Biased polls and the psychology of voter indecisiveness

Joshua J Bon, Timothy Ballard, and Bernard Baffour

Abstract

Accounting for undecided and uncertain voters is a challenging issue for predicting election results from public opinion polls. Undecided voters typify the uncertainty of swing voters in polls but are often ignored or allocated to each candidate in a simplistic manner. Historically this has been adequate because first, the undecided tend to settle on a candidate as the election day draws closer, and second, they are comparatively small enough to assume that the undecided voters do not affect the relative proportions of the decided voters. These assumptions are used by poll authors and meta-poll analysts, but in the presence of high numbers of undecided voters these static rules may bias election predictions. In this paper, we examine the effect of undecided voters in the 2016 US presidential election. This election was unique in that a) there was a relatively high number of undecided voters and b) the major party candidates had high unfavorability ratings. We draw on psychological theories of decision making such as decision field theory and prospect theory to explain the link between candidate unfavorability and voter indecisiveness, and to describe how these factors likely contributed to a systematic bias in polling. We then show that the allocation of undecided voters in the 2016 election biased polls and meta-polls in a manner consistent with these theories. These findings imply that, given the increasing number of undecided voters in recent elections, it will be important to take into account the underlying psychology of voting when making predictions about elections.
Introduction

Timely and accurate polls are crucial to describing current political sentiment and trends. Whilst no one poll will be sufficiently precise to enable reliable election predictions, combining the results of many pre-election polls has traditionally been viewed as a way to provide accurate forecasts. However, bias at the level of the individual poll can produce systematic error in aggregate results. One import source of polling bias arises from undecided voters. In the 2016 US presidential election, a large share of voters remained indecisive up until election day. When large in number, likely voters uncertain in their candidate preferences have the power to determine tight elections. Most polling firms deal with undecided voters using deterministic allocation methods, the most popular being proportional or equal allocation. However, these methods fail to account for the psychological factors at play whilst people are deciding between candidates, and therefore may be systematically biased in their assumptions about undecided voters.

In this paper, we investigate the impact of undecided voters in the 2016 US presidential election. We begin by providing background information on surveys, election polling, and undecided voters. We introduce the data on national undecided voter levels and unfavorability of presidential candidates, and the state-level polling data used in our analysis. We then motivate our analysis by comparing undecided voters and candidate unfavorability data in previous presidential elections to levels in 2016. We draw on psychological theories of decision making to explain the link between candidate unfavorability and voter indecisiveness, and to describe how these factors likely contributed to a systematic bias in polling that underestimated the extent to which undecided voters would eventually prefer Donald Trump. We then use statistical procedures to decompose the sources of bias in US presidential elections from 2004 onwards. We show that bias in the 2016 US presidential election is critically higher than in the previous presidential elections, and this increase in
bias can be accounted for by the high levels of undecided voters. Finally, we discuss our conclusions and recommendations from this work.

**Surveys, election polling and undecided voters**

*Surveys and election polling*

The accuracy (or lack thereof) of public opinion surveys\(^1\) and election polls has received substantial attention in recent years. All public opinion surveys are predicated on the assumption that citizens possess well developed attitudes on major political issues, and that surveys are passive measures of these attitudes (Converse and Traugott 1986, Zaller and Feldman 1992). In practice however, surveys may fail to adequately capture the sociological complexity around voting decisions and behavior (Crossley 1937, Gelman and King 1993, Jacobs and Shapiro 2005, Hillygus 2011). Increasingly, modern public opinion surveys also have to cope with challenges from declining response rates (Keeter, et al. 2000, Tourangeau and Plewes 2013, PRC 2012) combined with difficulties in achieving complete coverage of the population (Jacobs and Shapiro 2005, Traugott 2005, Leigh and Wolfers 2006, Erikson and Wlezien 2008). Robust evidence has demonstrated that the role of statistical uncertainty in the opinion polls has not been adequately understood (Martin, et al. 2005, Sturgis, et al. 2016, Hillygus 2011, Graefe 2014) and a failure to fully reflect this uncertainty leads to an over-statement of confidence level in predictions from survey results (Erikson and Wlezien 2008, Rothschild 2015, Lock and Gelman 2010).

There are a number of factors that influence this uncertainty in election polls. First, although polls play an important role in the democratic process it is becoming increasingly difficult to measure voting intention (Curtice and Firth 2008, Keeter and Igielnik 2016). Relatedly, there are differences between voting intentions and voting behavior (Wlezien, et al. 2013, Hopkins 2016).

---

\(^1\) We use the term survey as opposed to poll to indicate the generality of these statements.
2009, Veiga and Veiga 2004, Jennings and Wlezien 2016). It is also generally agreed that survey respondents will not be fully representative of the entire voting public. Finally, the disparities in the population result in differences in voter behavior by geography, ethnicity, social class, gender and age, which effectively exacerbates the level of uncertainty when it comes to generalizing from the sample survey to the broader population.

From this perspective, gaining a deeper understanding of the mechanisms that affect the accuracy of polls will provide valuable insights into obtaining better calibration and efficiency of individual polls and the models derived from them.

Undecided voters and election polling

Pre-election polls are typically conducted based on random sampling of likely voters who are asked their preference among the presidential candidates. Most polls record the percentage of voters who are undecided\(^2\), however dealing with this category is a challenge for prediction models (Hillygus 2011, Hoek and Gendall 1997).

To begin, we define undecided voters as individuals that are likely to vote but who have not formed a voting intention when surveyed prior to election day. Whilst similar to Kosmidis and Xezonakis (2010) our definition is restricted to likely voters as most election polls make adjustments to report results only for this group (Sturgis, et al. 2016).

Many rule-based methods have been proposed to handle undecided voters in elections (Crespi 1988, Daves and Warden 1995, Fenwick, et al. 1982) however some findings have indicated that various assignment methods may not improve forecast accuracy (Hoek and Gendall 1997). Simple rules for allocating undecided respondents may be adequate if the undecided voters are small in number but it is hard to accept use of these simple rules when there are

\(^2\) Which is not to say they always report the level on undecided voters.
relatively high numbers of undecided voters, as there are likely to be underlying causes and they have a greater chance of affecting the election outcome. Additionally, any deterministic rule will not allow for variability of allocations to be modelled in predictive outcomes, which may be problematic. Limited research into the impact of undecided voter allocation on election poll modelling still leaves many questions about the role of indecisive voters in election polling.

The effect of undecided voters on the assessment of predictive accuracy of election poll has been considered (Mitofsky 1998, Hoek and Gendall 1997, Visser, et al. 2000, Martin, et al. 2005). But the overall focus in this research has been on treatment of undecided voters so that consistent accuracy measures can be defined, rather than how the allocation assumptions impact the bias of polls. Visser, et al. (2000) state that there is little published “collective wisdom” on undecided voters and better guidelines are needed, especially since excluding undecided voters was the least effective strategy in their analysis.

Investigation into undecided voter behavior has occurred mostly in the context of election campaign assessment. For example, in US and Canada, voters who decide last minute may be more open to persuasion (Chaffee and Rimal 1996, Fournier, et al. 2004), and in the 2005 British elections, Kosmidis and Xezonakis (2010) concluded that perceived economic competence was a larger driver for the behavior of undecided voters. However, for election outcome modelers, little can be said on the correct treatment of undecided voters for election predictions. Most notably, imputing candidate preferences for undecided voters has been found to be somewhat beneficial in Fenwick, et al. (1982) whilst more recently Nandram and Choi (2008) proposed a Bayesian allocation. However evidence predictive benefits to US presidential elections is not yet clear. We show that more sophisticated evaluation of undecided voters will be necessary for accurate predictions of future US presidential election outcomes.
Meta-analysis of polls

Any one poll will be a snapshot of the sample collected, fraught with difficulties pertaining to sampling design, non-representativeness, and differences in methodological assumptions. For this reason, a single poll should be interpreted cautiously, even more so in situations when there is little previous experience to draw upon, for example in a referendum or, arguably, the 2016 US presidential election. Nonetheless, polling results from various sources can be compiled, compared, analyzed and then interpreted using meta-analysis techniques to combine (or pool) together different polls.

Meta-polls and poll modelling can compensate for the bias and inaccuracy of individual polls, but establishing well-calibrated models require understanding the inherent problems in polls, and defensible model assumptions. In election polling, deterministic (rule-based) allocation of undecided voters is widespread (Crespi 1988, Visser, et al. 2000, Martin, et al. 2005). These methods are appealingly simple and create a consistent set of data when polling organizations do not publish the number of undecided or third party voters. Undecided voters can be allocated (explicitly or implicitly) in a number of ways (Martin, et al. 2005, Mitofsky 1998). The most prevalent of these techniques are:

1. Splitting the undecided voters proportionately between the two leading candidates. This is equivalent to discarding the undecided voters and normalizing the two leading candidate’s voter proportions, and

2. Allocating half of the undecided voters to each of the leading candidates. This is equivalent to only reporting the margin between the two leading candidates.

Identifying the allocation procedures that polling firms use (if they do not report undecided voters) is difficult because they are averse to providing more information than necessary in
their commercial setting. Some meta-pollsters have published how they handle undecided voters in their models for at least the 2016 election³.

Meta-analysis of polls is crucial to obtaining reliable predictions for elections, however, it is very difficult for these models to account for systematic bias in polls. Investigating the role of undecided voters in polling bias will help to control one aspect that contributed to larger bias in the 2016 presidential election, which may occur again. Furthermore, considering psychological mechanisms that account for the voter behavior observed during the 2016 election will provide a direction for modeling in future elections.

**Data**

We examine the extent to which 2016 was an abnormal election year by considering a) the number of undecided voters, and b) the perceived unfavorability of the candidates relative to previous years. To investigate the extent to which the number of undecided voters in the 2016 election was unusual we compare national polling data in US presidential elections from 2004 onwards, totaling 616 national polls. Polls from 2012 and 2016 were obtained from the Huffington Post’s Pollster API (HP 2016, Arnold and Leeper 2016), data for 2008 were retrieved from an archived version of “Pollster.com” (HP 2009), and data from 2004 were reconstructed⁴ with polls available from RealClearPolitics (RCP 2004). Only publicly available polls with an undecided category and a sample size reported were used. Polling data that included an undecided voter category (even if implicit) in election years prior to 2004 were not found.

---

³ FiveThirtyEight split undecided evenly between the major-party candidates (Silver 2016), as did the Princeton Election Consortium implicitly when they use the margin between the two leading candidates (PEC 2016) for example. By contrast, the Huffington Post assumed (HP 2016) “one-third of undecided voters won’t vote; one-third will gravitate nationally toward either candidate; and the remaining one-third will add to this state’s margin of error”.

⁴ All polls that reported a third party candidate, but did not sum to 100% of the sample, were considered to have an undecided category of the remaining proportion.
The data used to assess the unfavorability of 2016’s candidates relative to previous candidates were extracted from Huffington Post (HP 2016) except for McCain 2008 data which was not available from this platform and was instead obtained from RealClearPolitics (RCP 2008). In total 506 polls were used. Polls of candidate’s favorability prior to 2008 could not be found.

State level polling data from 2004 to 2016 are used to model election polling bias and variance. The polls for 2012 and 2016 were obtained from Huffington Pollster (HP 2016) and state level polls for 2004 and 2008 were retrieved from US Election Atlas (Leip 2008) and occurred up to 35 days prior to respective elections. Whilst other poll repositories exist for 2004 and 2008 state-level election polling data, none consistently reported undecided voter counts. In total 2,044 state-level polls were analyzed.

**Was 2016 an abnormal presidential election year?**

*Comparison of undecided voters in US Presidential Elections*

Undecided voters were much higher during the 2016 US presidential election relative to previous years. Figure 1 shows the moving average number of undecided voters over the course of presidential elections from 2004 to 2016. It can be seen that the year 2016 had a larger number of undecided voters on average and that this trend was persistent over the course of the campaign. Whilst 2016’s pattern of undecided voters over time was similar to that of 2012, during the final week of polling the undecided voters did not continue to fall. It also appears that the 2004 and 2012 elections followed a similar pattern, however the extra variability in the 2004 election may be explained by lower numbers of polls and the reconstruction that took place. In the week prior to each election the weighted average of undecided voters was 5.1%, 3.5%, 3.9%, and 2.7% for 2016 to 2004 respectively.
Figure 1: Mean level of undecided voters, as captured by national polls, over the 90 days prior to US presidential elections from 2004 to 2016. The number of undecided voters on each day $x$ is the weighted average from national polls that occur within a two-week window centered at $x$.

The distribution of undecided voters in the months leading up to the elections also appear to vary over time, as seen in Figure 2. The undecided voters in 2016 and 2008 have relatively fatter tailed distributions, whilst the 2012 and 2004 elections appear to be centered between 3-4%. Undecideds voter levels higher than 10% occurred more frequently in the 2016 election than 2012 and 2004, and somewhat more frequently than in 2008. The similarities of 2016 and 2008 as well as 2012 and 2004 may be partially attributable to the nature of the elections in these years; the absence or presence of incumbent candidates, but this is difficult to infer from only 4 elections.
The levels of undecided voters in 2016 had an unusually high in mean, a larger tail in the distribution, and did not keep decreasing in the week prior to the election. This finding motivates an investigation of the effect of undecided voters on polling, and the potential causes for larger than usual numbers in this group during the 2016 US presidential election.

Figure 2: Histogram of undecided voters, as captured by national polls, over the course of 3 months prior to the US presidential elections 2004-2016. Each bar is relative to the number of polls from that year.

Comparison of candidate unfavorability in US Presidential elections

As we demonstrate, a defining characteristic of the 2016 US presidential election was the considerable unfavorability of both major-party candidates. Favorability ratings are a widespread public opinion tool often used to gauge the public’s sentiment toward politicians. Favorability questions in surveys generally ask respondents to rate a politician on some
favorability scale\footnote{Favorability scales may include answers such as: “very favorable”, “mostly favorable”, “neutral”, “mostly unfavorable”, and “very unfavorable”. They can also include “undecided”, “have not heard of”, or “refused”.}. We use aggregated sample proportions from each poll who respond negatively to a candidate, for example the sum of responses “mostly unfavorable” and “very unfavorable”.

In Figure 3 the unfavorability of presidential candidates in the 2008, 2012, and 2016 are displayed as a moving average in the 3 months prior to their respective elections. Compared to 2012, Donald Trump is 10% more than unfavorable than Mitt Romney on average, whilst Hillary Clinton is around 8% higher than Barack Obama. In the lead up to the 2016 election Trump and Clinton are both rated unfavorable by more than 50% of the people surveyed on average. The unfavorability of 2016’s candidates when compared to 2008’s is even starker. Clinton is around 15% more unfavorable than Obama 2008 throughout the 90 day election lead up. Further, Trump is around 18% more unfavorable than John McCain in the 30 days prior to the election but at times is over 30% more unfavorable.
The psychology of the undecided voter

The analysis presented above reveals that, compared to previous US elections, more people during the 2016 election campaign viewed the candidates as unfavorable and were undecided about for whom to vote. In this section, we use psychological theories of decision making to explain the link between candidate unfavorability and voter indecisiveness, and to describe how these factors likely contributed to a systematic bias in polling.

Candidate Unfavorability leads to Voter Indecisiveness

According to psychological theories of decision making, there is a link between unfavorability and indecisiveness. Psychologically speaking, choices between unfavorable
options (e.g., finding the better of two evils) take longer and result in more deliberation and indecisiveness than choices between favorable options. This has been observed in numerous empirical studies (Busemeyer and Townsend 1993, Houston, et al. 1991). Decision field theory (DFT) (Busemeyer and Townsend 1993) provides a formal explanation for this process. DFT assumes that people make decisions by sampling, one at a time, the consequences of choice options. The person’s preference for an action develops over time as he or she considers different consequences. This process continues until the preference for one action is strong enough that it breaches a threshold. The threshold represents the strength of preference required before one commits to a choice. Once this threshold is breached, the deliberation process terminates and the choice is executed. This process, referred to as sequential sampling, is one of the most widely accepted and successful accounts of the decision process (Brown and Heathcote 2008, Donkin, et al. 2011, Ratcliff and McKoon 2008, Usher and McClelland 2001).

According to DFT, when deciding between favorable options, preference for an option accelerates as it moves toward the decision threshold. In this case, the decision process is self-reinforcing. As the person gets closer to committing to a choice option, the desirable consequences of choosing that option become more salient, which leads the person to prefer that option even more strongly. As a result, the decision process terminates quickly. When deciding between unfavorable options, preference for an option slows down as it approaches the threshold. In this case, the deliberation process is self-negating. As the person gets closer to committing to a choice option, the undesirable consequences of that option become more salient, which leads to hesitation and a reduction in preference for that option. As a result, the person oscillates between options and the decision process takes a long time to terminate. The psychology of decision making therefore has clear implications for the link between candidate favorability and voter indecisiveness. When candidates are relatively unfavorable,
there should be more undecided votes than when candidates are favorable. The predictions of decision field theory are consistent with the findings of Lavine (2001), who showed that ambivalence (i.e., having negative as well as positive reactions to candidates) delayed the formation of voter intentions.

*Candidate Unfavorability leads Undecided Voters to Prefer High Risk Candidates*

Having established that unfavorable candidates lead to voter indecisiveness, it’s important to consider what factors influence the outcome of the decision process. As discussed, standard allocation methods generally assume that either 1) undecided voters have an equal chance of choosing either leading candidate or 2) the chance of choosing a candidate is proportional to the percentage of survey respondents who have indicated a preference for that candidate. However, these methods do not take into account factors that psychological theories of decision making suggest are highly influential. Prospect theory (Kahneman and Tversky 1979), another highly influential theory of decision making, suggests that choice behavior cannot be fully understood without considering the role of risk and uncertainty. According to this theory, a person’s attitude towards risk depends on whether the options being considered are desirable (which proponents of prospect theory refer to as gains) or undesirable (referred to as losses). When people are deciding between desirable options, they are risk averse. That is, they prefer courses of action with more certain outcomes. By contrast, when people are deciding between undesirable options, they are risk seeking. That is, they are more tolerant of courses of action that involve risk. This phenomenon is referred to as the *framing effect* and has substantial empirical support⁶.

Prospect theory highlights the important implications that candidate unfavorability has for voting behavior. The logic of the framing effect suggests that when people perceive

---

⁶ For review see (Edwards 1996).
candidates as relatively favorable, they should be more likely to vote for candidates for whom they have clear expectations. In other words, people should prefer candidates for whom they feel more certain about what the candidate will do once in office. However, when people perceive candidates as relatively unfavorable, they should be more likely to vote for candidates for whom they are less sure of what to expect. In other words, people should prefer candidates for whom they are less sure about what the candidate will do once in office, and therefore may be viewed as risky. Consider the recent US election, where both candidates were viewed as highly unfavorable. Hillary Clinton had a long track record as a politician, giving voters a reasonable degree of certainty. Donald Trump had no experience in politics, and could therefore plausibly be viewed as the risky choice. Consistent with prospect theory, voters demonstrated a stronger-than-anticipated preference for Trump. An important implication of the relationship between unfavorability, risk, and voting behavior is that the standard methods of allocating undecided voters are to be inappropriate, because they do not take into account the psychology of voting. To overcome the challenges discussed above, we need more sophisticated methods that are informed by psychological theories of decision making.

Methods

Assessing poll bias with the total survey error framework

We use a total survey error framework (Biemer 2010, Groves and Lyberg 2010) to analyse the polls from the US elections. As we are interested in ascertaining the impact of state-level influences, we consider each state-level election from each presidential election year to be a distinct election. With regard to modelling, henceforth an election refers to a state-level presidential election from an US election year, specifically, 2004, 2008, 2012 or 2016.
Under the total survey error framework, a survey error is defined as the deviation of a survey response from its true underlying value. This error can occur either through bias or variance (or precision). The bias term captures the systematic errors\(^7\) which are shared by all election polls, while the variance term captures the sampling variation due to different survey methodologies\(^8\) across the various polling organisations or simple random sample variance. Therefore, the poll error which is computed through comparing the election outcomes to the predictions from multiple election polls, can be decomposed into election level bias and variance terms. We adopt this framework to ensure that the analysis of undecided voters and their role in the bias is not conflated by non-sampling errors.

On the one hand, sampling errors arise from taking a sample rather than the whole population and are usually accounted for using standard survey sampling approaches\(^9\). On the other hand, non-sampling error is a catch-all term that refers to all other sources of error that are not a function of the sample chosen. In theory, although a specific poll estimate may differ from the true election outcome, under favorable repeated sampling conditions polls should produce reliable estimates (Assael and Keon 1982). However, in practice, it is well known that differences between poll results and election outcomes are only partially attributable to sampling error (Ansolabehere and Belin 1993). Most statistical procedures to compensate for non-sampling errors assume near universal (or high) response, but this is far from the norm: the majority of election surveys have less than 10% response rates (PRC 2012). Further, in polling there is a general difficulty in measuring voting intention and voting behaviour because polls measure what respondents beliefs and opinions are at the time of the survey, they cannot fully capture what respondents will do on election day (Bernstein, et al. 2001,

\(^7\) Systematic errors may be shared operational practices, infrastructure and sampling frames for example.  
\(^8\) Different survey methodologies may be proprietary software, statistical models and weighting adjustment procedures.  
\(^9\) For example post-stratification (Holt and Smith 1979), calibration (Deville and Särndal 1992), imputation (Gelman and Carlin 2002).
Silver, et al. 1986, Rogers and Aida 2014, Jowell, et al. 1993). Increasingly, efforts to mitigate against this can exacerbate the inaccuracy (Ansolabehere and Hersh 2012, Voss, et al. 1995, Gelman, et al. 2016, Bailey, et al. 2016). This is especially true when it comes to dealing with those who are undecided, either because they are truly undecided, or are hiding extreme voting preferences (Gerber, et al. 2013). The treatment of the group of polling responses that report to be undecided is therefore an important, yet relatively unstudied area of research.

*A Bayesian approach to total survey error incorporating undecided voters*

We use a meta-analytic approach to compare the estimates from the individual polls to the eventual election outcomes. This combines together information from the various polls to produce a pooled estimate for the differences between the state-election poll means and the election outcome – which is our ground truth. The modelling framework is based on the model proposed by Shirani-Mehr, et al. (2016). Their model, following standard practice in the literature, estimates the total survey error through estimating the vote share under a two-party preference, but does so excluding undecided voters. We extend their model to specifically include undecided voter proportions.

Since there are relatively few numbers of polls in some elections, taking a simple measure from the polls, such as root mean squared error, may yield imprecise estimates of the election-level bias. We address this by fitting a Bayesian hierarchical latent variable model (Gelman and Hill 2007). This method pools data to determine estimates of bias and variance in states with small numbers of polls, allows bias to vary over time, and better captures the variance in excess of that expected from a simple random sample. The model borrows strength across states and time to estimate smoothed within state trends of both polling bias and undecided voters in each election.
With small adjustments the notation in Shirani-Mehr, et al. (2016), each poll \( i \) is associated with an election denoted by the index \( r[i] \). Let \( p_i \) be the two party support\(^{10}\) for the Republican candidate of poll \( i \), \( n_i \) be the sample size, and \( t_i \) be the time at which the poll was conducted. The time \( t_i \) is the duration between the last day the poll was conducted and the relevant election date, and is scaled to be between 0 and 1. The Republican candidate’s final two-party vote outcome is denoted by \( v_r \). Each poll is assumed to be distributed by:

\[
p_i \sim N\left(v_{r[i]} + \alpha_{r[i]} + t_i \beta_{r[i]} + \sqrt{\frac{v_{r[i]}(1 - v_{r[i]})}{n_i}} + \tau_{r[i]}ight)
\]

(1)

where \( N \) denotes the normal distribution parametrized by mean and standard deviation. In this model the vote, \( v_r \), captures the true mean of the polls allowing election level bias to be estimated by \( \alpha_r + t_i \beta_r \). Bias on election day is simply \( \alpha_r \) and the time-varying bias coefficient is \( \beta_r \). As for the variance, \( \tau_r \) accounts for the excess deviation above what is expected in a simple random sample.

The model used is able to detect the bias in election polling at the state level by centring the model about the actual election outcome, whilst estimating the excess standard deviation by anchoring the model variance at the level expected from a simple random sample when the election outcome is known. Elections with few polls are estimated by pooling the data across elections using hierarchal priors.

By using two-party support the model implicitly assumes that undecided voters measured in polls are distributed proportionately to the major-party candidates. We relax this assumption by explicitly distributing the undecided voters in proportion but with flexibility. To illustrate,

\(^{10}\) Two party support meaning that proportionate allocation of the undecideds has been implemented.
take the Republican and Democratic support as measured in poll $i$, $R_i$ and $D_i$ respectively.

Scaling the polls to exclude third party candidates, we assume that

$$p'_i = \frac{R_i + \lambda U_i}{R_i + D_i + U_i}$$

(2)

where $0 \leq \lambda \leq 1$ allocates the undecided voters to the Republican candidate. Rather than using $\lambda = \frac{R_i}{R_i + D_i}$ or in other words proportionate allocation as is the case in model (1), we use

$$\lambda = \frac{R_i}{R_i + D_i} + \theta_i$$

(3)

where $\theta_i$ is an unknown bias (away from proportionate allocation) which occurs at some level (i.e. poll, election or election year). Simplifying equation (2) with (3) leads to the identity

$$p'_i = p_i + u_i \theta_i$$

where $p_i = \frac{R_i}{R_i + D_i}$, represents the Republican two-party vote share (excluding undecided voters) and $u_i = \frac{U_i}{R_i + D_i + U_i}$ represents the scaled proportion of undecided voters. This observation motivates changing model (1) to include undecided voters as an explanatory variable.

The term $\theta_i$ measures the bias away from a proportional two-party split. However, using poll-level undecided voters as an explanatory variable is problematic for two reasons; it is subject to measurement error and the level of undecided voters varies over time (see Figure 1). The latter issue may confound with estimates of the time-varying component of bias already in the model, $\beta_r^p$. 

19
To address these concerns we propose a model for the undecideds so that election day undecided voter levels can be included in model (1), rather than the undecided numbers from each poll. The model of the undecided voters is:

\[ u_i \sim \text{Normal}(\rho_{r[i]} + t_i \beta^u_{r[i]} + \eta_{y[i]} + \tau^u_{r[i]}) \]

(4)

where the election level mean, \( \rho_{r[i]} \), has election-year and state-level components in the form

\[ \rho_{r[i]} = \phi_{y[i]} + \alpha^u_{r[i]} \]

The index \( y[i] \) is for each US presidential election year from 2004 to 2016. The components \( \phi_{y} \) and \( \eta_{y} \) capture the election-year mean (on election day) and variance of the undecided voters, whilst \( \alpha^u_{r} \) and \( \tau^u_{r} \) account for the variation across state-level elections. The observed change in undecideds over time is estimated by \( \beta^u_{r} \). Finally the new polling model is given by:

\[ p_i \sim \text{Normal} \left( v_{r[i]} + \alpha^p_{r[i]} + t_i \beta^p_{r[i]} - \rho_{r[i]} \gamma_{y[i]} \sqrt{\frac{v_{r[i]}(1 - v_{r[i]})}{n_i}} + \tau^p_{r[i]} \right) \]

(5)

where \( \gamma_{y} \) has replaced \( \theta_i \) in (3) and is the bias attributable to mean undecided voters from each election-year. The \( \gamma \) coefficient is not estimated at the election level because of identifiability issues with \( \alpha^p_{r} \) which is retained for compatibility with model (1). In addition to accounting for measurement error, using (4) also allows polls that do not report undecided voters (i.e. they have missing data) to still be included in the model since only the state-level mean enters model (5). To ensure that the final inference is not substantially affected by the choice of prior, we specify weakly informative priors\(^{11}\), following Shirani-Mehr, et al.

\(^{11}\) The priors have the effect of pulling the estimates from the model from any given poll towards the average over all polls. However, the effect is related to the number of polls in the particular election year, and the
(2016), on the polling and undecided model mean and variance terms. The priors can be found in Table 3 in Appendix A.

**Results**

First, we compare our results from election years 2004 to 2016 with results obtained by Shirani-Mehr, et al. (2016) for 2000 to 2012 using the model specified in (1). In Table 1 the average absolute bias and election day bias\(^{12}\) are both considerably higher in 2016 than in the previous three election years. Both election polling bias quantities averaged at least 1.1% higher in 2016 than other years and had more than twice as much bias in the case of 2004 and 2008. The increased bias in 2016 can explain the increase to the overall 2004 – 2016 average bias compared to that of 2000 – 2012. The yearly averages reported in Shirani-Mehr, et al. (2016) are also consistent with the results in Table 1 (2004, 2008, and 2012).

Whilst bias in election polls in 2016 appeared to have played a large role in the abnormality of the 2016 election year’s polls, the average standard deviation appears to be consistent across time. The average standard deviation in 2016 was only 0.1% above the next highest year. This should not be considered a material difference given the range of values is only 2.1 to 2.4% from 2004 onwards. The consistency in average standard deviation over time lends strength to the conclusion that individual polls are subject to approximately twice as much standard deviation than what a simple random sampling calculation would suggest (Shirani-Mehr, et al. 2016).

\(^{12}\) See Appendix B for mathematical definitions.
Table 1: Average absolute bias and average standard deviation across state-election in given year(s) from model (1).

|                      | 2004 | 2008 | 2012 | 2016 | 2004–2016 | 2000–2012\(^{(a)}\) |
|----------------------|------|------|------|------|-----------|-------------------|
| Average absolute bias| 0.9% | 1.2% | 1.4% | 2.7% | 1.6%      | 1.0%              |
| Average absolute election day bias | 0.8% | 1.0% | 1.3% | 2.4% | 1.4%      | 1.0%              |
| Average standard deviation | 2.2% | 2.3% | 2.1% | 2.4% | 2.3%      | 2.2%              |

\(^{(a)}\) Results from identical model using data from 2000 to 2012 (Shirani-Mehr, et al. 2016)

Secondly, we examine the average results from the model including undecided voters in (5). This model includes an effect for the bias attributable to undecided voters on election day. The results from model (5) are presented in Table 2. The election level aggregation of undecided voters in model (5) predicts that there were between 3.1% and 3.8% undecided voters on election day between 2004 and 2012, whilst there were 5.5% in 2016. These results are consistent with Figure 1 which suggested much higher levels of undecideds in 2016 than previous years.

The average bias quantities in Table 2 are near identical regardless of whether the undecided bias component is included in the 2004 and 2008 elections. Since the posterior estimate for the effect of undecideds on bias (\(\gamma_y\)) is centered close to zero (see Figure 4) the role of undecided voters seems minimal in these years. In the 2012 election a small change occurs in the average absolute bias and election day bias when including or excluding the bias attributable to the undecided voters. The results from 2016 are most striking since the average absolute bias drops from 2.7% to 1.6% when excluding undecided voters and the average election day bias drops from 2.5% to 1.4%. Clearly undecided voters played an important role in the higher than expected bias in 2016 presidential election polls.
To further elicit the role of undecided voters in 2016, Figure 4 contains the 95% and 50% credible intervals of the effect size of undecided voters on the polling bias, $\gamma_y$. The credible intervals of $\gamma_y$ in election years 2004 to 2012 have a wide range which includes zero, indicating that the evidence for polling bias in these years is mixed (changing from state to state) or inconclusive. However the 95% credible intervals for 2016 range from 0.16 to 0.77 with a mean of 0.47. All things equal, this indicates that the level of undecided voters in each state contributed around half its value to the bias on average (centered on a proportionate allocation). In other words, a state undecided level of 4% led to a 2% contribution to the bias in favor of Trump.
Figure 4: Credible intervals of 95% (outer line) and 50% (inner line) for the effect of undecided voters on polling bias in the model ($\gamma_d$). A positive value indicates a bias away from proportional allocation of undecided voters in favor of the Republican candidate.

Figure 5 shows the distribution of state level average absolute bias from undecided voters on election day. This figure highlights the consequence of high numbers of undecided voters combined with their large biasing effect in 2016. We see clearly that across states in 2016 the effect of the undecideds contributed to between 2% and 3% on average whilst the overall effect of undecideds has been negligible in previous years. The low impact of undecided voters prior to 2016 is likely due to the relatively low levels observed, combined with the possibility that undecided voters did not bias polls cohesively in previous years.
Figure 5: Histograms of the average absolute bias from undecided voters for each state-level election, separated by year. The bias from undecided voters is the quantity $\rho r \gamma_y$ in the model. A positive value indicates a bias away from proportional allocation of undecided voters in favor of either candidate.

Discussion

While there have been methodological advances in election polling and modeling over time, perhaps due to the rapidly changing news cycle and the multi-faceted role of media, measuring public opinion is still difficult. As such, polls and meta-polls can be inaccurate. For example, polls have ‘failed’ to accurately predict winning candidates (according to the media) in several recent elections, such as the 2015 British election, the Scottish independence referendum, the Brexit referendum, the 2014 US House elections and the 2016 US presidential election. Our analyses revealed that one important source of bias in the polls
is undecided voters. Undecided voters biased polls in the 2016 US presidential election by 2-3% (all things being equal). This bias is particularly problematic given the increasing number of undecided voters observed in our analysis. We found that in 2016, 5.5% of voters were undecided on election day up from 3-4% in previous years. Others have also found that the percentage of voters who are undecided in the final week of an election campaign is high (up to 30% in some countries) and may be increasing (Irwin and Van Holsteyn 2008, Gelman and King 1993, Orriols and Martínez 2014). Given the rising prevalence of undecided voters, and the bias they may introduce to polling, more attention needs to be given to this group when predicting election outcomes.

It is well known within the survey research community that, polls suffer from both sampling (due to the fact that information has been collected from a sample rather than everyone in the population) and non-sampling (due to the fact that there is underlying differences in voting behavior and voting outcomes) errors. Statistical and operational adjustments compensate for sampling errors, but in reality it is the non-sampling errors that play a significant role in the discrepancies between the poll results and election outcomes. The total survey error approach provides a methodology for capturing both types of errors. We have used this approach to understand, interpret and report the various sources of error that in exist in election polling. We have focused specifically on undecided voters, and provide evidence that found that there was substantial differences in the degree of undecidedness in pre-election polling in the 2016 US election. Since the majority of polling agencies had no specific methodology to include this in their predictive models, the reported results over-estimated the lead of the Democratic candidate, Clinton, against the Republican candidate, Trump. Our results show that voters who were undecided at the time of being surveyed tended to behave differently to those who decided which party or candidate to vote for earlier. Although it is well recognized that undecided respondents contribute to polling error, there is no consensus about the inferences
that can be drawn from their data (Henderson and Hillygus 2016, Fenwick, et al. 1982, Hillygus 2011) but our research has demonstrated the impact a failure to adequately include them can lead to inaccuracies in polling predictions. We argue for probabilistic allocation of undecided voters in the future, so that this uncertainty can propagate through election models.

Our findings highlight the need to consider the psychology of decision making to make informed predictions about the behavior of undecided voters. High levels of perceived candidate unfavorability lead to greater indecisiveness, because voters oscillate back and forth between options over time, reluctant to commit to either candidate. When voters eventually make a decision, having unfavorable views of the candidates leads people to, all else being equal, prefer high risk options. Taken together, these psychological phenomena explain the higher-than-expected preference for Donald Trump in the 2016 US presidential election. They also explain why standard methods of dealing with undecided voters such as proportional or equal allocation were systematically biased against Donald Trump. Given the increase in voter indecisiveness over the last four US presidential elections, it will be important for polling firms to be aware of the underlying psychology of voter behavior when making predictions about elections.

Despite the novelty of our findings in ascertaining the role of undecided voters and the adoption of the total survey error framework, our analyses has some noteworthy limitations. Firstly, our models remain associational and only provide evidence to support the hypothesis that there is a relationship between the increase in undecidedness and polling accuracy. Properly understanding the underlying effects, and causal mechanisms surrounding how indecision directly influences election outcomes will require more complex psychological decision theory and models. Secondly, the factors that mediate the associations between voter decisions and election outcomes, particularly in the shifting landscape of what is being measured, remain admittedly broad. Despite the psychology of voting literature providing an
adequate explanation, more work is needed to fully incorporate this into a quantitative framework. Thirdly, though our modelling allows us to quantify the errors that are left unmeasured in standard election level estimates of accuracy, this does not yet translate to a model of how respondents will vote in future elections.

Undecided voters played a pivotal role in the 2016 US presidential election, contributing significantly to the bias observed in the polls. In light of the extensive literature surrounding decision theory it is not surprising that even or proportionate allocation failed to account for the voting decisions made by this group on election day. As stated, probabilistic allocation should be considered in future elections, but further investigation and validation of specific methods is needed especially considering the limited supplementary information provide by commercial polls.

References

Ansolabehere, Stephen, and Thomas R Belin. "Poll Faulting." *Chance* 6, no. 1 (1993): 22-28.
Ansolabehere, Stephen, and Eitan Hersh. "Validation: What Big Data Reveal About Survey Misreporting and the Real Electorate." *Political Analysis* 20, no. 4 (2012): 437-59.
Arnold, Jeffrey B., and Thomas J. Leeper. "Pollstr: R Client for Pollster Api. R Package Version 1.4.0." [https://cran.r-project.org/package=pollstr](https://cran.r-project.org/package=pollstr).
Assael, Henry, and John Keon. "Nonsampling Vs. Sampling Errors in Survey Research." *Journal of Marketing* 46, no. 2 (1982): 114-23.
Bailey, Michael A, Daniel J Hopkins, and Todd Rogers. "Unresponsive and Unpersuaded: The Unintended Consequences of a Voter Persuasion Effort." *Political Behavior* 38, no. 3 (2016): 713-46.
Bernstein, Robert, Anita Chadha, and Robert Montjoy. "Overreporting Voting: Why It Happens and Why It Matters." *Public Opinion Quarterly* 65, no. 1 (2001): 22-44.
Biemer, Paul P. "Total Survey Error: Design, Implementation, and Evaluation." *Public Opinion Quarterly* 74, no. 5 (2010): 817-48.
Brown, Scott D, and Andrew Heathcote. "The Simplest Complete Model of Choice Response Time: Linear Ballistic Accumulation." *Cognitive psychology* 57, no. 3 (2008): 153-78.
Busemeyer, Jerome R, and James T Townsend. "Decision Field Theory: A Dynamic-Cognitive Approach to Decision Making in an Uncertain Environment." *Psychological review* 100, no. 3 (1993): 432.

Chaffee, Steven H, and Rajiv Nath Rimal. "Time of Vote Decision and Openness to Persuasion." *Political persuasion and attitude change* (1996): 267-91.

Converse, Philip E, and Michael W Traugott. "Assessing the Accuracy of Polls and Surveys." *Science* 234, no. 4780 (1986): 1094-98.

Crespi, Irving. *Pre-Election Polling: Sources of Accuracy and Error*. Russell Sage Foundation, 1988.

Crossley, Archibald M. "Straw Polls in 1936." *Public Opinion Quarterly* 1, no. 1 (1937): 24-35.

Curtice, John, and David Firth. "Exit Polling in a Cold Climate: The Bbc–Itv Experience in Britain in 2005." *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 171, no. 3 (2008): 509-39.

Daves, Robert P, and Sharon Warden. "Methods of Allocating Undecided Respondents to Candidate Choices in Pre-Election Polls." *Presidential polls and the news media* (1995): 101-19.

Deville, Jean-Claude, and Carl-Erik Särndal. "Calibration Estimators in Survey Sampling." *Journal of the American Statistical Association* 87, no. 418 (1992): 376-82.

Donkin, Chris, Scott Brown, Andrew Heathcote, and Eric-Jan Wagenmakers. "Diffusion Versus Linear Ballistic Accumulation: Different Models but the Same Conclusions About Psychological Processes?". *Psychonomic bulletin & review* 18, no. 1 (2011): 61-69.

Edwards, Kimberley D. "Prospect Theory: A Literature Review." *International review of financial analysis* 5, no. 1 (1996): 19-38.

Erikson, Robert S., and Christopher Wlezien. "Are Political Markets Really Superior to Polls as Election Predictors?". *Public Opinion Quarterly* 72, no. 2 (2008): 190-215.

Fenwick, Ian, Frederick Wiseman, John F Becker, and James R Heiman. "Classifying Undecided Voters in Pre-Election Polls." *Public Opinion Quarterly* 46, no. 3 (1982): 383-91.

Fournier, Patrick, Richard Nadeau, André Blais, Elisabeth Gidengil, and Neil Nevitte. "Time-of-Voting Decision and Susceptibility to Campaign Effects." *Electoral Studies* 23, no. 4 (2004): 661-81.
Gelman, Andrew, and John B Carlin. "Poststratification and Weighting Adjustments." In *Survey Nonresponse*, edited by R. M. Groves, D. A. Dillman, J. L. Eltinge and R. J. A. Little. New York: Wiley, 2002.

Gelman, Andrew, Sharad Goel, Douglas Rivers, and David Rothschild. "The Mythical Swing Voter." *Quarterly Journal of Political Science* 11, no. 1 (2016): 103-30.

Gelman, Andrew, and Jennifer Hill. *Data Analysis Using Regression and Multilevel/Hierarchical Models.* Vol. 1, New York: Cambridge University Press, 2007.

Gelman, Andrew, and Gary King. "Why Are American Presidential Election Campaign Polls So Variable When Votes Are So Predictable?" *British Journal of Political Science* 23, no. 04 (1993): 409-51.

Gerber, Alan S, Gregory A Huber, David Doherty, Conor M Dowling, and Seth J Hill. "Who Wants to Discuss Vote Choices with Others? Polarization in Preferences for Deliberation." *Public opinion quarterly* 77, no. 2 (2013): 474-96.

Graefe, Andreas. "Accuracy of Vote Expectation Surveys in Forecasting Elections." *Public Opinion Quarterly* 78, no. S1 (2014): 204-32.

Groves, Robert M, and Lars Lyberg. "Total Survey Error: Past, Present, and Future." *Public opinion quarterly* 74, no. 5 (2010): 849-79.

Henderson, Michael, and D Sunshine Hillygus. "Changing the Clock the Role of Campaigns in the Timing of Vote Decision." *Public Opinion Quarterly* (2016): nfw027.

Hillygus, D. Sunshine. "The Evolution of Election Polling in the United States." *Public Opinion Quarterly* 75, no. 5 (2011): 962-81.

Hoek, Janet, and Philip Gendall. "Factors Affecting Political Poll Accuracy: An Analysis of Undecided Respondents." *Marketing Bulletin* 8 (1997): 1-14.

Holt, David T, and TM Fred Smith. "Post Stratification." *Journal of the Royal Statistical Society. Series A (General)* (1979): 33-46.

Hopkins, Daniel J. "No More Wilder Effect, Never a Whitman Effect: When and Why Polls Mislead About Black and Female Candidates." *The Journal of Politics* 71, no. 3 (2009): 769-81.

Houston, David A, Steven J Sherman, and Sara M Baker. "Feature Matching, Unique Features, and the Dynamics of the Choice Process: Predecision Conflict and Postdecision Satisfaction." *Journal of Experimental Social Psychology* 27, no. 5 (1991): 411-30.

HP, Huffington Post. "2016 President Forecast." [http://elections.huffingtonpost.com/2016/forecast/president](http://elections.huffingtonpost.com/2016/forecast/president)

———. "Pollster Api V2." [http://elections.huffingtonpost.com/pollster/api/v2](http://elections.huffingtonpost.com/pollster/api/v2).
Irwin, Galen A, and Joop JM Van Holsteyn. "What Are They Waiting For? Strategic Information for Late Deciding Voters." International Journal of Public Opinion Research 20, no. 4 (2008): 483-93.

Jacobs, Lawrence R., and Robert Y. Shapiro. "Polling Politics, Media, and Election Campaigns." Public Opinion Quarterly 69, no. 5 (2005): 635-41.

Jennings, Will, and Christopher Wlezien. "The Timeline of Elections: A Comparative Perspective." American Journal of Political Science 60, no. 1 (2016): 219-33.

Jowell, Roger, Barry Hedges, Peter Lynn, Graham Farrant, and Anthony Heath. "Review: The 1992 British Election: The Failure of the Polls." The Public Opinion Quarterly 57, no. 2 (1993): 238-63.

Kahneman, Daniel, and Amos Tversky. "Prospect Theory: An Analysis of Decision under Risk." Econometrica: Journal of the econometric society (1979): 263-91.

Keeter, Scott, and Ruth Igielnik. "Can Likely Voter Models Be Improved? Evidence from the 2014 U.S. House Elections." Pew Research Center, http://www.pewresearch.org/2016/01/07/can-likely-voter-models-be-improved/.

Keeter, Scott, Carolyn Miller, Andrew Kohut, Robert M Groves, and Stanley Presser. "Consequences of Reducing Nonresponse in a National Telephone Survey." Public opinion quarterly 64, no. 2 (2000): 125-48.

Kosmidis, Spyros, and Georgios Xezonakis. "The Undecided Voters and the Economy: Campaign Heterogeneity in the 2005 British General Election." Electoral Studies 29, no. 4 (12/ 2010): 604-16.

Lavine, Howard. "The Electoral Consequences of Ambivalence toward Presidential Candidates." American Journal of Political Science (2001): 915-29.

Leigh, Andrew, and Justin Wolfers. "Competing Approaches to Forecasting Elections: Economic Models, Opinion Polling and Prediction Markets." Economic Record 82, no. 258 (2006): 325-40.

Leip, Dave. "Atlas of Us Presidential Elections." http://uselectionatlas.org/.

Lock, Kari, and Andrew Gelman. "Bayesian Combination of State Polls and Election Forecasts." Political Analysis (2010): 337-48.

Martin, Elizabeth A, Michael W Traugott, and Courtney Kennedy. "A Review and Proposal for a New Measure of Poll Accuracy." Public Opinion Quarterly 69, no. 3 (2005): 342-69.
Mitofsky, Warren J. "Review: Was 1996 a Worse Year for Polls Than 1948?". *The Public Opinion Quarterly* 62, no. 2 (1998): 230-49.

Nandram, Balgobin, and Jai Won Choi. "A Bayesian Allocation of Undecided Voters." *Survey Methodology* 34, no. 1 (2008): 37-49.

Orriols, Lluis, and Álvaro Martínez. "The Role of the Political Context in Voting Indecision." *Electoral Studies* 35 (9// 2014): 12-23.

PEC, Princeton Election Consortium. "About Pec and the Meta-Analysis (Faq)." [http://election.princeton.edu/faq/](http://election.princeton.edu/faq/).

PRC, Pew Research Center. "Assessing the Representativeness of Public Opinion Surveys." [http://www.people-press.org/2012/05/15/assessing-the-representativeness-of-public-opinion-surveys/](http://www.people-press.org/2012/05/15/assessing-the-representativeness-of-public-opinion-surveys/).

Ratcliff, Roger, and Gail McKoon. "The Diffusion Decision Model: Theory and Data for Two-Choice Decision Tasks." *Neural computation* 20, no. 4 (2008): 873-922.

RCP, RealClearPolitics. "3-Way Race: Bush/Cheney Vs Kerry/Edwards Vs Nader/Camejo." [http://www.realclearpolitics.com/bush_vs_kerry.html](http://www.realclearpolitics.com/bush_vs_kerry.html)

Rogers, Todd, and Masahiko Aida. "Vote Self-Prediction Hardly Predicts Who Will Vote, and Is (Misleadingly) Unbiased." *American Politics Research* 42, no. 3 (2014): 503-28.

Rothschild, David. "Combining Forecasts for Elections: Accurate, Relevant, and Timely." *International Journal of Forecasting* 31, no. 3 (2015): 952-64.

Shirani-Mehr, Houshmand, David Rothschild, Sharad Goel, and Andrew Gelman. "Disentangling Bias and Variance in Election Polls." [www.stat.columbia.edu/~gelman/research/unpublished/pollposition_v2.pdf](http://www.stat.columbia.edu/~gelman/research/unpublished/pollposition_v2.pdf), 2016.

Silver, Brian D, Barbara A Anderson, and Paul R Abramson. "Who Overreports Voting?". *American Political Science Review* 80, no. 02 (1986): 613-24.

Silver, Nate. "A User’s Guide to Fivethirtyeight’s 2016 General Election Forecast." [https://fivethirtyeight.com/features/a-users-guide-to-fivethirtyeights-2016-general-election-forecast/](https://fivethirtyeight.com/features/a-users-guide-to-fivethirtyeights-2016-general-election-forecast/).

Sturgis, Patrick, Baker Nick, Callegaro Mario, Fisher Stephen, Green Jane, Will Jennings, Kuha Jouni, Lauderdale Ben, and Smith Patten. "Report of the Inquiry into the 2015 British General Election Opinion Polls." (2016).
Tourangeau, Roger, and Thomas J Plewes. *Nonresponse in Social Science Surveys: A Research Agenda*. National Academies Press, 2013.

Traugott, Michael W. "The Accuracy of the National Preelection Polls in the 2004 Presidential Election." *Public Opinion Quarterly* 69, no. 5 (2005): 642-54.

Usher, Marius, and James L McClelland. "The Time Course of Perceptual Choice: The Leaky, Competing Accumulator Model." *Psychological review* 108, no. 3 (2001): 550.

Veiga, Francisco José, and Linda Gonçalves Veiga. "The Determinants of Vote Intentions in Portugal." *Public Choice* 118, no. 3-4 (2004): 341-64.

Visser, Penny S, Jon A Krosnick, Jesse Marquette, and Michael Curtin. "Improving Election Forecasting: Allocation of Undecided Respondents, Identification of Likely Voters, and Response Order Effects." *Election polls, the news media, and democracy* (2000): 224-60.

Voss, D Stephen, Andrew Gelman, and Gary King. "A Review: Preelection Survey Methodology: Details from Eight Polling Organizations, 1988 and 1992." *The Public Opinion Quarterly* 59, no. 1 (1995): 98-132.

Wlezien, Christopher, Will Jennings, Stephen Fisher, Robert Ford, and Mark Pickup. "Polls and the Vote in Britain." *Political Studies* 61, no. 1 suppl (2013): 66-91.

Zaller, John, and Stanley Feldman. "A Simple Theory of the Survey Response: Answering Questions Versus Revealing Preferences." *American journal of political science* (1992): 579-616.

**Appendix A: Prior distributions for undecided voter analysis**

The priors used for the polling model, in Table 3, are identical to those from Shirani-Mehr, et al. (2016) expect for the undecided voter allocation, $\gamma_y$, which is new to the model. The prior probability distribution for $\gamma_y$ is weakly informative, centered on zero, with a large standard deviation (given that it represents is the bias for a proportional allocation) so that it has little influence on the posterior result. The priors from the polling model are duplicated for the undecided voter model where appropriate. This is reasonable because the undecided voter proportions (between approximately 0 and 0.2) are less variable and smaller in magnitude.
than the polling proportions (between approximately 0.1 and 0.9). The prior for the mean level of undecided voters in each year, $\phi_y$, is weakly-informative but centered on 0.04 since this value is close to the mean observed in Figure 1.

| Model    | Component | Prior                          | Hyper-prior                      |
|----------|-----------|--------------------------------|----------------------------------|
| Polling  | Mean      | $\alpha^p_r \sim \text{N}(\mu^p_\alpha, \sigma^p_\alpha)$ | $\mu^p_\alpha \sim \text{N}(0, 0.05)$, $\sigma^p_\alpha \sim N_+(0, 0.05)$ |
|          |           | $\beta^p_r \sim \text{N}(\mu^p_\beta, \sigma^p_\beta)$ | $\mu^p_\beta \sim \text{N}(0, 0.05)$, $\sigma^p_\beta \sim N_+(0, 0.05)$ |
|          |           | $\gamma_y \sim \text{N}(0, 0.5)$ |                                   |
|          | Variance  | $\tau^p_r \sim N_+(0, \sigma^p_r)$ | $\sigma^p_r \sim N_+(0, 0.02)$ |
| Undecided| Mean      | $\alpha^u_r \sim \text{N}(\mu^u_\alpha, \sigma^u_\alpha)$ | $\mu^u_\alpha \sim \text{N}(0, 0.05)$, $\sigma^u_\alpha \sim N_+(0, 0.05)$ |
|          |           | $\beta^u_r \sim \text{N}(\mu^u_\beta, \sigma^u_\beta)$ | $\mu^u_\beta \sim \text{N}(0, 0.05)$, $\sigma^u_\beta \sim N_+(0, 0.05)$ |
|          |           | $\phi_y \sim \text{N}(0.04, 0.02)$ |                                   |
|          | Variance  | $\tau^u_r \sim N_+(0, \sigma^u_r)$ | $\sigma^u_r \sim N_+(0, 0.02)$ |
|          |           | $\eta_y \sim \text{N}(0, 0.02)$ |                                   |

$N_+$ denotes the half-normal distribution.

*Table 3: Prior used in models for analysis of state polls.*

**Appendix B: Average bias quantity calculations**

The definitions of average bias quantities presented in Table 1, Table 2, and Figure 5 are taken from Shirani-Mehr, et al. (2016) where appropriate. Using the updated notation in this paper the average election-level polling bias from model (1) is given by

$$b_r = \frac{1}{|S_r|} \sum_{t \in S_r} (\alpha^p_r + t_i \beta^p_r)$$

where $S_r$ is the set of polls from state-level election $r$, and $|S_r|$ denotes the size of the set $S_r$.

This also represents the average election-level polling bias when excluding bias from undecided voters in model (5). When including undecided voters the bias is expressed as
$$b_r^u = \frac{1}{|S_r|} \sum_{i \in S_r} (\alpha_r^p + t_i \beta_r^p - \rho_r \gamma_y)$$.

Similarly, election day bias is defined with $t = 0$ so it is captured by $\alpha_r^p - \rho_r \gamma_y$ when including undecided voters and $\alpha_r^p$ otherwise. The term $\rho_r \gamma_y$ measures the bias attributable to the undecided voters in each election. The average absolute quantities of $b_r, b_r^u, \alpha_r^p$, and $\alpha_r^p - \rho_r \gamma_y$ can be calculated for a set of elections by taking the absolute value for each election and averaging.

The average election-level polling standard deviation is given by

$$\sigma_r = \frac{1}{|S_r|} \sum_{i \in S_r} \sqrt{\frac{v_r(1 - v_r)}{n_i} + \tau_r^p}$$.

and the average for a group of elections can be calculated based on these quantities.