What makes Australians vote the way they do?

A thesis submitted for the degree of

Econometrics Honours

by

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Preface

This document is a research proposal, intended for submission as part of the journey that is EBS Honours 2018.

The research proposed is an examination of the relationships that exist between socio-demographics and voting behaviour in Australian federal elections, and how this has changed over time. Considerations are The data used in this study from every election and Census conducted since 2001.

Chapter 1

Introduction

Over the last two decades the Australian demographic profile has changed significantly. An ageing population, higher levels of education across the board, soaring house prices, the list goes on. At the same time, the political landscape has been in a state of constant change, with the country recently experiencing four leadership changes in just a five year stretch. And yet the Australian support largely ebbs and flows between the two major parties vying for power.

This leads to the question - why do Australians vote the way they do?

This research will explore the relationships that exist between socio-demographics and voting behaviour in Australian federal elections, and how this has changed over time, examining each election since 2001.

Socio-demographics are characteristics of a population, such as percentage breakdowns by age, gender, ethnicity, education level and income. The socio-demographic information used in this study is from the Australian Census of Population and Housing, a country-wide survey conducted every five years.

Federal elections on the other hand, are conducted every three years.

Utilising new tools in spatial analysis, this study aims to build socio-demographic profiles for each electorate, at election time, using the available Census information. On reviewing the literature, it appears that the approach of imputing electorate profiles that is proposed in this study is a new innovation in socio-political analysis.

At the centre of this study are three key questions:

1. What are the demographic factors that affect preference between the two major parties?
2. What factors are linked with electorate support for the full political spectrum?
3. How have these changed over time?

There are three ways in which this research differs from other voting studies. Firstly, it uses spatial modelling tools to impute socio-demographic information for an election, using Census information from nearby years. Secondly, it considers predictive modelling for electorate voting behaviour, and thirdly it combines information for every election since 2001.

1.1 Data sources and mapping

In order to impute socio-demographics at election time, the algorithm proposed in this research follows the dominant approach in spatial studies by overlaying maps that are in Geographic Information Software (GIS) format. Overlaying GIS maps is used in other analyses of Australian voting behaviour, and other fields including; strategic planning (Valcik, 2012), healthcare (Ye et al., 2017) and geosciences. Maps are collected from the Australian Bureau of Statistics and the Australian Electoral Commission.

1.2 Modelling

Answering question (1) involves modelling the preference between the two major political parties as a function of an electorate's socio-demographics. The vote for one of these parties, TPP_i, sits in the interval $[0, 1]$, and can be modelled using a logistic transform, so that it maps on $\mathbb{R}$.

Question (2) involves modelling the votes for multiple groups. The votes for each party in an electorate can be treated as a proportion of the total votes for that electorate. Denoting FP_i as the proportion of vote for party i, then $\sum_{i=1}^{D} FP_i = 1$, for D parties, making this a compositional dataset. Candidate approaches for modelling include the Dirichlet distribution and logratio transformations of the data.

Observing how these relationships change over time will be embedded in the models addressing questions (1) and (2).

1.3 Reproducible and openly available

All content produced in this study reproducible and data used is publicly available, so this project provides a resource for future research. A key deliverable is the contribution made to the *eechidna* R package, which includes the GIS maps, data from both all censuses and elections, and the imputed socio-demographic electorate profiles at the time of each election. When the next elections and Censuses come around, the *eechidna* package will provide a resource for anyone to conduct their own socio-political analysis. The name *eechidna* is an acronym for 'Exploring Election and Census Highly Informative Data Nationally for Australia'.

Chapter 2

Literature Review

2.1 Spatial analysis of Australian elections

Existing spatial analyses of Australian elections appear to focus on a single federal election, with socio-demographic information pulled from the nearest census. This approach is used in Stimson, McCrea, and Shyy (2006), and is adapted to an online e-research platform by Liao, Shyy, and Stimson (2009). Both use GIS to connect Census and election data. However, both Stimson et al. and Liao et al. use information disaggregated to polling booth locations - a greater level of disaggregation than electorates, which the grouping of focus of this study.

Seemingly vacant in Australian studies is the examination of these socio-political relationships over time. It appears that no study has either attempted to create a collection of socio-demographics for multiple elections, or connect information from multiple censuses to a single election - an approach that will be explored for the election years in which a Census does not fall.

A popular approach in single-election studies is to focus analysis on a single electoral division (Forrest et al., 2001), or a particular political party (Davis and Stimson, 1998). Stimson and Shyy (2012) expand on this by modelling relationships between population variables and voter support for political parties, using univariate visualisations, linear regressions, summary statistics and discriminant analysis. Discriminant analysis is also used by Stimson, McCrea, and Shyy (2006) because it aims to distinguish between political parties in their voter support, rather than predict how areas would vote.

2.2 Modelling with compositional data

In order to answer research questions (1) and (2), this study focuses on regression models for inference and prediction. Response variables for these questions are non-negative and sum to unit, making them compositional with D components (Pawlowsky-Glahn and Buccianti, 2011).

The two popular approaches to modelling compositional data are by way of logratio analysis, and the Dirichlet distribution.

Logratio analysis (Aitchison, 1986) uses a transformation of the components, which then can be treated as a multivariate distribution. Available transformation methods are additive, centred and isometric (Egozcue et al., 2003). A common method is to treat the transformed data as multivariate normal, which allows for covariation between the parts. In modelling the 2001 Australian federal election, Chong et al. (2005) adopt this technique, using an additive logratio transformation.

The Dirichlet distribution also provides a candidate for modelling the distribution of votes, as the components estimated must sum to one. Campbell and Mosimann (1987) propose a covariate extension which allows for parameters to be functions of covariates. This approach is adopted by Gueorguieva, Rosenheck, and Zelterman (2008) in estimating component scores of a psychiatric assessment, with parametric regression used to estimate the Dirichlet parameters.

Chapter 3

Data

The two main data sources for this research are the Australian Census of Population and Housing from the Australian Bureau of Statistics (ABS), and published federal election results from the Australian Electoral Commission (AEC).

The Census of Population and Housing collects data on the key characteristics of every Australian, and is conducted every five years. There have been four censuses in the 21st century, being that in 2001, 2006, 2011 and 2016. The information contained in these collections are used to build the socio-demographic profiles for each electorate.

Federal elections typically occur every three years, and the those of interest are the 2001, 2004, 2007, 2010, 2013 and 2016 elections. All information from these sources are publicly available.

3.1 Electorates and their boundaries

Australian Federal elections are determined based on which party wins a majority of the 150 seats in the House of Representatives, with each seat corresponding to an electorate. The electorate boundaries are determined by population, and to ensure equal representation, the boundaries of these divisions have to be redrawn regularly by the AEC. Each redistribution typically affects a handful of electorates, with most remaining the same as previously defined.

Since changes are continually made to electoral boundaries, when it is time for a Census to be conducted, the ABS constructs an approximation to the current electorates and aggregates data at this level.

What this means is that the electorate boundaries in the election prior to a Census may not match the boundaries used in the Census, which may not match the boundaries in the following election and so on.

This presents a challenge. How does one construct socio-demographic profiles at election time for each electorate, when we cannot directly match that election with a censuses?

3.2 Census

3.2.1 Collection

Data for each Census are downloaded as a collection of Microsoft Excel spreadsheets, with each spreadsheet corresponding to a particular electorate, or a particular question (depending on the format used in that Census year).

In order to convert the information held in these spreadsheets into a summarised table containing selected socio-demographics for each electorate, a series of *R* scripts and *R-markdown* files have been created. The output of each file is an *R* data.frame object, which tabulates the selected metrics for that Census year.

There was no way to automate this process, and the formats of each Census collection change slightly each year. As such, it has taken a significant amount of time and effort to extract the information from excel, and wrangle the data into the desired metrics and format. A snippet of the raw data can be found in the appendix D.1.

The resultant data.frame for each election contains information for each electorate on:

- State
- Population
- Age

- Education
- Employment
- Religious and cultural identity
- Median incomes (personal, household, family)
- Median rent and loan payments
- Citizenship and birthplace
- Language at home
- Relationship status

All metrics are recorded as percentages, representing the percentage of people in that electorate who satisfy the category in question. For example, *AusCitizen* is the percentage of people in the electorate who are Australian citizens.

A full description of socio-demographic variables in the electorate profiles can be found in the appendix **??**.

3.2.2 Insights on the changing Australian demographic

Comparing Census data across years reveals many insights into how the Australian demographic has changed over the past 17 years. By examining visual distributions of metrics across Census years, trends can be identified for the entire country and for the spread amongst electorates.

As Australians grow old, some stay young

It is well documented that Australia has an ageing population, and this is reflected in the MedianAge plot [3.1], as we see the distribution of median age across electorates spread upwards, with some electorates in 2016 having a median age of 50 years old. However, some electorates are not ageing as others do, which makes intuitive sense, because some areas may be more suitable for particular age brackets.

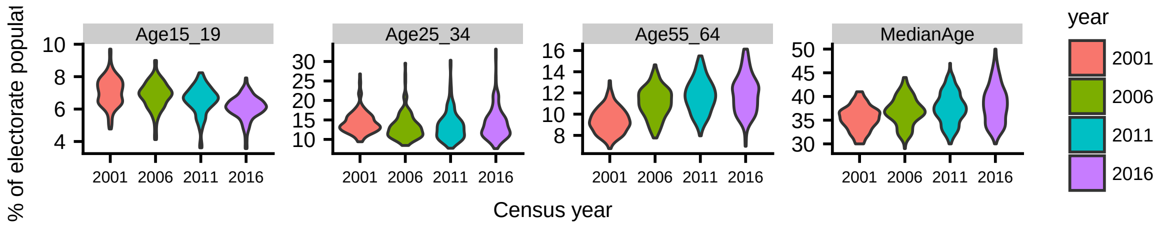


Figure 3.1: *Age profile of Australian electorates*

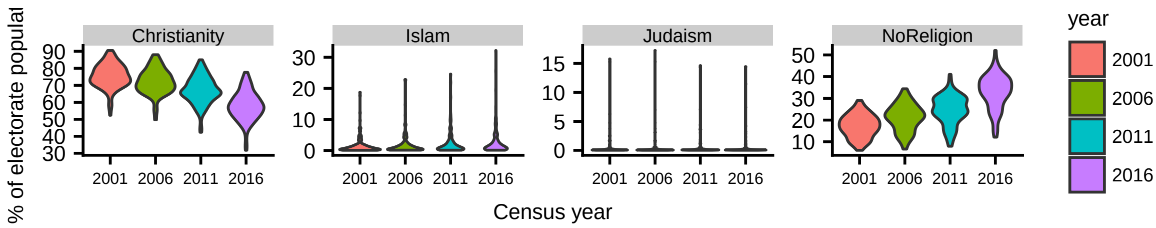


Figure 3.2: *Religious profile of Australian electorates*

This is exactly the effect we see in young adults. Those aged 25-34 are more likely to congregate in common electorates, and avoid other electorates than they were in 2001 - making up 35% of the population in some electorates.

Religion - a thing of the past?

Socially "progressive" movements continue to gather momentum all over the world, and as a result, Australia is moving away from traditional religious beliefs and values. The frequency of individuals not identifying with a religion has grown significantly over the years. This effect has stretched across (what appears to be) every electorate [3.2]. Having a religious identity of any kind would make you a minority in some electorates! At the same time, particular electorates maintain large representation of a particular religious group, as seen by thin upper tails of the Buddhism, Islam and Judaism metrics.

Investing in education

Australia has seen improvements in education outcomes across the board, experiencing continual increases in secondary and tertiary competion rates across the years [3.3]. It is encouraging to see that no electorates appear to be lagging behind, as the minimum values increase each year for all levels of education.

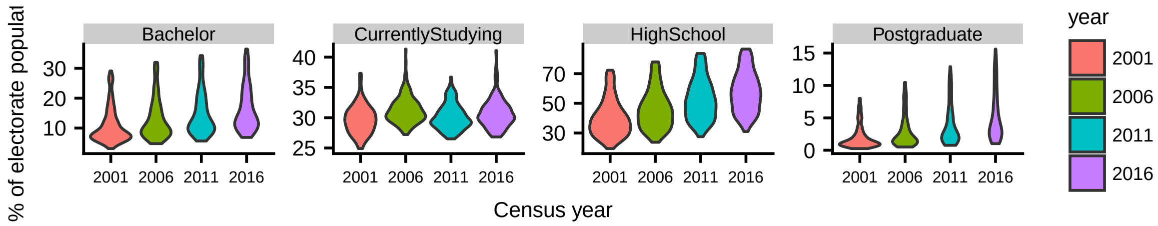


Figure 3.3: *Education profile of Australian electorates*

Violin plots of the complete set of variables in the electorate profiles can be found in the appendix, see **??**.

A note on Census non-response Like in any survey, non-response bias is a source of potential problems. ABS statements released with each Census assure a high quality of data collection, and this study assumes its reliability.

Non-response for key variables is imputed by the ABS (age, sex, martial status and usual residence) for 2006, 2011 and 2016, although is not clear whether this has been done in 2001. Non imputed items are treated as "not stated" or "not applicable", dependent on the imputed age of the person.

No adjustments or imputations are made in this study to the values derived from each Census. However, the frequency of "not stated" responses will be recorded for particular questions, and are included with other Census-derived metrics in the electorate profiles.

3.3 Elections

Within each electorate, candidates from various political parties will run for election to represent that electorate. Voting is compulsory in Australia, and the winning candidate is determined by preferential voting. This means that each person assigns a numbered preference to each candidate, and the winner is determined by receiving a majority of preference votes.

At the end of tallying the first round of preferences, if there is no majority, the party with the least votes will have its first preference vote distributed to the parties that voters had selected as their second preference. This is continued until a party receives an absolute majority of votes.

The three type of vote counts are published for each federal election, they are as follows.

- Division of preferences: distribution of preferences at each step of reallocation, beginning with first preferences.
- Two party preferred: distribution of preferences where, by convention, comparisons are made between the ALP and the leading Liberal/National candidates.
- Two candidate preffered: distribution of preferences to the two candidates who came first and second in the election.

For this study, the two party preferred and division of preferences outcomes are used to answer research questions (1), (2) and (3).

These can be downloaded directly from the AEC website, and have been compiled and stored in *R* data.frames, using the same method as described for the Census data.

3.4 Mapping socio-demographic profiles to election times

The elections and censuses have different frequencies, occuring every three and five years respectively. This naturally leads to a significant challenge in conducting socio-political analysis over time, mapping…

- A Census to an election that fall on the same year
- Census information to an election that does not fall on a Census year

3.4.1 Elections that fall on a Census year

When a Census is conducted in an election year the electorate boundaries used by the ABS match the AEC electoral divisions for that election, so the Census profiles for each electorate can be directly mapped to the election time. This is done by joining information from the 2001 and 2016 data.frames.

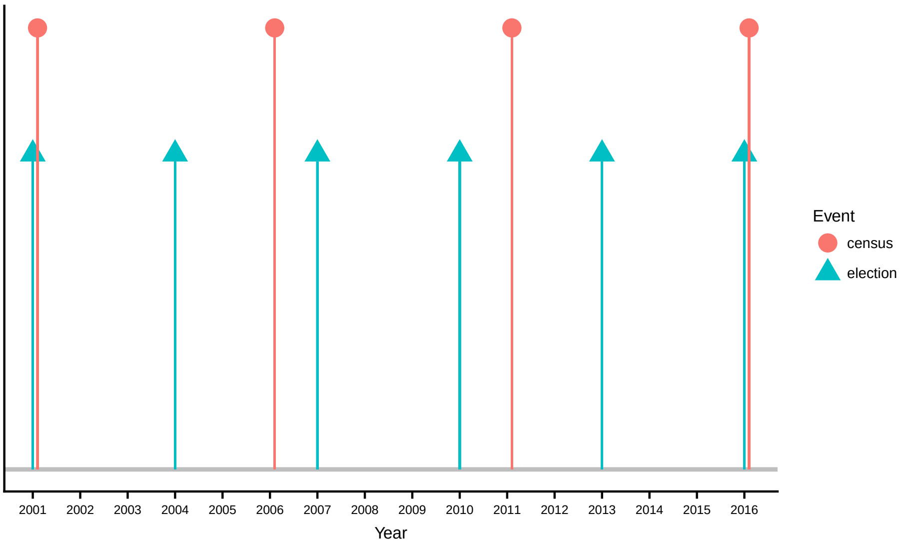


Figure 3.4: *Timeline of Australian elections and censuses*

3.4.2 Elections that do not fall on a Census year

If the election does not fall on the same year a Census is conducted, two problems arise:

- Electorate boundaries may not match any of the neighbouring censuses
- Demographics may have changed since the last Census was conducted

This study proposes an innovative projection algorithm using GIS maps, *k-centroidmapping*, for imputing the demographic profiles for each election, accounting for both the time of the election and the boundaries in place. The use of GIS maps to overlay data from multiple sources is a dominant approach in spatial studies, which provides the foundation for *k-centroidmapping*.

3.5 K-centroid mapping

For the purpose of illustrating the algorithm, "division" will be used instead of "electorate".

k-centroidmapping is a method of imputing Census demographics for divisions in place at the time of an election. Using tools predominantly from the *rgeos* package, each boundary at election time is superimposed on top of the divisions at a particular Census time to determine which of the Census divisions intersect with the superimposed boundary. For each division that intersects the boundary, its area of intersection with the superimposed boundary is computed. These areas are used to impute the composition of the population that sit within the election boundary, where each person is categorised by their Census division. A weighted average of demographics from the Census divisions is then used to impute the socio-demographic profile of the election boundary. This is done for each of the election divisions, and the process repeats for the other Census. Interpolating between the two censuses, based on time, yields the final imputed profiles.

The *k-centroidmapping* algorithm for imputing the socio-demographic profiles for divisions defined at the time of an election is as follows:

1. Select the nearest censuses that occur before and after election time.

To map the 2013 Federal election profiles, we would select the censuses from 2011 and 2016.

2. Simplify the GIS maps for the division boundaries for each Census, and the election.

Using $gSimplify$ from the *rgeos* package, we reduce the size of the maps (by reducing the number of points) to reduce computational burden. This step is not necessary but helps the processing of large maps.

3. For each map, calculate the centroid of each division.

Centroids for each polygon (division) are defined as using Euclidean distance.

4. Select an election division and create a map containing Census divisions with k closest centroids to the election division.

Now consider only the division "Brisbane" in the 2013 election. The polygon for its boundaries is shown in 3.5 by the dotted blue line, with the boundaries of the closest $k = 3$ divisions at the time of the 2011 Census shown in red.

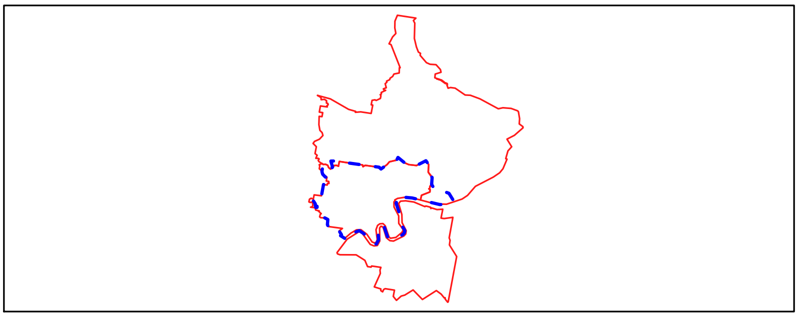


Figure 3.5: *Brisbane and the k=3 closest divisions*

Note: $k = 3$ is chosen here to illustrate how the algorithm functions. The selection of k depends on the properties of the two maps. We see here that $k = 3$ is a sufficient choice, because there do not appear to be parts of the 2013 division that sit outside of the 3 nearest divisions, but this may not be the case for other 2013 divisions. For this study, $k = 35$ is chosen due to the variation in sizes of the divisions, as a neighbouring division can be very large and have a distant centroid.

```
## integer(0)
```

5. For each of the k closest Census divisions, determine the area of intersection with the election division.

Continuing with Brisbane from 2013, we see the area of overlap each of Brisbane, Griffith and Lilley from the 2011 boundaries, given by the shaded blue region [3.6].

In general, this would be done between the Brisbane (2013) and every one of its k nearest 2011 divisions.

6. Calculate the number of people each intersect represents.

We see that the shaded intersection areas are only a piece of their 2011 Census division. The population of Lilley (2011) is $145,652$, and the intersection with Brisbane (2013) is approximately 2.22% of the total area in Lilley, so the population captured by the shaded area is $3,233$. Here we assume population is equally spread throughout each division.

$$PopulationInt_{Lill} = \frac{Area_{intersect}}{Area_{Lill}} \cdot Population_{Lill} = 0.222 \cdot 145,652 \approx 3233$$

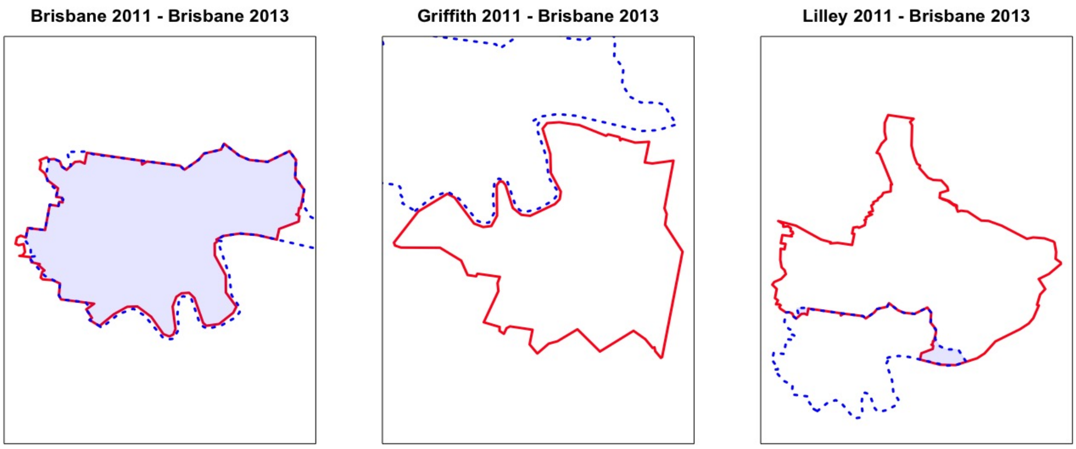


Figure 3.6: *Intersection of Brisbane (2013) and nearby Census divisions (2011)*

The intersection of Brisbane and Brisbane equates to 99.00% of the 2011 Brisbane division. Brisbane (2011) has a population of $145,051$, so intersection represents approximately $143,602$ people. There is no overlap with Griffith (2011).

7. Determine the socio-demographic profile based on the people in each intersection, where each person assumes the demographic composition of their Census division.

Brisbane (election, 2013) is made up of $143,602$ people from Brisbane (Census, 2011) and $3,233$ people from Lilley (Census, 2011). To impute each socio-demographic statistic for the Brisbane division (2013), we take a weighted average of the Census demographics, using the intersection populations, $PopulationInt$, used as the weights.

For example, estimating $AusCitizen$ for the superimposed Brisbane (2013) election boundary is done by a weighted average of its intersection with Lilley and Brisbane.

$$\hat{AusCitizen}_{Bris,Election} = \frac{AusCitizen_{Bris,Census} \cdot PopulationInt_{Bris} + AusCitizen_{Lill,Census} \cdot PopulationInt_{Lill}}{PopulationInt_{Bris} + PopulationInt_{Lill}}$$

8. Repeat steps 4-7 for each election division.

9. Interpolate between the Censuses by year to impute the socio-demographic division profile for the election year.

The 2013 election sits two years after the 2011 Census, and three years before the 2016 Census. Take a weighted average of each demographic across time points for each division.

$$\hat{AusCitizen}_{Bris,Election,2013} = \frac{2}{5} \cdot \hat{AusCitizen}_{Bris,Election,2011} + \frac{3}{5} \cdot \hat{AusCitizen}_{Bris,Election,2016}$$

Chapter 4

Modelling {ch: Modelling}

Now that estimated socio-demographic profiles have been obtained for each election, we begin modelling to answer the questions that were set out in the introduction:

1. What are the demographic factors that affect preference between the two major parties?
2. What factors are linked with electorate support for the full political spectrum?
3. How have these changed over time?

4.1 Major party preference

Question (1) is concerned with modelling the two party preferred vote, TPP, to analyse preference between Labor and Liberal/National parties. Since $TPP_{Labor} + TPP_{Liberal} = 1$, we can focus our models on the response TPP_Labor, which sits in the interval $(0, 1)$. This can be modelled using a logistic normal distribution:

$$f(TPP) = \frac{1}{\sigma\sqrt{2\pi}} \frac{1}{TPP(1-TPP)} \exp\left(-\frac{(logit(TPP)-\mu)^2}{2\sigma^2}\right)$$

where $logit(TPP)$ is the logistic transformation $ln(\frac{TPP}{1-TPP})$.

The mean μ is a parametric function of the socio-demographics $\mathbf{X}$ of each electorate $\mu = f(\mathbf{x})$. We can then use basic regression techniques to estimate the regression coefficients, by way of the $lm()$ function.

Inference can then be conducted on the output, in order to determine which factors are statistically significant, and their marginal effects on the two party preferred vote.

4.2 The full spectrum

In order to model support for all parties, the first preference allocation from the division of prefences is used. Let $\mathbf{v}_i = (v_{i1}, v_{i2}, ..., v_{iD})$ denote the vector holding the percentage of first preference votes for parties in electorate i, for each of the D parties. This presents an extension to the modelling for the two party preferred vote.

The two party preferred vote has $D = 2$ parties, so the data is compositional with $D = 2$ components. First preference vote has $D > 2$ for every electorate in each election, and we still have $\sum_{j=1}^{D} v_{ij} = 1$, so we have to consider other avenues for modelling.

Two candidate methods for modelling first preferences are:

- Logratio analysis
- Dirichlet covariate modelling

Both methods will be used to produce models for first preference, and I will draw conclusions based on the consistency of effect that socio-demographics across models.

4.2.1 Logratio analysis

Logratio analysis (Aitchison 1986) uses the transformation of the response $\mathbf{v}_i$ to $\mathbf{w}_i$, where $\mathbf{w}_i \in \mathbb{R}^D$ (or $\mathbb{R}^{D-1}$), so $\dim(\mathbf{w}_i)$ is $D \times 1$ or $(D-1) \times 1$, depending on the transformation method. To obtain $\mathbf{w} = (w_{i1}, w_{i2}, ..., w_{iD})$ or $\mathbf{w} = (w_{i1}, w_{i2}, ..., w_{i(D-1)})$ there are three available mappings: additive, centred and isometric. Each of these mapping techniques will be tested to see which performs best, and which is easily interpretable.

Note that the $D = 2$ case using the additive transformation is the same as doing a logistic transform, so answering question (1) is following the same method.

The transformed $\mathbf{w}_i$ can be modelled as multivariate normal, $\mathbf{w}_i \sim N(\mu_i, \blacksquare)$, where each component has a different mean modelled as a function of socio-demographics, $\bar{\ }_i = f(\mathbf{x}_i)$. Parametric specifications of $f(\mathbf{x}_i)$ will be used. Further investigation is required into a suitable functions for estimating the coefficients in $f(\mathbf{x}_i)$ and $\blacksquare$.

More on the three transformation methods can be found in the appendix **??**.

4.2.2 Dirichlet covariate modelling

A modified version of the Dirichlet distribution (Campbell and Mosimann, 1987) provides another method of modelling the vector of first preferences. This version, called the Dirichlet covariate model, the parameters of the Dirichlet distribution can be estimated as a function of covariates, $\lambda_j = h_j(\mathbf{x})$.

Dirichlet regression can be done in *R* using the *DirichReg* package, and parametric forms of $h(\mathbf{x})$ will be chosen.

4.3 Change over time

This is an area that requires some more thought. Current plans are to estimate models for each of the elections separately, and examine how the influence of factors differ across models.

An extension would be to track electorates over time - however this is tricky since electorate boundaries are changing across elections. It may be possible to gather votes from a different level of aggregation, like polling booths, and use a similar technique to *k-centroidmapping* to create voting statistics for each election, based on the 2016 boundaries.

4.4 Model Assessment and Diagnostics

Tests for high leverage and goodness of fit will be done for each category of models, as will model selection within each category.

High leverage will determine whether particular electorates are outliers from the rest, in terms of the relationship between socio-demographics and voting behaviour. Common tests for high leverage to be conducted will include Cook's distance and Likelihood distance (Cook and Weisberg, 1982).

Goodness of fit tests will determine how well the data fits the imposed model structure. Tests will include Pearson's Chi-Square and Aitchison's R^2 measure of total variability (Aitchison, 1986).

Comparative model assessment criteria will include Aikaike Information Criteria (AIC) and the Likelihood-ratio test, in order to determine the best models from each category.

Chapter 5

A brief reflection and discussion {#ch:Reflection & Discussion}

To date, all effort has been directed towards gathering, cleaning and wrangling the data from the ABS and AEC into workable *R* objects. Navigating the AEC and ABS websites to obtain the vote counts and Census data was relatively straightforward, although the 2001 election required direct contact with the AEC, as it is not downloadable online. Finding the GIS maps for each event was a little more difficult, but could be sourced from various government websites after some searching.

It was not immediately obvious that imputing socio-demographic profiles at election time would be a new idea. Having not worked with GIS maps, or any spatial data for that matter, understanding the structure of the GIS maps and developing a functioning algorithm has been the latest area of focus.

Although I have not started running any models, but the investigation into appropriate analyses of compositional data has been very interesting. This too is an area I have not dealt with before. I look forward to applying these techniques.

5.1 Limitations and improvements

Estimating electorate profiles with the *k-centroidmapping* algorithm is a good place to start, but there are undoubtedly improvements that can be made to this approach. Perhaps gathering Census data at a statistical level of aggregation that is lower than electorates, and using these areas to overlay the election map may provide a more accurate imputation of the profiles.

Matching polling booths with their Census equivalent, which is done in existing Australian socio-political studies, presents another way to model voter behaviour. However, modelling results at electorate level is still the key point of interest because they determine the results of Australian federal elections.

As mentioned in the modelling section, estimating the results within electorate boundaries from the 2016 election, for each of the previous elections would allow for the use of time series models. Fixed effects could then be estimated for each electorate. The issue here would be that the populations would not be the same across elections, but if there exists unobservable characteristics of an area, like goodwill towards a party, this may be able to be adjusted for. I intend to explore these avenues should time permit later in the year.

Appendix A

Socio-demographic metrics for each electorate

Derived from ABS Census data, spanning years 2001-2016.

ID: Commonwealth Electoral Divison (CED) number

Electorate: Name of Commonwealth Electoral Division

State: State of CED

Population: Count of persons in CED

A.0.1 Age

Age00_04: Percentage of population aged 0-4 years

Age05_14: Percentage of population aged 5-14 years

Age15_19: Percentage of population aged 15-19 years

Age20_24: Percentage of population aged 20-24 years

Age25_34: Percentage of population aged 25-34 years

Age35_44: Percentage of population aged 35-44 years

Age45_54: Percentage of population aged 45-54 years

Age55_64: Percentage of population aged 55-64 years

Age65_74: Percentage of population aged 65-74 years

Age75_84: Percentage of population aged 75-84 years

Age85plus: Percentage of population aged 85+ years

A.0.2 Median Statistics

MedianPersonalIncome: Median weekly personal income

MedianHouseholdIncome: Median weekly household income

MedianFamilyIncome: Median weekly family income

MedianAge: Median age

MedianRent: Median weekly rental payment amount (of those who rent)

MedianLoanPay: Median mortgage loan repayment amount (of mortgage payments)

PersonalIncome_NS: Rate of nonrespondence for questions relating to personal income, ie. percentage of people who did not answer the question (recorded as “not stated” or “inadequately stated”)

FamilyIncome_NS: Rate of nonrespondence for questions relating to family income, ie. percentage of people who did not answer the question (recorded as “not stated” or “inadequately stated”)

HouseholdlIncome_NS: Rate of nonrespondence for questions relating to household income, ie. percentage of people who did not answer the question (recorded as “not stated” or “inadequately stated”)

A.0.3 Religion

Christianity: Percentage of respondents that identified as Chrisitan

Catholic: Percentage of respondents that identified as Catholic

Buddhism: Percentage of respondents that identified as Buddist

Islam: Percentage of respondents that identified as Muslim

Judaism: Percentage of respondents that identified as Jewish

NoReligion: Percentage of respondents that identified as “no religion”, “athiest” etc.

Religion_NS: Rate of nonrespondence for questions relating to household income, ie. percentage of people who did not answer the question (recorded as “not stated” or “inadequately stated”)

A.0.4 Language, Heritage, Birthplace and Citizenship

Indigenous: Percentage of population that identify as Indigenous or Torres Strait Islander

AusCitizen: Percentage of population who are Australian Citizens

BornOverseas: Percentage of respondents born overseas

BornOverseas_NS: Rate of nonrespondence for questions relating to country of birth, ie. percentage of people who did not answer the question (recorded as “not stated” or “inadequately stated”)

EnglishOnly: Percentage of respondents that speak English only at home

EnglishOnly_NS: Rate of nonrespondence for questions relating to language spoken at home, ie. percentage of people who did not answer the question (recorded as “not stated” or “inadequately stated”)

OtherLanguageHome: Percentage of respondents that speak other languages at home (note: this is 100% - EnglishOnly)

A.0.5 Employment and Study

Unemployed: Unemployment rate (percentage)

LFParticipation: Labour force participation rate (percentage)

CurrentlyStudying: Percentage of population that are currently studying (Note that ‘not stated’ has not been taken into account as this is not available for 2016)

HighSchool: Percentage of respondents (15 years and over) that have finished High School

HighSchool_NS: Rate of nonrespondence for questions relating to High School completion

Bachelor: Percentage of respondents (15 years and over) that have completed a Bachelors degree

Postgraduate: Percentage of respondents (15 years and over) that have completed a Postgraduate degree

University_NS: Rate of nonrespondence for questions relating to higher education

Volunteer: Percentage of respondents (15 years and over) that do volunteer work [2006, 2011, 2016]

Volunteer_NS: Rate of nonrespondence for questions relating to volunteer work [2006, 2011, 2016]

EmuneratedElsewhere: Percentage of people who receive emuneration outside of Australia, out of the total population plus overseas visitors [2001 only]

A.0.6 Family and Relationship

Married: Percentage of respondents that are married

DeFacto: Percentage of respondents that are in a De Facto relationship

Relationship_NS: Rate of nonrespondence for questions relating to relationship, ie. percentage of people who did not answer the question (recorded as "not stated" or "inadequately stated")

FamilyRatio: Ratio of people in families to the number of total families (ie. average number of people per family)

A.0.7 Dwelling

NotOwned: Percentage of dwellings (respondents only) that are owned outright or on a mortgage

Tenure_NS: Rate of nonrespondence for questions relating to tenure, ie. percentage of people who did not answer the question (recorded as "not stated" or "inadequately stated")

InternetAccess: Percentage of dwellings with internet access (of respondents) [2006, 2011, 2016]

InternetAccess_NS: Rate of nonrespondence for questions relating to internet access at home [2006, 2011, 2016]

A.0.8 Other

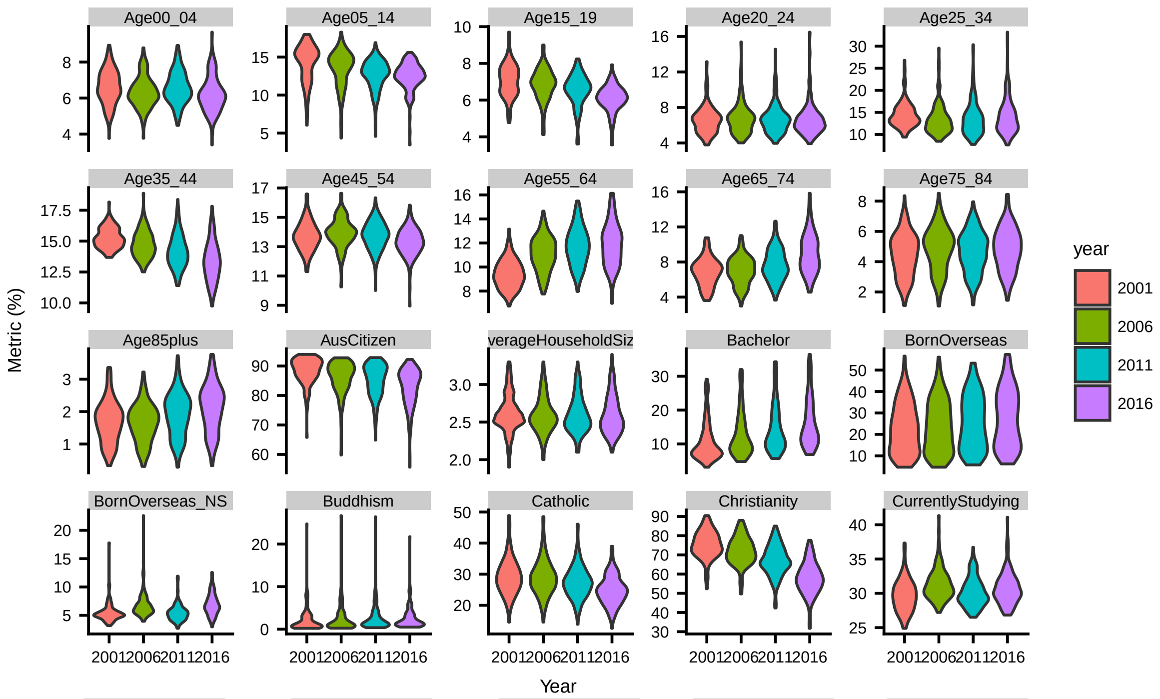
InternetUse: Percentage of people who used interent in the last week (of respondents) [2001 only]

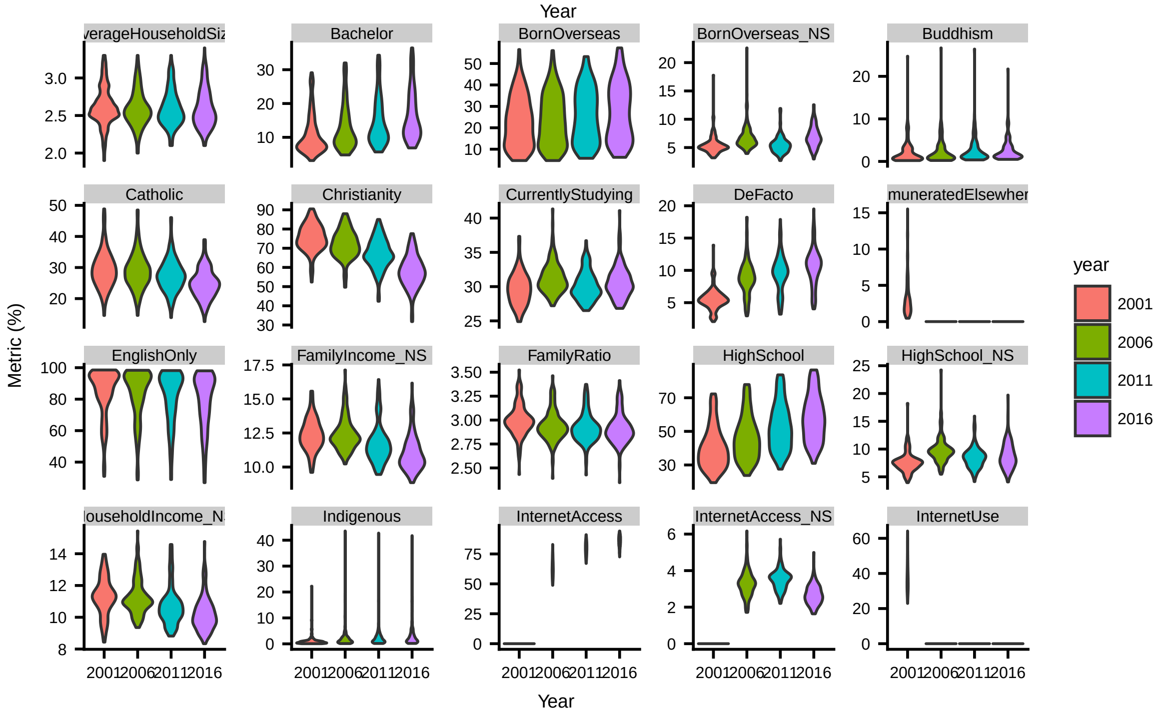
InternetAccess_NS: Rate of nonrespondence for questions relating to internet use [2001 only]

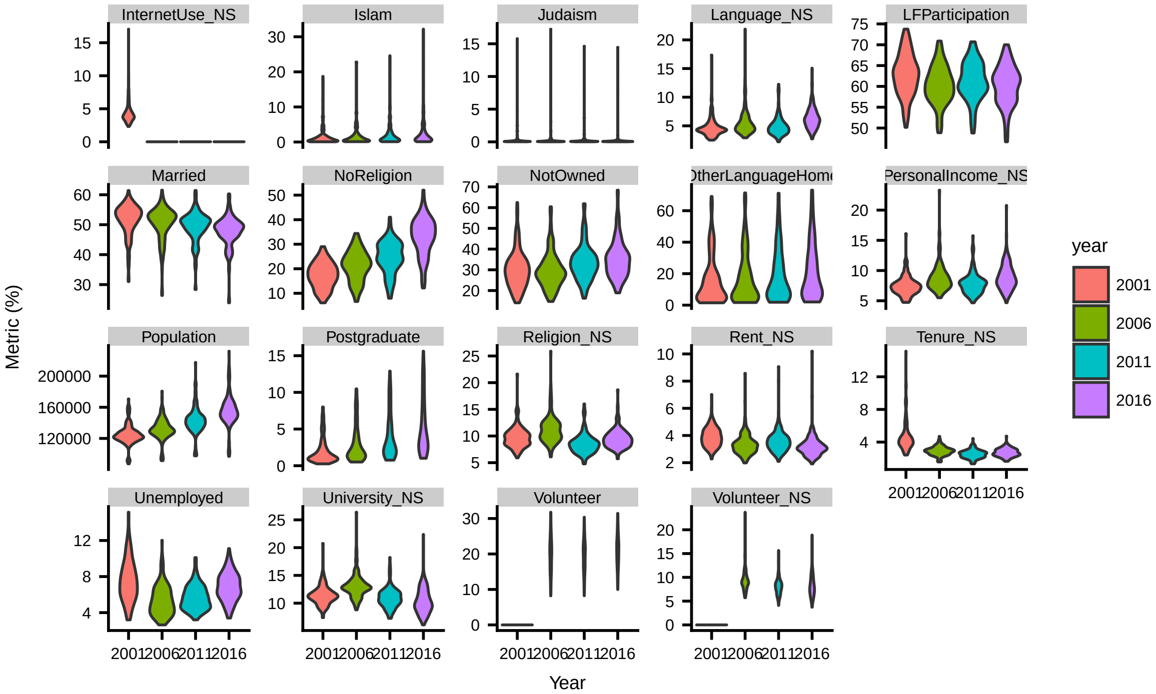
Appendix B

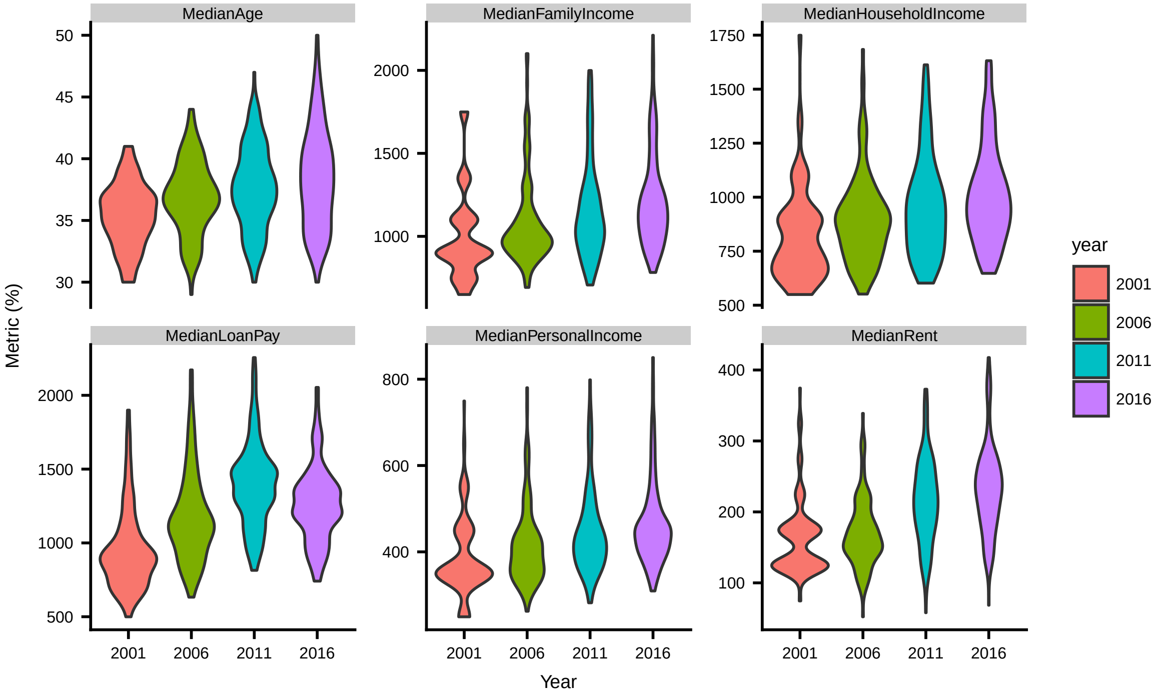
Metric distributions across Census years

The figure below shows violin plots for four variables across Census years, providing a snapshot of the variables recorded for each year.


Age00_04
Age05_14
Age15_19
Age20_24
Age25_34
Age35_44
Age45_54
Age55_64
Age65_74
Age75_84
Age85plus
AusCitizen
verageHouseholdSiz
Bachelor
BornOverseas
BornOverseas_NS
Buddhism
Catholic
Christianity
CurrentlyStudying
Metric (%)
Year
year
2001
2006
2011
2016


verageHouseholdSiz
Bachelor
BornOverseas
BornOverseas_NS
Buddhism
Catholic
Christianity
CurrentlyStudying
DeFacto
muneratedElsewher
EnglishOnly
FamilyIncome_NS
FamilyRatio
HighSchool
HighSchool_NS
ouseholdIncome_N
Indigenous
InternetAccess
InternetAccess_NS
InternetUse
Metric (%)
Year
year
2001
2006
2011
2016


InternetUse_NS
Islam
Judaism
Language_NS
LFParticipation
Married
NoReligion
NotOwned
OtherLanguageHome
PersonalIncome_NS
Population
Postgraduate
Religion_NS
Rent_NS
Tenure_NS
Unemployed
University_NS
Volunteer
Volunteer_NS
Metric (%)
Year
year
2001
2006
2011
2016


MedianAge
MedianFamilyIncome
MedianHouseholdIncome
MedianLoanPay
MedianPersonalIncome
MedianRent
Metric (%)
Year
year
2001
2006
2011
2016

Appendix C

Transformation methods for logratio analysis

C.0.1 Additive Logratio

Maps to $\mathbb{R}^D$ for $\mathbf{v}_i \to \mathbf{w}_i$

$$\mathrm{alr}(v_{ij}) = w_{ij} = \ln(v_{ij}/v_{iD}), \forall j \in \{1, ..., D\}$$

$$\mathrm{alr}(\mathbf{v}_i) = (\frac{\ln(v_{i1})}{\ln(v_{iD})}, ..., \frac{\ln(v_{i(D-1)})}{\ln(v_{iD})}, 1) = \ln(\mathbf{v}_i) \begin{bmatrix} 1 & 0 & ... & 0 \\ 0 & 1 & ... & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & ... & 1 \\ -1 & -1 & ... & -1 \end{bmatrix}$$

Transform back to $\mathbf{v}_i$ using: $\mathbf{v}_i = \exp(\mathbf{w}_i) \cdot v_{iD}$

C.0.2 Centred Logratio

Maps to $\mathbb{R}^D$ for $\mathbf{v}_i \to \mathbf{w}_i$. Let $g(\mathbf{v_i}) = \sqrt[D]{\prod_{j=1}^{D} v_{ij}}$.

$$\mathrm{clr}(v_{ij}) = w_{ij} = \ln(\frac{v_{ij}}{g(\mathbf{v_i})}), \forall j \in \{1, ..., D\}$$

$$\mathrm{clr}(\mathbf{v}_i) = \left(\ln(\frac{v_{i1}}{g(\mathbf{v_i})}), ..., \ln(\frac{v_{iD}}{g(\mathbf{v_i})})\right) = \frac{\ln(\mathbf{x}_i)}{D} \cdot \begin{bmatrix} D-1 & -1 & ... & -1 \\ -1 & D-1 & ... & -1 \\ \vdots & \vdots & \ddots & \vdots \\ -1 & -1 & ... & D-1 \end{bmatrix}$$

Transform back to $\mathbf{v}_i$ using: $v_{ij} = \frac{\exp(w_{ij})}{\sum_{j=1}^{D} \exp(w_{ij})}$

C.0.3 Isometric Logratio

Maps to $\mathbb{R}^{D-1}$ for $\mathbf{v}_i \rightarrow \mathbf{w}_i$.

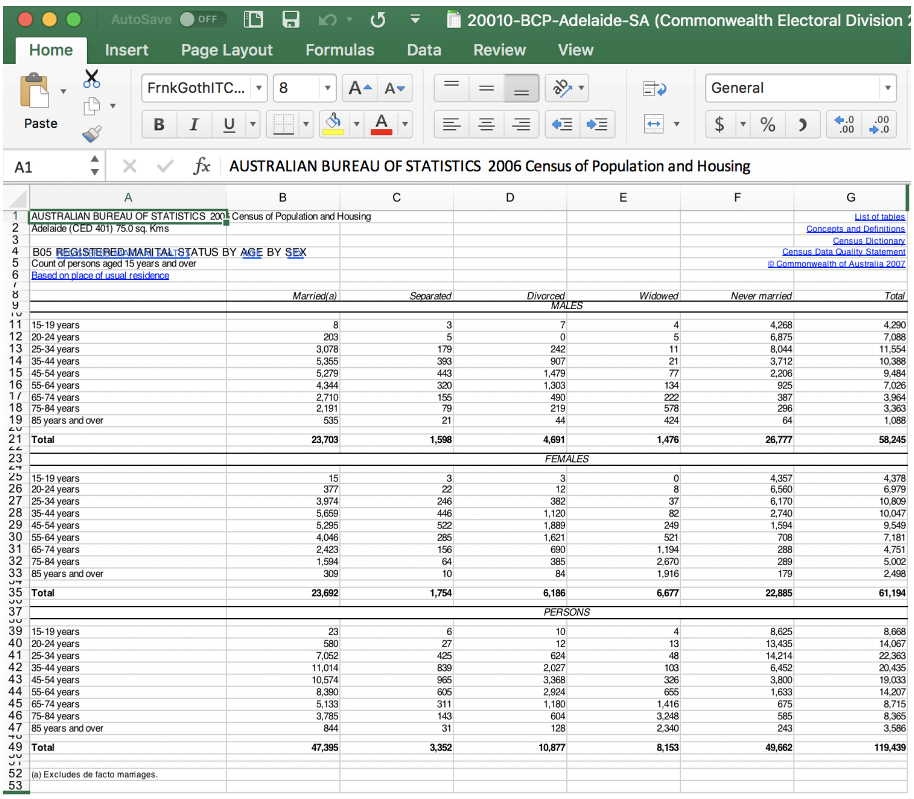
$$\mathrm{ilr}_M(\mathbf{v}_i) = clr(\mathbf{v}_i) \cdot \mathbf{M} = \ln(\mathbf{v}_i) \cdot \mathbf{M}$$

Where $\mathbf{M}$ is a matrix of D rows and $D-1$ columns such that $\mathbf{M} \cdot \mathbf{M}^t = \mathbf{I}_{D-1}$. $\mathbf{I}_{D-1}$ is the identity matrix of $D-1$ elements.

Transform back to $\mathbf{v_i}$ as: $\mathbf{v}_i = \exp(\mathbf{w}_i \cdot \mathbf{M^{-1}})$

Appendix D

Raw ABS Census data snapshot



AUSTRALIAN BUREAU OF STATISTICS 2006 Census of Population and Housing
Adelaide (CED 401) 75.0 sq. Kms

B05 REGISTERED MARITAL STATUS BY AGE BY SEX
Count of persons aged 15 years and over
Based on place of usual residence

List of tables
Concepts and Definitions
Census Dictionary
Census Data Quality Statement
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	Married(a)	Separated	Divorced	Widowed	Never married	Total
MALES						
15-19 years	8	3	7	4	4,268	4,290
20-24 years	203	5	0	5	6,875	7,088
25-34 years	3,078	179	242	11	8,044	11,554
35-44 years	5,355	393	907	21	3,712	10,388
45-54 years	5,279	443	1,479	77	2,206	9,484
55-64 years	4,344	320	1,303	134	925	7,026
65-74 years	2,710	155	490	222	387	3,964
75-84 years	2,191	79	219	578	296	3,363
85 years and over	535	21	44	424	64	1,088
Total	**23,703**	**1,598**	**4,691**	**1,476**	**26,777**	**58,245**
FEMALES						
15-19 years	15	3	3	0	4,357	4,378
20-24 years	377	22	12	8	6,560	6,979
25-34 years	3,974	246	382	37	6,170	10,809
35-44 years	5,659	446	1,120	82	2,740	10,047
45-54 years	5,295	522	1,889	249	1,594	9,549
55-64 years	4,046	285	1,621	521	708	7,181
65-74 years	2,423	156	690	1,194	288	4,751
75-84 years	1,594	64	385	2,670	289	5,002
85 years and over	309	10	84	1,916	179	2,498
Total	**23,692**	**1,754**	**6,186**	**6,677**	**22,885**	**61,194**
PERSONS						
15-19 years	23	6	10	4	8,625	8,668
20-24 years	580	27	12	13	13,435	14,067
25-34 years	7,052	425	624	48	14,214	22,363
35-44 years	11,014	839	2,027	103	6,452	20,435
45-54 years	10,574	965	3,368	326	3,800	19,033
55-64 years	8,390	605	2,924	655	1,633	14,207
65-74 years	5,133	311	1,180	1,416	675	8,715
75-84 years	3,785	143	604	3,248	585	8,365
85 years and over	844	31	128	2,340	243	3,586
Total	**47,395**	**3,352**	**10,877**	**8,153**	**49,662**	**119,439**

(a) Excludes de facto marriages.

Figure D.1: *Screenshot of excel document containing responses to a question from the 2004 Census*

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