A *Länder*-based Forecast of the 2017 German Bundestag Election

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Abstract

When elections are distant, polls are poor predictors. Too few voters are paying attention and too much can change before election day. Structural models can establish baseline expectations but suffer from high uncertainty and underspecification imposed by small samples. We present an early forecast of the 2017 Bundestag election results for individual parties that leverages economic and political data as well as state parliament (*Landtag*) election results in the German states (*Länder*) to sidestep these shortcomings. A linear random coefficients model provides our estimates. Länder elections are dispersed over the calendar and offer the advantage of capturing both actual voter preferences and new political issues. We argue that this approach offers a promising method for early forecasts when polls are not informative.

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1 Introduction

Unlike the United States and several other federal systems, state-level elections in Germany are scattered across the calendar. Each election garners national attention as a gauge of voter support, not only for the state (*Land*) government but for the national government in Berlin as well. We leverage these subnational elections to build a fundamentals-based (a.k.a., structural) forecast of the 2017 Bundestag election. Not only does this exercise offer a test of how predictive *Länder* elections actually are of national elections but it offers a means of circumventing two frequent shortcomings of fundamentals-based models: small samples due to the limited number of prior elections and an inability to capture changes that have occurred since the previous national election, usually multiple years prior.

The use of *Länder* elections in Germany at least partly addresses both of these shortcomings. *Länder* elections increase the number of observations (16-fold) and usually offer information temporally closer to each federal election than the previous federal election. Election polls and poll aggregates, may predict election outcomes more accurately shortly before elections, but this advantage diminishes and reverses as the time to the election increases (Erikson and Wlezien, 2012, 2014) and voters are paying less attention to parties and issues. Not only are fundamentals-based model superior predictors when elections are distant, however, but they also enjoy the advantage of actually forecasting. Although, the public often interpret polls and poll aggregates as forecasts (Blumenthal, 2014), they are better understood as snapshots in time.

Our forecast, estimated on March 1, 2017 to predict an election the 24th of September, will likely deviate farther from the actual outcome than polls taken close to the election. This should not, however, cast doubt on the value of structural models when elections are near. Because fundamentals-based forecasts, unlike polls, are based on theory and estimated on historical data, they serve an important function in setting expectations against which outcomes can be compared. By estimating a forecast model based on the relationship between prior elections and covariates, structural models are essentially predicting how an average candidate with an average campaign and opposition would fare in the predicted election. We establish one such expectation based on recent results in *Länder* elections, the expected levels of economic growth in the quarter prior to the election and other fundamentals. Our model, therefore, sets a benchmark against which the performance of parties can be evaluated.

While we contribute to the understanding of the 2017 election by setting expectations, we argue that our model also makes two contributions to the forecasting literature. First, we offer, to the best of our knowledge, the first forecast of national elections based on *Länder*-level data.[1] More precisely, we use, among other covariates, results from elections to the *Land*-level parliaments to fit a model on federal election results for each party in each of the *Länder* in all national elections since 1961. We then convert predicted state-level vote shares into votes, accounting for state turnout, and aggregate up to the national level. This exercise is already useful for investigating the empirical question, often raised in the German press, of how well state election results predict future national election outcomes.

There are also a number of reasons why a state-level analysis is useful for forecasting national elections in Germany. It provides us with more observations that, in turn, support more variables in our models but nevertheless lower the variable to observation ratio, implying that we are less likely to fit noise. More observations also provide more information, especially when they are distributed over the electoral calendar and can pick up events that have happened after the last national election.[2] Polling data, for instance on partisan identification (Kayser and Leininger, 2016) or the popularity of the chancellor (Norpoth and Gschwend, 2013), does this too to a certain extent. But unlike volatile opinion polls, additional information provided through state elections also reflects the actual voting behavior of actual voters. Moreover, as poll and forecast aggregators are keen to point

[1] Many scholars have used subnational units to forecast national outcomes in countries other than Germany – most notably presidential elections in the United States (for example, Campbell, 1992; Jerôme and Jerôme-Speziari, 2012; Linzer, 2013) but general elections in the United Kingdom (Rallings and Thrasher, 1999) as well – for many of the same reasons that we do. Germany, however, has the advantage of both dispersion across the electoral calendar and collective geographic coverage of the whole country.

[2] Although events that occur very late in an election cycle, such as the surge in popularity for the SPD after Martin Schulz became party leader might influence the last couple of state elections.

out, averaging over multiple (in our case, state-level) predictions attenuates out-of-sample forecast errors (Graefe, 2015) – even more so when, state elections are asynchronous and less likely to suffer from correlated errors.

Second, we also contribute to the literature by employing a multi-level model predicting outcomes for each party in each state. This decision builds on the realization that a single-equation model with a forecast of the outgoing coalition's voteshare would be of limited interest when the outgoing government was was grand coalition as is the case in 2017. We are not the first to forecast vote shares for individual parties in a German election – Jérôme, Jérôme-Speziari and Lewis-Beck (2013), for example, used a multiple-equation SUR model already in 2013 – but our model adds the advantage of estimates for multiple parties in each of the *Länder* with all of the advantages described above.

The previous German election cycle of 2013 saw a blossoming in what for a long time had been a relatively neglected field. The pioneering Chancellor model (Norpoth and Gschwend, 2013) was joined by structural models that employ German economic performance benchmarked against that of its neighbors (Kayser and Leininger, 2016) and multiple-equation models that forecast each party's vote share (Jérôme, Jérôme-Speziari and Lewis-Beck, 2013). Survey-based methods based on repondents' expected election outcomes (Ganser and Riordan, 2015) and poll adjustments for historic polling-house effects (Selb and Munzert, 2016) also emerged, as did several hybrid forecasts combining methods (e.g., Graefe, 2015; Küntzler, 2017). This new election cycle will hopefully spur similar innovation.

2 The model

We assembled a dataset of the state-level returns for all national as well state elections since 1961. This provides us with a panel dataset in which a party's result in a federal election in one of the 16 German states forms the unit of analysis. This is an unbalanced panel because not all parties campaigned in all elections in all states.[3] We focus on the *CDU/CSU*, *SPD*, *FDP*, *Bündnis*

[3]While the CDU/CSU, SPD and FDP competed in almost every national and state in every single state, the Green Party (*Bündnis 90 / Die Grünen*) and the Left Party

90/Die Grünen, *Die Linke/PDS* and a residual category *Others*. To predict the vote shares for these parties we estimate a linear random effects model, including random intercepts for states and parties.

Our model is composed of the following variables: the vote share a party obtained in the previous federal election, the vote share it obtained in the preceding state election, whether the chancellor was from that party at the time of the election, national quarterly GDP growth in the quarter preceding the election,[4] an interaction of these two variables, the number of years the chancellor has been in office, and an interaction with the chancellor's party dummy variable.

The inclusion of a party's vote share in the previous national election allows us to form a baseline prediction – we also use this variable by itself as a benchmark to assess the accuracy of our model. The inclusion of past outcomes effectively focuses the other predictors on changes from the previous vote share. We also include the vote share a party obtained in the preceding state election. State specific issues are of great importance in these contests and there are often quite substantial differences between a party's national and state result, although these diminish when one predicts national vote shares in each state, as we do. Nevertheless, vote shares in state elections are considered a thermometer for the popularity of the national government and the national opposition parties. This is particularly true when a federal election is looming.

We a code a dummy variable which indicates whether the current chancellor was from the given party. Consequently, it is only ever equal to 1 for the *CDU/CSU* and the *SPD*. Furthermore, we incorporate the growth rate of GDP in the quarter preceding the election compared to the same quarter of previous year, seasonally adjusted.[5] Growth is the main variable in

(*Die Linke*, formerly *PDS*) were only formed later. The Green party was founded in 1979 and competed in all national and most state elections since 1980. The Left Party formed in December of 1989, as *PDS*, competed in all national and East German state elections since then. After a merger with the *WASG* in 2007 it became *Die Linke* and since them competed in all state elections, also in West Germany.

[4]Some evidence suggests that real-time reports of economic performance, possibly because they are more reported in the media than later revised figures, can improve election forecasts (Kayser and Leininger, 2015). Time and data constraints preclude us from using them here.

[5]The data on growth rates from 1961 to 2016 and are from the OECD's Main Economic Indicators (MEI) database, predictions for 2017 were obtained from the consultancy Trading Economics.

	(1) Unweighted	(2) Weighted
Vote Share$_{t-1}$	0.541***	0.0995*
	(0.0279)	(0.0434)
Vote Share in Bundesland Election	0.382***	0.468***
	(0.0246)	(0.0736)
Chancellor's party	4.729***	8.695***
	(0.681)	(1.008)
GDP Growth	-0.00999	-0.0457
	(0.0419)	(0.0269)
Chancellor's party$\times$ Growth	0.249**	0.554**
	(0.0937)	(0.185)
Years in Office	0.0570	0.105*
	(0.0347)	(0.0453)
Chancellor's party $\times$ Years in office	-0.399***	-0.682***
	(0.0769)	(0.145)
Intercept	0.561	6.015***
	(0.332)	(0.988)
σ State: Voteshare in Bundesland election	4.31e-09	0.222***
	(.)	(0.0545)
σ State: Intercept	6.29e-08	2.749**
	(.)	(1.074)
σ Party$\times$State: Intercept	0.393	6.349***
	(.)	(0.938)
σ Residuals	3.828	2.401***
	(.)	(0.261)
N	872	872

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1: *Two multi-level election models. Model (2) is weighted so that state elections held on a date more closely approaching a federal election have more influence. Standard errors in parentheses.* * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the economic voting literature and has been successfully used for forecasting German elections before (e.g., in a benchmarked form, Kayser and Leininger, 2016). We interact the growth rate with the chancellor's party dummy because a responsibility for the state of the economy is primarily attributed to the head of government's party (Duch, Przepiorka and Stevenson, 2015).

We also include a count of the number of years that the chancellor at the time of the election has been in office to capture cost of ruling effects and interact it with the chancellor's party dummy.

Note that ours is a completely structural model which does not rely on any poll-based variables. We only make a small exception for the vote share in state elections. Due to differing term lengths[6] and four early federal elections[7] for some states for some federal elections there is no state election in-between two federal elections. In this case we impute the results from a state poll conducted at least six months prior to the federal election if such data is available.

3 Our forecast

We regress the vote share on our explanatory variables in a random effects model to obtain coefficient estimates which allow us to calculate the 2017 vote share of the five major parties and *Others* by plugging in up-to-date values for our explanatory variables. We estimate two models, an unweighted and weighted version, both of which are presented in table 1. The second model weights state elections closer to the federal election more heavily in order to pick up late-developing events.

All coefficients carry the expected sign. There is a strong positive correlation in a party's vote share over time. The same holds for state elections which postdate the preceding but pre-date the national election to be forecasted. A strong positive coefficient on the chancellor's party simply reflects the fact that in Germany one of the two larger parties always presents the chancellor. In addition, it may also reflect an incumbency advantage. The

[6] The term length at the federal level is four years while it is five years at the state-level in almost all states.

[7] 1972's re-election of Willy Brand in an early election following a lost vote of non-confidence in parliament, 1983's election confirming Helmut Kohl's chancellorship after he unseated social democrat Helmut Schmidt in a vote of no confidence, 1990's early election following re-unification and 2005's election after socialdemocrat Gerhard Schörder deliberately lost a vote of no confidence in parliament.

Party	Prediction	Prediction (weighted)	Feb. 2017 Polling	Pre-Schulz Poll
CDU/CSU	36.5 [35.5, 37.7]	34.8 [34.1, 35.5]	32.4	36
SPD	24.9 [24.4, 25.3]	26.6 [26.0, 27.2]	30.9	21
Die Linke/PDS	8.7 [8.3, 9.0]	9.3 [8.9, 9.7]	7.6	9
Bündnis 90/Die Grünen	10.5 [10.1, 10.9]	10.6 [10.3, 11]	7.9	10
FDP	6.1 [5.6, 6.5]	8.1 [7.8, 8.5]	6.6	6
Others	13.3 [12.9, 13.7]	10.6 [10.3, 10.9]	14.6	18

Table 2: *Predictions for the five major parties and a residual category – others (includes AfD) – from models without (column 2) and with (column 3) weights. Simulation-based 95% prediction intervals in square brackets. Columns 4 and 5 report an average of current polling at the time of draft (1 March 2017) and the final 'Forschungsgruppe Wahlen' poll before the SPD announced Martin Schulz's candidacy (14 January 2017), respectively.*

coefficient on GDP growth depends on the status of a party. As expected there is no association between economic growth and a party's vote share if it does not lead the national government. However, if it does we see the expected positive relationship. The chancellor's time in office by and large is not predictive of an opposition party's vote share. However, the coefficient on Years in Office for the chancellor's party is significantly negative representing the expected cost of ruling effect.

Inserting 2017 values for our explanatory variables into the equation, we obtain predictions for each of the parties for each of the 16 German *Länder*. We then aggregate these state results to the national level to obtain an estimate of the national vote distribution which determines the power balance in the *Bundestag*, Germany's lower house. To account for differences in the size of the electorates and levels of turnout between states we translate the party-state vote shares into vote totals by multiplying the current estimates of the electorate size provided by the federal returning office with the estimated vote shares and the expected turnout in each state. The latter is estimated in a separate model.[8] We then sum these vote totals across states within parties and transform them back into proportions to arrive at an estimate of the national vote share for each party. To incorporate the uncertainty stemming from the estimation of the vote shares as well as from the estimation of turnout we simulate many predictions from both models,

[8]We use a random effects model incorporating prior turnout, state-specific time trends and state fixed effects to predict state level turnout in 2017.

merge them and then aggregate over the simulated data to provide 95% prediction intervals.

We present our predictions in Table 2. In both models the *CDU/CSU* retains its plurality. However, this would represent a loss of at least 5% percentage points vis-à-vis their performance in the 2013 election.[9] Based on our model we expect the SPD to finish at 25 to 27 percent, about matching their result in the previous election. This is an improvement over polling before the former president of the European parliament Martin Schulz became the party's candidate for the chancellorship. Yet, our forecast also suggests that current polling is overstating the electoral support of the SPD. The forecasts for *Die Linke/PDS* and *Bündnis 90/Die Grünen* are relatively stable across both models. We expect a stronger finish for the *FDP* in the weighted model and weaker finish for the residual category *Others*, which is not surprising as both have been quite volatile in past national and state elections.

[9] The results for the 2013 federal election were as follows: CDU/CSU: 41.5%, SPD: 25.7%, Die Linke: 8.6%, Bündnis 90/Die Grünen: 8.4%, FDP: 4.8%, Others: 10.9%

Party	Unweighted model		Weighted model		Prior Vote Share		Average Vote Share	
	MAE	RMS	MAE	RMS	MAE	RMS	MAE	RMS
Federal level								
CDU/CSU	4.2	5.0	3.4	3.8	4.4	5.0	7.2	8.0
SPD	3.4	5.2	2.8	3.6	5.0	6.0	7.2	9.4
Die Linke/PDS	2.2	2.7	1.6	1.9	2.6	3.0	3.2	4.0
Bündnis 90/Die Grünen	1.6	1.9	1.8	1.9	1.5	1.8	2.6	2.8
FDP	2.8	3.8	2.5	2.8	3.8	5.0	3.1	3.6
Others	2.0	2.3	1.5	2.2	2.6	2.9	2.9	3.9
Overall	2.7	3.7	2.3	2.8	3.3	4.2	4.4	5.8
State level								
Overall	3.6	4.8	2.9	3.9	3.6	4.9	4.6	6.1

Table 3: Party specific and overall forecasting errors based on out-of-sample predictions of the federal elections 1998 - 2013, for the federal level, and overall forecasting error only for the state level. The mean absolute errors (MAE) and the root mean squared errors (RMSE) for the unweighted and weighted model are compared against two 'naive' prediction methods: predicting the vote share which obtained in the last election and predicting the average vote share in all previous elections.

The 2017 federal election will of course be the main test of our model's validity. A forecasting model's predictive validity rests on its ability to predict elections outside the sample on which it was estimated. When we crafted our model in early 2017 we conduced synthetic out-of-sample predictions to gauge the predictive ability of our model.

We did so by estimating the model on a reduced set of elections up to and excluding 1998, forecasting the 1998 election based on this model and then repeating this exercise for all further federal elections until 2013. For these five elections we compared our predictions to the actual outcome. We summarize the forecasting error, the deviation between prediction and actual result, as mean absolute errors (MAE) and root mean squared errors (RMSE) within and across parties (see Table 3). This gives us some indication of the degree of accuracy we can expect for our forecast for 2017. We also compare our regression-based model to two much simpler forecasts. The first treats the vote share a party obtained in the preceding election as a forecast and the second takes the average of a party's results in all preceding federal elections since 1961. Our model fares considerably better than these 'naive' benchmarks. This holds for all but one party and benchmark – the Greens are slightly better forecasted by their previous result than by our model. Careful readers might also notice the benefits of aggregating from the *Länder* up to the national level: for all methods of forecasting, the errors at the federal level are consistently and substantially smaller than for the state-level predictions.

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