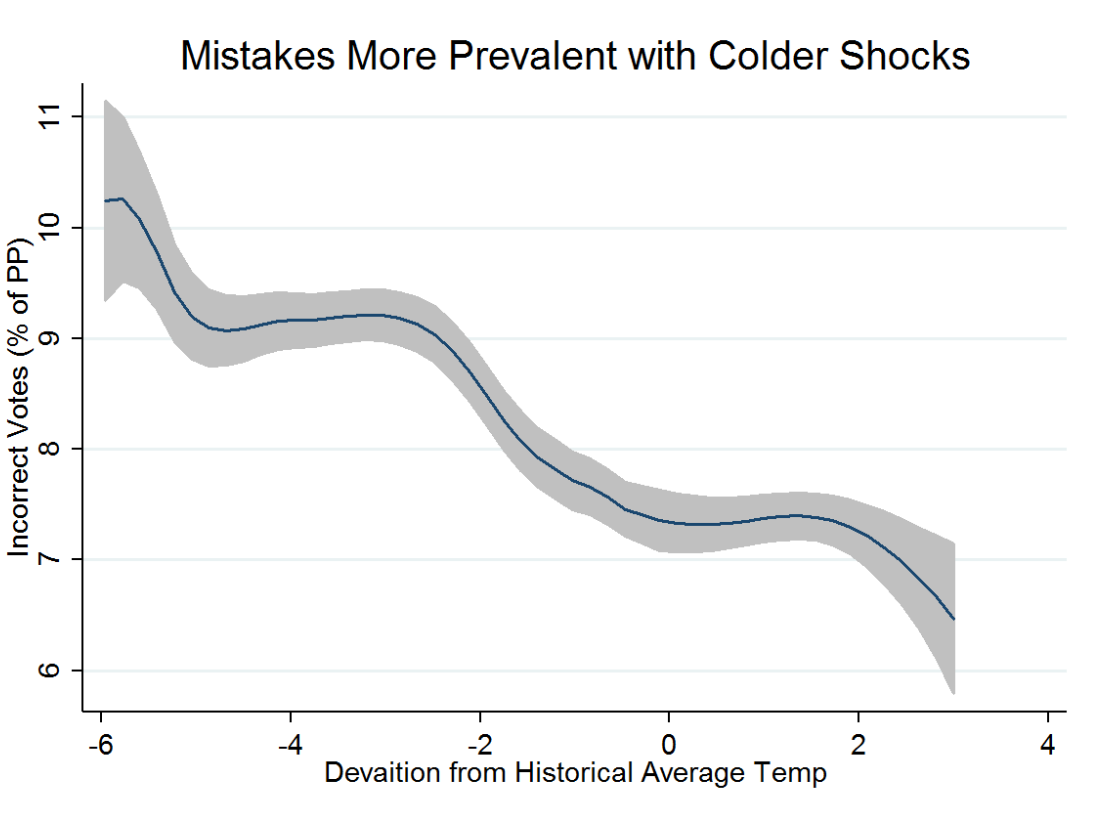
i.e. climate, can be interpreted as $\beta_1 + \beta_2$.

2.6 Results

2.6.1 Main Results

Figure 2.7 shows the relationship between a weather shock and voting mistakes using a non-parametric approach. There is a clear relationship showing that colder shocks are correlated with a higher incidence of voting mistakes.

Figure 2.7: Direct Effect of Cold Shocks on Voting Mistakes



The following table shows the regression results from the two specifications described in the last section. It shows very similar estimates indicating a significant effect of weather shocks on voting mistakes and provide evidence that this is not being driven by a climate effect.

Table 2.2: Effect of Weather Shock on Voting Mistakes

	(1)	(2)	(3)	(4)	(5)	(6)
Model (1)						
Temperature Shock[a]	-0.215**	-0.302***	-0.231***			
	(0.0861)	(0.106)	(0.0783)			
Model (2)						
Minimum Temperature				-0.292***	-0.302***	-0.283***
				(0.104)	(0.106)	(0.105)
Historical Average				0.128	0.303**	0.368**
Minimum Temperature				(0.0791)	(0.135)	(0.159)
Weather Shock Effect: β_1				-0.292***	-0.302***	-0.283***
SE(β_1)				(0.104)	(0.106)	(0.105)
Climate Effect: $\beta_1 + \beta_2$				-0.163**	0.002	0.085
SE($\beta_1 + \beta_2$)				(0.069)	(0.070)	(0.081)
P-value of $\beta_1 + \beta_2 = 0$				0.019	0.983	0.296
Electorate FE	No	Yes	Yes	No	Yes	Yes
Other Controls[b]	No	No	Yes	No	No	Yes
N	6132	6132	6132	6132	6132	6132
R^2	0.012	0.320	0.380	0.021	0.320	0.381

Standard errors in parentheses

Note: Obs with weather stations min distance further than 30 km dropped

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[a]Shock defined as realised minimum temperature as deviation from historical average

[b]Weather controls are: Precipitation, Humidity, Solar Exposure, Wind Speed, Air Pressure & Demographic controls are: Share of polling place that is female, tertiary educated, born overseas, unemployed as well as median age and income of polling place

There is no substantial difference between the point estimates and standard errors in both specifications, suggesting that the specification for model (1) is sufficient to capture the effect of temperature on voting mistakes. All model specifications suggest there is a weather shock effect that decreases voting mistakes as temperature increases (or, for our purposes, increases voting mistakes as temperature decreases). The specification for model (2), which splits the temperature and historical temperature variables apart, does support the hypothesis that the result is not being driven by climate effects but rather by a weather

shock effect. This can be seen from the coefficient for the climate effect ($\beta_1 + \beta_2$) which is described in section 2.5.2. In column (4) the coefficient is significant at the 5% level, however this significance disappears when fixed effects and other controls are added in columns (5) and (6).

From column (3), we can see that there is a statistically significant effect of a weather shock on voting mistakes at the 1% level. The point estimate for the effect of a temperature shock, measured as the realised temperature's deviation from historical means, is -0.231 ($p< 0.01$). To clarify, a 1°C cold shock, i.e. when D_{ij}^{T} is equal to -1, will increase voting mistakes by 0.231 percentage points. This indicates that a one standard deviation cold weather shock of -2.796°C would increase voting mistakes by 0.65 percentage points, or around 93,000 votes in the 2016 federal election. It should be stressed that this is a lower bound for this estimate. This is because the estimate does not include people who made mistakes which would not have allowed their vote to be counted.

Although my main specification is a linear model, I also show in table 2.3 that polynomial specifications of order 2 and 3 increase the size of my point estimate. However, because higher order polynomials do little to shrink standard errors, the effect can be said to be neatly captured by a linear model.

As mentioned before, the literature from political economy and psychology indicate that there may be asymmetric effects of hot and cold shocks. Table 2.4 tests for whether effects are not symmetric above and below the historical average temperature. Although my final specification appears to show a larger effect for warm shocks, I fail to reject the null that the coefficients on cold and warm shocks are the same. Therefore I conclude that the effects of cold and warm shocks are not asymmetric. This is likely due to the fact that, because this is a winter election, warm shocks are still relatively cold in absolute temperature.

Table 2.3: Effect of Cold Weather Shock: Polynomial Specification

	Voting Mistakes		
	(1)	(2)	(3)
Temp Dev from Historical Av	-0.231***	-0.236***	-0.429***
	(0.0783)	(0.0791)	(0.122)
Temp Dev from Historical Av ^{2}		-0.00519	-0.0244**
		(0.00664)	(0.0108)
Temp Dev from Historical Av ^{3}			0.00161**
			(0.000620)
Electorate FE	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes
N	6132	6132	6132
R^2	0.380	0.380	0.381

Standard errors in parentheses

Note: Obs with weather stations min distance further than 30 km dropped

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.4: Testing Symmetric Effects of Cold Weather Shock

	Voting Mistakes		
	(1)	(2)	(3)
(1) Cold Shock (Below Historical Average Temp)	-0.156	-0.347**	-0.230**
	(0.135)	(0.147)	(0.112)
(2) Warm Shock (Above Historical Average Temp)	-0.389**	-0.205	-0.233*
	(0.196)	(0.152)	(0.132)
P-value of test (1) = (2)	0.426	0.535	0.986
Electorate FE	No	Yes	Yes
Other Controls	No	No	Yes
N	6132	6132	6132
R^2	0.0129	0.320	0.380

Standard errors in parentheses

Note: Obs with weather stations min distance further than 30 km dropped

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.7 Heterogeneous Effects

I find evidence of some heterogeneous effects which are consistent with the result being driven by cognitive costs. I follow the approach of Dell et al. (2012) and construct indicators for areas with high levels of people born overseas, the top 25 percentile, and areas with low levels of tertiary education attainment, the bottom 25 percentile. Cold shocks have a markedly greater effect on increasing the prevalence of mistakes among people born overseas and people without tertiary education.

As can be seen in column (1) of table 2.5, the baseline estimate of a cold shock (i.e. a -1°C shock) increases voting mistakes by 0.231 ($p< 0.01$) percentage points. Controlling for other demographic variables, column (4) shows the effect on people born overseas is 0.352 ($p< 0.01$) percentage points, a 52 % increase in magnitude of the coefficient. For people without a tertiary level education the effect of a cold shock is 0.418 ($p< 0.01$) percentage points, a 26 % increase in magnitude of the coefficient.

Although more testing would need to confirm the factors driving these heterogeneous effects, the results lend support to the hypothesis that cold shocks increase the cognitive costs of voting. Citizens born overseas will, on average, be less familiar with Australia's electoral system which implies they will face a higher cost in the ballot booth. Citizens with lower levels of education may also face higher costs associated with educational disadvantage. Although not conclusive, this evidence lends further support in this direction.

Table 2.5: Heterogeneous Effects of Cold on Voting Mistakes

	Voting Mistakes						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temp Dev from Historical Av	-0.231***	-0.299***	-0.333***	-0.219***	-0.179	-0.215*	-0.330***
	(0.0783)	(0.106)	(0.105)	(0.0789)	(0.113)	(0.112)	(0.110)
Temp Dev x Born OS Dummy		-0.0361	-0.0350	-0.133*			
		(0.0926)	(0.0924)	(0.0799)			
Temp Dev x Low Tert Edu Dummy					-0.225***	-0.225***	-0.0881
					(0.0820)	(0.0834)	(0.0768)
Effect on People Born OS		-0.336	-0.368	-0.352			
SE		0.133	0.131	0.104			
P value		0.013	0.006	0.001			
Effect on Low Tertiary Edu					-0.405	-0.440	-0.418
SE					0.119	0.121	0.116
P value					0.001	0.000	0.000
Electorate FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	No	Yes	Yes	No	Yes	Yes
Other Controls	Yes	No	No	Yes	No	No	Yes
N	6132	6132	6132	6132	6132	6132	6132
R^2	0.380	0.320	0.322	0.379	0.323	0.325	0.342

Standard errors in parentheses

Note: Obs with weather stations min distance further than 30 km dropped

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.8 Robustness

2.8.1 Placebo Tests

I perform several robustness checks of the results. Firstly, I include lags of weather shock variables for one week leading up to the election. Secondly, I check that the result is not driven by climate effects by including only the historical average temperatures in the regression. Thirdly, I test for a spurious result by running placebo tests using historical weather data. Specifically, I create shock variables using weather data from previous years on the same day as the election to test for a result. Finally, I check to ensure that my result is not being driven by choice of weather station exclusion radius. The main results do not include any polling places whose closest weather station was farther than 30km away.

Controlling for Previous Week's Weather

If effects are truly driven by the weather shock experienced during the election then there should not be significant coefficients on lag variables. I include lags for the 6 days leading up to the election and find that all coefficients are insignificant. Moreover, the inclusion of the lags does not dramatically change the point estimate or standard error of the main result.

Table 2.6: Robustness: Weather Effects with Temperature Leads

Min Temp dev from 2008-15 mean	-0.226**
	(0.0921)
Temp Shock 1 day before election	-0.0696
	(0.149)
Temp Shock 2 days before election	0.0811
	(0.100)
Temp Shock 3 days before election	0.204
	(0.140)
Temp Shock 4 days before election	-0.137
	(0.141)
Temp Shock 5 days before election	-0.143
	(0.179)
Temp Shock 6 days before election	-0.129
	(0.147)
Electorate FE	Yes
Other Controls	Yes
N	6132
R^2	0.382

Standard errors in parentheses

Note: Obs with weather stations min distance further than 30 km dropped

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Testing for Climate and Regional Effects

As was previously mentioned, the creation of the shock variable D_{ij}^{T} means that there are technically two data generating processes underlying these results. Although the specification of model (2) helps to confirm that it is the deviation from the historical mean and not the historical mean itself that drives our result, this second robustness check provides more evidence to this effect. Although there is some evidence that historical air pressure has some effect, it is very small in magnitude and only significant at the 10% level.

Table 2.7: Robustness: Only Including Historical Average Weather Vars

	(1)	(2)
Historical Av Min Temp	0.0510	0.0314
	(0.0850)	(0.0836)
Historical Av Precipitation	-0.440*	-0.111
	(0.231)	(0.162)
Historical Av Humidity	-0.00525	-0.0199
	(0.0267)	(0.0240)
Historical Av Solar Exposure	-0.110	-0.0713
	(0.207)	(0.143)
Historical Av Wind Speed	0.0760	0.00509
	(0.0581)	(0.0469)
Historical Av Airpressure	-0.00100*	-0.000672*
	(0.000537)	(0.000376)
Electorate FE	Yes	Yes
Other Controls	No	Yes
N	6132	6132
R^2	0.321	0.379

Standard errors in parentheses

Note: Obs with weather stations min distance further than 30 km dropped

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Historical Placebo Test

I run placebo tests where I use the weather from the same day in previous years to see if I find an effect. I find no effects for the four years leading up to the election. There are

significant results for 2010 and 2009, however these are only at the 10% level. The more interesting result is for 2011, which shows a statistically significant effect at the 1% level. Follow up work should be done to find an explanation for this. A possible explanation could be that there are similar weather shocks which occur on 5 year cycles. See tables 2.14 to 2.21 in the appendix for these results.

2.8.2 Testing for Selection Effects of Excluding Data

Inclusion Radius

I also test to see if my results are sensitive to changing the radius which I use to exclude weather stations. I exclude all polling place observations where the nearest weather station is firstly farther than 10km, then farther than 20km, and then farther than 40km away. The results remain significant regardless of the inclusion radius chosen. As I decrease the size of the inclusion radius, the effect becomes larger. This supports my primary finding, as stations closer to polling places reflect a more accurate estimate of the weather experienced at polling places. They will therefore more precisely capture the effect of weather.

Table 2.8: Robustness: Excluding Weather Stations > 10 km away

Min Temp dev from 2008-15 mean	-0.293***
	(0.108)
Electorate FE	Yes
Analytic Weights	No
Other Controls	Yes
N	3549
R^2	0.471

Standard errors in parentheses

Note: Obs with weather stations min distance further than 10 km dropped

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9: Robustness: Excluding Weather Stations > 20 km away

Min Temp dev from 2008-15 mean	-0.221***
	(0.0672)
Electorate FE	Yes
Analytic Weights	No
Other Controls	Yes
N	5435
R^2	0.415

Standard errors in parentheses

Note: Obs with weather stations min distance further than 20 km dropped

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.10: Robustness: Excluding Weather Stations > 40 km away

Min Temp dev from 2008-15 mean	-0.216***
	(0.0750)
Electorate FE	Yes
Analytic Weights	No
Other Controls	Yes
N	6462
R^2	0.364

Standard errors in parentheses

Note: Obs with weather stations min distance further than 40 km dropped

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Voting Before the Election

Approximately 19% of votes are those cast at centralised voting centres, called pre poll voting centres (though it should be noted these votes are cast on election day). These are essentially large, central metropolitan centres where citizens can come to vote. Although these data pose no threat to our main result, as we can easily link pre poll voting centres to weather variables, they do pose potential problems to our demographics analysis. This is because the people voting in these centres are likely to not only be those living in the area, but individuals from other areas who decide to vote in large metropolitan centres. Table 2.11, below, shows the breakdown of included and excluded vote types.

Table 2.11: Robustness: Vote Types

	N	%
Vote Cast on Election Day (in sample)		
Regular Vote	858,191	62.01
Pre Poll Voting Centre Vote	258,882	18.71
Vote Cast on Election Day (not in sample)		
Absent Vote	69,109	4.99
Mobile Voting Units	10,679	0.77
Vote Not Cast on Election Day (not in sample)		
Postal Vote	119,978	8.67
Pre Poll Declaration Vote	54,776	3.96
Provisional Vote	12,277	0.89
Total	1,383,892	100.00

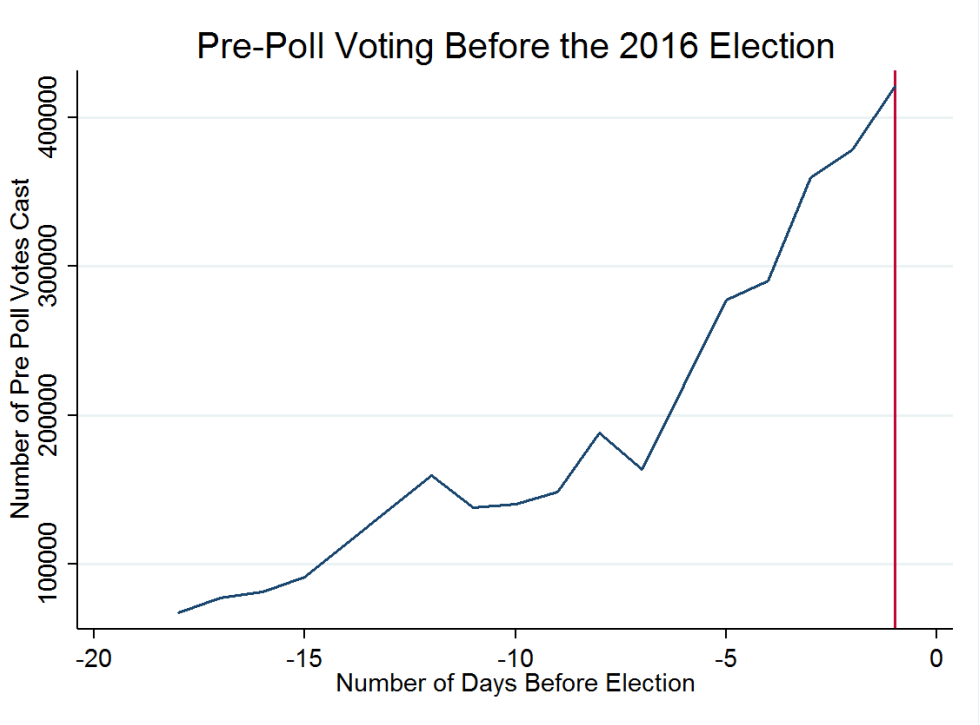
This is a 10% random sample of all above the line votes

Table 2.24 in the appendix shows the main results but exclude all of the pre poll voting centres. The main weather results do not change substantially, however certain demographics are now significant, namely gender ratio.

There are several other important vote types. Pre poll declaration voting involves a voter travelling to a Pre Polling Vote Centre and casting their vote before the election. Postal voting, rather unsurprisingly, involves sending in a ballot via the mail. Table 2.11 shows that the largest group of excluded votes is postal votes. Unfortunately, this is also the group of voters we know the least about. Postal votes only contain information about which electorate the individual belonged to, but not where or when they cast their vote.

We also cannot know much information about pre poll declaration voting, however we can test to see if expected weather shocks effected the likelihood of casting a pre poll vote. Figure 2.8 shows that early voting increases dramatically in the week leading up to election day.

Figure 2.8: Voting Frequency before Election Day



There is potential concern if selection into pre poll voting correlates with the treatment,

i.e. if people cast an early vote because of concerns about the cold temperature on election day. To test this I see whether temperature forecasts published by the Australian Bureau of Meteorology predict early voting patterns. It is possible to observe which electorate a pre poll vote was cast in though not precisely at which polling place on on which day. To provide evidence of no selection effect, I show that the average weather forecast for election day in an electorate does not increase (or decrease) the probability that there will be more or fewer pre poll votes in that electorate. I test this for forecasts up to 6 days before the election using weather forecast data from the Australian Bureau of Meteorology. Table 2.12 shows the raw coefficient results of a fractional logit regression where the dependent variable is share of electorate with pre poll votes. Column (1) shows that minimum temperature predictions published 1 day before the election did not have any effect on the probability of casting an early vote. Indeed, none of the forecasts for temperature predict an early voting. There is some evidence that that forecasts for rain predict early voting, however this evidence is mixed. Columns (4) suggests that as forecast rain level increases, individuals become less likely to cast early votes, whereas column (6) suggests that as forecast rain level increases, individuals become more likely to cast early votes. It is also worth noting that because not all weather stations update daily, there are some missing observations. Generally, however, this result provides evidence that individuals are not choosing to vote early because of concerns about temperature on election day. Unfortunately a similar analysis is not possible for postal voters as it is harder to assume that voters were in there electorate in the week leading up to the election. However, these comprise only 8.67% of the total sample and selection at this level is likely not driving the main results.

Table 2.12: Robustness: Probability of Pre-Poll Voting based on Weather Forecasts

	(1)	(2)	(3)	(4)	(5)	(6)
Min Temp Forecast 1 Day before Election Day	0.0917					
	(0.0587)					
Rainfall Forecast 1 Day before Election Day	0.0475					
	(0.0821)					
Min Temp Forecast 2 Day before Election Day		0.0279				
		(0.0676)				
Rainfall Forecast 2 Day before Election Day		0.149				
		(0.0926)				
Min Temp Forecast 3 Day before Election Day			0.0740			
			(0.0568)			
Rainfall Forecast 3 Day before Election Day			-0.103			
			(0.118)			
Min Temp Forecast 4 Day before Election Day				0.115		
				(0.0788)		
Rainfall Forecast 4 Day before Election Day				-0.174***		
				(0.0629)		
Min Temp Forecast 5 Day before Election Day					0.118	
					(0.0913)	
Rainfall Forecast 5 Day before Election Day					0.0119	
					(0.0566)	
Min Temp Forecast 6 Day before Election Day						0.101
						(0.0672)
Rainfall Forecast 6 Day before Election Day						0.486**
						(0.216)
Constant	-6.497***	-6.024***	-6.271***	-6.521***	-6.685***	-6.745***
	(0.470)	(0.472)	(0.383)	(0.589)	(0.621)	(0.521)
N	145	132	147	149	149	149

Note: Results from fractional logit regression: raw coefficients reported
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.8.3 Fractional Logit Specification

The dependent variable for this analysis is the share of polling place votes that were mistakes. The fact that the dependent variable is bounded means that linear regression may give biased results. However, this analysis was also conducted using a fractional logit regression model, with the results shown in table 2.13 below. It can be seen that the marginal effects evaluated at the means of the independent variables are very similar in magnitude to the linear model. It should be noted that in our linear model the dependent variable is a percentage number bounded between 0 and 100, whereas in the fractional logit regresison the dependent variable is a share bounded between 0 and 1. For comparability the marginal effects reported in table 2.13 have been multiplied by 100.

Table 2.13: Effect of Weather Shock on Voting Mistakes

	(1)	(2)	(3)
Temp Dev from Historical Av	-0.216**	-0.278**	-0.199**
	(0.0869)	(0.109)	(0.0794)
Electorate FE	No	Yes	Yes
Other Controls	No	No	Yes
N	6133	6133	6133

Standard errors in parentheses

Observations with weather stations min distance further than 30 km dropped

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.9 Conclusion

This paper finds evidence of weather shocks affecting voting behaviour at the intensive margin. I demonstrate that cold temperature shocks increase the prevalence of voting mistakes in Australia's 2016 federal election. There are also heterogeneous effects, with cold shocks having a greater effect on citizens born overseas and citizens with lower levels of education.

My main contribution to the literature is to highlight the importance of costs which

affect voter behaviour at the intensive margin. Existing studies of weather effects on voting behaviour focus on the extensive margin - turnout decisions. The combination of compulsory voting in Australia and a unique electoral rule allows us to observe voting behaviour at the individual level. A policy recommendation emanating directly from this study would be to avoid mid-winter elections to minimise the number of incorrect votes cast by minimising cross sectional differences in voting costs faced by individuals.

However there are also broader implications about the efficacy of compulsory voting systems and their ability to generate more complete preference aggregations than voluntary systems. This research shows that measuring the effectiveness on compulsory voting systems on turnout alone is insufficient. Rather, a full study of the effects of compulsory voting at both the intensive and extensive margin are necessary to draw conclusions about which system is truly preferable.

2.10 Appendix

The following tables show the main results using instead temperatures from 2nd July in previous years to check for spurious result.

Table 2.14: Robustness: Placebo Test Year 2015

Temp on 2nd July 2015 dev from 2008-15 mean	-0.165
	(0.121)
Electorate FE	Yes
Other Controls	Yes
N	6132
r2	0.382

Standard errors in parentheses
Note: Weather stations further than 30 km dropped
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.15: Robustness: Placebo Test Year 2014

Temp on 2nd July 2014 dev from 2008-15 mean	0.0298
	(0.0863)
Electorate FE	Yes
Other Controls	Yes
N	6132
r2	0.379

Standard errors in parentheses
Note: Weather stations further than 30 km dropped
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.16: Robustness: Placebo Test Year 2013

Temp on 2nd July 2013 dev from 2008-15 mean	-0.0535
	(0.0994)
Electorate FE	Yes
Other Controls	Yes
N	6132
r2	0.380

Standard errors in parentheses

Note: Weather stations further than 30 km dropped

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.17: Robustness: Placebo Test Year 2012

Temp on 2nd July 2012 dev from 2008-15 mean	-0.0842
	(0.151)
Electorate FE	Yes
Other Controls	Yes
N	6132
r2	0.379

Standard errors in parentheses

Note: Weather stations further than 30 km dropped

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.18: Robustness: Placebo Test Year 2011

Temp on 2nd July 2011 dev from 2008-15 mean	0.525***
	(0.115)
Electorate FE	Yes
Other Controls	Yes
N	6132
r2	0.386

Standard errors in parentheses

Note: Weather stations further than 30 km dropped

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.19: Robustness: Placebo Test Year 2010

Temp on 2nd July 2010 dev from 2008-15 mean	-0.168*
	(0.0974)
Electorate FE	Yes
Other Controls	Yes
N	6132
r2	0.380

Standard errors in parentheses

Note: Weather stations further than 30 km dropped

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.20: Robustness: Placebo Test Year 2009

Temp on 2nd July 2009 dev from 2008-15 mean	-0.308*
	(0.161)
Electorate FE	Yes
Other Controls	Yes
N	6132
r2	0.380

Standard errors in parentheses

Note: Weather stations further than 30 km dropped

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.21: Robustness: Placebo Test Year 2008

Temp on 2nd July 2008 dev from 2008-15 mean	0.0382
	(0.0929)
Electorate FE	Yes
Other Controls	Yes
N	6132
r2	0.379

Standard errors in parentheses

Note: Weather stations further than 30 km dropped

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The following table shows the main results but shows all covariates (excluding electorate fixed effects).

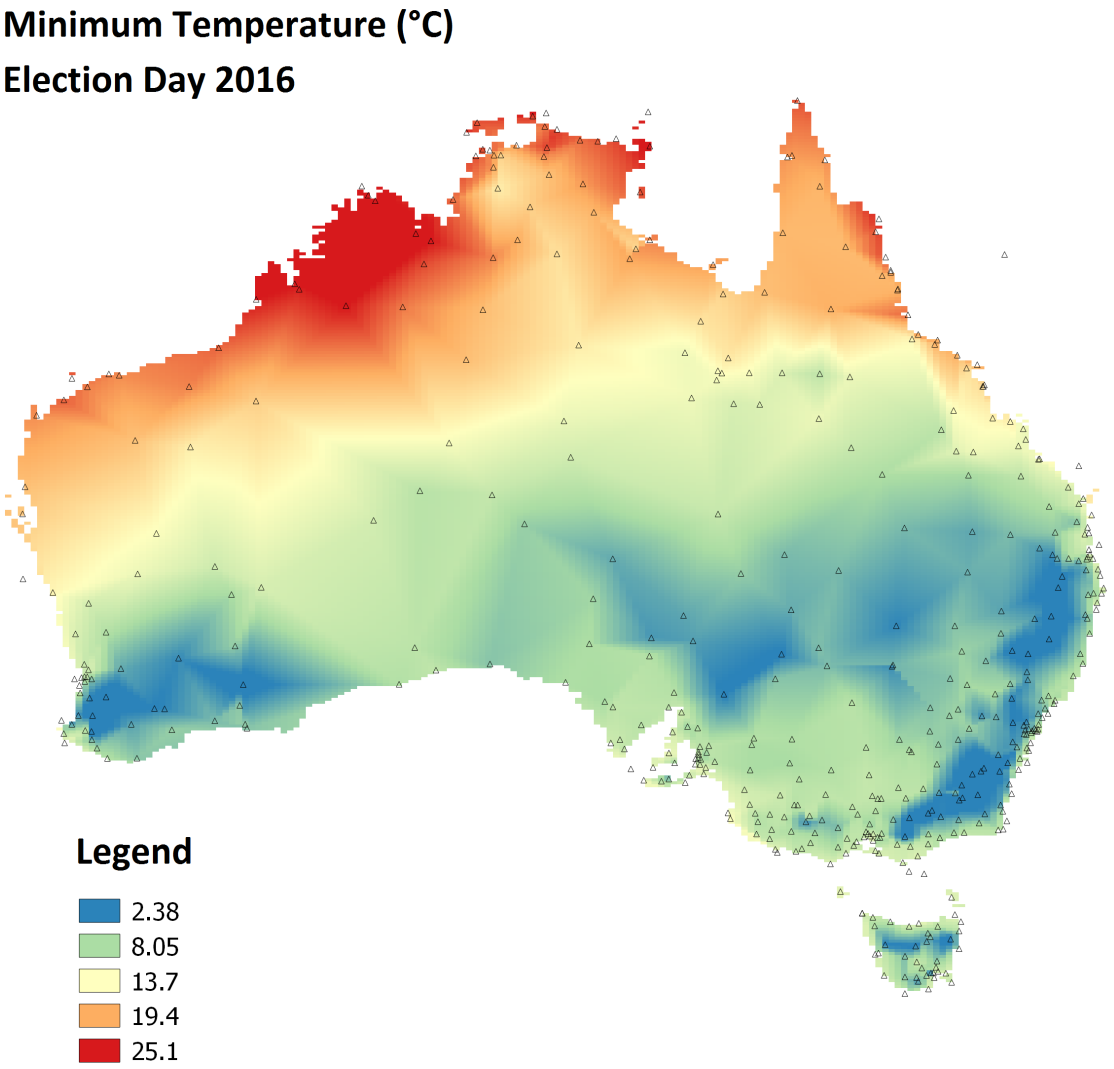
Table 2.22: Alternative Specification

Temp Dev from Historical Av	-0.215**	-0.302***	-0.231***			
	(0.0861)	(0.106)	(0.0783)			
Precipitation dev from 2008-15 mean			0.0149			
			(0.0859)			
Humidity dev from 2008-15 mean			0.0192			
			(0.0276)			
Wind Speed dev from 2008-15 mean			0.0473			
			(0.0561)			
Air Press dev from 2008-15 mean			0.00734			
			(0.00832)			
Solar Expose dev from 2008-15 mean			0.0398			
			(0.325)			
Female share of PP			3.154			2.842
			(3.084)			(3.078)
Tertiary education share of PP			-22.79***			-22.44***
			(2.200)			(2.193)
Born Overseas share of PP			2.375			2.295
			(1.676)			(1.640)
Unemployed share of PP			-2.365			-1.935
			(4.295)			(4.295)
Median age PP			0.0152			0.0155
			(0.0164)			(0.0159)
Median HH week income PP			-0.000106			-0.000129
			(0.000270)			(0.000265)
Min Temperature				-0.292***	-0.302***	-0.283***
				(0.105)	(0.105)	(0.105)
Historical Av Min Temp				0.128	0.303**	0.368**
				(0.0791)	(0.135)	(0.159)
Precipitation (mm)						-0.0329
						(0.0855)
Historical Av Precipitation						-0.123
						(0.152)
Humdity						0.0154
						(0.0306)
Historical Av Humidity						-0.0369
						(0.0306)
Solar Exposure						-0.0196
						(0.344)
Historical Av Solar Exposure						-0.231
						(0.398)
Wind Speed						0.0634
						(0.0594)
Historical Av Wind Speed						-0.0501
						(0.0869)
Air Pressure						0.00845
						(0.00908)
Historical Av Airpressure						-0.00906
						(0.00912)
Weather Shock Effect: β_1				-0.292	-0.302	-0.283
SE(β_1)				0.105	0.105	0.105
Climate Effect: $\beta_1 + \beta_2$				-0.163	0.002	0.085
SE($\beta_1 + \beta_2$)				0.069	0.070	0.081
P-value of $\beta_1 + \beta_2 = 0$				0.019	0.983	0.296
Electorate FE	No	Yes	Yes	No	Yes	Yes
Other Controls	No	No	Yes	No	No	Yes
N	6132	6132	6132	6132	6132	6132
r2	0.012	0.320	0.380	0.021	0.320	0.381

Standard errors in parentheses
Note: Obs with weather stations min distance further than 30 km dropped
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The following figure shows the distribution of weather stations and the variation in minimum temperature on election day. Weather stations are shown as semi-transparent triangles.

Figure 2.9: Weather Station Distribution and Temperature Variation



The following table shows the main results but includes analytic weights in one column. These are weights based on the number of people per polling place. Column (3) effectively grants a greater weight to larger polling places.

Table 2.23: Robustness: Main Results including Analytic Weights

	Incorrect Votes (% of PP)			
	(1)	(2)	(3)	(4)
Min Temp dev from 2008-15 mean	-0.215**	-0.263**	-0.166**	-0.207***
	(0.0859)	(0.105)	(0.0688)	(0.0793)
Electorate FE	No	Yes	Yes	Yes
Population Weights	No	No	Yes	No
Other Controls	No	No	Yes	Yes
N	6133	6133	6133	6133
r2	0.0124	0.321	0.589	0.381

Standard errors in parentheses

Note: Obs with weather stations min distance further than 30 km dropped

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The following table shows the main results but excludes all polling places that are designated pre poll voting centres. These are specifically the polling places that could not be reliable linked to voter demographic data such as age or income.

Table 2.24: Main Results excluding votes cast on election day in Pre Poll Voting Centres

Temp Dev from Historical Av	-0.232**	-0.288**	-0.229**			
	(0.0890)	(0.114)	(0.0889)			
Precipitation dev from 2008-15 mean			0.104			
			(0.102)			
Humidity dev from 2008-15 mean			0.0101			
			(0.0297)			
Wind Speed dev from 2008-15 mean			0.0645			
			(0.0589)			
Air Press dev from 2008-15 mean			0.00651			
			(0.00980)			
Solar Expose dev from 2008-15 mean			0.0702			
			(0.374)			
Female share of PP			5.823*			5.478*
			(3.279)			(3.295)
Tertiary education share of PP			-22.59***			-22.23***
			(2.086)			(2.072)
Born Overseas share of PP			5.033***			5.038***
			(1.796)			(1.740)
Unemployed share of PP			3.172			3.295
			(4.315)			(4.308)
Median age PP			0.0230			0.0241
			(0.0166)			(0.0158)
Median HH week income PP			-0.0000674			-0.000112
			(0.000285)			(0.000280)
Min Temperature				-0.303***	-0.287**	-0.245**
				(0.109)	(0.112)	(0.114)
Historical Av Min Temp				0.151*	0.293**	0.285
				(0.0819)	(0.145)	(0.175)
Precipitation (mm)						0.0216
						(0.0997)
Historical Av Precipitation						-0.248
						(0.185)
Humdity						0.00952
						(0.0344)
Historical Av Humidity						-0.0325
						(0.0336)
Solar Exposure						0.0275
						(0.397)
Historical Av Solar Exposure						-0.155
						(0.441)
Wind Speed						0.0705
						(0.0642)
Historical Av Wind Speed						-0.0581
						(0.0915)
Air Pressure						0.00612
						(0.0103)
Historical Av Airpressure						-0.00676
						(0.0103)
Weather Shock Effect: β_1				-0.303	-0.287	-0.245
SE(β_1)				0.109	0.112	0.114
Climate Effect: $\beta_1 + \beta_2$				-0.152	0.005	0.041
SE($\beta_1 + \beta_2$)				0.073	0.078	0.092
P-value of $\beta_1 + \beta_2 = 0$				0.040	0.944	0.660
Electorate FE	No	Yes	Yes	No	Yes	Yes
Other Controls	No	No	Yes	No	No	Yes
N	5593	5593	5593	5593	5593	5593
r2	0.015	0.345	0.409	0.022	0.345	0.410

Standard errors in parentheses
Note: Obs with weather stations min distance further than 30 km dropped
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 3

The People Have Spoken, But What Did They Say? What Ranked Voting Can Tell Us About Voter Preferences

3.1 Introduction

The 2019 Australian federal government's surprise election win, described by the winning Liberal party leader as a "miracle," was touted as giving the government a "mandate" to deliver policy.[1] Although democratic leaders often exclaim that election victory gives them a blank cheque to deliver policy, it is not always clear which policy stances actually brought them to victory. In a general election election, individual voters are tasked with selecting candidates or parties that have a variety of characteristics along numerous dimensions. Political parties serve to reduce information asymmetries between voters and candidates, by grouping candidates together under policy agendas. Nevertheless, political parties still put forward a complex set of policy stances across a range of social and political issues. It would seem a vast oversimplification to state that a vote for a particular party indicates an en-

[1] https://www.abc.net.au/news/2019-05-19/annabel-crabb-election-result-2019-scott-morrison-mandate/11127994 accessed 26/11/2019

dorsement of their entire policy platform. It is more likely that choosing a particular party reflects an endorsement of some of that party's policies, though not necessarily all.

This raises an important problem for policy researchers and governments alike; when citizens vote in elections and convey preferences over parties (or candidates) who offer a broad array of policies, how can we infer which policies voters agree with and which they do not? The seemingly obvious way to answer this question would be to simply look at the differences between the parties that people vote for in an election. However, most electoral systems require voters to only indicate their most preferred candidate or party. When the vast majority of votes cast go to only two or three political parties, as is the case in any stable two party system, then there is a lack of variation in the data to identify which policies are being selected on. For example, in Australia's 2016 Senate election over 73 % of voters chose one of the three largest political parties (Liberal, Labor, and the Greens) as their most preferred option.[2] There is also the concern that major parties may have little variation between their policies. Ideally, this question could be answered if individuals simultaneously voted for numerous parties, as is the case in Australia. Australia uses ranked voting mechanisms to elect the House of Representatives and Senate, which are the national legislative bodies. To overcome the issue of lack of policy variation between the most commonly chosen parties, this paper will utilise ranked preferences over individuals' 6 most preferred parties in the 2016 Australian Senate election.

Senate elections employ a single transferable vote system, which is a variant of instant runoff voting or alternative voting, where voters rank their most preferred candidates to elect multiple winners simultaneously. Although there are several ways in which a valid vote can be cast, the most common way by far is for individuals to indicate their six most preferred political parties. I collect voting data from 118,163 anonymised individual votes cast in the 2016 Australian senate election and match political parties to policy variables from the Australian Election Study.

[2]https://results.aec.gov.au/20499/website/SenateStateFirstPrefsByGroup-20499-NAT.htm accessed 03/12/2019

I approach this question as a classical public choice problem where individual choices reflect the attributes of elements in the choice set. The outcome chosen will maximise a latent utility function relative to other possible alternatives in the choice set. In competing with each other in elections, parties differentiate themselves from each other in several ways. They choose to stand in opposition to their competitors on key policy issues. They attack the character of other party candidates, especially leaders. They make election promises to target specific demographics. Voters then make electoral decisions over their preferred parties.

I use the rank ordered logit model which utilises rankings over political parties to analyse these data. There is a large literature looking at the usefulness of logit models for estimating voter preferences (Glasgow, 2001; Dow and Endersby, 2004; Quinn et al., 1999; Alvarez and Nagler, 1998), however these methods must necessarily rely on estimating voter parameters from voters' most preferred option only. The rank ordered logit model builds on the conditional logit model by incorporating lower ranked preferences in parameter estimation. There is a specialised literature that uses the rank ordered logit model for preference parameter estimation (Beggs et al., 1981; Hausman and Ruud, 1987; Allison and Christakis, 1994; Beresteanu and Zincenko, 2018), with Koop and Poirier (1994) notably looking at the topic of elections. However, of these papers use survey data which has the disadvantage of revealing stated rather than revealed preferences in this context.

I show that voter behaviour correlates strongly with party stances on defence, education, immigration and stance on same sex marriage. Voters appear more likely to vote for parties which advocate increased expenditure on defence and less likely to vote for parties which advocate for increased expenditure on education. They also support parties that favour increases to immigration numbers and support same sex marriage.

I also compare the results from the rank ordered logit model to the conditional logit model, which only uses first preferences. This could be broadly thought of employing a counterfactual test of what these results would look like if only first preferences were used to

analyse these election results. To meaningfully compare between the two models I use the method of Hausman and Ruud (1987) and Benjamin et al. (2014) and use one of the policy variables as a numeraire for the others to show trade offs relative to a specific policy. Using the conditional logit model rather than rank ordered logit gives a very different impression of policy trade offs. For example, when considering the trade off between immigration and defence, the conditional logit model finds that the utility weight on defence is 5.4 times larger than the weight on immigration. However, the rank ordered logit model finds that the utility weight on defence is only 1.6 times larger than the weight on immigration, This means that when considering the defence/immigration trade off, rank ordered logit finds that individuals have a comparatively higher weight on immigration than conditional logit. This difference between the two models is likely reflecting the lack of variation between parties when only first preferences are used. However, interpreting this result also requires an appreciation of voter strategies.

This paper hypothesises that a form of communicative voting may be occurring on this Australian data. Specifically, individuals may vote strategically with their first preference (e.g. intentionally convey a less preferred party that has a higher probability of winning) because the first rank is "more important" to the outcome and then vote sincerely for lower ranked parties because lower ranks are "less important." This behaviour would imply that voters use their lower ranked preferences to send a message to the elected government about which policies matter to them. The likelihood of this kind of voting behaviour existing in this context is discussed in the results section.

The paper is structured as follows, **Section 2** covers the literature closest to this paper. **Section 3** discusses the Australian election data, the Australian Election Study data and how the datasets are merged. **Section 4** describes the empirical approach of this paper, namely the rank ordered logit model, as well as the conditional logit model. **Section 5** discusses the main results of the paper and explored the way in which the results are consistent with a particular kind of communicative voting. **Section 6** concludes.

3.2 Literature Review

3.2.1 Social Choice and Voting Models

This paper follows a long tradition of applying the framework of rational choice to political decision making. Arrow (2012), originally published in 1951, laid the groundwork for approaching collective decisions in this way. It assumes that individuals have preferences over political parties and candidates and they make trade offs between these based on which maximises some latent utility function. Downs (1957) contributed to this kind of analysis by utilising the spatial model of Hotelling (1929) to instil the idea that these political preferences can be represented in Euclidean space and that voters choose parties or candidates that are "closest" to them. This paper applies a similar rationale, but assumes that voters make a series of choices to maximise their latent utility function based on which elements are left in the choice set each time they make a decision.

3.2.2 Communicative Voting

The communicative voting literature looks at settings in which individuals vote in such a way as to "send a message" to governments about their policy preferences. Piketty (2000) introduced the formal model of communicative voting in which voters implicitly make a sincere / strategic trade-off when voting. Sincere voting is when they vote their true preferences. Strategic voting is voting to maximise the chance of a vote being pivotal. In the Results section of this paper I discuss the possibility that this trade off may be occurring at the level of voter rankings. I hypothesise that first preference rankings are likely to be strategic as voters will condition on probability of that party being elected rather than policy preferences, which explains the large share of first preferences that the three largest parties receive (see figure 3.3). Whereas lower rankings are more like to be sincere in that they aim to communicate voter preferences to the government. Closely related to this is the concept developed in

Meirowitz and Tucker (2007) who show that when voting in sequential elections, individuals communicate preferences in earlier, less important rounds and instrumentally in later, more important rounds. Our set up is analogous to this, however rather than sequential rounds we have ranked preferences, with lower rankings being less important to the election outcome. Myatt (2016) describes a model of protest voting which has many of the same elements of this setting. In this set up, individuals do not vote for their most preferred option but rather vote for a smaller party so as to send the winner a message about policy. They trade off the probability that the message will be effective versus the probability their vote will push their preferred party out of office. This is also worth considering when discussing the motivations of individuals when casting their vote.

3.2.3 Heterogeneous Ranking Capabilities

My exploration of communicative voting draws heavily on the insights from the heterogeneous ranking capabilities literature. As was proposed by Hausman and Ruud (1987), it is possible that individuals are less capable of ranking lower order preferences than their most preferred options. There are several other papers that consider heterogeneous ranking capabilities. Chapman and Staelin (1982) discuss possibility that heterogeneous ranking capabilities may lead to biased estimates if individuals only really pay attention to their first few choices. Fok et al. (2012) develop a latent class model for heterogeneous ranking capabilities, which endogenously determined how many ranks to use for each individual. Beaumais et al. (2016) design a survey where individuals determine their own number of ranks provided. They find that allowing individuals to choose the degree to which their rankings are incomplete eliminates the heteroskedasticity associated with forcing them to provide full ranks when individuals have heterogeneous ranking capabilities. I utilise methods from this literature to show that individuals use their first preferences to vote in a systematically different way to lower order preferences.

3.3 Data

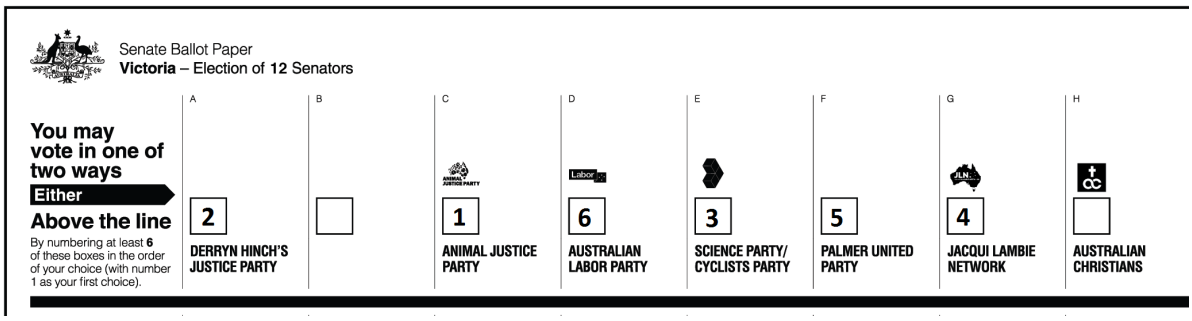
3.3.1 2016 Australian Senate Election Data

Voting in Australian Elections

The key data for this paper are the completed Senate ballots from the 2016 Australian federal election. This is a compulsory national election in which all registered voters must participate or face a fine. The election data are obtained from the Australian Electoral Commission Website[3]. The full dataset is essentially a reproduction of each ballot cast. The information that can be retrieved about voters from the ballots are the location of the polling place at which they cast their vote and who they voted for.

Australian Senate elections use a single transferable vote system to elect candidates. One of the key features of this voting rule is that individual voters must rank their options from most to least preferred. A "1" indicates the most preferred option. Although there are numerous ways in which individuals can cast a valid vote (for a greater discussion of this process see Jones (2020)) more than 92%[4] of voters choose to rank their preferences over political parties. The figure below shows an example of a ballot, showing the numbered rankings indicating preferences over political parties:

Figure 3.1: Example of ballot showing preference rankings



I take a random sample of 118,222 individuals which is balanced across Australia's 6

[3]https://www.aec.gov.au

[4]https://www.aec.gov.au/About_AEC/research/files/sbps-atl-and-btl-voting.pdf

states and 2 territories. Such a small sample is taken due to computational constraints[5] as the 118,222 individuals actually comprise 2,498,888 observations when I run the rank ordered logit model. There are a total of 51 political parties across Australia that contested the election.

The particular feature of the Australian data that makes it ideal for the rank ordered logit model, is that voters are asked to rank their 6 most preferred political parties. Individuals also have the option to instead rank their most preferred political candidates, however fewer than 8% of individuals vote in this way. They also have the option to rank more than 6 parties, which comprises 6% of votes.AEC (2016a) Following the most common form of voting, I consider individuals who convey their top 6 preferences over political parties.

Political Parties

Australia is a two party system with the two major parties being the conservative "Liberal Party" and the progressive "Australian Labor Party." However there are many more political parties that contested the 2016 election across the 8 states and territories. The following is a list of all the political parties that contested the Senate elections in 2016, broken up by state:

[5]The data represent a balanced sample across the 8 Australian States and Territories. Individuals are drawn at random without replacement. I do not weight observations.

Table: Political Parties of Australia

State Name	Party Name
ACT	Australian Greens
ACT	Australian Labor Party (ACT Branch)
ACT	Bullet Train For Australia
ACT	Liberal Party of Australia
ACT	Liberal Party of Australia - ACT Division
ACT	National Party of Australia
NAT	Liberal/Nationals
NAT	Science Party/Cyclists Party
NAT	Sex Party/HEMP
NSW	Sustainable Australia
NSW	Australia First Party (NSW) Incorporated
NSW	Australian Antipaedophile Party
NSW	Australian Cyclists Party
NSW	Australian Labor Party (N.S.W. Branch)
NSW	Australian Progressives
NSW	Christian Democratic Party (Fred Nile Group)
NSW	CountryMinded
NSW	Democratic Labour Party (DLP)
NSW	Help End Marijuana Prohibition (HEMP) Party
NSW	Liberal & Nationals
NSW	Liberal Democratic Party
NSW	Liberal Party of Australia, NSW Division
NSW	National Party of Australia - N.S.W.
NSW	Non-Custodial Parents Party (Equal Parenting)
NSW	Online Direct Democracy - (Empowering the People!)
NSW	Outdoor Recreation Party (Stop The Greens)
NSW	Pirate Party Australia
NSW	Renewable Energy Party
NSW	Science Party
NSW	Science Party/Cyclists Party
NSW	Seniors United Party of Australia
NSW	Shooters, Fishers and Farmers Party
NSW	Smokers Rights Party
NSW	Socialist Alliance
NSW	Socialist Equality Party
NSW	The Arts Party
NSW	Voluntary Euthanasia Party
NSW	VOTEFLUX.ORG — Upgrade Democracy!
NT	Australia's First Nations Political Party
NT	Australian Labor Party (Northern Territory) Branch
NT	Country Liberals (Northern Territory)
NT	Marijuana (HEMP) Party/Australian Sex Party
QLD	Australian Independents
QLD	Australian Labor Party (State of Queensland)
QLD	Australian Motoring Enthusiast Party
QLD	Australian Sex Party/Marijuana (HEMP) Party
QLD	Australian Voice Party
QLD	Consumer Rights & No-Tolls
QLD	Glenn Lazarus Team
QLD	Katter's Australian Party
QLD	Liberal National Party of Queensland
QLD	Mature Australia Party
QLD	Palmer United Party
QLD	Pauline Hanson's One Nation
QLD	Queensland Greens
QLD	Uniting Australia Party
SA	Australian Democrats
SA	Australian Labor Party (South Australian Branch)
SA	Australian Protectionist Party
SA	Family First Party
SA	Liberal Party of Australia (S.A. Division)
SA	Marijuana (HEMP) Party/Australian Sex Party
SA	National Party of Australia (S.A.) Inc.
SA	Nick Xenophon Team
TAS	Australian Labor Party (Tasmanian Branch)
TAS	Australian Recreational Fishers Party
TAS	Australian Sex Party/Marijuana (HEMP) Party
TAS	Jacqui Lambie Network
TAS	Liberal Party of Australia - Tasmanian Division
VIC	Animal Justice Party
VIC	Australian Country Party
VIC	Australian Defence Veterans Party
VIC	Australian Equality Party (Marriage)
VIC	Australian Labor Party (Victorian Branch)
VIC	Australian Liberty Alliance
VIC	Australian Sex Party
VIC	Australian Sex Party
VIC	Citizens Electoral Council of Australia
VIC	Derryn Hinch's Justice Party
VIC	Drug Law Reform Australia
VIC	Health Australia Party
VIC	John Madigan's Manufacturing and Farming Party
VIC	Liberal Party of Australia (Victorian Division)
VIC	Liberal/The Nationals
VIC	National Party of Australia - Victoria
VIC	Rise Up Australia Party
VIC	Science Party / Cyclists Party
VIC	Secular Party of Australia
WA	Australian Christians
WA	Australian Labor Party (Western Australian Branch)
WA	Australian Sports Party
WA	Liberal Party (W.A. Division) Inc
WA	Marijuana (HEMP) Party/Australian Sex Party
WA	National Party of Australia (WA) Inc
WA	The Greens (WA) Inc

It is worth noting that although some parties are listed more than once if they appear in multiple states or territories, they are treated as a single party for the purposes of this analysis. This is because the political parties that appear in multiple states primarily set policy at the national level.

The data are somewhat complicated by the existence of "how to vote" cards which are dispensed to voters at polling places. These cards are distributed by political parties and show voters how to cast a valid vote, which is required due to the high complexity of the voting mechanism. Below is an example of the Australian Greens' how to vote card from New South Wales. It shows clearly how to fill out the ballot in a valid way.

Figure 3.2: Example of how to vote card

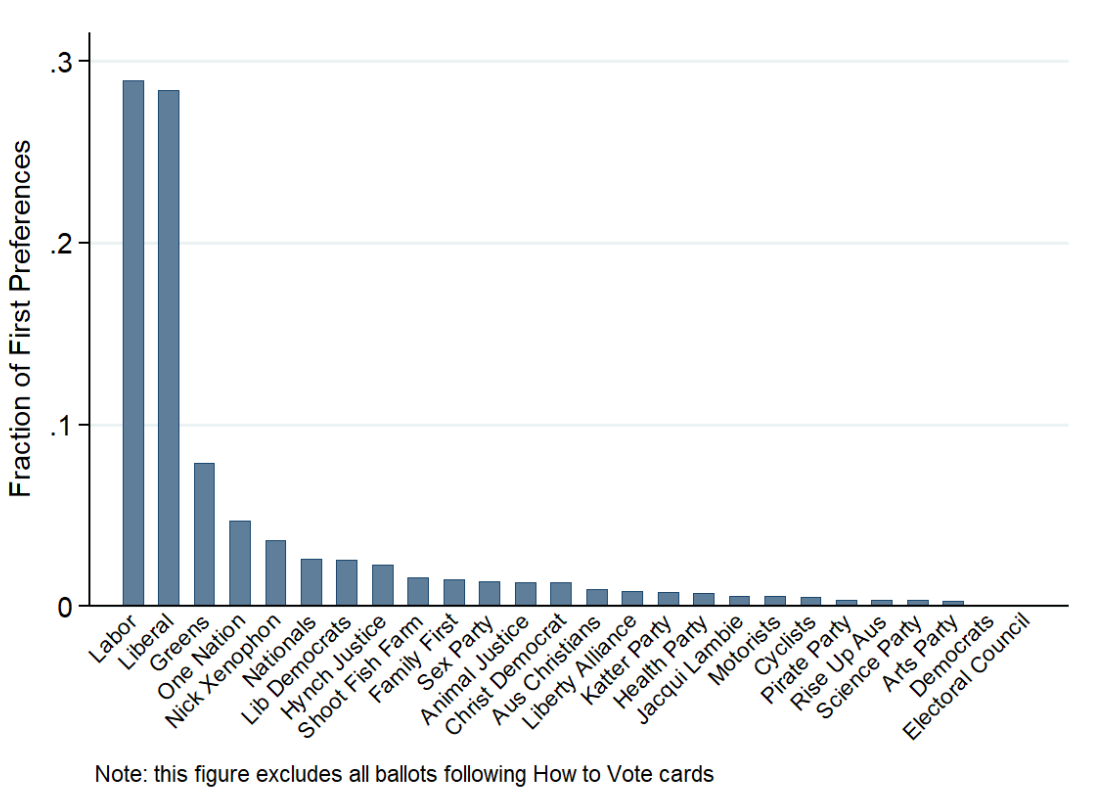
However, the cards also serve a second purpose; to show voters which political parties the distributing party would like them to vote for. This means that voters who want to strategically support a single party and do not feel the need to communicate their true preferences over parties will choose to vote using this method. For this reason, all voters who follow how to vote cards are dropped. There is some issue of sample selection in excluding this group of voters. The removal of how to vote cards likely removes the sample

of individuals who do not value their second, third, fourth preferences as much as their first in that they are happy to vote according to the preferences of their most preferred political party rather than their own. However, the advantage of removing these individuals is that they are potentially more likely to randomly number parties after conveying their first preference.

Preference Distributions

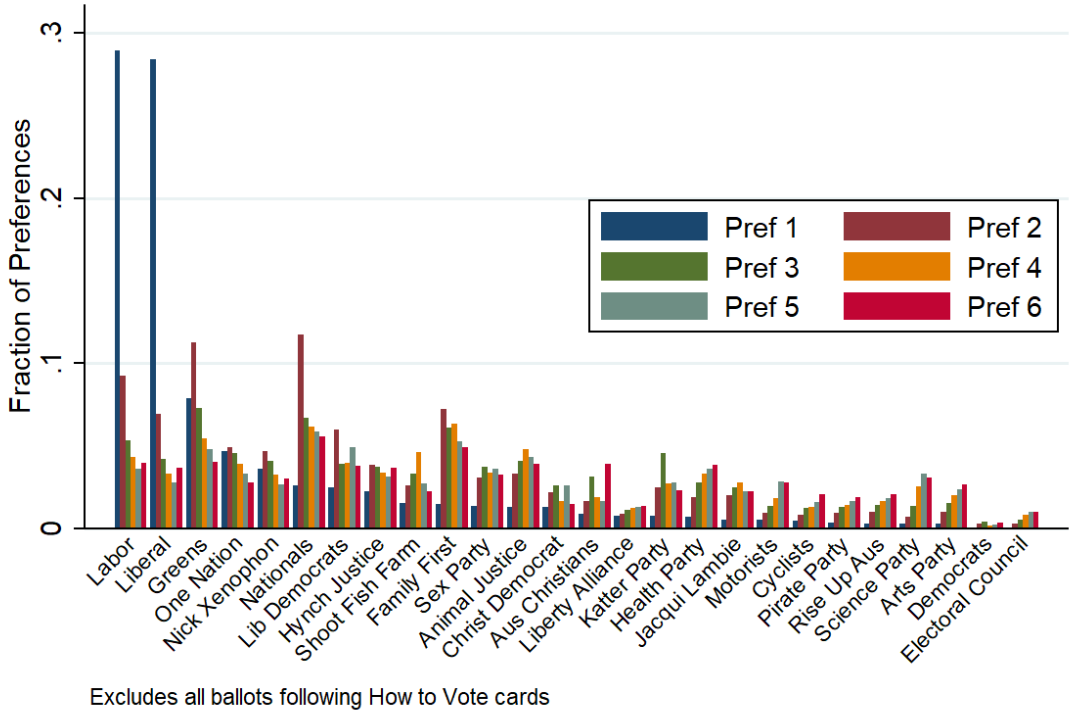
The main advantage of using the rank ordered logit model to analyse the preferences of Australian voters is the information contained in lower ranked preferences. If Australia were a political system that only required the ranking of most preferred option, then there would be little variation between parties to identify effects of different policies on voter choice. The following figure shows the distribution of first preferences across political parties. it is clear from this figure that the vast majority of first preferences go to the two major parties.

Figure 3.3: Distribution of First Preferences over Parties



The figure below, however, shows the distribution of all six preferences. This reveals the variation in the data from lower ranked preferences that can be used to identify coefficients.

Figure 3.4: Distribution of Top Six Preferences over Parties



3.3.2 Party Characteristic Data

In order to recover preference coefficients I need to assign variables to the elements of the choice set, in this case political parties. I do this using the Australian Election Study which surveys Australian voters and asks them about their policy preferences.

Australian Election Study (AES)

The main party characteristic data come from the Australian Election Study which is conducted though the Australian National University and is available on their website[6]. These

[6]https://australianelectionstudy.org

data come specifically from the AES 2016 Voter Study, which comprises 2,818 responses to a series of demographic and political questions including vote intention and party affiliation.

The variables are categorical variables indicating the responses to a variety of questions. For example, there are four variables that capture stance on government expenditure. These capture how political parties are likely to feel about expenditure on key public sectors including health, education, defence and public transport. Figure 3.5 shows how the questions that determine the key variables of interest were collected.

Figure 3.5: Source: Australian Election Study 2016 Questionnaire Booklet

D8 Please say whether there should be more or less public expenditure in each of the following areas. Remember if you say 'more' it could require a tax increase, and if you say 'less' it could require a reduction in those services.

	Much more than now	Somewhat more than now	The same as now	Somewhat less than now	Much less than now
Health	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
Education	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
Unemployment benefits	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
Defence	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
Old-age pensions	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
Business and industry	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
Police and law enforcement	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
The National Disability Insurance Scheme	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
Public transport infrastructure	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
Child care	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5

Each respondent is also asked to nominate their most preferred party that contended the Senate election. The respondent is then characterised as a supporter of that party.[7] The average responses of all people who indicated support for a sngle party is then taken as the political stance of that party. For example, if 40 respondents indicate that the Australian Greens is their most preferred party, then average response of those 40 people to the expenditure on health question in figure 3.5 is calculated. The Greens' stance on health expenditure then assumed to be this average. This means that I am not taking the official

[7]The Nationals ran on the joint ticket in NSW, QLD, VIC. They did not run in the ACT, NT, SA, TAS. They ran on their own ticket only in WA. In the instances that they ran on a joint ticket they are only considered to be the Liberal party for the purposes of policy characteristics.

party policy as the party characteristic, but rather how the average supporter of that party feels about this policy. See the appendix for the number of responses used to construct each party's variables.

It should be stressed that the variables "More Expenditure on HEALTH," "More Expenditure on EDUCATION," "More Expenditure on DEFENCE," and "More Expenditure on PUBLIC TRANSPORT" have been transformed for this analysis so that a response of "1" indicates "Much less than now" and a response of "5" means "Much more than now." This is to aid in interpreting coefficients, so that a higher number always means more expenditure is desired rather than less. Table 3.1, below, contains the questions for each variable of interest from the Australian Election Study, as well as the possible answers and numerical codes for each answer.

Unfortunately, this approach means that I do not have characteristic data for every party in the election. However, the parties for which there is not data were comparatively unpopular parties.

Table 3.1: Key Variables from the Australian Election Study (AES)

Variable	**AES Survey Question**	**Answer (Score)**
More Expenditure on HEALTH	Please say whether there should be more or less public expenditure in each of the following areas. Remember if you say 'more' it could require a tax increase and if you say less it could require a reduction in those services: Health	Much less than now (1); Somewhat less than now (2); The same as now (3); Somewhat more than now (4); Much more than now (5)
More Expenditure on EDUCATION	Please say whether there should be more or less public expenditure... : Education	Much less than now (1)... Much more than now (5)
More Expenditure on DEFENCE	Please say whether there should be more or less public expenditure... : Defence	Much less than now (1)... Much more than now (5)
More Expenditure on PUBLIC TRANSPORT	Please say whether there should be more or less public expenditure... : Public Transport Infrastructure	Much less than now (1)... Much more than now (5)
Stance on IMMIGRATION NUMBERS	The statements below indicate some of the changes that have been happening in Australia over the years. For each one, please say whether you think the change has gone too far, not gone far enough, or is it about right: The number of migrants allowed into Australia at the present time	Gone much too far (1) ; Gone too far (2); About right (3); Not gone far enough (4); Not gone nearly far enough (5)
Stance on SAME SEX MARRIAGE	Do you personally favour or oppose same sex couples being given the same rights to marry as couples consisting of a man and a woman?	Strongly favour (1); Favour (2); Oppose (3); Strongly oppose (4)

Previous Election Vote Share

It is clear that Australian voters have a preference for the larger political parties. This likely reflects a combination of factors such as strategic concerns, i.e. the higher likelihood a larger party will be elected and informational factors, i.e. the fact that larger parties tend to have been in power before and have more developed policy platforms.

To attempt to capture this effect, this paper uses data which shows the vote share of parties in the 2013 federal Senate election. This is obtained from the Australian Electoral Commission website. If a party did not exist in the 2013 election, its share is coded as being zero.

Party Summary Statistics

The following table shows the summary statistics of the political party characteristics.

Table 3.2: Summary Statistics for Political Parties

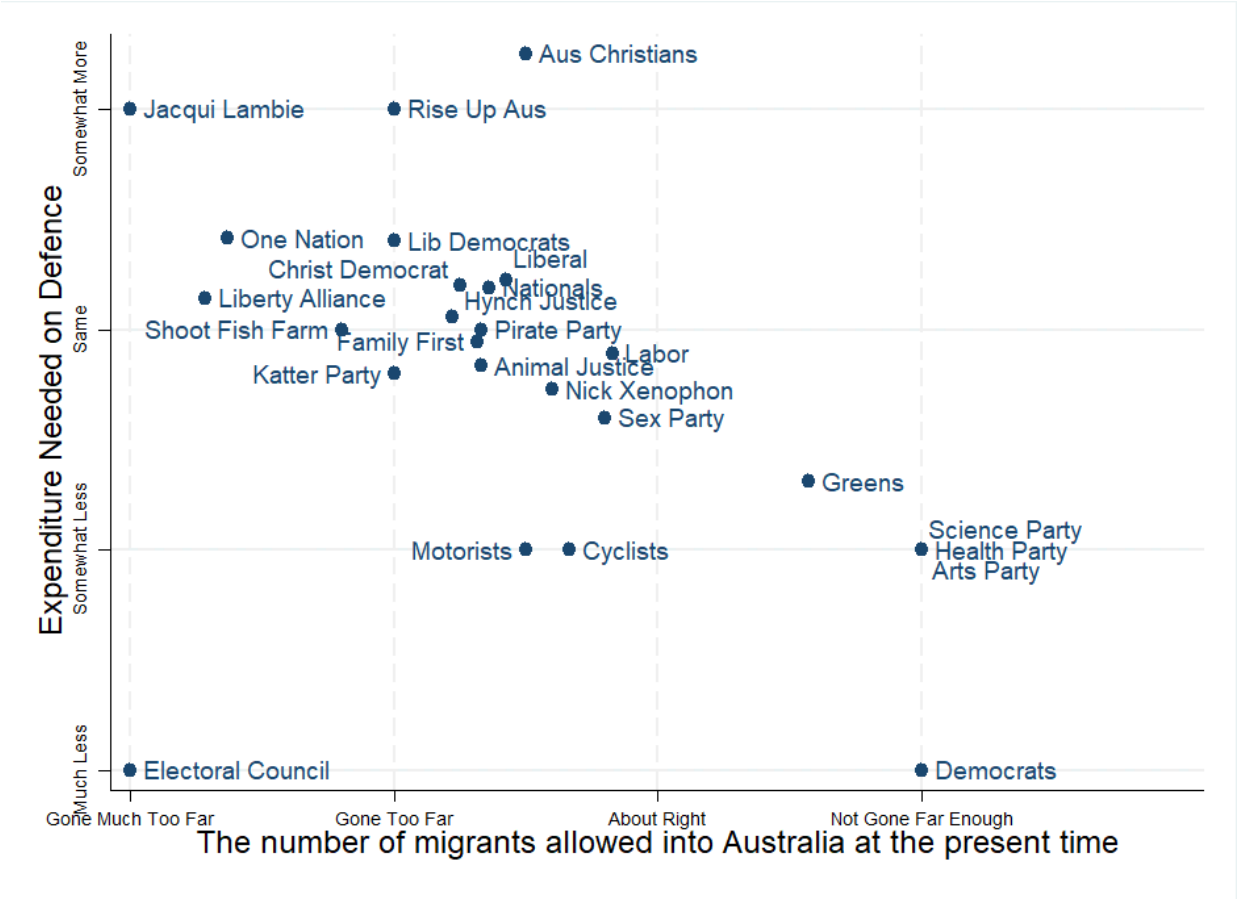
Variable	Mean	Std. Dev.	Min.	Max.
More Expenditure on HEALTH	3.836	0.445	3	4.667
More Expenditure on EDUCATION	3.787	0.504	2.8	4.667
More Expenditure on DEFENCE	2.769	0.811	1	4.25
More Expenditure on PUBLIC TRANSPORT	3.687	0.528	2	4.667
Stance on IMMIGRATION NUMBERS	2.468	0.874	1	4
Stance on SAME SEX MARRIAGE	2.408	0.99	1	4
Party Final Share of 2013 Senate Vote	3.471	9.115	0	37.19
Number of Political Parties		26		

If I consider that for the expenditure variables that a score of 3 indicates keeping expenditure at the same level as now, that parties on average advocate for an increase in expenditure for all these areas of policy except for defence. In terms of immigration and

same sex marriage, the average policy lies in the middle of the two issues.

Figure 3.6 aims to provide support to the validity of this paper's method for linking policy variables to political parties. Heuristically, similar kinds of parties seem fairly well grouped together in this figure. See table 3.12 in the appendix for full list of policy scores for all political parties.

Figure 3.6: Political Parties in Euclidean Policy Space



3.4 Empirical Approach

3.4.1 Conditional Logit Model

I use the rank ordered logit model to recover preference parameters from the ranked data. The rank ordered logit model builds off the framework of traditional discrete choice models

as developed by Luce (1959); McFadden (1974, 1975, 1976); Hausman and McFadden (1984); McFadden and Train (2000). The baseline conceptual model is the conditional logit model of McFadden (1973) where individuals convey their most preferred option only by making a single choice. For the purposes of this paper, the first preference conveyed by voters in their ranking will be considered as analogous to the situation in which they are only asked to choose a single most preferred option.[8] This model employs the random utility framework whereby individual $i \in N$ faces choices over $j \in J$ alternatives. Each alternative has a set of characteristics $\mathbf{X}_j$, which provide payoffs to the individual, implying the following latent utility model:

$$U_{ij} = V_j + \epsilon_{ij} = \mathbf{X}_j\beta + \epsilon_{ij}$$

Where V_j is the deterministic component of individual utility. Individual i chooses j if $U_{ij} > U_{ik}$ for all $j \neq k$. Because of the stochastic component, ϵ_{ij}, choices are probabilistic.

I assume that ϵ_{ij} is Type 1 Extreme Value distributed, with CDF $F(\epsilon_{ij}; \mu, \sigma) = e^{-e^{-(\epsilon_{ij}-\mu)/\sigma}}$. This distribution has the property that individual i's observed choice has the following closed form solution:

$$Pr[y_i = j; \beta] \;=\; Pr[U_{ij} \geq \max\{U_{ik}, ..., U_{iJ}\}] \;=\; \frac{\exp(\mathbf{X}_j\beta)}{\sum_{k=0}^{J}\exp(\mathbf{X}_k\beta)}$$

In this case the individuals $i \in N$ are voters, who chose political party j from J alternatives. The parties have a set of policy and other characteristics, $\mathbf{X}_j$, over which voters make their choice.

3.4.2 Rank Ordered Logit (ROL) Model

The conditional logit model described above only takes into account an individual's most preferred option, or the observed choice that they make. However, these data contain the

[8]It is worth noting however, that there is a possibility that this is not a perfect counter factual as voters may have voted differently if they knew thy only had a single preference to convey.

revealed preferences rankings of voters over a set of political parties. This allows for the use of the rank ordered logit model of Beggs et al. (1981).

Following Beggs et al. (1981) the preference ranking index is denoted as $h \in J$. This means that each individual has a ranking, h, of J choices which is denoted as: $R_i = (r_{i1}, ..., r_{iJ})$, where r_{ih} would denote the number of the alternative. So when $r_{i1} = 5$, this means that party number 5 was the highest ranked alternative.

Then the probability of individual i's observed ranking, R_i is:

$$\pi(R_i) = Pr[U_{ir_{i1}} > U_{ir_{i2}} > U_{ir_{i3}} > ... > U_{ir_{iJ}}] = \prod_{h=1}^{J-1} \left[\frac{\exp(X_{ir_h}\beta)}{\sum_{m=h}^{J} \exp(X_{ir_m}\beta)} \right]$$

The independence assumption made in the rank ordered logit model is analogous to the independence of irrelevant alternatives assumption of standard logit. The conditional distribution of the utility payoff from any element in the choice set is independent of the ranks of other alternatives. It also implies there are no combinatorial utility gains, in this sense each ranking is an independent choice. This formulation implies the following log likelihood function:

$$L(\beta) = \sum_{i=1}^{N} \log \pi(R_i)$$

$$L(\beta) = \sum_{i=1}^{N} \sum_{h=1}^{J-1} \exp(X_{ir_h}\beta) - \sum_{i=1}^{N} \sum_{h=1}^{J-1} \left[\log \sum_{m=h}^{J} \exp(X_{ir_m}\beta) \right] \tag{3.1}$$

An intuitive way of approaching this model is to think of how it assumes choices are made. The model uses conditional logit on the highest ranked preference as if it were the only choice, then kicks out that choice and re-runs conditional logit on the next highest preference as if it were the only choice using the reduced choice set (i.e. without the first choice) and so on. In this way it estimates parameters across all rankings simultaneously.

A fundamental assumption of this model is that all individuals have the same value

function, i.e. they apply the same decision weights to independent variables. This is also the standard formulation of the model where individuals rank all elements of the choice set. However, I employ the method for dealing with incomplete rankings (as I consider only individual's top 6 ranks) following Allison and Christakis (1994).

3.5 Main Results

Column (1) of table 3.3 shows the rank ordered logit regression coefficient estimates and standard errors. These estimates utilise all six preference rankings for each individual. Column (2) shows the coefficient estimates and standard errors from conditional logit, which only uses individual's first preferences.

Interpreting the raw coefficients is analogous to standard logit[9], i.e. they are the log odds ratios. As such, when deciding between two parties, j and k, the probability of choosing party j over party k is:

$$Pr[U_j > U_k, j \neq k] = \frac{e^{V_j}}{e^{V_j} + e^{V_k}} = \frac{e^{X_j\beta}}{e^{X_j\beta} + e^{X_k\beta}}$$

An intuitive interpretation can be found in Benjamin et al. (2014), that for any pair of parties A and B, a one unit increase in the difference in the regressor j, $X_{i,A,j} - X_{i,B,j}$, is associated with a β_j increase in the log odds ratio of choosing A over B. That is to say, the probability of choosing a party that is identical to all other parties, except that it X variable (for example: expenditure on defence) stance from 1 - 2 (which would be to go from "we need much less expenditure on defence" to "we need somewhat less expenditure on defence") on the 5 point Likert scale, is:

$$Pr[U_A > U_B, A \neq B] \;=\; \frac{e^{\beta}}{e^{\beta} + 1} \tag{3.2}$$

In column (1), the coefficient of 0.383 (p< 0.01) indicates that the probability of choosing

[9]Another shorthand way to interpret the log-odds coefficients is pointed out by Allison and Christakis (1994) that for small values of β one can use the approximation $e^{\beta} - 1 \approxeq \beta$

a party that is identical to all other parties, except that the party's stance on defence expenditure goes from 1 to 2 (which would be to go from "we need much less expenditure on defence" to "we need somewhat less expenditure on defence") on the 5 point Likert scale, is $\frac{e^{\beta}}{e^{\beta}+1} = \frac{e^{0.383}}{e^{0.383}+1} = 59.46\%$

Table 3.3: Rank Ordered Vs Conditional Logit Regression Results

	(1)	(2)
	RO Logit	C Logit
More Expenditure on HEALTH	0.0522	0.532***
	(0.0335)	(0.0544)
More Expenditure on EDUCATION	-0.263***	-0.147***
	(0.0215)	(0.0459)
More Expenditure on DEFENCE	0.383***	0.436***
	(0.0148)	(0.0156)
More Expenditure on PUBLIC TRANSPORT	0.0273	-0.216***
	(0.0214)	(0.0550)
Stance on IMMIGRATION NUMBERS	0.228***	0.0804***
	(0.0198)	(0.0311)
Stance on SAME SEX MARRIAGE	-0.206***	-0.415***
	(0.0109)	(0.0188)
Party Final Share of 2013 Senate Vote	0.0428***	0.0797***
	(0.000527)	(0.000630)
Number of Individuals	118,222	118,222
Number of Party/Individual Observations	2,498,888	2,498,888
Pseudo R-Squared	0.071	0.291

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

When using the rank ordered logit model, the coefficients on health and public transportation are not statistically significantly different from zero, however when using conditional logit these become significant. The two approaches, rank ordered logit and conditional logit, yield statistically significant differences in the coefficients. Table 3.4, below, shows the results of Wald tests testing the equivalence of coefficients between the two regressions. For

example, the Chi^2 statistic under the "Health" heading is computed as the result of the test of whether the coefficient on "Expenditure on Health" from the rank ordered logit model is equal to the coefficient on "Expenditure on Health" from the conditional logit model. $p< 0.01$ indicates that the coefficients are statistically significantly different at the 1% level. It is clear from the table that all coefficients are statistically significantly different form each other.

Table 3.4: Rank Ordered Vs Conditional Logit Regression Walt Tests

Health	
Chi2(1)	94.290
pval of ROL=CL	0.000
Education	
Chi2(1)	7.218
pval of ROL=CL	0.007
Defence	
Chi2(1)	10.074
pval of ROL=CL	0.002
Public Transport	
Chi2(1)	34.794
pval of ROL=CL	0.000
Immigration	
Chi2(1)	50.597
pval of ROL=CL	0.000
Same Sex Marriage	
Chi2(1)	93.806
pval of ROL=CL	0.000
Vote Share 2013	
Chi2(1)	8,344.285
pval of ROL=CL	0.000
All Vars	
Chi2(7)	13149.590
pval of ROL=CL	0.000

3.5.1 Marginal Rates of Substitution - Defence as denominator

Although the coefficients are directly comparable within columns, the point estimates have no clear interpretation between columns as they are utility weights. To understand the magnitude of the difference between columns I follow Hausman and Ruud (1987) and Benjamin et al. (2014) and use one of the policy variables as a numeraire for the others to show trade offs relative to a specific policy. The table below uses the expenditure on defence variable as numeraire for the others so that the two columns are directly comparable.

Table 3.5: Rank Ordered Vs Conditional Logit Regression Results

	(1)	(2)
	RO Logit	C Logit
More Expenditure on HEALTH	0.136	1.219***
	(0.0878)	(0.134)
More Expenditure on EDUCATION	-0.687***	-0.338***
	(0.0644)	(0.107)
More Expenditure on DEFENCE	1	1
	(.)	(.)
More Expenditure on PUBLIC TRANSPORT	0.0714	-0.494***
	(0.0568)	(0.127)
Stance on IMMIGRATION	0.595***	0.184***
	(0.0458)	(0.0677)
Stance on SAME SEX MARRIAGE	-0.539***	-0.951***
	(0.0319)	(0.0598)
Party Final Share of 2013 Senate Vote	0.112***	0.183***
	(0.00458)	(0.00687)
Number of Individuals	118,222	118,222
Number of Party/Individual Observations	2,498,888	2,498,888

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The coefficients can be interpreted as follows: the coefficient on "stance on immigration" in column (1) tells us that when rank ordered logit regression is used, the trade off between stance on immigration amount and expenditure on defence is such that the utility weight on stance on immigration amount is 0.595 ($p< 0.01$) times that of defence, which implies conversely that the utility weight on defence is 1.6 times larger than on immigration. However, when conditional logit utilising only the first preference rankings is utilised (in column (2)), the trade off is such that the utility weight on stance on immigration amount is 0.184 ($p< 0.01$) times that of defence, or conversely the utility weight on defence is 5.4 times larger than on immigration. This means that when considering the trade off between immigration numbers and defence spending, using rank ordered logit implies that immigration numbers receive a larger comparative weight in the trade off than when using conditional logit.

This result is significant when considering how these data could be used in determining policy importance of different issues. The following table shows the results of a Wald test of the equality of coefficients across the two regressions. It can be seen that the transformed coefficients are statistically significantly different from each other between the rank ordered logit model and the conditional logit model. This suggests that when considering the trade offs between defence expenditure and other policies, the lower ranked preferences pick up meaningful variation which provides a different picture of policy preferences.

Table 3.6: Rank Ordered Vs Conditional Logit Regression Wald Tests

Health Chi2(1)	71.337
pval of ROL=CL	0.000
Education Chi2(1)	11.670
pval of ROL=CL	0.001
Defence Chi2(1)	.
pval of ROL=CL	.
Public Transport Chi2(1)	37.718
pval of ROL=CL	0.000
Immigration Chi2(1)	89.051
pval of ROL=CL	0.000
Same Sex Marriage Chi2(1)	47.241
pval of ROL=CL	0.000
Vote Share 2013 Chi2(1)	117.337
pval of ROL=CL	0.000
All Vars Chi2(7)	475.766
pval of ROL=CL	0.000

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.5.2 Marginal Rates of Substitution - Education as denominator

The following table shows the main results using "expenditure on education" as numeraire.

Table 3.7: Rank Ordered Vs Conditional Logit Regression Results

	(1)	(2)
	RO Logit	C Logit
More Expenditure on HEALTH	-0.198*	-3.611***
	(0.119)	(1.054)
More Expenditure on EDUCATION	1	1
	(.)	(.)
More Expenditure on DEFENCE	-1.455***	-2.963***
	(0.136)	(0.935)
More Expenditure on PUBLIC TRANSPORT	-0.104	1.464***
	(0.0822)	(0.468)
Stance on IMMIGRATION	-0.865***	-0.546**
	(0.0736)	(0.245)
Stance on SAME SEX MARRIAGE	0.784***	2.819***
	(0.0687)	(0.828)
Party Final Share of 2013 Senate Vote	-0.163***	-0.541***
	(0.0127)	(0.169)
Number of Individuals	118,222	118,222
Number of Party/Individual Observations	2,498,888	2,498,888

Standard errors in parentheses

Standard Errors Clustered at Electorate Level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Again there are some sizeable differences in the magnitude of the coefficients, for example the coefficient on the trade off between defence and education. However, as the table below shows, when a Wald test of the equality of coefficients across the two regressions is applied not all of the parameters are statistically significantly different at the 5% level. The trade off between defence and education as well as immigration and education are not significant at the 5% level (p$\geq$ 0.05). As well as this, the trade off between vote share in 2013 and education as well as same sex marriage and education are not significant at the 1% level (p$\geq$ 0.01). This gives us some meaningful insight into the kinds of variation in the data, that when considering the trade offs between education expenditure and other policies, the lower ranked preferences pick up variation for some policies but not for others.

Table 3.8: Rank Ordered Vs Conditional Logit Regression Wald Tests

Health Chi2(1)	11.631
pval of ROL=CL	0.001
Education Chi2(1)	.
pval of ROL=CL	.
Defence Chi2(1)	2.842
pval of ROL=CL	0.092
Public Transport Chi2(1)	13.715
pval of ROL=CL	0.000
Immigration Chi2(1)	1.890
pval of ROL=CL	0.169
Same Sex Marriage Chi2(1)	6.692
pval of ROL=CL	0.010
Vote Share 2013 Chi2(1)	5.274
pval of ROL=CL	0.022
All Vars Chi2(7)	56.126
pval of ROL=CL	0.000

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.5.3 Communicative Voting

The prevalence of first preference votes for the three major parties observed in figure 3.3 and the much more even distribution for lower order preferences observed in figure 3.4 can potentially be explained by a form of communicative voting. It is possible that individuals use their first preference to vote strategically, that is to maximise the probability that they cast a pivotal vote, and they use their second, third, fourth, fifth and sixth preferences to vote expressively, that is to reflect their true policy preferences which they wish to communicate to government. This particular kind of voting could be considered a particular variant of communicative voting and is similar to the kind found in Meirowitz and Tucker (2007) where in sequential elections individuals vote expressively in earlier, less important, rounds and instrumentally in later, more important, rounds.

To try and find support for the hypothesis that voters are using their first preference ranking and lower order preference rankings for different purposes, I employ a Hausman test to the data following a method proposed in StataCorp (2013). I use the Hausman test to see if the same decision weights are applied when conveying first preferences and lower ranked preferences. I compare the estimator $\hat{\theta}_1$, which is estimated using all 6 preferences, with an estimator $\hat{\theta}_2$ that is efficient under the null hypothesis, which is estimated using fewer than 6 preferences, such preferences 1 through 5 or 1 through 4. This is testing whether the same decision weights are being used for the rankings as we remove the lower ranked preferences one by one. I find that there are systemic differences between the parameter estimated using all 6 rankings, regardless of how many rankings after the first are used.

However, if I remove the first preference of every voter and repeat the test, the Hausman test does not find evidence of inconsistent parameter estimates. This indicates that there are not systematic differences between preference estimators that use any number of rankings as long as the first preference ranking is excluded from estimation. This could be explained by individual voters treating their first preference differently from lower order preferences.

The following shows the results of the rank ordered logit regression with "expenditure on defence" as the only variable included in the model.

Table 3.9: Hausman Test using all 6 preferences

	Hausman Test
Hausman Test:	
Using top 6 ranks Chi2(1)	1,015.040
Pval	0.000
Hausman Test:	
Using top 5 ranks Chi2(1)	932.474
Pval	0.000
Hausman Test:	
Using top 4 ranks Chi2(1)	743.792
Pval	0.000
Hausman Test:	
Using top 3 ranks Chi2(1)	597.498
Pval	0.000
Hausman Test:	
Using top 2 ranks Chi2(1)	466.000
Pval	0.000

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Regardless of how many subsequent rankings are used, when I assume that the estimator utilising all 6 preferences is consistent, then there are systematic differences between that estimator and one which uses fewer lower order rankings. The Chi^2 statistics are very large, indicating substantial differences between each model. However, when I remove every voter's first preference vote and re-run the test, then regardless of how many rankings are considered, then I no longer find evidence of systematic differences at the 1% level (see table below).

Table 3.10: Hausman Test - Excluding First Preference

	Hausman Test
Hausman Test:	
Using top 5 ranks Chi2(1)	1.167
Pval	0.280
Hausman Test:	
Using top 4 ranks Chi2(1)	3.935
Pval	0.047
Hausman Test:	
Using top 3 ranks Chi2(1)	4.356
Pval	0.037
Hausman Test:	
Using top 2 ranks Chi2(1)	0.969
Pval	0.325

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

When using variables other than defence (see appendix - only results where first preference is removed are shown) there is a broadly similar story with some mixed results. For example, similar results are found when "health," "education," and "public transport" are used as regressors. However, this story is not supported when "immigration," "same sex marriage," "vote share," or when all variables are used at once. As a result, this could be considered evidence that implies the existence of communicative voting, but necessitates further study to vindicate these findings.

3.6 Conclusion

The main aim of this paper is to analyse the information in voter preference rankings. This information is significant when considering which policies should be made priorities. To achieve this, I use the rank ordered logit model to recover preference parameters from the ranked data. I also compare the rank ordered logit model with the conditional logit model to compare the information that can be recovered from first preferences with the lower ranked preferences. It notes some interesting patterns in voter preferences for policy and puts forward a potential method for using ranked voting in elections to decide the importance of

various policy issues to voters. This method, if properly refined, could be used as a powerful tool for public policy, giving researchers insights into which policy areas should be addressed to satisfy the voting populace.

This paper also puts forward a possible explanation for the observed voting patterns, namely a particular kind of communicative voting. Namely, individuals may vote strategically with their first preference to try and maximise the probability that their vote is pivotal and then vote sincerely with their lower ranked preferences.

This paper shows the value of considering voter choices beyond their most preferred political party to identify policy preferences. There is obvious scope to extend this paper in several directions. For example, further research can be done on the heterogeneous ranking capabilities of individuals (Chapman and Staelin, 1982; Koop and Poirier, 1994; Fok et al., 2012; Beaumais et al., 2016) within this election. Differences in ranking capabilities that may be the result on individual characteristics or informational asymmetries across the choice set could be explored. There is also scope to incorporate voter demographic data to further explain variation in the data.

Ultimately, this paper proposes a starting point for the analysis of ranked data in elections with a view to using this analysis to guide public policy.

3.7 Appendix

The variables from the Australian Election Study are linked to political parties and then the average score of those respondents is used. The table below shows the number of respondents who preferred a particular party in the Senate election.

Table 3.11: Number of AES respondents used to create party variables

	Number of Respondents
Liberal Party	970
Labor Party (ALP)	641
Greens	296
National (Country) Party	104
Nick Xenophon Team	75
One Nation	72
Family First Party	20
Derryn Hinch's Justice Party	18
Christian Democratic Party	16
The Australian Sex Party	11
Australian Liberty Alliance	8
Liberal Democrats	6
Animal Justice Party	6
Shooters, Fishers and Farmers Party	5
Katter's Australia Party	5
Australian Christians	4
Pirate Party	4
Science Party	3
Australian Cyclists Party	3
Motoring Enthusiasts Party	2
Jacquie Lambie	2
Arts Party	2
Health Australia Party	2
Australian Democrats	1
Citizens Electoral Council	1
Rise Up Australia	1

Table 3.12: Summary Statistics: Public Expenditure and Party Stance

	Liberal	Labor	Greens	Australian Christians	Liberty Alliance	Motorists	Christian Democrat	Hynch Justice Party	Family First	Health Party	Katter Party	Liberal Democrats	Nationals	Nick Xenophon	One Nation	Rise Up Australia	Shooters Fishers Farmers	Average
More Expenditure on HEALTH	3.671	4.083	4.048	4.333	3.667	5	4	1	3.714	4.500	3.500	2.667	3.605	4.200	3.706	4	4.500	3.745
More Expenditure on EDUCATION	3.523	4.062	4.107	4	3.333	5	3.800	5	3.286	4.500	3.500	3.333	3.473	4	3.412	3	4	3.845
More Expenditure on UNEMP BENEFIT	2.572	3.137	3.187	3.333	2.333	2	3	1	2.500	3.500	2.250	2.333	2.631	2.600	2.471	3	2.500	2.605
More Expenditure on DEFENCE	3.240	2.818	2.235	4	4.333	3	3.400	2	3.167	2	2.750	2.667	3.306	2.600	3.706	4	2.500	3.009
More Expenditure on AGE PENSION	3.603	3.793	3.529	3.667	4.333	3	3.700	5	3.500	3.500	3.750	3.333	3.652	3.200	4.176	4	4	3.773
Party Final Share of 2013 Senate Vote	37.19	30.11	8.650	0.400	0	0.500	0.540	0	1.110	0	0.890	3.910	0.520	1.930	0.530	0.370	0.950	5.971

Note: This table shows the policy scores for all expenditure variables across all political parties in the sample

Main Results with different variables as denominator

Table 3.13: Rank Ordered Vs Conditional Logit Regression Results

	RO Logit	C Logit
HEALTH	-0.198*	-3.611***
	(0.119)	(1.054)
EDUCATION	1	1
	(.)	(.)
DEFENCE	-1.455***	-2.963***
	(0.136)	(0.935)
PUBLICTRANSPORT	-0.104	1.464***
	(0.0822)	(0.468)
IMMIGRATION	-0.865***	-0.546**
	(0.0736)	(0.245)
SAMESEXMARRIAGE	0.784***	2.819***
	(0.0687)	(0.828)
PARTYVOTESHARE	-0.163***	-0.541***
	(0.0127)	(0.169)
Number of Individuals		
Number of Party/Individual Observations	2,498,888	2,498,888
Pseudo R-Squared		

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.14: Rank Ordered Vs Conditional Logit Regression Results

Health Chi2(1)	11.631
pval of ROL=CL	0.001
Education Chi2(1)	.
pval of ROL=CL	.
Defence Chi2(1)	2.842
pval of ROL=CL	0.092
Public Transport Chi2(1)	13.715
pval of ROL=CL	0.000
Immigration Chi2(1)	1.890
pval of ROL=CL	0.169
Same Sex Marriage Chi2(1)	6.692
pval of ROL=CL	0.010
Vote Share 2013 Chi2(1)	5.274
pval of ROL=CL	0.022
All Vars Chi2(7)	56.126
pval of ROL=CL	0.000

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.15: Rank Ordered Vs Conditional Logit Regression Results

	RO Logit	C Logit
HEALTH	1	1
	(.)	(.)
EDUCATION	-5.038*	-0.277***
	(3.025)	(0.0808)
DEFENCE	7.330	0.820***
	(4.715)	(0.0904)
PUBLICTRANSPORT	0.524	-0.405***
	(0.649)	(0.0758)
IMMIGRATION	4.357	0.151**
	(2.807)	(0.0648)
SAMESEXMARRIAGE	-3.952	-0.781***
	(2.435)	(0.0863)
PARTYVOTESHARE	0.820	0.150***
	(0.525)	(0.0151)
Number of Individuals		
Number of Party/Individual Observations	2,498,888	2,498,888
Pseudo R-Squared		

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.16: Rank Ordered Vs Conditional Logit Regression Results

Health Chi2(1)	.
pval of ROL=CL	.
Education Chi2(1)	2.542
pval of ROL=CL	0.111
Defence Chi2(1)	1.934
pval of ROL=CL	0.164
Public Transport Chi2(1)	2.189
pval of ROL=CL	0.139
Immigration Chi2(1)	2.254
pval of ROL=CL	0.133
Same Sex Marriage Chi2(1)	1.765
pval of ROL=CL	0.184
Vote Share 2013 Chi2(1)	1.669
pval of ROL=CL	0.196
All Vars Chi2(7)	19.975
pval of ROL=CL	0.003

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.17: Rank Ordered Vs Conditional Logit Regression Results

	RO Logit	C Logit
HEALTH	0.229	6.618**
	(0.148)	(2.839)
EDUCATION	-1.156***	-1.833**
	(0.0983)	(0.822)
DEFENCE	1.682***	5.430***
	(0.130)	(1.996)
PUBLICTRANSPORT	0.120	-2.682*
	(0.0918)	(1.436)
IMMIGRATION	1	1
	(.)	(.)
SAMESEXMARRIAGE	-0.907***	-5.166**
	(0.0905)	(2.031)
PARTYVOTESHARE	0.188***	0.992***
	(0.0159)	(0.384)
Number of Individuals		
Number of Party/Individual Observations	2,498,888	2,498,888
Pseudo R-Squared		

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.18: Rank Ordered Vs Conditional Logit Regression Results

Health Chi2(1)	5.096
pval of ROL=CL	0.024
Education Chi2(1)	0.721
pval of ROL=CL	0.396
Defence Chi2(1)	3.899
pval of ROL=CL	0.048
Public Transport Chi2(1)	4.100
pval of ROL=CL	0.043
Immigration Chi2(1)	.
pval of ROL=CL	.
Same Sex Marriage Chi2(1)	4.606
pval of ROL=CL	0.032
Vote Share 2013 Chi2(1)	4.659
pval of ROL=CL	0.031
All Vars Chi2(7)	23.489
pval of ROL=CL	0.001

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.19: Rank Ordered Vs Conditional Logit Regression Results

	RO Logit	C Logit
HEALTH	1.910	-2.468***
	(2.368)	(0.461)
EDUCATION	-9.621	0.683***
	(7.609)	(0.219)
DEFENCE	14.00	-2.024***
	(11.12)	(0.519)
PUBLICTRANSPORT	1	1
	(.)	(.)
IMMIGRATION	8.322	-0.373*
	(6.360)	(0.200)
SAMESEXMARRIAGE	-7.547	1.926***
	(5.916)	(0.506)
PARTYVOTESHARE	1.565	-0.370***
	(1.222)	(0.0945)
Number of Individuals		
Number of Party/Individual Observations	2,498,888	2,498,888
Pseudo R-Squared		

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.20: Rank Ordered Vs Conditional Logit Regression Results

Health Chi2(1)	3.767
pval of ROL=CL	0.052
Education Chi2(1)	1.899
pval of ROL=CL	0.168
Defence Chi2(1)	2.226
pval of ROL=CL	0.136
Public Transport Chi2(1)	.
pval of ROL=CL	.
Immigration Chi2(1)	1.939
pval of ROL=CL	0.164
Same Sex Marriage Chi2(1)	2.918
pval of ROL=CL	0.088
Vote Share 2013 Chi2(1)	2.822
pval of ROL=CL	0.093
All Vars Chi2(7)	24.505
pval of ROL=CL	0.000

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.21: Rank Ordered Vs Conditional Logit Regression Results

	RO Logit	C Logit
HEALTH	-0.253	-1.281***
	(0.156)	(0.142)
EDUCATION	1.275***	0.355***
	(0.112)	(0.104)
DEFENCE	-1.855***	-1.051***
	(0.110)	(0.0660)
PUBLICTRANSPORT	-0.133	0.519***
	(0.104)	(0.136)
IMMIGRATION	-1.103***	-0.194**
	(0.110)	(0.0761)
SAMESEXMARRIAGE	1	1
	(.)	(.)
PARTYVOTESHARE	-0.207***	-0.192***
	(0.0110)	(0.00880)
Number of Individuals		
Number of Party/Individual Observations	2,498,888	2,498,888
Pseudo R-Squared		

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.22: Rank Ordered Vs Conditional Logit Regression Results

Health Chi2(1)	54.967
pval of ROL=CL	0.000
Education Chi2(1)	97.689
pval of ROL=CL	0.000
Defence Chi2(1)	51.073
pval of ROL=CL	0.000
Public Transport Chi2(1)	52.706
pval of ROL=CL	0.000
Immigration Chi2(1)	91.087
pval of ROL=CL	0.000
Same Sex Marriage Chi2(1)	.
pval of ROL=CL	.
Vote Share 2013 Chi2(1)	1.238
pval of ROL=CL	0.266
All Vars Chi2(7)	394.903
pval of ROL=CL	0.000

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.23: Rank Ordered Vs Conditional Logit Regression Results

	RO Logit	C Logit
HEALTH	1.220	6.674***
	(0.781)	(0.672)
EDUCATION	-6.147***	-1.848***
	(0.480)	(0.576)
DEFENCE	8.942***	5.475***
	(0.366)	(0.206)
PUBLICTRANSPORT	0.639	-2.705***
	(0.499)	(0.691)
IMMIGRATION	5.316***	1.008***
	(0.448)	(0.390)
SAMESEXMARRIAGE	-4.821***	-5.210***
	(0.255)	(0.239)
PARTYVOTESHARE	1	1
	(.)	(.)
Number of Individuals		
Number of Party/Individual Observations	2,498,888	2,498,888
Pseudo R-Squared		

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.24: Rank Ordered Vs Conditional Logit Regression Results

Health Chi2(1)	49.387
pval of ROL=CL	0.000
Education Chi2(1)	49.075
pval of ROL=CL	0.000
Defence Chi2(1)	103.969
pval of ROL=CL	0.000
Public Transport Chi2(1)	54.671
pval of ROL=CL	0.000
Immigration Chi2(1)	190.050
pval of ROL=CL	0.000
Same Sex Marriage Chi2(1)	1.267
pval of ROL=CL	0.260
Vote Share 2013 Chi2(1)	.
pval of ROL=CL	.
All Vars Chi2(7)	1,237.688
pval of ROL=CL	0.000

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Hausman tests after first preference has been removed using variables other than defence as regressor:

Table 3.25: Hausman Tests: Health as Regressor

Hausman Test: 6 ranks Chi2(1)	2.148
Pval	0.143
Hausman Test: 5 ranks Chi2(1)	2.147
Pval	0.143
Hausman Test: 4 ranks Chi2(1)	1.552
Pval	0.213
Hausman Test: 3 ranks Chi2(1)	3.140
Pval	0.076
Hausman Test: 2 ranks Chi2(1)	42.858
Pval	0.000

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.26: Hausman Tests: Education as Regressor

Hausman Test: 6 ranks Chi2(1)	46.622
Pval	0.000
Hausman Test: 5 ranks Chi2(1)	46.568
Pval	0.000
Hausman Test: 4 ranks Chi2(1)	31.170
Pval	0.000
Hausman Test: 3 ranks Chi2(1)	6.488
Pval	0.011
Hausman Test: 2 ranks Chi2(1)	5.110
Pval	0.024

Standard errors in parentheses
Standard Errors Clustered at Electorate Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.27: Hausman Tests: Public Transport as Regressor

Hausman Test: 6 ranks Chi2(1)	1.949
Pval	0.163
Hausman Test: 5 ranks Chi2(1)	1.957
Pval	0.162
Hausman Test: 4 ranks Chi2(1)	6.651
Pval	0.010
Hausman Test: 3 ranks Chi2(1)	4.417
Pval	0.036
Hausman Test: 2 ranks Chi2(1)	0.867
Pval	0.352

Standard errors in parentheses

Standard Errors Clustered at Electorate Level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.28: Hausman Tests: Immigration as Regressor

Hausman Test: 6 ranks Chi2(1)	441.014
Pval	0.000
Hausman Test: 5 ranks Chi2(1)	440.910
Pval	0.000
Hausman Test: 4 ranks Chi2(1)	389.491
Pval	0.000
Hausman Test: 3 ranks Chi2(1)	271.883
Pval	0.000
Hausman Test: 2 ranks Chi2(1)	140.201
Pval	0.000

Standard errors in parentheses

Standard Errors Clustered at Electorate Level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.29: Hausman Tests: Same Sex Marriage as Regressor

Hausman Test: 6 ranks Chi2(1)	495.017
Pval	0.000
Hausman Test: 5 ranks Chi2(1)	494.800
Pval	0.000
Hausman Test: 4 ranks Chi2(1)	365.170
Pval	0.000
Hausman Test: 3 ranks Chi2(1)	313.529
Pval	0.000
Hausman Test: 2 ranks Chi2(1)	227.859
Pval	0.000

Standard errors in parentheses

Standard Errors Clustered at Electorate Level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.30: Hausman Tests: 2013 Vote Share as Regressor

Hausman Test: 6 ranks Chi2(1)	4,014.213
Pval	0.000
Hausman Test: 5 ranks Chi2(1)	4,014.523
Pval	0.000
Hausman Test: 4 ranks Chi2(1)	3,744.748
Pval	0.000
Hausman Test: 3 ranks Chi2(1)	3,023.299
Pval	0.000
Hausman Test: 2 ranks Chi2(1)	1,767.793
Pval	0.000

Standard errors in parentheses

Standard Errors Clustered at Electorate Level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.31: Hausman Tests: All Regressors Used

Hausman Test: 6 ranks Chi2(1)	4,704.539
Pval	0.000
Hausman Test: 5 ranks Chi2(1)	4,704.642
Pval	0.000
Hausman Test: 4 ranks Chi2(1)	4,363.578
Pval	0.000
Hausman Test: 3 ranks Chi2(1)	3,540.893
Pval	0.000
Hausman Test: 2 ranks Chi2(1)	2,225.684
Pval	0.000

Standard errors in parentheses

Standard Errors Clustered at Electorate Level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 4

The effect of other people's tax payments on life satisfaction. Evidence from the US 2008-2015.

Co-authored with Paul Frijters[1]

4.1 Introduction

Life satisfaction as a measure of wellbeing is gaining more traction in public policy with the Sen and Stiglitz report advocating it as the most useful summary measure (Stiglitz et al., 2017). The UK Office of National Statistics has collected life satisfaction data in all its surveys since 2010. More recently, the UK treasury updated their policy evaluation guide, or 'Green Book,' to make wellbeing more central, using life satisfaction as the basis of distributional analyses and non-market externalities. In early 2019, the New Zealand government presented a 'wellbeing budget' with the explicit aim to improve the wellbeing of its citizens. Life satisfaction research is hence gradually starting to be taken up in policy circles. Policy relevant life satisfaction research has already been conducted in the areas of

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income, labour, health, crime, political participation, and public finance (see Frijters et al. (2019)). In this paper we investigate the relationship between state income tax in the United States and life satisfaction, combining the Gallup Daily poll data between 2008 and 2015 that interviewed 2,106,874 individuals with ZIP code level tax data from the Internal Revenue Service (IRS). US states have a variety of income tax schedules that changed in this period, allowing for temporal and cross-sectional identification of income tax effects: some states levy no income tax, some have a flat tax, and some a progressive tax. The primary question we seek to answer is: "how does an individual's life satisfaction vary due to changes in the amount of taxes paid per household in their ZIP code, net of the effect of own income?" This is the effect of other people's taxes on own life satisfaction. We find that income tax paid by others has a positive effect on own life satisfaction when those in the highest tax band are taxed more, not the poor (those in the lowest tax band). Increasing tax on the poor has a negative effect on everyone's life satisfaction. Surprisingly, both these findings hold irrespective of an individual's own level of income and hence their own income tax bill. This means that the life satisfaction effect of income tax on a particular income group is not determined by membership of that group. The main identification challenge is that the total amount of taxes collected in a ZIP code per tax band might pick up the effect of own personal income or the level of public goods: because reported own income is likely to measured with substantial error, observed levels of tax collected in the area might simply pick up the actual effect of own income. Also, levels of tax collected in the area might pick up the quality of the neighbourhood. To address this endogeneity we use an instrumental variables approach that relies on yearly state-level changes in tax policy. We instrument the log of state income tax paid per household by high and low income groups with the effective marginal tax rates on different income bands. This identifies the immediate effect of taxes paid on life satisfaction, which include things like expectations of future public goods provision, which is thus what we identify. The paper is structured as follows. **Section 2** reviews the life satisfaction and public policy literature. **Section 3** introduces the data which come from the Gallup Daily

Poll, the Internal Revenue Service and the National Bureau of Economic Research. **Section 4** describes our empirical approach and identification strategy. **Section 5** discusses the key results and **Section 6** explores heterogeneous effects of income tax on different income groups. **Section 7** conducts robustness checks and **Section 8** concludes.

4.2 Literature Review

Our paper is the first to investigate the effect of other people's taxes on own life satisfaction. The most closely related paper is Akay et al. (2012), who look at how an individual's own income taxes directly affect their life satisfaction. Using the German SOEP data, they regress income and payroll tax payments on individual life satisfaction, controlling for net income, other demographics and individual and time fixed effects. Their primary finding is that wellbeing increases with higher individual tax payments. This result is surprising considering that increases in one's own disposable income generates higher life satisfaction, where taxation reduces disposable income. Other authors have found equally surprising results. Lubian and Zarri (2011) use the Survey of Italian Households' Income and Wealth to find that people are happier when they pay their taxes. They argue that this result is "in line with the well-known neuroeconomic experiment on taxation run by Harbaugh et al. (2007), where even mandatory, tax-like transfers to a charity elicit neural activity in areas related to reward processing." Ferrer-i Carbonell and Gërxhani (2016) use cross-sectional data from the *Public Goods through Private Eyes* survey collected on 14 Central and Eastern European countries between 2013 and 2014 by the University of Warsaw. They employ a fixed effects model to show that there is a clear negative relation between tax evasion and life satisfaction. They conclude that this result is driven by "a positive perception of formal tax-related institutions and a high level of formal social capital." So in line with the main results of our paper, these studies find that many individuals get life satisfaction from paying more taxes themselves, at least in Europe. There are three related literatures that the studies

on tax and subjective wellbeing fall into: the literature on tax morale that looks at when individuals feel positive about paying taxes; the literature on life satisfaction and public good provision that looks at how much individuals value public goods and other outcomes they might attribute to the state (like unemployment); and the literature on life satisfaction and income that looks at what type of income that individuals value and how that relates to the outcomes of others. A large body of literature studies attitudes towards taxation to explain why such high levels of tax compliance are observed relative to what rational selfish individuals would be predicted to pay. One hypothesis is that individuals receive intrinsic payoffs from the act of complying with the tax laws, known in the literature as a positive tax morale or just tax morale. Torgler et al. (2008) find that tax morale has a strong negative correlation with tax evasion and a positive correlation with the degree to which people identify with the taxing entity, a connection with strongly positive effects on wellbeing. Positive tax morale would mean that paying taxes can be felt as a positive affirmation of identity and thus increase life satisfaction. For a review of the tax morale literature, see Luttmer and Monica (2014). The tax moral literature also looks at how the systems around taxes affect tax morale, which gives indications as to how people feel about the taxes paid by others. Frey and Stutzer (2005, 2006) for instance look at the concept of procedural utility, closely related to the concept of procedural justice in political science, which tests whether individuals receive utility payoffs from not only outcomes but the conditions which lead to the outcomes. Frey and Stutzer (2006) thus find evidence that citizens of democratic countries gain more life satisfaction from democratic institutions than foreign nationals. Lago-Peñas and Lago-Peñas (2010) use data from the *European Social Survey* which covers 17 European countries between 2004 and 2005. They find that individual demographics, personal financial experiences and political attitudes all affect tax morale. They also find context specific factors such as regional redistribution, national tax arrangements and ethnic-linguistic fractionalisation affect tax morale What this suggests is that changes in how others are taxed might affect own tax morale and thereby life satisfaction. Frey et al. (2004) point to

procedural utility aspects and argue that "when the tax officials treat them [tax payers] with respect and dignity, their willingness to pay taxes may be supported or even raised." Torgler et al. (2008) and Lago-Peñas and Lago-Peñas (2010) similarly argue that individuals are more inclined to pay taxes and feel better about it when the tax system is more moral, as for instance measured by lower perceived corruption and higher trust in officials and the state. Oishi et al. (2012, 2018) thus argue that individuals receive a positive life satisfaction payoff from more progressive tax systems, a hypothesis we explicitly test by looking at the effects of changes to the higher and lower tax bands. A different literature considers preferences for public goods and outcomes associated with government policies. Scholars have investigated life satisfaction in relation to unemployment (Clark and Oswald, 1994; Lucas et al., 2004), job loss (Kassenboehmer and Haisken-DeNew, 2009), crime (Powdthavee, 2005; Johnston et al., 2018), and social welfare (Ifcher, 2011). [2] Some studies combine an interest in public goods with taxes. Albanese et al. (2015) look at the ratio between taxes and social provision and find that individuals have higher life satisfaction payoffs if their tax dollars are more effectively spent on public goods. Boyd-Swan et al. (2016) use difference in differences to show that increases in the Earned Income Tax Credit (EITC) have a positive effect on life satisfaction as well. Oishi et al. (2012) use life satisfaction data from the Gallup World Poll to show that nations with more progressive tax systems have higher life satisfaction on average. They do not find a relationship, however, between life satisfaction and the overall tax rate or government spending. Finally, our paper relates to the question of what aspect of income relates to individual and collective life satisfaction. Importantly, the lack of a strongly negative effect of taxes paid on life satisfaction might be partially explained by the importance of relative concerns: when marginal tax rates change, they change for everyone in the state, keeping the relative income rank between individuals as they are. So if the positive relation between own income and own life satisfaction is largely the result of relative consideration (ie having more than the neighbours), the effects of changes in taxes

[2] See Oishi and Diener (2014) for a general discussion of how life satisfaction can be used as a public policy tool.

via relative consumption is very small. Many empirical papers show this importance of relative considerations in the income-wellbeing link ((Clark et al., 2016), (Luttmer, 2005; Layard, 2006), (Stutzer, 2004)). From that literature one does not expect strong negative effects of own taxes paid, in line with the main results in this paper.

4.3 Data

The analysis combines three datasets: the Gallup data with over 2 million individuals surveyed from 2008 to 2015; Internal Revenue Service (IRS) data on the taxes paid by income band by ZIP code; and data from the TAXSIM model of the NBER on changes over time in state marginal rates of taxation by income bands. We first introduce the three datasets and then compare the income bands.

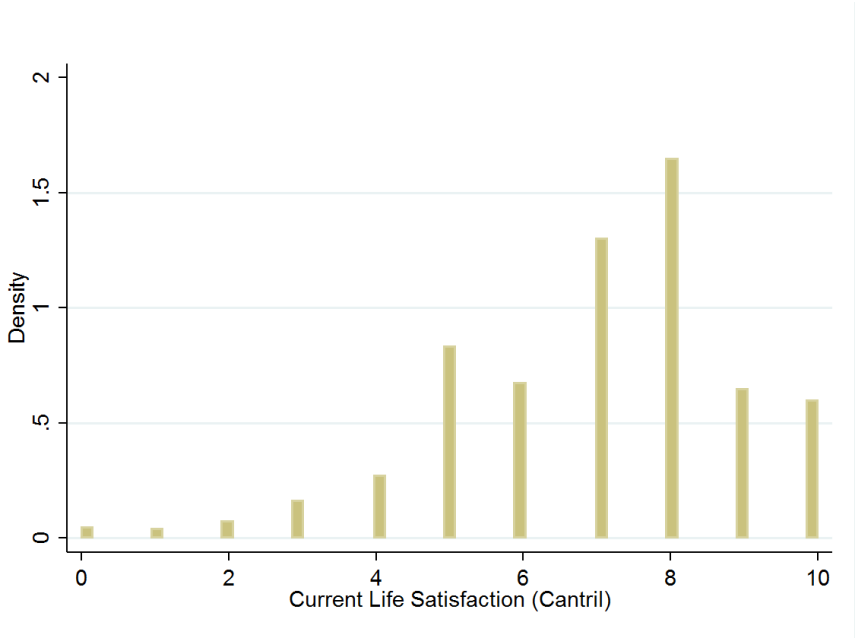
4.3.1 Life Satisfaction Data: Gallup Daily Poll

Our data come from the Gallup Daily Poll, with 2,106,874 individual observations in the total sample. The data are collected via phone interview and the life satisfaction variable is constructed using Cantril's Self-Anchoring Ladder of Life Satisfaction, an 11 point scale. Individuals are asked the following question:

> "Please imagine a ladder with steps numbered from zero at the bottom to 10 at the top. The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life for you. On which step of the ladder would you say you personally feel you stand at this time?"

The following figure shows the distribution.

Figure 4.1: Distribution of US Life Satisfaction



Individuals are also asked a battery of demographics questions. Since we want to control for many of these in our regressions, there is the potential to lose many observations due to missing data, which would make the sample more selective. In order to reduce the loss in sample size from missing data, we imputed missing values in the following standard way: for continuous variables the missing observations are replaced with the mean of the variable, whilst we also create a dummy variable indicating the variable was missing. What this effectively assumes is that the missing variable has the same, but unknown, level for all individuals with missing information for that variable. The sign and size of the dummy for a missing variable then identifies that unknown level as it differs from the mean of the observed valued. For categorical variables a category for missing observations is included, where the value of the dummy for the missing variable again identifies the common category of the individuals involved. The following summary statistics show the Gallup variables before imputation.

Table 4.1: Gallup Summary Statistics (before imputation)

	Mean	SD	Min	Max	N
Current Life Satisfaction (Cantril)	7.00	1.96	0.00	10.00	2177333
Life Satisfaction in 5 Years (Cantril)	7.51	2.30	0.00	10.00	2075899
Gender (Female=1)	0.51	0.50	0.00	1.00	2237999
Age (Years)	54.50	17.61	18.00	99.00	2203936
Race (Categorical)	1.44	1.05	1.00	5.00	2176709
Highest Level Education (Categorical)	3.99	1.55	1.00	6.00	2211405
Marital Status (Categorical)	2.62	1.58	1.00	8.00	2216903
Number of Children in HH	0.54	1.03	0.00	15.00	2234078
Employment Status (Categorical)	2.79	2.21	1.00	6.00	2238006
Annual Income (Categorical)	3.13	1.73	1.00	6.00	1795364
Body Mass index	27.38	5.11	7.71	152.56	2238006
Has Health Problems = 1	0.23	0.42	0.00	1.00	2227685
Party Affiliation (Categorical)	2.05	0.84	1.00	4.00	1764094
Religion Important (Yes=1)	0.66	0.42	0.00	1.00	2238006

See Appendix for Details of Categorical Variables

For our heterogeneity analysis we consider the life satisfaction payoffs to individuals in different income brackets. These individual income brackets correspond to the following individual annual incomes (in USD):

1. Individuals earn less than $23,999 p.a.
2. Individuals earn $24,000 - $47,999 p.a.
3. Individuals earn $48,000 - $59,999 p.a.
4. Individuals earn $60,000 - $89,999 p.a.
5. Individuals earn $90,000 - $119,999 p.a.
6. Individuals earn more than $120,000 p.a.

It should be noted that these bands do not perfectly correspond to the income brackets in the IRS or TAXSIM data, making it important to bear in mind that the bottom income

group in one dataset is not quite the same group in another.

4.3.2 Tax Data: Internal Revenue Service

Our tax data come from the publicly available IRS Statistics of Income at the ZIP code level. There are 213,745 ZIP code-year observations. The data come from administrative records of individual income tax returns (1040 forms). For each ZIP code this gives us state and local income taxes, salary and wages, and adjusted gross income. Taxes are broken into six adjusted gross income categories, which reflect the adjusted gross income of the tax units[3] filing the returns. Adjusted gross income (AGI) is the taxable income of a household. It is total income, including wages, dividends, capital gains, interest etc., minus any eligible deductions. The adjusted gross income bands correspond to the following realised annual incomes in US dollars:

1. Households in this band have an AGI of $1 - $25,000 p.a.
2. Households in this band have an AGI of $25,000 - $50,000 p.a.
3. Households in this band have an AGI of $50,000 - $75,000 p.a.
4. Households in this band have an AGI of $75,000 - $100,000 p.a.
5. Households in this band have an AGI of $100,000 - $200,000 p.a.
6. Households in this band have an AGI of more than $200,000 p.a.

Due to the fact that the number of returns approximates households, we will refer to tax units as households from this point onwards, though the distinction should be borne in mind. It is also worth noting that ZIP codes with fewer than 100 returns, or those identified as a single building or non-residential zip code are excluded from the data. The following table shows the summary statistics for our tax data.

[3]the tax unit is the unit at which people file their tax returns; i.e. single, married joint-filing, married separate filing etc. It approximates households.

Table 4.2: Sum Stats: Tax Variables of Interest

	Mean	SD	Min	Max	N
Log State Income Tax Per HH for Low Income Bands (Bands 1,2)	4.50	1.15	1.15	6.15	213745
Log State Income Tax Per HH for High Income Bands (Bands 5,6)	8.85	0.97	5.30	10.16	213745
State Income Tax per HH for Income Band 1	34	26	0	169	213745
State Income Tax per HH for Income Band 2	292	167	7	894	213745
State Income Tax per HH for Income Band 3	1014	553	25	2622	213745
State Income Tax per HH for Income Band 4	2065	1100	47	4705	213745
State Income Tax per HH for Income Band 5	4710	2335	113	8957	213745
State Income Tax per HH for Income Band 6	25087	15082	518	71272	213745
Wages and Salary per HH for Income Band 1	9271	679	7121	10948	213745
Wages and Salary per HH for Income Band 2	29219	900	25907	32134	213745
Wages and Salary per HH for Income Band 3	47883	1319	43884	52912	213745
Wages and Salary per HH for Income Band 4	66548	2200	59419	73104	213745
Wages and Salary per HH for Income Band 5	101472	5045	81400	112060	213745
Wages and Salary per HH for Income Band 6	253040	38136	158264	387417	213745

According to the Institute on Taxation and Economic Policy (2015) report, state income taxes are the main progressive element of state and local taxes, with the main regressive element being consumption and property taxes (progressive meaning that the poor pay a lower share of their income than the rich and regressive being the opposite). There are 9 states that have no state income taxes: Alaska, Florida, Nevada, New Hampshire (there is tax on dividends and investment income), South Dakota, Tennessee (there is tax on dividends and investment income), Texas, Washington, and Wyoming. There are 8 states who have a flat-tax on income: Colorado, Illinois, Indiana, Massachusetts, Michigan, North Carolina, Pennsylvania, and Utah. The remaining 33 states and DC have progressive tax systems (i.e. higher rates for higher incomes), although in practice some states, such as Alabama, have little difference between marginal tax rates and so are similar to a flat tax.

We can here have a preliminary look at the main relationship between life satisfaction

and the (log of) taxes raised in a ZIP code area. This is done in Figure (10), showing a very clear positive relationship on average: where taxes are higher, life satisfaction is higher.

4.3.3 Marginal Tax Rate Data: TAXSIM

Our data on the effective marginal tax rates for state and local income are obtained from the National Bureau of Economic Research's (NBER) TAXSIM tax calculator. We use two data sets from the TAXSIM website, one for effective marginal tax rates across 5 state income tax bands and one for effective marginal state income tax rate on individuals earning more than $1.5 million. The TAXSIM data on the 5 marginal tax rates are estimated by averaging across four household types (singles, joint, family, elderly) for households earning adjusted gross incomes of $10,000; $25,000; $50,000; $75,000; $100,000. The TAXSIM data are based on the assumption that

> "Income is 91% wages, 6% dividends and 3% from taxable interest. Itemized deductions are $100 plus 2% of income for real estate taxes, $100 + 2% charitable giving and $100 plus 6% for mortgage interest. Marginal tax rates are from finite differences applied to wage income and include the effects of clawbacks, phase-outs and the deductibility of federal income tax on some state returns."Feenberg (2019a)

For details on how the state income tax rate on individuals earning over $ 1.5 million is calculated, see Feenberg (2019b). The following table contains the summary statistics for the TAXSIM variables.

Table 4.3: Tax Summary Statistics (before imputation)

	Mean	SD	Min	Max	N
State Marginal Tax Rates					
State MTR on wage income of $10,000	0.17	2.36	-11.00	34.00	408
State MTR on wage income of $25,000	2.92	3.15	0.00	13.95	408
State MTR on wage income of $50,000	4.38	2.58	0.00	9.09	408
State MTR on wage income of $75,000	4.55	2.57	0.00	9.00	408
State MTR on wage income of $100,000	4.96	2.94	0.00	14.10	408
State MTR on wage income of $1,000,000	5.25	3.09	0.00	14.10	408

It is worth noting that although TAXSIM standardises the state marginal tax rate on income to the same 5 (6 including millionaire rate) income amounts, in reality the states have different income tax brackets with different rates applying to each. For example, California has 10 income brackets, each with a different marginal rate, whereas Louisiana only has three. Further, the marginal tax rates used for instrumental variables estimation are not the stated marginal rates. They include the effect of clawbacks, phaseouts and deductions of federal income tax on state income taxes (where applicable). These terms are defined below.

Clawbacks: Tax clawbacks exist as a means for state governments to reclaim lost revenue. For example, the California clawback which came into effect in 2014 targeted individuals who made capital gains on Californian property, but avoided capital gains tax by exchanging the property for one in another state.

Phaseouts: A tax phaseout is a gradual reduction in payout of a tax credit as individual income increases towards the limit of eligibility. For example the Earned Income Tax Credit is phased in and then phased out for varying income levels.

Deductibility of federal income tax on state tax: In 2019 the following states allowed individuals to deduct their federal taxes from state taxes: Alabama, Iowa, Louisiana, Missouri, Montana, Oregon.

Our measures for changes in marginal tax rates thus include changes in state taxes as well as changes in clawbacks, phaseouts, and tax deductibles.

4.3.4 Comparing the three datasets

At this point we have introduced three different income related bands or brackets. Firstly, individual's income bands from the Gallup data, relating to self-reported annual income. Secondly, the adjusted gross income brackets from the IRS data which indicate aggregate income levels of tax filers. Thirdly, the marginal tax rate faced by individuals with various levels of adjusted gross income.

For analyses that do not disaggregate effects of income taxes, these distinctions are not important, but for most of the analyses of interest we wish to know the effects of changes in taxes collected by band on households of different income levels, where we want to match them as best as possible. Similarly, when using the TAXSIM data to instrument for tax revenue by income band, we also need to line up the income definitions in TAXSIM with those of the IRS. These need not allign perfectly because we can use the full set of instruments for all the tax levels raised and instrumentation also works when there is some measurement error in the instrument, but it is still desirable for statistical power and plausibility that the basic groupings overlap.

The following table shows how the different categories line up across the three datasets:

Table 4.4: Income Categories

Category Number	Aggregate Taxes paid by HHs in Adjusted Gross Income Band...	Marginal Tax Rate on HHs Earning...	Individual Income Bands
1	< \$25,000	\$10,000	< \$23,999
2	\$25,000 - \$50,000	\$25,000	\$24,000 - \$47,999
3	\$50,000 - \$75,000	\$50,000	\$48,000 - \$59,999
4	\$75,000 - \$100,000	\$75,000	\$60,000 - \$89,999
5	\$100,000 - \$200,000	\$100,000	\$90,000 - \$119,999
6	> \$200,000	\$1,000,000	> \$120,000

We should here hence note that the categories line up reasonably well, but not perfectly, particularly not for the top groups.

4.4 Empirical Approach

Our initial equation is the following fixed-effects model,

$$\text{SWB}_{izst} = \sum_{B} \beta_B \log(\text{IncomeTax}_{zst} \in \text{bracket}_B) + \alpha_s + \alpha_t + \delta \mathbf{X}_{it} + \gamma \Gamma_{zst} + \epsilon_{izst} \quad (4.1)$$

Where SWB_{izst} is the life satisfaction of individual i in Zip Code z in State s in Year t. $\log(\text{IncomeTax}_{zst})$ is the log of income tax per household levied on households in Adjusted Gross Income bracket $B \in \{low, high\}$ in zip code z ("low" corresponds to households with AGI less than \$ 50,000 and "high" corresponds to households with AGI greater than \$ 100,000).

$\mathbf{X}_{it}$ is a matrix of individual specific covariates, Γ_{zst} a matrix of zip code specific covariates (zip code level income, zip code population), and the error term ϵ_{zst} is assumed to have zero

mean and is orthogonal to all other variables.

The key parameters of interest here are the β_B which denote the effects of taxes collected by income band on an individual in that ZIP code.

The key problem is the likely endogeneity of amounts of taxes at the ZIP code level with the quality of the neighbourhood (which changes over time), own income (in the case of measurement error), and average incomes in the neighbourhood (which themselves can change for many endogenous reasons). There is also endogeneity with public goods, but that is part of the effect of higher taxes we are interested in. We thus use an instrumental variables approach to capture the effects of changes in taxation that are the result of changes to tax policy, rather than changes in ZIP code income levels or the other endogeneity sources. We estimate the following two-stage least squared model, with as the first stage:

$$\sum_B \log(\text{IncomeTax}_{zst} \in \text{bracket}_B) = \sum_L \theta_L(\text{MTR}_{st} \in \text{Income Level}_L) + \phi_s + \phi_t + \xi \mathbf{X}_{it} + \omega \Gamma_{zst} + \nu_{izst} \tag{4.2}$$

and as the second stage:

$$\text{SWB}_{izst} = \sum_B \beta_B \log(\widehat{\text{IncomeTax}_{zst}} \in \text{bracket}_B) + \alpha_s + \alpha_t + \delta \mathbf{X}_{it} + \gamma \Gamma_{zst} + \epsilon_{izst} \tag{4.3}$$

Here, $\text{MTR}_{st} \in \text{Income Level}_L$ is the state marginal tax rate on wage income from TAXSIM for households earning Income Level_L. Due to the fact that we consider high and low income tax groups, we use marginal tax rates for high and low income levels, so that $L \in \{25,000; 100,000; 1,500,000\}$. Note that we do not use the marginal tax rate for individuals paying \$ 10,000 as an instrument. This is because nuances of the tax system cause this particular effective rate to behave unusually when simulated.[4]

[4]For example the California clawback of 2013 causes the state income tax rate for those earning \$10,000 to be 34% which is not reasonable for the vast majority of those in this category as the clawback was on

4.4.1 Heterogeneous Analysis of Incomes

We also estimate the following model in which individual incomes are interacted with state income taxes.

$$\text{SWB}_{izst} = \sum_B \beta_B \log(\text{IncomeTax}_{zst} \in \text{bracket}_B) \; + \sum_b \beta_b \; I(\text{income}_{ist} \in \text{band}_b) + \sum_b \sum_B \beta_{bB} \; I(\text{income}_{ist} \in \text{band}_b) * \log(\text{IncomeTax}_{zst} \in \text{bracket}_B) + \alpha_s + \alpha_t + \delta \mathbf{X}_{it} + \gamma \Gamma_{zst} + \epsilon_{izst} \tag{4.4}$$

$I(\text{income}_{ist} \in \text{band}_b)$ is a categorical variable indicating that individual self reported income falls into the income band $b \in \{1, 2, 3, 4, 5, 6\}$. When extending the analysis using the interaction terms to instrumental variables, we include instruments for all interaction terms as follows,

$$\sum_B \log(\text{IncomeTax}_{zst} \in \text{bracket}_B) + \sum_b \; I(\text{income}_{ist} \in \text{band}_b) \; + \sum_b \sum_B \; I(\text{income}_{ist} \in \text{band}_b) * \log(\text{IncomeTax}_{zst} \in \text{bracket}_B) = \sum_L \theta_L(\text{MTR}_{st} \in \text{Income Level}_L) \; + \sum_b \sum_L \theta_{bL} \; I(\text{income}_{ist} \in \text{band}_b) * (\text{MTR}_{st} \in \text{Income Level}_L) + \sum_b \; I(\text{income}_{ist} \in \text{band}_b) \; + \phi_s + \phi_t + \xi \mathbf{X}_{it} + \omega \Gamma_{zst} + \nu_{izst} \tag{4.5}$$

$$\text{SWB}_{izst} = \sum_b \beta_b \; I(\text{income}_{ist} \in \text{band}_b) + \sum_B \beta_B \; \log(\widehat{\text{IncomeTax}_{zst}} \in \text{bracket}_B) + \sum_b \sum_B \beta_{bB} \; I(\text{income}_{ist} \in \text{band}_b) * \widehat{\log(\text{Inc}}\text{omeTax}_{zst} \in \text{bracket}_B) + \alpha_s + \alpha_t + \delta \mathbf{X}_{it} + \gamma \Gamma_{zst} + \epsilon_{izst} \tag{4.6}$$

capital gains, which are minute for the vast majority with these low incomes, meaning that the number is likely driven by a few unusual observations (millionaires with high capital gains claiming to have very low incomes).

We repeat these heterogeneity tests for political attitudes, education level, gender, age, race, etc.

4.5 Results

Table 4.5 contains the main results from our four specifications. Columns (1) and (3) refer to the OLS and IV models without interactions respectively.

If we compare Column 1 with Column 3, we see the estimated effect of taxes on low-income groups switch signs, whilst the effect of taxes on high-income groups increases strongly. The IV results find that more taxes raised on low-income groups decreases life satisfaction whilst raising more taxes from high-income groups raises it. We interpret this to say that there is a large degree of selectivity about the ZIP codes where taxes on the low-income groups and high-income groups is higher: taxes are probably higher in deprived areas where there are higher public good needs, which depresses the OLS effect of taxes on higher income bands.

The estimates in our final and preferred specification (Column 3 and 4) are relatively large: the coefficient on log income tax levied on low-income groups per household in column (3) of -0.762 ($p<0.01$) indicates that on average, an increase in the per household tax burden on low-income groups of 100 % will decrease individual life satisfaction by 0.762. Similarly, the coefficient on log income tax on high-income groups per person of 0.736 ($p<0.01$) indicates that on average, an increase in the per person tax burden on high-income groups of 100% will increase individual life satisfaction by 0.736. These effects are of a similar magnitude as about two-thirds of the effect of own income on life satisfaction (which is about 1 unit when going from the bottom income group to the top income group).

The results in Column 4 show a heterogeneous effect of taxation on individuals with different income levels, where for each income band one has to add up the intercept at the top of the column to the interaction term specific to the income band. The largest effects

in magnitude are on low-income individuals, who receive the largest positive life satisfaction payoff from taxing the rich and the largest negative payoff from taxing the poor. Individuals at all income levels receive negative life satisfaction payoffs when low-income households pay more tax, however only very low and very high income individuals receive a positive payoff when high-income households pay more tax, with the effect being insignificant (at the 5 % level) for individuals earning between $48,000 to $120,000 per annum.

Table 4.5: Effect of Log Income Tax Paid on CM of Current LS

	OLS		IV	
	(1)	(2)	(3)	(4)
Log State Income Tax Per HH for Low Income Bands	0.0256**	-0.0690***	-0.762***	-0.865***
	(0.0114)	(0.0135)	(0.120)	(0.121)
Log State Income Tax Per HH for High Income Bands	0.0580***	0.158***	0.736***	0.861***
	(0.0187)	(0.0207)	(0.116)	(0.118)
Income < 24,000	0	0	0	0
	(.)	(.)	(.)	(.)
Income 24,000 - 48,000	0.275***	0.687***	0.275***	0.777***
	(0.00483)	(0.0667)	(0.00484)	(0.118)
Income 48,000 - 60,000	0.488***	1.086***	0.488***	1.497***
	(0.00568)	(0.0768)	(0.00569)	(0.137)
Income 60,000 - 90,000	0.619***	1.339***	0.619***	1.648***
	(0.00529)	(0.0694)	(0.00529)	(0.123)
Income 90,000 - 120,000	0.756***	1.536***	0.756***	1.776***
	(0.00614)	(0.0795)	(0.00615)	(0.135)
Income > 120,000	0.907***	1.456***	0.907***	1.571***
	(0.00561)	(0.0692)	(0.00562)	(0.119)
Income Unknown	0.573***	1.026***	0.573***	1.052***
	(0.00527)	(0.0713)	(0.00527)	(0.129)
Income < 24,000 × Log State Income Tax Per HH for Low Income Bands		0		0
		(.)		(.)
Income 24,000 - 48,000 × Log State Income Tax Per HH for Low Income Bands		0.0899***		0.0896***
		(0.00968)		(0.0207)
Income 48,000 - 60,000 × Log State Income Tax Per HH for Low Income Bands		0.124***		0.164***
		(0.0113)		(0.0240)
Income 60,000 - 90,000 × Log State Income Tax Per HH for Low Income Bands		0.145***		0.168***
		(0.0102)		(0.0215)
Income 90,000 - 120,000 × Log State Income Tax Per HH for Low Income Bands		0.155***		0.155***
		(0.0117)		(0.0239)
Income > 120,000 × Log State Income Tax Per HH for Low Income Bands		0.126***		0.0984***
		(0.0103)		(0.0211)
Income Unknown × Log State Income Tax Per HH for Low Income Bands		0.0928***		0.0622***
		(0.0104)		(0.0229)
Income < 24,000 × Log State Income Tax Per HH for High Income Bands		0		0
		(.)		(.)
Income 24,000 - 48,000 × Log State Income Tax Per HH for High Income Bands		-0.0922***		-0.102***
		(0.0117)		(0.0234)
Income 48,000 - 60,000 × Log State Income Tax Per HH for High Income Bands		-0.131***		-0.197***
		(0.0135)		(0.0271)
Income 60,000 - 90,000 × Log State Income Tax Per HH for High Income Bands		-0.155***		-0.202***
		(0.0123)		(0.0243)
Income 90,000 - 120,000 × Log State Income Tax Per HH for High Income Bands		-0.167***		-0.194***
		(0.0140)		(0.0267)
Income > 120,000 × Log State Income Tax Per HH for High Income Bands		-0.126***		-0.125***
		(0.0122)		(0.0235)
Income Unknown × Log State Income Tax Per HH for High Income Bands		-0.0984***		-0.0857***
		(0.0126)		(0.0256)
Constant	7.197***	6.729***	5.399***	4.754***
	(0.104)	(0.117)	(0.368)	(0.383)
Year-Month FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Other Covariates	Yes	Yes	Yes	Yes
N	2106874	2106874	2106874	2106874
R^2	0.172	0.172	0.170	0.170

Standard errors in parentheses
Standard Errors Clustered at Zipcode Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 4.2: Marginal Effects of Income Tax paid on Wellbeing by Income Bracket

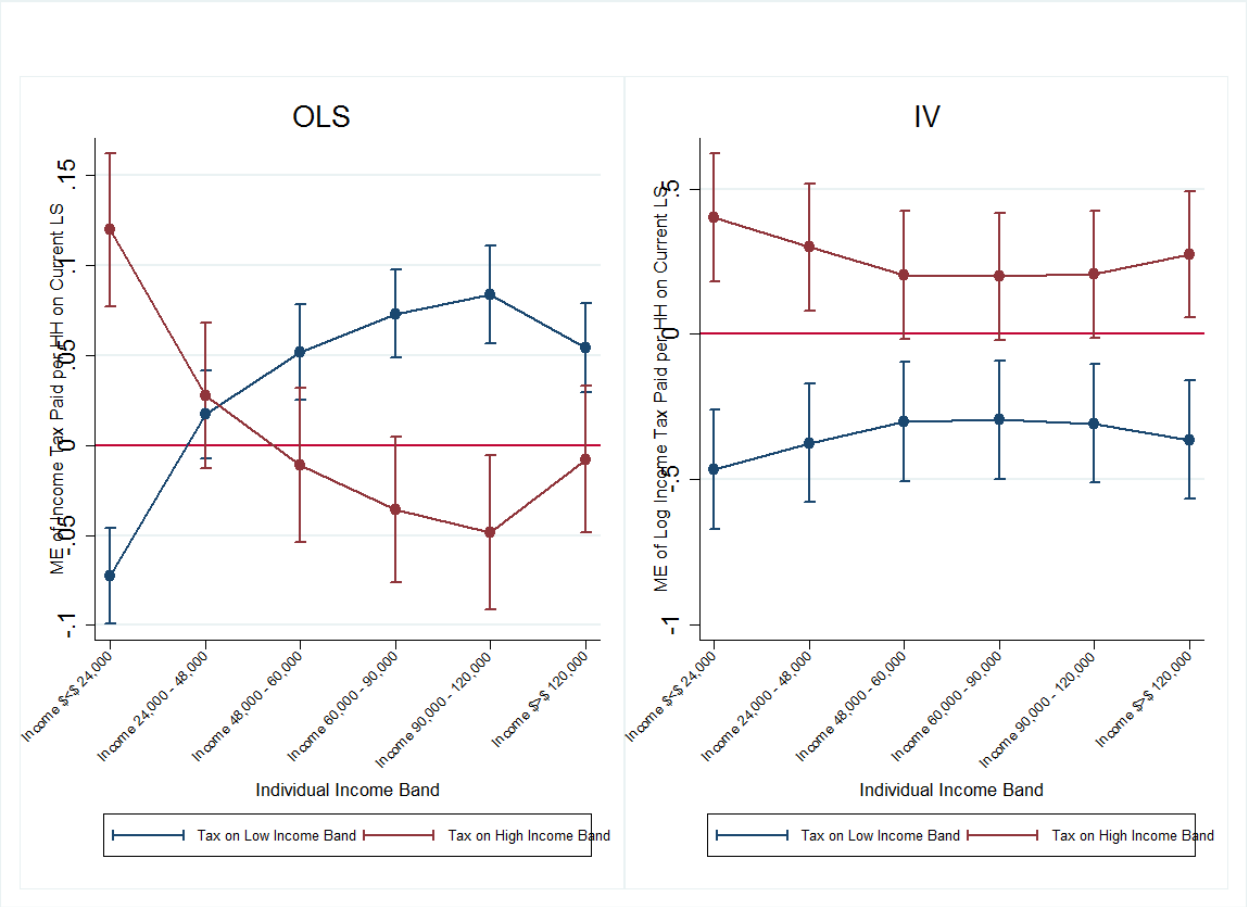


Figure 4.2 shows the differences in marginal effects between OLS and IV. The biggest difference is with the middle income groups ($60,000 - $120,000). In the OLS these are found to be negatively affected by higher top income tax revenue (and positively by higher taxes on the poorest group), a result that switches with the IV where they are found to benefit from higher top income taxes, as one would expect. The main lesson we take from this is that there is likely strong tax endogeneity in the middle: taxes are higher for the low-income groups where general wellbeing is lower (i.e. in deprived areas), whilst they are lower for the high-income groups in areas with lower wellbeing. The IV overcomes that endogeneity in that the immediate effects of the marginal tax changes picks up the effect of more taxes raised and the expectations that go with that.

The main message from the IV results on the interactions is then that all income groups

prefer to see more taxes paid by the rich rather than the poor. The slightly negative slope of the IV graph suggests that the lower-income bands are more strongly positive about higher taxes for the higher band and more strongly negative about higher taxes for the lower bands, but this is not a significant difference.

4.5.1 Heterogeneity across traits

We can repeat the specifications in Column (1) and (3) of the main table above for different education and political affiliation groups (repeating Columns 2 and 4 leads to general insignificance as we run out of identifying variation). We show in Tables 4.6 and 4.7 the headline results on the effect of more taxes on the top or bottom income groups for different characteristics, and depict the results in Figures 4.3 and 4.4.

Table 4.6: Heterogeneous Effects of Political Affiliation

	OLS	IV
	(1)	(2)
Log State Income Tax Per HH for Low Income Bands	0.160***	-0.275***
	(0.0123)	(0.103)
Log State Income Tax Per HH for High Income Bands	-0.125***	0.181*
	(0.0207)	(0.110)
Republican	0	0
	(.)	(.)
Democrat	-1.130***	-0.687***
	(0.0507)	(0.0888)
Independent	-0.979***	-0.930***
	(0.0493)	(0.0901)
OTHER PARTY (volunteered)	-0.870***	-0.759**
	(0.186)	(0.330)
Missing	-0.812***	-0.644***
	(0.0561)	(0.110)
Republican × Log State Income Tax Per HH for Low Income Bands	0	0
	(.)	(.)
Democrat × Log State Income Tax Per HH for Low Income Bands	-0.221***	-0.108***
	(0.00764)	(0.0164)
Independent × Log State Income Tax Per HH for Low Income Bands	-0.175***	-0.148***
	(0.00749)	(0.0166)
OTHER PARTY (volunteered) × Log State Income Tax Per HH for Low Income Bands	-0.130***	-0.105*
	(0.0302)	(0.0637)
Missing × Log State Income Tax Per HH for Low Income Bands	-0.165***	-0.109***
	(0.00836)	(0.0201)
Republican × Log State Income Tax Per HH for High Income Bands	0	0
	(.)	(.)
Democrat × Log State Income Tax Per HH for High Income Bands	0.238***	0.130***
	(0.00907)	(0.0180)
Independent × Log State Income Tax Per HH for High Income Bands	0.185***	0.166***
	(0.00891)	(0.0184)
OTHER PARTY (volunteered) × Log State Income Tax Per HH for High Income Bands	0.144***	0.118*
	(0.0341)	(0.0682)
Missing × Log State Income Tax Per HH for High Income Bands	0.170***	0.123***
	(0.00996)	(0.0221)
Constant	8.078***	7.438***
	(0.116)	(0.385)
Year-Month FE	Yes	Yes
State FE	Yes	Yes
Other Covariates	Yes	Yes
N	2106874	2106874
R^2	0.173	0.172

Standard errors in parentheses
Standard Errors Clustered at Zipcode Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 4.3: Marginal Effects of Income Tax paid on Wellbeing by Political Affiliation

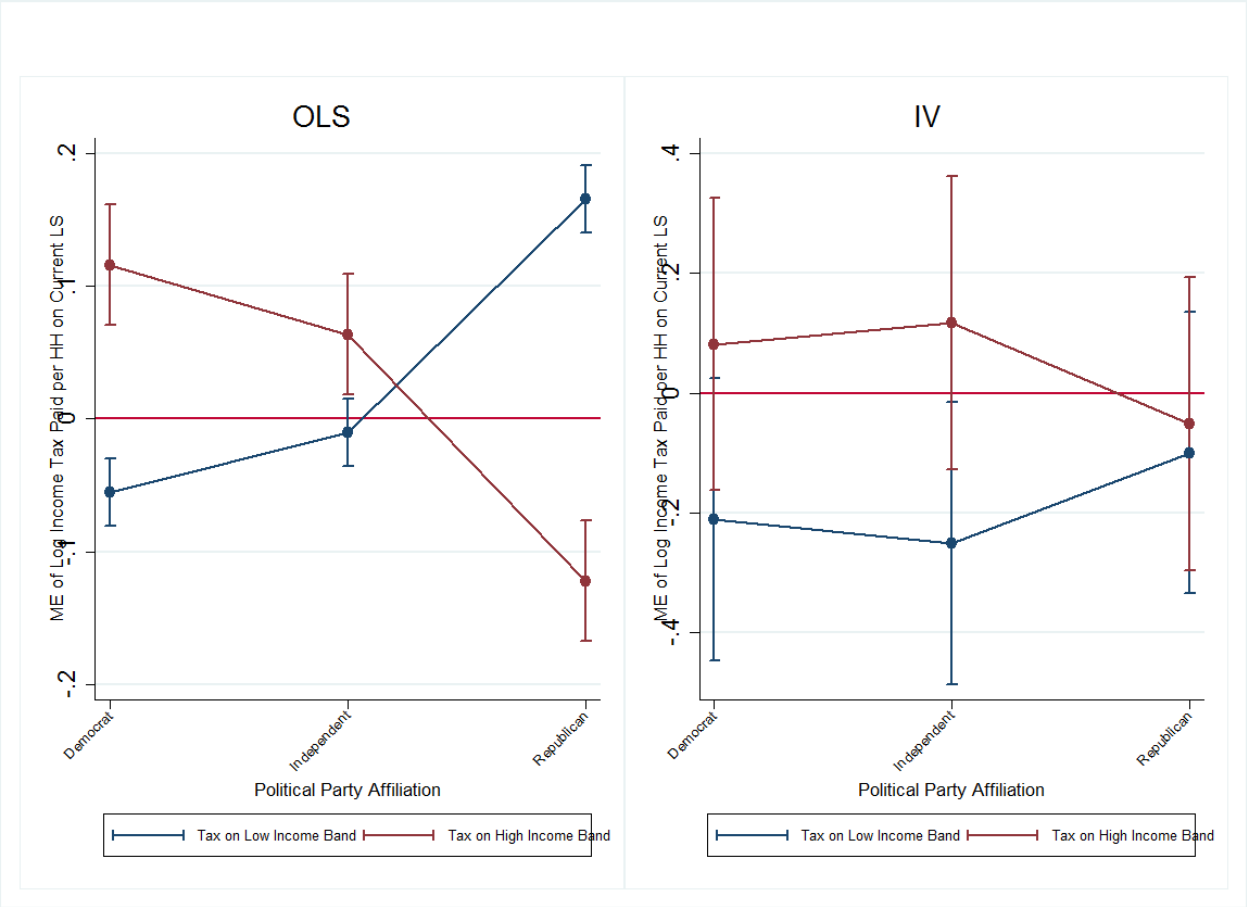


Figure 4.3 and table 4.6 again show a large change from OLS to IV for Republican voters: the IV results higher taxes are an insignificant negative for Republican voters no matter where it raised on, whilst the OLS results suggested they were happier with higher taxes on the poor and unhappy with higher taxes on the rich. The IV results suggest there is hence a large degree of selectivity in happier and less happy Republican areas related to differential levels of taxation. In other words, Republicans are unhappy in areas with high taxation on the rich.

The IV results mainly suggest that Democrats are happier with taxes on the rich than Republicans, but the differences are only borderline significant.

4.5.2 Education

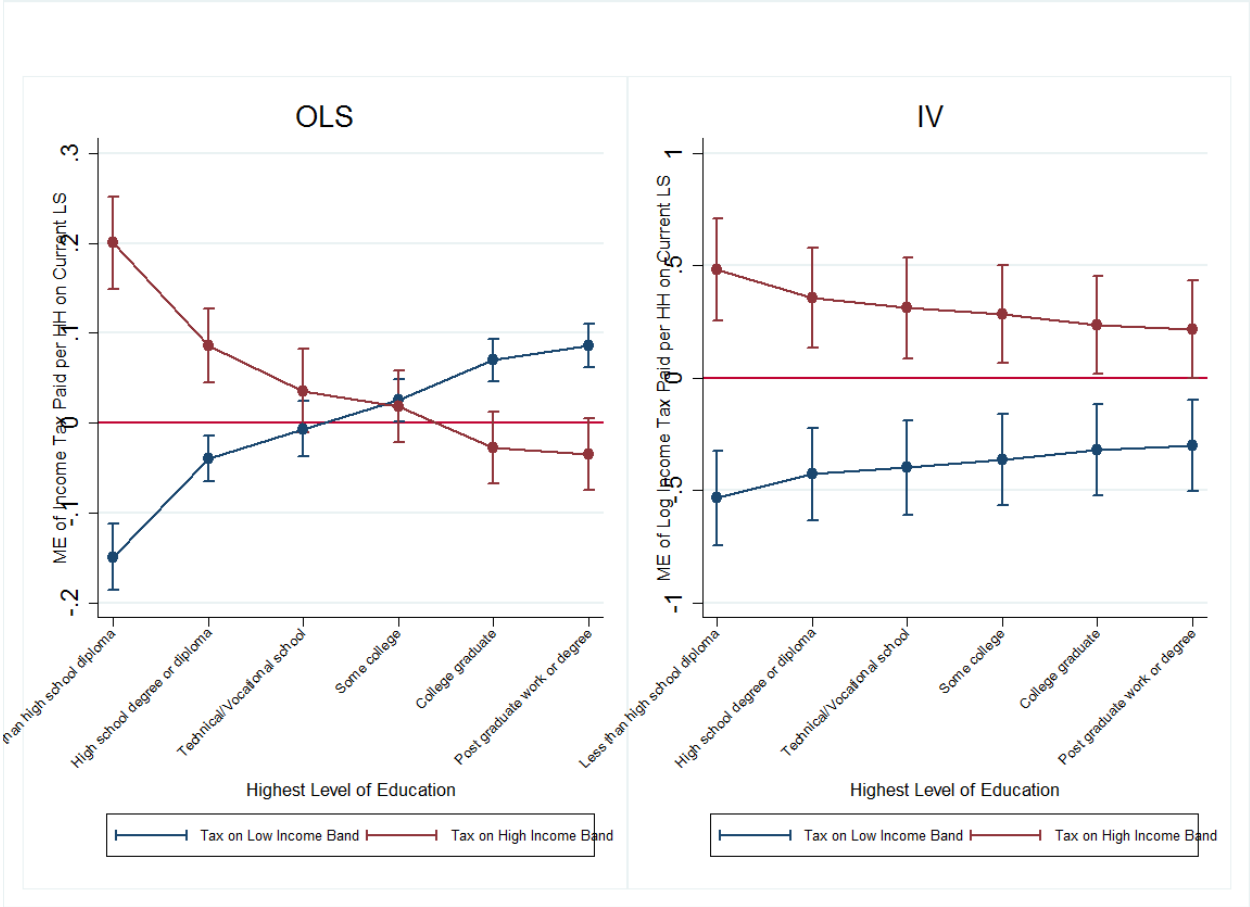
Breaking up individuals by education level reveal a similar picture to income levels.

Table 4.7: Heterogeneous Effects of Education

	OLS	IV
	(1)	(2)
Log State Income Tax Per HH for Low Income Bands	-0.149***	-0.535***
	(0.0186)	(0.108)
Log State Income Tax Per HH for High Income Bands	0.200***	0.484***
	(0.0264)	(0.116)
Less than high school diploma	0	0
	(.)	(.)
High school degree or diploma	0.477***	0.609***
	(0.106)	(0.175)
Technical/Vocational school	0.678***	0.773***
	(0.123)	(0.208)
Some college	0.737***	0.915***
	(0.105)	(0.171)
College graduate	1.092***	1.280***
	(0.105)	(0.171)
Post graduate work or degree	1.247***	1.519***
	(0.105)	(0.170)
Less than high school diploma × Log State Income Tax Per HH for Low Income Bands	0	0
	(.)	(.)
High school degree or diploma × Log State Income Tax Per HH for Low Income Bands	0.109***	0.107***
	(0.0161)	(0.0316)
Technical/Vocational school × Log State Income Tax Per HH for Low Income Bands	0.142***	0.135***
	(0.0186)	(0.0376)
Some college × Log State Income Tax Per HH for Low Income Bands	0.174***	0.170***
	(0.0160)	(0.0308)
College graduate × Log State Income Tax Per HH for Low Income Bands	0.219***	0.213***
	(0.0159)	(0.0309)
Post graduate work or degree × Log State Income Tax Per HH for Low Income Bands	0.235***	0.236***
	(0.0161)	(0.0310)
Less than high school diploma × Log State Income Tax Per HH for High Income Bands	0	0
	(.)	(.)
High school degree or diploma × Log State Income Tax Per HH for High Income Bands	-0.114***	-0.128***
	(0.0190)	(0.0349)
Technical/Vocational school × Log State Income Tax Per HH for High Income Bands	-0.164***	-0.172***
	(0.0221)	(0.0416)
Some college × Log State Income Tax Per HH for High Income Bands	-0.182***	-0.200***
	(0.0189)	(0.0341)
College graduate × Log State Income Tax Per HH for High Income Bands	-0.228***	-0.246***
	(0.0188)	(0.0341)
Post graduate work or degree × Log State Income Tax Per HH for High Income Bands	-0.236***	-0.267***
	(0.0188)	(0.0341)
Constant	6.607***	5.934***
	(0.147)	(0.418)
Year-Month FE	Yes	Yes
State FE	Yes	Yes
Other Covariates	Yes	Yes
N	2106874	2106874
R^2	0.172	0.172

Standard errors in parentheses
Standard Errors Clustered at Zipcode Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 4.4: Marginal Effects of Income Tax paid on Wellbeing by Education Level



The figure on education again reveals a strong difference between OLS and IV, with the IV results in line with the previous headline finding that all groups get high life satisfaction with higher taxes on the rich over higher taxes on the poor. The graph suggests these effects are stronger and more pronounced for those with lower education than higher education, though the confidence intervals overlap.

4.6 Robustness

4.6.1 Possible Selection Effect of Instrument

There is a possibility that because state taxes are deductible from federal taxes that our instrument might have another effect on total taxes raised, changing the interpretation of

the effects. This would be where an increase in the marginal tax rate induced more people to claim the state tax deduction (as opposed to the standard deduction) and therefore the increase in state taxes paid is both from paying more state taxes and more people claiming it as a deduction. To control for this we conduct a robustness test which denominates the state tax variable by number of deductions claimed rather than by population. The disadvantage of this approach is that we lose 2008 from our sample (this variable was not recorded in 2008 IRS data). As can be seen in table 4.8, the IV estimates do not change much when accounting for this possibility. So we conclude that deductions are not a large driving force in our main findings.

Figure 4.5: Robustness: Marginal Effects of Income Tax paid on Wellbeing by Income Level

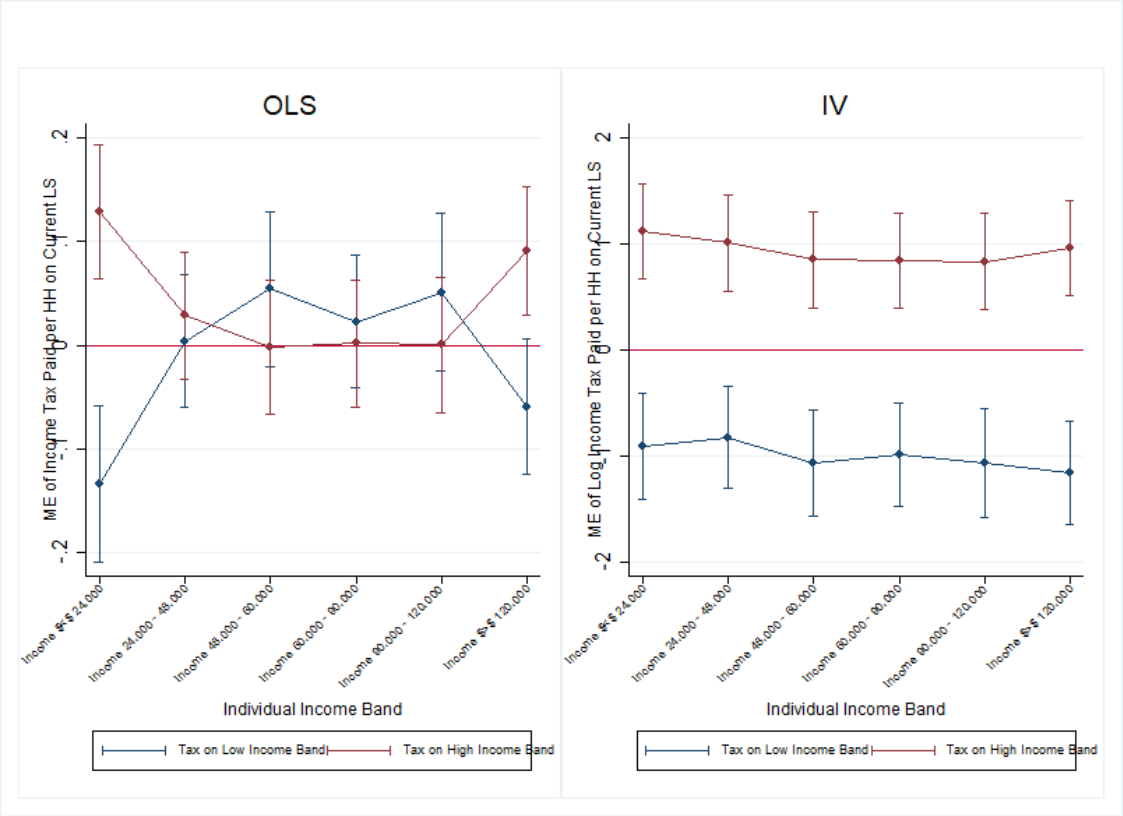


Table 4.8: Effect of Log Income Tax Paid on CM of Current LS

	OLS		IV	
	(1)	(2)	(3)	(4)
Log State Income Tax Per HH for Low Income Bands	-0.0257	-0.134***	-1.034***	-0.905***
	(0.0262)	(0.0384)	(0.238)	(0.256)
Log State Income Tax Per HH for High Income Bands	0.0550*	0.128***	1.012***	1.116***
	(0.0299)	(0.0327)	(0.226)	(0.231)
Income < 24,000	0	0	0	0
	(.)	(.)	(.)	(.)
Income 24,000 - 48,000	0.249***	0.174	0.249***	0.722
	(0.00510)	(0.213)	(0.00511)	(1.063)
Income 48,000 - 60,000	0.444***	0.292	0.444***	4.178***
	(0.00606)	(0.244)	(0.00607)	(1.257)
Income 60,000 - 90,000	0.568***	0.611***	0.568***	3.856***
	(0.00559)	(0.215)	(0.00559)	(1.111)
Income 90,000 - 120,000	0.696***	0.544**	0.696***	4.597***
	(0.00651)	(0.249)	(0.00651)	(1.290)
Income > 120,000	0.840***	0.645***	0.840***	4.256***
	(0.00598)	(0.223)	(0.00598)	(1.139)
Income Unknown	0.535***	0.418*	0.535***	2.758**
	(0.00565)	(0.223)	(0.00565)	(1.258)
Income < 24,000 × Log State Income Tax Per HH for Low Income Bands		0		0
		(.)		(.)
Income 24,000 - 48,000 × Log State Income Tax Per HH for Low Income Bands		0.138***		0.0766
		(0.0363)		(0.128)
Income 48,000 - 60,000 × Log State Income Tax Per HH for Low Income Bands		0.188***		-0.161
		(0.0421)		(0.151)
Income 60,000 - 90,000 × Log State Income Tax Per HH for Low Income Bands		0.156***		-0.0849
		(0.0371)		(0.134)
Income 90,000 - 120,000 × Log State Income Tax Per HH for Low Income Bands		0.185***		-0.162
		(0.0428)		(0.157)
Income > 120,000 × Log State Income Tax Per HH for Low Income Bands		0.0744**		-0.253*
		(0.0378)		(0.139)
Income Unknown × Log State Income Tax Per HH for Low Income Bands		0.0766**		-0.134
		(0.0387)		(0.151)
Income < 24,000 × Log State Income Tax Per HH for High Income Bands		0		0
		(.)		(.)
Income 24,000 - 48,000 × Log State Income Tax Per HH for High Income Bands		-0.0996***		-0.110***
		(0.0174)		(0.0375)
Income 48,000 - 60,000 × Log State Income Tax Per HH for High Income Bands		-0.131***		-0.267***
		(0.0204)		(0.0447)
Income 60,000 - 90,000 × Log State Income Tax Per HH for High Income Bands		-0.126***		-0.279***
		(0.0182)		(0.0399)
Income 90,000 - 120,000 × Log State Income Tax Per HH for High Income Bands		-0.128***		-0.283***
		(0.0210)		(0.0446)
Income > 120,000 × Log State Income Tax Per HH for High Income Bands		-0.0377**		-0.162***
		(0.0184)		(0.0388)
Income Unknown × Log State Income Tax Per HH for High Income Bands		-0.0475**		-0.129***
		(0.0189)		(0.0420)
Constant	7.545***	7.640***	7.000***	4.941***
	(0.179)	(0.244)	(0.340)	(0.880)
Year-Month FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Other Covariates	Yes	Yes	Yes	Yes
N	1765329	1765329	1765329	1765329
r2	0.180	0.180	0.179	0.179

Standard errors in parentheses
Standard Errors Clustered at Zipcode Level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.7 Discussion

We use over 2 million respondents in the Gallup Daily Poll for the US in 2008-2015 to identify the effect of changes in taxes paid by different income band on individual life satisfaction. The main result is that all income groups appear to prefer that high income groups pay more income tax, though the benefit of higher taxes on life satisfaction is (understandably) strongest for low income individuals. Our findings may be driven by several possible mechanisms that we cannot unpick in this data. The increase in individual life satisfaction also be driven by updated expectations about future public good provision, which would outweigh negative effects of own higher taxes when the current level of public good provision is sub-optimal. The results may also reflect normative preferences for redistributing income to the extent that there is a preference for taxing rich versus poor. The implications for tax policy are intriguing. Prima facie, our result suggests that Americans would benefit in life satisfaction terms from an increase in income tax paid by the wealthy and a reduction of income tax levied on the poor. Importantly, this is the ex-post experience with changes in tax policies and does not necessarily reflect what individuals ex-ante believe or vote for.

4.8 Appendix

4.8.1 Life satisfaction and Income

The following table shows the distribution of wellbeing by individual income, showing a clear positive correlation.

Table 4.9: Gallup Happiness by Individual Income Bracket

	mean	sd	min	max	N
Income < 24,000					
Happiness Today (Cantril Scale)	6.2765	2.3610	0.0000	10.0000	317600
Income 24,000 - 48,000					
Happiness Today (Cantril Scale)	6.8163	1.9253	0.0000	10.0000	382587
Income 48,000 - 60,000					
Happiness Today (Cantril Scale)	7.1176	1.7366	0.0000	10.0000	163945
Income 60,000 - 90,000					
Happiness Today (Cantril Scale)	7.2973	1.6023	0.0000	10.0000	274205
Income 90,000 - 120,000					
Happiness Today (Cantril Scale)	7.4650	1.5063	0.0000	10.0000	121793
Income > 120,000					
Happiness Today (Cantril Scale)	7.6410	1.5222	0.0000	10.0000	227224

4.8.2 First Stage Analysis

The following tables show the first stage regressions for column (3) of our main results in table 5. Our instrument has a significant positive correlation with the income tax variables, as would be expected.

Table 4.10: First Stage Regression - Table 1

VARIABLES	Log State Income Tax Per HH for Low Income Bands		Log State Income Tax Per HH for High Income Bands	
	Coefficient	SE	Coefficient	SE
	(1)	(2)	(3)	(4)
State MTR Wages (Income Band 2)	0.00540***	(0.000978)	0.0152***	(0.000785)
State MTR Wages (Income Band 5)	0.106***	(0.00321)	0.0710***	(0.00184)
State MTR Wages (Top Income Earners)	0.0249***	(0.000602)	0.0412***	(0.000518)
income_band = 2, Income 24,000 - 48,000	0.000297	(0.000298)	9.38e-05	(0.000155)
income_band = 3, Income 48,000 - 60,000	-6.81e-05	(0.000383)	0.000195	(0.000199)
income_band = 4, Income 60,000 - 90,000	2.77e-05	(0.000350)	2.09e-05	(0.000183)
income_band = 5, Income 90,000 - 120,000	0.000374	(0.000447)	0.000458**	(0.000230)
income_band = 6, Income > 120,000	0.000491	(0.000383)	0.000495**	(0.000204)
income_band = 99, Income Unknown	8.08e-05	(0.000323)	7.04e-05	(0.000166)
Zipcode Population	-8.38e-08***	(1.45e-09)	2.08e-08***	(1.32e-09)
Gender (Female=1)	0.000528***	(0.000193)	-0.000338***	(9.68e-05)
Age (Years)	-7.43e-05**	(3.23e-05)	-5.83e-05***	(1.67e-05)
Age Squared	7.73e-07**	(3.04e-07)	2.57e-07*	(1.55e-07)
Race (Categorical) = 2, Other	-0.00177***	(0.000607)	-0.00308***	(0.000322)
Race (Categorical) = 3, Black	0.00156***	(0.000361)	-3.30e-05	(0.000220)
Race (Categorical) = 4, Asian	0.00336***	(0.000674)	0.00232***	(0.000371)
Race (Categorical) = 5, Hispanic	0.00658***	(0.000606)	0.00428***	(0.000370)
Highest Level Education (Categorical) = 2, High school degree or diploma	-0.000767*	(0.000443)	-0.000927***	(0.000229)
Highest Level Education (Categorical) = 3, Technical/Vocational school	-0.000150	(0.000533)	-0.000354	(0.000265)
Highest Level Education (Categorical) = 4, Some college	-0.000365	(0.000449)	-0.000615***	(0.000230)
Highest Level Education (Categorical) = 5, College graduate	-0.000923**	(0.000455)	-0.000773***	(0.000231)
Highest Level Education (Categorical) = 6, Post graduate work or degree	-0.000500	(0.000474)	-0.000440*	(0.000243)
Marital Status (Categorical) = 2, Married	-0.000791***	(0.000291)	-0.000500***	(0.000154)
Marital Status (Categorical) = 3, Separated	-0.00202***	(0.000706)	-0.000651*	(0.000384)
Marital Status (Categorical) = 4, Divorced	-0.000726**	(0.000366)	-0.000518***	(0.000196)
Marital Status (Categorical) = 5, Widowed	-0.000771*	(0.000400)	-0.000421**	(0.000213)
Marital Status (Categorical) = 8, Domestic partnership/Living with partner	0.000449	(0.000524)	0.000274	(0.000278)
Religion Important (Yes=1)	0.000460*	(0.000258)	0.00428***	(0.000140)
missreligion_important_dum	0.000124	(0.000432)	-0.000551*	(0.000285)
Number of Children in HH	-0.000461***	(0.000101)	-0.000357***	(5.26e-05)
Employment Status (Categorical) = 2, Employed Full Time (Self)	-0.00243***	(0.000406)	-0.000609**	(0.000250)
Employment Status (Categorical) = 3, Employed Part Time, Do Not Want Full Time	-0.00154***	(0.000372)	-8.92e-05	(0.000201)
Employment Status (Categorical) = 4, Unemployed	-0.00220***	(0.000437)	0.000318	(0.000264)
Employment Status (Categorical) = 5, Employed Part Time, Want Full Time	-0.00156***	(0.000396)	-0.000317	(0.000251)
Employment Status (Categorical) = 6, Not in Work Force	-0.00370***	(0.000381)	-0.000824***	(0.000165)
Employment Status (Categorical) = 99, 99	0.00237***	(0.000641)	0.00483***	(0.000594)
Health (Categorical) = 2, Very good	0.000413*	(0.000236)	0.000265*	(0.000138)
Health (Categorical) = 3, Good	-8.69e-05	(0.000255)	0.000111	(0.000148)
Health (Categorical) = 4, Fair, OR	-5.72e-05	(0.000324)	6.26e-05	(0.000190)
Health (Categorical) = 5, Poor	0.000287	(0.000456)	0.000745***	(0.000275)
Health (Categorical) = 99, 99	0.00414	(0.00285)	0.00108	(0.000963)
Body Mass index	0.000141***	(1.70e-05)	2.47e-06	(1.02e-05)
missbmi_dum	-0.00228***	(0.000463)	-0.001000***	(0.000286)
Party Affiliation (Categorical) = 2, Democrat	-0.00190***	(0.000292)	-0.00152***	(0.000161)
Party Affiliation (Categorical) = 3, Independent	-3.16e-05	(0.000278)	-0.000689***	(0.000139)
Party Affiliation (Categorical) = 4, OTHER PARTY (volunteered)	-0.00198**	(0.000948)	-0.000821	(0.000505)
Party Affiliation (Categorical) = 99, Missing	-0.00127***	(0.000342)	-0.00118***	(0.000197)
Observations	2,106,874		2,106,874	
N_clust	35153		35153	
k_eq	2		2	
df_m	192		192	
df_r	2.107e+06		2.107e+06	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4.11: First Stage Regression - Table 2

VARIABLES	Log State Income Tax Per HH for Low Income Bands Coefficient (1)	SE (2)	Log State Income Tax Per HH for High Income Bands Coefficient (3)	SE (4)
Month Year Fixed Effects = 577	5.46e-05	(0.00185)	0.00148***	(0.000491)
Month Year Fixed Effects = 578	0.00107	(0.00180)	0.00173***	(0.000473)
Month Year Fixed Effects = 579	0.00224	(0.00183)	0.00236***	(0.000482)
Month Year Fixed Effects = 580	-0.00118	(0.00181)	0.00155***	(0.000474)
Month Year Fixed Effects = 581	-0.000116	(0.00186)	0.00139***	(0.000499)
Month Year Fixed Effects = 582	-0.000467	(0.00177)	0.00162***	(0.000470)
Month Year Fixed Effects = 583	0.00158	(0.00179)	0.00111**	(0.000472)
Month Year Fixed Effects = 584	-0.00236	(0.00313)	-0.00150	(0.000986)
Month Year Fixed Effects = 585	0.00364	(0.00337)	0.00221**	(0.00107)
Month Year Fixed Effects = 586	0.00379	(0.00336)	0.00284***	(0.00106)
Month Year Fixed Effects = 587	0.00607*	(0.00343)	0.00210*	(0.00108)
Month Year Fixed Effects = 588	-0.373***	(0.00412)	-0.205***	(0.00206)
Month Year Fixed Effects = 589	-0.374***	(0.00415)	-0.205***	(0.00208)
Month Year Fixed Effects = 590	-0.375***	(0.00412)	-0.206***	(0.00202)
Month Year Fixed Effects = 591	-0.374***	(0.00403)	-0.203***	(0.00190)
Month Year Fixed Effects = 592	-0.375***	(0.00406)	-0.203***	(0.00191)
Month Year Fixed Effects = 593	-0.373***	(0.00406)	-0.204***	(0.00194)
Month Year Fixed Effects = 594	-0.373***	(0.00404)	-0.204***	(0.00190)
Month Year Fixed Effects = 595	-0.374***	(0.00408)	-0.203***	(0.00194)
Month Year Fixed Effects = 596	-0.375***	(0.00406)	-0.204***	(0.00193)
Month Year Fixed Effects = 597	-0.373***	(0.00404)	-0.202***	(0.00189)
Month Year Fixed Effects = 598	-0.376***	(0.00406)	-0.204***	(0.00190)
Month Year Fixed Effects = 599	-0.372***	(0.00406)	-0.204***	(0.00189)
Month Year Fixed Effects = 600	-0.394***	(0.00404)	-0.104***	(0.00137)
Month Year Fixed Effects = 601	-0.393***	(0.00404)	-0.105***	(0.00138)
Month Year Fixed Effects = 602	-0.393***	(0.00404)	-0.105***	(0.00137)
Month Year Fixed Effects = 603	-0.393***	(0.00405)	-0.105***	(0.00137)
Month Year Fixed Effects = 604	-0.392***	(0.00404)	-0.105***	(0.00138)
Month Year Fixed Effects = 605	-0.393***	(0.00403)	-0.105***	(0.00137)
Month Year Fixed Effects = 606	-0.393***	(0.00403)	-0.105***	(0.00137)
Month Year Fixed Effects = 607	-0.393***	(0.00404)	-0.106***	(0.00137)
Month Year Fixed Effects = 608	-0.393***	(0.00403)	-0.105***	(0.00137)
Month Year Fixed Effects = 609	-0.393***	(0.00403)	-0.105***	(0.00137)
Month Year Fixed Effects = 610	-0.393***	(0.00404)	-0.105***	(0.00137)
Month Year Fixed Effects = 611	-0.392***	(0.00405)	-0.105***	(0.00137)
Month Year Fixed Effects = 612	-0.413***	(0.00427)	-0.111***	(0.00151)
Month Year Fixed Effects = 613	-0.413***	(0.00427)	-0.111***	(0.00152)
Month Year Fixed Effects = 614	-0.411***	(0.00424)	-0.110***	(0.00151)
Month Year Fixed Effects = 615	-0.414***	(0.00427)	-0.112***	(0.00152)
Month Year Fixed Effects = 616	-0.414***	(0.00427)	-0.112***	(0.00151)
Month Year Fixed Effects = 617	-0.415***	(0.00427)	-0.112***	(0.00152)
Month Year Fixed Effects = 618	-0.414***	(0.00426)	-0.112***	(0.00151)
Month Year Fixed Effects = 619	-0.415***	(0.00427)	-0.112***	(0.00151)
Month Year Fixed Effects = 620	-0.413***	(0.00425)	-0.112***	(0.00151)
Month Year Fixed Effects = 621	-0.414***	(0.00427)	-0.112***	(0.00151)
Month Year Fixed Effects = 622	-0.414***	(0.00427)	-0.112***	(0.00151)
Month Year Fixed Effects = 623	-0.414***	(0.00427)	-0.112***	(0.00152)
Month Year Fixed Effects = 624	-0.469***	(0.00444)	-0.0679***	(0.00159)
Month Year Fixed Effects = 625	-0.471***	(0.00442)	-0.0682***	(0.00160)
Month Year Fixed Effects = 626	-0.467***	(0.00442)	-0.0682***	(0.00160)
Month Year Fixed Effects = 627	-0.467***	(0.00444)	-0.0680***	(0.00159)
Month Year Fixed Effects = 628	-0.468***	(0.00443)	-0.0684***	(0.00160)
Month Year Fixed Effects = 629	-0.471***	(0.00440)	-0.0681***	(0.00159)
Month Year Fixed Effects = 630	-0.468***	(0.00443)	-0.0685***	(0.00160)
Month Year Fixed Effects = 631	-0.468***	(0.00441)	-0.0679***	(0.00159)
Month Year Fixed Effects = 632	-0.469***	(0.00442)	-0.0680***	(0.00159)
Month Year Fixed Effects = 633	-0.468***	(0.00445)	-0.0678***	(0.00160)
Month Year Fixed Effects = 634	-0.465***	(0.00443)	-0.0674***	(0.00160)
Month Year Fixed Effects = 635	-0.470***	(0.00444)	-0.0690***	(0.00159)
Month Year Fixed Effects = 636	-0.523***	(0.00425)	-0.0389***	(0.00167)
Month Year Fixed Effects = 637	-0.523***	(0.00425)	-0.0402***	(0.00169)
Month Year Fixed Effects = 638	-0.523***	(0.00426)	-0.0398***	(0.00167)
Month Year Fixed Effects = 639	-0.523***	(0.00425)	-0.0404***	(0.00166)
Month Year Fixed Effects = 640	-0.522***	(0.00426)	-0.0396***	(0.00166)
Month Year Fixed Effects = 641	-0.522***	(0.00425)	-0.0394***	(0.00166)
Month Year Fixed Effects = 642	-0.523***	(0.00425)	-0.0393***	(0.00167)
Month Year Fixed Effects = 643	-0.521***	(0.00424)	-0.0392***	(0.00166)
Month Year Fixed Effects = 644	-0.523***	(0.00424)	-0.0386***	(0.00167)
Month Year Fixed Effects = 645	-0.522***	(0.00424)	-0.0392***	(0.00166)
Month Year Fixed Effects = 646	-0.522***	(0.00424)	-0.0379***	(0.00167)
Month Year Fixed Effects = 647	-0.523***	(0.00425)	-0.0386***	(0.00168)
Month Year Fixed Effects = 648	-0.665***	(0.00467)	-0.0885***	(0.00169)
Month Year Fixed Effects = 649	-0.666***	(0.00469)	-0.0895***	(0.00170)
Month Year Fixed Effects = 650	-0.666***	(0.00467)	-0.0898***	(0.00169)
Month Year Fixed Effects = 651	-0.667***	(0.00465)	-0.0904***	(0.00169)
Month Year Fixed Effects = 652	-0.667***	(0.00467)	-0.0912***	(0.00170)
Month Year Fixed Effects = 653	-0.665***	(0.00464)	-0.0919***	(0.00171)
Month Year Fixed Effects = 654	-0.665***	(0.00465)	-0.0907***	(0.00170)
Month Year Fixed Effects = 655	-0.667***	(0.00468)	-0.0908***	(0.00171)
Month Year Fixed Effects = 656	-0.665***	(0.00466)	-0.0906***	(0.00170)
Month Year Fixed Effects = 657	-0.665***	(0.00467)	-0.0902***	(0.00169)
Month Year Fixed Effects = 658	-0.669***	(0.00471)	-0.0891***	(0.00171)
Month Year Fixed Effects = 659	-0.668***	(0.00468)	-0.0888***	(0.00171)
Month Year Fixed Effects = 660	-0.591***	(0.00429)	-0.0589***	(0.00175)
Month Year Fixed Effects = 661	-0.589***	(0.00431)	-0.0586***	(0.00178)
Month Year Fixed Effects = 662	-0.589***	(0.00429)	-0.0591***	(0.00175)
Month Year Fixed Effects = 663	-0.590***	(0.00432)	-0.0599***	(0.00177)
Month Year Fixed Effects = 664	-0.591***	(0.00426)	-0.0617***	(0.00176)
Month Year Fixed Effects = 665	-0.592***	(0.00429)	-0.0612***	(0.00177)
Month Year Fixed Effects = 666	-0.591***	(0.00433)	-0.0602***	(0.00177)
Month Year Fixed Effects = 667	-0.591***	(0.00431)	-0.0598***	(0.00175)
Month Year Fixed Effects = 668	-0.590***	(0.00430)	-0.0602***	(0.00177)
Month Year Fixed Effects = 669	-0.592***	(0.00430)	-0.0615***	(0.00176)
Month Year Fixed Effects = 670	-0.588***	(0.00427)	-0.0584***	(0.00179)
Month Year Fixed Effects = 671	-0.590***	(0.00433)	-0.0586***	(0.00179)
Observations	2,106,874		2,106,874	
N_clust	35153		35153	
k_eq	2		2	
df_m	192		192	
df_r	2.107e+06		2.107e+06	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.12: First Stage Regression - Table 3

VARIABLES	Log State Income Tax Per HH for Low Income Bands Coefficient (1)	SE (2)	Log State Income Tax Per HH for High Income Bands Coefficient (3)	SE (4)
State Abbreviation (Official, Based on Zip Code) = 2, AL	2.640***	(0.0157)	2.667***	(0.00915)
State Abbreviation (Official, Based on Zip Code) = 3, AR	1.829***	(0.0264)	2.753***	(0.0150)
State Abbreviation (Official, Based on Zip Code) = 4, AZ	2.389***	(0.0133)	2.757***	(0.00837)
State Abbreviation (Official, Based on Zip Code) = 5, CA	4.422***	(0.0530)	2.474***	(0.0443)
State Abbreviation (Official, Based on Zip Code) = 6, CO	2.656***	(0.0158)	2.913***	(0.00941)
State Abbreviation (Official, Based on Zip Code) = 7, CT	1.637***	(0.0447)	2.956***	(0.0256)
State Abbreviation (Official, Based on Zip Code) = 8, DC	2.377***	(0.0280)	3.346***	(0.0158)
State Abbreviation (Official, Based on Zip Code) = 9, DE	2.128***	(0.0222)	2.836***	(0.0124)
State Abbreviation (Official, Based on Zip Code) = 10, FL	1.573***	(0.0240)	1.794***	(0.0215)
State Abbreviation (Official, Based on Zip Code) = 11, GA	3.106***	(0.0233)	2.778***	(0.0146)
State Abbreviation (Official, Based on Zip Code) = 12, HI	2.175***	(0.0261)	2.625***	(0.0147)
State Abbreviation (Official, Based on Zip Code) = 13, IA	2.257***	(0.0233)	2.737***	(0.0129)
State Abbreviation (Official, Based on Zip Code) = 14, ID	2.114***	(0.0240)	2.847***	(0.0139)
State Abbreviation (Official, Based on Zip Code) = 15, IL	3.178***	(0.0211)	2.744***	(0.0158)
State Abbreviation (Official, Based on Zip Code) = 16, IN	2.942***	(0.0141)	2.915***	(0.00896)
State Abbreviation (Official, Based on Zip Code) = 17, KS	1.944***	(0.0208)	2.844***	(0.0115)
State Abbreviation (Official, Based on Zip Code) = 18, KY	2.662***	(0.0240)	2.861***	(0.0139)
State Abbreviation (Official, Based on Zip Code) = 19, LA	2.210***	(0.0121)	2.769***	(0.00699)
State Abbreviation (Official, Based on Zip Code) = 20, MA	3.003***	(0.0194)	3.175***	(0.0113)
State Abbreviation (Official, Based on Zip Code) = 21, MD	3.579***	(0.0171)	3.331***	(0.0100)
State Abbreviation (Official, Based on Zip Code) = 22, ME	2.055***	(0.0264)	2.878***	(0.0152)
State Abbreviation (Official, Based on Zip Code) = 23, MI	2.916***	(0.0188)	2.708***	(0.0126)
State Abbreviation (Official, Based on Zip Code) = 24, MN	2.674***	(0.0232)	2.948***	(0.0132)
State Abbreviation (Official, Based on Zip Code) = 25, MO	2.458***	(0.0180)	2.918***	(0.0104)
State Abbreviation (Official, Based on Zip Code) = 26, MS	1.920***	(0.0171)	2.719***	(0.00966)
State Abbreviation (Official, Based on Zip Code) = 27, MT	2.307***	(0.0186)	2.897***	(0.0104)
State Abbreviation (Official, Based on Zip Code) = 28, NC	2.985***	(0.0254)	2.814***	(0.0154)
State Abbreviation (Official, Based on Zip Code) = 29, ND	1.044***	(0.0106)	2.422***	(0.00596)
State Abbreviation (Official, Based on Zip Code) = 30, NE	2.026***	(0.0217)	2.916***	(0.0124)
State Abbreviation (Official, Based on Zip Code) = 31, NH	1.728***	(0.00470)	2.512***	(0.00187)
State Abbreviation (Official, Based on Zip Code) = 32, NJ	2.557***	(0.0198)	3.092***	(0.0128)
State Abbreviation (Official, Based on Zip Code) = 33, NM	1.831***	(0.0158)	2.683***	(0.00899)
State Abbreviation (Official, Based on Zip Code) = 34, NV	0.565***	(0.00559)	1.978***	(0.00311)
State Abbreviation (Official, Based on Zip Code) = 35, NY	3.770***	(0.0314)	3.385***	(0.0231)
State Abbreviation (Official, Based on Zip Code) = 36, OH	3.232***	(0.0202)	2.985***	(0.0141)
State Abbreviation (Official, Based on Zip Code) = 37, OK	1.976***	(0.0183)	2.771***	(0.0102)
State Abbreviation (Official, Based on Zip Code) = 38, OR	2.529***	(0.0305)	2.759***	(0.0170)
State Abbreviation (Official, Based on Zip Code) = 39, PA	3.507***	(0.0183)	3.002***	(0.0144)
State Abbreviation (Official, Based on Zip Code) = 40, RI	2.315***	(0.0192)	3.061***	(0.0108)
State Abbreviation (Official, Based on Zip Code) = 41, SC	2.431***	(0.0224)	2.836***	(0.0130)
State Abbreviation (Official, Based on Zip Code) = 42, SD	-0.286***	(0.00571)	1.323***	(0.00244)
State Abbreviation (Official, Based on Zip Code) = 43, TN	0.647***	(0.00865)	1.400***	(0.00691)
State Abbreviation (Official, Based on Zip Code) = 44, TX	1.652***	(0.0336)	0.441***	(0.0304)
State Abbreviation (Official, Based on Zip Code) = 45, UT	2.587***	(0.0202)	2.938***	(0.0115)
State Abbreviation (Official, Based on Zip Code) = 46, VA	2.979***	(0.0214)	2.862***	(0.0129)
State Abbreviation (Official, Based on Zip Code) = 47, VT	1.748***	(0.0217)	2.867***	(0.0128)
State Abbreviation (Official, Based on Zip Code) = 48, WA	0.973***	(0.00938)	1.107***	(0.00767)
State Abbreviation (Official, Based on Zip Code) = 49, WI	2.732***	(0.0229)	2.872***	(0.0130)
State Abbreviation (Official, Based on Zip Code) = 50, WV	1.549***	(0.0212)	2.793***	(0.0118)
State Abbreviation (Official, Based on Zip Code) = 51, WY	0.114***	(0.00603)	1.735***	(0.00245)
Constant	2.496***	(0.00578)	5.554***	(0.00217)
Observations	2,106,874		2,106,874	
N_clust	35153		35153	
k_eq	2		2	
df_m	192		192	
df_r	2.107e+06		2.107e+06	
rmse	0.127		0.0662	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Chapter 5

Conclusion

This dissertation uses empirical methods in economics to address public policy issues with the aim of providing practical methods for guiding the implementation and analysis of public policy. It employs the use of geospatial microdata to better understand electoral design. Specifically, it looks at the effect of weather shocks on voting mistakes. By spatially linking weather data to polling places it is possible to show that cold shocks increase the prevalence of voting errors. This uncovers insights into individual behaviour which are important to understand in a policy context. It provides a framework for which spatial data can be useful for informing public policy

It also looks at how ranked electoral data can be used to guide public policy by highlighting the relative importance of policy issues as perceived by voters. Ranked voting data have the potential to relay important information about individual policy preferences that is impossible to extract from electoral data where voters convey only their most preferred option. By utilising lower order rankings, it is possible to observe which policy stances drive voting behaviour. It also uses this approach to try and understand the ways in which voters may be directly communicating to government through ranked elections by exploring the possibility of communicative voting in an Australian election. In this way, the chapter proposes a method by which ranked voting outcomes could be used by public policy makers to

determine which issues really matter to the public at the time of an election.

It also shows how wellbeing data can be used to analyse and guide public policy. US wellbeing and tax data are used to show how tax payments other than own income tax affects personal wellbeing. This highlights the ways in which self reported wellbeing measures can be used to meaningfully guide and evaluate public policy beyond conventional measures of consumption and productive output.

This thesis explores ways in which applied microeconomic research can be used to inform public policy in a way that relies on empirical data. Continuing to develop these methods and how they can be incorporated into policy structures is vital to the successful delivery of policy now and in the future.

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