A Methodological Framework for Constituency-Level Election Forecasting

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ABSTRACT

Scholarly efforts to forecast parliamentary elections predominantly target the national level and disregard outcomes of constituency races. In doing so, they frequently fail to account for systematic bias in the seats-votes curve and are unable to provide candidates and campaign strategists with constituency-level information. On the other hand, existing accounts of constituency-level election forecasting suffer from data sparsity and, as a consequence, lack of precision. In this paper, I propose a methodological framework that allows correcting individual constituency-level forecast models for systematic errors and combining them according to their past performance. I demonstrate the use of this framework with an out-of-sample forecast of 299 district races at the 2013 German federal election.

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> 'I think you'll have a big increase in the number of poll-driven forecasts here. We need more polling here. If you don't know what's happening in individual constituencies that's a bit tricky. Especially if you have votes drifting off to Ukip and these third and fourth parties, that makes it more complicated than just assuming a uniform swing, potentially. And generally the volatility is higher the more parties are involved in the campaign, because voters can say "I want to vote for Ukip but they're not going to win in my constituency so I'll have to vote for the Tories instead."' – *Nate Silver (2013)*

1. INTRODUCTION

Academic election forecasting has flourished over the last years. Moreover, current practice has overcome many of the drawbacks inherent to fundamentals-based regression approaches which used to dominate this subfield of electoral research (e.g., Sigelman, 1979; Hibbs, 1982; Lewis-Beck and Rice, 1984*a*,*b*; Abramowitz, 1988; Lewis-Beck and Rice, 1992). New models which provide timely, dynamic and, most importantly, reliable forecasts are of great interest for campaign organizers and financial contributors who want to target their resources efficiently. Further, they offer valuable information for voters and are staple food for horse race journalism. From the scholarly perspective, election forecasts can inform research on the nexus between public opinion and campaign dynamics (Lodge, Steenbergen and Brau, 1995; Wlezien and Erikson, 2002; Zaller, 2004; Panagopoulos, 2009) and on methodological issues in the measurement of public opinion (Gelman and King, 1993; Graefe, 2014; Smidt, 2014).

Recent efforts to forecast state-level outcomes at U.S. Presidential elections have profited from both a substantial increase in pre-election polls at the state level and very efficient modeling strategies (Linzer, 2013; Lock and Gelman, 2010), and in the end obtained spectacular success.[1] However, these models have been developed for a very specific context—essentially, a set of two-candidate races with a long election record—and cannot be applied to other settings without further ado. The opening quote of Silver, whose attempt to forecast the 2010 UK General Election with a modified uniform swing model produced rather underwhelming results (Silver, 2010), illustrates a few of the challenges: If an election involves races of more than just two parties in a multitude of constituencies, one is hardly befallen of hundreds of constituency-level vote intention polls. This renders pure poll-averaging approaches useless if one is interested in constituency-level forecasts. Additionally, multiparty settings in combination with FPTP rules induces strategic voting incentives that blur the link between party preferences and actual voting behavior. Consequently, election forecasts in parliamentary settings usually target the national level.

In this paper, I propose a framework to forecast electoral outcomes at the constituency level. While local data to inform forecasting models about voter preferences are generally sparse at any single election, the electoral history of constituencies—and forecast models—can be used to unbias forecasts and ultimately improve model performance. Additionally, I suggest to pool information by combining several available models. The technical procedure breaks down to three stages. In the first, distinct constituency-level forecasts are produced (or collected) for past elections. In the application, these are a set of forecasts based on past election results and a set based on polling data. As the forecasts of these models might be both unreliable and biased

[1] For example, state-level forecasts offered by Silver (2012), Linzer (2013), and Jackman (2012) for the 2012 U.S. Presidential election remained flawless, each of them forecasting the winner in all of the 50 states correctly.

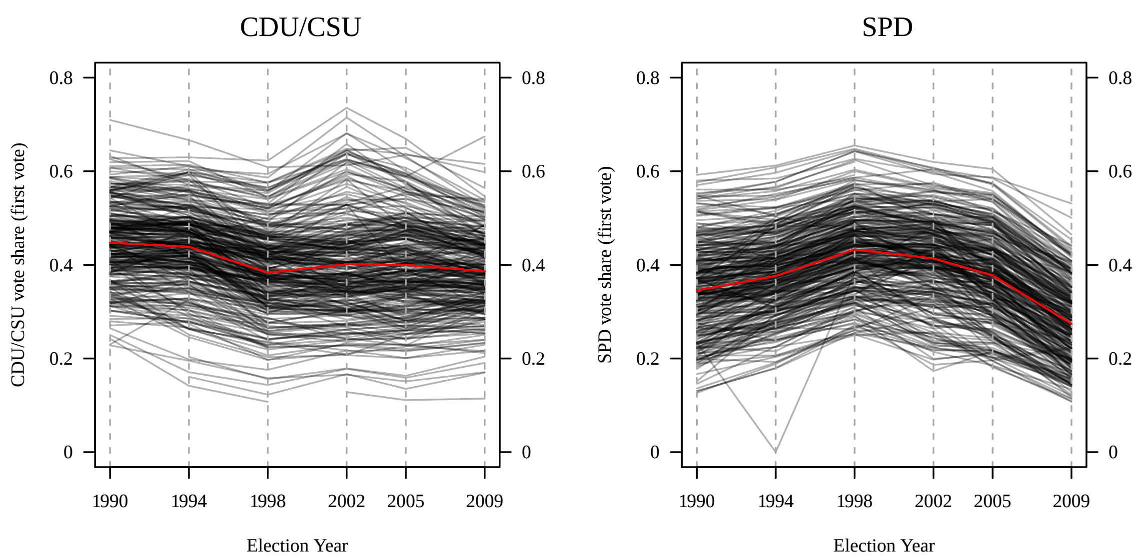
because of data scarcity and disparity or fundamental flaws in the models, I unbias forecasts by regressing previous actual results on forecasts and a set of additional predictors (if at hand). Simultaneously, the out-of-sample forecasts are corrected. In the third step, corrected forecasts are combined and weighted according to their performance in past elections.

To demonstrate the use of the approach and to illustrate the gain in precision, I present a forecast of the German federal election held in September 2013—a multi-party setting with a considerable number of districts (299). The corrected and combined forecasts perform very well; the forecast distribution of seats is almost identical to the actual outcome of the election.

2. POTENTIALS AND CHALLENGES

Forecasting models that provide genuine information about constituency-level outcomes bear great potential. First, constituency-level outcomes are important for the actual distribution of seats at the national level in many electoral systems with a significantly biased votes-seats curve. For example, in majoritarian systems like the United Kingdom, the relationship between the aggregated share of votes and the share of seats a party gains is blurred by the plurality rule at the district level. In the general election of 2010, the winning Conservatives gained 47% of the seats, but only 36% of the popular vote. It has been shown that the bias in votes-seats curves is not constant over time (see, e.g., Blau, 2004; Jackman, 1994; Norris and Crewe, 1994; Tufte, 1973) which makes it difficult to forecast the distribution of seats from national-level polls alone. In general, specific characteristics of electoral rules may prohibit forecast-

Figure 1: Election results on district level at German Bundestag elections for the parties CDU/CSU and SPD. The red line displays the mean share of the party's first vote over all districts; the black lines display constituency-level first vote shares.



ers to infer both constituency- and national-level outcomes from trends that are identified in national-level polls. However, the most important statistic of interest in parliamentary elections is the distribution of seats, as it determines who actually comes to power. Forecasting at the level where the race is decided is therefore best suited for answering questions about the prospective allocation of seats.

Constituency-level forecasts can also be useful in non-majoritarian settings. The internal composition of parliaments in mixed electoral systems with a strong PR component, as given in the German electoral system, could be forecast more precisely with constituency-level information (see Manow, 2011). Further, such forecasts would provide valuable for local candidates and party campaign strategists, as they may reduce uncertainty and give information where local effort should be concentrated.

Forecasting dozens or even hundreds of outcomes in one election is a more ambitious task than merely generating expected national-level vote shares for a few parties or candidates. To illustrate some of the involved challenges, Figure 1 provides an insight into the multitude of constituency-level election results for the two grand parties blocs (the Conservatives, CDU/CSU, and the Social Democrats, SPD) in Germany over the last six elections. There is considerable variance around the overall mean of results on the constituency level. Moreover, district deviations from the mean are not stable over time. Lines running parallel to the aggregated trend indicate that time-invariant, district-specific components are highly predictive for constituency-level party shares. However, there is a considerable number of cases that run counter the trend. Constituency-level outcomes are not generated as simple projections of a national-level swing on the local level. Regional and constituency-level factors are likely to play a role, too, as, for example, candidates' campaigning skills, scandals, district history, specific constituency-level politics—in fact, the very factors which are also included in standard national-level and theory-driven forecasting models, but the effects of which might vary over contexts. As I will argue in the following section, existing forecasting models tend to ignore constituency-specific campaign data at the cost of precision. Those who try to implement current local information, on the other hand, often face problems of data scarcity.

The main challenge in disaggregated forecasting lies in collecting data that are informative at the constituency level, as this helps explain and anticipate the heterogeneity of results. In many of the current forecasting approaches, up-to-date public opinion data provide an important predictor. However, as political polls are usually conducted at the national level, information for single districts is sparse, and a considerable amount of districts might not even be covered by the survey sample at all. Further, in order to correct for population changes in districts' territories, electoral districts' boundaries are often subject to redistricting. This makes it difficult to inform models with district history predictors like the former winner, previous vote shares, or times a party has taken the district over a certain period of elections. These factors boil down to a fundamental dilemma of constituency-level election forecasting: the scarcity of information at this very level on the one hand, and a multitude of forecasts to be made on the other.

3. STATE OF THE ART

The majority of established forecasting models that target the outcome of parliamentary elections can be broadly divided into five general types, depending on (a) the forecast level (national or constituency outcomes) and (b) the type of information used.[2]

The first branch comprises national-level models that forecast aggregate vote or seat shares using structuralist information and regression analysis. They have been developed in the context of elections for the US House (for recent applications see, e.g., Abramowitz, 2010; Campbell, 2010; Lewis-Beck and Tien, 2010, 2012; Klarner, 2012), the British House of Commons

[2] In this review, I do not discuss poll-aggregating approaches which recently have been developed for U.S. Senate races (e.g., Linzer, 2013; Sides, Highton and McGhee, 2014; Silver, 2014), as they pose an exception in terms of data availability and electoral rules, and can hardly be translated into parliamentary settings where constituency-level outcomes are of relevant quantities. They work on the state level and can draw on large amounts of polling data. Usually based on a firm Bayesian model framework and providing dynamic forecasts by design, such models are built to combine historical as well as polling data and give more weight to the latter as the election date approaches and more and more polls accumulate over the course of the campaign.

(e.g., Lebo and Norpoth, 2011; Lewis-Beck, Nadeau and Bélanger, 2011; Whiteley et al., 2011), the German parliament (e.g., Gschwend and Norpoth, 2001, 2005; Jérôme, Jérôme-Speziari and Lewis-Beck, 2013; Kayser and Leininger, 2013) and other settings, and often merely build on a sparse set of economic and public opinion-based predictors which are shown to be strongly correlated with the party vote or seat shares of interest. While, given their sparseness, these models tend to produce fairly accurate forecasts, they come with a considerable amount of uncertainty and have been criticized for their weak data basis and tendency for overfitting (Gelman, 1993; van der Eijk, 2005). Moreover, lacking any local component, they do not inform about constituency-level campaign dynamics.

A second branch of models relies on information from national opinion polls. Instead of merely taking published vote intentions as a forecast, the idea is to exploit systematic trends in the historical relationship between polls and the vote that can be affected by institute- or party-specific biases or cyclical patterns that occur over the course of a campaign. Models of this flavor have been developed, among others, for Westminster elections (e.g., Fisher et al., 2011; Fisher, 2015), the Australian federal election (Jackman, 2005), and the German federal election (Selb and Munzert, 2015). Poll-based approaches exploit data that are an almost natural by-product of national-level election campaigns. In contrast to structural approaches, they often allow dynamic forecasts of public opinion.[3] On the other hand, such models have to operate on the level of the polls, which is, more often than not, the national level. Furthermore, they are built to capitalize on the existence of systematic errors of trial-heat polls. The existence of such

[3] See, however, Gelman and King (1993) for a painstaking exploration of the volatility of pre-election polls and a discussion on why short-term variations in public opinion are rather endogenous to the campaign and do not provide crucial information for forecasting efforts.

errors sometimes is an overly optimistic assumption (see Selb and Munzert, 2015). Depending on the context of elections, some of these models incorporate algorithms which take the seat-vote bias into account. This can be done by applying 'cube rule' (see Whiteley, 2005) or by predicting the bias with previous election data (see, e.g., Whiteley, 2005; Lebo and Norpoth, 2007; Nadeau, Lewis-Beck and Bélanger, 2009; Lebo and Norpoth, 2011; Whiteley et al., 2011). However, such approaches are hardly robust against regional shifts in party support or the emergence of new parties, which makes the volatility of the bias difficult to predict.

A third group of models combines national-level polling and historic constituency data. Essentially, these models project swings in public opinion, that is shifts from one party to the other based on past election results and current polling trends, on previous election results at the constituency level. As the assumption is that the change in vote shares is constant over all constituencies, the underlying mechanism is often referred to as 'Uniform Swing' or 'Uniform National Swing' (e.g., Miller, 1972; Tufte, 1973; Johnston and Hay, 1982; Butler and Beek, 1990; Payne, 1992). After projecting the anticipated swing on previous district results, the forecast local winners are aggregated again to arrive at a seat share forecast. While the simplicity of this approach certainly has its own charm,[4] it rests on the critical assumption that swings are distributed equally over constituencies or are likely to 'cancel out' (Butler and Beek, 1990, 179). More sophisticated variants therefore introduce regional and tactical swing parameters or add information about incumbency status (Bafumi, Erikson and Wlezien, 2008, 2010). Ultimately, this approach generates constituency-level forecasts but does not incorporate any campaign

[4] In fact, the simple intuition of these models is the main reason for their popularity among pundits and the media; the approach has been featured on various online platforms, e.g., http://www.electoralcalculus.co.uk/userpoll.html for Westminster constituency forecasts.

information at this level, so the accuracy of this methodology essentially hinges on the forecast of the national trend.

More recent approaches turn to new data sources which offer short-term information on candidates' winning odds at the constituency level. For example, Murr (2011) uses citizens' expectations about election outcomes in their own district, exploiting the 'wisdom of the crowds' effect. The idea is that aggregated group forecasts outperform individual forecasts if the individual probability of a correct forecast averages more than 0.5. While it is difficult to generate precise constituency-level forecasts from national-level survey data on peoples' *vote intentions*, asking for local *expectations* is far more efficient. Following a similar logic, Wall, Sudulich and Cunningham (2012) exploit constituency-level betting markets at Westminster elections. For the U.S. house elections, Sides, Highton and McGhee (2014) incorporate fundraising data in the pre-primary model and substitute it with candidate information during the general campaign. These approaches provide important contributions to the existing set of forecasting tools, as they overcome the votes-to-seats problem by design and are able to capture local campaign dynamics that can easily be overseen in models that rely on overall trend measures. However, they still rely on exotic survey instruments or other data that are likely to be not available in many scenarios (as reported by Murr, 2011), or have been shown to add no predictive power compared to traditional approaches (see Wall, Sudulich and Cunningham, 2012).

Depending on the context, there are models that perform reasonably well in the aggregate but miss to generate reliable constituency-level forecasts. Models that try to assess the local level often fail to incorporate actual local information on the race, lack the necessary data in most contexts, or produce underwhelming results.

A very recent constituency- and national-level forecasting effort has been presented by Hanretty, Lauderdale and Vivyan (Forthcoming) who suggest an integrated approach of combining national and constituency polls, historical election results and census data to forecast the 2015 Westminster election.[5] Their approach is customized for the British case, takes into account the compositional nature of multiparty election outcomes, and provides local as well as national, dynamic, and probability-based forecasts. As I will set forth in the following section, my suggested framework is similar in terms of goals–combining various sources of information at both the national and the constituency level–, but different regarding the technical procedure.

4. A CORRECTION-COMBINATION PROCEDURE

So, how to improve constituency-level forecasts? As I discussed above, the main challenge to be addressed is data scarcity at the local level, especially when there is reason to assume that local campaign dynamics deviate from the national trend. I suggest two strategies to alleviate this problem: The first is model correction that is based on identifying bias in previous forecasts, the second is model combination. My approach does not start with the development of a singular forecast model, as data availability may vary by setting. Instead, it builds upon existing sets of constituency-level forecasts and offers a framework to improve their predictive

[5] See also http://www.electionforecast.co.uk/ (accessed Wednesday 18th November, 2015).

performance. The basic intuition behind my approach is that while many existing forecasting models exploit past information, e.g., by incorporating previous constituency-level election results into the regression equation or by evaluating the historical relationship between seats and votes, they neglect what can be learned from past forecasting efforts *per se*. Since constituency-level models accumulate a vast number of forecasts from election to election, this holds a great source to further improve forecasting performance. Similar strategies to exploit forecast residuals to obtain better forecasts were suggested earlier (Wallace and Hussain, 1969; Issler and Lima, 2009) and have been used to improve forecasts of, e.g., weather conditions (Glahn and Lowry, 1972; Bao et al., 2010), daily bank transaction volumes (Mabert, 1978), and commodity prices (Issler, Rodrigues and Burjack, 2014). However, existing strategies use to capitalize on expansive time series data. I present an approach that fits the given data structure of a panel of constituency-level election outcomes (N, usually large) for a set of elections (K, usually small), allowing to borrow information both over time and constituencies.

Given a set of forecasts for previous elections, f_{pjk}, where $p = 1, \ldots, P$ indexes the pth party, $j = 1, \ldots, J$ the jth district and k the corresponding election from a set of K past elections.[6] As historical constituency-level outcomes are known, the performance of forecasts at past elections can be evaluated. To this end, I model the actual vote share y of party p in district j at election k as a function of a constant α_p, the forecast forecast itself weighted with β_p (both allowed to vary by party), a vector of further covariates $\mathbf{X}$ (with coefficient γ_p also allowed

[6]There is an infinite number of ways to produce such forecasts, depending on the information available (and relevant) for specific elections or institutional settings. In the test case I present below, I will employ two different models. As indicated by the notation, a necessary condition is that the single model provides constituency-specific forecasts for both the current election and a set of past elections ($K \geq 2$).

to vary by party) and party-district random effects (ξ_{pj}). Formally, I assume y_{pjk} to follow a normal distribution with mean μ_{pjk} and variance σ^2,

$$y_{pjk} \sim N(\mu_{pjk}, \sigma^2), \tag{1}$$

with

$$\mu_{pjk} = \alpha_{p[jk]} + \beta^{\text{forecast}}_{p[jk]} \mathrm{f}_{pjk} + \gamma_{p[jk]} \mathbf{X} + \xi_{pj}. \tag{2}$$

The core idea behind this model is that raw forecasts can carry election-invariant, systematic bias or serial correlation of constituency-specific forecasts. The error can be party- and/or district-specific and furthermore be correlated with omitted variables. By decomposing past outcomes into parts explained by the forecasting model and other systematic and random components, we can identify bias and correct for it, drawing on the weights of the link function, α_p, $\beta^{\text{forecast}}_p$ and γ_{pj} as well as the party-district errors, ξ_{pj}. If the forecasting model provides unbiased forecasts, we would expect $\alpha = 0$, $\beta^{\text{forecast}} = 1$, $\gamma = 0$ for all p, and $\xi = 0$ for all p and j. The proposed link function in Equation 2 could be further expanded, e.g., by introducing additional regressors which are motivated by the forecast scenario and method. For instance, a model that is ignorant towards local dynamics could be evaluated using information on the number of candidates which run in a district, their incumbency status or other campaign information, if available. If constituencies are frequently subject to politically motivated redistricting, a variable whether redistricting occurred in a district or not could added in this evaluation step. Further, one could include party-election-specific errors to absorb over-or underestimation of party vote shares at a specific election. However, election-specific errors cannot be identified for a true forecast and are therefore disregarded here. In its suggested specification, the model carries a linear interpolation of the original forecasts specific to each party (the linear relationship is allowed to vary over parties) and captures party-district idiosyncratic effects that are missed by systematic components. This accounts for the fact that parties may perform systematically superior or worse in specific districts relative to the national or regional trend.

Next, the estimated coefficients and error components can be used to correct forecasts made in a new setting at election k^*. One could do this separately by first estimating Equation 2 and correcting the set of raw forecasts f_{pjk^*} in a second step.[7] However, in a Bayesian estimation framework (which I follow in the application), a more natural way to correct an out-of-sample forecast is to integrate the to-be-forecast cases into the set of modeled data and keep the values of $y^*_{pjk^*}$ as missing data. The missing values will then be treated as stochastic nodes and the Gibbs sampler returns imputations from the posterior predictive density, conditional on the other parameter draws (Gelman and Hill, 2007, p.367). The advantage of this integrated imputation approach is that it generates a natural quantification of uncertainty through the simulation of the posterior predictive densities of all $y^*_{pjk^*}$ as a by-product of the correction procedure, which can be used to compute constituency-level winning probabilities, probability densities for the aggregated distribution of seats, or other quantities of interest.

[7] To do so, one would proceed as follows:

$$y^*_{pjk^*} = \hat{\alpha}_{p[jk*]} + \hat{\beta}_{p[jk*]}\mathrm{f}_{pjk*} + \hat{\beta}_{p[jk]}X + \hat{\xi}_{pj} \tag{3}$$

This general way of evaluating forecasting performance and simultaneously correcting for historical bias enables forecasters to exploit information delivered by one model more efficiently, as the set of constituency-level forecasts is large, which makes the identification of sources of bias computationally feasible. I expect the amount of benefit from this step to be related with both model and election characteristics. If the original set of forecasts is generated using a model that already incorporates specific constituency-level predictors, introducing this information as a possible source of forecast bias in the evaluation step is of little use. However, if one prefers to construct 'naïve' models in the first step or to borrow forecasts from others—probably even without full knowledge about the original model specification or if qualitative forecasts are used—, the evaluation overhead allows to improve their accuracy, as the model pulls itself up by its own bootstraps. Note that this procedure may also be of use in the process of developing and improving an own constituency-level forecasting model.

While the first step allows incorporating further information into single models ex post to exploit forecast error patterns in the original model, the second is to pool multiple forecasts from different models. As has been discussed above, existing approaches of constituency-level election forecasting come with unique strengths and weaknesses. For instance, uniform swing models are very easy to implement but do not use local-level campaign information. On the other hand, models which incorporate current district data (e.g., Murr, 2011) can capture recent local trends but may not cover the whole set of constituencies. More generally, models exclusively focusing on past election results or other economic or political indicators naturally fail at predicting the success of new parties by construction. On the other hand, dynamics in public opinion make vote intention surveys a shaky prediction instrument (see Gelman and King, 1993). At the district level, it is not clear a priori if there are election-, or population- or data-specific conditions under which one of the approaches has a clear advantage. One could hypothesize that survey-based approaches are inferior when the survey data at hand are extraordinarily sparse or of bad quality. At the same time, in settings where the electoral setting has altered substantively between elections, e.g., because of massive redistricting, local strongholds of a new party on the block or new candidates, survey data should be expected to perform better, as they do not rely on previous (and less useful) information.

As has been demonstrated frequently, combining several forecasts helps reduce forecast error because more information is exploited and bias which is immanent in single models can be canceled out in the aggregate forecast (e.g., Bates and Granger, 1969; Armstrong, 2001; Clemen, 1989; Raftery et al., 2005; Graefe, 2014). The strategy to combine several forecasts has already be applied to forecast U.S. Presidential elections: Montgomery, Hollenbach and Ward (2012*a*,*b*) promote the use of Ensemble Bayesian Model Averaging which provides a weighting algorithm based on each components' past performance and uniqueness. Similarly, Graefe et al. (2014) pool forecasts within and between methods, but use equal weights.

The combination procedure I employ here is based on past performance of the corrected forecasts, measured at the constituency level. Suppose one has two different constituency-level forecasting models, the first relying mainly on historical information, producing a set of forecasts $\mathrm{f}_{jk*}^{\mathrm{hist}}$, the other exploiting current polling information, leading to another set of forecasts $\mathrm{f}_{jk*}^{\mathrm{polls}}$. As described above, these forecasts can be improved following the correction procedure, leading to $\text{f}^{\text{hist}^*}_{jk^*}$ and $\text{f}^{\text{polls}^*}_{jk^*}$. A naïve solution to combine both would be to employ equal weights and just take the mean of forecast values for each district. This, however, would disregard that models can perform differently in general or produce forecasts which, on average, fit well in some districts but not so well in others, even after correction. Therefore, I employ a marginally more sophisticated procedure: First, I estimate party-district-specific forecast variance, that is mean-square error $\sigma^2_{\cdot,pj}$, for every set of corrected forecasts.[8] This is a measure of how well the corrected forecast model performed in past elections. As it is plausible that one model performs better in a subset of districts and worse in another, forecast variance is estimated at the district level and for every party. In the two-forecasts case with $\text{f}^{\text{hist}^*}_{pjk^*}$ and $\text{f}^{\text{polls}^*}_{pjk^*}$, weighting proceeds as follows:

$$\text{f}^{\text{comb}}_{pjk^*} = \omega_{pj}\text{f}^{\text{hist}^*}_{pjk^*} + (1 - \omega_{pj})\text{f}^{\text{polls}^*}_{pjk^*}, \tag{4}$$

with

$$\omega_{pj} = \frac{\hat{\sigma}^2_{\text{polls},pj}}{\hat{\sigma}^2_{\text{polls},pj} + \hat{\sigma}^2_{\text{hist},pj}} \tag{5}$$

The weight ω_{pj} of the corrected district forecast is inversely proportional to the estimated district-specific forecast variance of previous corrected forecasts. In other words, the more reliable a forecast model proves for one specific district relative to another model, the more weight is attached to this more reliable model's forecast.

[8] The weights have to be party-district-specific because the models are run separately for each party.

5. APPLICATION: FORECAST OF THE GERMAN BUNDESTAG ELECTION 2013

In the following, I present an out-of-sample forecast of outcomes of district races at the German Bundestag election 2013 that was produced two weeks before Election Day (September 22nd, 2013). It provides a setting with a considerable number of electoral districts (299) and regional heterogeneity in party support. Six parliamentary parties entered the race and, according to some published polls, two emerging parties—the German Pirate Party (*Piratenpartei*) and the *Alternative für Deutschland, AfD* (Alternative for Germany)— had realistic chances to enter parliament. In the German electoral system on federal level, people have two votes. The first is a personal vote for a candidate in the voter's district (candidates are elected via first-past-the-post on this level), the second is a party vote which essentially determines the distribution of seats in parliament (Saalfeld, 2008).

In this application, I focus on a forecast of first vote shares, as they are more likely to be affected by local campaign dynamics than the second (party) vote shares, and thus pose the more challenging exercise. Further, forecasting first vote shares and district winners is the more relevant application for constituency-level forecasts because they directly affect the internal composition of parliamentary groups in parliament. In advance of the election, no published efforts of constituency-level election forecasting in Germany existed.[9] Therefore, I employ two different forecasting models: The first mainly relies on historical constituency-level data and a

[9]The only exception I am aware of is the semi-commercial platform election.de, which has been selling constituency-level forecasts prior to the last three federal elections. These forecasts are not freely accessible and therefore disregarded in the forecast. However, I use the aggregated forecasts from this source in order to evaluate the overall performance of my model in a later stage.

poll-driven national-level trend estimate, the second draws on a large individual-level polling database that is mapped on the constituency level.

5.1. *Exploiting past election results*

In established democracies, past political outcomes are usually a good predictor for future outcomes. In the German case, we can observe a strong relationship between first vote shares from one election to the other, especially for the two large parties CDU/CSU and SPD (see also Figure D.1 in the Supplementary Materials). Differences between current and past election outcomes can be explained with nation-wide trends as well as local factors like incumbent performance, the pool of local candidates, and other local or regional determinants.

I employ a very ascetic uniform swing approach to exploit past election results. Specifically, I draw on constituency-level first vote shares in the past election and add a uniform swing constant for every candidate (i.e. party) which mirrors the national trend of the respective party from one election to the other. As discussed above, the attractiveness of this approach lies in its simplicity. On the other hand, it rests on some heroic assumptions, one being that there is a stable set of parties over time, another presuming no regional variation in shifts. Besides, potential bottom or ceiling effects for constituency-level vote shares are not taken into account. Further, it is assumed that every district has a preceding district. However, districts are sometimes abandoned or newly created, and at most elections at least some of the constituencies are subject to redistricting. In Appendix A, I present a way to construct a district panel data set which is employed in the forecast.

In order to identify the swing component in the model, I need an estimate of the current national trend to calibrate constituency-level election forecasts. For past elections, I use the final aggregated party vote shares of the first vote to avoid disturbances induced by polling data. For the current election, the trend is estimated by drawing on an existing forecast of the national-level outcome (Selb and Munzert, 2015).[10] Next, the constituency-level forecasts are computed as difference between the current national-level vote share (or polling estimate) for each party and the relative position of a district for each party in the past election.

The upper panel of Table 1 shows that the uniform swing model performs generally well at past elections since 1994 (see also Figure D.2 in the Appendix for a graphical display of the model's performance). This reflects in rather small mean absolute errors (absolute difference between actual first vote share and predicted first vote share) which mostly do not exceed 3 percentage points. On average, 90% of the winners of the district are forecast correctly.

Next, I employ the suggested procedure of identifying and correcting forecast bias. Following Equations 2 and 3, I model past constituency-level outcomes as a function of past forecasts and include two further predictors: a dummy variable *party dominance*, which indicates whether a party has won the direct mandate in the district at least the last three times in a row and a dummy variable *pioneer*, which indicates whether the party runs in the district for the

[10] The forecast party shares were: CDU/CSU 38.1%, SPD 28.2%, B'90/Die Grünen 13.5%, Die Linke 7.7%, and FDP 5.4%. This is equivalent to the following trends: CDU/CSU +4.3%, SPD +5.2%, B'90/Die Grünen + 2.8%, Die Linke -4.2%, and FDP -9.2%

first time.[11] I suspect that the *party dominance* dummy captures parts of the underestimates of the first vote shares which should occur when, e.g., party strongholds are less affected by national losses. The *pioneer variable* is used to correct for a natural problem in the uniform swing forecast: When a party runs in a district for the first time, the model predicts a vote share of zero (plus/minus the national swing). This is likely an underestimation of the actual outcome which is technically counterbalanced by a party-specific estimate of β^{pio}. I adopt MCMC methods for inference and use vague prior distributions for the model parameters. To run the simulations, I use WinBUGS (Lunn et al., 2000). The code of the sampler is reported in Appendix C.

The results are presented in Table 2. The near one-to-one relationship between true and forecast values mirrors in the estimates for α and β^{swing}, although there is some between-party variation in the effects: Uniform swing forecasts for the two large parties (CDU/CSU and SPD) and the FDP are discounted to a certain extent, indicating some regression-to-the-mean dynamics that are not fully captured by the uniform swing model. The estimated effects for party dominance are negligible.[12] The pioneer predictor is very important to correct forecasts of SPD candidates in constituencies where the party did not run in the previous election (which is, however, a historically negligible scenario). The estimated party-constituency-level variance is zero, which indicates that the forecasts are not substantively distorted by other unaccounted district-level factors.

[11] This was the case in the early 1990s in some districts where B'90/Die Grünen and Die Linke (formerly PDS) had not run for a direct mandate.

[12] Note that the negative and large coefficients for FDP and B'90/Die Grünen have no empirical relevance because those too parties were virtually never dominant in any of the constituencies.

Table 1: Predictive performance of the uniform swing model, uncorrected and corrected forecasts. The first five columns report mean absolute errors over all 299 districts at each election. The last column reports the percentage of correctly forecast districts (predicted winner equals actual winner). Cells where the corrected forecast outperforms the uncorrected forecast are highlighted in grey.

	CDU/CSU	SPD	FDP	B'90/Die Grünen	Die Linke	% Overall correct
Uncorrected						
1994	0.021	0.025	0.019	0.014	0.024	90.0
1998	0.025	0.017	0.005	0.011	0.008	88.6
2002	0.030	0.027	0.009	0.011	0.012	87.0
2005	0.023	0.022	0.011	0.009	0.016	92.6
2009	0.031	0.024	0.013	0.014	0.011	89.6
Corrected						
1994	0.022	0.023	0.013	0.012	0.020	90.6
1998	0.025	0.017	0.007	0.010	0.008	88.6
2002	0.031	0.028	0.009	0.011	0.013	87.6
2005	0.022	0.023	0.010	0.009	0.017	92.3
2009	0.027	0.022	0.014	0.014	0.012	90.0

Using the corrected results for prediction in order to assess the performance of the unbiased model, it turns out that the corrections tend to improve the model's performance, although to a very modest extent. This mirrors in the lower part of Table 1. In a majority of cases, the mean absolute errors over all districts for each party at the previous five elections decrease, and in three of five elections, the overall share of correctly forecast districts increases marginally, with an average amount of about 90%. These results imply that the uncorrected uniform swing model is not severely affected by systematic bias that persists over time. This is probably not too surprising, as the model essentially builds on past information—while it obvious that a national trend projection leads to under- or overestimates of district-specific party vote shares, it is less likely that this procedure induces strong, time-persistent and party-specific bias.

Table 2: Bayesian median estimates and 95% credible estimates for the model of party first vote shares, based on uniform swing model (see Equation 2).

Predictor		95% CI
Intercept α		
CDU/CSU	0.031	[0.025;0.038]
SPD	0.021	[0.016;0.025]
FDP	0.010	[0.007;0.013]
B'90/Die Grünen	−0.001	[-0.004;0.002]
Die Linke	0.001	[-0.001;0.004]
Uniform swing estimate β^{swing}		
CDU/CSU	0.918	[0.899;0.936]
SPD	0.948	[0.934;0.961]
FDP	0.806	[0.762;0.849]
B'90/Die Grünen	1.000	[0.959;1.042]
Die Linke	1.015	[0.996;1.033]
Party dominance β^{dom}		
CDU/CSU	0.005	[0.002;0.009]
SPD	−0.004	[-0.008;-0.001]
FDP	−0.176	[-0.228;-0.122]
B'90/Die Grünen	−0.042	[-0.563;0.468]
Die Linke	0.002	[-0.017;0.022]
Pioneer β^{pio}		
CDU/CSU	0.085	[-0.781;0.912]
SPD	0.304	[0.253;0.354]
FDP	0.014	[-0.011;0.040]
B'90/Die Grünen	0.026	[0.020;0.032]
Die Linke	−0.007	[-0.010;-0.004]
Party-constituency-level variance σ^2_ξ	0.000	[0.000;0.001]
Residual variance σ^2_η	0.026	[0.025;0.026]
N	8.970	

The estimates are nevertheless used to correct the forecast for the 2013 election, which is generated on the basis of a national swing forecast according to the party share estimates by Selb and Munzert (2015). According to this estimate, the uncorrected as well as the corrected forecasts suggest a distribution of the direct seats as shown in the first row of Table 5. The district-level forecasts are listed in Table D.2 in the Supplementary Materials.

5.2. *Exploiting individual-level polling data*

The main limitation of uniform-swing based forecasts is that they fail to incorporate campaign-specific, constituency-level information. The uniform-swing model is ignorant towards local campaign dynamics as long as they are not explicitly incorporated in the correction procedure. Polls on voting intention can serve as a remedy to this problem. District-level polls are rarely available, and the 2013 German election campaign was no exception. However, I can capitalize on an exceptionally rich polling database, provided by the German *forsa* institute.[13] *forsa* surveys 500 respondents every working day and asks them, among other things, about their vote intention for the next general election. This allows me to construct a forecasting model which, in contrast to the uniform swing model, incorporates local information.[14]

In order to stabilize the constituency-level forecasts, I employ a Bayesian modeling strategy which has been suggested by Selb and Munzert (2011) to estimate constituency preferences using survey data and geographic information. The method is presented in-depth by Selb and Munzert (2011), so I limit the description to the gist of the matter. The vote intention of a respondent in a constituency is modeled as a function of a global mean, the individual voting behavior at the last election, a constituency-level covariate (log inverse district size) and two constituency-level random effects, one of which is assumed to vary independent and identically across districts following a normal distribution, and another which is imposed to follow an intrinsic conditional auto-regressive (CAR) distribution (see Besag, York and Mollié,

[13] Data for previous years are available at http://www.gesis.org/en/elections-home/other-surveys/forsa-bus/.

[14] Note that alternative data sources like local betting markets or vote expectation surveys which target the local level were not available.

1991). As true party vote shares for past elections are known at the district level, the predicted probabilities of voting for a party are then weighted according to the recalled voting coefficient (see Park, Gelman and Bafumi, 2004). For the estimation procedure, I pool survey data in the period of five months to one month before the election date to be able to draw a reasonable number of respondents per district for the estimation procedure.[15] Table D.1 in the Appendix provides summary statistics for the utilized polling data.[16]

The prediction results at the previous three elections are reported in Table 3. Using the uncorrected estimates, no more than 85% of the district outcomes are forecast correctly.[17] Therefore, I again apply the correction strategy and regress actual first vote shares in every district in the three elections on the poll model predictions and party-constituency random effects (see again Equation 2). The results are presented in Table 4. While the relationship between actual first vote shares and the poll model forecast is, on average, nearly one-to-one, the party-specific slopes and intercepts reveal substantive bias in the original model. Specifically, SPD and Die Linke vote shares are underestimated in constituencies where the parties' candidates performed well, whereas the opposite is true for candidates the other parties, where the model

[15] If the chosen time window is too narrow, the constituency-level estimates would tend to rely more on the grand mean instead of the local (or neighboring) information, which would curtail the model of its desired feature to capture actual local preferences.

[16] As has been described above, it is challenging to assign electoral districts to respondents. While most election studies provide such identification variables, polling data that are not primarily used for scientific purposes sometimes come with no geographical identifier at all or locate respondents in other than electoral units. The *forsa* data come with identifier variables of German administrative units. There are several ways to attach district identifiers to respondents which I discuss in more detail in Appendix B. In short, I identify all possible districts for each respondent and randomly assign the respondent to one of them. With regards to the forecasting method that uses respondents from neighboring districts to estimate vote intentions, an exact match should not substantively improve forecasting performance compared to this simplifying approach.

[17] See also Figure D.3 in the Appendix, which visualizes the relationship between the poll-based estimation results and the actual election results. Although the fit seems to be rather good, the polls are significantly biased. For instance, SPD vote shares tend to be under-estimated.

Table 3: Predictive performance of the polling model, uncorrected and corrected forecasts. The first five columns report party specific mean absolute errors over all 299 districts in each election. The last column reports the percentage of correctly forecast districts (predicted winner equals actual winner). Cells where the corrected forecast outperforms the uncorrected forecast are highlighted in grey.

	CDU/CSU	SPD	FDP	B'90/Die Grünen	Die Linke	% Overall correct
Uncorrected						
2002	0.034	0.07	0.043	0.014	0.025	85.0
2005	0.033	0.105	0.026	0.016	0.024	62.5
2009	0.051	0.056	0.057	0.019	0.034	83.3
Corrected						
2002	0.021	0.024	0.008	0.007	0.015	96.0
2005	0.031	0.035	0.005	0.008	0.015	80.9
2009	0.023	0.024	0.008	0.011	0.015	92.0

corrects the original forecasts towards the mean (slopes < 1). Further, the estimated variance of the party-district-specific errors is substantive, indicating that there are other unaccounted factors at the district level which play a role in second vote polling to first vote share transformation.

The gain of the correction procedure for the polling model is impressive (see Table 3 and Figure D.3 in the Appendix). The fit of the forecasts improves considerably over all parties and years, both in terms of mean absolute errors and correctly predicted district winners.

Next, the polling forecasts for the 2013 election are generated. According to the uncorrected forecast, 290 districts are attributed to the CDU/CSU and 9 to the SPD, mirroring the great advantage of the CDU/CSU in the raw polls. The corrected forecasts iron out this bias to a certain extent. Still, this forecast is significantly more favorable for the conservative parties than the corrected uniform swing model, with 261 vs. 224 seats for CDU/CSU and 34 vs. 70 seats for the SPD, respectively.

Table 4: Bayesian estimates of the model of party first vote shares, based on polls model

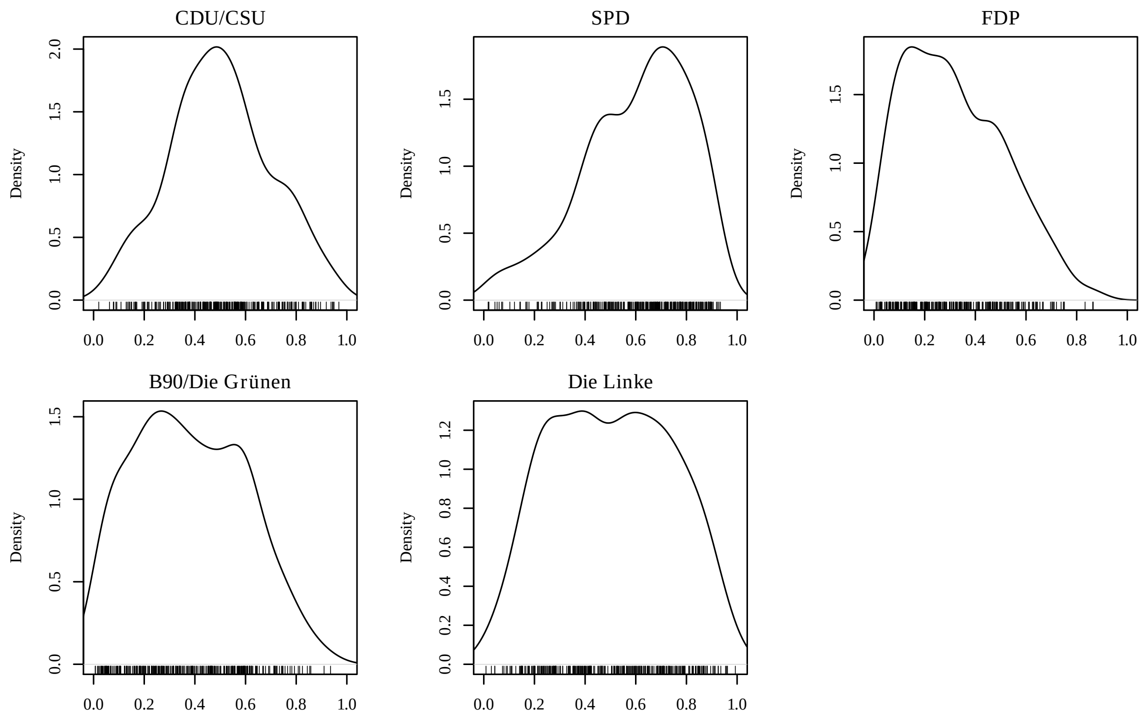
Predictor		95% CI
Intercept α		
CDU/CSU	0.126	[0.115;0.139]
SPD	0.038	[0.030;0.046]
FDP	0.004	[-0.003;0.010]
B'90/Die Grünen	0.011	[0.005;0.017]
Die Linke	0.003	[-0.002;0.007]
Polls estimate β^{polls}		
CDU/CSU	0.716	[0.685;0.744]
SPD	1.127	[1.099;1.153]
FDP	0.508	[0.532;0.634]
B'90/Die Grünen	0.894	[0.813;0.968]
Die Linke	1.291	[1.237;1.345]
Party-constituency-level variance σ^2_ξ	0.024	[0.023;0.026]
Residual variance σ^2_η	0.028	[0.027;0.028]
N	5.980	

5.3. *Forecast combination and retrospective evaluation*

In the final step, the two forecasting components are combined following Equation 4. Therefore, I compute party-district-specific weights ω_{pj} based on the ratios of the estimated forecast variances of each model (see Equation 5). None of the forecast components seems to be superior for one party in general, but there is significant leverage at the constituency level. While more weight is attached to the historical model for SPD vote share forecasts, the polling model seems to have performed better in most of the districts for the FDP.

Finally, the weights are used to combine the single forecasting models and compute an aggregated forecast. This is done separately for every party and district and over all iterations of the Bugs simulations. The party with the highest vote share after this computation is taken as the winner in each of the iterations, and the final forecast of the winner for a district is

Figure 2: Distribution of forecast weight parameter (see Equation 5). Large values are weights in favor of the historical model, small values are weights in favor of the polling model. Ticks on the horizontal axis indicate single constituency weights.



determined aggregating the winners of each of the iterations and identifying the party with most wins. The aggregate results are reported in Table 5; the constituency-level forecasts are reported in Table D.2 in the Appendix. As outlined above, the simulations can also be used to derive a natural quantification of uncertainty of the estimates at both the constituency and the national level. Figure 3 provides probability distributions of the aggregate number of forecast seats per party, generated from all iterations. It shows that according to the model, one would expect the CDU/CSU to gain between 235 and 245 direct mandates in total, between 50 and 60 seats for the SPD, one seat of Bündnis 90/Die Grünen (which, according to the model, is a very safe seat), and three seats for Die Linke with a probability around 80%.

The combined forecast provides a compromise between the uniform swing and the polling model. A comparison with the actual results reveals that the combined forecast was very close to the actual outcome. In total, 279 out of 299 districts or about 93% were forecast correctly. Note that the raw combined forecast performs equally well, too, but has a larger mean absolute error.

As an additional benchmark, I also inspected the share of correctly forecast districts in the subset of marginal seats. I defined those seats as marginal where the difference between first- and second-placed candidate was less than 10%.[18] Those cases are expected to be much more difficult to forecast. Accordingly, the share of correctly forecast districts in this subset is markedly lower for all of the models (see Table 5, next to last column), with the combined uncorrected model performing best (81% of the cases correct) and the raw polling model worst (56% correct).

Disentangling actual versus predicted winners gives a more detailed picture of the forecast performance for the corrected and combined model (see Table 6). It shows that eleven seats won by the SPD were wrongly attributed to the CDU/CSU, whereas eight out of nine seats wrongly attributed to the SPD were actually won by a candidate running on a CDU/CSU ticket. Taken together, these wrong forecasts virtually cancel each other out. All other models, including the combined uncorrected model that performs equally well in terms of overall correctly forecast seats, are more biased towards one of the larger parties.

[18] See also Wall, Sudulich and Cunningham (2012) for a similar procedure.

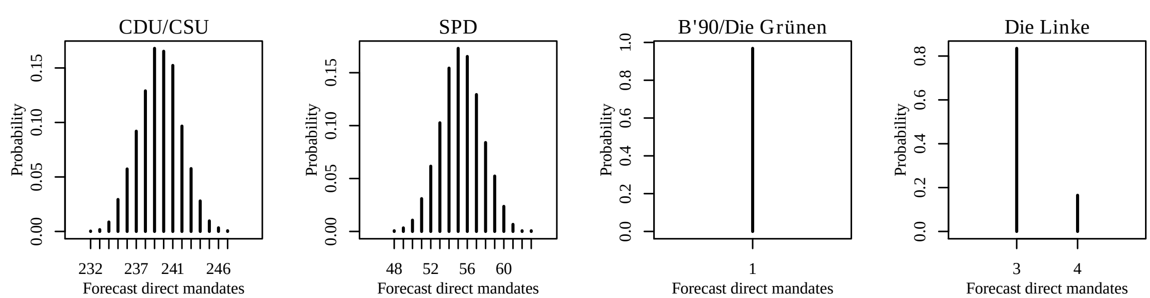
Table 5: Distribution of forecast winners over parties, by model

	CDU/CSU	SPD	FDP	B'90/Die Grünen	Die Linke	% correct	% correct, marg. dist.	MAE
Uniform swing, raw	224	70	0	1	4	92.3	78.8	0.031
Polling, raw	290	9	0	0	0	81.6	55.6	0.046
Combined, raw	229	65	0	1	4	93.3	80.8	0.028
Uniform swing	224	70	0	1	4	91.6	76.8	0.029
Polling	261	34	0	1	3	90.6	71.7	0.029
Combined	239	56	0	1	3	93.3	80.1	0.025
election.de (14.09.13)	224	69	0	1	5	?	?	?
spiegel.de (21.09.13)	181	89	0	3	13	?	?	?
Actual result	236	58	0	1	4			

Table 6: Actual (rows) vs. predicted (columns) winners, corrected and combined model

	CDU/CSU	SPD	FDP	B'90/Die Grünen	Die Linke
CDU/CSU	228	8	0	0	0
SPD	11	47	0	0	0
FDP	0	0	0	0	0
B'90/Die Grünen	0	0	0	1	0
Die Linke	0	1	0	0	3

Figure 3: Distribution of forecast seats per party, corrected and combined model



I found two other sources of constituency-level forecasts against which my forecasting models can be compared. The first is provided by the semi-commercial platform election.de.[19] The authors remain silent about details of their forecasting technique, but seem to implement a uniform swing-type model. Indeed, their forecasts are virtually identical with my uniform swing model (see Table 5) and underestimate the performance of the Conservatives. Another forecast approach was provided by the online newspaper site spiegel.de, which aggregated user expectations about the outcome in their home districts.[20] Apparently, the sample of users was strongly biased towards the left parties, as the aggregated forecast significantly underestimates the Conservatives' performance. This again indicates that individual models that mainly rest upon one source of information to inform constituency-level forecasts (a poll-derived national trend in the election.de model and expectations of the readership in the spiegel.de forecast) can be significantly biased. If components of this bias are stable over time (such as systematic, election-invariant trends in polls or readership preferences), they can be corrected in the future, following my suggested procedure.

What can be learned from the districts where the combined forecast failed? Table 7 lists the erroneous districts. By and large, the wrongly predicted cases were districts where the winning margin, i.e. the difference between the winner's and the second runner's vote share, was very small – less than 4 percentage points in 75% of the cases. The more interesting cases are at the bottom of the table. I argued above that it is extraordinarily difficult to incorporate district-

[19] See http://www.election.de/cgi-bin/content.pl?url=/img/poll/btw_wp_130914.html (accessed Wednesday 18th November, 2015).

[20] The original website wahlwette.spiegel.de has already been taken offline; a summary on the last forecasts which slightly depart from the reported figures can be accessed at http://www.spiegel.de/politik/deutschland/bundestagswahl-wahlwette-von-spiegel-online-a-923650.html (accessed Wednesday 18th November, 2015).

Table 7: Wrongly predicted districts (based on combination forecast of corrected models)

District name	Combined	Actual result	Margin
Essen III	SPD	CDU	0.000
Waldeck	SPD	CDU	0.002
Köln I	CDU	SPD	0.003
Potsdam	SPD	CDU	0.004
Oldenburg	CDU	SPD	0.006
Bonn	CDU	SPD	0.007
Bielefeld	CDU	SPD	0.008
Hildesheim	SPD	CDU	0.010
Gifhorn	CDU	SPD	0.012
Kaiserslautern	CDU	SPD	0.013
Darmstadt	CDU	SPD	0.014
Berlin-Neukölln	CDU	SPD	0.017
Leverkusen - Köln IV	CDU	SPD	0.020
Hamburg-Wandsbek	CDU	SPD	0.026
Prignitz	SPD	CDU	0.039
Hamburg-Eimsbüttel	CDU	SPD	0.042
Berlin-Pankow	SPD	Die Linke	0.044
Freiburg	SPD	CDU	0.049
Berlin-Charlottenburg	SPD	CDU	0.056
München-Nord	SPD	CSU	0.118

election specific information into the model. The polling model was built for this purpose, but is partly blurred by the smoothing mechanism of the model itself. In case of the Freiburg district, it was known in advance that the left parties SPD and Bündnis 90/Die Grünen both nominated popular candidates, thereby mutually taking off votes. Regarding the München-Nord district, the incumbent of the CSU managed to retain the seat against a newcomer SPD candidate. Indeed, none of the models considered incumbency status or integrated the popularity of candidates. One lesson to take away from these erroneously predicted cases is that it can be worth to collect and integrate more campaign information into the models. However, this often is a costly endeavor and, therefore, rarely done.[21]

6. CONCLUSION

Electoral research that takes the role of institutions seriously should—both in terms of theory and analysis—address the level where votes are transformed into seats. In many electoral systems, this is not (only) the national level but (also) the level of electoral districts. Consequently, efforts to forecast elections in such systems should be aware of local outcomes. In this paper, I proposed a correction-combination strategy to forecasting electoral outcomes at the constituency level. The approach accounts for bias in forecast time series that may occur because the original forecast model leaves important predictors unaccounted. Further, constituency-specific weighting of several forecasting components provides an easy way to exploit information from several sources. I demonstrated the use of the procedure by forecasting first vote shares at the 2013 German Bundestag election, drawing on historical district and disaggregated polling data. Both the correction and the combination component contributed to an improvement of the forecast in terms of mean absolute error and share of correctly predicted outcomes.

[21] In fact, one of my efforts to forecast the outcome of the 2013 election involved an online survey among local journalists who were asked to report their expectation on the outcome in the home and neighboring constituencies. However, the response rate was underwhelming (less than 150 out of 1990 invited journalists took part), which kept me from integrating these data into the forecasting model.

To be sure, I do not claim that the correction-combination procedure involves any magic that leads to precise forecasts every time. The disaggregated evaluation of the steps has shown that not all models are subject to time-invariant bias that can be exploited (see the uniform swing model in the application), and that the success of combination procedure rests on the assumption that errors of individual models cancel each other out in the aggregate. This happened to be the case in the application, where the uniform swing model underestimated the conservatives' success while the polling model overestimated it. If several models err in the same direction or rely on similar information, the combination step can be of little use.[22]

The contribution of this paper to the current state of election forecasting is threefold. First, it offers an easy-to-implement approach to unbias any type of constituency-level forecasting model with a certain historical record. The procedure allows incorporating additional substantive predictors that are not part of the original model, but also works by merely identifying district-party specific bias in historical forecasts. Even if forecasters are not interested in modifying their model or combining it with other information or models, this can be a useful procedure to test whether a model produces locally or party-specific biased forecasts. Secondly, it demonstrates the benefit of model combination at the constituency level. Previous applications of combining several models for election forecasting purposes used to operate at the national level. Using party-district-specific weights, I offer a flexible way of exploiting past models' performance to generate a new, synthetic forecast. Finally, it offers an alternative strategy to approaches that rest upon massive amounts of data (as suggested by Silver (2013) in

[22] A fruitful extension of the approach could be to apply more sophisticated model averaging procedures like Ensemble Bayesian Model Averaging (Raftery et al., 2005; Montgomery, Hollenbach and Ward, 2012*a*) to take the uniqueness of individual model's forecasts into account.

the opening quote), which are unlikely to be realized due to time and money constraints, and highly sophisticated modeling efforts that try to integrate information from different sources into one single forecasting model (e.g., Lock and Gelman, 2010; Jackman, 2012; Linzer, 2013; Hanretty, Lauderdale and Vivyan, Forthcoming).

The presented application provided a first test case for the method. There are other, potentially more relevant applications where district-level outcomes are essential for the distribution of seats in parliament, as is the case in First-Past-The-Post systems such as the United Kingdom. It is easy to argue that under such conditions, knowledge about the constituency-level distribution of voting preferences is of great value for estimating the distribution of seats in the parliament. Furthermore, constituency-level forecasts provide an opportunity for evaluating reasons of forecasting performance of different approaches (e.g., model-based vs. survey-based forecasts). In general, analyses of forecast bias are rare in election forecasting but could move forward the discussion about strengths and weaknesses of the various approaches on the market.

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Appendix A BUILDING A PANEL DATA SET OF ELECTORAL DISTRICTS

Important determinants of constituency-level election results are historical information like, for instance, past election results or candidates' incumbency or seniority status. However, identifying such information is not a trivial task, because of redistricting (which affects the composition of the electorate), renaming and changes in the electoral system. For example, in advance of the 2002 German Bundestag election the number of districts was reduced from 328 to 299, disrupting the history of many districts.

To be nevertheless able to use past district information for the estimation and forecasting procedure, I constructed a panel data set of electoral districts. Therefore, I coded changes which are documented in amendments of the *Bundeswahlgesetz* (Federal Electoral Law) in which redistricting and renaming are published about a year before an election takes place. In the cases where districts where abandoned without replacement, a district's history ends. Its area is usually distributed to neighboring districts that persist in the panel. Newly created districts are usually constructed from several existing districts. If all constituent districts persist as well, a new district is introduced in the panel. The constructed panel data set consists of 358 districts that, of course, have never been part of the electoral map simultaneously.

Appendix B MATCHING RESPONDENTS AND ELECTORAL DISTRICTS

In the best of all worlds, polls come with an identifier that matches every respondent to one and only one electoral district. However, this is not always the case. Many publicly available polls are rendered useless for constituency-level analysis as they are not delivered disaggregatedly or lack a geographical identifier. Still others are conducted for a more general purpose than predictive or even political interest, and therefore do not contain a constituency identifier but some other form of direct or indirect geographical variable. These might be dialing codes, zip codes, identifiers of other (mostly larger) political units like states, regions or provinces, or indicators for administrative units. As long as these units are not overly bigger than electoral units, that is, if the number of geographical identifiers is not much lesser than the number of constituencies, and if the geographical units do not typically contain many constituencies at once, the polls can still be considered useful for inference on constituency-level, because in this case respondents can be matched to one or only few constituencies.

The polling data available for the German showcase belong to the latter group. They are delivered with identifiers of administrative boundaries of *Kreise* and *Kreisfreie Städte*, which is the second-lowest administrative unit in Germany. Depending on the year, there are around 400 to 440 unique administrative units of that kind. A major problem for matching administrative with electoral units arises from the fact that they are not always congruent. To illustrate this disparity, Figure B.4 gives a view on a subset of electoral and administrative districts for the 2013 German Bundestag election. Qualitatively, there are two different cases of overlap between the geographical unit from the poll (PU) and from the election (EU) when it comes to an attribution of PU observations to EUs:[23]

1. The PU is completely contained in the EU. This is the case if the PU is congruent with the EU or if the EU contains one or more PUs entirely and some others partly. Consider the electoral district 63 in the map. The PUs "Oder-Spree" and "Frankfurt (Oder)" are entirely enclosed by the EU. In such cases poll respondents can be uniquely assigned to one EU.

2. The PU is dissected by one or several EU borders. This is the case for most PUs shown in Figure B.4. For instance, the PU "Teltow-Fläming" is part of the EUs 60, 61 and 62 (although the largest share of its area belongs to EU 62). To pick another example, the PU "Havelland" is part of the EUs 56 (not shown on the map), 58 and 60. In cases such as these, uncertainty arises to which EU an observation from a PU should be assigned. The city of Berlin in the map is a special case of this category, and at the same time the worst-case scenario in the data: This PU contains no less than 12 EUs, which makes the attribution of a respondent to one specific EU very uncertain.

In order to assign PU observations to EUs, I proceed in two steps. In the first step, possible EUs are assigned to PUs. I exploit the Federal Electoral Law that lists the administrative units of each electoral district. In the second step, one has to account for the attribution uncertainty in the estimate of EU-level aggregate statistics. There are two possible strategies here. The first

[23]This is the only direction of interest in this case. If one wanted to transfer information in the other direction, that is from EUs to PUs, there were other, mirror-imaged cases to consider.

Figure B.4: Disparity between electoral district boundaries (grey) and administrative units (blue) for a subset of electoral districts of the 2013 German Bundestag election. The electoral districts are labeled with their respective numbers, the administrative units with their name.

is to account for this uncertainty in the assignment process and match observations from a PU to a EU with a probability of $p = \frac{area_{intersect}(EU,PU)}{area(PU)}$. The advantage of this solution is that such probabilities are easy to obtain when geographical data of both EU and PU units is available, and estimation of EU-level statistics is straightforward as there is a fixed set of respondents for every district once the assignment is done. On the downside, many different combinations of assignments are possible, and the areal share is only a proxy of population density. Another strategy would be to account for uncertainty in the estimation of EU-level quantities. Many different procedures are imaginable, such as cross-classifying observations into districts. The procedure I employed here is to assign respondents randomly to one of their assigned districts.

Appendix C WINBUGS MODEL CODE

3.1 *Uniform swing correction model (see Section 5.1)*

```
model
{
    for (i in 1:N) {
        y[i] ~ dnorm(mu[i], tau.y)
        mu[i] <- alpha[party[i]] + b.project[party[i]] * project[i] +
            b.dominance[party[i]] * dominance[i] + b.newrun[party[i]] *
            newrun[i] + u[partyXwkr[i]]
    }
    for (j in 1:J) {
        alpha[j] ~ dnorm(alpha.hat[j], tau.alpha)
        b.project[j] ~ dnorm(b.project.hat[j], tau.b.project)
        b.dominance[j] ~ dnorm(b.dominance.hat[j], tau.b.dominance)
        b.newrun[j] ~ dnorm(b.newrun.hat[j], tau.b.newrun)
        alpha.hat[j] <- mu.alpha
        b.project.hat[j] <- mu.b.project
        b.dominance.hat[j] <- mu.b.dominance
        b.newrun.hat[j] <- mu.b.newrun
    }
    for (k in 1:K) {
        u[k] ~ dnorm(0.00000E+00, tau.u)
    }
    mu.alpha ~ dnorm(0.00000E+00, 1.00000E-04)
    mu.b.project ~ dnorm(0.00000E+00, 1.00000E-04)
    mu.b.dominance ~ dnorm(0.00000E+00, 1.00000E-04)
    mu.b.newrun ~ dnorm(0.00000E+00, 1.00000E-04)
    tau.y <- pow(sigma.y, -2)
    tau.alpha <- pow(sigma.alpha, -2)
    tau.b.project <- pow(sigma.b.project, -2)
    tau.b.dominance <- pow(sigma.b.dominance, -2)
    tau.b.newrun <- pow(sigma.b.newrun, -2)
    tau.u <- pow(sigma.u, -2)
    sigma.y ~ dunif(0.00000E+00, 100)
    sigma.alpha ~ dunif(0.00000E+00, 100)
    sigma.b.project ~ dunif(0.00000E+00, 100)
    sigma.b.dominance ~ dunif(0.00000E+00, 100)
    sigma.b.newrun ~ dunif(0.00000E+00, 100)
    sigma.u ~ dunif(0.00000E+00, 100)
}
```

3.2 Polls correction model (see Section 5.2)

```
model
{
    for (i in 1:N) {
        y[i] ~ dnorm(mu[i], tau.y)
        mu[i] <- alpha[party[i]] + b.polls[party[i]] * polls[i] +
            u[partyXwkr[i]]
    }
    for (j in 1:J) {
        alpha[j] ~ dnorm(alpha.hat[j], tau.alpha)
        b.polls[j] ~ dnorm(b.polls.hat[j], tau.b.polls)
        alpha.hat[j] <- mu.alpha
        b.polls.hat[j] <- mu.b.polls
    }
    for (k in 1:K) {
        u[k] ~ dnorm(0.00000E+00, tau.u)
    }
    mu.alpha ~ dnorm(0.00000E+00, 1.00000E-04)
    mu.b.polls ~ dnorm(0.00000E+00, 1.00000E-04)
    tau.y <- pow(sigma.y, -2)
    tau.alpha <- pow(sigma.alpha, -2)
    tau.b.polls <- pow(sigma.b.polls, -2)
    tau.u <- pow(sigma.u, -2)
    sigma.y ~ dunif(0.00000E+00, 100)
    sigma.alpha ~ dunif(0.00000E+00, 100)
    sigma.b.polls ~ dunif(0.00000E+00, 100)
    sigma.u ~ dunif(0.00000E+00, 100)
}
```

Appendix D FIGURES AND TABLES

Figure D.1: Constituency-level first vote shares of consecutive elections, 1990 - 2009. The red lines are linear fits of bivariate linear models.

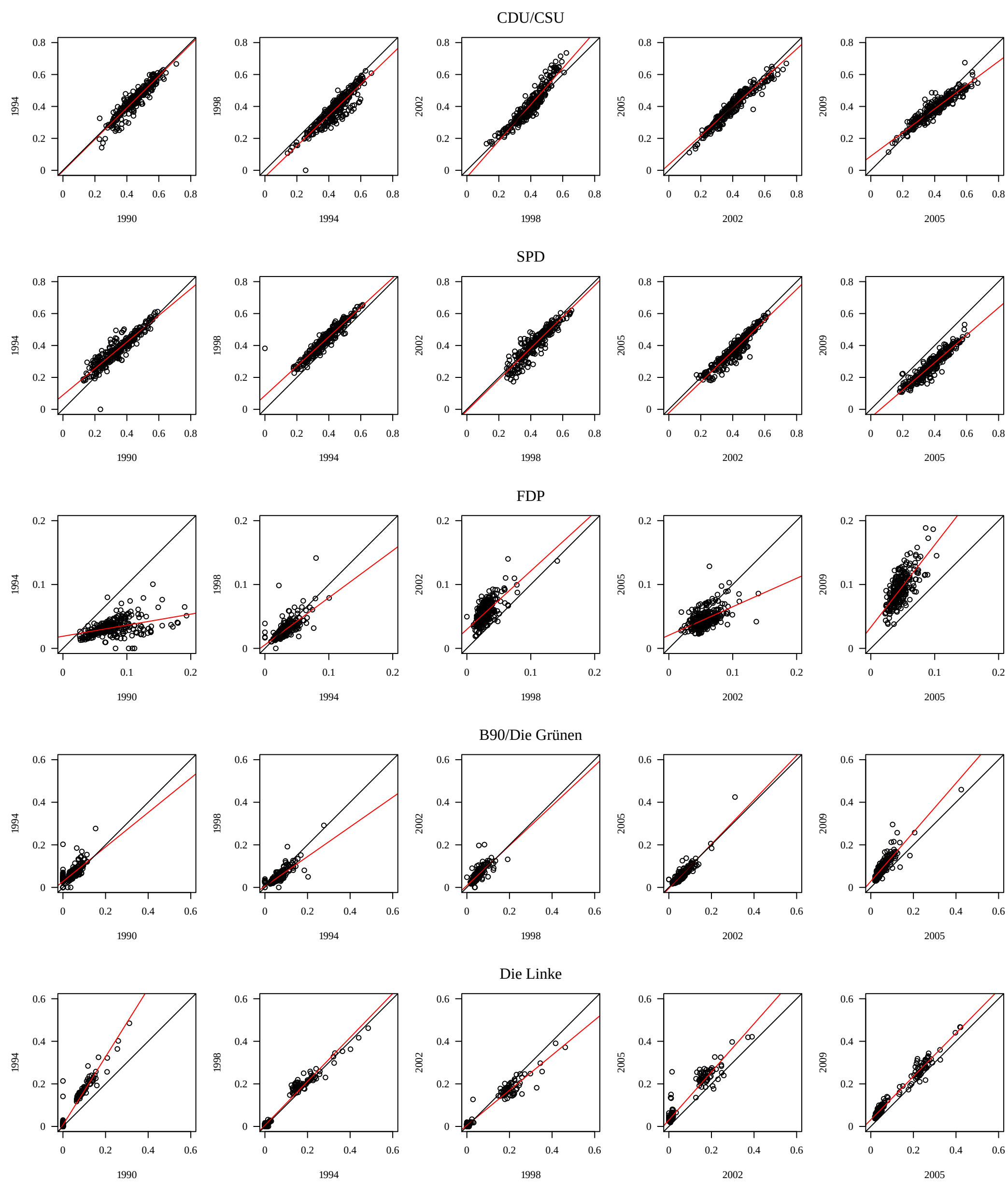
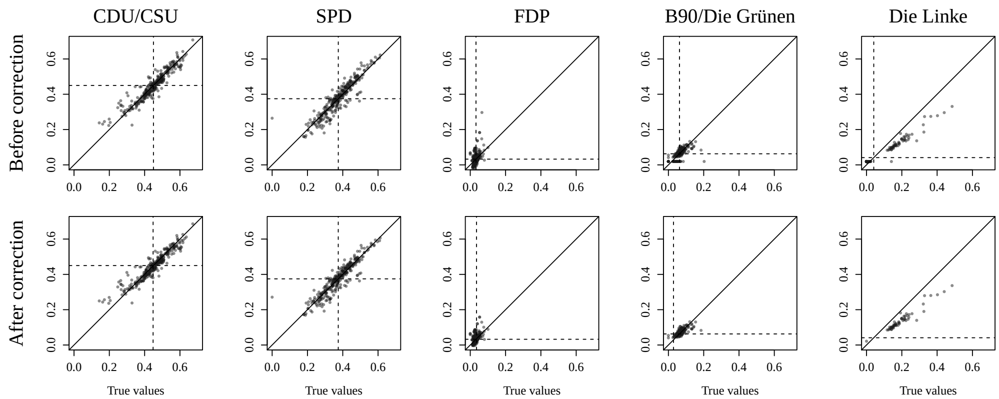
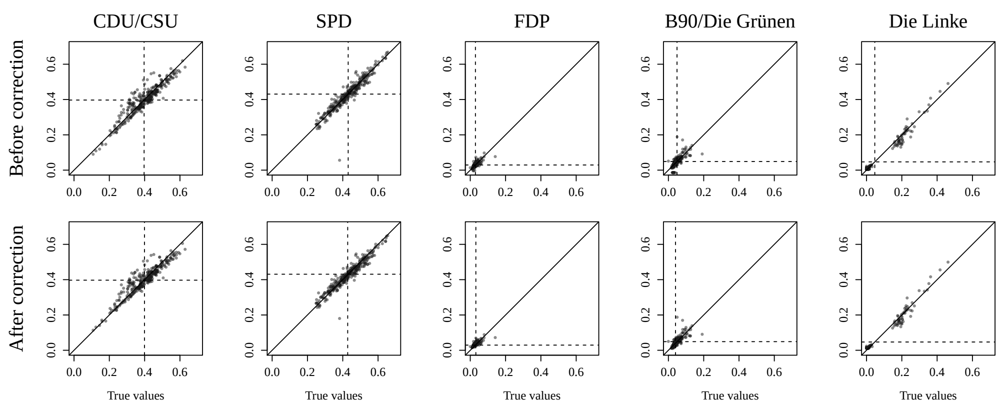


Figure D.2: Constituency-level estimation results the uniform swing forecasting model, before and after correction.

1994



1998



2002

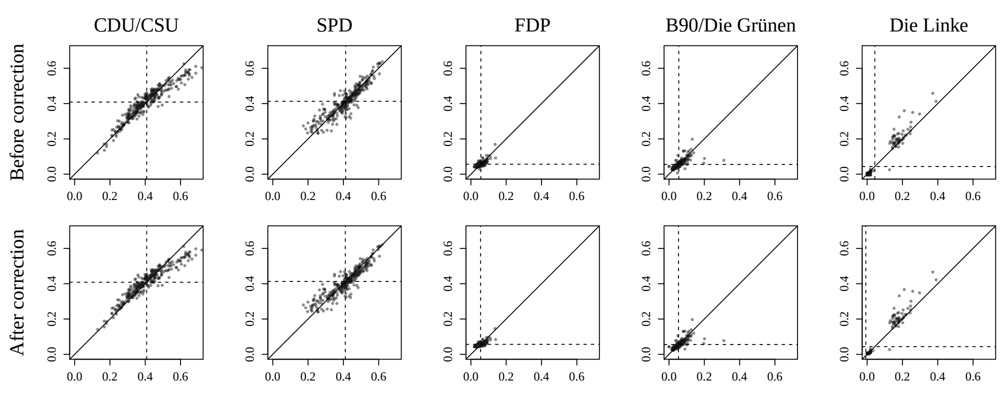
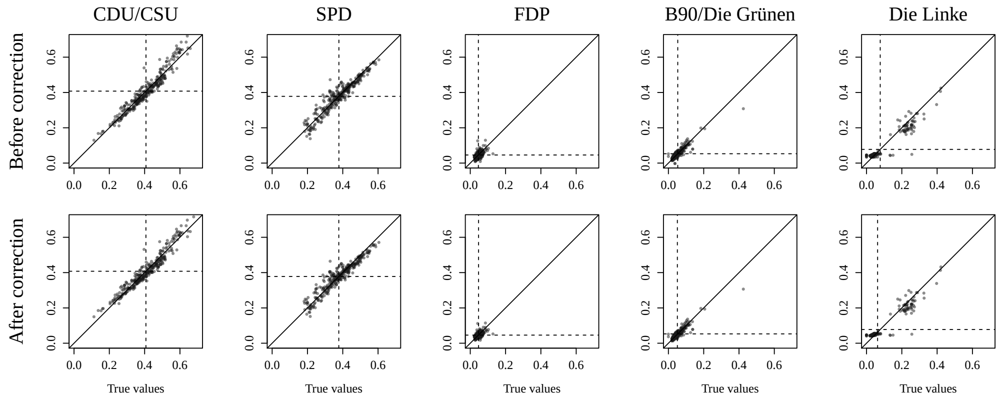


Figure D.2, *continued*: Constituency-level estimation results the uniform swing forecasting model, before and after correction.

2005



2009

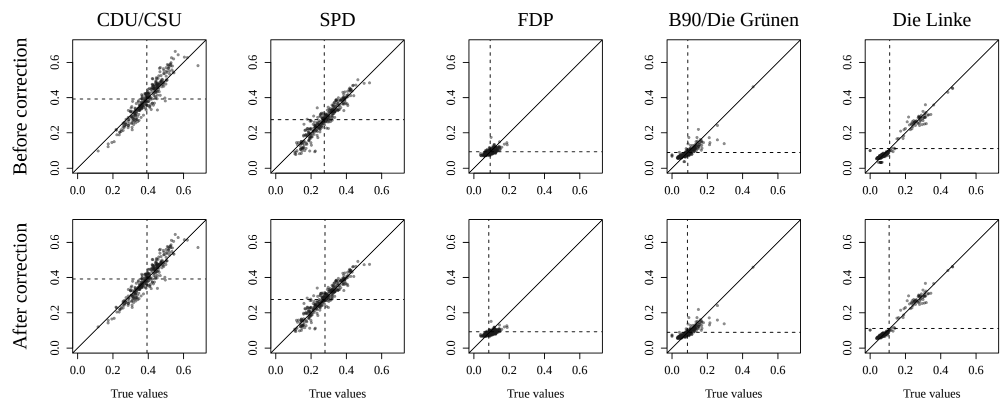


Figure D.3: Constituency-level estimation results the poll-based forecasting model, before and after correction.

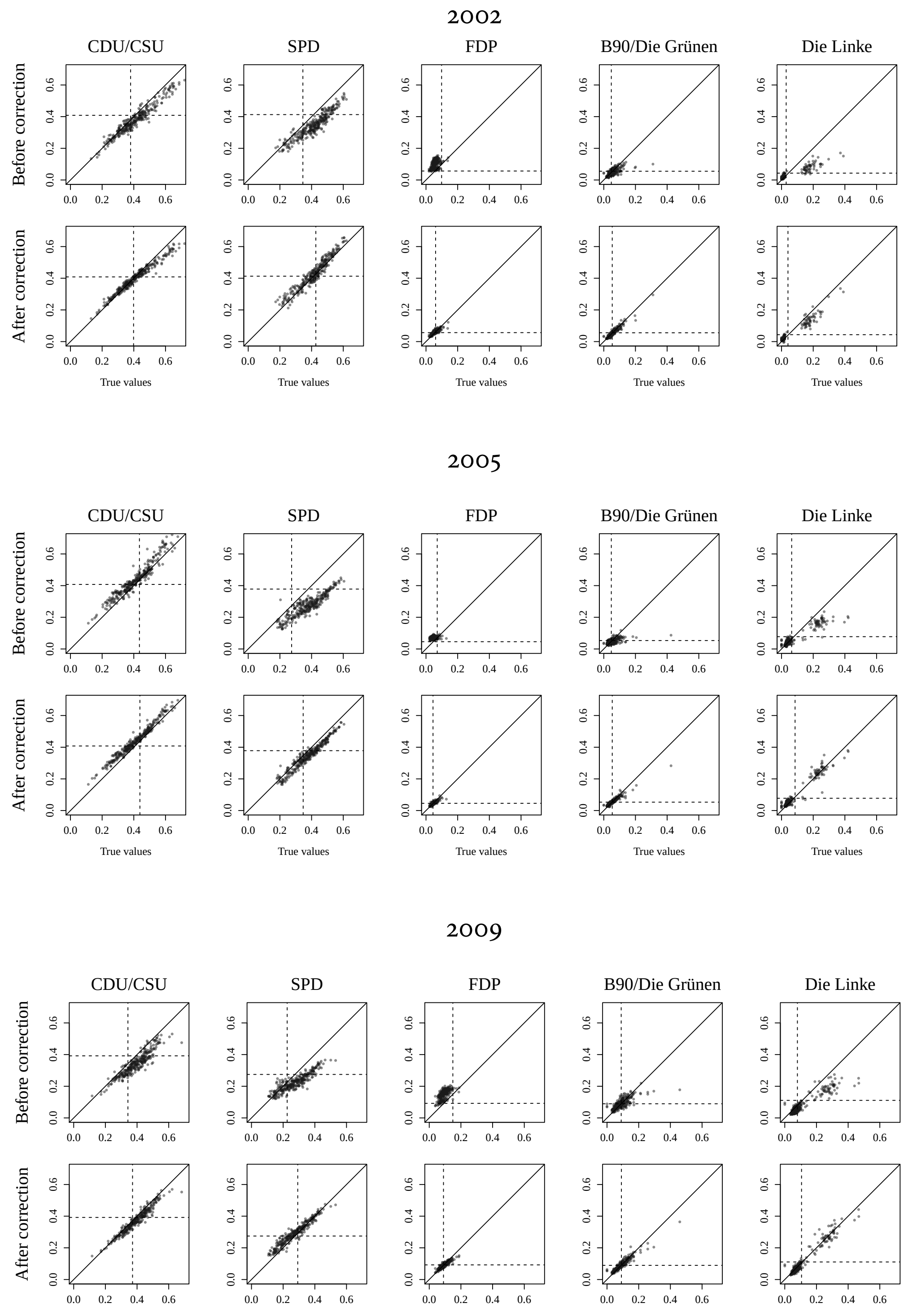


Table D.1: Summary statistics of the raw poll data utilized to inform poll-based model: numbers of respondents, N, numbers of districts covered, J, average numbers of respondents per district, $\bar{N}_j$, their standard deviations, minimum and maximum values.

	N	J	mean(N_j)	sd(N_j)	min(N_j)	max(N_j)
2002	30,627	298	103	49	5	321
2005	28,878	297	97	27	34	216
2009	28,216	297	95	29	35	233
2013	29,767	299	100	27	28	197

Table D.2: Overview of 2013 forecasts

NR	District name	Winner	Uniform Swing	Polls	Combined	Predicted vote shares, combined model CDU/CSU	SPD	FDP	Greens	Left
1	Flensburg – Schleswi...	CDU	CDU	CDU	CDU	0.41	0.37	0.01	0.13	0.03
2	Nordfriesland – Dith...	CDU	CDU	CDU	CDU	0.45	0.32	0.02	0.11	0.03
3	Steinburg – Dithmars...	CDU	CDU	CDU	CDU	0.43	0.34	0.03	0.10	0.03
4	Rendsburg-Eckernförd...	CDU	CDU	CDU	CDU	0.42	0.37	0.01	0.12	0.02
5	Kiel	SPD	SPD	SPD	SPD	0.33	0.41	0.01	0.17	0.05
6	Plön – Neumünster	CDU	CDU	CDU	CDU	0.40	0.37	0.01	0.12	0.03
7	Pinneberg	CDU	CDU	CDU	CDU	0.43	0.36	0.01	0.12	0.03
8	Segeberg – Stormarn-...	CDU	CDU	CDU	CDU	0.42	0.34	0.02	0.12	0.03
9	Ostholstein – Storma...	CDU	CDU	CDU	CDU	0.41	0.36	0.02	0.11	0.03
10	Herzogtum Lauenburg ...	CDU	CDU	CDU	CDU	0.43	0.33	0.02	0.12	0.03
11	Lübeck	SPD	SPD	SPD	SPD	0.34	0.38	0.02	0.14	0.05
12	Schwerin – Ludwigslu...	CDU	CDU	CDU	CDU	0.37	0.23	0.02	0.07	0.18
13	Ludwigslust-Parchim ...	CDU	CDU	CDU	CDU	0.34	0.27	0.01	0.07	0.20
14	Rostock – Landkreis ...	CDU	CDU	CDU	CDU	0.31	0.23	0.01	0.11	0.22
15	Vorpommern-Rügen – V...	CDU	CDU	CDU	CDU	0.50	0.16	0.00	0.05	0.18
16	Mecklenburgische See...	CDU	CDU	CDU	CDU	0.41	0.17	0.02	0.06	0.17
17	Mecklenburgische See...	CDU	CDU	CDU	CDU	0.38	0.23	0.02	0.06	0.18
18	Hamburg-Mitte	SPD	SPD	SPD	SPD	0.31	0.37	0.01	0.18	0.08
19	Hamburg-Altona	SPD	SPD	CDU	SPD	0.33	0.37	0.01	0.17	0.06
20	Hamburg-Eimsbüttel	SPD	CDU	CDU	CDU	0.34	0.30	0.01	0.24	0.05
21	Hamburg-Nord	CDU	CDU	CDU	CDU	0.40	0.34	0.01	0.15	0.03
22	Hamburg-Wandsbek	SPD	CDU	CDU	CDU	0.39	0.38	0.00	0.12	0.05
23	Hamburg-Bergedorf – ...	SPD	SPD	SPD	SPD	0.37	0.42	0.00	0.11	0.06
24	Aurich – Emden	SPD	SPD	SPD	SPD	0.30	0.46	0.00	0.13	0.06
25	Unterems	CDU	CDU	CDU	CDU	0.48	0.33	0.02	0.08	0.04
26	Friesland – Wilhelms...	SPD	SPD	CDU	SPD	0.37	0.41	0.02	0.10	0.05
27	Oldenburg – Ammerlan...	SPD	CDU	CDU	CDU	0.39	0.35	0.02	0.16	0.05
28	Delmenhorst – Weserm...	CDU	SPD	CDU	CDU	0.39	0.37	0.02	0.11	0.05
29	Cuxhaven – Stade II	CDU	CDU	CDU	CDU	0.41	0.39	0.01	0.09	0.04
30	Stade I – Rotenburg ...	CDU	CDU	CDU	CDU	0.47	0.35	0.00	0.09	0.02
31	Mittelems	CDU	CDU	CDU	CDU	0.57	0.30	0.01	0.08	0.02
32	Cloppenburg – Vechta	CDU	CDU	CDU	CDU	0.64	0.23	0.02	0.06	0.02
33	Diepholz – Nienburg ...	CDU	CDU	CDU	CDU	0.42	0.37	0.02	0.11	0.03
34	Osterholz – Verden	CDU	SPD	CDU	CDU	0.40	0.40	0.01	0.11	0.05
35	Rotenburg I – Heidek...	CDU	CDU	CDU	CDU	0.43	0.39	0.01	0.10	0.03
36	Harburg	CDU	CDU	CDU	CDU	0.43	0.34	0.02	0.12	0.03
37	Lüchow-Dannenberg – ...	CDU	CDU	CDU	CDU	0.36	0.34	0.01	0.17	0.05
38	Osnabrück-Land	CDU	CDU	CDU	CDU	0.47	0.36	0.01	0.09	0.03
39	Stadt Osnabrück	CDU	CDU	CDU	CDU	0.41	0.37	0.02	0.13	0.03
40	Nienburg II – Schaum...	SPD	SPD	CDU	SPD	0.41	0.42	-0.01	0.10	0.02
41	Stadt Hannover I	SPD	SPD	SPD	SPD	0.36	0.38	0.01	0.12	0.04
42	Stadt Hannover II	SPD	SPD	SPD	SPD	0.34	0.39	-0.00	0.14	0.05
43	Hannover-Land I	CDU	SPD	CDU	CDU	0.41	0.39	0.00	0.10	0.02
44	Celle – Uelzen	CDU	CDU	CDU	CDU	0.45	0.36	0.00	0.10	0.03
45	Gifhorn – Peine	SPD	SPD	CDU	CDU	0.40	0.40	-0.01	0.09	0.03
46	Hameln-Pyrmont – Hol...	SPD	SPD	CDU	SPD	0.39	0.41	0.01	0.11	0.05
47	Hannover-Land II	SPD	SPD	CDU	SPD	0.39	0.40	-0.00	0.10	0.03
48	Hildesheim	CDU	SPD	CDU	SPD	0.39	0.42	-0.01	0.11	0.03
49	Salzgitter – Wolfenb...	SPD	SPD	SPD	SPD	0.36	0.42	0.00	0.09	0.04
50	Braunschweig	SPD	SPD	CDU	SPD	0.37	0.37	-0.01	0.11	0.04
51	Helmstedt – Wolfsbur...	CDU	CDU	CDU	CDU	0.42	0.37	-0.00	0.10	0.03
52	Goslar – Northeim – ...	SPD	SPD	CDU	SPD	0.39	0.41	0.01	0.09	0.05
53	Göttingen	SPD	SPD	CDU	SPD	0.38	0.40	-0.00	0.15	0.04
54	Bremen I	SPD	SPD	SPD	SPD	0.31	0.36	0.01	0.18	0.07
55	Bremen II – Bremerha...	SPD	SPD	SPD	SPD	0.29	0.40	0.01	0.13	0.09

Table D.2: Overview of 2013 forecasts

NR	District name	Winner	Uniform Swing	Polls	Combined	Predicted vote shares, combined model CDU/CSU	SPD	FDP	Greens	Left
56	Prignitz – Ostprigni...	CDU	SPD	SPD	SPD	0.28	0.29	0.01	0.07	0.22
57	Uckermark – Barnim I	CDU	SPD	CDU	CDU	0.30	0.28	0.01	0.06	0.21
58	Oberhavel – Havellan...	CDU	SPD	CDU	CDU	0.32	0.29	0.02	0.09	0.16
59	Märkisch-Oderland – ...	CDU	Left	CDU	CDU	0.28	0.24	0.01	0.06	0.26
60	Brandenburg an der H...	SPD	SPD	SPD	SPD	0.29	0.30	0.01	0.06	0.19
61	Potsdam – Potsdam-Mi...	CDU	SPD	CDU	SPD	0.29	0.30	0.01	0.09	0.19
62	Dahme-Spreewald – Te...	CDU	SPD	CDU	CDU	0.30	0.29	0.02	0.07	0.18
63	Frankfurt (Oder) – O...	CDU	SPD	CDU	CDU	0.28	0.25	0.01	0.07	0.21
64	Cottbus – Spree-Neiß...	CDU	SPD	CDU	CDU	0.29	0.25	0.02	0.06	0.24
65	Elbe-Elster – Obersp...	CDU	CDU	CDU	CDU	0.33	0.26	0.02	0.05	0.20
66	Altmark	CDU	CDU	CDU	CDU	0.35	0.23	0.01	0.06	0.23
67	Börde – Jerichower L...	CDU	CDU	CDU	CDU	0.37	0.25	0.02	0.05	0.17
68	Harz	CDU	CDU	CDU	CDU	0.36	0.22	0.02	0.07	0.19
69	Magdeburg	CDU	CDU	CDU	CDU	0.35	0.25	0.01	0.07	0.23
70	Dessau – Wittenberg	CDU	CDU	CDU	CDU	0.39	0.20	0.02	0.06	0.18
71	Anhalt	CDU	CDU	CDU	CDU	0.36	0.23	0.02	0.05	0.19
72	Halle	CDU	CDU	CDU	CDU	0.34	0.19	0.01	0.09	0.28
73	Burgenland – Saalekr...	CDU	CDU	CDU	CDU	0.37	0.20	0.03	0.05	0.21
74	Mansfeld	CDU	CDU	CDU	CDU	0.36	0.20	0.02	0.05	0.23
75	Berlin-Mitte	SPD	SPD	SPD	SPD	0.25	0.28	0.01	0.21	0.14
76	Berlin-Pankow	Left	SPD	SPD	SPD	0.23	0.27	0.01	0.16	0.21
77	Berlin-Reinickendorf	CDU	CDU	CDU	CDU	0.41	0.30	0.02	0.12	0.04
78	Berlin-Spandau – Cha...	CDU	CDU	CDU	CDU	0.39	0.34	0.01	0.11	0.05
79	Berlin-Steglitz-Zehl...	CDU	CDU	CDU	CDU	0.41	0.31	0.02	0.14	0.02
80	Berlin-Charlottenbur...	CDU	SPD	CDU	SPD	0.34	0.34	0.03	0.18	0.03
81	Berlin-Tempelhof-Sch...	CDU	CDU	CDU	CDU	0.34	0.26	0.01	0.24	0.04
82	Berlin-Neukölln	SPD	CDU	CDU	CDU	0.34	0.29	0.01	0.15	0.08
83	Berlin-Friedrichshai...	Greens	Greens	Greens	Greens	0.17	0.19	0.01	0.39	0.14
84	Berlin-Treptow-Köpen...	Left	Left	Left	Left	0.25	0.23	0.00	0.09	0.35
85	Berlin-Marzahn-Helle...	Left	Left	Left	Left	0.23	0.19	0.01	0.07	0.31
86	Berlin-Lichtenberg	Left	Left	Left	Left	0.22	0.21	0.01	0.09	0.34
87	Aachen I	CDU	CDU	CDU	CDU	0.42	0.32	0.01	0.15	0.04
88	Aachen II	CDU	CDU	CDU	CDU	0.43	0.37	0.01	0.10	0.04
89	Heinsberg	CDU	CDU	CDU	CDU	0.53	0.28	0.01	0.09	0.03
90	Düren	CDU	CDU	CDU	CDU	0.48	0.35	-0.00	0.09	0.03
91	Rhein-Erft-Kreis I	CDU	CDU	CDU	CDU	0.42	0.38	0.02	0.09	0.02
92	Euskirchen – Rhein-E...	CDU	CDU	CDU	CDU	0.47	0.33	0.03	0.09	0.03
93	Köln I	SPD	SPD	CDU	CDU	0.37	0.37	0.01	0.13	0.04
94	Köln II	CDU	CDU	CDU	CDU	0.37	0.34	0.02	0.17	0.02
95	Köln III	SPD	SPD	SPD	SPD	0.33	0.38	0.00	0.18	0.05
96	Bonn	SPD	SPD	CDU	CDU	0.37	0.35	0.07	0.12	0.03
97	Rhein-Sieg-Kreis I	CDU	CDU	CDU	CDU	0.46	0.30	0.02	0.11	0.02
98	Rhein-Sieg-Kreis II	CDU	CDU	CDU	CDU	0.52	0.28	0.02	0.10	0.02
99	Oberbergischer Kreis	CDU	CDU	CDU	CDU	0.51	0.32	0.01	0.09	0.03
100	Rheinisch-Bergischer...	CDU	CDU	CDU	CDU	0.52	0.31	0.01	0.11	0.02
101	Leverkusen – Köln IV	SPD	SPD	CDU	CDU	0.38	0.38	0.00	0.12	0.04
102	Wuppertal I	SPD	SPD	CDU	SPD	0.37	0.38	0.01	0.11	0.06
103	Solingen – Remscheid...	CDU	CDU	CDU	CDU	0.42	0.38	0.01	0.10	0.04
104	Mettmann I	CDU	CDU	CDU	CDU	0.47	0.32	0.01	0.10	0.02
105	Mettmann II	CDU	CDU	CDU	CDU	0.43	0.38	0.01	0.09	0.04
106	Düsseldorf I	CDU	CDU	CDU	CDU	0.46	0.32	0.02	0.12	0.03
107	Düsseldorf II	CDU	CDU	CDU	CDU	0.40	0.37	0.01	0.12	0.05
108	Neuss I	CDU	CDU	CDU	CDU	0.49	0.34	0.01	0.08	0.02
109	Mönchengladbach	CDU	CDU	CDU	CDU	0.48	0.31	0.02	0.09	0.03
110	Krefeld I – Neuss II	CDU	CDU	CDU	CDU	0.46	0.33	0.03	0.09	0.02
111	Viersen	CDU	CDU	CDU	CDU	0.51	0.30	0.02	0.10	0.03
112	Kleve	CDU	CDU	CDU	CDU	0.51	0.31	0.01	0.09	0.02
113	Wesel I	CDU	SPD	CDU	CDU	0.42	0.41	0.00	0.09	0.03
114	Krefeld II – Wesel I...	SPD	SPD	CDU	SPD	0.39	0.42	0.01	0.10	0.04
115	Duisburg I	SPD	SPD	SPD	SPD	0.35	0.44	-0.01	0.10	0.05
116	Duisburg II	SPD	SPD	SPD	SPD	0.31	0.49	-0.01	0.08	0.06
117	Oberhausen – Wesel I...	SPD	SPD	SPD	SPD	0.32	0.47	-0.00	0.11	0.05
118	Mülheim – Essen I	SPD	SPD	SPD	SPD	0.36	0.42	0.01	0.10	0.04
119	Essen II	SPD	SPD	SPD	SPD	0.32	0.49	-0.00	0.09	0.06
120	Essen III	CDU	SPD	CDU	SPD	0.39	0.40	0.00	0.12	0.03
121	Recklinghausen I	SPD	SPD	SPD	SPD	0.35	0.45	0.00	0.09	0.06
122	Recklinghausen II	SPD	SPD	SPD	SPD	0.35	0.43	0.01	0.09	0.05
123	Gelsenkirchen	SPD	SPD	SPD	SPD	0.30	0.54	0.00	0.10	-0.02
124	Steinfurt I – Borken...	CDU	CDU	CDU	CDU	0.49	0.34	0.03	0.09	0.02
125	Bottrop – Recklingha...	SPD	SPD	SPD	SPD	0.37	0.45	-0.01	0.08	0.05
126	Borken II	CDU	CDU	CDU	CDU	0.55	0.29	0.01	0.09	0.02
127	Coesfeld – Steinfurt...	CDU	CDU	CDU	CDU	0.53	0.30	0.02	0.10	0.02
128	Steinfurt III	CDU	CDU	CDU	CDU	0.46	0.42	0.01	0.06	0.03
129	Münster	CDU	CDU	CDU	CDU	0.42	0.36	0.02	0.15	0.02
130	Warendorf	CDU	CDU	CDU	CDU	0.50	0.34	0.03	0.07	0.04
131	Gütersloh I	CDU	CDU	CDU	CDU	0.47	0.35	0.01	0.10	0.03
132	Bielefeld – Güterslo...	SPD	CDU	CDU	CDU	0.39	0.38	-0.00	0.15	0.05
133	Herford – Minden-Lüb...	SPD	SPD	CDU	SPD	0.40	0.41	0.01	0.09	0.04
134	Minden-Lübbecke I	CDU	CDU	CDU	CDU	0.44	0.42	-0.00	0.08	0.03
135	Lippe I	SPD	SPD	CDU	SPD	0.40	0.42	0.02	0.09	0.03
136	Höxter – Lippe II	CDU	CDU	CDU	CDU	0.48	0.35	0.01	0.09	0.04
137	Paderborn – Güterslo...	CDU	CDU	CDU	CDU	0.54	0.28	0.02	0.09	0.03
138	Hagen – Ennepe-Ruhr-...	SPD	SPD	SPD	SPD	0.37	0.44	0.01	0.08	0.04

Table D.2: Overview of 2013 forecasts

NR	District name	Winner	Uniform Swing	Polls	Combined	Predicted vote shares, combined model CDU/CSU	SPD	FDP	Greens	Left
139	Ennepe-Ruhr-Kreis II	SPD	SPD	SPD	SPD	0.34	0.43	0.02	0.11	0.04
140	Bochum I	SPD	SPD	SPD	SPD	0.35	0.46	-0.01	0.11	0.05
141	Herne – Bochum II	SPD	SPD	SPD	SPD	0.31	0.52	-0.00	0.12	-0.02
142	Dortmund I	SPD	SPD	SPD	SPD	0.32	0.40	0.01	0.13	0.05
143	Dortmund II	SPD	SPD	SPD	SPD	0.33	0.45	-0.00	0.11	0.05
144	Unna I	SPD	SPD	SPD	SPD	0.36	0.45	-0.00	0.11	0.05
145	Hamm – Unna II	SPD	SPD	SPD	SPD	0.37	0.44	0.01	0.08	0.03
146	Soest	CDU	CDU	CDU	CDU	0.48	0.33	0.02	0.09	0.04
147	Hochsauerlandkreis	CDU	CDU	CDU	CDU	0.53	0.31	0.01	0.08	0.03
148	Siegen-Wittgenstein	CDU	CDU	CDU	CDU	0.44	0.40	0.02	0.06	0.04
149	Olpe – Märkischer Kr...	CDU	CDU	CDU	CDU	0.49	0.33	0.02	0.08	0.03
150	Märkischer Kreis II	SPD	SPD	CDU	SPD	0.41	0.41	0.00	0.07	0.04
151	Nordsachsen	CDU	CDU	CDU	CDU	0.44	0.19	0.02	0.05	0.16
152	Leipzig I	CDU	CDU	CDU	CDU	0.37	0.22	0.02	0.09	0.16
153	Leipzig II	CDU	CDU	CDU	CDU	0.33	0.25	0.02	0.13	0.17
154	Leipzig-Land	CDU	CDU	CDU	CDU	0.44	0.21	0.02	0.06	0.15
155	Meißen	CDU	CDU	CDU	CDU	0.47	0.17	0.02	0.07	0.14
156	Bautzen I	CDU	CDU	CDU	CDU	0.46	0.17	0.04	0.06	0.16
157	Görlitz	CDU	CDU	CDU	CDU	0.46	0.16	0.02	0.06	0.19
158	Sächsische Schweiz-O...	CDU	CDU	CDU	CDU	0.49	0.17	0.03	0.06	0.15
159	Dresden I	CDU	CDU	CDU	CDU	0.41	0.22	0.02	0.10	0.20
160	Dresden II – Bautzen...	CDU	CDU	CDU	CDU	0.41	0.19	0.04	0.13	0.14
161	Mittelsachsen	CDU	CDU	CDU	CDU	0.47	0.18	0.03	0.06	0.17
162	Chemnitz	CDU	CDU	CDU	CDU	0.37	0.24	0.03	0.07	0.19
163	Chemnitzer Umland – ...	CDU	CDU	CDU	CDU	0.45	0.19	0.03	0.06	0.15
164	Erzgebirgskreis I	CDU	CDU	CDU	CDU	0.45	0.15	0.05	0.05	0.16
165	Zwickau	CDU	CDU	CDU	CDU	0.43	0.19	0.02	0.06	0.19
166	Vogtlandkreis	CDU	CDU	CDU	CDU	0.44	0.19	0.02	0.06	0.17
167	Waldeck	CDU	SPD	CDU	SPD	0.39	0.40	0.02	0.11	0.04
168	Kassel	SPD	SPD	SPD	SPD	0.34	0.38	0.00	0.15	0.05
169	Werra-Meißner – Hers...	SPD	SPD	CDU	SPD	0.38	0.43	0.01	0.08	0.04
170	Schwalm-Eder	SPD	SPD	SPD	SPD	0.38	0.41	0.01	0.10	0.04
171	Marburg	SPD	SPD	CDU	SPD	0.39	0.41	0.00	0.11	0.04
172	Lahn-Dill	CDU	CDU	CDU	CDU	0.45	0.36	0.01	0.10	0.04
173	Gießen	CDU	CDU	CDU	CDU	0.40	0.37	0.03	0.11	0.03
174	Fulda	CDU	CDU	CDU	CDU	0.51	0.25	0.01	0.09	0.03
175	Main-Kinzig – Wetter...	CDU	CDU	CDU	CDU	0.40	0.37	0.03	0.12	0.03
176	Hochtaunus	CDU	CDU	CDU	CDU	0.48	0.28	0.03	0.11	0.03
177	Wetterau I	CDU	CDU	CDU	CDU	0.44	0.37	0.01	0.10	0.03
178	Rheingau-Taunus – Li...	CDU	CDU	CDU	CDU	0.49	0.31	0.02	0.10	0.02
179	Wiesbaden	CDU	CDU	CDU	CDU	0.43	0.34	0.01	0.11	0.03
180	Hanau	CDU	CDU	CDU	CDU	0.41	0.35	0.01	0.09	0.03
181	Main-Taunus	CDU	CDU	CDU	CDU	0.50	0.26	0.03	0.12	0.02
182	Frankfurt am Main I	CDU	CDU	CDU	CDU	0.37	0.31	0.02	0.15	0.05
183	Frankfurt am Main II	CDU	CDU	CDU	CDU	0.38	0.29	0.01	0.19	0.04
184	Groß-Gerau	CDU	CDU	CDU	CDU	0.39	0.38	0.00	0.12	0.04
185	Offenbach	CDU	CDU	CDU	CDU	0.43	0.32	0.02	0.12	0.04
186	Darmstadt	SPD	CDU	CDU	CDU	0.37	0.36	0.00	0.15	0.03
187	Odenwald	CDU	CDU	CDU	CDU	0.43	0.33	0.02	0.12	0.03
188	Bergstraße	CDU	CDU	CDU	CDU	0.47	0.35	0.01	0.10	0.02
189	Eichsfeld – Nordhaus...	CDU	CDU	CDU	CDU	0.46	0.21	0.02	0.06	0.18
190	Eisenach – Wartburgk...	CDU	CDU	CDU	CDU	0.38	0.24	0.01	0.06	0.19
191	Kyffhäuserkreis – Sö...	CDU	CDU	CDU	CDU	0.37	0.21	0.02	0.06	0.22
192	Gotha – Ilm-Kreis	CDU	CDU	CDU	CDU	0.34	0.26	0.02	0.07	0.19
193	Erfurt – Weimar – We...	CDU	CDU	CDU	CDU	0.34	0.22	0.01	0.09	0.22
194	Gera – Jena – Saale-...	CDU	CDU	CDU	CDU	0.33	0.22	0.03	0.08	0.24
195	Greiz – Altenburger ...	CDU	CDU	CDU	CDU	0.40	0.21	0.02	0.06	0.21
196	Sonneberg – Saalfeld...	CDU	CDU	CDU	CDU	0.35	0.22	0.02	0.05	0.22
197	Suhl – Schmalkalden-...	CDU	CDU	CDU	CDU	0.35	0.22	0.02	0.06	0.23
198	Neuwied	CDU	CDU	CDU	CDU	0.43	0.38	0.02	0.08	0.03
199	Ahrweiler	CDU	CDU	CDU	CDU	0.49	0.29	0.04	0.09	0.03
200	Koblenz	CDU	CDU	CDU	CDU	0.47	0.32	0.02	0.11	0.03
201	Mosel/Rhein-Hunsrück	CDU	CDU	CDU	CDU	0.50	0.28	0.04	0.09	0.03
202	Kreuznach	CDU	CDU	CDU	CDU	0.48	0.32	-0.00	0.09	0.04
203	Bitburg	CDU	CDU	CDU	CDU	0.50	0.28	0.04	0.09	0.03
204	Trier	CDU	CDU	CDU	CDU	0.48	0.30	0.01	0.10	0.04
205	Montabaur	CDU	CDU	CDU	CDU	0.46	0.31	0.02	0.09	0.04
206	Mainz	CDU	CDU	CDU	CDU	0.39	0.34	0.04	0.13	0.03
207	Worms	CDU	SPD	CDU	CDU	0.40	0.39	0.02	0.10	0.03
208	Ludwigshafen/Franken...	CDU	CDU	CDU	CDU	0.42	0.36	0.01	0.09	0.04
209	Neustadt – Speyer	CDU	CDU	CDU	CDU	0.47	0.29	0.02	0.11	0.03
210	Kaiserslautern	SPD	SPD	CDU	CDU	0.37	0.37	0.02	0.09	0.06
211	Pirmasens	CDU	CDU	CDU	CDU	0.43	0.30	0.03	0.09	0.06
212	Südpfalz	CDU	CDU	CDU	CDU	0.44	0.31	0.03	0.11	0.04
213	Altötting	CSU	CSU	CSU	CSU	0.60	0.17	0.01	0.09	0.02
214	Erding – Ebersberg	CSU	CSU	CSU	CSU	0.51	0.21	0.03	0.14	0.02
215	Freising	CSU	CSU	CSU	CSU	0.50	0.19	0.03	0.17	0.02
216	Fürstenfeldbruck	CSU	CSU	CSU	CSU	0.51	0.23	0.02	0.13	0.03
217	Ingolstadt	CSU	CSU	CSU	CSU	0.58	0.18	0.01	0.10	0.03
218	München-Nord	CSU	CSU	CSU	SPD	0.39	0.39	0.02	0.12	0.03
219	München-Ost	CSU	CSU	CSU	CSU	0.39	0.31	0.04	0.16	0.03
220	München-Süd	CSU	CSU	CSU	CSU	0.39	0.33	0.02	0.16	0.03
221	München-West/Mitte	CSU	CSU	CSU	CSU	0.39	0.32	0.02	0.16	0.04

Table D.2: Overview of 2013 forecasts

NR	District name	Winner	Uniform Swing	Polls	Combined	Predicted vote shares, combined model CDU/CSU	SPD	FDP	Greens	Left
222	München-Land	CSU	CSU	CSU	CSU	0.48	0.24	0.03	0.13	0.02
223	Rosenheim	CSU	CSU	CSU	CSU	0.52	0.18	0.01	0.14	0.02
224	Starnberg	CSU	CSU	CSU	CSU	0.55	0.19	0.04	0.12	0.02
225	Traunstein	CSU	CSU	CSU	CSU	0.56	0.18	0.00	0.12	0.02
226	Weilheim	CSU	CSU	CSU	CSU	0.54	0.19	0.02	0.13	0.02
227	Deggendorf	CSU	CSU	CSU	CSU	0.54	0.19	0.03	0.09	0.03
228	Landshut	CSU	CSU	CSU	CSU	0.53	0.18	0.04	0.12	0.02
229	Passau	CSU	CSU	CSU	CSU	0.51	0.18	0.07	0.09	0.04
230	Rottal-Inn	CSU	CSU	CSU	CSU	0.56	0.19	0.02	0.08	0.02
231	Straubing	CSU	CSU	CSU	CSU	0.58	0.21	0.01	0.06	0.02
232	Amberg	CSU	CSU	CSU	CSU	0.50	0.21	0.03	0.11	0.03
233	Regensburg	CSU	CSU	CSU	CSU	0.48	0.23	0.03	0.10	0.02
234	Schwandorf	CSU	CSU	CSU	CSU	0.54	0.24	0.01	0.06	0.03
235	Weiden	CSU	CSU	CSU	CSU	0.48	0.22	0.00	0.07	0.02
236	Bamberg	CSU	CSU	CSU	CSU	0.52	0.22	0.02	0.12	0.02
237	Bayreuth	CSU	CSU	CSU	CSU	0.52	0.23	0.01	0.12	0.02
238	Coburg	CSU	CSU	CSU	CSU	0.49	0.27	0.01	0.08	0.03
239	Hof	CSU	CSU	CSU	CSU	0.49	0.30	0.00	0.08	0.04
240	Kulmbach	CSU	CSU	CSU	CSU	0.65	0.18	-0.01	0.07	0.02
241	Ansbach	CSU	CSU	CSU	CSU	0.49	0.25	0.02	0.11	0.02
242	Erlangen	CSU	CSU	CSU	CSU	0.48	0.28	0.02	0.13	0.02
243	Fürth	CSU	CSU	CSU	CSU	0.46	0.29	0.01	0.12	0.04
244	Nürnberg-Nord	CSU	CSU	CSU	CSU	0.39	0.33	0.01	0.14	0.04
245	Nürnberg-Süd	CSU	CSU	CSU	CSU	0.42	0.33	0.01	0.11	0.04
246	Roth	CSU	CSU	CSU	CSU	0.47	0.27	0.02	0.12	0.02
247	Aschaffenburg	CSU	CSU	CSU	CSU	0.46	0.23	0.02	0.18	0.03
248	Bad Kissingen	CSU	CSU	CSU	CSU	0.55	0.21	0.01	0.11	0.04
249	Main-Spessart	CSU	CSU	CSU	CSU	0.54	0.22	0.01	0.11	0.02
250	Schweinfurt	CSU	CSU	CSU	CSU	0.49	0.24	0.02	0.12	0.05
251	Würzburg	CSU	CSU	CSU	CSU	0.47	0.26	0.02	0.16	0.02
252	Augsburg-Stadt	CSU	CSU	CSU	CSU	0.44	0.22	0.02	0.16	0.03
253	Augsburg-Land	CSU	CSU	CSU	CSU	0.55	0.18	0.02	0.11	0.02
254	Donau-Ries	CSU	CSU	CSU	CSU	0.55	0.19	0.03	0.09	0.02
255	Neu-Ulm	CSU	CSU	CSU	CSU	0.53	0.20	0.03	0.12	0.03
256	Oberallgäu	CSU	CSU	CSU	CSU	0.55	0.16	0.02	0.16	0.02
257	Ostallgäu	CSU	CSU	CSU	CSU	0.53	0.15	0.03	0.13	0.02
258	Stuttgart I	CDU	CDU	CDU	CDU	0.38	0.24	0.02	0.25	0.04
259	Stuttgart II	CDU	CDU	CDU	CDU	0.38	0.30	0.02	0.18	0.04
260	Böblingen	CDU	CDU	CDU	CDU	0.48	0.24	0.02	0.15	0.03
261	Esslingen	CDU	CDU	CDU	CDU	0.46	0.31	0.01	0.16	0.04
262	Nürtingen	CDU	CDU	CDU	CDU	0.46	0.27	0.02	0.16	0.02
263	Göppingen	CDU	CDU	CDU	CDU	0.46	0.30	0.01	0.14	0.03
264	Waiblingen	CDU	CDU	CDU	CDU	0.46	0.28	0.02	0.14	0.03
265	Ludwigsburg	CDU	CDU	CDU	CDU	0.44	0.24	0.02	0.17	0.04
266	Neckar-Zaber	CDU	CDU	CDU	CDU	0.45	0.26	0.04	0.14	0.03
267	Heilbronn	CDU	CDU	CDU	CDU	0.48	0.26	0.02	0.12	0.03
268	Schwäbisch Hall – Ho...	CDU	CDU	CDU	CDU	0.46	0.25	0.04	0.14	0.03
269	Backnang – Schwäbisc...	CDU	CDU	CDU	CDU	0.48	0.29	0.02	0.13	0.03
270	Aalen – Heidenheim	CDU	CDU	CDU	CDU	0.48	0.30	0.02	0.12	0.04
271	Karlsruhe-Stadt	CDU	CDU	CDU	CDU	0.40	0.28	0.02	0.16	0.04
272	Karlsruhe-Land	CDU	CDU	CDU	CDU	0.48	0.30	0.02	0.13	0.02
273	Rastatt	CDU	CDU	CDU	CDU	0.51	0.27	0.01	0.14	0.03
274	Heidelberg	CDU	CDU	CDU	CDU	0.40	0.34	0.03	0.19	0.02
275	Mannheim	CDU	CDU	CDU	CDU	0.40	0.34	0.01	0.14	0.05
276	Odenwald – Tauber	CDU	CDU	CDU	CDU	0.53	0.25	0.02	0.11	0.03
277	Rhein-Neckar	CDU	CDU	CDU	CDU	0.45	0.30	0.03	0.13	0.03
278	Bruchsal – Schwetzin...	CDU	CDU	CDU	CDU	0.50	0.28	0.02	0.11	0.03
279	Pforzheim	CDU	CDU	CDU	CDU	0.45	0.26	0.05	0.12	0.04
280	Calw	CDU	CDU	CDU	CDU	0.50	0.25	0.03	0.13	0.03
281	Freiburg	CDU	SPD	CDU	SPD	0.33	0.33	0.01	0.20	0.04
282	Lörrach – Müllheim	CDU	CDU	CDU	CDU	0.42	0.35	0.02	0.13	0.03
283	Emmendingen – Lahr	CDU	CDU	CDU	CDU	0.45	0.26	0.02	0.17	0.03
284	Offenburg	CDU	CDU	CDU	CDU	0.50	0.23	0.02	0.14	0.03
285	Rottweil – Tuttlinge...	CDU	CDU	CDU	CDU	0.50	0.20	0.06	0.12	0.02
286	Schwarzwald-Baar	CDU	CDU	CDU	CDU	0.50	0.24	0.03	0.14	0.03
287	Konstanz	CDU	CDU	CDU	CDU	0.47	0.24	0.05	0.17	0.04
288	Waldshut	CDU	CDU	CDU	CDU	0.45	0.30	0.03	0.13	0.03
289	Reutlingen	CDU	CDU	CDU	CDU	0.44	0.26	0.03	0.16	0.04
290	Tübingen	CDU	CDU	CDU	CDU	0.42	0.24	0.01	0.20	0.04
291	Ulm	CDU	CDU	CDU	CDU	0.46	0.27	0.02	0.16	0.04
292	Biberach	CDU	CDU	CDU	CDU	0.48	0.18	0.04	0.15	0.03
293	Bodensee	CDU	CDU	CDU	CDU	0.48	0.19	0.04	0.19	0.03
294	Ravensburg	CDU	CDU	CDU	CDU	0.48	0.23	0.03	0.18	0.03
295	Zollernalb – Sigmari...	CDU	CDU	CDU	CDU	0.52	0.21	0.03	0.13	0.03
296	Saarbrücken	CDU	CDU	CDU	CDU	0.36	0.28	-0.00	0.09	0.14
297	Saarlouis	CDU	CDU	CDU	CDU	0.41	0.34	0.00	0.07	0.09
298	St. Wendel	CDU	CDU	CDU	CDU	0.43	0.32	-0.00	0.06	0.10
299	Homburg	CDU	CDU	CDU	CDU	0.37	0.32	0.01	0.07	0.13