

Turnout and Mail Voting in Colorado

A Thesis
Presented to
the Interdivisional Committee for Mathematics and Natural Sciences,
History and Social Sciences
(Mathematics and Political Science)
Reed College

In Partial Fulfillment
of the Requirements for the Degree
Bachelor of Arts

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December 2018

Approved for the Committee
(Mathematics and Political Science)

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Preface

This is an example of a thesis setup to use the reed thesis document class.

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Introduction

The democratic system is based on procedures as much as principles. The way that democracies chose to tally the will of the people is always a messy, controversial process. Thus the design and implementation of voting systems is far from being neutral; the decisions made on who votes, and how, when, and where they do so is inherently coupled with the outcome. Underlying those decisions is a nebulous, inconclusively answered question: are elections fair, and how can we make them more so.

The passage of the Help America Vote Act—or HAVA—(Robert Nay, 2002), which mandated states to update and consolidate public voter registration files, and created the US Elections Assistance Commission that makes available county level data, innovated the way we use data based approaches to answer this question. HAVA offered political scientists and statisticians direct access to the voting population’s voting patterns, political registration, age, geolocation and much more; information that up to then was only accessible by sampling through surveys. The immense leap here happens because true population data does away with the need for sampling techniques that are often biased and inaccurate. We can now not only get a complete picture of the data, but also link and merge with other sources of information such as US Census data on religion, race, education, or income—work that has been lucrative for firms such as Catalist or Target Smart. By posing Political Scientific questions, and trying to respond with rigorous statistics, both disciplines tackle these data to face joint problems such as quantifying the quality of voter registration files (Ansolabehere & Hersh, 2010), or linking disparate voter records (Ansolabehere & Hersh, 2017).

Chapter 1

The State of the Literature

In this chapter I will go through the existing literature on Vote-By-Mail (VBM). I will first go through some general literature on theories of voting decisions. I will define what Vote-By-Mail is; I will then summarize the expectations that researchers have of the effects of VBM on turnout, based on existing theories of electoral participation. I will continue with a summary of previous quantitative research on the effects that VBM and similar policies have had on turnout.

1.1 Deciding to Vote

1.1.1 Why Turnout Matters

Turnout is the most commonly used measure for electoral participation. It is important because it signifies the level of engagement of the population with the state, the level of incorporation of different subgroups of the population into democratic processes, and the legitimacy of elected officials. It is widely accepted that turnout should be maximized so that the democratic franchise represents the majority of citizens. Turnout for an election can be calculated or predicted, the difference being that in the former case we use data post-election to measure its absolute value, while in the latter we use a series of individual and community covariates to infer the levels of turnout for a future or past election.

Calculating turnout, at its core, involves the following equation:

$$\% \text{ Turnout} = \frac{\textit{Total Ballots Cast}}{\textit{Measure of Total Voting Population}} \times 100\% \quad (1)$$

The choice of numerator is fairly obvious and universal; the denominator, however, is a different story. The two main statistics used are the total voting age population, and the raw number of registered voters in the geographical location we are examining. The total voting age population is used as a measure to incorporate the total amount of possible voters in a geographical area, and can be measured using data from the US Census. This causes some issues with voters that cross over to different districts; if someone lives in district A, it is still likely that they are registered to vote in

district B. If this is not considered, the calculation of voting age population might be misrepresentative.

Using registered voters also brings with it two problems. First, the calculation necessarily occurs using voter registration files, which many times can include discrepancies, like deceased voters, voters included in multiple counties, or individual voters included multiple times. Furthermore, the total amount of actual voters among registered voters can be misrepresentative of democratic participation; consider that if a certain minority community has historically low registration rates, their lack of engagement will not be included in turnout rates, thus misrepresenting the level of inclusion in the district they reside in.

The punch line here is that how the turnout statistic is calculated is not a clear choice, and will have an impact on how studies are set up. To give one example, consider Oregon's Motor Voter program, that automatically registers voters when they interact with government services, like the DMV. It is conceivable that this reform will *decrease* turnout when measured as a percentage of the total registered voter count, but *increase* turnout when measured against total population. I will specify how I calculate turnout in the next chapter.

Statistical models of turnout can be constructed at either the individual or community level. At the individual level, a model is built to predict the probability of voting for every member of a group, and then sum over the members to create an estimate for turnout. Probit or Logit models are preferred. At the community level, researchers first choose a geographical level at which to calculate, which then constitutes the individual observation in the data that is used to create the model.

Both these models include a standard set of societal variables—at the individual and aggregate level—, policy variables—whether the district does Postal Voting, whether Voter ID requirements are particularly strict—, election-specific variables—closeness of election or campaign expenditure—and sometimes time-series data—previous levels of turnout—to make predictions on turnout levels. This type of analysis is not exclusively used to predict turnout but also to, as will be later shown, draw inferences on the effects that certain explanatory variables have on electoral participation.

Through meta-analyses on studies of turnout, it is possible to get a clear picture on what variables effect individual and collective choices to turn out. Three such studies are conducted by Geys (2006), Geys and Cancela (2016), and Smets (2013). Geys includes 83 studies of national US elections in his initial meta-analysis (Geys, 2006), later increasing that number to 185 (Geys and Cancela, 2016) and adding local elections. On aggregate-level models for national elections they conclude that competitiveness, campaign financing, and registration policy have the most pronounced effects, while on the sub-national level there are more pronounced effects for societal variables and characteristics of election administration (spending, voting policy, etc.). Smets and Van Ham (2013) examine individual-level predictors for turnout in a similar meta-analysis, and conclude that “age and age squared, education, residential mobility, region, media exposure, mobilization (partisan and nonpartisan), vote in previous election, party identification, political interest, and political knowledge” (Smets & Ham, 2013) are the most significant explanatory variables for turnout, along with income and race. I will specify the model I will use for turnout in the second chapter.

1.1.2 Theories of Voting

Here I take one step back from turnout, and examine the theories surrounding individual choices to vote or abstain. There are three main theories outlined in the literature on why individuals chose to vote. While there is some overlap, the following are mostly distinct:

- *Decision “at the margins”*: In his 1993 study, Aldrich posits that voting is a low cost-low benefit behavior. Therefore, he continues, voting is a decision that individuals make “at the margins”; in most people, the urge to vote is not overwhelmingly strong, and therefore individuals will vote when it is convenient to them, when they are motivated by a competitive race, when policies are put in place to help them, and when they are subjected to GOTV (Get Out the Vote) efforts. For Aldrich, this is corroborated by the fact that most turnout models present consistent, yet weak, relational variables; if decisions are made “at the margins”, then no single predictor would have an overwhelming result. This is also supported by Matsusaka (1997), and Burden & Neiheisel (2012). Matsusaka expresses support for a more “random” process of voting, where turnout models are ambiguous because of the difficulty that predicting “at the margins” entails (Matsusaka & Palda, 1999). Burden & Neiheisel (2013) also demonstrate support for Aldrich’s thesis by using data from Wisconsin to calculate a net negative effect of 2% on turnout due to a similar slight shift in turnout. (Aldrich, 1993; Neiheisel & Burden, 2012)
- *Habitual Voting*: While Aldrich supports that there is no single overwhelming predictor of turnout, Fowler (2006) posits that future voting behavior can be strongly predicted using individual voting history. This leads to the conclusion that individuals are set to either be habitual voters, or habitual non-voters (Plutzer, 2002) by their upbringing and social circumstances, locking them into distinct groups. (Fowler, 2006)
- *Social/Structural Voting*: Close to habitual voting are those that support a model of social and structural voting; these researchers claim that the decision to vote or not is deeply rooted in socioeconomic factors, which means that the divide between traditionally voting and non-voting groups can only be bridged by directly dealing with the socioeconomic divide between them (Berinsky, 2005; Edlin, Gelman, & Kaplan, 2007). Their reasoning is that “at the margins” voting only addresses groups that do not face significant burdens against voting—like the working poor, or marginalized racial groups—, and are usually already registered. Similarly, they address habitual voting claims by arguing that they are too short-sighted; individuals themselves might be habitually voting, but their decision to do so is rooted in strong societal and policy factors.

1.2 From Theory to Policy

1.2.1 Voting Methods

I have already flagged in my introduction the reason why theories behind voting choice matter: each construct an image of the electorate that reacts differently to policy change around voting. They are all an answer to the fact that voting policy, and how we conduct elections, is not value neutral but has implications for turnout, which in turn has implications on the franchise of democracy.

In trying to respond to the issues set up by theoretical paradigms, different states—both in the world and US contexts—have adapted to different ways of conducting elections. In the US, voting styles can be simplified into three categories:

- *In-Person Election Day*, for which all individuals are required to vote at a polling place, on a single election day. There can be some leeway for overseas voters, or excused absentee voters, but the vast majority of people will have to be present to vote in a particular time frame.
- *In-Person Early Voting*, for which all individuals must vote in person at a polling place or vote center, but the timeframe for voting extends for around two weeks, not a single day.
- *Vote-By-Mail, Absentee Early Voting*, for which individuals have a clear, no-excuse-necessary option for not being present when they vote, or for filing in a mailed ballot and dropping it off at designated locations.

For the purposes of this thesis I will examine the latter category, and specifically Vote-By-Mail. The reason behind this is that the model of in-person, election day voting is usually seen as the baseline, the “vanilla” way of conducting elections if you will. Therefore it has been of interest for researchers to examine if other systems can outperform that baseline. Specifically, it is most interesting to examine voting styles that are heralded for their expansion of turnout, to see whether popular beliefs on their benefits and drawbacks hold; if they are different from the base model of conducting American elections, or if they present new challenges and unique selling points. Vote-By-Mail is particularly interesting because it is quickly taking the form of a trend in state elections, as more and more states are enforcing more open models of VBM. In the next section, I will more closely examine the particulars of Vote-By-Mail.

1.2.2 What is VBM?

Vote-By-Mail is a process by which voters receive a ballot delivered by mail to their homes. Voters then have a variety of options on how to return these ballots, ranging from dropping them off at pre-designated locations, to mailing them in, to bringing them to a polling place and voting conventionally. This varies across states that have implemented VBM. Some common forms of the VBM policy are:

- *Postal Voting*: All voters receive a ballot by mail, which can then be returned to a pre-designated location or mailed in to be counted. This is the current system in Oregon, is an option in Colorado, and is implemented by a number of counties in California, Utah, and Montana.
- *No-Excuse Absentee*: Voters can choose to register as absentee voters without giving any reason related to disability, health, distance to polling place etc. This is the case in 27 states and the District of Columbia.
- *Permanent No-Excuse Absentee*: This is similar to the previous system, but allows voters to register as absentees indefinitely, without having to renew their registration each year; they become de facto all-mail voters. This is in place in Washington, Kansas, and New Jersey.
- *Hybrid or Transitional Systems*: In hybrid systems, voters receive a mail ballot but can choose to disregard it and vote conventionally. This is the case in Colorado. Transitional systems exist in states that have chosen to eventually conduct all elections by postal voting, but have given counties an adjustment period during which this shift is not mandatory, or mandatory only for certain elections. This is the case in California, Utah, and Montana.

Vote-By-Mail is also commonly considered a type of early voting, since voters receive their ballots around two weeks in advance of election day; they are also able to return that ballot whenever they wish within that time-frame. This means that Vote-By-Mail can be counted as a “convenience voting” reform. These are usually implemented by state and local governments with the argument that they either expand the democratic franchise by bringing in new voters, or by making it more likely that current registered voters participate in the electoral process.

1.2.3 How Theories Apply to VBM

Under Aldrich’s paradigm, vote by mail would not effect significant change in voting behaviour. The whole concept of a decision “at the margins” is that the forces at play when an individual decides to vote are overwhelmingly strong both ways, so any effect that policy can have will minimally shift these margins. If, for example, we take a presidential election the forces at play include the media, national committees, social effects etc. In this environment some added convenience does not significantly add to an individual’s decision to turn out. However, this would indicate that at a local level, where national and media effects are less strong, the effect of VBM on turnout might be more significant. The effect would be present for all groups, not only those currently registered, since voting would be easier uniformly.

If we assume habitual voting, the conclusion on VBM would differ significantly. In this case, the effect to be considered is how VBM impacts already formed habits around voting. It could be argued that VBM has no effect, which follows if we assume that voting habits formed do not shift if the mode of voting changes. It could also be

argued that VBM might have a negative effect on turnout in the short term, because it disrupts the habit of election day for a readjustment period, before people settle into new groups of habitual voters and non-voters, adapted to the new policy context.

Under social and structural voting contexts, VBM retains rather than stimulates new voters (Berinsky, 2005). This means that already registered and semi-active voters are more likely to participate, but there is no significant change in the amount of new voters entering the franchise. This would mean that traditional forms of voting policy that emphasize access to the polls will do nothing to bring in disenfranchised people, and potentially hide the problem under an inflated turnout statistic calculated on registered voters. Berinsky in particular emphasizes the need for a shift towards voter education, rather than early voting or VBM policies (Berinsky, 2005).

1.3 Previous Study Results

In this section I will go through previous results from studies of Vote-By-Mail. I will also include a series of studies that are not necessarily about VBM, but have either been conducted in Vote-By-Mail states, or have to do with early voting which, as I have mentioned, is frequently linked to VBM. Most studies include a set of models or predictions of turnout, which are split into individual or county level results. I will group the studies according to whether the result shows a negative or positive effect on turnout.

1.3.1 General Results on VBM

I will start with studies that show a negative effect on turnout. Bergman (2011) uses a series of logit models of individual voting probability in California, during a period where part of the state conducted VBM elections, while others maintained traditional voting. This is called a “quasi-experiment”, and is frequent throughout the literature. Bergman’s results show a statistically significant drop in voting probability in VBM counties (Bergman & Yates, 2011). Using a similar method, Keele (2018) takes a single city in Colorado, Basalt City, which is divided into two different voting districts using different voting systems. The conclusion is, again, a 2-4% drop in turnout along the VBM part of the city (Keele & Titunik, 2017). Burden et al. (2014) takes a different approach, using country-wide election data from 2004 and 2008 presidential elections, and compares districts based on early voting practices. Their results show a significant drop in turnout, which can be associated to VBM as well due to its closeness to EV (Burden, Canon, Mayer, & Moynihan, 2014).

In contrast, Gerber et al. (2013), applying both individual and county-level models for the state of Washington, reach the conclusion that VBM increases turnout by around 2-4%; they use the same quasi-experimental model that offers itself to researchers in states that are under transitional systems (Gerber, Huber, & Hill, 2013). R.M. Stein also reaches a similar conclusion when examining Colorado’s practice of “vote centers”, which are non-precinct attached polling places, which can service multiple counties (Stein & Vonnahme, 2008). I include this paper here due to the link

that voting centers have with VBM, as they serve as drop-off points for mail-in ballots. Richey (2008) examines the effects that Oregon’s VBM program has on turnout by using past elections data, concluding a 10% positive trend associated with the policy (Richey Sean, 2008). This effect is studied again by Gronke et al.(2012) who find a similar positive effect with much lower magnitude, which might point to a novelty effect: the existence of diminishing returns in turnout after the implementation of this policy (Gronke & Miller, 2012). Gronke et al. (2017), again studying Oregon but focusing on Oregon’s Motor Voter program, find evidence of positive association to turnout [④]. I include these effects due to Oregon being an exclusively VBM state, and because this paper uses a “synthetic control group” model, a particularly interesting statistical technique. Lastly, I include a study conducted by Pantheon Analytics on Colorado, which compares actual turnout to predicted levels for VBM counties in Colorado. The results show a positive effect of approximately 3.3% due to VBM (Edelman & Glastris, 2018).

The conclusion to be drawn from this section is that results on VBM vary significantly. There are multiple studies, using multiple methods, on multiple states, with multiple results. This only adds to the importance of being careful when constructing models and hypotheses to test VBM’s effects on turnout, as assumptions made in the process can critically impact the results.

1.4 Voter Registration Files as Data Sources

1.4.1 Inaccuracy of Survey Data

Apart from Voter Registration Files, the main source of data on the American electorate is national surveys, like the American NAtional Election Studies’ survey (ANES), or the Cooperative Congressional Elections Study (CCES). These are post-election surveys, distributed to voters, which include fields associated directly with voting—participation, precinct, which party you voted for—and indirectly, through questions on societal factors like race, income, or gender. On the surface these seem like a better source of data, since no record linkage or ecological inference need be made to connect individual voters with an extensive list of covariates. There is, however, a significant problem with these data: survey misreporting.

Even without resorting to advanced statistical or data gathering methods, the fact that the CCES and NES often misrepresent the electorate is apparent just through looking at turnout statistics; both show higher turnout than what the true value, calculated from the population, was. When looking at surveys a bit closer, using either private, extensive data files like Catalyst (Ansolabehere & Hersh, 2012) or validated voter files from the late 20th century (Deufel & Kedar, 2010), the results show consistent misreporting among certain groups, that tend to either be politically engaged non-voters or minorities and low socioeconomic status individuals. This gap, according to Deufel et al. (2010), has served to propagate societal stereotypes and class entrenchment into studies on turnout, which in turn negatively effect policy, since research using the ANES and CCES are widely used to study turnout among the groups

that are consistently misreporting. Admittedly, the fact that misreporting happens among specific groups does open the way for statistical methods to compensate for the bias introduced, but for the purpose of my thesis I will prefer the use of VRF.

A last issue with surveys worth mentioning is that they are contingent on quantity of responses as well as quality. There is no guarantee that the CCES or NES will receive enough responses to correctly infer population-wide statistics; something which is more likely for the American Community Survey or the Census, which are backed by the legitimacy of the federal government. Survey under-reporting is directly linked with the practices of the groups conducting the survey, and as such is hard to control for after the results are published (Burden, 2000).

1.4.2 The Importance of VRF

As mentioned in my introduction, access to voter registration files has provided researchers with unique insight into the voting process. Quantitative research has expanded significantly, for three key reasons. First, VRF data exists in a consolidated, state-wide format at least for national elections. This means that the process of data collection involves interaction with significantly fewer government agencies, and a data wrangling process that can be quickly adapted to a set format. This is, of course, not to say that the process of data collection and handling doesn't still pose a significant challenge, as will become apparent in my second chapter. Second, there is a huge benefit attached to the fact that VRF data describes the whole population, rather than a sample. As mentioned in the previous section, survey data might give more insight into variables not included in VRF, but that comes at a steep cost for accuracy. Using VRF, the problem of self-reporting bias is eliminated for some studies, and transformed into a problem of record linkage and ecological inference for others (Ansolabehere & Hersh, 2017, Burden & Kimball (1998)). Third, wide public access means reproducibility and accessibility, which translates into greater accountability for researchers. This effect is important, even if mitigated somewhat by private data companies and access fees.

Chapter 2

Hypotheses and Methods

In this chapter, I introduce a series of questions resulting from the literature review of Chapter 1, which I will use to formulate hypotheses. I will then operationalize these hypotheses, and attempt to predict analytical outcomes based on the theories of Chapter 1. Following these hypotheses, I will outline key methods I will use to test them.

2.1 Hypotheses

2.1.1 Questions

Before moving in to outlining hypotheses, the first step necessary is to frame a series of questions, which the hypotheses will flow from. Based on relevant research, the most obvious first question to ask would be:

Q1: *What is the effect of mail voting on turnout?*

I went through this question substantially in the previous chapter; it should be clear that depending on which paradigm of participation choice is present, the answer here can be radically different. In order to best answer the previous question, it is necessary to establish some conditions on importance of effect. Therefore it is also necessary to ask the following question:

Q2: *Is this effect significant when compared to other metrics that affect turnout?*

The last question asked in this thesis is more specific to a particular formulation of Aldritch's hypothesis on voting "at the margins". I mentioned in the previous section that VBM could be theorized to have a more significant effect when discussing elections at the local level, or the regional level, rather than national general elections. Therefore a third question is:

Q3: *Is the effect of VBM more pronounced as significant, national determinants of turnout dull?*

2.1.2 Hypotheses

Using the above questions I can now move on to formulate more clear hypotheses. Before diving right into that, I note that I intend this thesis to serve two purposes: first, to test voter choice theories between each other; second, to serve as an analytical tool for later evaluations of mail voting as policy. Based on the theoretical review of the previous chapter it should be apparent that of these two purposes, the former is primarily addressed, with the later tangentially arising from my conclusions. The hypotheses in this section spring mostly from a wish to test theories of voter choice, and in particular a wish to defend the theory of voting “at the margins” as introduced by Aldrich. Therefore all hypotheses in this section will be phrased from the perspective of this theory, with the competing alternate hypotheses being counter-claims potentially rooted in different theories of voter participation.

In response to Q1, Q2, a first hypothesis is:

H1: *Mail voting is another marginal effect on voting decisions, and therefore does not significantly affect turnout*

The alternative hypothesis would be:

H1': *Mail voting significantly affects turnout, even compared to other metrics*

Similarly, for the third question, a corresponding hypothesis derived from Aldrich's paradigm is:

H2: *The effect of VBM on turnout is more pronounced as national effects dull*

The alternative hypothesis is:

H2': *The effect of VBM on turnout is consistent and independent*

2.1.3 Criteria

A first, glaring issue that needs to be clarified is the apparent contradictions between my two hypothesized results. This becomes clear, however, if I define “significant effect” in the context of my first hypothesis. Aldrich's paradigm does state that “conveniences” like mail voting should not have significant effects, but those effects are defined in the context of huge, clashing forces that vastly outweigh them. This does not necessarily mean that they are literally non-existent, but that they are poor indicators of consistently increased turnout. Therefore, I will confirm my first hypothesis not only if the effect of mail voting on turnout is statistically insignificant, but also if it is relatively small in comparison to the effects of other variables I include. I will confirm the alternative hypothesis if, across multiple of the models I will parametrize and fit, VBM retains a consistent, significant effect on turnout. If the effect is negative, this may point to a habitual or structural voting paradigm being present. If the effect is positive, this may be a signifier that issues of convenience in voting—having a mail

delivered ballot, voting from your kitchen table etc.—have a particularly strong effect in the examined elections.

Moving on to the second hypothesis. It is extremely hard to correctly operationalize and account for all variables going into turnout. Therefore, instead of trying to include all national effects into a model and try to see how they interact with VBM, I will test my hypothesis on more localized elections. At least in theory, I can assume that if mail voting significantly impacts people’s decision to vote, it will be in a context where the convenience of voting significantly outweighs information effects from national media, communal pressures, or national campaigns. This can be found to some extent in primary elections, but much more significantly in off year local state elections. A potential re-formulation of the second hypothesis, that makes it more specific to the criteria I have set, is:

H3: The effect of VBM on turnout is more pronounced in local or off year elections

I will confirm this hypothesis if mail voting has significantly larger positive effects on turnout in smaller, local elections.

2.1.4 Importance of Hypotheses

The importance of these hypotheses is intrinsically tied to the importance of different theories of electoral participation. Confirming or rejecting each hypothesis—even when only applied to a single state—serves as an argument for or against one of the aforementioned theories. The theories in and of themselves are significant, since they form a part of a broader literature on elections, democracy, and electoral processes, that can be said to be foundational to political science as a whole. Elections are the root from which all democratic governing springs; understanding why people participate in them is understanding how they choose to be included or excluded from the process of policy-building, and how they interact with the state.

Additionally, from a public policy perspective, these hypotheses are significant since they serve as metrics for the effectiveness of mail voting as an electoral reform. Whether, in general, mail voting increases turnout is directly connected to whether it is successful in expanding the democratic franchise. If it is not, questions can be raised as to the effectiveness of expanding voter access through elections administration, rather than education, or even measures like voting-day-holidays or local transportation to polling places. In local elections in particular, significant effects of mail voting could be precursors to more general involvement of individuals in their local politics. This may open the way to numerous comparative studies on local politics between states that apply VBM and states that do not.

Lastly, from a narrower perspective specific to the study of early and mail voting, my first hypothesis can still be said to be significant, yet mundane. It does its job according to the particular state I chose to look at—in this case Colorado—to add to existing literature on mail voting effects in different parts of the country. However, my second and third hypotheses are much more unique in their scope. There have not been many studies that look at VBM at a more localized level, and any addition to the literature on this front—however limited—could be significant.

2.2 Methodology

Before directly defining all parameters of the models I will later use in writing this thesis, I will go through each type of method to provide some background on the statistics behind the models. In the next chapter, I will introduce the data and fully outline my models. This section should serve as a general introduction to the methods. I will not extensively go through the statistics behind linear or multiple regression, but will assume that it is common knowledge. For an extensive introduction to such methods, James et al.(2017) or Chihara and Hesterberg (2011) are particularly useful.

2.2.1 Logistic Regression

Let function $f : [0, 1] \rightarrow \mathbb{R}$ be defined as:

$$f(p) = \text{logit}(p) = \log\left(\frac{p}{1-p}\right)$$

This is called the logit function or, when p refers to a probability, the log-odds function. When modelling a binary response Y , which follows a Bernoulli distribution:

$$Y \sim \text{Bernoulli}(p),$$

the logit function can be used as a link function to model Y in a generalized linear model. The generic form of a generalized linear model looks like:

$$f(Y) = XB,$$

where Y is a vector of response variable values, X is a matrix of predictors, and B is a matrix of coefficients to be estimated. The function f is called a link function, because it “links” the response variable with the set of predictors included in the model. This is typically done to ensure that the range of values outputted by the model are consistent with the range of the response variable. When wanting to compute a model on a binary response through its corresponding Bernoulli distribution probability parameter, the inverse logit function should be a perfect fit for a link function, since it maps values from all real numbers to a range between 0 and 1. Using the inverse logit function, we arrive at the final form of logistic regression, which is:

$$\mathbb{P}(Y_i = 1) = \text{logit}^{-1}(XB)$$

Conveniently, despite the use of a link function, there is an easy way to interpret the coefficients of such a regression. While obviously individual values from the B matrix will not be particularly helpful, e^B can be used as a matrix of multiplicative, one-unit shifts in the value of the probability that $Y_i = 1$. This means that a one unit increase in any predictor will cause an effect equal to multiplying p by the exponent of the corresponding coefficient. (James, Witten, Hastie, & Tibshirani, 2017)

2.2.2 Generalized Additive Models

In simple logistic or linear regression, there is an assumption made on the functional form of the relationship between predictors and response variable. These are called parametric models, where the data is exclusively used to estimate values for coefficients. Non-parametric models, on the other hand, use the data to estimate both coefficients and the function that serves to connect response to predictors. While on the surface this seems like a great idea (more reliance on your data and less assumptions!), such an exclusively non-parametric model would suffer greatly from the curse of dimensionality—where the addition of multiple predictors or overreliance on data leads to substantial over-fitting.

The solution, then, is a Generalized Additive Model, or GAM. This model lets us fit a different functional form to each observation, allowing for assumptions to be made on the data where it is safe to do so, and for non-parametric fitting when it is necessary. This model looks like:

$$y_i = \alpha + \sum_{j=1}^p \beta_j f_j(x_{ij}),$$

where y_i the i -th response variable, α is the intercept term, f_j, β_j a series of p functions and coefficients, and x_{ij} the i -th observation for the j -th predictor. Note that for $f_j(x_j) = x_j$, this is a multilinear regression! (James et al., 2017)

A type of most commonly fit functions—and the type I will make use of—are smoothing splines. These are cubic functions connected at specific points called “knots”, with the limitation that the full function must be continuous and smooth. These are particularly useful when modeling time variables, as they can be fitted to variables like years or months in order to distinguish a secular trend from a general trend over time. In terms of this thesis, this will help when responding to Q2 as it was framed earlier in this chapter. (Barr, Diez, Wang, Dominici, & Samet, 2012)

2.2.3 Multilevel Models

Multilevel models—otherwise known as hierarchical or “mixed effects” models—can be intuitively pictured in two ways: either as a set of models working on different “levels”, where one is calculated first, with its effects having implications for the second, or as a model where some of the parameters estimated act under a particular series of constraints. Multilevel models are, in essence, a compromise between levels of “pooling” data. If the dataset on which parameters are being estimate operates in different units of observation—say on the individual and county level—you could run a model that treats all individuals as coming from the same larger group; this would be a complete pooling model. You could also add indicator variables for each and every group, de facto estimating n different models for n groups; this would be a no pooling model. Multilevel modelling offers partial pooling (Gelman & Hill, 2006).

To consider what this model looks like, let’s assume a dataset comprising of a vector of values for the response variable Y , a matrix of i individual level predictors X , a matrix of j group level predictors U , intercept terms α , individual level coefficients

B, and group level coefficients Γ . Based on this, a multilevel model with intercept terms varying by group looks like:

$$Y_i = \alpha_{[i],j} + X_i B, \quad \alpha_{[i],j} \sim N(U_{j[i]}\Gamma, \sigma_\alpha^2)$$

Chapter 3

Case Selection, Data, Model Parametrization

In this chapter, I will first go through a description of the state of Colorado; its demographics, its politics, and its selection for the purposes of this thesis. I will then go through the sources and wrangling of the data I obtained on Colorado’s elections. Finally, I will fully define the models I will be using to test the hypotheses outlined in the previous chapter.

3.1 The Centennial State and Its Voters

3.1.1 Demographics and Characteristics

Colorado—named the Centennial State due to assuming statehood on the centennial of the Union—lies in the Southwestern United States, with its Western half squarely atop the Rocky Mountains. Based on its estimated population of just over 5.5 million, Colorado is the 21st most populous state, and ranks 37th in population density. The vast majority of that population is gathered in a series of urban areas that comprise a North-to-South strip in the middle of the state, containing the Denver-Aurora-Lakewood Metro Area, Colorado Springs, Pueblo, and Fort Collins. Apart from the Western town of Grand Junction, the rest of the population resides in vast rural areas.

Continuing with demographic characteristics, Colorado has a median age of 34.3, and median household income of \$65,685. Colorado’s population is mostly white, with a higher minority group population density in its Southern regions, as shown in figure 3.1. (Bureau, 2010)

The State Capital is Denver. Colorado is split into 64 Counties, of which the most populous are, in no particular order, the following eight: El Paso, Denver, Arapahoe, Jefferson, Adams, Larimer, Boulder, and Douglas. These counties comprise 73% of the total population of Colorado.

County	Total Population	CO Population %	Largest Metro Area
Adams	441603	0.0878079	Denver-Aurora-Lakewood Metro Area

County	Total Population	CO Population %	Largest Metro Area
Arapahoe	572003	0.1137365	Denver-Aurora-Lakewood Metro Area
Boulder	294567	0.0585714	Boulder
Denver	600158	0.1193348	Denver
Douglas	285465	0.0567616	Denver-Aurora-Lakewood Metro Area
El Paso	622263	0.1237301	Colorado Springs
Jefferson	534543	0.1062880	Denver-Aurora-Lakewood Metro Area
Larimer	299630	0.0595781	Fort Collins
Other	1378964	0.2741917	
Colorado	5029196	100.0000000	

3.1.2 Voting in Colorado

Each County individually administrates local, coordinated, primary, and general elections, under the supervision of the Colorado Secretary of State. This means that each county individually handles the voters registered in that county. Unsurprisingly, the same eight most populous counties are also the counties with the majority of registered voters, as their registrants comprise 73% of total Colorado registered voters (as of November 2017). As the following table shows, these eight counties have a registration rate between 60-80%, compared to a Colorado-wide rate of about 67%. Registration rates for all counties are also graphically depicted in figure 3.2.

County	Total Registered Voters	County Voter Registration Rate	% of Statewide Registrants
Adams	270303	0.612095026528352	0.0723838
Arapahoe	410546	0.717733997898612	0.1099391
Boulder	237091	0.804879704787026	0.0634900
Denver	450616	0.750828948376927	0.1206694
Douglas	237659	0.832532884942112	0.0636421
El Paso	445708	0.716269487338955	0.1193551
Jefferson	422362	0.790136621375642	0.1131033
Larimer	250626	0.836451623669192	0.0671145
Other	1009392	—	0.2703027
Colorado	3734303	—	100.0000000

In terms of Party registration, Colorado as a whole leans democratic by a very narrow margin. This is also reflected in the state's Cook Partisan Voting Index of D +1, making it a solidly purple battleground state (figure 3.3).

In the past 25 years, there have been a series of key changes in the way Colorado administers elections, in relation to Vote By Mail and other reforms targeted and expanding the democratic franchise. In 1992, Colorado introduced no-excuse absentee voting, allowing voters to either physically pick up a mail ballot at a Vote Center or County Office, or have a ballot mailed to them prior to election day. In 2008, this

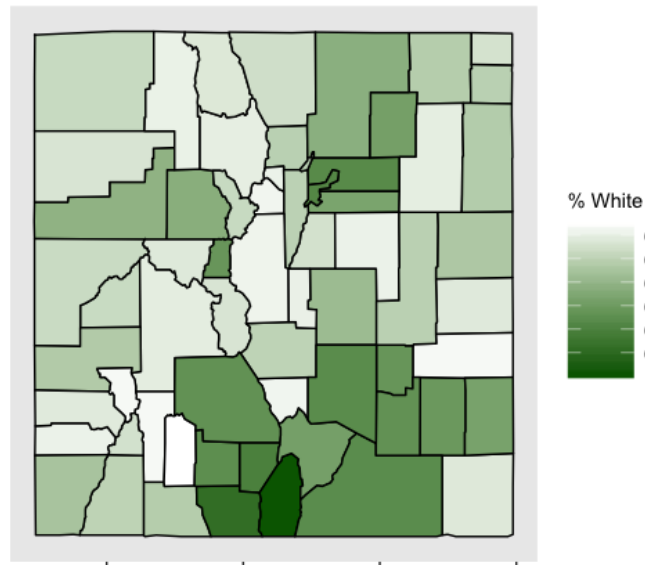


Figure 3.1: White voters per Colorado county

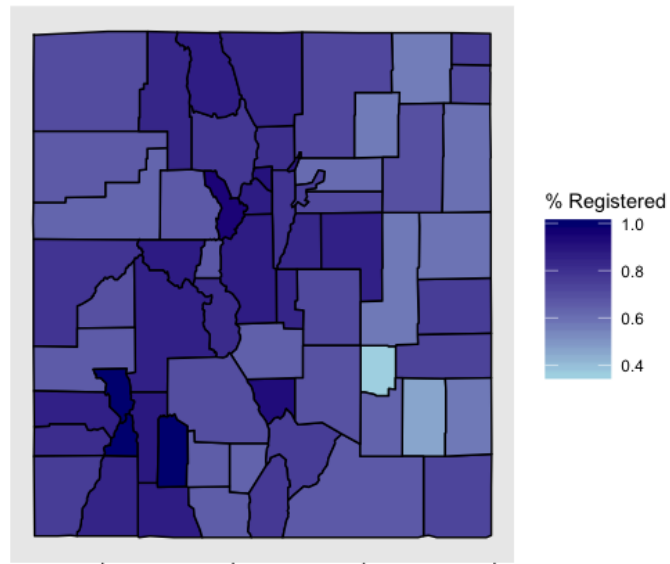


Figure 3.2: Registration rates per Colorado county

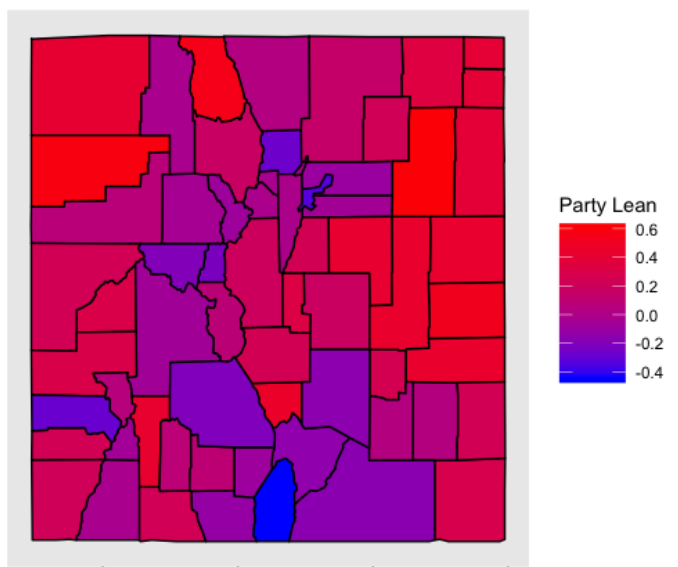


Figure 3.3: Democratic/Republican party lean per Colorado county

reform was expanded to a permanent Vote-By-Mail system, which gave voters the option to be permanently put on a list of addresses that received mail ballots prior to the election. The State also entered a transitional status to full mail elections, giving counties the option to make all coordinated local elections, general elections, and primary elections exclusively VBM. In 2013, the Colorado State Legislature passed HB13-1303: The Voter Access and Modernized Elections Act, which mandated that every voter currently registered receive a mail ballot for all future elections. The Act also expanded the use of Vote Centers instead of traditional polling places, instituted same-day voter registration, and revamped the way active and inactive voter status was designated on voter rolls—more on this in future sections. These changes are summarised in Table.

Year	Key Changes
1992	No Excuse Absentee Statewide Implementation
2008	Permanent No-Excuse VBM Lists, Option of Full-VBM Elections
2013	Automatic Mail Ballot System Implemented Statewide, Established Vote Centers

Colorado presents such an interesting case for research on Vote By Mail exactly because it has gone through such a long transitional process to reach its current elections system. It has steadily developed voting policy through a mixture of state mandates, county action, and outside policy motivations. It gives researchers access to approximately 22 years during which at least part of the state conducted elections partially by mail, making comparative, county- or individual- level case studies particularly alluring.

3.2 Acquiring the Data

This thesis relies on county and individual level models to draw conclusions on voting behaviours, and how they are affected by voting method. As such, the data I need will optimally contain the following:

3.2.1 Sources and first glance

I used two sources of data: Colorado voter records procured from the Colorado Secretary of State’s office, and demographic data from the 2010 US Census. In the process of procuring these data I was aided by a series of other researchers and professionals with experience in the field of elections administration; they are mentioned in my acknowledgements.

2010 US Census

The US Census is conducted country-wide every ten years, with the goal of procuring accurate data on the demographic characteristics of the population. The Census uses a combination of federal field workers conducting door-to-door canvassing and statistical methods for data aggregation. From the 2010 Census—which is publically available online—I get total population counts, characteristics on race, and rural/urban population counts for Colorado.

I use two datasets from the Census. For both, the unit of observation is one of the 64 counties of Colorado, and both include the same total population counts. One contains racial demographic characteristics and the other contain percentages of rural and urban populations in each county. The racial demographic dataset needed some wrangling work to extract a percentage of white residents in each county. Individuals were coded as “white” when they identified as exclusively white—this doesn’t include mixed-race individuals reporting white ancestry.

Colorado Voter Files

As any state, Colorado maintains a statewide registry of all currently registered voters. This registry is typically under the purview of the Secretary of State—in this case, Wayne W. Williams. Voter Registration Files are constantly updated with new information on existing voters, new voters, or with the removal of inactive or otherwise ineligible voters. Therefore, this file will be different every time it is accessed or shared. Based on when this file is accessed, only a “snapshot” of the file can be obtained. I have managed to procure “snapshots” for each year between 2012 and 2017.

Similarly with VRFs, a Voter History File is maintained and constantly updated by the state. This file is uniquely connected to its VRF: only voters showing up as registrants will have their histories included. I have similarly procured “snapshots” of the Voter History File for the years between 2012 and 2017.

In the Voter Registration files, the unit of observation is the individual voter, and all variables are initially coded as character strings. Each voter is assigned a unique voter ID, which serves as a point of reference between the two files. Broadly speaking, data in this file can be divided between three categories: first, personal identification information like address, ZIP code, or phone number; second, demographic information like age and gender; third, information pertinent to elections administration like congressional district, local elections for which the individual should receive a ballot, voter ID, and party registration. I will further elaborate on relevant variables in the wrangling section.

In the Voter History files, the unit of observation here is a single ballot cast, and all variables are initially coded as character strings. This means that for each voter registered—and so included in the VRF—the history file should contain an observation for each time they voted. This file includes two types of data: first, identifiers for the election like county, date, description, and type; second, identifiers for the individual vote including voter ID and voting method.

3.3 Wrangling the Data

The process of “wrangling” refers to manipulating the data into a form that can then be used for graphing, exploratory data analysis, modelling, or presentation. In this case, wrangling also included aggregating data across multiple sources and datasets. For this purpose, I made heavy use of the tidyverse R package, and in particular the dplyr package. In this section I will go through some of the key problems encountered during the wrangling of these data, and then discuss the final form each variable takes.

3.3.1 Initial Problems with the 2017 Voter File and Solution

The first major issue I encountered—which merits discussion in its own section—derives from the aforementioned fact that the voter records I had access to are “snapshots”. What this means, is that for each person in each year of voter registration files, I will have their corresponding history files for all ballots they have cast in Colorado, but not their own history of registration and migration. If, say, a voter moved from Boulder County to Summit County, I would have their votes in Boulder County show up in the voter history file, but them being registered in Summit. If you recall the turnout calculations specified earlier on, this implies an overestimation when looking back at elections that happened some time before the date of the “snapshot”. Additionally, “snapshots” of current voter files do not reflect voters dropping off the rolls for whatever reason—death, moving out of the state, long term inactivity, non-confirmable personal data etc. Since for these voters the history files would also not be included, the issue created is less one of overestimation of turnout like before, but just the inclusion of additional room for error that is created when subtracting one from the denominator and enumerator of turnout.

This was a significant problem from the beginning of this thesis, since I started out with only one “snapshot” from 2017. After going through turnout calculations, a significant majority of counties appeared to have turnout exceeding 100%, particularly for years between 2000 and 2012. This was, to put it mildly, concerning. With the help of my advisers, I was able to procure similar “snapshots” for each year between 2012-2016. After similar calculations, I returned figure 3.4 for the eight most populous counties as described above, including different shapes for election type, colors for county, and a vertical line at 2013 to signify the latest major change in how Colorado administers elections.

To also further illustrate the in-county migration and dropped voter problem, I created a graph that includes logged total counts of registered voters calculated using

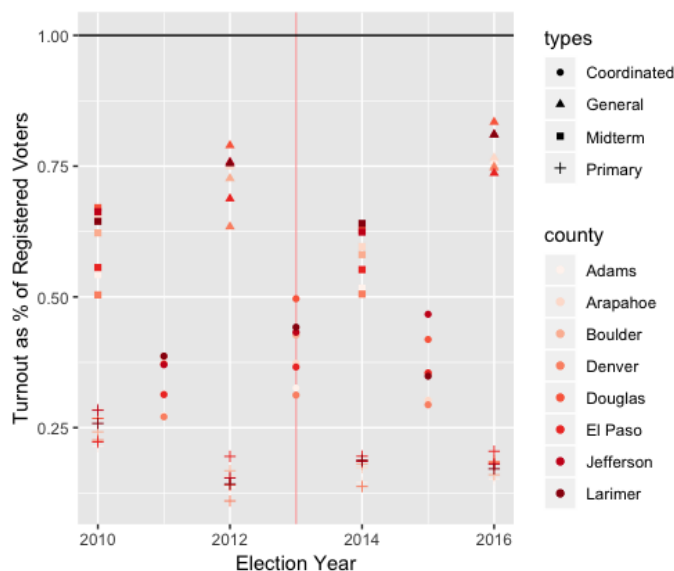


Figure 3.4: Turnout plot for eight largest Colorado counties, 2012-2016

the 2017 and the 2012-2016 files. The plot also includes a line at $y=x$. If in-Colorado migration and dropped voters are not an issue, most points on this graph should be at this line.

Two things should be clear from figure 3.5. First, there is significant deviation between the counts using just the 2017 file and all files across years. Specifically, the 2017 count consistently underestimates the total amount of registered voters—this is shown by the red linear model smoothing line. This consistent difference confirms the hypothesis that there is a substantial benefit to using “snapshots” for multiple years. Second, counts get more accurate the closer to 2017 we get. This should be even more apparent in figure 3.6, which limits the scale to only some high registration counties, and adds a shape indicator for county.

Here the structure of the data becomes clear: for each county, there are a series of almost vertically distributed points, which get closer to the $y = x$ line the closer the counts get to 2017. Through this series of tests, it became clear that using multiple years of data was necessary in order to conduct an accurate test of my hypotheses. My selection was later vindicated, when looking at comparisons between reported rates of turnout¹ and turnout calculated through my dataset for the 2014 midterm election (see fig. 3.7).

The differences are insignificant. They exist because of “noise” added on because of errors in the data, misreporting, private voter registration files, voters dropped before the “snapshot” occurred, and other similar factors.

¹Turnout is calculated over all registered voters

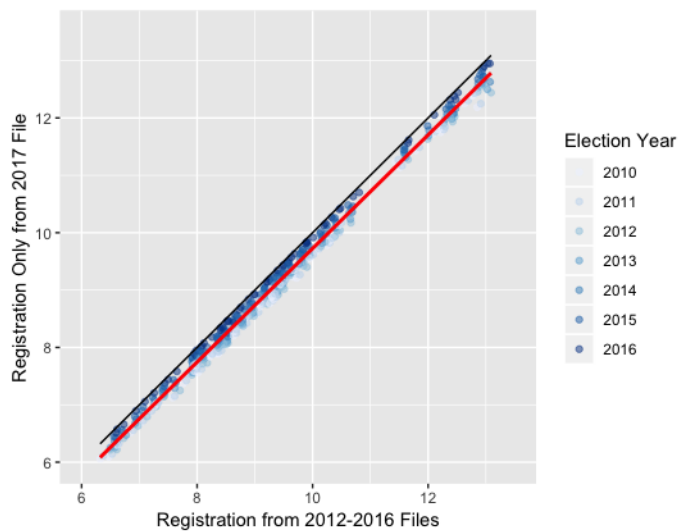


Figure 3.5: Comparison of registration count methods

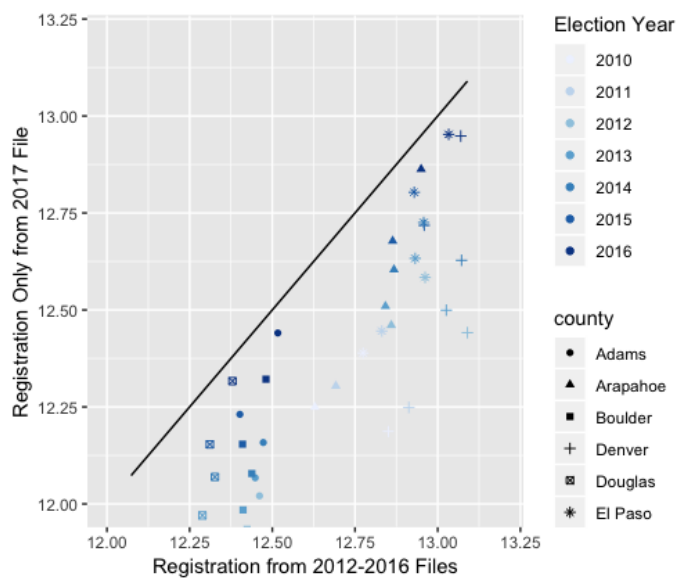


Figure 3.6: Comparison of registration count methods only for a few counties, 2012-2016

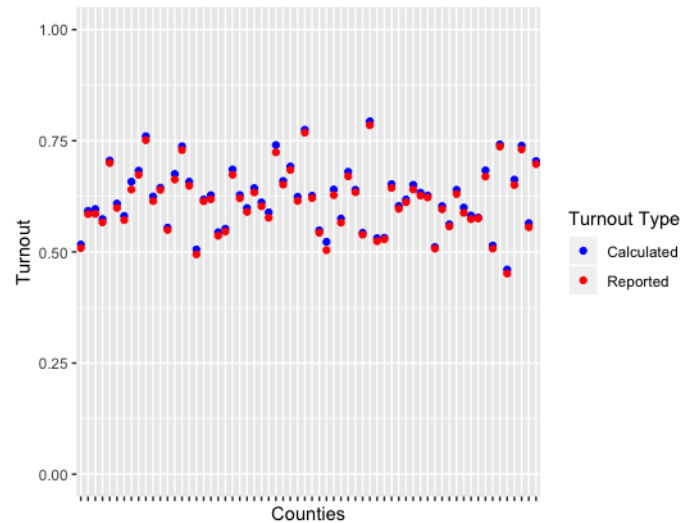


Figure 3.7: Comparison of reported and calculated turnout for 2014 midterms across county

3.3.2 Other Wrangling Issues Faced

Suffice to say, wrangling data was the majority of the work that went into this thesis. Doing a full account would probably read like the world’s most cliché crime novel: a series of elusive final datasets, a plucky yet occasionally naive young detective, two wisened mentors, clues, dead ends, frustration, compromise, and... spreadsheets. I will spare the reader the whole story, but I will include a non-comprehensive list of some of the difficulties associated with wrangling voter files, as it was a crucial part of the learning process I underwent while doing my research.

Missing Values: The decision on how to deal with missing values—or NAs—in a dataset is a lot more important than it may initially seem. A first, intuitive reaction might be to just disregard them; however this works under the assumption that there is no structure inherent to why these data are missing! To give just two examples, in the data I have collected, the PARTY value for the 2015 voter registration file is missing. If I excluded all observations with missing PARTY values, I would be excluding a fifth of my data. Missing values were also present in the VOTING_METHOD variable of the voter history files. While this may have seemed troubling, after closer examination it was revealed that the vast majority of such missing values was concentrated in Jefferson County, and in elections prior to 2002. Therefore, these observations could be ignored, since they played no role in my final dataset. The conclusion should be that choices made on exclusion, inclusion, or estimation of missing data are very important, and should be taken with much care and consideration for the underlying structure of the data.

Data Input Errors: Is “Greece” a legitimate voting method? Probably not. However, “Greece” did show up as a value in the VOTING_METHOD variable for my 2012 voter history file snapshot. This may have occurred for a series of reasons, like data reading issues—the data I acquired had changed hands some times, and also

changed platforms between STATA and R—or issues at time of input—each county counts votes individually, and *then* the state aggregates the data—, or some bug in my code. Having adequately checked for the later of these reasons, I treated all values that seemed more likely than not to be errors as NAs. There were not many of these—less than .001% of my data—but they were a hassle to find, analyze, and then recode into some useful value.

Data Size: Nothing to write home about here, just an observation that multiple voter registration files can be *huge*, which puts considerable strain on a computer’s processing power. This means that wrangling has to comprise of a series of careful, deliberate moves. Brute force should be discouraged, as a dead end means several hours of melodic computer fan panic.

Joining, Merging, Spreading, and the Multiplicity of Levels: For the data to end up in any functional shape, it eventually becomes necessary to start joining datasets. Thankfully, a clear division of modelling tasks between county and individual level models means that joining on COUNTY or VOTER_ID is ideal, and fairly straightforward. As will become clear in later sections, I also had to consider the variety of different units of observation, specifically: county, individual, ballot, election, county-by-election.

3.3.3 Final Variable Specifications

After the conclusion of the wrangling process, the resulting dataset included a series of discrete and continuous variables. I will briefly outline them here, along with their range and values.

- VOTER_ID: Discrete variable, unique value given to each individual voter. Useful for merging.
- COUNTY: Discrete variable, the 64 counties of Colorado.
- REGISTRATION_DATE: Discrete variable, date of registration for each registrant. Useful to get total registrants on election day.
- TURNOUT: Continuous variable, in the range [0,1]. The response variable for my county-level models.
- ELECTION_TYPE: Discrete variable, the four types of elections: Primary, Coordinated, Midterm, Presidential.
- ELECTION_DATE: Discrete variable, self-explanatory.
- VBM_PCT: Continuous variable, in the range [0,1]. This is the focus of my analysis, as it counts the percentage of total ballots that were mail ballots.
- PCT_WHITE: Continuous variable, in the range [0,1]. Percentage of white residents per county.
- PCT_URBAN: Continuous variable, in the range [0,1]. Percentage of urban residents per county.
- PARTY: Discrete variable. For each voter, the party they are registered with. Can be: Republican, Democrat, Other, or Unaffiliated.
- GENDER: Discrete binary variable, Male or Female.
- AGE: The age of the individual registrant.

- **VOTING_METHOD**: The method used by an individual voter to cast their ballot. Is coded as either VBM or In Person, according to the following table:

Voting Method	Description of Method	Final Designation
Absentee Carry	Voters who carried an absentee ballot with them from an early voting location	VBM
Absentee Mail	Voters who were sent an absentee ballot, and mailed it in	VBM
Early Voting	Voters who physically went to an Early Voting location and voted	In Person
In Person	Voters who physically went to a polling place and voted on paper	In Person
Mail Ballot	Vote By Mail	VBM
Polling Place	Traditional polling place voting, discontinued in 2013	In Person
Vote Center	Voters who cast their ballots at Vote Centers	In Person

3.4 Model Parametrization

3.4.1 Notation for predictors

There are four distinct types of predictors for use in these models.

County and County-per-Election Level

First, I define the following indicator variables:

- x_c , for $c \in [1, 64]$, dummy variables for each county in Colorado.
- Furthermore, I have two county-level predictors:
- $x^{white} \%$, a vector of length 64, percentage of county population that identifies as only white.
 - $x^{urban} \%$, a vector of length 64, percentage of county population living in an urban area.

There are two other predictors, varying by county and election. These are of particular interest, as one is the response variable for my county-level models, and the other is the variable of interest for this study. Specifically:

- $x^{mail\ vote} \%$, a vector of percentage of votes that was cast using mail ballots, per county and election.
- $y^{turnout} \%$, a vector with turnout counts per county and election. Coded with a y to identify as a response variable

Since the unit of observation for the county level models I will apply are all counties

per election, I define an aggregate matrix of length equal to the number of elections times 64—the number of counties—and width equal to 3. This matrix includes all county level predictors: $X = (x^{white \%}, x^{urban \%}, x^{mail\ vote \%})$. Note that this matrix includes percentage of mail ballots cast, which is the variable whose coefficient I am interested in testing.

Election Level

There are two exclusively election-level discrete variables: year, and type of election. For both I define a series of indicator variables:

- $w^{election\ type}$, for each election type (Midterm, Primary, Coordinated, General).
- $w^{election\ year}$, for each election year, between 2010 and 2016.

I will also use *year* as a variable for models using smoothing splines. All election level predictors will be summarized for the purposes of modelling in the 9 by 2 matrix $W = (w^{election\ type}, w^{election\ year})$.

Individual and Individual-per-Election Level

The two aforementioned predictors—urban population and race—could be defined as aggregates of individual level observations. I also have five other distinct individual level variables:

- z^{gender} , a vector of discrete gender identifications for each voter, varying only by voter.

- z^{age} , a vector of age for each vote, varying by voter and election.

- z^{party} , a vector of party registration for each voter, varying by voter and election. Coded as Republican, Democratic, Other, or Unaffiliated.

- z^{voted} , with $z_{i,j}^{voted} = 1$ if person *i* voted in election *j*, and $z_{i,j}^{voted} = 0$ if they did not.

- $z^{mail\ ballot}$, a vector of binary values depending on whether voting method was by mail for each voter, varying by voter and election. Coded 0 if the individual did not vote.

Since the unit of observation for the individual level models I will apply are all individuals in a particular election, I define an aggregate matrix of length equal to the total number of voters, and width equal to 4. This matrix includes all individual level predictors: $Z = (z^{gender}, z^{age}, z^{party}, z^{mail\ ballot})$. The fourth variable defined in this section is the response variable in the individual level model, and as such is not included in the predictors.

3.4.2 County Level Models

Model 1 is a fixed-effects, bare-bones model that exclusively includes percentage of VBM votes, and dummy variables for year, election type, and county. Its call would look a bit like:

$$y_{c,l}^{turnout \%} \sim x_{c,l}^{mail\ vote \%} \beta_1 + \sum_{k=1}^4 w_{k,l}^{election\ type} \beta_{k+1} + \sum_{j=1}^7 w_{j,l}^{election\ year} \beta_{j+5} + \sum_{c=1}^{64} x_c \beta_{c+13}$$

Where k sums over the four types of election, j sums over years between 2010 and 2016, c sums over counties, and l sums over elections

Model 2 A more informed baseline, model 1 plus variables of urban and white population:

$$y_{c,l}^{turnout \%} \sim x_{c,el}^{mail\ vote \%} \beta_1 + \sum_{k=1}^4 w_{k,l}^{election\ type} \beta_{k+1} + \sum_{j=1}^7 w_{j,l}^{election\ year} \beta_{j+5} + \sum_{c=1}^{64} x_c \beta_{c+13} + x_c^{white \%} \beta_{78} + x_c^{urban \%} \beta_{79}$$

This would be the “individual” level model from Gelman and Hill. I’m unsure what the “group” level for county would be. Maybe that part of the book would be more helpful for discerning effects on people’s individual p-vote?

Maybe more informative is what I did with exercise 12.2. The model tries to predict the concentration of a particular chemical based on treatment of children across time. Therefore the two levels are a visit by one individual child (here an election! so type, vbm_pct, year) and predictors for that individual child that are stable across time, like treatment type, or demographics (here race and urban pop per county).

This means I can fit a model only based on election facts, with a variable for county (models 1,3) or one that takes into account stable characteristics of the county (models 2, 4).

Model 3 A mixed-effects version of model 1, just adds mixed effects for county:

$$y_{c,l}^{turnout \%} \sim x_{c,l}^{mail\ vote \%} \beta_1 + \sum_{k=1}^4 w_{k,l}^{election\ type} \beta_{k+1} + \sum_{j=1}^7 w_{j,l}^{election\ year} \beta_{j+5} + \alpha_{[c],l}$$

$$\alpha_{[c],l} \sim N(0, \sigma_\alpha^2)$$

Model 4 A mixed-effects version of model 2:

$$y_{c,l}^{turnout \%} \sim x_{c,l}^{mail\ vote \%} \beta_1 + \sum_{k=1}^4 w_{k,l}^{election\ type} \beta_{k+1} + \sum_{j=1}^7 w_{j,l}^{election\ year} \beta_{j+5} + \alpha_{[c],l}$$

$$\alpha_{[c]l} \sim N(x^{white \%} \gamma_1 + x^{urban \%} \gamma_2, \sigma_\alpha^2), \text{ for } c = 1, \dots, 64$$

Where D is a 2 x 64 matrix of the county level predictors and γ a vector of coefficients for the county-level regression.

Model 5 During one of my discussions with Andrew, we discussed the possibility of making a model that answers the question: “Does VBM affect counties with some particular characteristic *for which I don’t have data* more than others?” As such, this model would substitute county-level effects with a set of 3-4 dummy variables created through my intuitive understanding of Colorado politics and counties. For example, maybe a distinction between central Colorado urban counties, East Colorado plains counties, and West Colorado mountain counties. The model would look a bit like:

$$y_{c,l}^{turnout \%} \sim x_{c,l}^{mail\ vote \%} \beta_1 + \sum_{k=1}^4 w_{k,l}^{election\ type} \beta_{k+1} + \sum_{j=1}^7 w_{j,l}^{election\ year} \beta_{j+5} + \sum_{c=1}^n x_c^{county\ classification} \beta_{c+13}$$

Where $x_c^{county\ classification}$ are n dummy variables, one for each county classification group.

Model 6 As a check on the previous model, run a Principle Components Analysis on full demographic data from the 2010 census, to classify counties in the same number of groups. This model would be expected to *massively overfit*. Learning experience for all!

Note All models can work as General Additive Models with some sort of non-linear smoothing function for year. Just replace $\sum_{j=1}^7 w_j^{election\ year} \beta_{j+5}$ with $ns(year)$.

Model 7 In order to test the hypothesis that voting by mail varies by election type, I can also construct the following model, based on model 4:

$$x_{c,l}^{mail\ vote \%} \sim \sum_{k=1}^4 w_{k,l}^{election\ type} \beta_k + \sum_{j=1}^7 w_{j,l}^{election\ year} \beta_{j+4} + \alpha_{[c]}$$

$$\alpha_{[c],l} \sim N(x^{white \%} \gamma_1 + x^{urban \%} \gamma_2, \sigma_\alpha^2), \text{ for } c = 1, \dots, 64$$

This would predict whether there are specific county or election characteristics that increase the amount of mail ballots individuals cast.

3.4.3 Individual Level Models

This section follows directly from the intro to Gelman & Hill’s 11th chapter.

Model 8 As a baseline for all further analysis, a logistic regression that treats each vote in a single election as uniform across counties, as such not including any group-level predictors.

$$P(z_{i,l}^{voted} = 1) = \text{logit}^{-1}(Z_{i,l}\delta + W_l\beta)$$

Where matrices Z , Y are as described above, i is an indice for each voter, and l for each election. δ, β are vectors of coefficients to be estimated.

Model 9 Add group level mixed effects and predictors.

$$P(z_{i,l}^{voted} = 1) = \text{logit}^{-1}(Z_{i,l}\alpha + W_l\beta + \alpha_{[c],l})$$

$$\alpha_{[c],l} \sim N(X_c \gamma, \sigma_\alpha^2), \text{ for } c = 1, \dots, 64$$

Where X_c as defined above, and γ a vector of coefficients.

Model 10 Include extra model with EM algorithm applied to 2015 data maybe?

Chapter 4

Results

4.1 EDA

4.2 Models

4.2.1 County Level Models

4.2.2 Individual Level Models

Chapter 5

Expanding on the Previous Models

Conclusion

References

- Aldrich, J. H. (1993). Rational Choice and Turnout. *American Journal of Political Science*, 37(1), 246–278. <http://doi.org/10.2307/2111531>
- Ansolabehere, S., & Hersh, E. (2010). The Quality of Voter Registration Records: A State-by-State Analysis. *Institute for Quantitative Social Science and Caltech/MIT Voting Technology Project Working Paper*. Retrieved from <https://dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/18550>
- Ansolabehere, S., & Hersh, E. (2012). Validation: What Big Data Reveal About Survey Misreporting and the Real Electorate. *Political Analysis*, 20(04), 437–459. <http://doi.org/10.1093/pan/mps023>
- Ansolabehere, S., & Hersh, E. D. (2017). ADGN: An Algorithm for Record Linkage Using Address, Date of Birth, Gender, and Name. *Statistics and Public Policy*, 4(1), 1–10. <http://doi.org/10.1080/2330443X.2017.1389620>
- Barr, C. D., Diez, D. M., Wang, Y., Dominici, F., & Samet, J. M. (2012). Comprehensive Smoking Bans and Acute Myocardial Infarction Among Medicare Enrollees in 387 US Counties: 1999–2008. *American Journal of Epidemiology*, 176(7), 642–648. <http://doi.org/10.1093/aje/kws267>
- Bergman, E., & Yates, P. A. (2011). Changing Election Methods: How Does Mandated Vote-By-Mail Affect Individual Registrants? *Election Law Journal: Rules, Politics, and Policy*, 10(2), 115–127. <http://doi.org/10.1089/elj.2010.0079>
- Berinsky, A. J. (2005). The Perverse Consequences of Electoral Reform in the United States. *American Politics Research*, 33(4), 471–491. <http://doi.org/10.1177/1532673X04269419>
- Burden, B. C. (2000). Voter Turnout and the National Election Studies. *Political Analysis*, 8(4), 389–398. <http://doi.org/10.1093/oxfordjournals.pan.a029823>
- Burden, B. C., & Kimball, D. C. (1998). A New Approach to the Study of Ticket Splitting. *The American Political Science Review*, 92(3), 533–544. <http://doi.org/10.2307/2585479>
- Burden, B. C., Canon, D. T., Mayer, K. R., & Moynihan, D. P. (2014). Election Laws, Mobilization, and Turnout: The Unanticipated Consequences of Election Reform. *American Journal of Political Science*, 58(1), 95–109. <http://doi.org/10.1111/>

ajps.12063

- Bureau, U. C. (2010). US Census Bureau QuickFacts: Colorado. Retrieved from <https://www.census.gov/quickfacts/co>
- Deufel, B. J., & Kedar, O. (2010). Race And Turnout In U.S. Elections Exposing Hidden Effects. *Public Opinion Quarterly*, 74(2), 286–318. <http://doi.org/10.1093/poq/nfq017>
- Edelman, G., & Glastris, P. (2018). Analysis Letting people vote at home increases voter turnout. Here’s proof. *Washington Post*. Retrieved from https://www.washingtonpost.com/outlook/letting-people-vote-at-home-increases-voter-turnout-heres-proof/2018/01/26/d637b9d2-017a-11e8-bb03-722769454f82_story.html
- Edlin, A., Gelman, A., & Kaplan, N. (2007). Voting as a Rational Choice: Why and How People Vote To Improve the Well-Being of Others. *Rationality and Society*, 19(3), 293–314. <http://doi.org/10.1177/1043463107077384>
- Fowler, J. H. (2006). Habitual Voting and Behavioral Turnout. *Journal of Politics*, 68(2), 335–344. <http://doi.org/10.1111/j.1468-2508.2006.00410.x>
- Gelman, A., & Hill, J. (2006). *Data Analysis Using Regression and Multi-level/Hierarchical Models* (1 edition). Cambridge ; New York: Cambridge University Press.
- Gerber, A. S., Huber, G. A., & Hill, S. J. (2013). Identifying the Effect of All-Mail Elections on Turnout: Staggered Reform in the Evergreen State[*](#). *Political Science Research and Methods*, 1(1), 91–116. <http://doi.org/10.1017/psrm.2013.5>
- Geys, B. (2006). Explaining voter turnout: A review of aggregate-level research. *Electoral Studies*, 25(4), 637–663. <http://doi.org/10.1016/j.electstud.2005.09.002>
- Gronke, P., & Miller, P. (2012). Voting by Mail and Turnout in Oregon: Revisiting Southwell and Burchett. *American Politics Research*, 40(6), 976–997. <http://doi.org/10.1177/1532673X12457809>
- James, G., Witten, D., Hastie, T., & Tibshirani, R. (2017). *An Introduction to Statistical Learning: With Applications in R* (1st ed. 2013, Corr. 7th printing 2017 edition). New York: Springer.
- Keele, L., & Titiunik, R. (2017). Geographic Natural Experiments with Interference: The Effect of All-Mail Voting on Turnout in Colorado.
- Matsusaka, J. G., & Palda, F. (1999). Voter turnout: How much can we explain? *Public Choice*, 98(3-4), 431–446. <http://doi.org/10.1023/A:1018328621580>
- Neiheisel, J. R., & Burden, B. C. (2012). The Impact of Election Day Registration on

-
- Voter Turnout and Election Outcomes. *American Politics Research*, 40(4), 636–664. <http://doi.org/10.1177/1532673X11432470>
- Plutzer, E. (2002). Becoming a Habitual Voter: Inertia, Resources, and Growth in Young Adulthood. *The American Political Science Review*, 96(1), 41–56. Retrieved from <https://www.jstor.org/stable/3117809>
- Richey Sean. (2008). Voting by Mail: Turnout and Institutional Reform in Oregon*. *Social Science Quarterly*, 89(4), 902–915. <http://doi.org/10.1111/j.1540-6237.2008.00590.x>
- Robert Nay. (2002). The Help America Vote Act of 2002.
- Smets, K., & Ham, C. van. (2013). The embarrassment of riches? A meta-analysis of individual-level research on voter turnout. *Electoral Studies*, 32(2), 344–359. <http://doi.org/10.1016/j.electstud.2012.12.006>
- Stein, R. M., & Vonnahme, G. (2008). Engaging the Unengaged Voter: Vote Centers and Voter Turnout. *The Journal of Politics*, 70(2), 487–497. <http://doi.org/10.1017/S0022381608080456>