How Swing Model Assumptions Shape Vote-to-Seat Predictions*

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Abstract

Most democracies distribute parliamentary seats based on electoral districts. Due to a lack of district-level polls, forecasters project national voting trends to district-level outcomes – drawing substantial public attention from voters. We know little about how different assumptions about these models influence forecasts. We address this gap comparing uniform and proportional swing models, alongside additional variants. Using data from the past eight German federal elections, we assess predictive performance and complement the analysis with a simulation study. The findings from Germany demonstrate that while differences between swing models are generally modest, model choice affects the precision of predictions. The simulation further reveals that uniform swing performs better with larger national swings, lower volatility between districts, and more parties.

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1 Introduction

Most democracies translate votes into parliamentary representation through districted electoral systems (Kedar et al. 2021) where seats are contested within geographically defined constituencies. Predicting election outcomes at the district level matters because winning seats rather than votes determine who eventually gets elected, how much power parties hold in parliament, and which parties are likely to form the next government.

Even in mixed-member systems such as Germany's, where seats at the district level are compensated by party-list allocations and therefore only indirectly affect the overall balance of power, district-level forecasts remain substantively relevant. They not only carry symbolic weight by shaping public and media attention. They inform public expectations about district competitiveness and thereby influence candidate entry, local campaign strategies, the allocation of party resources and, thus, shape at least indirectly also voting behaviour (e.g., Gschwend and Zittel 2015). In addition, district-level projections are essential for evaluating consequences of various former and current electoral reform proposals, as the geographic distribution of district winners per party determines the emergence of overhang and compensatory seats and can lead to substantial variation in parliamentary size under otherwise identical vote shares (e.g., Behnke 2009; Weinmann 2013).

Therefore, it is no surprise that district-level forecasts attract substantial public attention. For instance, during the 2025 German *Bundestag* election campaign, the website Zweitstimme.org (2025), which features swing-based district forecasts, attracted more than 1.5 million visitors. Similarly, The Economist (2024) continually publishes swing-based district forecasts for UK general elections.

In the absence of district-level polls, election forecasters typically rely on national or regional surveys to estimate how party vote shares are expected to change relative to the previous election. These aggregate swings must then be translated into district-level predictions using explicit assumptions about how national-level vote changes map onto party support in individual districts (e.g., Bafumi et al. 2018; Fisher et al. 2011; Hanretty et al. 2016). Importantly, this is not only a data-availability problem: in the 2015 UK election forecasting context, adding constituency polls did not improve and in some cases worsened forecast performance, indicating that swing-model assumptions remain central even when local polling information is available (Ford et al. 2016).

Two swing models prevail. *Uniform swing* assumes that, for each party, the observed percentage-point change in national (or regional) vote share since the last election is applied identically across all districts. *Proportional swing*, by contrast, assumes that district-level changes scale with parties' prior vote shares, applying relative (percentage) changes uniformly across districts. Despite their ubiquity in district-level forecasting, systematic evaluations comparing the performance of these swing assumptions across electoral contexts are rare. In this study, we examine how swing assumptions shape the projection of aggregate vote changes onto district-level outcomes.

The paper–as part of the special issue *The 2025 German Election*–makes three contributions. First, we introduce a relatively understudied case—district-level outcomes in German federal elections—that is especially informative for evaluating uniform and proportional swing assumptions. Germany's two-vote system separates district-level competition—determined by the candidate vote (*Erststimme*) in 299 single-member districts—from national party strength, which is determined by the party-list vote (*Zweitstimme*) under proportional representation.

Second, we provide empirical evidence from real elections using an out-of-sample forecasting framework building on the Zweitstimme.org forecasting model for the 2025 *Bundestag* election (Erfort et al. 2026; Gschwend et al. 2022; Neunhoeffer et al. 2020). Systematically evaluating uniform versus proportional swing as our primary comparison, while also examining additional variants (Wilson and Grofman 2022) retrospectively to the eight most recent German federal elections yields over 20,000 party–district–year observations and allows us to assess how these assumptions shape district-level outcomes under realistic forecasting conditions. We find that while average performance differences between swing models are typically modest, the choice of swing assumption can nonetheless meaningfully affect seat projections.

Third, we complement the empirical analysis with a simulation framework that varies key electoral contexts beyond what real elections allow. We find that higher national vote variance favors proportional swing models, while greater between-district volatility favors uniform swing models, providing practical guidance for choosing swing assumptions in district-level forecasting across countries.

2 District-level Forecasting Models

Forecasting district-level election outcomes in the absence of district-level polling requires assumptions about how national or regional vote swings translate into geographically disaggregated vote changes. Across the applied forecasting literature, this mapping is implemented—implicitly or explicitly—through *swing assumptions*. These assumptions impose structure on how aggregate vote changes are projected onto districts, thereby forming expectations about district-level outcomes and seat allocations. Despite their central role in applied forecasting, swing assumptions are usually not evaluated empirically. This paper treats swing assumptions as objects of evaluation and assesses how alternative specifications shape district-level predictions.

The most prominent and historically entrenched approach is the *uniform swing* assumption. It has long served as what Curtice and Steed (1982, p. 256) described as "a widely accepted nostrum," not only in district-level election forecasting but also in studies of electoral change (Curtice and Steed 1982; Johnston 1983) and of fairness evaluations when drawing new district boundaries (e.g., Katz et al. 2020). Applications span British and U.S. elections and elections in New Zealand (Curtice and Steed 1982; Johnston 1983;

Wilson and Grofman 2022). In addition to these contexts, German work has used district-level simulations to evaluate aggregate electoral consequences under different institutional rules, including overhang-seat dynamics and Bundestag size effects (Behnke 2009; Weinmann 2013). At the same time, uniform swing is known to suffer from conceptual and practical limitations. By construction, it treats party strongholds and marginal districts symmetrically and can produce implausible predictions, including negative vote shares or vote shares exceeding 100 percent—particularly for small parties or in elections with large national swings (e.g., Hanretty et al. 2016; Neunhoeffer et al. 2020). Moreover, the assumption of uniform national swing is frequently violated, as electoral change varies systematically across constituencies, reflecting regional patterns, party competition, and local dynamics (e.g., Curtice and Firth 2008). In response, many forecasting models extend this baseline by incorporating district-level deviations from national trends. For example, Ford et al. (2016) combine national and regional swing estimates with district-specific deviations from uniform swing, allowing district-level outcomes to vary around aggregate trends. Despite these refinements, uniform swing remains widely used, often not as a serious forecasting model but as a heuristic baseline against which more elaborate approaches are evaluated (e.g., Fisher et al. 2011; Jackman 2014; Lauderdale et al. 2020; Mellon and Fieldhouse 2016).

Proportional swing is often used as a pragmatic alternative, especially in multiparty systems with smaller parties. Unlike uniform swing, proportional swing lacks a clear canonical formulation or point of origin. It appears to have emerged as a practitioner heuristic motivated by the intuition that changes in party support should scale with baseline vote shares, thereby limiting out-of-bounds predictions and differentiating more clearly between strongholds and competitive districts (e.g., Fisher et al. 2011; Hanretty et al. 2016; Neunhoeffer et al. 2020). While this intuition is widely shared in applied forecasting, it rests largely on plausibility rather than systematic evidence. To our knowledge, no study has demonstrated that proportional swing is generally superior in multiparty contexts. On the contrary, Wilson and Grofman (2022) show that proportional swing violates key axiomatic properties and performs no better than uniform swing in two-party U.S. elections. This suggests that the presumed advantage of proportional swing in multiparty systems is best understood as an assumption worth testing rather than an established result.

Recent district-level election forecasts have largely moved away from conceptualizing swing as purely deterministic. Instead, estimation uncertainty in national or regional vote shares is propagated to the district level, often in combination with covariates capturing district-specific characteristics (e.g., Bafumi et al. 2018; Erfort et al. 2026; Hanretty et al. 2016; Neunhoeffer et al. 2020). Importantly, these approaches relax strict deterministic implications swing assumptions. Deterministic swing rules continue to define the expected district-level mean outcomes conditional on included covariates to distinguish between systematic and stochastic or idiosyncratic deviations (Bafumi et al. 2018; Mellon and Fieldhouse 2016; Gschwend et al. 2022; Munzert 2017). Transformations are often employed to avoid out-of-bounds predictions

(Gschwend et al. 2022; Hanretty et al. 2016; Neunhoeffer et al. 2020).

A parallel strand replaces explicit swing formulas with model-based approaches that nonetheless address the same underlying problem: how to map national trends to sub-national outcomes. For example, Lauderdale et al. (2020) use multilevel regression and post-stratification to generate national and district-level forecasts in the US and UK, allowing heterogeneity in "swing" to arise through interactions between individual-level and contextual variables. Even in these frameworks, however, traditional swing projections are typically retained as simple benchmarks rather than treated as maintained assumptions. We position our contribution relative to established work on swing-based constituency forecasting (e.g., Curtice and Firth 2008; Ford et al. 2016).

We provide the first systematic comparison of alternative swing assumptions for forming district-level expectations. Rather than treating uniform or proportional swing as innocuous modeling conveniences, we assess how different assumptions shape district-level predictions across a range of empirical and simulated multiparty electoral contexts.

3 Empirical Analysis

3.1 The German Case

We choose Germany as our empirical application for several reasons. District-level polling in Germany is virtually non-existent, while the effective number of parties is relatively high and has increased further with recent party entry and rising inter-election volatility. The country's electoral geography combines long-standing party strongholds with pronounced regional variation, complicating the translation of national vote changes into district-level expectations. In addition, incentives for strategic voting shaped by the institutional features of Germany's electoral system introduce further complexity (e.g., Gschwend 2007).

On the other hand, one limitation of the empirical case is that strategic voting under mixed electoral rules partly follows other incentives than under single-vote plurality systems (Gschwend 2007), and might produce both different kinds and levels of strategic voting at the district level. For instance, the availability of a separate party-list (second) vote can facilitate ticket splitting—using the first vote to back a viable constituency candidate while casting the second vote sincerely for the preferred party—which can dampen pressures for full coordination on a single viable option in the district (Pappi and Thurner 2002; Herrmann and Pappi 2008). Moreover, strategic first-vote considerations are likely to be concentrated in a subset of competitive constituencies and among politically sophisticated voters with better information about candidate viability, rather than operating uniformly across districts (Gschwend 2007). Overall, this could limit the generalizability of our findings to other settings.

Taken together, Germany provides a substantively demanding and analytically informative case for assessing the consequences of alternative swing assumptions, extending the existing forecasting literature beyond single-vote systems. Germany provides a useful stress test for swing assumptions because its party system and electoral institutions create substantial cross-district heterogeneity. At the same time, mixed-member rules and strategic voting incentives differ from pure plurality systems, so external validity should be interpreted conditionally.

3.2 Data and Methodology

Our empirical analysis uses district-level election results from all eight German federal elections since 1998, covering all 299 (1998: 328) electoral districts. The dataset contains more than 20,000 observations representing individual candidacies, with "other candidates" aggregated as a single observation. For each election, we collect district-level vote shares for all parties and their respective candidates that received at least 5% of the national vote or won at least three district seats. We also incorporate district-level demographic and socioeconomic variables to capture local contextual factors. We employ an out-of-sample forecasting framework where we train our models on seven elections and predict the eighth, rotating through all possible combinations to ensure robust evaluation. This approach mirrors real-world forecasting conditions where models must generalize to unseen electoral contexts.

Our forecasting models combine national polling trends with district-level historical patterns. We focus on comparing three main approaches: (1) uniform swing models that apply identical percentage-point changes across all districts, (2) proportional swing models that scale changes relative to past vote share, and (3) hybrid variants —piecewise and interaction models—that allow swing behavior to vary depending on existing party support levels Wilson and Grofman (2022). All models are estimated using ordinary least squares regression.

Model Variants Our empirical evaluation includes eight distinct model specifications, each representing different theoretical assumptions about electoral dynamics. All models include candidate- and district-specific covariates to control for systematic factors that influence electoral outcomes beyond national-level swings (see SM A.1). An overview of the different models and implied mechanics is provided in Table 1.

1. **No Adjustment Model:** This baseline specification contains all candidate and district covariates plus past party vote share at the district level (v^d_{t-1}) but excludes any swing component, serving as a control to assess the value added by swing modeling. The predictions largely reflect the past vote share.

2. **Proportional and Uniform Models:** The proportional model uses

proportional change in the national party vote share $r \equiv V_t/V_{t-1}$, while the uniform model uses the national uniform change $\Delta^U \equiv V_t - V_{t-1}$. These models represent the core theoretical distinction between proportional and uniform swing assumptions.

3. **Mixed Swing Model:** This specification includes both proportional change r and uniform change Δ^U in a single model, allowing the regression estimation to find an optimal balance between proportional and uniform components based on the data.

4. **Piecewise Models:** Piecewise models allow swing effects to differ between districts where a party performed above or below the party's average vote share $\bar{v}_{t-1}$. This captures the intuition that swing behavior may vary systematically with past party vote share, as suggested by Wilson and Grofman (2022). Piecewise models are evaluated for both proportional and uniform swing.

5. **Interaction Models:** Similar to piecewise models but more flexible, these specifications allow for continuous interactions between past vote share and swing coefficients. The interaction models include an interaction term between past vote share and the swing component.

Model	**Inputs**	**Swing parametrization**	**Predicted district vote share $\hat{v}_t^d$**	**Intuition**
No adjustment	v_{t-1}^d (+covariates)	No swing term	$\hat{v}_t^d = v_{t-1}^d$ (plus covariate effects)	Baseline: predictions largely track the last election.
Uniform swing	v_{t-1}^d, Δ^U	Additive shift	$\hat{v}_t^d = v_{t-1}^d + \Delta^U$	Every district moves by the same number of percentage points.
Proportional swing	v_{t-1}^d, r	Multiplicative change	$\hat{v}_t^d = v_{t-1}^d \cdot r$	High-baseline districts move more in absolute pp; low-baseline districts move less.
Mixed swing	v_{t-1}^d, Δ^U, r	Weighted combination of uniform and proportional components	$\hat{v}_t^d = v_{t-1}^d + \alpha\, \Delta^U + \beta\big(v_{t-1}^d(r-1)\big)$	Lets the data choose the balance between uniform and proportional swing.
Piecewise uniform	v_{t-1}^d, Δ^U, $\bar{v}_{t-1}$	Different shifts above/below mean	$\hat{v}_t^d = v_{t-1}^d + \begin{cases} \Delta_{\text{low}}^U, & v_{t-1}^d < \bar{v}_{t-1} \\ \Delta_{\text{high}}^U, & v_{t-1}^d \geq \bar{v}_{t-1} \end{cases}$	Allows distinct swing in weak vs strong districts.
Piecewise proportional	v_{t-1}^d, r, $\bar{v}_{t-1}$	Different proportional factors above/below mean	$\hat{v}_t^d = v_{t-1}^d \times \begin{cases} r_{\text{low}}, & v_{t-1}^d < \bar{v}_{t-1} \\ r_{\text{high}}, & v_{t-1}^d \geq \bar{v}_{t-1} \end{cases}$	Proportional responsiveness differs in weak vs strong districts.
Interaction uniform	v_{t-1}^d, Δ^U	Continuous moderation by baseline vote share	$\hat{v}_t^d = v_{t-1}^d + \Delta^U\big(\gamma_0 + \gamma_1 v_{t-1}^d\big)$	Swing size changes smoothly with past vote share.
Interaction proportional	v_{t-1}^d, r	Continuous moderation of proportional component	$\hat{v}_t^d = v_{t-1}^d\Big(1+(r-1)\big(\eta_0+\eta_1 v_{t-1}^d\big)\Big)$	Proportional effect varies continuously with baseline strength.

Table 1: **Swing-model mechanics: mapping national-level change to district vote shares.** This table summarizes how different swing specifications transform a party's past district vote share v_{t-1}^d into a predicted district vote share $\hat{v}_t^d$ using national election information. In *Inputs*, v_{t-1}^d denotes the party's past district vote share; V_{t-1} and V_t denote the party's national vote shares at $t-1$ and t; $\Delta^U \equiv V_t - V_{t-1}$ is the national *uniform* (additive) change in percentage points; $r \equiv V_t/V_{t-1}$ is the national *proportional* (multiplicative) change; and $\bar{v}_{t-1}$ is the party's mean district vote share at $t-1$. In *Predicted district vote share* v^d, parameters (α, β) and (γ_0, γ_1) or (η_0, η_1) are estimated from the data.

Evaluation Criteria While accuracy in predicting the winning district is a key measure of model performance, it is not the only aspect that matters. We evaluate models across several additional dimensions that are critical for practical forecasting, interpretation, and understanding how predictions may vary under different conditions:

1. **Winner accuracy.** Share of districts where the predicted plurality winner matches the realized winner. This is what pundits and audiences are often most focused on—i.e., correctly predicting the outcome in each district. This metric is focused on predicting the candidate with the highest vote share within each district whereas the vote shares of the remaining candidates is not taken into account.

2. **Average vote-share error (MAE, RMSE).** MAE summarizes the typical miss in percentage points; RMSE emphasizes large errors that can flip winners or distort seat projections. The mean error is also a measure for the precision of predicted vote shares which is important for uncertainty communication: smaller errors enable tighter, more credible confidence or prediction intervals and make the forecasts easier to interpret for audiences.

3. **Out-of-bounds predictions.** Share of predictions below 0% or above 100%. Such violations signal misspecification. Although one can "fix" these by truncating or renormalizing (e.g., setting negatives to 0%), those post-hoc corrections require extra explanation and can introduce

their own problems by distorting party relationships. It is therefore preferable to avoid out-of-bounds predictions in the first place.

3.3 Empirical Results

Our empirical analysis reveals that differences between swing models are generally very small, but meaningful patterns emerge across different performance metrics. One could argue that getting the district winner correct is the substantive most important criterion. We report results averaged across elections and, where informative, disaggregated by election and party. Figure 1 shows the winner prediction accuracy for all model variants on average and across elections. The color shading facilitates comparison of values here red indicates lower values and green higher values.

In terms of district winner prediction accuracy, the differences between the best performing model (mixed swing) with on average about 87.4% correctly predicted district winners and the worst performing model (proportional piecewise) with on average about 86.5% correctly predicted district winners translates to fewer than 3 out of 299 districts. This indicates that, for the primary objective of predicting district winners, the selection of swing model has limited practical effect, although the presence of three affected districts is not negligible. However, there are also some differences within elections. For example, in 2025, the uniform interaction model performs notably worse whereas the proportional model performs very well.

However, model performance should not depend on only one measure.

	1998	2002	2005	2009	2013	2017	2021	2025	Average
Mixed	81.4%	88.0%	89.3%	87.0%	92.6%	92.6%	80.3%	88.3%	**87.4%**
Uniform	82.9%	87.3%	89.0%	87.6%	91.6%	93.3%	80.3%	86.6%	**87.3%**
Uniform piecewise	82.9%	90.0%	88.6%	87.0%	92.6%	90.3%	81.9%	85.3%	**87.3%**
Proportional interaction	82.6%	86.0%	90.6%	88.0%	92.6%	93.3%	79.9%	85.3%	**87.3%**
Uniform interaction	82.9%	87.0%	89.0%	88.3%	93.0%	92.3%	82.3%	80.6%	**86.9%**
Proportional	80.2%	88.0%	89.3%	85.6%	92.6%	92.3%	79.3%	88.0%	**86.9%**
Proportional piecewise	80.2%	88.6%	88.6%	87.0%	93.0%	89.6%	78.3%	86.6%	**86.5%**
No adjustment	65.5%	88.0%	90.3%	72.9%	90.0%	93.3%	67.6%	68.9%	**79.6%**

Figure 1: Out-of-sample Performance of Correctly Predicted Districts (Winner Accuracy) Across Models and Elections 1998-2025

Consequently, Figure 2 compares all tested models across different performance measures. The color shading shows relative performance within each column: green indicates better values and red indicates worse. For accuracy, higher values are better (green), whereas for the other metrics, lower values are better (green) and higher values worse (red). Accuracy summarizes winner classification performance, whereas error-based metrics capture calibration of district-level vote-share predictions. For applied electoral analysis, these metrics answer different questions: winner counts inform direct-mandate expectations, while vote-share errors determine how prediction uncertainty propagates into aggregate seat outcomes.

	Winner accuracy	MAE	RMSE	Out-of-bounds (share)
Mixed	87.4%	2.7%	3.8%	1.0%
Uniform piecewise	87.3%	2.7%	3.8%	1.4%
Uniform	87.3%	2.7%	3.9%	1.9%
Proportional interaction	87.3%	2.5%	3.6%	0.0%
Uniform interaction	86.9%	2.5%	3.6%	0.9%
Proportional	86.9%	2.7%	3.9%	0.4%
Proportional piecewise	86.5%	2.7%	3.8%	0.4%
No adjustment	79.6%	4.1%	5.3%	0.0%

Figure 2: Comprehensive Model Performance Heatmap

In contrast to district winner prediction accuracy, more substantial differences emerge when examining mean error of vote share predictions. Here, adding interaction terms to both uniform and proportional swing models significantly reduces prediction errors. These interaction terms allow swings to affect districts differently based on prior vote share for a party, capturing the intuition that swing behavior may vary systematically with past party vote share. This finding aligns with theoretical expectations that more sophisticated models should better capture the heterogeneity of electoral dynamics across districts.

Models also differ substantially in their production of out-of-bounds predictions (i.e., predicted vote shares below 0% or above 100%). Out-of-bounds predictions occur when swing models predict that a party will receive negative vote shares or more than 100% of the vote in a district—both physically impossible outcomes that violate the fundamental constraints of electoral systems. These predictions arise when models fail to account for the bounded nature of vote shares or when the relationship between national-level changes and district-level outcomes becomes non-linear.

The uniform swing model without covariates for candidate or district-specific characteristics performs worst on this metric, while the proportional model with interaction terms performs very well. This suggests that interaction terms not only improve prediction accuracy but also help maintain realistic vote share bounds by capturing the complex, context-dependent relationships between past vote share and swing behavior. While out-of-bounds predictions can technically be handled by truncating negative predictions to 0% and normalizing district sums to 100%, this approach is problematic because it distorts the relative relationships between parties. Avoiding out-of-bounds predictions in the first place is therefore crucial for practical electoral forecasting because they can lead to nonsensical seat projections and undermine the credibility of forecasts.

We compare both the proportional and uniform models with covariates in terms of predicting the correct winner (logistic regression) and mean error (linear regression) to uncover effects of state, election year and the party winning a district. The results show small but systematic differences in prediction accuracy and mean error (see SM A.2). We further find geographical patterns of mispredictions clustered in regions which we discuss further in

SM A.3. A comparison between actual and predicted results for different model specifications can be found in SM A.5.

4 Simulation

Real elections provide valuable tests about the consequences of particular vote swing assumptions, yet they offer only a narrow window into the range of possible scenarios as they hard-wire particular party system characteristics. To move beyond the limits of observed election outcomes, we employ simulations, i.e., computer-based experiments that replicate the logic of observational research within a controlled, hypothetical setting. This approach allows us to manipulate core contextual features of electoral systems—such as party system size, volatility, and regional concentration of party-level support—and observe how these factors influence the relative performance of different swing model assumptions. In doing so, we can systematically evaluate theoretical expectations about swing behavior under conditions that are not observed in real German elections and helps to generalize our findings.

Our simulation framework is theory-driven, grounded in an explicit assumed data-generating process that formalizes how national vote swings translate into district-level outcomes through varying degrees of proportional and uniform swing. Using a factorial experimental design, we vary key parameters of this process across their full plausible ranges, creating a structured exploration of the underlying parameter space. This design combines the rigor of experimental control with the substantive realism of actual party systems, allowing us to isolate causal relationships between electoral context and model performance.

The simulation also serves as a practical guide for other electoral contexts. By systematically varying core parameters—number of parties, national vote volatility, and between-district volatility—it provides conditional recommendations that can be mapped to specific countries using the descriptive benchmarks in Appendix Tables 2, 3, and 4.

Simulation Design Our simulations employ a realistic data generating process that captures the essential dynamics of electoral systems. We provide formal definitions of our framework in SM B.3. This factorial design creates 152,460 unique scenario combinations, with five simulations per scenario, resulting in 762,300 total simulations that provide sufficient statistical power for identifying key factors affecting model performance. Each scenario generates baseline vote shares for a set of 2-7 political parties ($P \in \{2, 3, 4, 5, 6, 8, 10\}$) across 100 districts ($D = 100$), with party characteristics varying systematically across the parameter space. Large parties receive baseline support of 25-35% with district-level variation (standard deviation $\sigma_{district} \in \{0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.10, 0.12, 0.15\}$), while small parties receive baseline support of 5-15% with district-level variation (same levels of standard deviation). Geographic clustering is modelled through stronghold districts, where specific parties receive elevated support (30-60% of baseline vote share, $\phi \in \{0.3, 0.45, 0.60\}$) in 10-40 designated districts ($D_{strong} \in \{10, 25, 40\}$). All vote shares are normalized to sum to 100% within each district to ensure realistic electoral outcomes.

National-level party vote share changes are drawn from a normal distribution with mean zero and standard deviation varying from 0.01 to 0.09 across scenarios ($\sigma_{national} \in \{0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07\}$), reflecting different levels of electoral volatility. The uniform share parameter ($\alpha \in \{0, 0.1, 0.2, \ldots, 0.9, 1.0\}$) controls the balance between uniform and proportional swing components in the data generating process. When uniform share equals zero, the simulation generates purely proportional swing behavior, while when it equals one, it generates purely uniform swing behavior. Values in between create hybrid scenarios that combine both approaches. We use this formulation to nest uniform and proportional swing in a single data-generating process. It allows for a continuous spectrum from purely proportional to purely uniform swing behavior, enabling fine-grained analysis of the transition between these assumptions.

Model Training and Prediction Framework The simulation employs an out-of-sample prediction framework that mirrors real-world electoral forecasting. For each scenario, five historical elections are simulated using identical parameters, creating a training dataset with district-party-election observations. This training data includes past vote shares, actual vote shares, and national swings, providing the foundation for model estimation. We describe the model specification in SM B.1

The trained models predict district-level vote shares using past district vote shares and national swing, and these predictions are compared to true vote shares to assess accuracy. This out-of-sample framework ensures that model performance reflects genuine predictive ability rather than overfitting to the training data.

Performance Evaluation Performance is evaluated using district winner prediction accuracy, defined as the proportion of districts where the model correctly predicts the winning party, and average errors (MAE and RMSE). These metrics directly correspond to the practical goal of electoral forecasting and provide an intuitive measure of model effectiveness. Our analysis compares uniform versus proportional swing models across the parameter space to identify optimal conditions for each approach.

The statistical analysis employs regression models to identify the factors that explain performance differences between swing assumptions. The dependent variable is the accuracy difference between models, while independent variables include log-transformed parameters and interaction terms. Key variables include the number of parties, number of small parties, swing concentration, and district-level volatility.

4.1 Simulation Results

Our analysis, exploring 152,460 unique scenario combinations, reveals two main findings. While higher national vote variance (capturing electoral volatility) actually makes proportional swing models perform better, higher district vote volatility favors uniform swing models.

The regression analysis of all scenarios (Figure 3) documents systematic patterns in model performance. The first differences plot standardizes effects by showing the change in model performance when moving from the minimum to maximum value of each parameter, making effects comparable across different parameter scales and ranges.[1] Figure 3 provides evidence for three interesting findings. First, the uniform share parameter in the DGP significantly increases the advantage of uniform swing models, which is expected since higher uniform share means the data generating process more closely resembles uniform swing behavior.

[1] We report the regression coefficients in SM B.4.

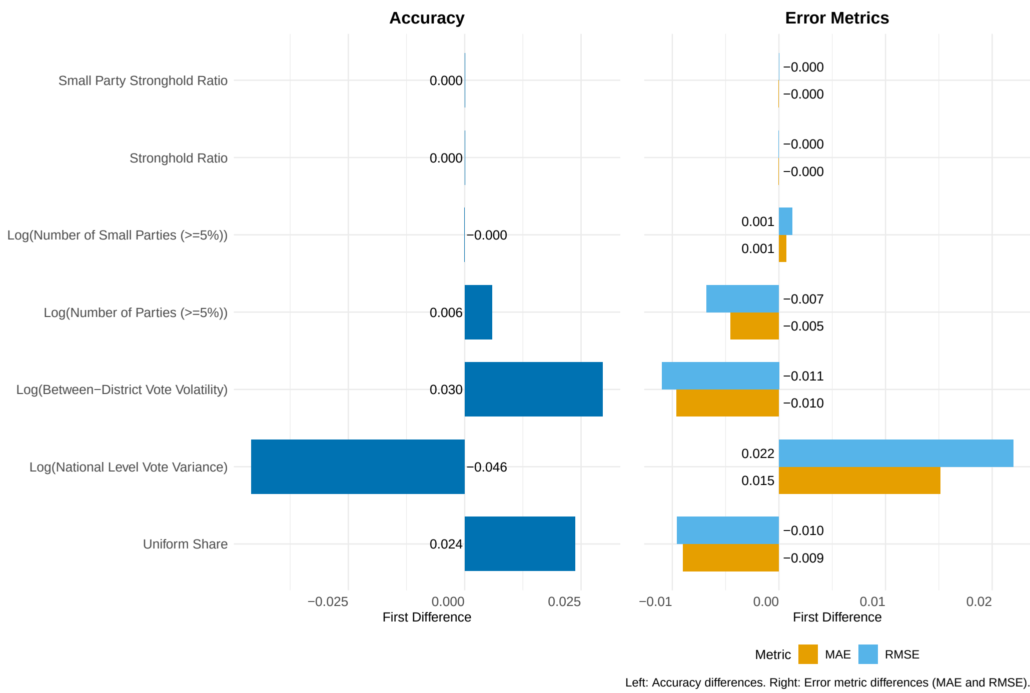

Figure 3: First differences: standardized effects on the performance difference between uniform and proportional swing. Positive values indicate an advantage for uniform swing for accuracy-type metrics (higher is better), whereas for error-type metrics (lower is better) positive values indicate an advantage for proportional swing.

Second, higher national vote variance (capturing electoral volatility) actually makes proportional swing models perform better. This finding can be explained by the DGP structure: when national-level changes are large, the proportional swing model's ability to scale changes relative to past vote shares becomes more valuable, as it can better capture the heterogeneous impact of large national swings across districts with different past party vote shares.

Third, higher district-level vote volatility is associated with better performance of uniform swing models. A plausible interpretation is that when district-specific variation is large, national-level swings translate less systematically across districts, making projections based on proportional scaling of past vote shares less stable. In such settings, the uniform swing model's more conservative assumption of equal changes across districts may be comparatively robust.

Considering these simulation results from the simulation, we can connect to the empirical patterns observed in Germany: Over the period we study, Germany sits relatively low to average on both dimensions national vote volatility and district vote volatility. These forces point in different directions and largely offset one another: across elections, neither uniform nor proportional swing clearly dominates on average.

Practical guidance for other contexts Using the descriptive country-level benchmarks in Appendix Tables 2, 3, and 4, our results suggest the following heuristics: (i) countries with a larger average number of parties (e.g., Spain, UK, Lithuania) tend to tilt toward uniform models performing better; (ii) contexts with high between-district volatility (e.g., Canada, UK, France) also favor uniform assumptions; and (iii) where national vote volatility is high (e.g., Canada, Japan, UK), proportional assumptions often perform better by scaling changes with baseline support. Appendix Figure 12 complements this by showing that aggregation at the party-mandate level primarily reveals systematic distributional bias: uniform swing tends to over-allocate direct mandates to smaller parties, and this bias increases with national-level volatility.

5 Conclusion

This study provides evidence on the performance of different swing model assumptions in electoral forecasting of district-level vote shares. We show that the choice of assumption is more nuanced than previously understood, with systematic patterns emerging that can guide forecasters in selecting appropriate models for specific electoral contexts. Our findings indicate that the optimal swing assumption depends on party system characteristics, electoral volatility, and geographic clustering patterns, contributing to the broader literature on vote-to-seat translation and offering practical guidance for electoral forecasting.

Our empirical analysis of German federal elections, based on more than 20,000 observations across eight elections and 299 districts, reveals that differences between uniform and proportional swing models are generally small in terms of predicting the correct winner yet meaningful in terms of the precision of predictions. Forecasters can leverage these findings to make their predictions both more reliable and precise.

Our simulation framework introduces a more sophisticated approach to understanding swing model performance. By systematically varying electoral system parameters, we can identify the specific conditions under which each swing assumption performs optimally. The simulation results provide broader theoretical insights into when different swing assumptions are most appropriate. Higher national vote volatility tends to favor proportional swing, whereas higher between-district volatility favors uniform swing.

The practical implications of our findings are important for forecasting electoral districts. Our results suggest that forecasters should consider the specific contextual characteristics such as the party system when choosing swing assumptions. Our simulation results provide guidance for how different swing assumptions are likely to perform across electoral contexts beyond the German case. They suggest that systems with many parties or high between-district volatility (e.g., Spain, the UK, Lithuania, Canada, France) tend to favor uniform swing, whereas contexts with high national vote volatility (e.g., Canada, Japan, the UK) often favor proportional swing. Importantly, these patterns need not apply uniformly at the country level: different assumptions may be appropriate for distinct regional clusters of districts, reflecting heterogeneous electoral dynamics (e.g., Ford et al. 2016). Future research should extend this framework to additional settings and explore systematically cases where these characteristics point in different directions to study the implicit trade-off more directly.

For Germany, a parallel extension is to use district-level forecast diagnostics to evaluate electoral reform proposals, as the geographic distribution of district outcomes determines the incidence of overhang seats, the allocation of compensatory seats, and the resulting variation in parliamentary size under alternative vote-to-seat translation rules. District-level forecasting models can further enrich such analyses by providing empirically grounded, probabilistic projections of various district-level outcomes, enabling scholars to assess not only expected seat allocations but also the distribution and likelihood of institutional consequences under alternative electoral designs.

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Supplementary Materials

How Swing Model Assumptions Shape Vote-to-Seat Predictions

Table of Contents

A Empirical Analysis

A.1 Candidate and District Covariates

All models include the following covariates: `ncand` (number of candidates in the district), `propPlatz` (relative measure for the list position), `alsoList` (indicates whether a candidate also runs on a party list), `res_l1_E` (past first vote share), `formercand` (whether this candidate already ran in past election), `east` (East Germany indicator), `female` (gender indicator), `incumbent` (incumbency status), `akad` (PhD title indicator), `incumbent_in_wkr` (whether the incumbent is running in the district), and `no_cand_l1` (indicator for parties without a candidate in the previous election).

A.2 Regression Coefficient Plots

The following figures provide detailed coefficient plots from our regression analyses. While the main text summarizes the key findings, these visualizations show the specific effects of different variables on model performance.

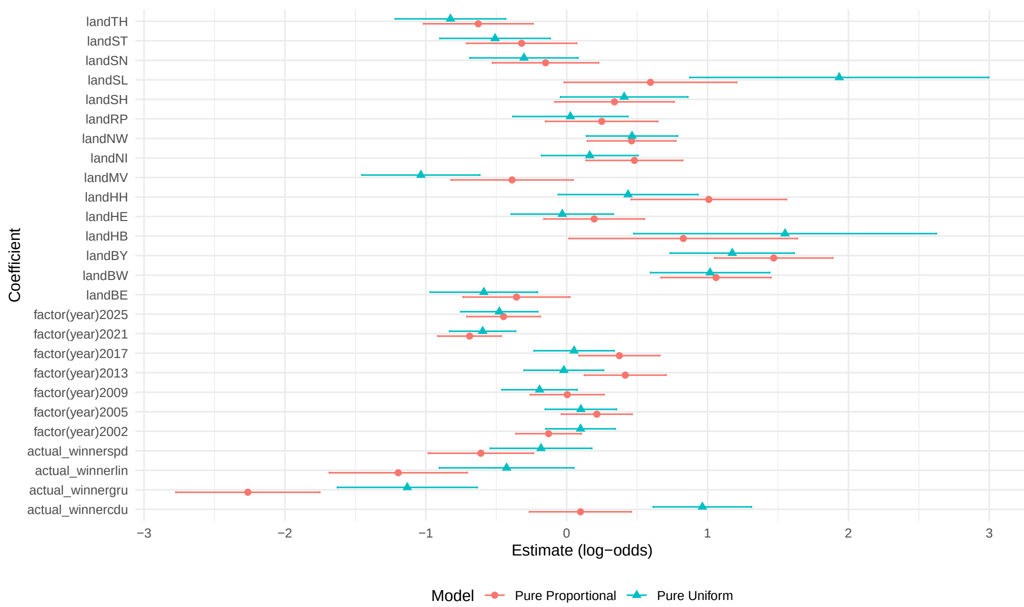

Figure 4: Results from logistic regression: Probability for correct prediction

Note: Brandenburg as state, AfD as party, and 1998 as election year are the excluded reference categories.

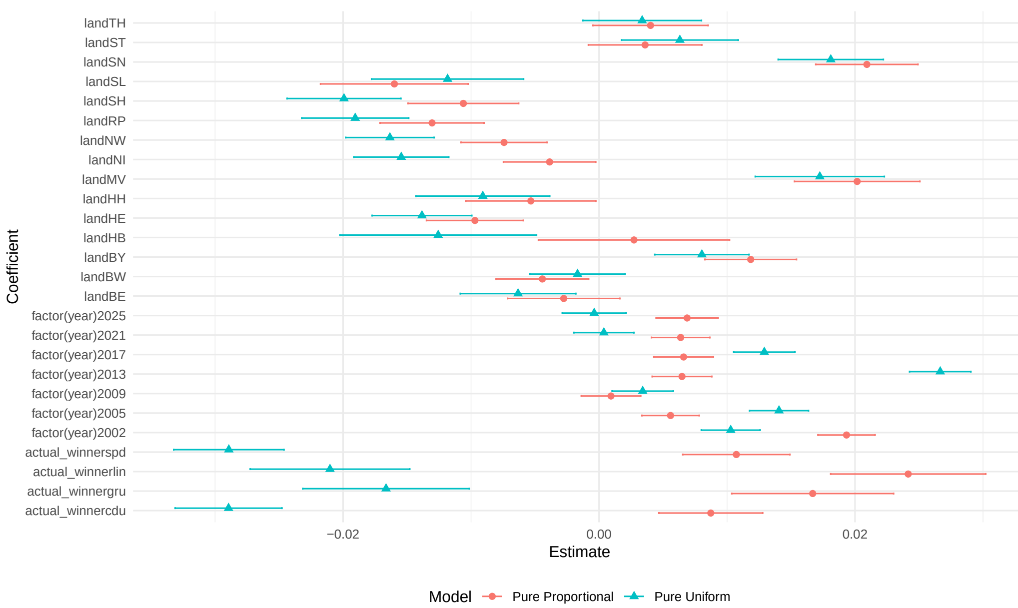

Figure 5: Results from linear regression: Size of absolute error (winners only)

Note: Brandenburg as state, and 1998 as election year are the excluded reference categories.

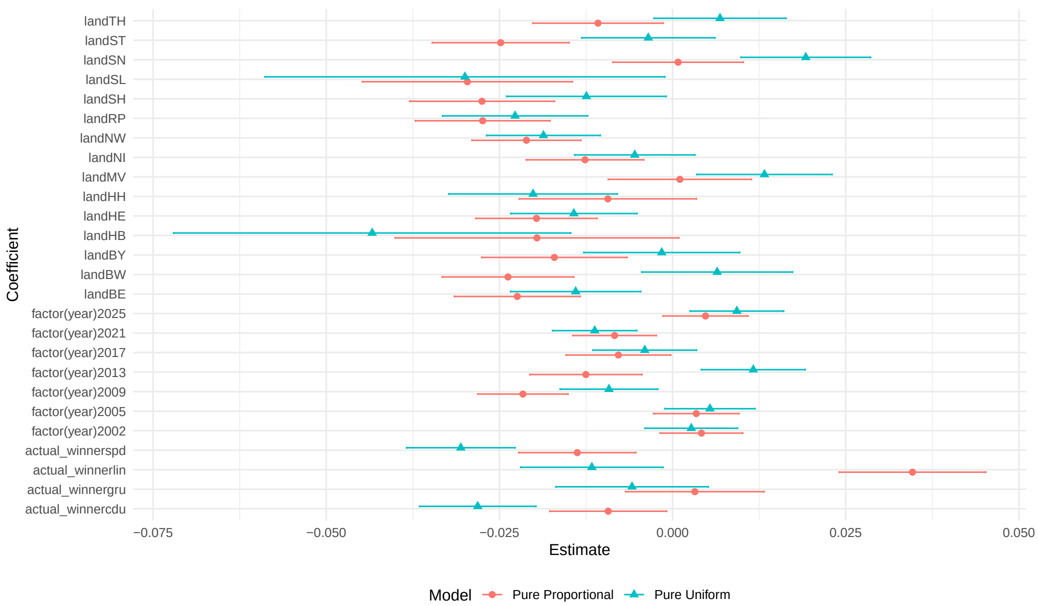

Figure 6: Results from linear regression: Size of absolute error (mispredicted winners only)

Note: Brandenburg as state, and 1998 as election year are the excluded reference categories.

A.3 Geographical patterns of model performance

Figure 7 shows the geographical distribution of mispredicted electoral districts, i.e., of districts where the actual plurality winner of the candidate vote shares is different than predicted by our model. Mispredicted electoral districts often cluster regionally and by party, indicating that one or more parties perform much better in entire regions than expected. This regional clustering suggests that local factors and party organizational strength play important roles that are not captured by the assumed data generating process of national swing models.

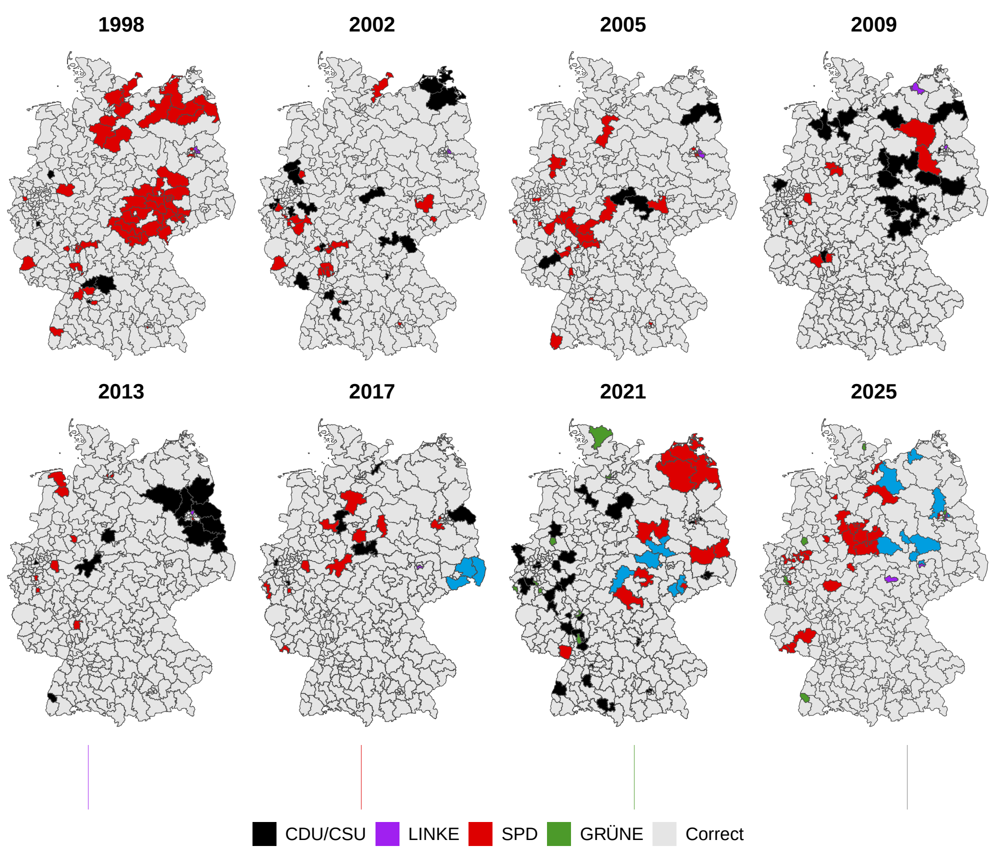

Figure 7: Geographical distribution of mispredicted districts by election

Note: Predictions based on the model with highest average winner accuracy. Colours show actual winner of mispredicted districts.

A.4 Party-level direct-mandate deviations

To complement district-level error summaries, we report party-level deviations in direct mandates. Figure 8 shows absolute deviations by party and election, and Figure 9 shows signed deviations to indicate systematic over- or underprediction. These diagnostics provide a party-specific perspective on forecast relevance beyond aggregate hit-rate and vote-share error metrics. No clear pattern emerges.

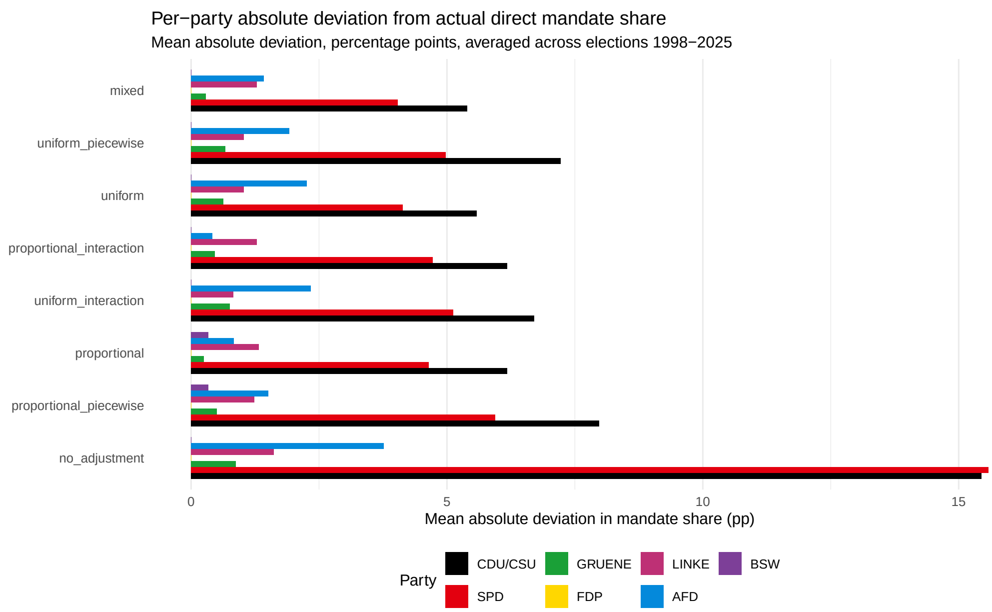

Figure 8: Absolute deviation in predicted direct mandates by party and election

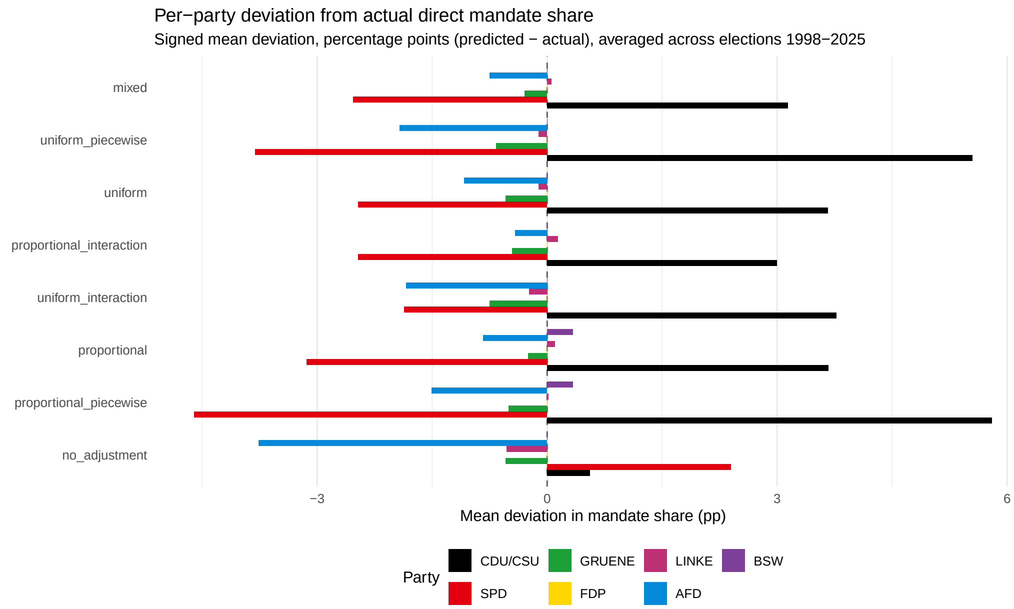

Figure 9: Signed deviation in predicted direct mandates by party and election

A.5 Comparing predictions from different models

When comparing actual and predicted results for mispredicted electoral districts (Figure 10), we observe differences in predictions across models and elections. Notably, in some elections like 2025, predictions of plurality winners in electoral districts assuming uniform swing appears to underperform relative to predictions assuming proportional swing as the triangles are on average further away from the dashed diagonal line than the dots, suggesting that the electoral context may favor different swing assumptions. Additionally, there are more triangles than dots, indicating more mispredicted districts in the uniform model for this election.

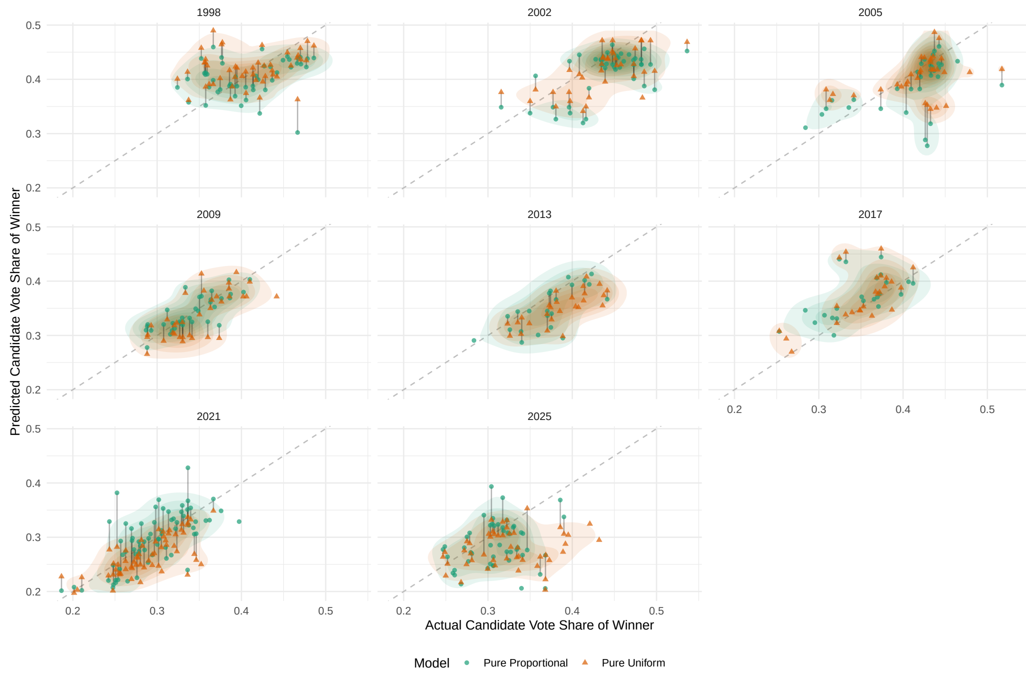

Figure 10: Actual and Predicted Results for Mispredicted District Winners

Note: Lines connect observations from different models of the same mispredicted electoral district. Shaded areas indicate density of all observations.

B Simulation

B.1 Model specification

Three models are specified and estimated using ordinary least squares regression on the training data. The uniform swing model takes the form: $true\_share \sim uniform\_swing$, the proportional swing model takes the form: $true\_share \sim proportional\_swing$, and the mixed swing model combines both approaches: $true\_share \sim uniform\_swing + proportional\_swing$. In all specifications, the swing variables are pre-calculated using single coefficients that combine past district vote share with national-level changes, ensuring that the models learn the true relationship between national-level changes and district-level outcomes without overfitting to interaction terms. Our primary focus is on comparing the performance of uniform versus proportional swing models.

B.2 Additional Tables

Table 2 reports the average number of parties per country based on the ParlGov dataset (Döring et al. 2022).

Country	Number of Elections	Average Number of Parties
Belgium	3	8.30
Iceland	3	7.70
Israel	3	7.70
Slovakia	3	7.00
Netherlands	3	7.00
Sweden	3	7.00
Czech Republic	3	6.70
Latvia	3	6.70
Lithuania	3	6.70
Denmark	3	6.70
Germany	3	6.00
Finland	3	6.00
Switzerland	3	6.00
Slovenia	3	5.70
Estonia	3	5.70
Bulgaria	3	5.70
Poland	3	5.30
Cyprus	3	5.30
Luxembourg	3	5.30
Norway	3	5.30
Japan	3	5.30
Romania	3	5.00
Ireland	3	5.00
Austria	3	5.00
France	3	4.70
Italy	3	4.70
Spain	3	4.70
Turkey	3	4.70
Australia	3	4.30
Hungary	3	4.00
New Zealand	3	4.00
Croatia	3	4.00
Portugal	3	4.00
Greece	3	4.00
Canada	3	4.00
UK	3	3.30
Malta	3	2.00

Table 2: Average Number of Parties per Election by Country ($\geq$5% vote share)

Table 3 reports the average national vote volatility by country (Döring et al. 2022).

Country	Number of Elections	National Vote Volatility
France	3	0.08
Hungary	3	0.08
New Zealand	3	0.07
Italy	3	0.07
Romania	3	0.06
Ireland	3	0.06
Slovenia	3	0.06
Czech Republic	3	0.06
Poland	3	0.05
Latvia	3	0.05
Slovakia	3	0.04
Spain	3	0.04
Netherlands	3	0.04
UK	3	0.04
Estonia	3	0.04
Austria	3	0.04
Lithuania	3	0.03
Croatia	3	0.03
Portugal	3	0.03
Cyprus	3	0.03
Greece	3	0.03
Iceland	3	0.03
Luxembourg	3	0.03
Norway	3	0.03
Germany	3	0.03
Israel	3	0.03
Denmark	3	0.03
Finland	3	0.02
Japan	3	0.02
Turkey	3	0.02
Canada	3	0.02
Belgium	3	0.02
Switzerland	3	0.02
Bulgaria	3	0.02
Sweden	3	0.01
Australia	3	0.01
Malta	3	0.01

Table 3: National Vote Volatility by Country (parties $\geq$5% vote share)

Table 4 reports the between district volatility by country (Kollman et al. 2024).

Country	Number of Elections	Between District Volatility (SD)	Max Number of Districts
Luxembourg	3	0.14	4.00
Croatia	3	0.13	11.00
Japan	3	0.13	303.00
Turkey	3	0.13	87.00
Canada	3	0.13	338.00
UK	3	0.12	647.00
New Zealand	3	0.11	73.00
Malta	3	0.11	13.00
Romania	3	0.09	315.00
France	3	0.09	571.00
Australia	3	0.09	151.00
Lithuania	3	0.08	72.00
Hungary	3	0.08	107.00
Italy	3	0.08	237.00
Ireland	3	0.07	43.00
Germany	3	0.06	315.00
Bulgaria	3	0.06	31.00
Latvia	3	0.06	5.00
Estonia	2	0.06	12.00
Portugal	3	0.06	22.00
Poland	3	0.05	41.00
Slovenia	3	0.05	88.00
Norway	3	0.05	19.00
Cyprus	3	0.04	6.00
Spain	3	0.04	54.00
Greece	3	0.03	60.00
Sweden	3	0.03	29.00
Czech Republic	3	0.03	14.00

Table 4: Between District Volatility and Max Number of Districts by Country (Parties with $\geq$5% Aggregate Vote Share)

B.3 Formalization

The simulation generates synthetic election data using a hybrid swing model that combines uniform and proportional swing components. The key innovation is the **uniform share parameter** $\alpha \in [0, 1]$ that controls the balance between these two swing mechanisms.

Parameter Definitions First, we define the key parameters and variables:

- $P \in \{2, 3, 4, 5, 6, 8, 10\}$: Total number of parties
- $P_{small} \in \{0, 1, 2, 3, 4\}$: Number of small parties
- $P_{large} = P - P_{small}$: Number of large parties
- $D = 100$: Number of electoral districts
- $D_{strong} \in \{10, 25, 40\}$: Number of stronghold districts
- $\phi \in \{0.3, 0.45, 0.60\}$: Stronghold vote share
- $\sigma^2_{national} \in \{0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07\}$: National-level volatility
- $\sigma^2_{district} \in \{0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.10, 0.12, 0.15\}$: District-level volatility
- $\alpha \in \{0, 0.1, 0.2, \ldots, 0.9, 1.0\}$: Uniform share parameter

Party System and Past Vote Share Generation The simulation models a party system with P total parties consisting of nationally large (P_{large}) and small (P_{small}) parties across $D = 100$ electoral districts. Past vote shares for large parties are smaller, the more large parties there are. Past vote shares are generated through:

$$\text{National baselines:} \quad \mu_p = \begin{cases} \text{Large parties: } \{0.35, 0.30, 0.25, \ldots\} \\ \text{Small parties: } 0.06 \end{cases} \tag{1}$$

$$\text{District-level variation:} \quad V_{dp}^{initial} \sim \mathcal{N}(\mu_p, \sigma^2_{district}) \tag{2}$$

$$\text{Stronghold assignment:} \quad V_{dp}^{strong} \sim \mathcal{N}(\phi, \sigma^2_{district}) \quad \forall d \in \mathcal{D}_p^{strong} \tag{3}$$

where $\mathcal{D}_p^{strong}$ represents the set of D_{strong} randomly selected stronghold districts for party p, ϕ is the stronghold vote share. Past vote shares are then truncated and normalized:

$$\begin{align} \text{Truncation:} \quad V_{dp}^{truncated} &= \max(0.05, \min(0.90, V_{dp}^{initial})) \tag{4} \\ \text{Normalization:} \quad V_{dp}^{past} &= \frac{V_{dp}^{truncated}}{\sum_{j=1}^{P} V_{dj}^{truncated}} \tag{5} \end{align}$$

The normalization ensures that vote shares sum to 100% within each district.

Hybrid Swing Mechanism For election e, district d and party p, we first define the swing components:

$$\begin{align} \text{National swing:} \quad S_p^{(e)} &\sim \mathcal{N}(0, \sigma^2_{national}) \tag{6} \\ \text{District-specific variation:} \quad \eta_{dp}^{(e)} &\sim \mathcal{N}(0, \sigma^2_{district}) \tag{7} \\ \text{Uniform Component:} \quad U_{dp}^{(e)} &= S_p^{(e)} + \eta_{dp}^{(e)} \tag{8} \\ \text{Proportional Component:} \quad P_{dp}^{(e)} &= S_p^{(e)} \cdot V_{dp}^{past} + \eta_{dp}^{(e)} \cdot V_{dp}^{past} \quad = U_{dp}^{(e)} \cdot V_{dp}^{past} \tag{9} \end{align}$$

The actual swing applied to each district–party combination at election e is calculated as a weighted average, using the uniform share parameter α to mix proportional and uniform swing components as follows:

$$A_{dp}^{(e)} = \alpha \cdot U_{dp}^{(e)} + (1 - \alpha) \cdot P_{dp}^{(e)} \tag{10}$$

Final Vote Shares The final vote shares result if you add the actual swing to the parties past district vote shares and are calculated as:

$$V_{dp}^{(e)} = V_{dp}^{past} + A_{dp}^{(e)} \tag{11}$$

Final vote shares are then truncated and normalized:

$$\text{Truncation:} \quad V_{dp}^{truncated} = \max(0, V_{dp}^{(e)}) \tag{12}$$

$$\text{Normalization:} \quad V_{dp}^{final} = \frac{V_{dp}^{truncated}}{\sum_{j=1}^{P} V_{dj}^{truncated}} \quad \forall d \tag{13}$$

The truncation ensures non-negativity (vote shares cannot be negative), while the normalization ensures that vote shares sum to 100% within each district.

Interpretation of Uniform Share Parameter The uniform share parameter α creates a continuous spectrum:

- $\alpha = 0$ **(Pure Proportional):** Swing magnitude is proportional to past vote share
- $\alpha = 1$ **(Pure Uniform):** All parties experience the same absolute swing
- $0 < \alpha < 1$ **(Hybrid):** Weighted combination of both mechanisms

B.4 Regression results

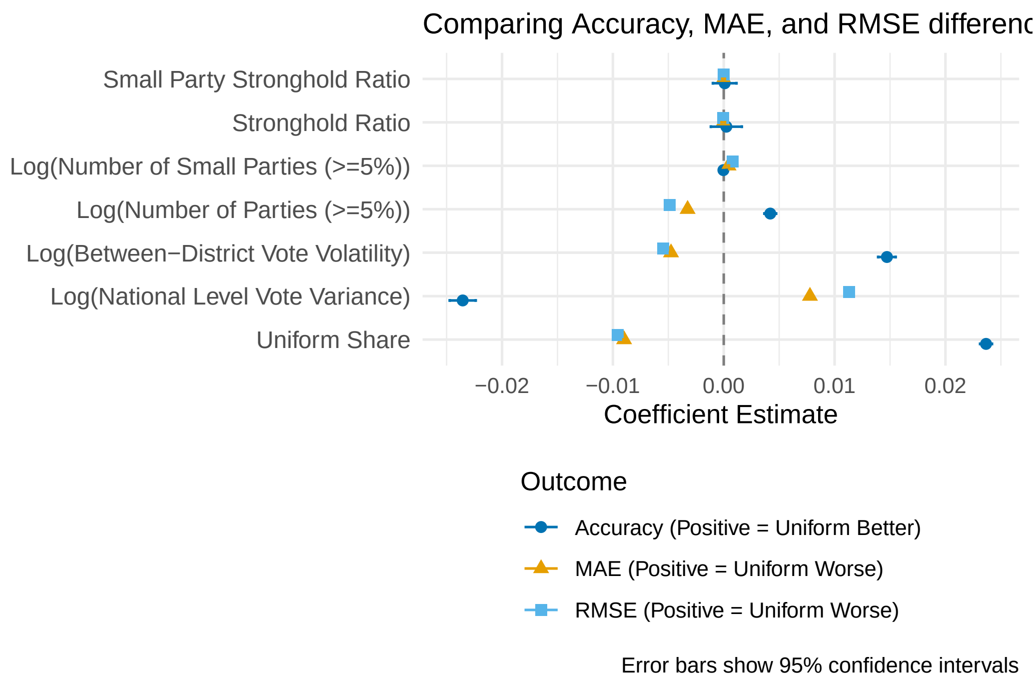

Figure 11: Regression Coefficients Analysis

B.5 Party-mandate aggregation result

Figure 12 reports first differences when performance is aggregated at the party-mandate level. The substantive takeaway differs from average error comparisons: while overall error differences remain small, the aggregation-by-party view reveals systematic allocation bias. Uniform swing systematically over-allocates direct mandates to small parties, and this bias grows with national-level volatility. No clear pattern emerges for a general superiority in aggregate error metrics.

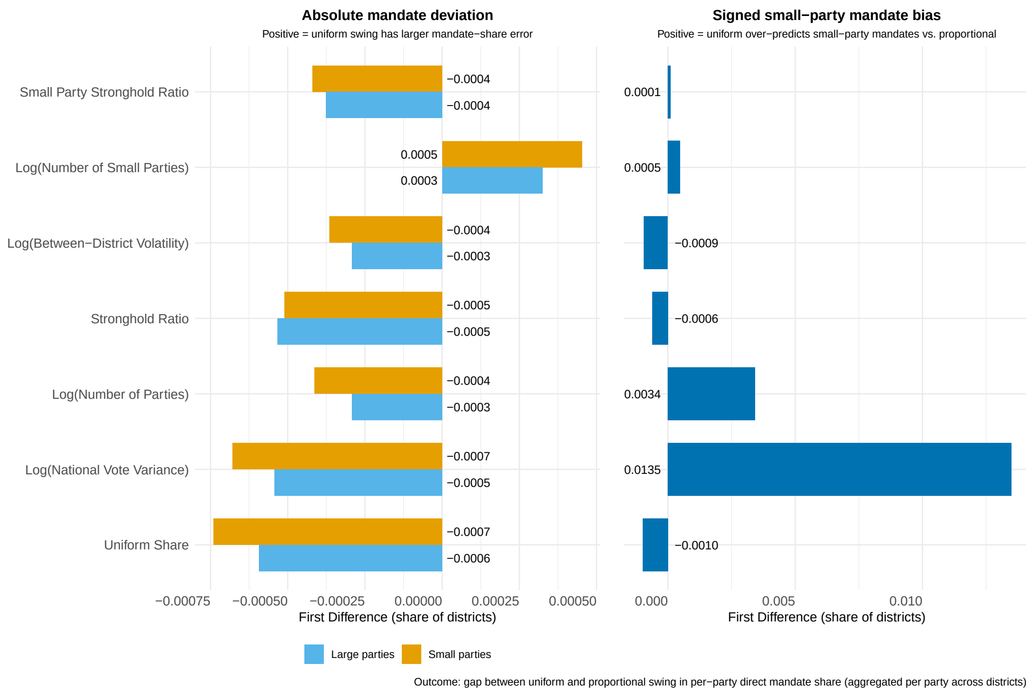

Figure 12: First differences (party-mandate aggregation): bias patterns in direct-mandate allocation