**VOTE EXPECTATIONS VERSUS VOTE INTENTIONS**
**Rival Forecasting Strategies**[1]

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*Abstract:* Are ordinary citizens better at predicting election results than conventional voter intention polls? We address this question by comparing eight forecasting models for British general elections: one based on voters' expectations of who will win and seven based on who voters themselves intend to vote for (including "uniform national swing model" and "cube rule" models). The data come from ComRes and Gallup polls as well as the Essex Continuous Monitoring Surveys, 1950–2017, yielding 449 months with both expectation and intention polls. The large sample size allows us to compare the models' prediction accuracy not just in the months prior to the election, but over the years leading up to it. In predicting both the winning party and parties' seat shares, we find that vote expectations outperform vote intentions models. Vote expectations thus appear an excellent tool for predicting the winning party and its seat share.

*Keywords:* election forecasting, British Elections, opinion polls, prediction models, election surveys, uniform swing, cube rule

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**VOTE EXPECTATIONS VERSUS VOTE INTENTIONS: Rival Forecasting Strategies**

The 2015 and 2017 British general elections were closely watched, heavily handicapped, and poorly forecast. Regardless of their stripes, election prognosticators failed. Different approaches were followed – experts, markets, models, polls – but none yielded success. The most common strategy was to rely on the polls, particularly the current vote intention data. However, in a fashion similar to that of 1992, these numbers were woefully inaccurate in 2015 and 2017. The essential difficulty, similar to 1992, was correct prediction of support for the two main parties. As Fisher and Lewis-Beck (2016, 229) observed in the conclusion of their critical analysis: "polling data on 2015 vote intentions, which ought to come close to any election result, no matter how strange, led to serious forecasting error for the Conservatives and Labour."

A major forecasting issue for subsequent contests, then, involves the reduction of these polling errors. An accurate estimate of the vote share forms a requirement for almost all the forecasting methods used, because these methods count on a two-step process: first estimate the party vote share, then transform that estimate into a seat share, with the highest seat share estimate indicating the parliamentary winner. Such a procedure has two sources of error, one coming from the vote intention estimate, the other coming from the transformation of that estimate into seats. In a recent compendium of *ex ante* forecasting papers, written by a dozen academic teams investigating the 2015 election, only one forecast seats directly, thereby producing relatively more accurate seat share estimates for the Conservative and Labour parties (Fisher and Lewis-Beck 2016, Table 1; Murr 2016).

The method employed by Murr (2016) to forecast British seat shares utilised polling data, but based on *vote expectations* rather than *vote intentions*. This approach, which has been labelled "citizen forecasting," dispenses with an intention item, e.g., "If there were a general election tomorrow, which party would you vote for?" and replaces it with an expectation item, e.g., “Who do you think will win the next general election?” The citizen forecasting approach found its first British application, at the national level, in the 2010 general election (Lewis-Beck and Stegmaier 2011). Later, Murr (2011) applied it effectively, *ex post*, to the constituency level for the 2010 contest and, in another article, for prior contests (Murr 2016). Here, we test the hypothesis that, in general, vote expectations offer a better election forecasting instrument than vote intentions.

Why should vote expectations predict better than vote intentions? Murr (2017) and Leiter et al. (2018) argue that a big part of the answer lies in the fact that vote expectations include information from citizens’ social networks. The expectation item “who will win?” gives people a chance to report what they heard from family, friends, and “in the pub or on the bus” (King et al. 2000: 1f). Using a German survey, Leiter et al. (2018) find that characteristics of citizens’ social networks (size, political composition, and frequency of discussion) are among the most important variables when predicting their election forecasts. Since vote expectations carry information about the respondent and his/her social network, whereas vote intentions do so only about the respondent, vote expectations should predict better than vote intentions.

Below, we introduce the large monthly dataset we have assembled on vote expectations and vote intentions in Great Britain, across the election cycles 1950 to 2017. We present models for forecasting from these data, including those based on the “uniform national swing” (e.g., Fisher et al. 2011; Ford et al. 2016; Hanretty et al. 2016) and on the “cube rule” and its modifications (e.g., Whiteley 2005; Whiteley et al. 2011, 2016). Next, these estimation results are evaluated. Expectation models are consistently able to predict which party will win and the parties’ seat shares, clearly outperforming intention models. The implications are pursued, especially as they bear on prediction accuracy as distance from the election increases. For the expectations model, optimal lead time annually falls anytime within the two years before the election; its optimal lead time quarterly falls in the quarter before the election.

## 2. Previous research

Lewis-Beck and Skalaban (1989) and Lewis-Beck and Tien (1999) tested the simple hypothesis that voters in American presidential elections do better than chance when asked to forecast who would be elected president. Utilising responses to the American National Election Studies (ANES) item, "Who do you think will be elected President in November?" it was found that voters, in eleven elections, accurately forecast the presidential winner 71 percent of the time, an estimate statistically significant at $p < .001$ (Lewis-Beck and Tien 1999, 176).

These efforts were extended to the British case, first by Lewis-Beck and Stegmaier (2011), taking on what turned out to be the task of forecasting the "hung parliament" of the 2010 general election. Murr (2011) then took up the cudgel, continuing the exploration of citizen forecasting in Britain and – most noteworthy – doing so at the constituency level. He showed vote expectations for the winning party, as recorded in British Election Study constituency subsamples, to be accurate – even though disaggregated, small, and seemingly unrepresentative. [Murr (2015) goes on to show the same citizen forecasting ability within subsample constituencies (states) of American voters in the ANES.]

In the first study addressing whether citizen forecasting forecasts more accurately than vote intentions, Lewis-Beck and Tien (1999) compared the forecasting accuracy of citizen forecasts with vote intentions in US presidential elections. Despite the much longer lead time of citizen forecasts, Lewis-Beck and Tien (1999) found that citizen forecasts achieved a similar level of accuracy as the vote intentions. Later, Graefe (2014) expanded the comparison of forecasting approaches for US presidential elections to citizen forecasting, vote intentions, prediction markets, expert surveys, and quantitative models. In terms of forecasting the winner, he found that citizen forecasts were as good as quantitative models, but better than vote intentions, prediction markets, and expert surveys. In addition, in terms of forecasting the winner's vote share, he found that citizen forecasting had a lower mean absolute error. In other words, vote expectations were among the best – if not the best – approach to forecasting both the winner and the two-party vote share in US presidential elections.

Here we examine whether vote expectations are also better than vote intentions in forecasting election winners and seat shares of multiple parties in British parliamentary elections. Because of its many parties and the changing seats–votes ratio over time, the British case presents a more difficult test of the accuracy of vote expectations compared to the US.

In addition, we compare expectations and intentions not just in the 100 days before the election, but in the four years prior. To forecast is to tell of something in advance. The greater the lead time of an accurate forecast, the more impressive (Lewis-Beck 2005). Forecasts made a day before the election risk being trivial; forecasts made years before the election are daring. We hope to uncover accurate forecasts made systematically well before the election, certainly months before it.

**3. Methodology**

Below we describe the eight standard vote intention forecasting models of a party's seat share. These models fall into two groups, depending on how they translate intentions into seat share forecasts: either assuming a uniform national swing (e.g., Fisher et al. 2011; Fisher 2015, 2016; Ford et al. 2016; Hanretty et al. 2016; Wlezien et al. 2013) or relying on the "cube law" and its modifications (e.g., Whiteley 2005; Whiteley et al. 2011, 2016).

The uniform national swing (UNS) models assume that the change in a party's vote share from one election to the next (“swing”) is the same in every constituency (“uniform”). We identified five forecasting models based on the assumption of uniform national swing:

1. NAI: Intentions in a naïve UNS model (British Broadcasting Service and Guardian). This model takes a current vote intention poll as the national vote share forecast, derives the implied UNS to calculate a constituency vote share forecast, then forecasts that the party with the largest constituency vote share forecast will win the seat, and, finally, aggregates the forecast per party across constituencies.

2. NON: Intentions in a non-naïve UNS model (Fisher et al. 2011; Ford et al. 2016; Wlezien et al. 2013). This model proceeds as NAI except that it uses a regression model to forecast a party's national vote share, and then translates the implied constituency vote share into a probability of winning the constituency (Curtice and Firth 2008). The regression model includes the party's current vote intention poll.

3. GOV: Intentions and government status in a non-naïve UNS model (Fisher 2015, 2016). This model proceeds as NON except that the regression model also includes a dummy variable indicating whether the party is in government and the party's current vote intention poll.

4. LAG: Intentions and lagged vote share in a non-naïve UNS model (Fisher 2015, 2016) This model proceeds as GOV except that the regression model replaces government status by lagged vote share.

5. CHA: Intentions and change in vote share in a non-naïve UNS model (Fisher 2015, 2016; Hanretty et al. 2016). This model proceeds as LAG except that it regresses the change in a party's national vote share on the change in its vote intention poll relative to the previous national vote share.

The UNS models translate votes into seats via the previous constituency election results. Hence, these models can only be used when the constituency boundaries remain constant. By contrast, the next forecasting models can always be used as they forecast seats from votes directly.

The (modified) “cube law” forecasting model assumes a stable relationship between the vote and seat share across time:

6. LOG: Intentions, lagged seat share, and party split in a log-linear model (Whiteley 2005; Whiteley et al. 2011, 2016). This model regresses the logged seat shares on logged previous seat shares, the logged voting intentions for two parties, and a dummy variable indicating the split in the party system in 1983 and 1987.

We propose one forecasting model similar to the above vote intention models, but using vote expectations instead:

7. EXP: Expectations and lagged seat share in a linear model (Lewis-Beck and Stegmaier 2011). This model regresses the seat share on the previous seat share and the vote expectations for two parties.[2]

[2] Lewis-Beck and Stegmaier (2011) actually regress the winning party's seat share on the winning party's vote expectation; we generalise their model to all parties.

Our expectation model differs from the intention models used by others in more ways than just replacing expectations with intentions. Hence, to ensure that gains in accuracy between expectations and intentions do result from the different survey question, we also fit the forecasting model with intentions instead of expectations:

8. LIN: Intentions and lagged seat share in linear model. This model is the same as EXP except that it replaces vote expectations by vote intentions.

Detailed variable definitions and data sources are provided in Online Appendix 1. The eight forecasting models are presented in detail in Online Appendix 2.

The initial sample period for estimation was 1950 to 1983. The in-sample estimation procedure was ordinary least squares (with estimates presented in Online Appendix 3). We used the estimated models to generate forecasts for the out-of-sample election 1987 by plugging in values of the predictors. Then the 1987 election was added to the estimation sample, coefficients re-estimated, and a new set of forecasts was generated for 1992. We proceeded thusly, adding an additional election, re-estimating coefficients, generating out-of-sample forecasts for the next election, finally reaching the 2017 election.

We used two measures to judge the models' forecasts. First, we compare the forecast accuracy via correct prediction of winner (CPW): we calculate what proportion of forecasts correctly identified the party with most seats. Second, we compare the forecast accuracy via the mean absolute error (MAE) in seat shares.

## 4. Results

Table 1 presents the correct prediction of winner and the mean absolute error for the three forecasting models for all elections, and for the eight forecasting models for the elections with constant constituency boundaries. The first column contains the overall performance for each model, computed by averaging across all months. The remaining eight columns show the measures for each election, computed by averaging across all months in the relevant election.[3]

Looking first at the correct prediction of winner (CPW), we see that for all elections the proportion ranges from 50 to 80 percent overall and from 0 to 100 percent across election years. Overall, the EXP forecast is best, followed by the LIN forecast. The LOG forecast is last overall. The EXP forecast performs worse than the LIN forecast in one out of eight elections, the same in four, and better in three.

For elections with constant constituency boundaries, the proportion of CPW ranges from 41 to 100 percent overall and from 0 to 100 percent across election years. The EXP forecast is best overall, followed by the LAG forecast. The worst forecasts are by the LOG and NAI models. The EXP forecast performs the same as the LAG forecast in five of the six elections, and better in one.

Moving on to the mean absolute error (MAE) in seat shares, we see that for all elections the MAE ranges from 3.9 to 5.3 percent overall and from 0.8 to 10.8 percent across election years. Overall, the EXP forecast is best, followed by the LIN forecast. The LOG forecast is last overall. The EXP forecast is less accurate than the LIN forecast in two out of eight elections and more accurate in the remaining six.

For elections with constant constituency boundaries, the MAE ranges from 2.6 to 7.9 percent overall and from 0.8 to 10.8 across election years. The EXP forecast is best overall, followed by the GOV forecast. The worst forecasts are by the LAG and NAI models. The EXP forecast is more accurate than the GOV forecast in all five elections. [4]

[3] Tables 8 and 9 in Online Appendix 4 present the correct prediction of winner and whether or not the winner has an overall majority by election year and by time until election. The results are similar.

[4] Figures 1–3 in Online Appendix 5 supplement these results by graphing the three accuracy measures for every month of every election.

Table 1: Out-of-sample forecasting accuracy by election year.

| Model | Overall | 1987 | 1992 | 1997 | 2001 | 2005 | 2010 | 2015 | 2017 |
|---|---|---|---|---|---|---|---|---|---|
| **All elections** | | | | | | | | | |
| *Correct prediction of winner (in %)* | | | | | | | | | |
| Expectations (EXP) | 80 | 100 | 100 | 15 | 100 | 100 | 61 | 100 | 100 |
| Intentions (LIN) | 73 | 100 | 100 | 62 | 100 | 92 | 59 | 37 | 100 |
| Intentions (LOG) | 50 | 100 | 0 | 76 | 100 | 100 | 26 | 20 | 100 |
| *Mean absolute error (in %-points)* | | | | | | | | | |
| Expectations (EXP) | 3.9 | 0.8 | 2.0 | 12 | 1.5 | 2.1 | 2.2 | 5.0 | 2.0 |
| Intentions (LIN) | 4.9 | 1.4 | 1.8 | 11.2 | 3.3 | 5.7 | 2.3 | 8.6 | 3.6 |
| Intentions (LOG) | 5.3 | 1.8 | 4.0 | 10.5 | 1.1 | 4.1 | 4.0 | 8.7 | 1.3 |
| *N* | 230 | 42 | 36 | 34 | 7 | 13 | 46 | 46 | 6 |
| **Elections with constant constituency boundaries** | | | | | | | | | |
| *Correct prediction of winner (in %)* | | | | | | | | | |
| Expectations (EXP) | 100 | 100 | 100 | – | 100 | – | – | 100 | 100 |
| Intentions (LAG) | 85 | 100 | 100 | – | 100 | – | – | 54 | 100 |
| Intentions (GOV) | 84 | 100 | 94 | – | 100 | – | – | 57 | 100 |
| Intentions (CHA) | 84 | 100 | 100 | – | 100 | – | – | 52 | 100 |
| Intentions (LIN) | 79 | 100 | 100 | – | 100 | – | – | 37 | 100 |
| Intentions (NON) | 69 | 100 | 92 | – | 100 | – | – | 13 | 100 |
| Intentions (LOG) | 47 | 100 | 0 | – | 100 | – | – | 20 | 100 |
| Intentions (NAI) | 41 | 52 | 56 | – | 100 | – | – | 2 | 100 |
| *Mean absolute error (in %-points)* | | | | | | | | | |
| Expectations (EXP) | 2.6 | 0.8 | 2.0 | – | 1.5 | – | – | 5.0 | 2.0 |
| Intentions (GOV) | 3.8 | 2.4 | 2.8 | – | 2.4 | – | – | 5.9 | 5.2 |
| Intentions (LIN) | 4.1 | 1.4 | 1.8 | – | 3.3 | – | – | 8.6 | 3.6 |
| Intentions (NON) | 4.4 | 3.3 | 2.6 | – | 2.8 | – | – | 7.1 | 4.1 |
| Intentions (LOG) | 4.6 | 1.8 | 4.0 | – | 1.1 | – | – | 8.7 | 1.3 |
| Intentions (CHA) | 4.7 | 3.7 | 3.5 | – | 3.6 | – | – | 6.4 | 7.7 |
| Intentions (LAG) | 6.1 | 7.9 | 3.7 | – | 1.9 | – | – | 6.3 | 10.6 |
| Intentions (NAI) | 7.9 | 7.5 | 5.4 | – | 9.8 | – | – | 10.8 | 2.3 |
| *N* | 137 | 42 | 36 | – | 7 | – | – | 46 | 6 |

Expectations (EXP) = Expectations and lagged seat share in linear model
Intentions (LIN) = Intentions and lagged seat share in linear model
Intentions (LOG) = Intentions and lagged seat share in log-linear model
Intentions (LAG) = Intentions and lagged vote share in non-naïve UNS model
Intentions (GOV) = Intentions and government status in non-naïve UNS model
Intentions (CHA) = Intentions and change in vote share in non-naïve UNS model
Intentions (NON) = Intentions in non-naïve UNS model
Intentions (NAI) = Intentions in naïve UNS model
*N* = Number of survey months

## 5. Lead Time: Is there an Optimal Forecasting Distance?

A tension always exists between distance from the election, on the one hand, and accuracy, on the other hand. Conventional wisdom suggests that the closer the forecast to the election itself, the greater the accuracy. Table 2 shows the two accuracy measures for the forecasting models for the four years before the election, computed by averaging the relevant months across all elections. The year before the election is broken down into quarters.

In Table 2, we see that, generally, regardless of equation type or outcome measure, as the years until election decrease, the forecast gains in accuracy. Still, if the forecast comes on the heels of the election, it may be regarded as trivial. Lead time counts for quality forecasting. As Lewis-Beck (2005, 151) observed, "giving the forecast a full horizon, say six months to a year, allows for an impressive performance." Accepting that charge, we examine the results one year before the election, quarter by quarter. When we do so, the accuracy trend ceases to be monotonic downward. In particular, for the decisive dependent variable - correct prediction of the winner - the accuracy award goes to Q1 for EXP or Q3 for LIN, since both attain perfect scores.

With both EXP and LIN equally accurate, does one offer more optimality? An answer from practice comes via examination of what lead times UK forecasters have actually used. Nadeau, Lewis-Beck and Bélanger (2009) note that most UK analysts have used a two or three month lead. More recently, the median lead for the 12 forecasting teams facing the 2015 General Election was 22 days (Fisher and Lewis-Beck 2016). These field results, falling in the last quarter before the election, argue for the expectations measure (EXP) from Q1 over the intentions measure (LIN) from Q3. Further, the argument for LIN has a weak spot, given its forecasting power, oddly, deteriorates as the election approaches - by Q1 it registers only 83%. This perverse lead-accuracy trade-off may make it tough for some forecasters to decide on their modelling strategy. If they wish to increase their chances of being correct at last call, they best stick with the expectations model (and Q1). However, if they want to rely on a model with more lead, they might turn to the intentions model (and Q3).

Table 2: Out-of-sample forecasting accuracy in the quarters and years before the election.

| | | Quarters | | | | Years | | |
|---|---|---|---|---|---|---|---|---|
| Model | Overall | 1 | 2 | 3 | 4 | 2 | 3 | 4 |
| **All elections** | | | | | | | | |
| *Correct prediction of winner (in %)* | | | | | | | | |
| Expectations (EXP) | 80 | 100 | 93 | 88 | 87 | 86 | 67 | 74 |
| Intentions (LIN) | 73 | 83 | 93 | 100 | 93 | 79 | 61 | 59 |
| Intentions (LOG) | 50 | 67 | 80 | 69 | 67 | 53 | 43 | 34 |
| *Mean absolute error (in %-points)* | | | | | | | | |
| Expectations (EXP) | 3.9 | 3.9 | 3.3 | 3.2 | 3.5 | 3.4 | 4.5 | 4.3 |
| Intentions (LIN) | 4.9 | 4.7 | 4.5 | 4.3 | 4.7 | 4.6 | 5.3 | 5.2 |
| Intentions (LOG) | 5.3 | 4.8 | 5.0 | 4.7 | 4.8 | 5.1 | 6.1 | 5.4 |
| *N* | 230 | 12 | 15 | 16 | 15 | 57 | 54 | 61 |
| **Elections with constant constituency boundaries** | | | | | | | | |
| *Correct prediction of winner (in %)* | | | | | | | | |
| Expectations (EXP) | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Intentions (LAG) | 85 | 100 | 100 | 100 | 100 | 89 | 67 | 85 |
| Intentions (GOV) | 84 | 100 | 100 | 100 | 100 | 89 | 64 | 85 |
| Intentions (CHA) | 84 | 100 | 100 | 100 | 100 | 89 | 64 | 85 |
| Intentions (LIN) | 79 | 100 | 100 | 100 | 86 | 74 | 64 | 83 |
| Intentions (NON) | 69 | 100 | 71 | 88 | 57 | 63 | 58 | 76 |
| Intentions (LOG) | 47 | 83 | 86 | 62 | 43 | 40 | 36 | 46 |
| Intentions (NAI) | 41 | 83 | 29 | 38 | 14 | 29 | 24 | 66 |
| *Mean absolute error (in %-points)* | | | | | | | | |
| Expectations (EXP) | 2.6 | 2.2 | 2.8 | 2.7 | 2.6 | 2.4 | 2.7 | 2.8 |
| Intentions (GOV) | 3.8 | 2.8 | 2.8 | 3.3 | 3.6 | 4.2 | 4.1 | 3.7 |
| Intentions (LIN) | 4.1 | 3.4 | 3.6 | 3.2 | 4.0 | 4.1 | 4.6 | 4.1 |
| Intentions (NON) | 4.4 | 2.9 | 4.0 | 4.1 | 4.4 | 4.8 | 4.9 | 4.0 |
| Intentions (LOG) | 4.6 | 3.0 | 4.3 | 4.0 | 4.7 | 4.5 | 5.6 | 4.3 |
| Intentions (CHA) | 4.7 | 4.3 | 3.5 | 3.5 | 4.1 | 5.4 | 4.7 | 4.8 |
| Intentions (LAG) | 6.1 | 7.8 | 5.8 | 5.4 | 5.3 | 6.3 | 6.5 | 5.6 |
| Intentions (NAI) | 7.9 | 3.8 | 6.7 | 6.6 | 8.2 | 9.5 | 9.0 | 6.8 |
| *N* | 137 | 6 | 7 | 8 | 7 | 35 | 33 | 41 |

Abbreviations as in Table 1.

## 6. Conclusion

Election forecasting represents a lively enterprise in Western democracies, and Great Britain is no exception (Stegmaier and Norpoth 2017). Take the run-up to the 2015 general election, where different approaches – markets, models, and polls – were used. Yes, the big Conservative victory was unforeseen. This miss dealt a severe blow to the polling industry, where vote intention results were touted. Should this approach be forsaken, or does a polling alternative exist? We argue that the relatively neglected vote expectation polls are the answer. While vote intention carries information only about the citizen, vote expectation carries additional information about the citizen's social network (Murr 2017; Leiter et al. 2018).

Looking at over 400 monthly expectation-intention matches, 1950-2017, we observe that citizen forecasting outperforms traditional vote intention forecasts. As a recent piece of evidence, we can focus on the 2015 match, and the 48 months leading up to that contest. Over that period, vote intentions – in "uniform national swing" and "cube rule" models – called the election for the Conservatives only about half of the time, while vote expectations always did so. Moreover, vote expectations were consistently better, in terms of their seat share forecasts, over that time period.

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