Comparative vote switching

A new framework for studying dynamic multi-party competition

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Abstract

Large literatures focus on voter reactions to parties' policy strategies, agency, or legislative performance. While many inquiries make explicit assumptions about the direction and magnitude of voter flows between parties, comparative empirical analyses of vote switching remain rare. In this paper, we overcome three challenges that have previously impeded the comparative study of dynamic party competition based on voter flows: We present a novel conceptual framework for studying voter retention, defection, and attraction in multi-party systems, showcase a newly compiled data infrastructure that marries comparative vote switching data with information on party behavior and party systems in over 250 electoral contexts, and introduce a statistical model that renders our conceptual framework operable. These innovations enable first-time inquiries into the polyadic vote switching patterns underlying multi-party competition and unlock major research potentials on party competition and party system change.[1]

Keywords: Vote switching, party competition, multi-party systems, data and methods

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[1]Replication files are available in the JOP Data Archive on Dataverse (https://dataverse.harvard.edu/dataverse/jop). The empirical analysis has been successfully replicated by the JOP replication analyst. The authors acknowledge support by the state of Baden-Württemberg through the provision of high-performance computing services via bwHPC.

Information on vote switching between two elections is a core component of how commentators, researchers, and politicians understand political competition in modern representative democracy. Fig. 1 shows two common descriptions of election results as frequently found in election coverage. The left-hand side shows candidate vote shares in the first round of the 2017 French Presidential Election, contrasting parties' 2017 results with their electoral performances in 2012. The right-hand side shows the underlying voter transitions, highlighting the gains of the first-time competitor and plurality winner Emmanuel Macron of *La République en Marche* (REM). Election night commentary frequently features such descriptive portrayals of voter transitions for the in-depth insights they grant: Unlike vote share changes displayed on the left – which tell us *that* Macron gained massive votes – the voter transitions on the right uncover *at whose expense* Macron gained these votes.

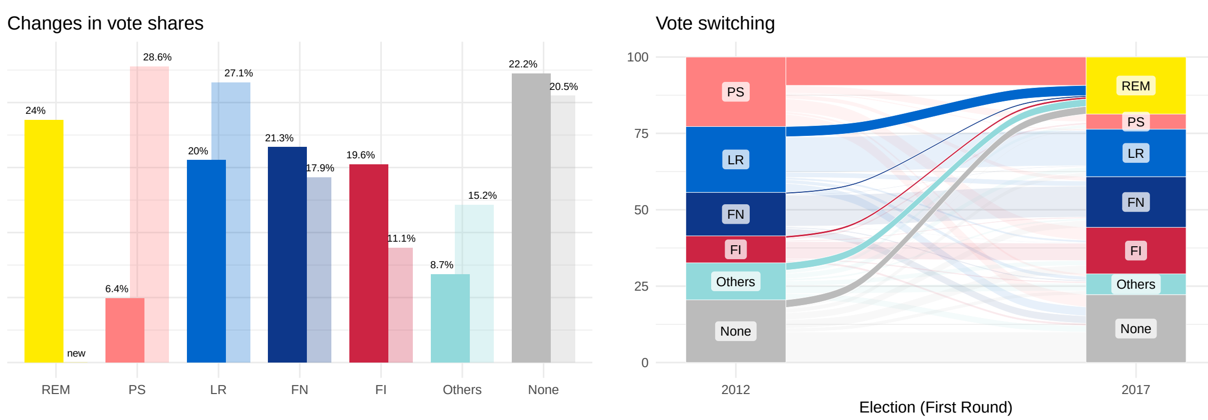

Figure 1: Election results for the French Presidential Election 2017, first round. Left: Vote share changes, normalized such that they sum to 100% without abstentions. Right: Voter transitions, selectively highlighted for La République en Marche (REM).

Whereas election observers and analysts intuitively turn to vote switching data to make sense of the dynamics of multi-party competition for specific elections, political research has so far hardly leveraged this type of data in comparative perspective. This is puzzling, seeing how many political science theories rest on assumptions about micro-level processes of voter de- and realignment that underlie parties' growth and decline and, more generally, compositional changes in party systems. For instance, theories of economic voting, electoral engineering, or institutional reform stipulate dynamic voter reactions to these electoral context conditions (e.g., Nooruddin and Chhibber 2008; Lewis-Beck and Stegmaier 2000; Hernández and Kriesi 2016; Söderlund 2016; Grant 2021); theories of party competition argue that parties' behavior affects their electoral gains and losses (e.g., Tavits 2008; Fortunato 2019; Klüver and Spoon 2020); and voter transitions constitute a defining feature of electoral volatility and dwindling stability in theories of party system change (Kristín Birnir 2007; Bischoff 2013).

While researchers increasingly acknowledge the importance of voter transitions for testing theories about the causes and effects of voter de- and realignment (e.g., Abou-Chadi and Stoetzer 2020), the comparative study of vote switching remains embryonic. Although a few studies offer comparative analyses on the determinants of isolated aspects of vote switching, such as defection from one party family to another (e.g., Spoon and Klüver 2019, 2020; Krause, Cohen, and Abou-Chadi 2022), none provide systematic analyses of the multidimensional and interrelated voter flows that each party faces in multi-party competition.

We see three reasons for this lack of comprehensive comparative inquiries into vote switching. First, analyses of comparative vote switching require complex data pre-processing: Survey-based voter transitions merely indicate switches between nominal parties in idiosyncratic party systems, which does not immediately lend itself to generalized comparative inquiries. Secondly, we lack conceptual parameters that allow us to derive intuitive quantities of interest from the complex multidimensional voter transitions. As a result, existing research has not been able to leverage the full breadth of insights that the study of voter transitions can produce. Thirdly, we lack a statistical method to produce reliable estimates of the relationships between these conceptual quantities and their presumed causes in an integrated methodological framework.

To overcome these limitations, this article proposes three contributions that, jointly, enable the comparative study of the micro-dynamics of electoral change: An original conceptual framework, a newly compiled data infrastructure, and a novel statistical model. We introduce five quantities of interest based on voter transfers between parties: *gross gains*, *gross losses*, *trade volumes*, *trade balances*, and the *voter retention rate*. Our data infrastructure augments vote switching data from 35 OECD countries with contextual information on 1685 parties-within-elections and 254 elections. Using this data within our custom statistical framework, we can model variation in our conceptual quantities across a large number of elections and party systems. These innovations allow for an integrated assessment of the micro-dynamics underlying party competition and thereby enable new research opportunities for the study of parties' records of voter retention, attraction, and defection.

We showcase or approach by studying a question that has received much attention in the public and scholarly debate. We investigate how mainstream party convergence affects vote switching between established and challenger parties and thereby contributed to mainstream party decline and challenger party growth. This application highlights the benefits of our proposed framework for the study of comparative vote switching between party families in response to party repositioning. However, our approach offers a general toolkit that can be used for a variety of research questions in comparative politics and political behavior. For instance, researchers can equally use our framework to analyze the effects of issue-specific pledge fulfillment on vote switches between different government and opposition parties, or whether the election-level salience of gender equality issues prompts vote switching between male and female-led parties.

Our article is accompanied by the open-source `R` package `voteswitchR` (Cohen 2023), which allows users to execute our data-processing routine, estimate our statistical model, and retrieve estimates of our conceptual quantities of interest. This enables researchers to apply our framework for their own inquiries into the micro-dynamic underpinnings of electoral competition. This unlocks large potentials for novel research on democratic representation, party competition, and party system change, and allows political science scholarship to get the most out of the ever-growing comparative data sources on voting and party behavior.

The empirical study of dynamic multi-party competition

The macro-level: Tests based on aggregate vote shares

Questions about the electoral consequences of party behavior have traditionally been studied at the macro-level based on vote shares. For instance, many empirical contributions have investigated the electoral consequences of policy shifts (see, e.g., Meguid 2008; Adams and Somer-Topcu 2009; Ezrow et al. 2011; Adams 2012; Williams 2015; Abou-Chadi and Wagner 2019; De Vries and Hobolt 2020). This approach comes with an inherent tension. On the one hand, theoretical arguments stipulate dyadic or polyadic voter flows – i.e., they formulate expectations about one party's gains from or losses to (a) specific competitor(s). On the other hand, applied empirical tests usually remain strictly monadic: They involve the analysis of vote shares of a single party at a time, either as a function of its own policy strategies (e.g., Adams and Somer-Topcu 2009; Krause 2020) or of those of specific competitors (e.g., Meguid 2008; Spanje 2018).

The macro-level approach, thus, focuses on the evolution of parties' overall electoral support in isolation. It usually neither explicitly models concurrent gains and losses of other parties, nor does it take into account the underlying patterns of vote switching that presumably drive the observed party-level variation. Despite this, macro-level relationships between party behavior and vote shares are often interpreted as indicative of a proposed micro-level mechanism.[2] We caution against two types of ecological fallacy associated with this approach.

False positives mistake an association between party behavior and parties' vote share gains or losses as indicative of a presumed pattern of underlying voter transitions – even though it is partly or entirely driven by different voter flows. For instance, according to the much-debated accommodation hypothesis, one would expect that a mainstream party's positional shift towards a radical party result in voter defection from the radical party to the accommodating

[2]While we situate our discussion in the literature on electoral shifts in response to party behavior, the points we raise equally apply to other causes of electoral change, like economic conditions or institutional reform.

mainstream party (Downs 1957, 131). This hypothesis is typically tested by regressing the vote shares of radical parties on the policy positions of one or several mainstream competitors (e.g., Meguid 2008; Spanje 2018). Yet, other underlying switching patterns may produce aggregate-level results that seemingly support this hypothesis. One such example is electoral mobilization in response to the mainstream party's policy shift: We may see increased turnout among previous non-voters who either support the mainstream right's repositioning (and therefore vote for it) or oppose it (and therefore vote for progressive parties). An apparent relationship between accommodation and a decline in radical parties' nominal vote share would then be a mere artifact of this entirely different micro-mechanism.

False negatives, on the other hand, mistake stability in parties' vote shares as indications of stability in parties' electorates. This occurs when there is significant switching into and out of parties' voter bases that cancel out in aggregation. In the 2019 Danish Parliamentary Election, for instance, the Social Democrats' rightward shift resulted in the loss of about as many voters to other left-wing parties as gains from the right-wing bloc. An isolated focus on the vote share change of the Social Democrats, however, would miss these significant voter flows. A possible remedy for this problem is to move beyond monadic approaches: Philips, Rutherford, and Whitten (2016) introduce an aggregate-level approach for analyzing dynamic multi-party competition as a polyadic zero-sum game, which models the effects of a presumed cause on the aggregate gains and losses of *all* parties. However, even this approach cannot capture the simplest case of false negatives – namely a situation in which two parties exchange large but balanced numbers of voters.

The micro-level: Tests based on comparative survey-based vote switching data

In light of the limitations of studying aggregate changes in party vote shares, an increasing number of contributions now turns to the comparative study of vote switching (e.g., Spoon and Klüver 2019, 2020; Abou-Chadi, Cohen, and Wagner 2022). Unlike aggregate-level studies of party vote shares, this approach leverages reports of vote switching in subsequent elections from national election surveys. In contrast to 'classical' studies of vote switching that analyze which voter characteristics predict inter-individual variation in micro-level probabilities of vote switching, comparative studies of vote switching analyze how contextual variation in parties' policy strategies, agency, or legislative performance predicts party or election-specific *patterns of vote switching* across electoral contexts. In this type of analysis, the primary level of explanation is party-specific or election-specific but the outcomes of interest are inter-party voter flows aggregated from individual-level data.

With this approach, party strategies are clearly linked to voter transfers. This addresses the inherent tension of macro-level studies, where theories acknowledge the complexities of polyadic multi-party competition but empirical analyses typically adopt monadic perspectives on parties' vote shares. Yet, existing contributions to this emerging literature often rely on conceptual estimands and empirical approaches that fail to capture the theoretical relationships of greatest substantive interest.

To illustrate, Fig. 2 shows hypothetical voter transfers in a three-party system with a leftist party A, a centrist party B, and a rightist party C. We assume that all illustrated voter flows are caused by party B's strategic positioning vis-à-vis party C. All plots show the exact same transitions but differ in their selective foci, which reflect existing approaches in the applied literature. Such selective foci capture different parameters of multi-party competition and therefore provide insights into different aspects of the electoral effects of parties' strategic behavior. We explicate three caveats that researchers ought to consider when squaring theoretical arguments with conceptual quantities of interest and empirical strategies.

1. Unidirectional dyadic defection paints an incomplete picture of dyadic competition: We caution against drawing conclusions about the effects of party behavior on dyadic voter transfers based on *unidirectional* voter flows alone. The logic of this approach is illustrated in Scenario I in Fig. 2: The scope of the inquiry focuses solely on the effect of party B's behavior on its dyadic losses to party C, ignoring all else. This neglects that dyadic voter transfers run both ways and, thus, ignores that party B's behavior may simultaneously catalyze vote

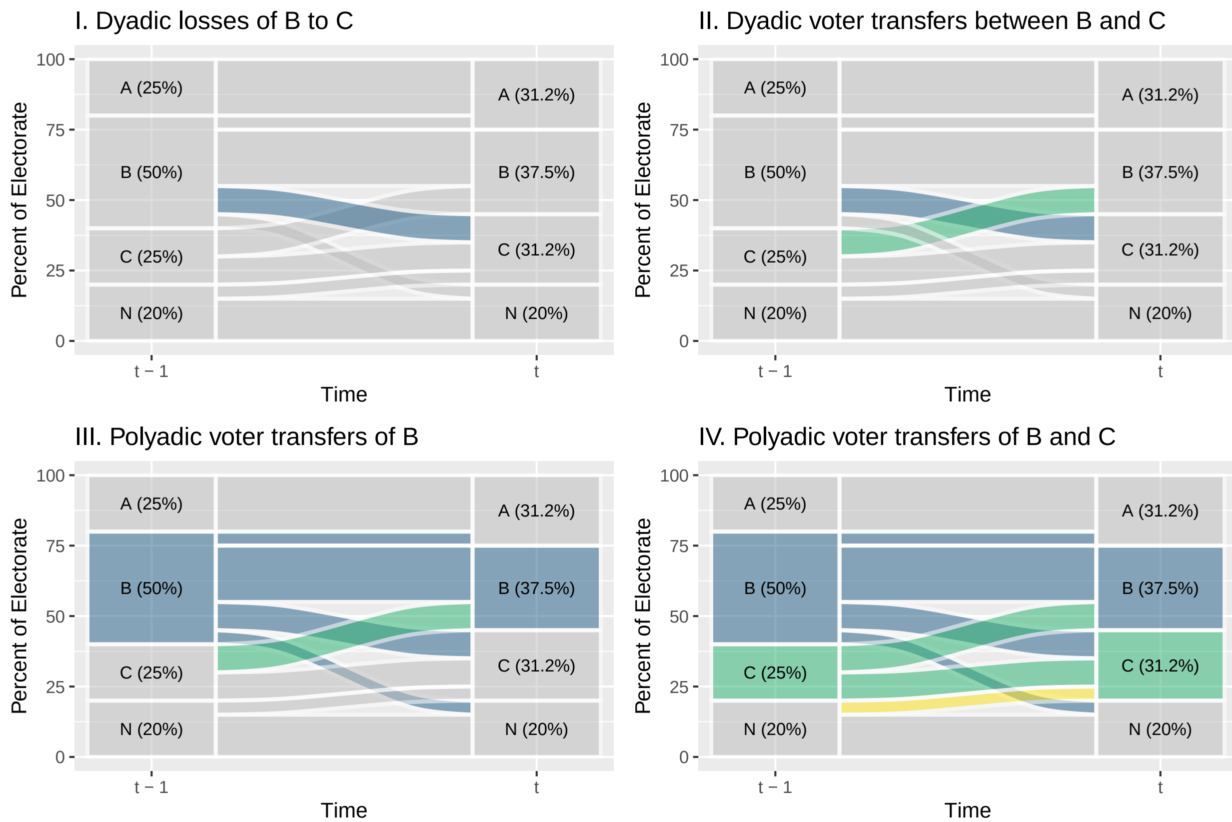

Figure 2: Selective foci on specific aspects of vote switching yield different – and often incomplete – insights.

gains from and vote losses to its competitors. This is illustrated in Scenario II: Party B's behavior results in equally large gains from and losses to party C. Neglecting the concurrent stream of counter-directional vote switching therefore gives an incomplete answer to questions about the electoral effectiveness of party B's strategies. While there may be valid reasons for focusing on unidirectional gains or losses alone, analyses of dyadic vote switching can benefit from jointly analyzing gains and losses and weighing these bidirectional transfers against one another.

2. Transfer balances reveal little about the intensity of dyadic competition: As a corollary of the balanced voter transfers between B and C in Scenario II, we emphasize the importance of moving beyond net transfers when analyzing the intensity of dyadic competition. Even when a parties' behavior does not affect the net balance of dyadic voter transfers, they can significantly catalyze bidirectional vote switching. An exclusive focus on transfer balances may mask intense dyadic competition. Researchers should therefore explicitly distinguish if the expected effects concern the intensity of dyadic competition, its directionality, or both.

3. Dyadic transfers reveal little about overall (polyadic) trade-offs: Even when dyadic competition is convincingly conceptualized and modeled, it still only captures one (potentially small) part of the electoral returns of party behavior, as any given dyad captures merely one avenue for bi-directional voter flows in the complex interplay of polyadic multi-party competition. Even if a strategy maximizes parties' electoral returns in one pattern of dyadic competition, we cannot assume that the same strategy concurrently maximizes their overall electoral returns. This is illustrated in Scenario III in Fig. 2: Party B's behavior not only causes balanced bi-directional voter transfers with party C but concurrently results in net losses to party A and to non-voters N. As a result, party B's vote share decreases from $t-1$ to t. Concurrently, as shown in Scenario IV, party B's behavior also drives previous non-voters toward party C. Party B's behavior therefore simultaneously weakens party B and strengthens party C – even though neither effect unfolds via dyadic transfers between the two.

Conceptual framework

This section proposes a comprehensive conceptual framework for reaping the full benefits of comparative vote switching data for the study of dynamic multi-party competition. Our conceptual framework rests on a series of theoretically important parameters that describe the micro-dynamic underpinnings of electoral competition, each of which is defined for any given dyad and can be aggregated up to any desired polyad or to party-specific totals.

Our conceptual framework rests on the established representation of voter transfers in a transition matrix, which cross-tabulates votes for parties in election $t-1$ (rows) with votes for parties in election t (columns). Its cells contain counts for each possible transfer pattern, which can equally be expressed as cell percentages. We denote the cell percentage in the i^{th} row and j^{th} column as $p_{i,j}$. Table 1 gives an example: An estimate of the voter transition matrix for the 2010 UK General Election, in which three main parties competed: Labour, Liberal Democrats, and Conservatives. Supplemented by residual other parties (e.g., Greens and UKIP) and non-voters, voter transfers between the 2005 and 2010 elections can be summarized in a 5×5 transition matrix. The marginal distributions, which show the total vote percentages in 2005 and 2010, reflect the parties' true vote shares.[3]

	LAB '10	**LIB '10**	**CON '10**	**OTH '10**	**NON '10**	**2005**
LAB '05	12.6	2.4	2.2	0.6	3.9	**21.6**
LIB '05	1.5	8.8	1.8	0.6	0.9	**13.5**
CON '05	0.8	1.0	14.8	0.9	2.4	**19.9**
OTH '05	0.6	0.5	0.7	3.5	1.1	**6.4**
NON '05	3.5	2.3	4.1	2.1	26.6	**38.6**
2010	**18.9**	**15.0**	**23.5**	**7.7**	**34.9**	**100.0**

Table 1: A voter transition matrix.

The cells of such voter transition matrices constitute the building blocks of our conceptual quantities of interest. They yield direct representations of three basic quantities: Diagonal cells $p_{i,i}$ represent the *voter retention rate*, R_i, of a given party i. The off-diagonal cells, $p_{i,j}$ and $p_{j,i}$, represent the dyadic *gross gains* of party i from party j, $G_{i,j}$, and its *gross losses* to party j, $L_{i,j}$, respectively. We illustrate these quantities by focusing on Labour, the incumbent government party heading into the 2010 election. Retained voters are given by the first diagonal cell, $p_{1,1}$: 12.6% of all eligible 2010 voters voted for Labour in both 2005 and 2010. The remaining entries of the first row capture Labour's gross losses to each of its competitors: 2.4% of the 2010 electorate switched from Labour to the LibDems, 2.2% switched from Labour to the Conservatives, 0.6% to other competitors, and 3.9% to the non-voter camp. Conversely, the remaining entries of the first column show Labour's dyadic gross gains from each competitor: 1.5% switched from LibDems to Labour, and 0.8%, 0.6%, 3.5% switched to Labour from the Conservatives, others, and non-voters, respectively.

[3]Note that party vote shares are reported as percentages of the *eligible electorate* (including non-voters) and are thus not normalized by the percentage of valid votes (excluding non-voters) as typically reported in official election results.

Dyadic gross gains and gross losses are the building blocks of two other central quantities of interest: Dyadic transfer volumes and dyadic transfer balances. *Transfer volumes* concern the question of whether a given cause activates voter transfers between parties, irrespective of the resulting net balance. Defined as the *sum* of gross gains and gross losses, $V_{i,j} = p_{j,i} + p_{i,j}$, they capture the *intensity* of dyadic competition for every dyad $\{i, j\}$. In the case of dyadic competition between Labour ($i = 1$) and the Liberal Democrats ($j = 2$), for instance, $V_{1,2} = p_{2,1} + p_{1,2} = 1.5 + 2.4 = 3.9$. This indicates that indicates that 3.9% of the 2010 electorate switched between Labour and LibDems. At a purely descriptive level, transfer volumes can be used for assessing which competitors a focal party competes with most strongly. They also shield us against false negatives: By studying transfer volumes, we avoid interpreting stability in vote shares as stability in parties' electorates.

Transfer balances, on the other hand, capture the net balance of *winning* and *losing* electoral support. For each dyad $\{i, j\}$, they are defined as the *difference* between i's gross gains from, and gross losses to, j: $B_{i,j} = p_{j,i} - p_{i,j}$. For instance, from Labour's perspective, the dyadic trade balance with the LibDems is $B_{1,2} = p_{2,1} - p_{1,2} = 1.5 - 2.4 =$ -0.9, which indicates dyadic net losses by the magnitude of 0.9 percentage points. Transfer balances capture the *directionality* of dyadic competition. They allow us to study if parties' behavior results in net gains or net losses with each competitor. Aggregated across all dyads, transfer balances sum to parties' overall vote gains or vote losses from one election to the next.

The dyadic quantities G, L, V, and B can be freely aggregated to match any polyadic quantity of substantive interest. For instance, competition between Labour (i), LibDems (j), and Conservatives (k) can be conceptualized as a manifestation of competition between government and opposition. To study incumbent Labour's *combined* voter transfers with its two main oppositional competitors, we can derive transfer volumes $V_{i,\{j,k\}} = p_{j,i} + p_{j,k} + p_{i,j} + p_{i,k} \approx 6.9$ and transfer balances as $B_{i,\{j,k\}} = p_{j,i} + p_{j,k} - (p_{i,j} + p_{i,k}) \approx$ -2.3. These numbers show that roughly 6.9% of all eligible voters in 2010 switched between the governing

Labour and the two main opposition parties, with a net loss of 2.3 percentage points for Labour.

Studying these conceptual quantities across many electoral contexts can inform comparative inquiries that unlock research potentials which existing approaches cannot address. These quantities capture key parameters of stability and change in dynamic polyadic multi-party competition. Unlike changes in vote shares, they shield us from erroneously mistaking stability in parties' overall electoral support for stability in their electorates and offer insights into the intensity and directionality of voter transfers between all available dyads of parties, including the group of non-voters. While the overall electoral gains and losses of a party, captured by (changes in) vote shares, remain important reference points for evaluating the effects of party behavior, testing the micro-logic underlying theories of party competition requires that we uncover the multi-directional transfers between parties as captured by the conceptual parameters we proposed in this section.[4]

Analyzing comparative vote switching data

This section first showcases our data infrastructure. It then introduces a new statistical model. Jointly, these empirical contributions render our proposed conceptual framework operable for broad, comparative inquiries.

Data infrastructure

A key challenge in studying comparative vote switching is that we cannot directly observe voter transition matrices. Unlike the true *marginal* distribution of a voter transition matrix – i.e., the official vote shares and abstention rates in consecutive elections – we never know the true *joint* distribution, i.e., the number or percentage of voters in each cell. We must therefore rely on estimates. To maximize the comparative scope of vote switching analyses

[4]We illustrate this general framework in our empirical application later on but note two conceptual extensions, which we describe in Online Appendix A2: The study of *party electorates*, which focuses on the retention, gains, and losses of a focal party relative to its (current or past) size, and the study of *electorate subgroups* to analyze heterogeneous effects on patterns of voter retention, attraction, and defection within different parts of the electorate.

across time and space, our approach uses estimates from cross-sectional surveys. We note that doing so rests on stringent assumptions about the representativeness of survey samples and the validity of survey-based reports of vote switching, which we address below and in Online Appendices A1 and A6.

Our newly compiled data infrastructure includes a combined total of 557989 respondents from 254 post-election surveys collected across 35 EU and OECD countries, covering comparative survey projects like *The European Voter* (TEV) and the *Comparative Study of Electoral Systems* (CSES) and over 100 national election studies. All surveys include information on respondents' vote recall in the current and previous general elections. To process this large collection of raw survey data into valid and reliable representations of election-specific voter transition matrices that can ultimately be used for comparative inquiries, we have implemented a generalized five-step data processing routine.[5]

The first step *harmonizes* codings of respondents' vote recall at t and $t-1$ as well as political and demographic auxiliary variables. In the second step, these auxiliary variables can be used to inform the *imputation* of missing vote recall information via hot deck imputation. The third step involves the *mapping* of respondents' vote choices at t and $t-1$ to party and election IDs from *ParlGov* (Döring and Manow 2018) and the *Manifesto Project* (Volkens et al. 2021). Based on these IDs, we can link each voter transition matrix to external information on its constitutive parties and its electoral context. This external information then informs the final two steps of the routine.

In the fourth step, we augment the vote switching data with official election results to *rake* each voter transition matrix by official vote shares and abstention rates at t and $t-1$. Raking is an iterative reweighting algorithm commonly used in survey research that "adjusts a set of data so that its marginal totals match control totals on a specified set of variables" (Battaglia, Hoaglin, and Frankel 2009, 2) while incorporating idiosyncratic influences due to sampling

[5] Per the generalized implementation as part of the `voteswitchR` package, our data-processing routine can be flexibly used for various substantive applications. We provide additional details on the routine, including the results of the raking sub-routine, in Online Appendix A1.

or post-stratification weights. This addresses concerns about the data quality related to item and unit non-response, social desirability, and recall bias (e.g., Selb and Munzert 2013; Dassonneville and Hooghe 2017). The final step involves the *generalized aggregation* of the rake-weighted cell counts of each election-specific transition matrix. Instead of retrieving these counts for each nominal party in a given voter transition matrix, we use externally supplied schematic categorizations of parties (e.g., in terms of party family or government status), which makes the data eligible for substantively focused comparative inquiries. With $c = 1, ..., C$ distinct categories in both rows and columns, this yields a generalized $C \times C$ transition matrix with C^2 rake-weighted cell counts w_{jc} for each election $j = 1, .., J$.

Statistical model

Our statistical model uses these processed cell counts w_{jc} to explain variation in all switching patterns captured in the generalized voter transition matrices as a function of contextual covariates across the J elections. It seeks to model *latent election-level cell proportions*, to be estimated as a function of cell counts w_{jc} relative to the total number of voters in each transition matrix, n_j. This constitutes a classic use case for a hierarchical model: The model of primary interest is a contextual model, where an aggregate-level quantity constitutes the outcome of interest but – for a lack of direct measures – has to be estimated from micro-level data (see, e.g., Gelman 2005). For each election $j = 1, ..., J$, we thus capture the C^2 latent cell proportions via random effects.

The data-generating process must accommodate two characteristics: At the micro-level, the underlying switches are mutually exclusive; at the aggregate election level, the cell proportions are jointly exhaustive (i.e., they sum to one). At the micro-level, this stipulates a categorical likelihood, known from standard multinomial choice models. Rather than estimating idiosyncratic probability parameters that govern a categorical process which produces discrete individual choices $y_i = c$, however, we want to estimate election-level proportion parameters that produce the aggregate counts of these choices in each election j, $n_{jc} = \sum_i^{n_j} 1\{y_i = c\}$ relative to the total number of micro-level observations in each electorate, n_j. We estimate these vote switching proportions per average election-level vote switching probabilities: $\Pr(y_{ij} = c|\mathbf{x}_j) = \Pr(y_j = c|\mathbf{x}_j)$ for all $i = 1, ..., n_j$. We can then model variation in these election-cell-specific proportions as a function of contextual covariates, $\mathbf{x}_j$.[6] This yields a multinomial quasi-likelihood at the level of electorates.

Additionally, we incorporate the possibility of varying choice sets to make our methods applicable across heterogeneous party systems: When one or more of the C party types in the generalized voter transition matrix are non-existent in an election j, specific cells of the voter transition remain deterministically empty. Vote switches can then only occur within a constrained choice set S_j, a subset of the full choice set S that comprises all C^2 cells. By accommodating such varying choice sets, comparative inquiries neither require the exclusion of electoral contexts with "incomplete" party systems nor the subsumption of "occasional competitors" under a residual "others" category. Following Yamamoto (2014), we implement this feature through an adjustment to the denominator of the softmax function:

$$\Pr(y_j = c|\mathbf{x}_j) = \frac{\exp(\mu_{jc})}{\sum_{c \in S_j} \exp(\mu_{jc})}, \tag{1}$$

where

$$\mu_{jc} = \alpha_c + \mathbf{x}_j' \beta_c + \nu_{jc} \text{ for each } c \in S_j. \tag{2}$$

In Eq. (2), $\mathbf{x}_j$ is a covariate vector that contains all relevant election or country-level predictors for election j. α_c are cell-specific intercepts; β_c are cell-specific coefficient vectors. ν_{jc} represents the election-cell-specific random intercepts and capture election-specific deviations from the respective cell intercepts α_c. Following standard practice in multinomial and mixed

[6]Our model, like models for comparative analyses of vote shares, is designed to analyze election-level outcomes as a function of election-specific party behaviors as well as electoral or national context conditions. This precludes the inclusion of individual-level covariates. However, like in vote share analyses, practitioners can control for compositional social and political differences by including election-level aggregate measures.

logit regression, we set the coefficients for one outcome category to zero to ensure that the model parameters are statistically identified.[7]

The log-likelihood of the model is

$$\log L = \sum_{j=1}^{J} \sum_{c \in S_j} w_{jc} \log \Pr(y_j = c | \mathbf{x}_j). \tag{3}$$

Here, J denotes the number of elections and S_j denotes the election-specific choice sets. The frequency weight w_{jc} represents the cell-specific raked counts from the final step of our data processing routine, which multiply the corresponding outcome-specific conditional log-probabilities.

We implement and estimate the model in Stan, a platform for statistical modeling and high-performance statistical computation using full Bayesian inference through Hamiltonian Monte Carlo sampling (Stan Development Team 2021). Online Appendix A3 gives further information on the MAVCL model, including default choices for prior specifications. Functions for model estimation and the post-estimation calculation of quantities of interest, like conditional expected values and average marginal effects, are available as part of the `voteswitchR` package.

Empirical application

This section presents an empirical application of our proposed framework. We illustrate how a comparative vote switching perspective can inform long-standing debates and extend recent advances in the study of the electoral consequences of mainstream party convergence (hereafter: MPC) in Western Europe. Since the 1990s, scholars have prominently argued that MPC enabled the success of new party families at the expense of mainstream parties (e.g., Katz and Mair 1995; Kitschelt and McGann 1995). According to this argument, challenger parties, such as radical right, radical left, and Green parties, benefit from positional convergence: As

[7] Note that this baseline category must not be deterministically empty in any of the J voter transition matrices. A solution which always satisfies this criterion is using the non-voter retention cell.

mainstream parties move away from the classical left and right poles, non-centrist voters defect them in favor of more "radical" competitors. While many empirical studies support the convergence hypothesis (e.g., Carter 2005; Spies and Franzmann 2011; Grant 2021), nearly all share an important limitation: Due to their focus on macro-level vote shares, they cannot test the underlying assumption that MPC leads to challenger party success *by prompting mainstream-to-challenger defection*.

A recent study by Spoon and Klüver (2019), however, uses comparative vote switching data to study mainstream parties' unidirectional gross losses to challengers. While the study finds a positive effect of MPC on mainstream-to-challenger defection, it does not consider mainstream parties' concurrent gains *from* challengers. As a result, the effect on net transfer balances in mainstream-challenger switching remains unknown: Mainstream parties' gross losses could be aggravated by concurrently decreasing gains or, at least in part, compensated by simultaneous vote gains from challengers. Additionally, MPC may have secondary electoral effects which contribute to mainstream party decline and challenger party growth beyond mainstream-challenger voter transfers, for instance by demobilizing erstwhile mainstream party voters or prompting challenger vote gains from non-voters and other parties. Lastly, we do not know yet if these potential mechanisms underlying mainstream party decline and challenger party growth affect different mainstream and challenger party families equally.

Empirical setup

Given that the existing debate has focused on multiparty systems in Western Europe, we study the electoral consequences of MPC across 156 electoral contexts from 18 West European countries.[8] We model vote switching across $C = 7$ marginal categories: Next to the mainstream left and mainstream right, we include three challenger party families (radical left, green, and radical right parties) as well as residual "others" and non-voters.

For each election, we retrieve vote switching counts from the cells of the 7×7 transition matrices and model the corresponding cell proportions as a function of MPC, measured as left-

[8]The country sample as well as summary statistics are reported in Online Appendix A4.

right distances: $\text{MCP}_j = \text{LR}_{l,j} - \text{LR}_{r,j}$. Here, j denotes elections, l denotes the mainstream left (social democratic parties), and r the mainstream right (conservative, Christian democratic, and liberal parties). In case of multiple mainstream left and/or mainstream right parties per electoral context, the measure reflects the positions of the strongest party in each camp. Left-right positions LR are log-ratio scales (Lowe et al. 2011) based on MARPOR data (Volkens et al. 2021). The resulting measure of MPC ranges from -4.14 to 0, where negative values indicate positional divergence and 0 indicates perfect convergence.[9] As convergence is typically conceptualized as a dynamic process that unfolds within party systems over time, we include country fixed effects in our model.

Findings

We now showcase how a single comparative vote switching model allows us to study the electoral effects of MPC at unparalleled levels of rigor and detail. Our application stresses the immunity of our approach to ecological fallacies by separating effects that would remain inseparable in macro-level analyses. We isolate *primary effects* on mainstream-challenger switching from *secondary effects* on residual voter flows that can affect mainstream party decline and challenger party growth, such as gains from, and losses to, other parties and non-voters. Initially, we pool effects from across various cells of the underlying 7×7 voter transition matrix to draw broad inferences about competition between the two mainstream party families on the one hand and the three challenger party families on the other. Eventually, we show how we can leverage the fine-grained structure of the transition matrix to obtain nuanced insights about the dyadic foundations that underlie this pooled mainstream-challenger competition.

Primary effects: In Fig. 3, we turn to the *primary effects* of theoretical interest: We show how MPC affects vote switching between mainstream and challenger parties. Panel A of Fig. 3 reports average marginal effects on mainstream parties' gross gains (G), gross losses

[9] In two elections where the mainstream left stood to the right of the mainstream right, the measure produced positive values. We recoded these to 0 as positional leapfrogging is functionally equivalent to positional convergence.

(L), transfer volumes (V), and transfer balances (B) with challenger parties. Since balances are the key parameter for understanding parties' growth and decline, we not only need to understand when they become more or less favorable for a party in response to MPC (as captured by the average effect) but also the sign and magnitude of their expected *levels*. Panel B therefore shows the expected values of transfer balances as a function of MPC.

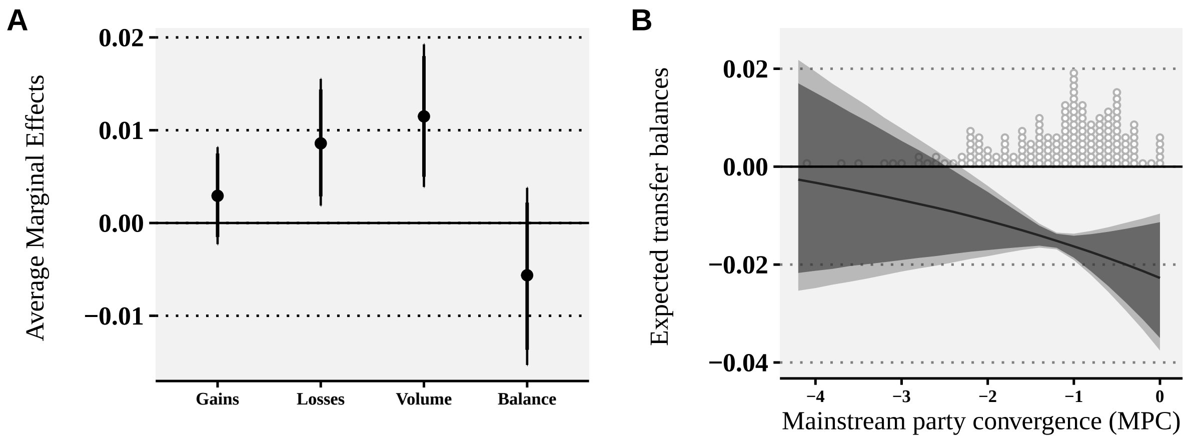

Figure 3: A: Average marginal effects of mainstream party convergence (MPC) on mainstream party gains, losses, volumes and balances with challenger parties. B: Expected mainstream party transfer balances with challenger parties as a function of MPC. Posterior medians with 90% and 95% credible intervals.

In line with Spoon and Klüver (2019), we find a pronounced positive effect on gross mainstream-to-challenger defection (L): Per one-unit increase in MPC, mainstream parties lose an additional 0.86 (0.19, 1.55) percentage point to challengers. At the same time, and in contrast to existing insights, we find an effect of 0.29 (-0.23, 0.82) on challenger-to-mainstream switches (G). Albeit comparatively small and positive with a posterior probability of only 85.6%, this effect pulls the effect on net transfer balances (B) toward zero. Consequently, we find only limited support for the hypothesized effect on *net defection* from mainstream to challenger parties with a posterior probability of 87.5% – even though the expected levels of mainstream-challenger trade balances are generally in line with the theory, ranging from null when MPC is low to -2.27 (-3.76, -0.96) percentage points when MPC is high. While we can safely infer that MPC increases the *intensity* of mainstream-challenger competition (V), we should thus reserve some skepticism as to whether mainstream-to-challenger defection due to MPC can credibly serve as an explanation for mainstream party decline and challenger party growth.

Secondary and overall effects: The evidence presented in Fig. 3 prompts the question if existing macro-level analyses may have mistaken secondary effects as support for the existence of primary effects. Fig. A5.3 in the Online Appendix does not support this concern: For mainstream and challenger parties alike, MPC does not systematically predict any residual switching patterns. Therefore, the overall effects on mainstream and challenger parties' records of voter attraction, defection, and retention (cf. Fig. A5.4) are dominated by the primary effects. MPC unambiguously increases the intensity in voter transfer between mainstream and challenger parties and, thereby, also decreases mainstream party voter retention. Its effects on mainstream party decline and challenger party growth, however, come with considerable uncertainty.

Party-family-specific effects: Whereas we have so far discussed pooled effects on mainstream-challenger competition, we now forego effect pooling and study detailed effects on dyadic vote switching between the two mainstream and the three challenger party families. This nuanced perspective yields important insights. Fig. A5.6 in the Online Appendix shows that MPC systematically predicts mainstream right decline, a pattern that can be almost exclusively attributed to systematic effects on dyadic net losses to the radical right. Thus, although MPC does not generally contribute to mainstream party decline and challenger party growth by prompting mainstream-to-challenger net defection, the theory applies selectively to right-wing competition in West European party systems.

In contrast, as we find in Fig. A5.5 in the Online Appendix, the theory does not apply to left-wing competition. Even though mainstream left parties, on average, experience greater net losses than their mainstream right counterparts, their decline is not systematically linked to MPC. We do, however, find that MPC catalyzes bidirectional switching into and out of social democrats' electorates and thereby lowers their records of voter retention. While

MPC thus cannot explain mainstream left parties' decline (nor green or radical left growth, as shown in Figs. A5.7 and A5.8), it systematically predicts increasing turnover in their electorates.

Conclusion

Virtually all theories of representation and political competition are based on assumptions about the dynamic behavior of voters. Yet, few empirical approaches to date do these assumptions justice. Existing comparative studies have either analyzed vote shares at the party-level or adopted highly selective perspectives on vote switching. As we have shown, these practices fall short of unlocking comprehensive insights into the underlying patterns of voter reactions to election contexts or party behaviors. To understand parties' growth or decline and the resulting compositional changes in party systems, we must study comprehensive patterns of vote switching instead. To overcome various obstacles that previously impeded the comparative study of vote switching, we have introduced a conceptual and statistical framework along with a newly compiled data infrastructure. Using these tools, political scientists can analyze the underlying micro-dynamics of electoral competition in so far unparalleled depth and detail.

We have presented an empirical application of our approach to the question of how mainstream party convergence affects the patterns of competition between mainstream and challenger parties. While our application has illustrated the effects of an election-level phenomenon — positional similarity of mainstream parties — on vote switching between various party families, our approach can equally be applied to the analyses of *party electorates*, which allows studying how individual parties' behavior affects their own electorates.

Given its flexibility and comprehensiveness, researchers can use our framework to assess many of the underlying assumptions of behavioral theories of party competition and party system change. Concerning the vivid academic and public debates about what constitutes "successful" programmatic party strategies, our framework provides a more differentiated perspective on electoral trade-offs. For instance, the question if a strategy that wins back voters from one party comes at the cost of lower retention and concurrent losses to other parties, is of great relevance for researchers, pundits, and party strategists alike. Aside from these perspectives from the party competition literature, our approach can be applied to many other comparative research agendas. These include the study of the electoral consequences of institutional designs, changing economic conditions and shocks, or media attention. Additionally, analyses of national and party electorates can be stratified across *electorate subgroups* and thereby integrate insights from electoral sociology: Researchers can study vote switching across groups with different socio-structural characteristics, such as gender, age, or education.

Beyond such potential applications of our conceptual framework, our data infrastructure can benefit other research. First, it provides an unparalleled scope of mappings of core variables from election studies – including vote choice, party identification, left-right party-placements, and party like/dislike scores – to party-level and election-level information. This can be used for 'classical' comparative analyses of political behavior. Secondly, our mapped estimates of election-specific voter transition matrices can not only be studied as outcomes but also as *predictors* of party behavior. Studying how political elites respond to selective gains and losses allows researchers to study important phenomena such as accountability, responsiveness, and representation.

By implementing our data processing routine, statistical model, and quantities of interest in the open-source software `voteswitchR`, we provide future academic work with all the tools necessary to apply our framework. This unlocks vast new research potentials and enables political science scholarship to get the most out of the existing and ever-growing body of data on voters, parties, and elections.

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Online appendix: Comparative vote switching

A1 Data Processing

This section provides a detailed explanation of our data processing routine, acronymized as *HIMRA: Harmonization, imputation, mapping, raking, and aggregation.* As explained in the paper, the goal of this routine is to process raw vote switching data from micro-level election studies such that we can retrieve valid and reliable estimates of voter transition matrices that characterize the totality of vote switching in any given electorate.

A1.1 Harmonization

Harmonization involves the processing of the micro-level survey data so that they can be effectively used for comparative research. Toward this end, we identified a number of relevant concepts that are frequently recorded in election studies. As part of harmonization, we ensure that all concepts are measured equivalently. For instance, numerical values representing parties or non-voting are harmonized across the concepts of current vote choice and past vote choice within each election study, and continuous measures like left-right placements are normalized onto a common scale across all election studies. The list below gives a complete overview of the concepts we extracted from each election survey (provided the variables were included) and the harmonizations we applied.

1. **Vote choice at t**
   - Harmonized numerical codes across *vote choice at* t, *vote choice at* $t-1$, and *party identification*
   - Integrated turnout and vote choice (where necessary)
   - Adjusted for party/coalition votes and party mergers (where applicable)
2. **Vote choice at $t-1$**
   - Harmonized numerical codes across *vote choice at* t, *vote choice at* $t-1$, and *party identification*
   - Integrated turnout and vote choice (where necessary)
   - Adjusted for party/coalition votes and party mergers (where applicable)
3. **Party identification**
   - Harmonized numerical codes across *vote choice at* t, *vote choice at* $t-1$, and *party identification*
   - Integrated binary party identification (yes/no) and party respondent identifies with
   - Adjusted for party/coalition votes and party mergers (where applicable)
4. **Left-right self-placement**
   - Rescaled to 0 (left) to 10 (right) scale
5. **Left-right party placements**
   - Rescaled to 0 (left) to 10 (right) scale
   - Averaged across parties where vote choice recorded votes for multi-party coalitions (e.g., CD&V–N-VA in Belgium-Flanders, 2007)

6. **Party like/dislike scores**
   - Rescaled to 0 (dislike) to 10 (like) scale
   - Averaged across parties where vote choice recorded votes for multi-party coalitions (e.g., CD&V–N-VA in Belgium-Flanders, 2007)
7. **Satisfaction with democracy**
   - Recoded to match a four-point scale from 1 (very satisfied) to 4 (not at all satisfied)
8. **Sex**
   - Harmonized to binary format with 0 (female) and 1 (male)
9. **Age**
   - Harmonized to continuous format; where age was recorded in categories, the midpoint of each age bracket is used
10. **Weights**
    - Used weights in the following preference order, depending on availability: Post-stratification weights > sampling weights > unit weights (i.e., a weight of one for each respondent)
    - Rescaled to unit-mean, sum-to-N weights

A1.2 Imputation

Imputation addresses the problem of item non-response in survey data, i.e., missing values that result from respondents' refusal to disclose or failure to recall their vote choices. Discarding individual observations with missing information is problematic because the representativeness of an (appropriately weighted) survey sample hinges on the completeness of the data. We therefore impute missing data points on the vote recall variables by leveraging all auxiliary concepts available in a given election study. In doing so, we invoke the missing at random (MAR) assumption, which stipulates that missingness is as-if-random conditional on the observed auxiliary variables (e.g., Lall 2016). We implement the imputation procedure within each electoral context using hot deck imputation (Cranmer and Gill 2013), an algorithm specifically designed for the imputation of categorical variables. This algorithm is applied to all categorical variables (vote choice, past vote choice, party identification, sex, and satisfaction with democracy). Continuous auxiliary variables (left-right self-placement, left-right party placements, party like/dislike scores, and age) are subsequently imputed using Multivariate Imputation by Chained Equations (MICE) (Van Buuren and Groothuis-Oudshoorn 2011).

A1.3 Mapping

Mapping is by far the most important – and the most work-intensive – step of our data processing effort. It involves linking vote switching data from the election surveys to external context data. This not only requires that each of the election studies is mapped to the current and past elections to which the vote recall variables pertain. It also requires that we precisely map the numerical values of the vote choice variable in each electoral context to external identifiers of the parties in question. Therefore, we mapped respondents' vote choices in both the current and the previous election to party IDs from *ParlGov* (Döring and Manow 2018) and the *Manifesto Project* (Volkens et al. 2021) for a total of 1685 party-by-election observations, based on 420 parties contesting in 254 elections (so-called party-elections), which we also mapped to *ParlGov* election IDs and election dates from the *Manifesto Project*. Based on these IDs, we can link each voter transition matrix and its constitutive parties to external information on parties and elections. The contextual information included for each party-election, along with a codebook, is available as part of the `voteswitchR` package. It is this part of our data collection effort that enables first-time tests of various theories of dynamic voter reactions to party behavior and electoral context characteristics in comparative perspective.

Fig. A1.1 illustrates the spatio-temporal coverage of the resulting data infrastructure. For each of the 35 polities, it shows a time series from 1965 until today. Circles denote electoral contexts for which we were able to retrieve post-election survey data. The numbers inside the circles indicate the number of parties per election for which we successfully mapped reported votes to contextual information. On average, the parties for which we successfully mapped respondents' vote choices to party-level information account for 94.4% of the valid votes cast.

A1.4 Raking

Raking describes a curating procedure to enhance data quality. Even in socio-structurally representative election surveys, proportions of reported vote choice may differ notably from true election results (e.g., Selb and Munzert 2013). The reasons include unit non-response (i.e., refusal to participate in the survey), item non-response (i.e., refusal to disclose one's vote choice), and recall bias (i.e., inability to correctly remember one's vote choice) – all of which may be systematically related to individual turnout or voting decisions. Recall bias has been shown to be particularly pronounced when individuals are prompted to recall their vote choice from several years ago in the previous election at $t-1$, which may result in the underestimation of vote switching (Dassonneville and Hooghe 2017).

To alleviate these well-known problems, we rake each voter transition matrix. Raking is an iterative reweighting algorithm commonly used in survey research. It "adjusts a set of data so that its marginal totals match control totals on a specified set of variables" (Battaglia, Hoaglin, and Frankel 2009, 2), all while retaining information on the differential influence of individual observations due to idiosyncratic sampling or post-stratification weights. We exploit the fact that after mapping vote choices to contextual party and election information, we have complete knowledge of parties' true vote shares and true turnout rates at both t and $t-1$. This allows us to rake each voter transition matrix – i.e., the joint distribution of reported vote choice at t and $t-1$ – so that its marginals reflect the true marginals given by official vote shares and turnout rates.

Fig. A1.2 shows the benefits of this procedure. The upper panel shows the discrepancies between true vote shares at t, $t-1$, and changes from $t-1$ to t (x-axis) and the (weighted and imputed but unraked) proportions from the survey data (y-axis), disaggregated by party family. The scatter plots show notable variation indicative of both overestimation (above the 45° line) and underestimation (below the 45° line) of the true marginals. The average relationships, shown by the linear predictions, indicate that the underestimation of voter proportions is particularly pronounced for non-voting and, to a lesser extent, for voting for radical right parties and residual other parties. Vote switching, on the other hand, is underestimated for all groups but radical left parties. As we can see in the lower panel, raking completely eliminates these discrepancies in both reported vote choice and reported vote switching. This not only boosts the validity of survey-based estimates of vote switching patterns but also ensures that the macro-level implications of vote switching analyses are representative of the electorates we aim to study.

A1.5 Aggregation

Aggregation, lastly, describes a two-step procedure for making the data operable for comparative research. The first step involves the extraction of the (raked) cell counts from the "raw" voter transition matrix of each context. "Raw", here, means a transition matrix that tabulates switching counts for any given pair of parties without classifying parties according to a meaningful scheme for comparative inquiry. However, counts for such "nominal" switches are hardly useful for comparative research. For comparative inquiries, we must collapse these monadic or dyadic counts into broader categories that reduce the tremendous heterogeneity of multi-party systems. Therefore, in a second step, we once again rely on our mappings and use external data to classify parties by substantively meaningful and comparable characteristics. Depending on one's research interest, these can be ideological groupings such as party family, government status in the preceding legislative cycle, or the gender composition of the party leadership. As a result, we can express switches from Labour to LibDems in the UK 2010 case in more general terms as switches from social democratic to liberal parties, from governing parties to opposition parties, or from one male-led party to another. With C distinct categories in the marginals, this then yields a generalized $C \times C$ transition matrix for each electoral context. Details and illustrations of the implementation of the aggregation procedure are presented in the documentation of the `voteswitchR` package.

Figure A1.1: Sample coverage. Circles denote electoral contexts for which post-election survey data has been collected and mapped to party and election information. The numbers inside the circles indicate the number of parties included per election.

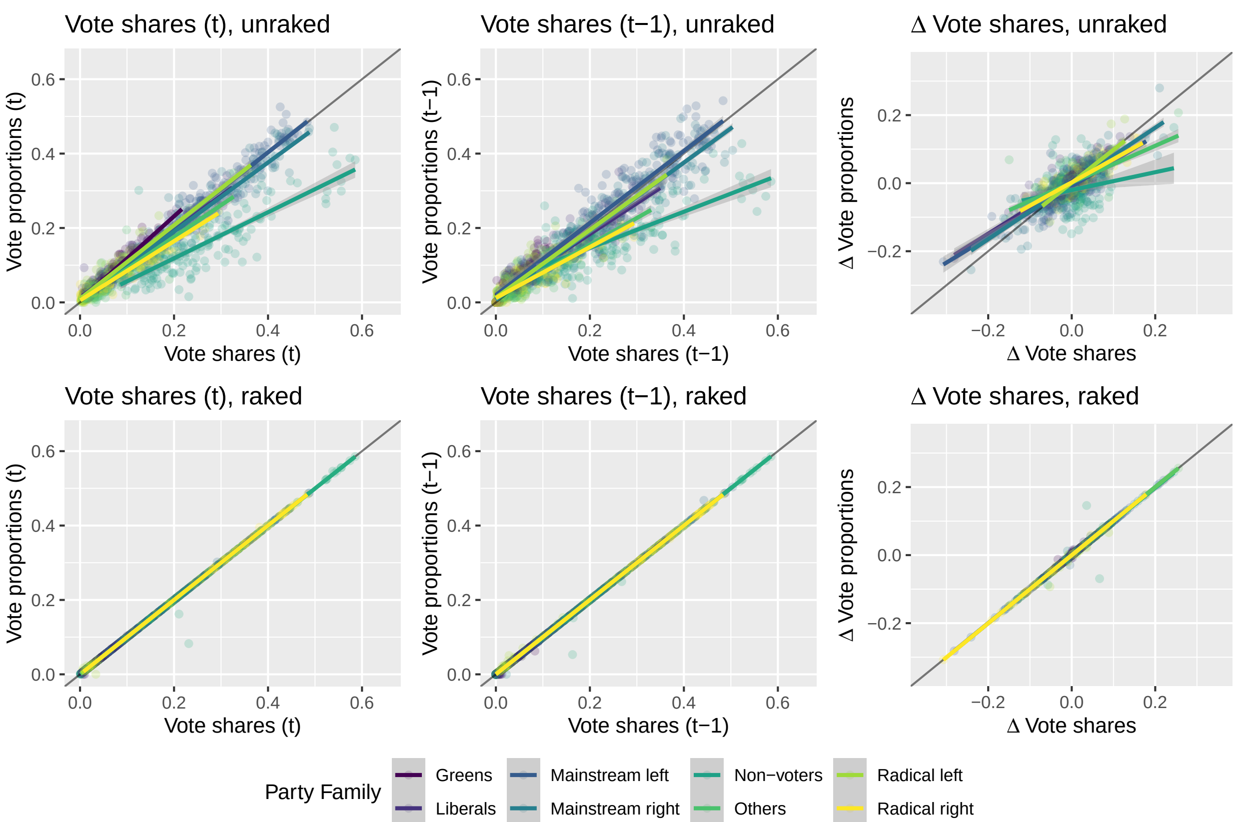

Figure A1.2: Validation of vote choice and vote switching data, before and after raking

A2 Extensions

A2.1 Party-level analyses

Studying party electorates involves focusing on the retention, gains, and losses of a focal party and re-expressing the absolute cell percentages relative to its (current or past) size. Whereas the study of national electorates lends itself to the study of the micro-foundations of structural changes in party systems, the study of party electorates is preferable when researchers want to understand when and why specific parties grow and shrink as a result of their own strategies or agency.

Relative vs. absolute quantities of interest

Existing analyses of vote switching that focus on the fate of specific political parties focus on parties' (net) gains or losses in *absolute* terms. This neglects the considerable variation in party size that exists even *within* party families. This may be misleading when inquiries focus on how parties' behavior affects their own electoral fortunes: An absolute net loss of one percentage point to the radical right reflects a much smaller *relative* loss for a center-right party that holds nearly 50% of the vote (e.g., the German CDU/CSU in 1983) than for a center-right party that holds 10% of the vote (such as the Dutch CDA in 2021). We therefore propose using quantities based on *relative* proportions, normalized by party size, when inquiries focus on the effects of party behavior or party strategies on changes in parties' own electoral fortunes. Nominal absolute proportions, in contrast, should be used when inquiries focus on changes in the composition of party systems.

Normalizing the quantities of interest by party size S_i, however, begs the question of when party size is best captured. In political punditry, losses are typically discussed relative to parties' past electorate at $t-1$ ("10% of its past voters left party A"), whereas gains are frequently reported relative to parties' current support base at t ("5% of its current voters came from party B"). The best frame of reference certainly depends on the specific focus of a substantive inquiry. Next to the size of parties' electorates at $t-1$ or t, we propose using parties' average inter-election electorate, $S_i = 0.5\left(\sum_j p_{i,j} + \sum_j p_{j,i}\right)$ to normalize these absolute quantities.

Analyzing party electorates: Stacked party-specific vote switching

Researchers may wish to focus on *party electorates* as opposed to national electorates. Studying party electorates involves focusing on the retention, gains, and losses of a focal party and re-expressing the absolute cell percentages relative to its (current or past) size. Table A2.1 gives an example by showing all cells pertaining to Labour relative to its 2005 party electorate.

We learn, among other, that Labour lost an estimated 11% of its past electorate to the LibDems, whereas its gains from the LibDems only amount to 6.8%, which yields a *relative trade balance* of -4.2. Next to relative dyadic gains and losses, we learn about Labour's *relative retention rate* (58.2%) and about the overall relative net change in its electorate (down 12.6 percentage points to 87.4%).

Whereas the study of national electorates lends itself to the study of the micro-foundations in structural change in party systems, the study of party electorates is preferable when researchers want to understand when and why specific parties grow and shrink as a result of their own strategies, agency, or performance. Effectively, this involves extracting relative party-specific transition matrices for various focal parties, using a separate modification

	LAB '10	LIB '10	CON '10	OTH '10	NON '10	2005
LAB '05	58.2	11.0	10.0	2.8	18.0	**100.0**
LIB '05	6.8					
CON '05	3.5					
OTH '05	2.6					
NON '05	16.2					
2010	**87.4**					

Table A2.1: A party-specific voter transition matrix: Labour's retention, gains, and losses relative to its 2005 electorate.

of the absolute election-specific transition matrix for each, and connecting this to party-specific explanatory variables. One can use this approach to study, for instance, how parties' government status affects voter transfers with coalition partners, opposition parties, or non-voters.

Analyzing vote switching at the level of party electorates based on relative quantities of interest involves three steps:

Stacking. Stacking means replicating the election-level voter transition matrix for each party to be included. In our running example of the 2010 UK General Election with three focal parties and additional categories for residual other parties and non-voters, this involves generating a copy of the "raw" voter transition matrix for each Labour, the Conservatives, and the Liberal Democrats.

Party-specific aggregation. As we previously explained, the aggregation step of our HIMRA-routine involves applying a meaningful generalized scheme for comparative inquiries to the raw, context-specific voter transition matrix. For instance, one could classify the unique categories of the context-specific raw voter transition matrices according to government status, using a trichotomous classification that distinguishes incumbent government parties from opposition parties and non-voters to obtain a generalized 3×3 transition matrix. In the case of the UK 2010 General Election, we would thus classify Labour as *government*, the Conservatives, LibDems, and others as *opposition*, and non-voters as *non-voters*. For an *election-specific* aggregation, this would then simply yield nine cells recording all available switching patterns: Government to government/opposition/non-voters, opposition to government/opposition/non-voters, and non-voters to government/opposition/non-voters. As a result of applying this generalized scheme, we typically lose information on the specific parties underlying the generalized transition matrix. In this specific example, three parties constitute the *opposition* category. In other examples with coalition governments, multiple parties would consitute the *government* category. As a result, explanations for explaining switches across the three categories must be based at the level of *electoral contexts* (e.g., GDP growth), not at the level of individual parties.

Party-specific aggregation overcomes this limitation by applying the generalized scheme to party-specific copies of the original 5×5 transition matrix such that information on the focal party is preserved. With a generalized scheme with categories $c = 1, .., C$, one ends up with

$2 + 2C$ cells for each focal party p: retention, $p \to p$, generalized losses $p \to c$ for $c = 1, .., C$, generalized gains $c \to p$ for $c = 1, .., C$, and residual other switches that do not involve p. When applying the trichotomous scheme for government status to the three focal parties in the UK 2010 General Election, this would imply classifying the 25 cells into $2 + 2 \times 3$ categories as follows:

1. **Labour**
    1. *Retention*: Voters staying with Labour
    2. *Losses to government*: Deterministically zero as Labour led a single-party government; not zero in other contexts with coalition governments
    3. *Gains from government*: Deterministically zero as Labour led a single-party government; not zero in other contexts with coalition governments
    4. *Losses to opposition*: Aggregation of Labour's dyadic losses to Conservatives, LibDems, and others
    5. *Gains from opposition*: Aggregation of Labour's dyadic gains from Conservatives, LibDems, and others
    6. *Losses to non-voters*: Labour's dyadic losses to non-voters
    7. *Gains from non-voters*: Labour's dyadic gains from non-voters
    8. *Residual switches*: Aggregation of all remaining cells (e.g., Conservatives' retention, LibDem's losses to non-voters, etc)
2. **Conservatives**
    1. *Retention*: Voters staying with Conservatives
    2. *Losses to government*: Conservatives' losses to Labour
    3. *Gains from government*: Conservatives' gains from Labour
    4. *Losses to opposition*: Aggregation of Conservatives' dyadic losses to LibDems and others
    5. *Gains from opposition*: Aggregation of Conservatives' dyadic gains from LibDems and others
    6. *Losses to non-voters*: Conservatives' dyadic losses to non-voters
    7. *Gains from non-voters*: Conservatives' dyadic gains from non-voters
    8. *Residual switches*: Aggregation of all remaining cells (e.g., Labour's retention, LibDem's losses to non-voters, etc)
3. **Liberal Democrats**
    1. *Retention*: Voters staying with LibDems
    2. *Losses to government*: LibDems' losses to Labour
    3. *Gains from government*: LibDems' gains from Labour
    4. *Losses to opposition*: Aggregation of LibDems' dyadic losses to Conservatives and others
    5. *Gains from opposition*: Aggregation of LibDems' dyadic gains from Cosnervatives and others
    6. *Losses to non-voters*: LibDems' dyadic losses to non-voters
    7. *Gains from non-voters*: LibDems' dyadic gains from non-voters

8. *Residual switches*: Aggregation of all remaining cells (e.g., Conservatives' retention, Labour's losses to non-voters, etc)

Analysis. Applying the party-specific generalized aggregation scheme outlined above leaves us with eight-cell transition matrices for $\sum_{j=1}^{J} N_j^{\text{parties}}$ parties nested within electoral contexts ("party-elections"). These now constitute the primary units of analysis for the study of party-electorates. The fact that each party-election is now representative of a single identifiable party allows us now to study each party's records of voter retention, attraction, and defection as a function of its own strategies or behavior. For instance, we could focus on the subset of governing parties and study the degree to which their party-specific pledge fulfillment (i.e., the proportion of policies advocated for in their manifesto at $t-1$ that they actually enacted in government between $t-1$ and t) affects vote switching to other government parties (where available), oppositional parties, and the non-voter camp.

The initial predictions from such a model still reflect absolute quantities of interest. This is because the $2+2C$ cell proportions contain exhaustive information on the entire electorate at t. However, these quantities can easily be normalized post-estimation by the predicted size of a party-election. For instance, the predicted relative retention rate, normalized by parties' predicted electorate size at $t-1$, can be derived as $\frac{\Pr(y_j = \text{retention} | \mathbf{x}_j)}{\Pr(y_j \in \{\text{retention, losses to government, losses to opposition, losses to non-voters}\})}$.

A2.2 Subgroup-specific analyses

Subgroup-specific voter transition matrices

The logic of both analyses of national electorates and party electorates can be extended to accommodate subgroup-specific analyses. Here, subgroups can be defined by any available characteristics that are measured consistently in the post-election surveys from which we retrieve the (raked) vote switching counts. Examples include binary gender, age groups, cohorts, party identifiers vs. non-identifiers, or broad ideological categories based on respondents' left-right placement (e.g., leftists, centrists, and rightists). To see how this logic applies to our running example, Table A2.2 reproduces Table 1 with gender-specific cell percentages. In each cell, the first value indicates the subgroup-specific cell percentage for the female electorate, whereas the second value indicates the corresponding percentage for the male electorate.

Subgroup-specific voter transition matrices can be processed in the same way as regular voter transition matrices for the study of both national and party electorates: One simply applies a generalized scheme to classify parties as belonging to comparatively meaningful categories and obtains the (raked) vote switching counts for each cell within each subgroup.

Analyzing subgroup electorates

Research on vote switching can focus on heterogeneous effects of party strategies or electoral context characteristics on vote switching across different *electorate subgroups*. Voter transition matrices have to be estimated from election surveys, which typically contain rich information on voter characteristics. Therefore, one can retrieve separate voter transition matrix for different subgroups, defined in socio-structural or attitudinal terms, and analyze the effect of a stipulated cause on patterns of voter retention, attraction, and defection within each. This can be applied to the study of national electorates and party electorates alike. Researchers can use this extension to study, for instance, gender-specific voter reactions to

	LAB '10	LIB '10	CON '10	OTH '10	NON '10	2005
LAB '05	13.1; 13.7	2.2; 2.5	2.0; 1.9	0.8; 0.7	3.1; 3.9	**21.3; 22.7**
LIB '05	1.5; 1.1	10.1; 7.9	1.6; 2.0	0.0; 0.9	0.6; 1.2	**13.9; 13.2**
CON '05	0.8; 0.9	0.9; 1.2	16.4; 14.2	1.3; 0.4	2.0; 2.3	**21.3; 19.1**
OTH '05	0.0; 0.2	0.1; 1.1	0.7; 0.3	2.7; 5.6	1.1; 0.4	**4.7; 7.6**
NON '05	3.2; 3.9	2.4; 2.1	3.9; 4.2	1.6; 1.3	27.9; 25.8	**38.9; 37.3**
2010	**18.6; 19.8**	**15.8; 14.9**	**24.5; 22.7**	**6.4; 8.9**	**34.7; 33.6**	**100.0; 100.0**

Table A2.2: A gender-specific voter transition matrix: Gender-specific cell percentages for the 2010 UK General Election. Cell percentages for female and male sub-electorates separeted by semicolons. Cell percentages for each sugroup normalized such that they sum to 100.

the increasing feminization of party leadership or to study generational differences in vote switching to challenger parties.

The are two primary approaches for analyzing subgroup-specific vote switching: Wide and long. The wide variant involves modeling subgroup-specific voter transitions across national and/or party electorates using *voter transition arrays* that combine subgroup-specific voter transition matrices and enforce a sum-to-one constraint for the entire array. The wide variant is much more flexible than the long variant, albeit at the cost of greater computational intensity. In the wide variant, the cells of G subgroup-specific voter transition matrices are considered to belong to a voter transition array of dimensions $C \times C \times G$. As a result, we obtain J election-specific transition arrays that combine the cells of subgroup-specific transition matrices. Once subgroup-specific matrices are combined in a common array, the sum-to-one constraint is enforced for the switching proportions at the level of the array. Consequently, the estimated vote switching proportions sum to one *across* subgroups and sum to the subgroup size *within* subgroups. For example, if we were to analyze gender-specific vote switching and the female-to-male respondent ratio in our data was 55-to-45, then the C^2 estimated vote switching proportions for the female electorate would sum to 0.55 and the C^2 estimated vote switching proportions for the male electorate would sum to 0.45. As each subgroup-election-specific cell of the transition array gets its own equation in the MAVCL model, all estimated effects can freely vary across subgroups. Thus, the wide variant is highly flexible. This flexibility, however, comes at the cost that the number of the parameters α and β increases by the number of subgroups G.

The long variant, in contrast, involves stacking subgroup-specific voter transitions and treating them as (de facto) independent observations. For instance, an analysis of J national electorates across G subgroups would yield $J \times G$ unique voter transition matrices of dimensions $C \times C$. In the context of gender-specific vote switching, for example, the electoral context UK 2010 would yield two observations: UK 2010 (women) and UK 2010 (men). By default, the MAVCL model would treat both of these as independent "level 2" (i.e., subgroup-election-level) observations. The interdependence of both observations from the same electoral context could then be accounted for by using "level 3" (i.e., election-level) random intercepts. As each subgroup-election is treated as a separate observation, its estimated cell-specific vote switching proportions sum to one. As a result, all quantities of interest are by default normalized by subgroup size. Therefore, one cannot meaningfully compare the absolute magnitude of quantities of interest across subgroups. An additional limitation is that all estimated effects are, by default, invariant across subgroups. That means, for example, that the effect of a predictor of interest does not vary across subgroups by default. Thus, effect heterogeneity across subgroups must be modeled explicitly via interaction effects.

A3 Statistical model: Details

The MAVCL model is, in essence, a hierarchical (multi-level) multinomial logistic model with upper-level covariates only. As the model only allows for upper-level covariates $\mathbf{x}_j$ (e.g., at the level of elections) and not for micro-level covariates (at the voter-level where individual vote switches are being observed), it is designed to estimate election-level *vote switching proportions* per average micro-level *vote switching probabilities* $\Pr(y_j = c|\mathbf{x}_j)$. To reflect this intuition, the log-likelihood of the model is specified directly at the upper level, where the raked-weighted counts w_{jc} for cell c in electoral context j reflect the weighted sample count of a specific switching pattern. The w_{jc}'s serve as frequency weights that multiply the corresponding log probabilities $\log \Pr(y_j = c|\mathbf{x}_j)$.

For modeling a $C \times C$ voter transition matrix with C marginal categories, the model comprises an equation for each of the C^2 cells. A distinct feature of our implementation of this model is that it allows for varying choice sets S_j (cf. Yamamoto 2014). Effectively, we implement this feature by deterministically setting the linear predictor $\mu_{jc} = -\infty$ when category c is non-existent in electoral context j, which ensures $\Pr(y_j = c|\mathbf{x}_j) = 0$.

By default, our model includes election-and-cell-specific random intercepts, which are mutually correlated across the C^2 cell-specific equations. It can be easily extended to include election-and-cell-specific random slopes by setting `random_slopes = TRUE` in `voteswitchR`'s estimation function. These election-cell-specific parameters capture heterogeneity in the mechanisms we model across elections j, and thereby across party systems with different choice sets S_j, which relaxes the independence of irrelevant alternatives (IIA) assumption.

We note that incomplete choice sets, e.g., elections with party systems in which specific party families do not yet exist, may be endogenously determined by some selection mechanism. In the case of our empirical application that spans elections from the 1970s until today, for instance, the breakthrough of new challenger party families may itself be an outcome of mainstream party behavior. While our model does not allow researchers to explicitly model these potential selection mechanisms, researchers can plausibilize the assumption of conditionally exogeneity of the choice sets by including covariates in the model that they expect to determine pattern of party system incompleteness.

Following standard practice in multinomial and mixed logit regression, we set the coefficients for a "baseline" outcome category to zero to ensure that the model parameters are statistically identified. Note that this baseline category must not be a deterministically empty cell in any of the J voter transition matrices. A choice which always satisfies this criterion is the non-voter retention cell.

Linear component

$$\mu_{jc} = \begin{cases} \alpha_c + \mathbf{x}_j' \beta_c + \nu_{jc} & \text{if } c \in S_j \\ -\infty & \text{otherwise} \end{cases}$$

Link function

$$\Pr(y_j = c|\mathbf{x}_j) = \begin{cases} \frac{\exp(\mu_{jc})}{\sum_{c \in S_j} \exp(\mu_{jc})} & \text{if } c \in S_j \\ 0 & \text{otherwise} \end{cases}$$

Likelihood

$$\log L = \sum_{j=1}^{J} \sum_{c \in S_j} w_{jc} \log \Pr(y_j = c|\mathbf{x}_j)$$

Priors
The random intercepts ν_{jc} are allowed to correlate across the outcome-specific equations $c = 1, ..., C^2$. Specifically, they are drawn from a joint multivariate normal distribution with means of zero and variance-covariance matrix Σ: $\nu \sim \text{MVN}(\mathbf{0}, \mathbf{\Sigma})$.

The priors for Σ are provided in the form of an $LKJ(2)$-prior on the Cholesky factor of the correlation matrix, whose diagonal is pre-multiplied by a vector of C^2 standard deviation parameters σ_c, which have been assigned half-t priors with $df = 3$ and a standard deviation of 2.5. The coefficients α_c and β_c are assigned weakly informative zero-mean normal priors with a standard deviation of 2.5.

Estimation and diagnosis
In our empirical application, we estimate the model in Stan (Stan Development Team 2019) using full Bayesian inference through Hamiltonian Monte Carlo (HMC) sampling. Specifically, we run sets of $S = 2$ HMC samplers across $M = 5$ raked imputations of the vote switching counts. Each of these ten samplers takes 3000 samples, of which we discard the first 2000 as warm-up draws. We thin the remaining 1000 samples by a factor of two to preserve memory.

This yields 1000 posterior samples for each of the $M = 5$ imputations. We assess convergence within each pair of chains by confirming that the Gelman-Rubin diagnostic ($\hat{R}$-value) remains below 1.05 for all parameters. We then pool the posterior draws across all imputations to obtain a total of 5000 posterior draws.

A4 Empirical application: Summary statistics

Table A4.3: Summary statistics. Vote switching patterns reported as sample percentages. Missingness of a switching pattern indicates deterministic zeroes due to the non-existence of parties in a subset of the electoral contexts.

	Unique (#)	Missing (%)	Mean	SD	Min	Median	Max
Green -> Green	102	35	2.4	2.2	0.0	1.9	8.9
Green -> Mainstream Right	102	35	0.8	0.7	0.0	0.7	6.3
Green -> Non-voters	102	35	0.8	0.5	0.0	0.8	2.6
Green -> Other parties	94	36	0.3	0.7	0.0	0.2	6.6
Green -> Radical Right	79	44	0.2	0.2	0.0	0.1	1.1
Green -> Mainstream Left	101	35	0.8	0.8	0.0	0.5	3.6
Mainstream Right -> Green	103	35	0.9	0.8	0.0	0.7	4.2
Mainstream Right -> Mainstream Right	156	0	24.5	8.1	6.1	24.8	43.5
Mainstream Right -> Non-voters	156	0	4.4	2.3	1.2	3.9	18.1
Mainstream Right -> Other parties	155	1	1.2	1.2	0.0	0.8	7.2
Mainstream Right -> Radical Right	108	31	1.7	1.6	0.1	1.4	8.9
Mainstream Right -> Mainstream Left	156	0	2.2	1.4	0.2	1.9	7.4
Non-voters -> Green	103	35	1.0	0.6	0.1	0.9	3.6
Non-voters -> Mainstream Right	156	0	4.0	2.2	0.7	3.7	21.8
Non-voters -> Non-voters	156	0	13.7	9.8	1.9	11.2	47.1
Non-voters -> Other parties	153	1	1.1	1.0	0.0	0.7	5.6
Non-voters -> Radical Right	105	31	1.2	1.1	0.0	1.0	5.9
Non-voters -> Mainstream Left	156	0	2.7	1.5	0.0	2.5	10.9
Other parties -> Green	95	35	0.4	0.6	0.0	0.2	3.4
Other parties -> Mainstream Right	155	0	1.3	1.7	0.0	0.7	10.7
Other parties -> Non-voters	151	0	1.3	1.3	0.0	0.9	6.1

Other parties -> Other parties	154	1	2.5	3.5	0.0	1.3	18.5
Other parties -> Radical Right	96	31	0.4	0.6	0.0	0.2	3.5
Other parties -> Mainstream Left	154	0	0.8	0.9	0.0	0.4	4.3
Radical Right -> Green	73	49	0.2	0.2	0.0	0.1	1.2
Radical Right -> Mainstream Right	98	38	1.2	1.1	0.0	0.9	4.7
Radical Right -> Non-voters	96	38	1.2	1.1	0.0	0.8	4.9
Radical Right -> Other parties	83	38	0.2	0.3	0.0	0.1	1.8
Radical Right -> Radical Right	98	38	3.5	3.3	0.0	3.1	11.6
Radical Right -> Mainstream Left	94	38	0.5	0.4	0.0	0.3	2.4
Mainstream Left -> Green	103	35	1.1	0.9	0.0	0.7	4.8
Mainstream Left -> Mainstream Right	156	0	2.5	1.6	0.4	2.2	8.5
Mainstream Left -> Non-voters	156	0	3.0	1.6	0.3	2.6	9.3
Mainstream Left -> Other parties	155	1	0.8	1.0	0.0	0.5	7.3
Mainstream Left -> Radical Right	106	31	0.7	0.7	0.0	0.5	4.4
Mainstream Left -> Mainstream Left	156	0	15.2	7.5	0.6	15.2	34.2
Green -> Radical Left	64	57	0.3	0.3	0.0	0.2	1.6
Radical Left -> Green	64	58	0.3	0.3	0.0	0.2	1.4
Radical Left -> Radical Left	105	33	2.6	2.8	0.0	2.4	21.4
Radical Left -> Mainstream Right	104	33	0.6	0.4	0.0	0.6	1.8
Radical Left -> Non-voters	103	33	1.0	1.0	0.0	0.8	5.9
Radical Left -> Other parties	99	33	0.4	0.5	0.0	0.2	2.6
Radical Left -> Radical Right	66	52	0.2	0.3	0.0	0.2	1.4

Radical Left -> Mainstream Left	106	33	0.7	0.7	0.0	0.6	3.3
Mainstream Right -> Radical Left	107	31	0.7	0.5	0.0	0.5	2.6
Non-voters -> Radical Left	107	31	1.1	1.2	0.0	0.8	9.4
Other parties -> Radical Left	103	31	0.5	0.6	0.0	0.2	4.2
Radical Right -> Radical Left	60	56	0.2	0.3	0.0	0.1	2.1
Mainstream Left -> Radical Left	106	31	1.0	1.1	0.0	0.7	7.5
Year	48	0	1999.8	13.4	1973.0	2002.0	2021.0
Positional distance (main MSP)	148	0	-1.2	0.8	-4.1	-1.0	0.0
Positional std. dev. (all MSP)	150	0	0.7	0.3	0.1	0.6	1.6
Sample size	154	0	2316.8	1446.1	533.0	1930.0	8286.0

Country selection: We include Austria, Belgium (Flanders), Belgium (Wallonia), Denmark, Finland, France, Germany, Greece, Ireland, Iceland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. We treat the Belgian regions of Flanders and Wallonia as separate entities due to the linguistically divided Belgian party system.

A5 Empirical application

A5.1 Secondary and combined electoral effects of mainstream party convergence

Secondary effects

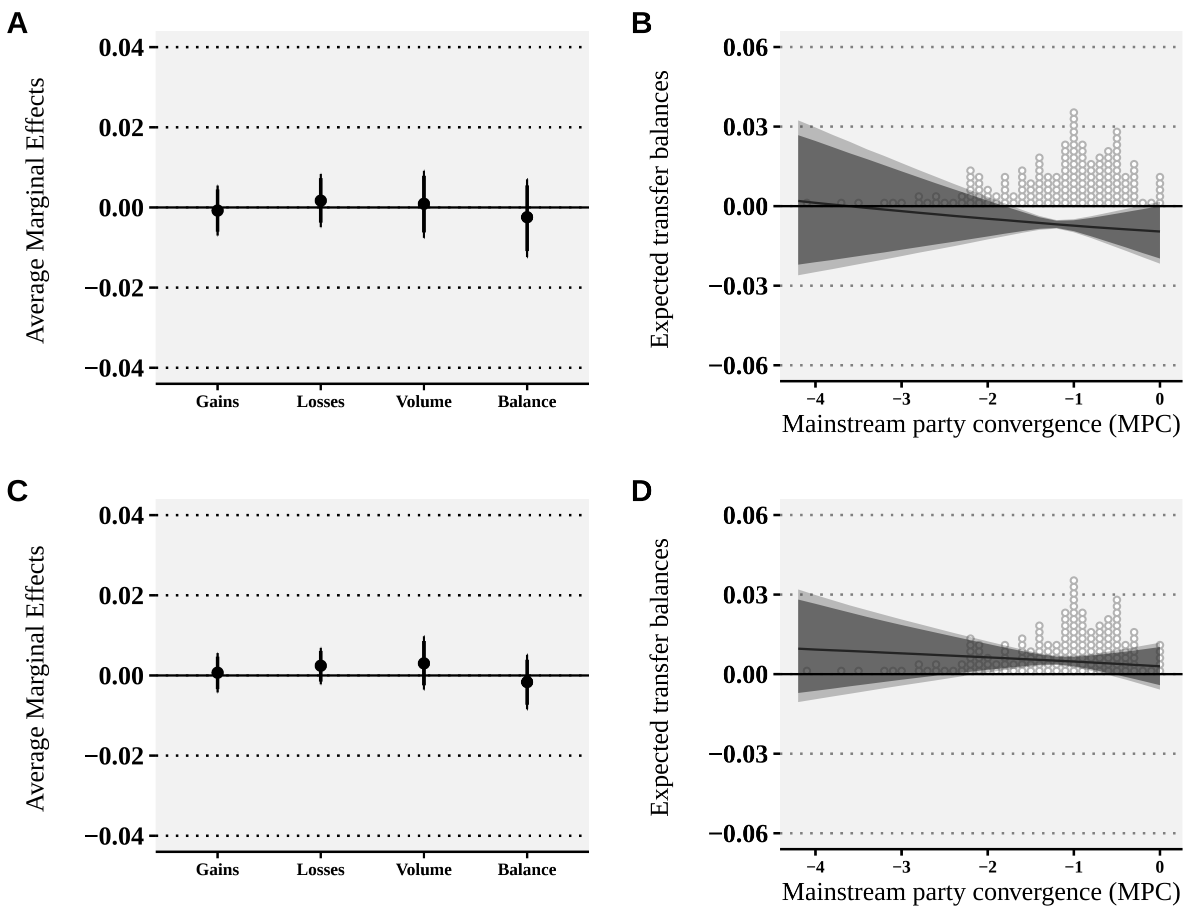

Figure A5.3: A: Average marginal effects of mainstream party convergence (MPC) on mainstream party gains, losses, volumes and balances with other parties and non-voters. B: Expected mainstream party transfer balances with other parties and non-voters as a function of MPC. C: Average marginal effects of mainstream party convergence (MPC) on challenger party gains, losses, volumes and balances with other parties and non-voters. D: Expected challenger party transfer balances with other parties and non-voters as a function of MPC. Posterior medians with 90% and 95% credible intervals.

Overall effects

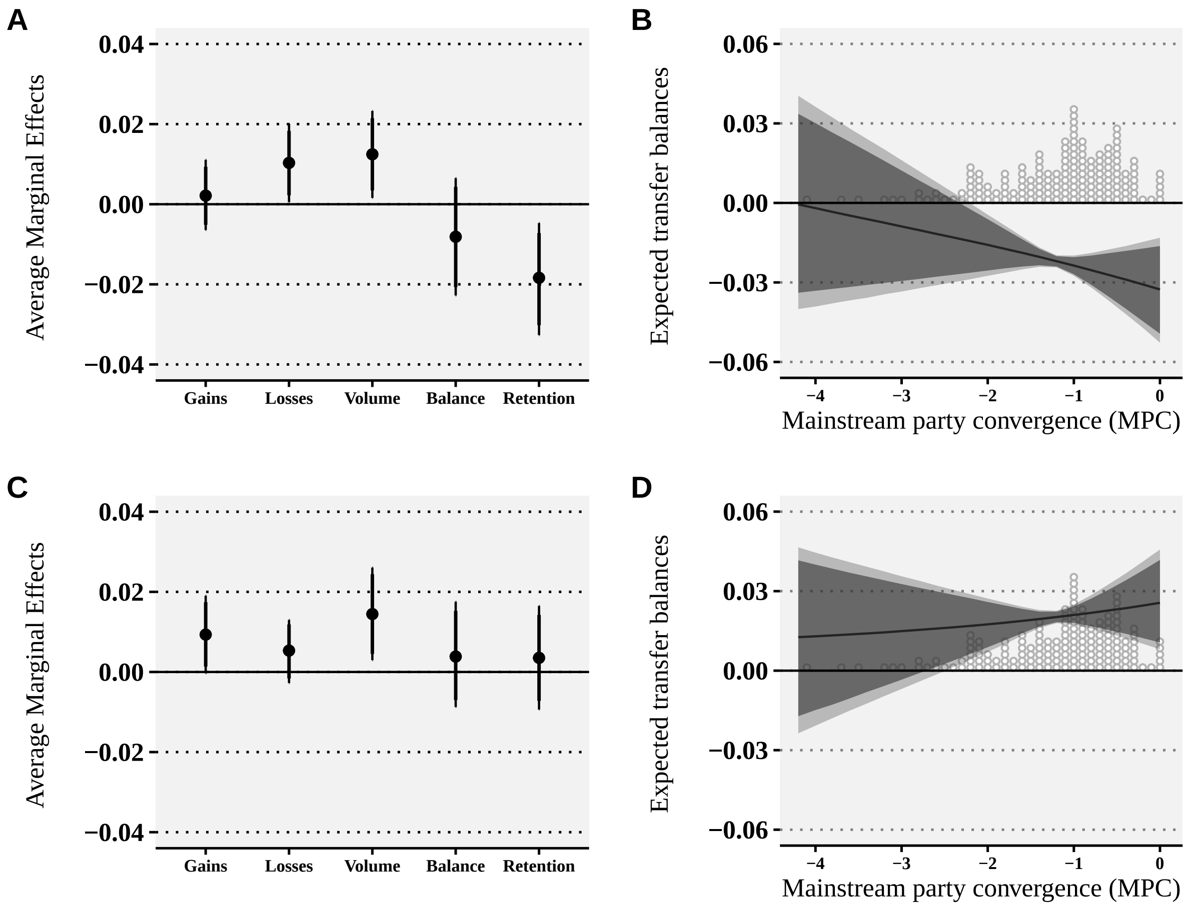

Figure A5.4: A: Average marginal effects of mainstream party convergence (MPC) on mainstream party overall gains, losses, volumes, balances, and retention. B: Expected overall mainstream party transfer balances as a function of MPC. C: Average marginal effects of mainstream party convergence (MPC) on challenger party overall gains, losses, volumes, balances, and retention. D: Expected overall challenger party transfer balances as a function of MPC. Posterior medians with 90% and 95% credible intervals.

A5.2 Full quantities of interest

Focal category: Mainstream left parties

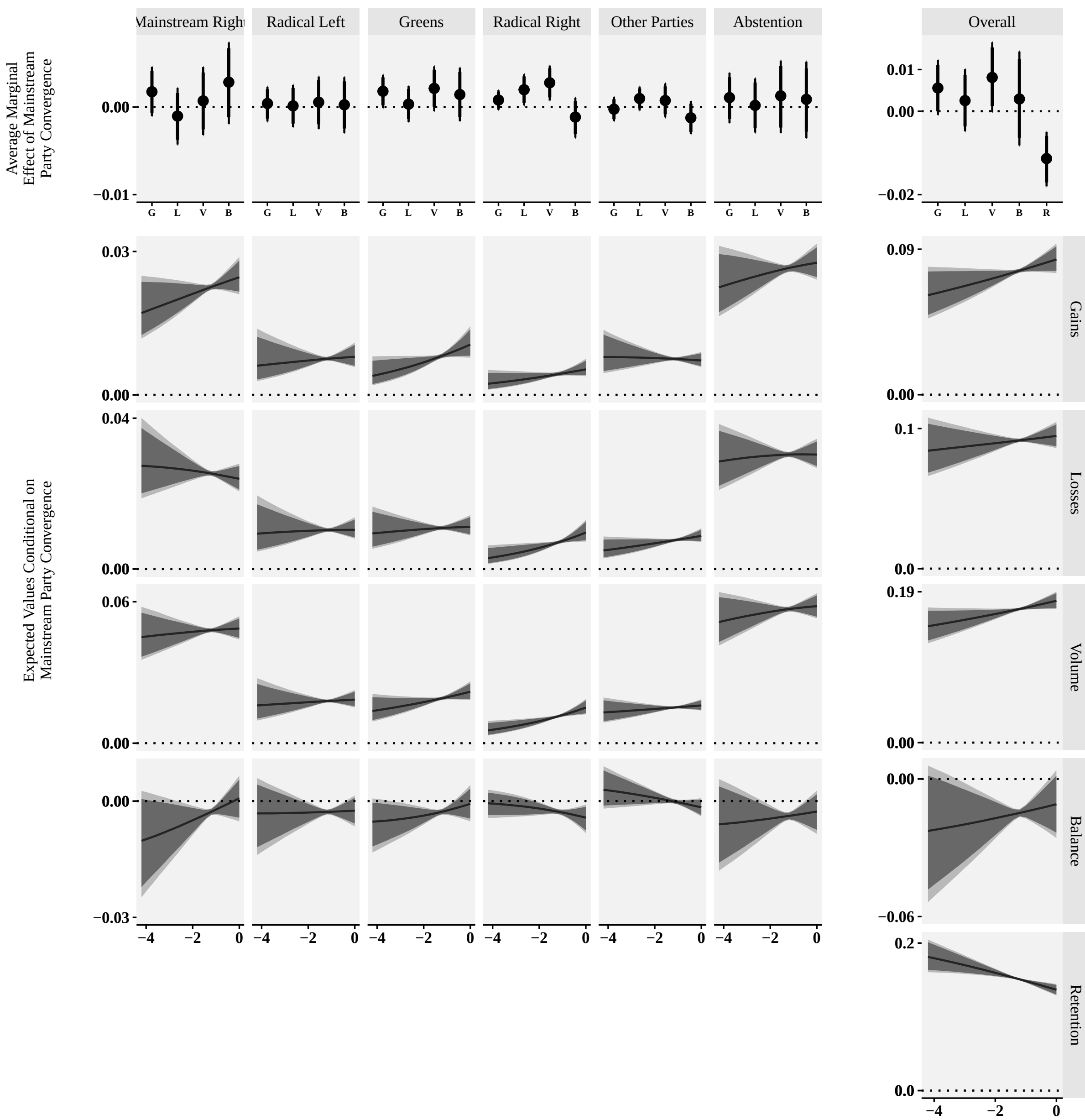

Figure A5.5: Vote switching quantities of interest as a function of positional convergence. Mainstream left parties only. Based on the estimates reported in Online Appendix A5.3.

Focal category: Mainstream right parties

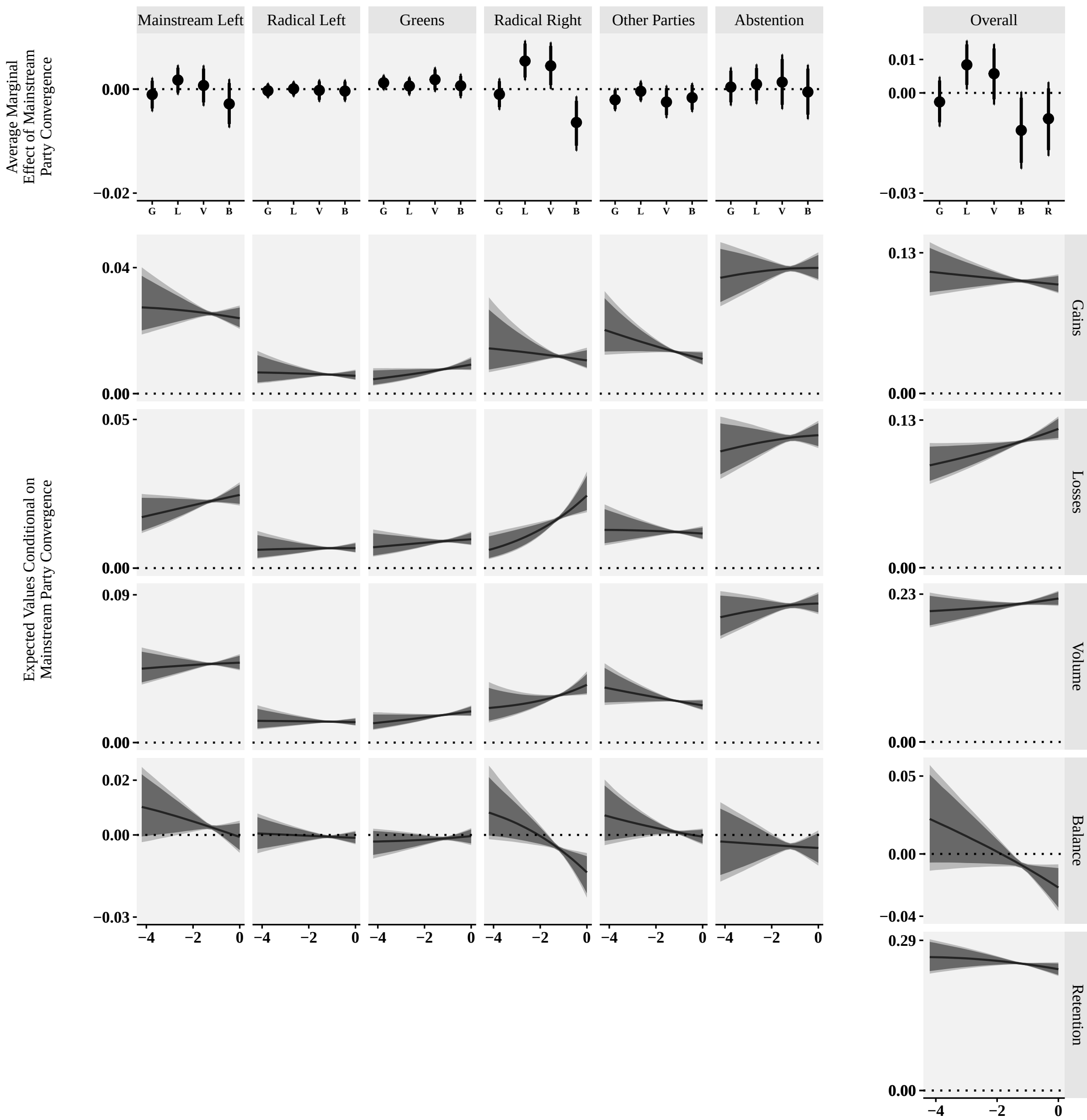

Figure A5.6: Vote switching quantities of interest as a function of positional convergence. Mainstream right parties only. Based on the estimates reported in Online Appendix A5.3.

Focal category: Green parties

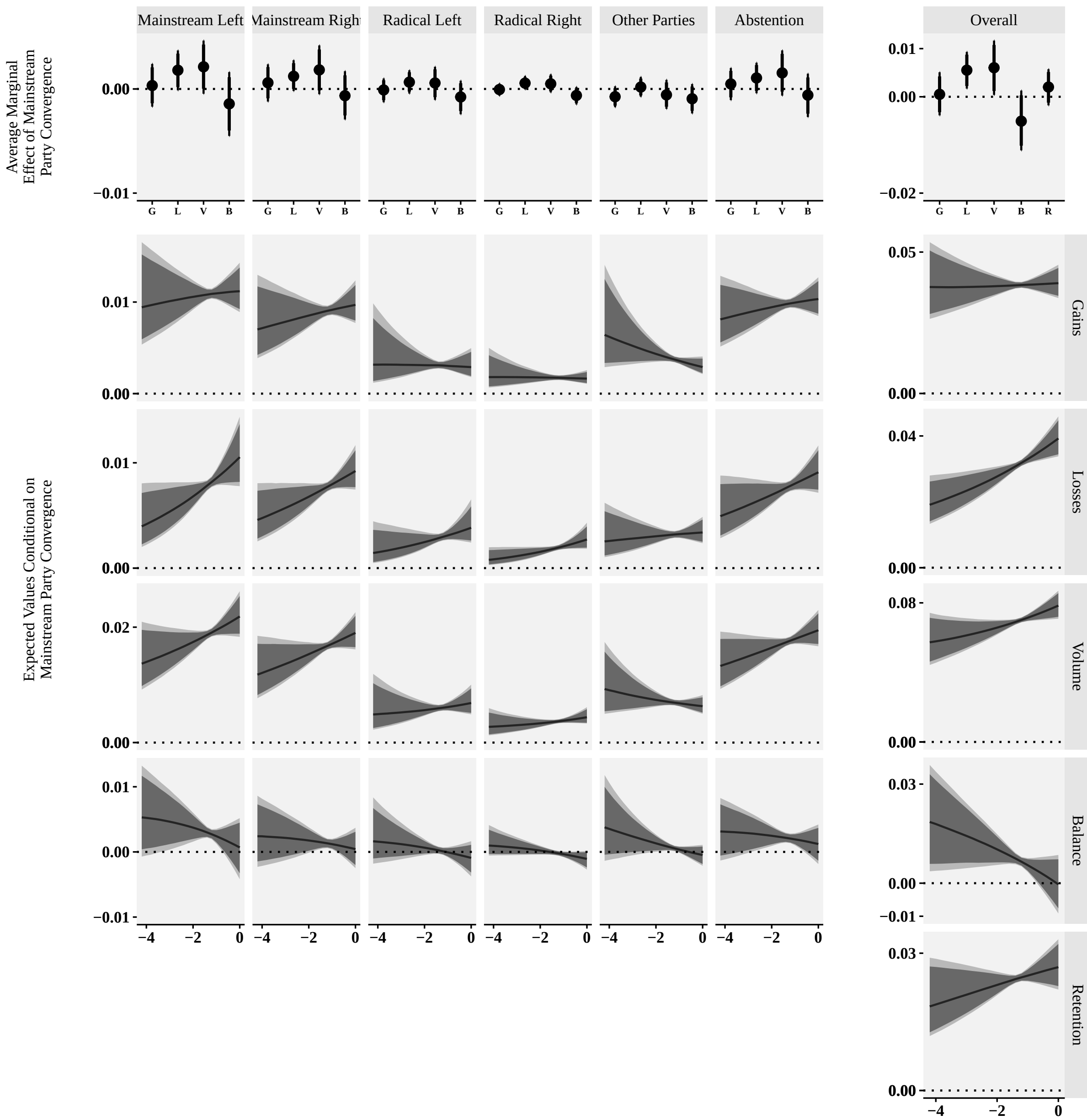

Figure A5.7: Vote switching quantities of interest as a function of positional convergence. Green parties only. Based on the estimates reported in Online Appendix A5.3.

Focal category: Radical left parties

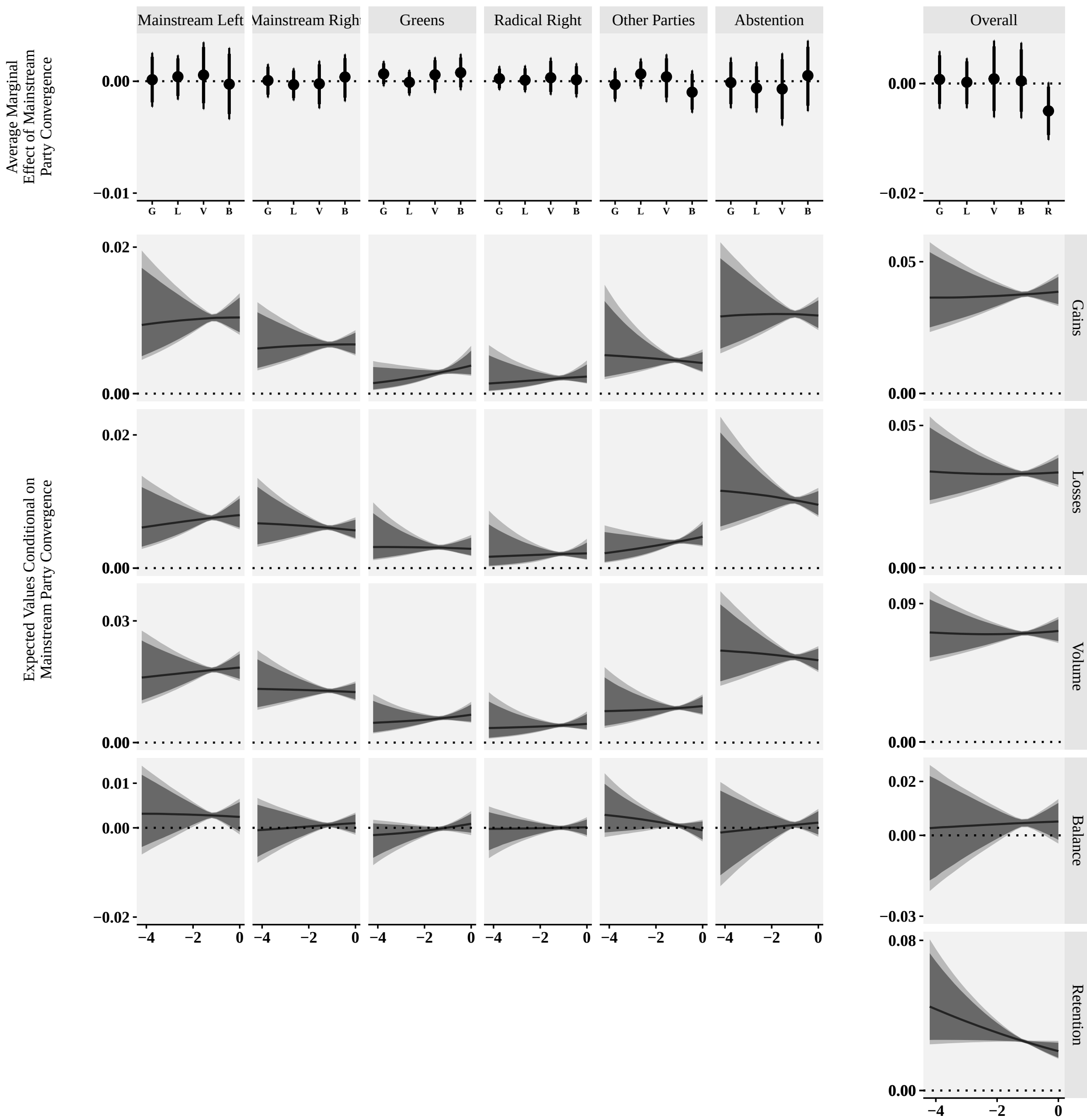

Figure A5.8: Vote switching quantities of interest as a function of positional convergence. Radical left parties only. Based on the estimates reported in Online Appendix A5.3.

Focal category: Radical right parties

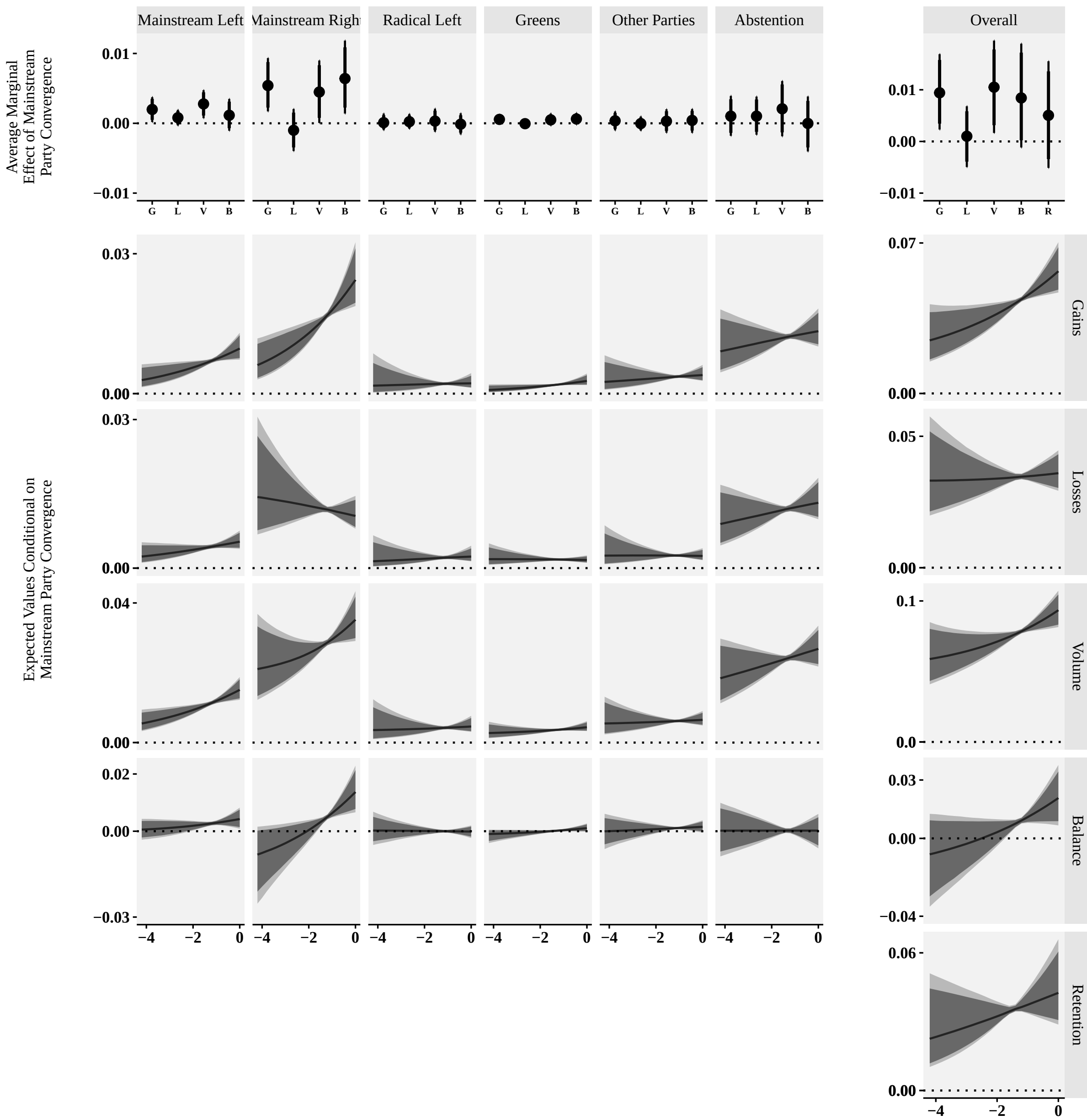

Figure A5.9: Vote switching quantities of interest as a function of positional convergence. Radical right parties only. Based on the estimates reported in Online Appendix A5.3.

Focal category: Non-voting

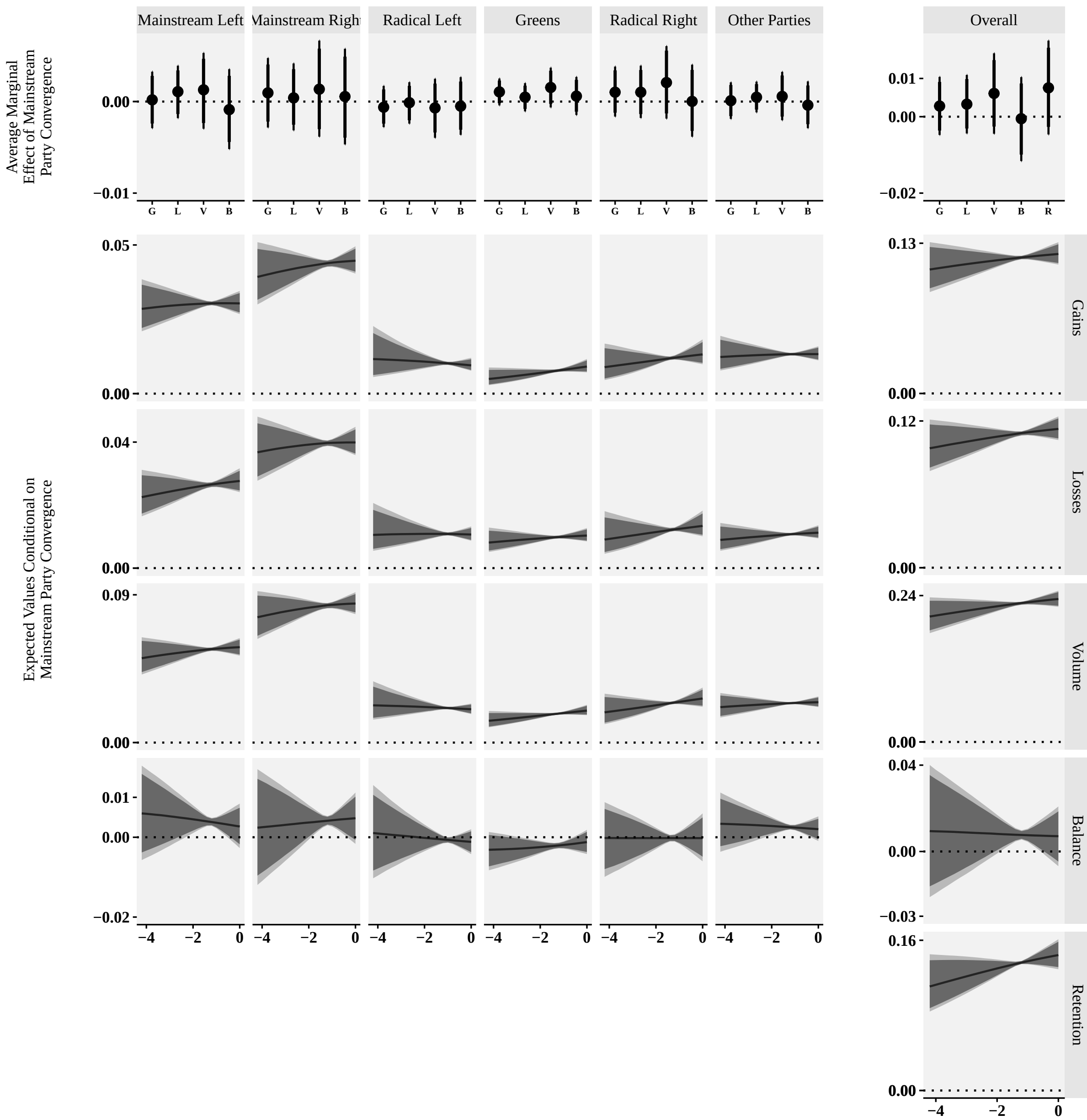

Figure A5.10: Vote switching quantities of interest as a function of positional convergence. Non-voting only. Based on the estimates reported in Online Appendix A5.3.

A5.3 Regression tables

Table A5.4: Columns 1-10 of the cell-specific parameter estimates for the main text analysis of the 7 × 7 voter transition matrices across 156 electoral contexts. Posterior medians with 95% credible intervals in parentheses. $\sigma_{\nu_{jc}}$ denotes the standard deviation of the election-cell-specific random intercepts. Parameters for the last equation set to 0 for identification. Party family abbreviations: eco = Ecologists/Greens, lef = Radical Left, mrp = Mainstream Right, non = Non-voters, oth = Other parties, rrp = Radical Right, soc = Social Democrats/Mainstream Left.

	eco→eco	eco→lef	eco→mrp	eco→non	eco→oth	eco→rrp	eco→soc	lef→eco	lef→lef	lef→mrp
(Intercept)	−1.85 [−2.50, −1.22]	−2.73 [−3.80, −1.66]	−2.53 [−3.31, −1.85]	−2.36 [−3.06, −1.60]	−3.70 [−4.66, −2.78]	−3.84 [−4.89, −2.98]	−2.33 [−3.11, −1.53]	−3.87 [−5.17, −2.45]	−1.91 [−3.03, −0.68]	−2.95 [−4.12, −1.77]
MSP Convergence	0.17 [−0.01, 0.34]	0.29 [−0.07, 0.65]	0.28 [0.11, 0.48]	0.24 [0.06, 0.43]	0.11 [−0.17, 0.42]	0.37 [0.06, 0.67]	0.31 [0.08, 0.55]	0.02 [−0.33, 0.37]	−0.12 [−0.35, 0.12]	0.04 [−0.16, 0.26]
Country: BE-VL	0.68 [−0.12, 1.47]	1.30 [−0.31, 3.00]	0.66 [−0.20, 1.51]	−0.25 [−1.14, 0.64]	0.53 [−0.56, 1.63]	0.46 [−0.67, 1.63]	−0.02 [−1.02, 0.98]	−0.53 [−3.18, 1.92]	0.24 [−1.40, 1.81]	0.87 [−0.86, 2.60]
Country: BE-WA	0.50 [−0.16, 1.25]	−0.71 [−2.53, 1.28]	0.45 [−0.34, 1.27]	−0.48 [−1.28, 0.37]	−0.32 [−1.43, 0.69]	−0.05 [−1.20, 1.09]	−0.47 [−1.36, 0.51]	0.71 [−1.35, 2.64]	−0.99 [−2.69, 0.82]	−2.59 [−5.94, 0.03]
Country: CH	0.57 [−0.16, 1.25]	−1.72 [−2.99, −0.40]	0.45 [−0.33, 1.25]	1.22 [0.42, 2.10]	0.56 [−0.43, 1.63]	1.28 [0.18, 2.38]	0.21 [−0.75, 1.14]	−1.50 [−3.11, 0.02]	−3.67 [−5.12, −2.31]	−1.61 [−3.00, −0.23]
Country: DE	0.05 [−0.61, 0.76]	−1.34 [−2.40, −0.10]	−0.61 [−1.42, 0.21]	−0.62 [−1.39, 0.20]	−1.13 [−2.17, −0.09]	−1.71 [−2.87, −0.54]	−0.21 [−1.08, 0.63]	−0.46 [−2.00, 1.00]	−0.42 [−1.74, 0.81]	−0.52 [−1.77, 0.74]
Country: DK	0.76 [0.10, 1.40]	−0.90 [−2.12, 0.33]	−0.34 [−1.07, 0.42]	−0.51 [−1.24, 0.24]	−1.15 [−2.12, −0.13]	0.00 [−0.93, 1.01]	0.03 [−0.80, 0.87]	0.00 [−1.42, 1.56]	−0.96 [−2.26, 0.17]	−0.56 [−1.88, 0.72]
Country: ES	0.02 [−4.74, 4.85]	0.06 [−5.27, 4.98]	0.17 [−5.51, 5.24]	−0.06 [−4.66, 4.77]	0.02 [−4.97, 5.11]	0.05 [−4.71, 4.65]	−0.04 [−4.63, 4.94]	0.09 [−4.62, 4.70]	−0.32 [−1.56, 0.82]	−0.42 [−1.66, 0.79]
Country: FI	0.41 [−0.34, 1.14]	−0.31 [−1.46, 0.85]	0.23 [−0.60, 1.08]	0.23 [−0.57, 1.10]	−0.23 [−1.29, 0.82]	0.09 [−1.05, 1.22]	−0.45 [−1.43, 0.50]	0.61 [−0.82, 2.08]	0.76 [−0.48, 1.96]	0.12 [−1.15, 1.43]
Country: FR	−1.08 [−1.99, −0.14]	−1.55 [−3.12, −0.01]	−0.53 [−1.51, 0.44]	0.47 [−0.43, 1.48]	0.21 [−0.89, 1.44]	−0.34 [−1.68, 1.05]	−0.61 [−1.80, 0.51]	−0.28 [−1.95, 1.41]	0.70 [−0.57, 2.03]	0.29 [−1.11, 1.69]
Country: GB	−3.08 [−3.99, −2.18]	0.19 [−5.01, 4.85]	−1.42 [−2.31, −0.59]	−1.92 [−2.79, −0.96]	−2.04 [−3.26, −0.80]	−2.16 [−3.63, −0.81]	−1.64 [−2.67, −0.72]	0.01 [−4.92, 4.96]	0.07 [−4.39, 4.97]	0.00 [−4.93, 4.91]
Country: GR	0.02 [−5.02, 4.69]	0.09 [−5.12, 5.25]	−0.01 [−5.06, 4.86]	0.11 [−4.95, 4.63]	0.06 [−4.78, 4.94]	0.10 [−4.89, 5.17]	0.15 [−5.20, 4.82]	0.05 [−4.77, 4.97]	2.05 [0.70, 3.30]	0.49 [−0.88, 1.83]
Country: IE	−0.41 [−1.28, 0.52]	−0.03 [−1.31, 1.31]	1.11 [0.21, 2.04]	1.15 [0.25, 2.04]	0.65 [−0.56, 1.94]	0.04 [−5.10, 5.01]	−0.48 [−1.68, 0.70]	−0.14 [−2.09, 1.52]	1.00 [−0.49, 2.28]	1.61 [0.33, 2.98]
Country: IS	1.44 [0.72, 2.16]	0.19 [−4.60, 4.93]	0.63 [−0.18, 1.54]	0.78 [−0.01, 1.63]	2.15 [1.15, 3.24]	−0.16 [−4.86, 5.30]	0.70 [−0.23, 1.60]	0.02 [−5.14, 5.15]	1.53 [0.16, 2.78]	1.02 [−0.34, 2.45]
Country: IT	−2.19 [−3.12, −1.40]	−1.50 [−2.90, −0.17]	−0.16 [−1.06, 0.72]	−0.61 [−1.46, 0.30]	−0.18 [−1.26, 1.02]	0.09 [−1.07, 1.30]	−0.97 [−2.02, 0.09]	−1.48 [−3.38, 0.29]	−0.48 [−1.81, 0.78]	0.26 [−1.07, 1.52]
Country: NL	−0.23 [−0.92, 0.49]	−0.80 [−1.95, 0.44]	−0.27 [−1.09, 0.52]	−0.79 [−1.65, 0.06]	−0.77 [−1.82, 0.36]	−0.91 [−2.14, 0.19]	−0.51 [−1.48, 0.41]	0.16 [−1.33, 1.55]	−0.55 [−1.87, 0.65]	−0.39 [−1.59, 0.86]
Country: NO	−2.42 [−3.61, −1.33]	−2.04 [−3.53, −0.57]	−1.63 [−2.77, −0.51]	−1.46 [−2.65, −0.29]	−2.62 [−5.11, −0.74]	−1.37 [−3.16, 0.14]	−2.37 [−3.77, −0.98]	−0.03 [−1.66, 1.51]	−0.38 [−1.66, 0.79]	−0.30 [−1.56, 0.96]
Country: PT	−2.27 [−4.21, −0.66]	−1.84 [−4.27, 0.41]	−1.90 [−4.12, −0.18]	−0.95 [−2.35, 0.36]	0.05 [−5.05, 5.36]	−1.58 [−4.78, 0.91]	−2.44 [−4.92, −0.41]	0.22 [−1.74, 2.23]	0.49 [−0.82, 1.80]	−0.17 [−1.51, 1.17]
Country: SE	−0.86 [−1.61, −0.13]	−1.23 [−2.33, −0.05]	−0.55 [−1.42, 0.23]	−1.22 [−2.02, −0.41]	−1.92 [−2.93, −0.84]	−0.87 [−2.03, 0.25]	−1.01 [−1.94, −0.12]	−0.30 [−1.73, 1.17]	−0.59 [−1.82, 0.59]	−0.73 [−1.95, 0.58]
$\sigma_{\nu_{jc}}$	0.54 [0.47, 0.63]	0.70 [0.51, 0.94]	0.57 [0.48, 0.69]	0.54 [0.44, 0.66]	0.66 [0.52, 0.85]	0.74 [0.54, 0.98]	0.72 [0.60, 0.87]	0.75 [0.59, 0.96]	0.67 [0.58, 0.77]	0.57 [0.48, 0.68]
$N_{\text{Electoral contexts}}$	156	156	156	156	156	156	156	156	156	156

Table A5.5: *Continued:* Columns 11-20 of the cell-specific parameter estimates for the main text analysis of the 7 × 7 voter transition matrices across 156 electoral contexts.

	lef→non	lef→oth	lef→rrp	lef→soc	mrp→eco	mrp→lef	mrp→mrp	mrp→non	mrp→oth	mrp→rrp
(Intercept)	−2.71 [−3.93, −1.51]	−3.50 [−4.82, −2.32]	−4.13 [−5.53, −2.80]	−2.67 [−3.90, −1.48]	−2.73 [−3.58, −1.93]	−2.99 [−3.98, −2.12]	0.31 [−0.02, 0.65]	−1.36 [−1.90, −0.84]	−3.11 [−3.87, −2.21]	−1.85 [−2.63, −1.06]
MSP Convergence	−0.01 [−0.23, 0.22]	0.17 [−0.15, 0.49]	0.16 [−0.26, 0.60]	0.18 [−0.07, 0.42]	0.17 [−0.03, 0.38]	0.11 [−0.09, 0.33]	0.04 [−0.02, 0.11]	0.11 [0.01, 0.20]	0.07 [−0.13, 0.25]	0.43 [0.19, 0.66]
Country: BE-VL	−1.67 [−4.26, 0.51]	−2.05 [−5.82, 0.91]	−2.07 [−6.25, 0.82]	0.49 [−1.25, 2.39]	0.85 [−0.12, 1.84]	0.90 [−0.55, 2.39]	0.97 [0.55, 1.33]	0.53 [−0.04, 1.17]	0.77 [−0.23, 1.72]	0.99 [0.03, 2.02]
Country: BE-WA	−3.21 [−6.65, −0.63]	1.12 [−0.75, 2.98]	−2.11 [−5.89, 0.91]	−0.16 [−1.93, 1.67]	0.84 [−0.09, 1.77]	−0.11 [−1.68, 1.30]	0.06 [−0.34, 0.49]	−0.38 [−0.95, 0.27]	0.71 [−0.24, 1.71]	−0.86 [−1.90, 0.11]
Country: CH	−0.72 [−2.09, 0.70]	−1.38 [−2.92, 0.07]	−0.45 [−2.10, 1.14]	−1.89 [−3.36, −0.59]	0.54 [−0.31, 1.50]	−1.19 [−2.24, −0.09]	0.44 [0.07, 0.79]	1.38 [0.83, 1.93]	0.77 [−0.22, 1.72]	1.39 [0.44, 2.26]
Country: DE	−0.44 [−1.75, 0.84]	−1.04 [−2.39, 0.49]	−0.42 [−1.94, 1.01]	−0.58 [−1.93, 0.65]	−0.01 [−0.90, 0.92]	−0.55 [−1.57, 0.48]	0.28 [−0.11, 0.65]	−0.07 [−0.63, 0.50]	−0.58 [−1.51, 0.31]	−1.14 [−2.05, −0.22]
Country: DK	−1.39 [−2.72, 0.03]	−1.28 [−2.69, 0.08]	−0.40 [−2.15, 1.24]	−1.32 [−2.66, −0.02]	−0.16 [−0.99, 0.74]	−0.38 [−1.39, 0.71]	0.14 [−0.22, 0.51]	−0.54 [−1.08, 0.02]	−0.81 [−1.75, 0.05]	0.06 [−0.86, 0.84]
Country: ES	0.05 [−1.20, 1.32]	0.24 [−0.94, 1.54]	0.34 [−1.29, 2.09]	−0.25 [−1.52, 1.05]	−0.09 [−4.91, 4.66]	−0.21 [−1.13, 0.81]	−0.11 [−0.49, 0.22]	0.03 [−0.53, 0.59]	0.35 [−0.52, 1.21]	0.89 [−0.27, 2.11]
Country: FI	0.70 [−0.59, 2.00]	−0.11 [−1.44, 1.37]	0.30 [−1.18, 1.86]	−0.13 [−1.44, 1.10]	0.37 [−0.54, 1.36]	0.05 [−0.94, 1.12]	0.60 [0.17, 0.98]	0.72 [0.18, 1.35]	0.83 [−0.12, 1.76]	−0.26 [−1.28, 0.68]
Country: FR	1.13 [−0.18, 2.47]	1.18 [−0.29, 2.58]	1.43 [−0.30, 3.07]	0.84 [−0.54, 2.21]	−0.66 [−1.81, 0.48]	0.00 [−1.13, 1.11]	0.46 [0.02, 0.87]	1.22 [0.61, 1.88]	1.89 [0.88, 2.89]	−0.23 [−1.44, 0.85]
Country: GB	−0.06 [−4.98, 5.14]	0.24 [−4.69, 5.26]	0.04 [−4.73, 4.86]	0.14 [−4.64, 4.67]	−1.23 [−2.24, −0.17]	−0.06 [−4.96, 4.26]	0.32 [−0.07, 0.66]	0.60 [0.04, 1.13]	0.41 [−0.50, 1.29]	−1.14 [−2.20, −0.16]
Country: GR	2.10 [0.72, 3.42]	1.17 [−0.26, 2.67]	1.54 [−0.04, 3.30]	0.31 [−1.11, 1.68]	−0.02 [−5.22, 4.76]	1.37 [0.27, 2.53]	0.37 [−0.06, 0.80]	1.29 [0.66, 1.95]	0.66 [−0.54, 1.75]	0.48 [−0.68, 1.57]
Country: IE	1.86 [0.40, 3.12]	1.33 [−0.16, 2.85]	−0.06 [−5.35, 5.22]	0.07 [−1.44, 1.50]	1.06 [0.01, 2.15]	2.50 [1.45, 3.64]	1.95 [1.45, 2.39]	2.78 [2.15, 3.51]	2.92 [1.85, 3.90]	0.03 [−4.86, 4.99]
Country: IS	0.88 [−0.49, 2.32]	2.43 [1.01, 3.85]	0.04 [−5.21, 4.95]	1.11 [−0.18, 2.59]	0.69 [−0.25, 1.59]	0.62 [−0.41, 1.78]	0.66 [0.28, 1.04]	0.52 [−0.05, 1.13]	2.12 [1.23, 2.97]	−0.13 [−5.36, 4.77]
Country: IT	0.12 [−1.22, 1.46]	0.33 [−0.98, 1.76]	0.40 [−1.17, 1.98]	−0.02 [−1.39, 1.31]	−0.16 [−1.16, 0.93]	0.46 [−0.46, 1.55]	0.21 [−0.20, 0.58]	0.78 [0.24, 1.40]	1.70 [0.78, 2.57]	0.49 [−0.46, 1.39]
Country: NL	−0.56 [−1.92, 0.70]	−1.00 [−2.34, 0.46]	0.15 [−1.31, 1.68]	−0.78 [−2.01, 0.55]	0.04 [−0.90, 1.00]	0.27 [−0.73, 1.33]	0.66 [0.29, 1.02]	0.38 [−0.17, 0.95]	0.62 [−0.28, 1.46]	−0.23 [−1.15, 0.65]
Country: NO	−0.43 [−1.71, 0.85]	−0.84 [−2.22, 0.45]	−0.70 [−2.13, 0.74]	0.09 [−1.16, 1.31]	−0.70 [−1.90, 0.52]	−0.21 [−1.17, 0.83]	−0.04 [−0.42, 0.32]	0.05 [−0.51, 0.64]	−0.08 [−0.98, 0.78]	−0.04 [−0.93, 0.80]
Country: PT	0.96 [−0.39, 2.34]	−0.75 [−2.29, 0.86]	−0.66 [−3.01, 1.63]	−0.17 [−1.59, 1.18]	−0.50 [−2.01, 1.14]	0.55 [−0.60, 1.63]	−0.16 [−0.63, 0.25]	0.44 [−0.23, 1.07]	−0.01 [−1.12, 1.13]	−1.61 [−3.59, 0.18]
Country: SE	−1.12 [−2.32, 0.16]	−1.24 [−2.54, 0.06]	−0.69 [−2.29, 0.88]	−0.27 [−1.57, 0.93]	−0.44 [−1.38, 0.48]	−0.72 [−1.59, 0.32]	−0.05 [−0.43, 0.28]	−0.65 [−1.19, −0.07]	−0.74 [−1.65, 0.13]	−0.52 [−1.52, 0.41]
$\sigma_{\nu_{jc}}$	0.58 [0.49, 0.68]	0.81 [0.68, 1.00]	0.86 [0.67, 1.12]	0.64 [0.54, 0.77]	0.65 [0.55, 0.76]	0.56 [0.47, 0.68]	0.26 [0.23, 0.29]	0.38 [0.34, 0.42]	0.65 [0.57, 0.74]	0.78 [0.68, 0.90]
$N_{\text{Electoral contexts}}$	156	156	156	156	156	156	156	156	156	156

Table A5.6: *Continued:* Columns 21-30 of the cell-specific parameter estimates for the main text analysis of the 7 × 7 voter transition matrices across 156 electoral contexts.

	mrp→soc	non→eco	non→lef	non→mrp	non→non	non→oth	non→rrp	non→soc	oth→eco	oth→lef
(Intercept)	−2.21 [−2.84, −1.52]	−2.30 [−2.92, −1.63]	−2.57 [−3.47, −1.67]	−1.24 [−1.77, −0.70]	0.13 [−0.48, 0.72]	−2.64 [−3.42, −1.94]	−2.11 [−2.90, −1.37]	−1.18 [−1.74, −0.67]	−4.09 [−4.96, −3.23]	−3.38 [−4.43, −2.41]
MSP Convergence	0.13 [0.00, 0.24]	0.16 [−0.01, 0.34]	0.10 [−0.13, 0.30]	0.09 [−0.02, 0.20]	0.14 [0.02, 0.27]	0.13 [−0.03, 0.29]	0.22 [−0.01, 0.48]	0.13 [0.01, 0.24]	−0.10 [−0.37, 0.18]	0.06 [−0.23, 0.35]
Country: BE-VL	0.65 [−0.09, 1.38]	−0.13 [−0.91, 0.69]	−0.88 [−2.88, 0.92]	0.19 [−0.44, 0.84]	−0.39 [−1.12, 0.37]	−0.29 [−1.19, 0.59]	0.09 [−0.89, 1.06]	−1.02 [−1.68, −0.36]	0.51 [−0.61, 1.56]	−2.50 [−5.98, 0.10]
Country: BE-WA	0.17 [−0.59, 0.93]	−0.38 [−1.15, 0.38]	−0.83 [−2.60, 0.83]	−0.73 [−1.37, −0.08]	−0.99 [−1.69, −0.32]	−0.73 [−1.58, 0.20]	−1.29 [−2.24, −0.26]	−1.31 [−1.95, −0.65]	0.41 [−0.61, 1.50]	1.69 [0.04, 3.24]
Country: CH	0.27 [−0.47, 0.98]	1.23 [0.46, 1.96]	−0.92 [−1.85, 0.07]	1.08 [0.49, 1.67]	2.29 [1.61, 2.96]	1.30 [0.56, 2.17]	1.81 [0.94, 2.77]	0.77 [0.18, 1.37]	0.35 [−0.68, 1.39]	−1.60 [−2.82, −0.32]
Country: DE	0.46 [−0.25, 1.13]	−0.43 [−1.14, 0.29]	−0.41 [−1.35, 0.58]	−0.36 [−0.89, 0.24]	−0.60 [−1.23, 0.06]	−1.23 [−2.00, −0.39]	−1.57 [−2.35, −0.65]	−0.64 [−1.23, −0.05]	−0.93 [−1.99, 0.04]	−1.39 [−2.50, −0.26]
Country: DK	0.06 [−0.62, 0.75]	−0.47 [−1.17, 0.17]	−1.43 [−2.44, −0.44]	−0.54 [−1.09, 0.01]	−0.81 [−1.46, −0.16]	−1.54 [−2.30, −0.72]	−1.15 [−1.93, −0.22]	−1.04 [−1.60, −0.44]	−0.81 [−1.84, 0.18]	−1.77 [−2.99, −0.46]
Country: ES	0.08 [−0.61, 0.75]	−0.03 [−5.17, 4.71]	0.02 [−0.91, 0.93]	−0.17 [−0.71, 0.38]	0.02 [−0.59, 0.68]	0.50 [−0.27, 1.28]	−0.03 [−1.23, 1.22]	−0.24 [−0.79, 0.34]	−0.03 [−4.72, 4.94]	−0.03 [−1.01, 0.98]
Country: FI	0.23 [−0.49, 0.92]	0.61 [−0.11, 1.34]	0.43 [−0.55, 1.37]	0.51 [−0.11, 1.11]	0.86 [0.16, 1.56]	0.65 [−0.17, 1.52]	0.28 [−0.60, 1.24]	−0.11 [−0.72, 0.55]	0.38 [−0.74, 1.44]	−0.18 [−1.29, 0.96]
Country: FR	0.54 [−0.27, 1.29]	0.39 [−0.47, 1.25]	0.71 [−0.40, 1.75]	0.65 [−0.06, 1.28]	0.48 [−0.22, 1.30]	1.13 [0.19, 2.00]	0.13 [−1.06, 1.33]	0.41 [−0.21, 1.14]	0.92 [−0.20, 2.18]	0.83 [−0.35, 2.10]
Country: GB	0.73 [0.05, 1.39]	−1.28 [−2.07, −0.48]	−0.04 [−5.03, 5.26]	0.40 [−0.15, 0.95]	0.16 [−0.49, 0.77]	−0.03 [−0.79, 0.76]	−1.16 [−2.16, −0.14]	0.12 [−0.45, 0.68]	−1.05 [−2.15, 0.09]	0.09 [−4.94, 4.83]
Country: GR	0.27 [−0.59, 1.18]	0.07 [−4.52, 4.84]	2.09 [1.09, 3.14]	0.51 [−0.16, 1.24]	1.17 [0.39, 1.99]	0.95 [0.01, 1.83]	0.61 [−0.41, 1.72]	−0.27 [−0.97, 0.47]	−0.14 [−5.01, 4.87]	1.56 [0.48, 2.79]
Country: IE	2.13 [1.31, 2.94]	1.00 [0.16, 1.85]	2.43 [1.42, 3.51]	2.44 [1.69, 3.10]	1.73 [0.95, 2.44]	2.29 [1.39, 3.27]	−0.11 [−4.88, 4.44]	1.06 [0.33, 1.77]	1.13 [−0.08, 2.36]	1.50 [0.17, 2.73]
Country: IS	0.69 [−0.03, 1.39]	0.61 [−0.08, 1.30]	0.51 [−0.56, 1.68]	0.36 [−0.24, 0.94]	−0.28 [−0.95, 0.40]	1.65 [0.86, 2.47]	−0.16 [−4.88, 4.61]	−0.29 [−0.88, 0.28]	2.50 [1.54, 3.51]	2.29 [1.04, 3.50]
Country: IT	0.60 [−0.14, 1.32]	−0.74 [−1.56, 0.07]	0.19 [−0.79, 1.16]	0.49 [−0.07, 1.04]	−0.08 [−0.76, 0.60]	0.97 [0.16, 1.79]	−0.09 [−1.00, 0.80]	−0.28 [−0.89, 0.34]	0.40 [−0.82, 1.45]	0.27 [−0.82, 1.36]
Country: NL	0.58 [−0.11, 1.24]	−0.55 [−1.30, 0.18]	−0.28 [−1.19, 0.68]	0.23 [−0.37, 0.76]	−0.33 [−0.96, 0.34]	−0.23 [−0.99, 0.60]	−0.34 [−1.23, 0.55]	−0.65 [−1.21, −0.06]	−0.05 [−1.12, 0.99]	−0.75 [−1.94, 0.41]
Country: NO	0.35 [−0.37, 1.08]	−1.13 [−2.07, −0.15]	−0.15 [−1.08, 0.78]	−0.20 [−0.77, 0.35]	−0.62 [−1.28, 0.04]	−0.96 [−1.71, −0.10]	−0.21 [−1.07, 0.64]	−0.59 [−1.18, 0.00]	−0.35 [−1.74, 1.06]	−0.28 [−1.20, 0.84]
Country: PT	0.30 [−0.59, 1.14]	−0.68 [−1.99, 0.54]	0.67 [−0.30, 1.71]	−0.01 [−0.73, 0.65]	0.79 [0.04, 1.53]	−0.01 [−1.04, 0.96]	−1.57 [−3.41, 0.23]	0.04 [−0.62, 0.77]	0.30 [−1.49, 1.98]	−0.06 [−1.41, 1.20]
Country: SE	0.13 [−0.56, 0.77]	−1.26 [−1.96, −0.55]	−1.26 [−2.12, −0.36]	−0.83 [−1.37, −0.28]	−1.29 [−1.89, −0.66]	−1.32 [−2.10, −0.55]	−1.05 [−1.99, −0.03]	−1.03 [−1.55, −0.47]	−2.09 [−3.26, −1.01]	−2.01 [−3.01, −0.79]
$\sigma_{\nu_{jc}}$	0.49 [0.43, 0.56]	0.52 [0.44, 0.61]	0.59 [0.51, 0.68]	0.43 [0.39, 0.48]	0.50 [0.45, 0.56]	0.60 [0.53, 0.69]	0.79 [0.68, 0.91]	0.42 [0.37, 0.49]	0.73 [0.59, 0.92]	0.72 [0.59, 0.87]
$N_{\text{Electoral contexts}}$	156	156	156	156	156	156	156	156	156	156

Table A5.7: *Continued:* Columns 31-40 of the cell-specific parameter estimates for the main text analysis of the 7×7 voter transition matrices across 156 electoral contexts.

	oth→mrp	oth→non	oth→oth	oth→rrp	oth→soc	rrp→eco	rrp→lef	rrp→mrp	rrp→non	rrp→oth
(Intercept)	−2.11 [−2.84, −1.37]	−2.44 [−3.15, −1.72]	−2.49 [−3.37, −1.60]	−3.08 [−4.02, −2.04]	−3.15 [−3.88, −2.35]	−4.07 [−5.13, −3.03]	−4.07 [−5.35, −2.80]	−2.21 [−3.11, −1.33]	−2.03 [−2.86, −1.21]	−3.97 [−5.06, −2.86]
MSP Convergence	−0.04 [−0.21, 0.13]	0.08 [−0.09, 0.24]	−0.04 [−0.25, 0.16]	0.04 [−0.29, 0.37]	0.02 [−0.16, 0.20]	0.01 [−0.32, 0.34]	0.07 [−0.45, 0.56]	0.02 [−0.25, 0.30]	0.22 [−0.03, 0.46]	0.07 [−0.33, 0.48]
Country: BE-VL	0.06 [−0.79, 0.91]	0.20 [−0.70, 1.03]	0.59 [−0.45, 1.65]	0.55 [−0.64, 1.66]	0.10 [−0.88, 1.03]	0.07 [−1.18, 1.32]	−0.20 [−3.11, 2.29]	0.00 [−1.04, 1.09]	−0.70 [−1.71, 0.29]	−0.28 [−1.66, 1.05]
Country: BE-WA	−0.91 [−1.82, −0.04]	−0.92 [−1.82, −0.04]	−0.39 [−1.49, 0.69]	−0.71 [−1.89, 0.52]	−0.24 [−1.12, 0.66]	−0.62 [−1.86, 0.65]	1.92 [−0.25, 3.91]	−1.20 [−2.34, −0.25]	−1.58 [−2.59, −0.57]	−0.92 [−2.31, 0.51]
Country: CH	−0.07 [−0.89, 0.74]	1.21 [0.45, 1.98]	0.64 [−0.36, 1.67]	0.37 [−0.75, 1.51]	0.29 [−0.59, 1.19]	0.68 [−0.41, 1.86]	−0.88 [−2.48, 0.65]	0.35 [−0.63, 1.35]	1.76 [0.76, 2.75]	1.16 [−0.16, 2.42]
Country: DE	−2.20 [−2.99, −1.34]	−1.35 [−2.13, −0.52]	−1.65 [−2.64, −0.66]	−2.35 [−3.46, −1.20]	−1.30 [−2.12, −0.43]	−1.20 [−2.40, 0.00]	−1.22 [−2.64, 0.13]	−1.61 [−2.54, −0.55]	−1.85 [−2.78, −0.90]	−1.98 [−3.32, −0.79]
Country: DK	−1.92 [−2.72, −1.05]	−1.50 [−2.27, −0.72]	−1.58 [−2.50, −0.70]	−2.20 [−3.28, −1.19]	−1.66 [−2.50, −0.79]	−0.72 [−1.82, 0.40]	−0.49 [−2.04, 1.01]	−0.57 [−1.54, 0.44]	−0.74 [−1.62, 0.17]	−1.64 [−2.85, −0.46]
Country: ES	−0.56 [−1.34, 0.27]	0.44 [−0.40, 1.24]	1.47 [0.51, 2.40]	−0.87 [−2.38, 0.57]	0.32 [−0.53, 1.17]	−0.17 [−5.14, 4.56]	−1.29 [−3.13, 0.67]	−2.16 [−3.63, −0.72]	−1.40 [−2.76, −0.16]	−1.37 [−3.12, 0.20]
Country: FI	−0.02 [−0.86, 0.85]	0.51 [−0.35, 1.29]	1.05 [−0.01, 2.04]	−0.56 [−1.78, 0.62]	−0.08 [−1.01, 0.81]	−0.10 [−1.37, 1.21]	−0.73 [−2.31, 0.74]	−0.63 [−1.78, 0.44]	−0.10 [−1.13, 0.91]	−0.13 [−1.63, 1.21]
Country: FR	0.74 [−0.14, 1.69]	1.53 [0.58, 2.42]	0.66 [−0.48, 1.68]	−0.22 [−1.57, 1.21]	1.07 [0.12, 1.98]	−0.13 [−1.57, 1.43]	0.58 [−1.03, 2.16]	0.09 [−1.26, 1.21]	1.01 [−0.19, 2.16]	1.20 [−0.24, 2.80]
Country: GB	−0.93 [−1.69, −0.08]	−0.23 [−0.97, 0.58]	0.21 [−0.65, 1.16]	−1.42 [−2.73, −0.27]	−0.20 [−1.08, 0.57]	−1.69 [−3.15, −0.19]	0.06 [−4.97, 5.11]	−0.84 [−1.98, 0.32]	−1.03 [−2.15, 0.03]	−0.45 [−1.85, 0.94]
Country: GR	−0.50 [−1.60, 0.53]	0.69 [−0.24, 1.71]	0.74 [−0.50, 1.86]	−0.09 [−1.60, 1.28]	−0.05 [−1.17, 1.05]	−0.12 [−4.81, 5.15]	1.77 [0.14, 3.27]	−1.00 [−2.51, 0.28]	0.86 [−0.36, 2.02]	−0.22 [−2.02, 1.46]
Country: IE	1.81 [0.84, 2.80]	2.22 [1.26, 3.11]	1.76 [0.63, 2.98]	0.00 [−4.96, 4.76]	1.62 [0.55, 2.66]	0.10 [−4.99, 4.45]	0.04 [−4.76, 4.73]	0.03 [−4.88, 4.94]	−0.15 [−4.72, 5.01]	−0.18 [−4.78, 5.15]
Country: IS	1.31 [0.55, 2.11]	1.64 [0.81, 2.45]	2.73 [1.83, 3.70]	−0.06 [−5.17, 5.12]	1.89 [1.02, 2.71]	0.00 [−5.23, 5.22]	−0.07 [−4.92, 4.92]	−0.10 [−5.00, 5.00]	0.10 [−4.68, 4.80]	−0.16 [−4.99, 4.67]
Country: IT	0.59 [−0.21, 1.46]	0.94 [0.14, 1.73]	0.90 [−0.10, 1.88]	0.22 [−0.87, 1.33]	1.22 [0.35, 2.12]	−0.73 [−2.11, 0.67]	−0.01 [−1.34, 1.43]	0.02 [−0.94, 1.08]	−0.20 [−1.14, 0.72]	0.50 [−0.78, 1.76]
Country: NL	−0.32 [−1.11, 0.48]	−0.30 [−1.09, 0.47]	0.63 [−0.32, 1.54]	−0.36 [−1.49, 0.71]	−0.09 [−0.91, 0.73]	−1.22 [−2.55, 0.19]	−0.06 [−1.49, 1.49]	−0.88 [−2.01, 0.12]	−1.10 [−2.10, −0.12]	−1.51 [−3.07, −0.13]
Country: NO	−1.50 [−2.28, −0.68]	−1.15 [−1.97, −0.37]	−1.50 [−2.51, −0.58]	−1.93 [−3.03, −0.91]	−0.93 [−1.78, −0.06]	−0.86 [−2.47, 0.72]	−0.93 [−2.28, 0.40]	−0.24 [−1.19, 0.73]	−0.38 [−1.30, 0.51]	−0.49 [−1.71, 0.82]
Country: PT	−1.21 [−2.19, −0.13]	−0.13 [−1.08, 0.86]	−1.04 [−2.31, 0.17]	−2.19 [−4.50, −0.06]	−0.54 [−1.59, 0.48]	0.17 [−5.04, 5.11]	−0.03 [−5.14, 4.77]	−0.11 [−4.65, 4.83]	0.13 [−4.34, 4.87]	0.06 [−4.96, 4.98]
Country: SE	−1.91 [−2.68, −1.05]	−2.01 [−2.79, −1.28]	−1.82 [−2.73, −0.94]	−2.79 [−4.17, −1.48]	−1.33 [−2.18, −0.53]	−1.36 [−2.75, −0.08]	−1.73 [−3.36, −0.17]	−1.22 [−2.35, −0.06]	−2.00 [−3.07, −0.94]	−1.20 [−2.72, 0.17]
$\sigma_{\nu_{jc}}$	0.63 [0.56, 0.71]	0.61 [0.53, 0.69]	0.81 [0.71, 0.93]	0.91 [0.76, 1.13]	0.64 [0.56, 0.74]	0.84 [0.66, 1.08]	0.96 [0.72, 1.30]	0.86 [0.74, 1.00]	0.81 [0.70, 0.95]	1.08 [0.89, 1.33]
$N_{\text{Electoral contexts}}$	156	156	156	156	156	156	156	156	156	156

Table A5.8: *Continued:* Columns 41-49 of the cell-specific parameter estimates for the main text analysis of the 7 × 7 voter transition matrices across 156 electoral contexts.

	rrp→rrp	rrp→soc	soc→eco	soc→lef	soc→mrp	soc→non	soc→oth	soc→rrp	soc→soc
(Intercept)	−1.48 [−2.43, −0.61]	−3.40 [−4.36, −2.46]	−2.74 [−3.56, −1.99]	−2.41 [−3.33, −1.53]	−2.12 [−2.80, −1.47]	−1.29 [−1.84, −0.77]	−2.79 [−3.59, −2.03]	−2.09 [−2.92, −1.24]	0
MSP Convergence	0.23 [−0.09, 0.56]	0.22 [−0.06, 0.48]	0.12 [−0.07, 0.31]	0.10 [−0.12, 0.35]	0.02 [−0.13, 0.15]	0.09 [−0.02, 0.19]	0.22 [0.02, 0.39]	0.39 [0.13, 0.66]	0
Country: BE-VL	1.06 [−0.02, 2.32]	0.08 [−1.12, 1.22]	0.43 [−0.46, 1.44]	0.56 [−0.91, 2.03]	0.71 [−0.04, 1.45]	−0.51 [−1.13, 0.11]	−0.46 [−1.36, 0.48]	0.33 [−0.69, 1.33]	0
Country: BE-WA	−1.68 [−3.06, −0.52]	−0.62 [−1.80, 0.43]	0.54 [−0.28, 1.45]	0.45 [−1.13, 1.87]	0.08 [−0.64, 0.94]	−0.79 [−1.39, −0.18]	−0.16 [−1.03, 0.84]	−0.91 [−1.86, 0.10]	0
Country: CH	1.98 [0.90, 3.20]	0.92 [−0.21, 2.08]	0.91 [0.06, 1.83]	−1.93 [−3.03, −0.86]	0.18 [−0.60, 0.92]	0.70 [0.17, 1.27]	0.57 [−0.27, 1.47]	0.18 [−0.81, 1.16]	0
Country: DE	−3.15 [−4.31, −2.03]	−0.66 [−1.71, 0.47]	0.44 [−0.38, 1.34]	−0.51 [−1.51, 0.53]	0.38 [−0.35, 1.09]	−0.37 [−0.95, 0.22]	−1.03 [−1.81, −0.12]	−2.03 [−2.96, −1.11]	0
Country: DK	0.60 [−0.39, 1.61]	0.18 [−0.81, 1.21]	0.08 [−0.71, 0.99]	−1.59 [−2.57, −0.50]	−0.14 [−0.78, 0.53]	−0.81 [−1.36, −0.25]	−1.89 [−2.67, −0.99]	−0.76 [−1.60, 0.12]	0
Country: ES	−1.79 [−3.44, −0.14]	−1.43 [−2.89, 0.08]	−0.04 [−4.82, 4.52]	−0.44 [−1.38, 0.54]	0.04 [−0.64, 0.77]	−0.18 [−0.76, 0.33]	0.13 [−0.67, 1.01]	−1.04 [−2.32, 0.28]	0
Country: FI	−0.87 [−1.99, 0.41]	−0.19 [−1.33, 0.98]	0.02 [−0.87, 1.01]	−0.19 [−1.17, 0.86]	0.30 [−0.45, 1.03]	0.02 [−0.57, 0.64]	−0.14 [−1.09, 0.82]	−0.55 [−1.58, 0.49]	0
Country: FR	0.77 [−0.70, 2.14]	0.94 [−0.32, 2.25]	0.34 [−0.70, 1.35]	0.34 [−0.79, 1.45]	0.23 [−0.57, 1.15]	0.64 [−0.04, 1.32]	0.81 [−0.19, 1.81]	−0.94 [−2.20, 0.39]	0
Country: GB	−1.95 [−3.28, −0.70]	−0.94 [−2.12, 0.20]	−1.21 [−2.07, −0.19]	−0.02 [−4.74, 4.89]	0.59 [−0.08, 1.32]	0.14 [−0.38, 0.70]	−0.02 [−0.77, 0.87]	−1.45 [−2.55, −0.43]	0
Country: GR	0.55 [−0.79, 2.01]	−0.37 [−1.87, 1.12]	0.08 [−4.70, 4.80]	1.09 [0.01, 2.27]	0.27 [−0.59, 1.13]	0.63 [−0.06, 1.33]	0.86 [−0.11, 1.85]	−0.57 [−1.79, 0.60]	0
Country: IE	0.05 [−4.77, 4.55]	−0.17 [−5.18, 4.70]	0.46 [−0.68, 1.50]	0.86 [−0.26, 1.96]	1.73 [0.91, 2.63]	1.01 [0.32, 1.69]	1.52 [0.55, 2.58]	−0.07 [−5.15, 5.20]	0
Country: IS	0.02 [−5.13, 4.41]	0.00 [−4.77, 5.37]	1.55 [0.70, 2.44]	0.32 [−0.87, 1.56]	0.85 [0.10, 1.61]	−0.10 [−0.67, 0.50]	1.74 [0.91, 2.57]	0.04 [−4.99, 4.74]	0
Country: IT	−0.41 [−1.58, 0.78]	0.53 [−0.53, 1.54]	−1.00 [−1.99, −0.03]	0.24 [−0.79, 1.33]	0.70 [0.00, 1.49]	0.05 [−0.51, 0.65]	1.09 [0.27, 1.99]	−0.32 [−1.24, 0.66]	0
Country: NL	−1.15 [−2.40, 0.11]	−1.01 [−2.27, 0.22]	0.35 [−0.46, 1.34]	−0.13 [−1.08, 0.85]	0.69 [0.01, 1.38]	−0.27 [−0.78, 0.31]	−0.13 [−1.00, 0.76]	−0.93 [−1.97, 0.08]	0
Country: NO	−0.11 [−1.12, 1.04]	0.03 [−1.08, 1.11]	−1.01 [−2.15, 0.21]	−0.52 [−1.50, 0.46]	0.29 [−0.44, 0.92]	−0.11 [−0.68, 0.49]	−1.37 [−2.23, −0.44]	−0.74 [−1.62, 0.11]	0
Country: PT	0.02 [−4.62, 4.92]	−0.11 [−4.60, 4.95]	−0.93 [−2.64, 0.60]	−0.18 [−1.28, 0.93]	−0.36 [−1.24, 0.46]	0.04 [−0.65, 0.67]	−1.18 [−2.28, 0.00]	−2.23 [−4.68, −0.25]	0
Country: SE	−1.09 [−2.41, 0.13]	−0.58 [−1.68, 0.60]	−0.50 [−1.32, 0.41]	−0.37 [−1.28, 0.63]	−0.11 [−0.81, 0.57]	−0.82 [−1.36, −0.19]	−1.38 [−2.09, −0.43]	−0.80 [−1.78, 0.21]	0
$\sigma_{\nu_{jc}}$	1.11 [0.98, 1.29]	0.82 [0.68, 0.99]	0.59 [0.51, 0.70]	0.67 [0.58, 0.79]	0.53 [0.47, 0.60]	0.39 [0.35, 0.44]	0.60 [0.52, 0.69]	0.83 [0.70, 0.99]	
$N_{\text{Electoral contexts}}$	156	156	156	156	156	156	156	156	156

A5.4 Robustness: Alternative Specifications

As an alternative to the positional convergence measure used in the main text (the positional distance between the electorally strongest parties of the mainstream left and the mainstream right), this robustness check uses the standard deviation across *all* mainstream right and mainstream left parties in a given electoral context. The scale of this measure ranges from 0.06 to 1.64. Contrary to the main text, higher values indicate greater positional distinctiveness: Standard deviations close to zero reflect a high degree of positional convergence, whereas large standard deviations indicate stronger positional divergence. Consequently, as we can see from the plots below, findings from this robustness check tend to show the opposite sign as those shown in the main text.

Main effects

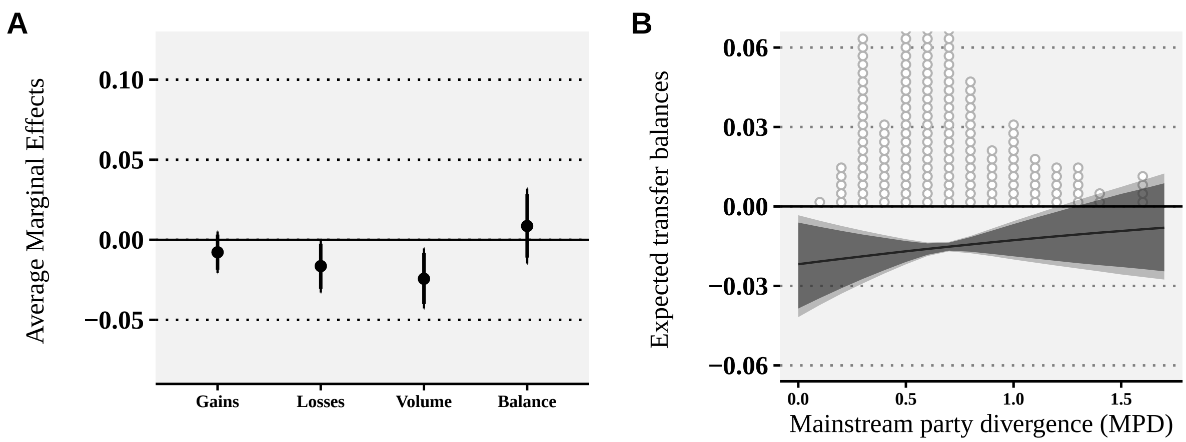

Figure A5.11: A: Average marginal effects of mainstream party divergence (MPD) on mainstream party gains, losses, volumes and balances with challenger parties. B: Expected mainstream party transfer balances with challenger parties as a function of MPC. Posterior medians with 90% and 95% credible intervals.

Secondary effects

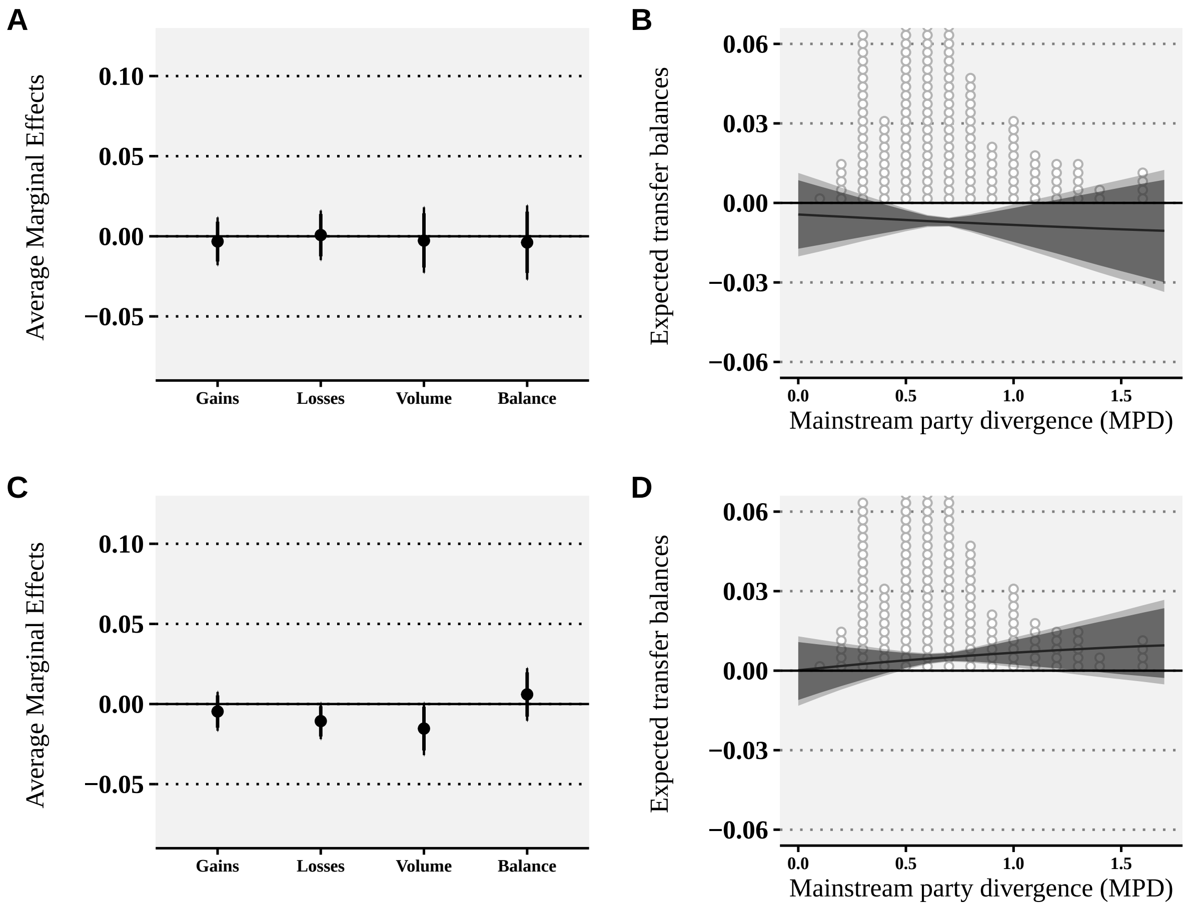

Figure A5.12: A: Average marginal effects of mainstream party divergence (MPD) on mainstream party gains, losses, volumes and balances with other parties and non-voters. B: Expected mainstream party transfer balances with other parties and non-voters as a function of MPC. C: Average marginal effects of mainstream party divergence (MPD) on challenger party gains, losses, volumes and balances with other parties and non-voters. D: Expected challenger party transfer balances with other parties and non-voters as a function of MPC. Posterior medians with 90% and 95% credible intervals.

Overall effects

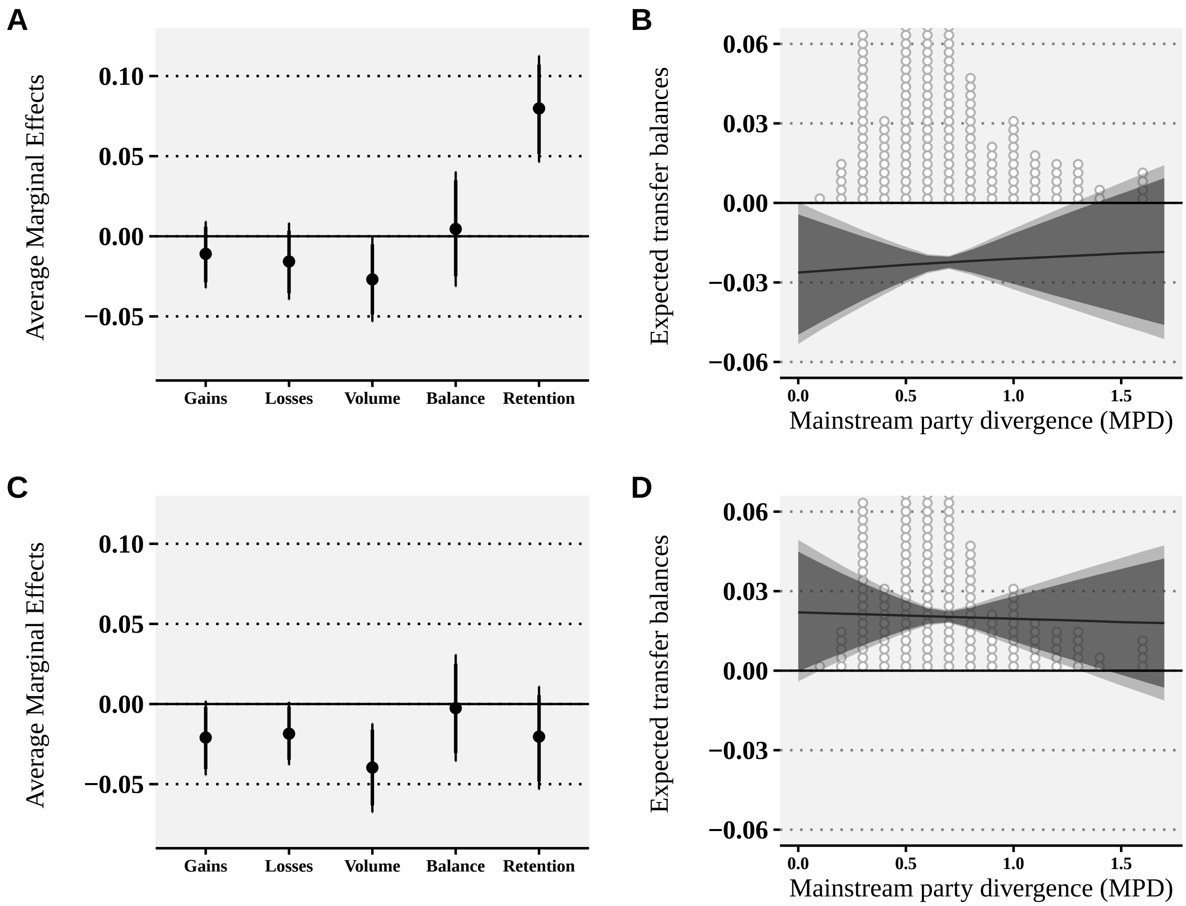

Figure A5.13: A: Average marginal effects of mainstream party divergence (MPD) on mainstream party overall gains, losses, volumes, balances, and retention. B: Expected overall mainstream party transfer balances as a function of MPC. C: Average marginal effects of mainstream party divergence (MPD) on challenger party overall gains, losses, volumes, balances, and retention. D: Expected overall challenger party transfer balances as a function of MPC. Posterior medians with 90% and 95% credible intervals.

Focal category: Mainstream right parties

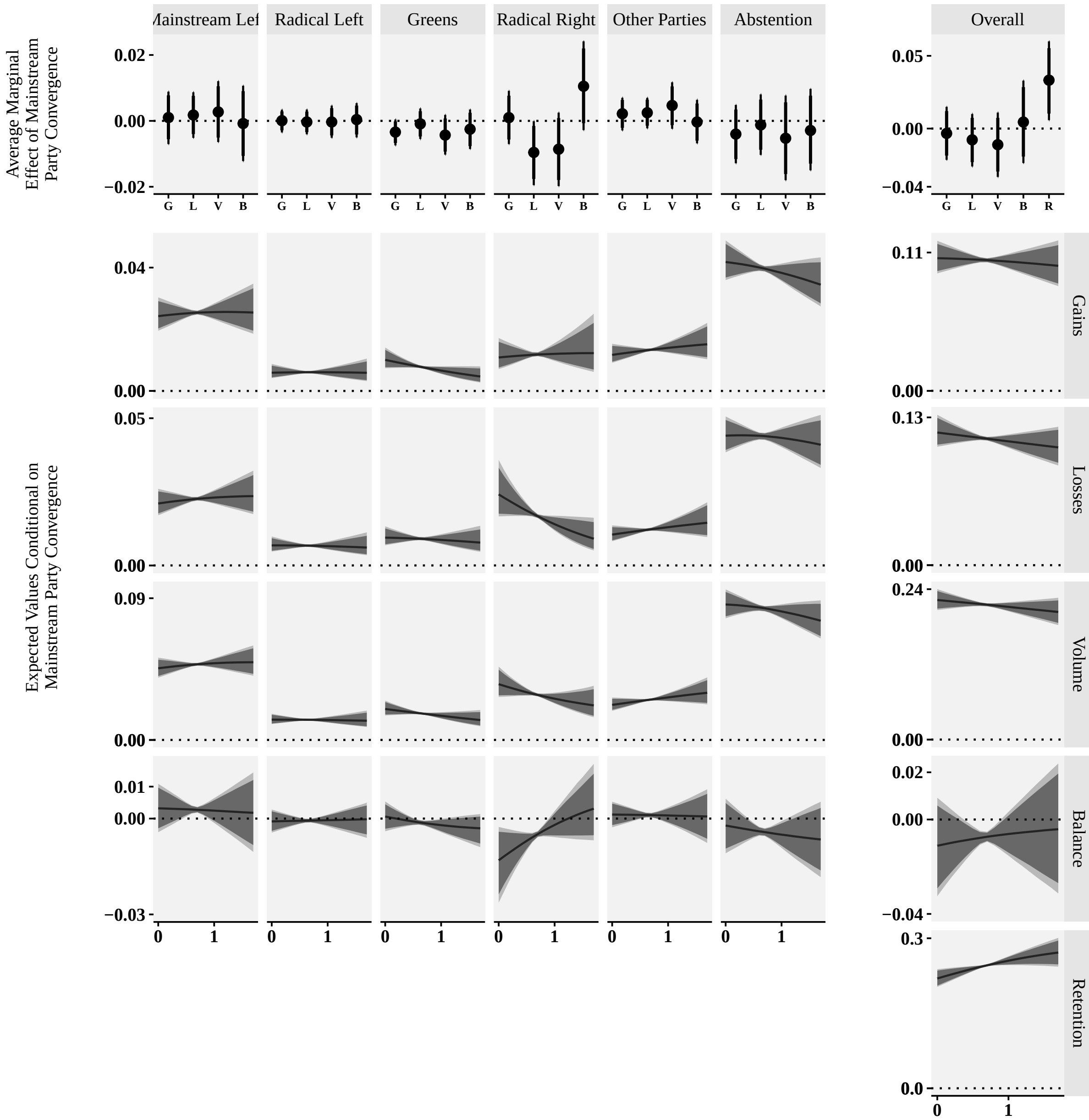

Figure A5.14: Vote switching quantities of interest as a function of mainstream party divergence (MPD). Mainstream right parties only.

Focal category: Mainstream left parties

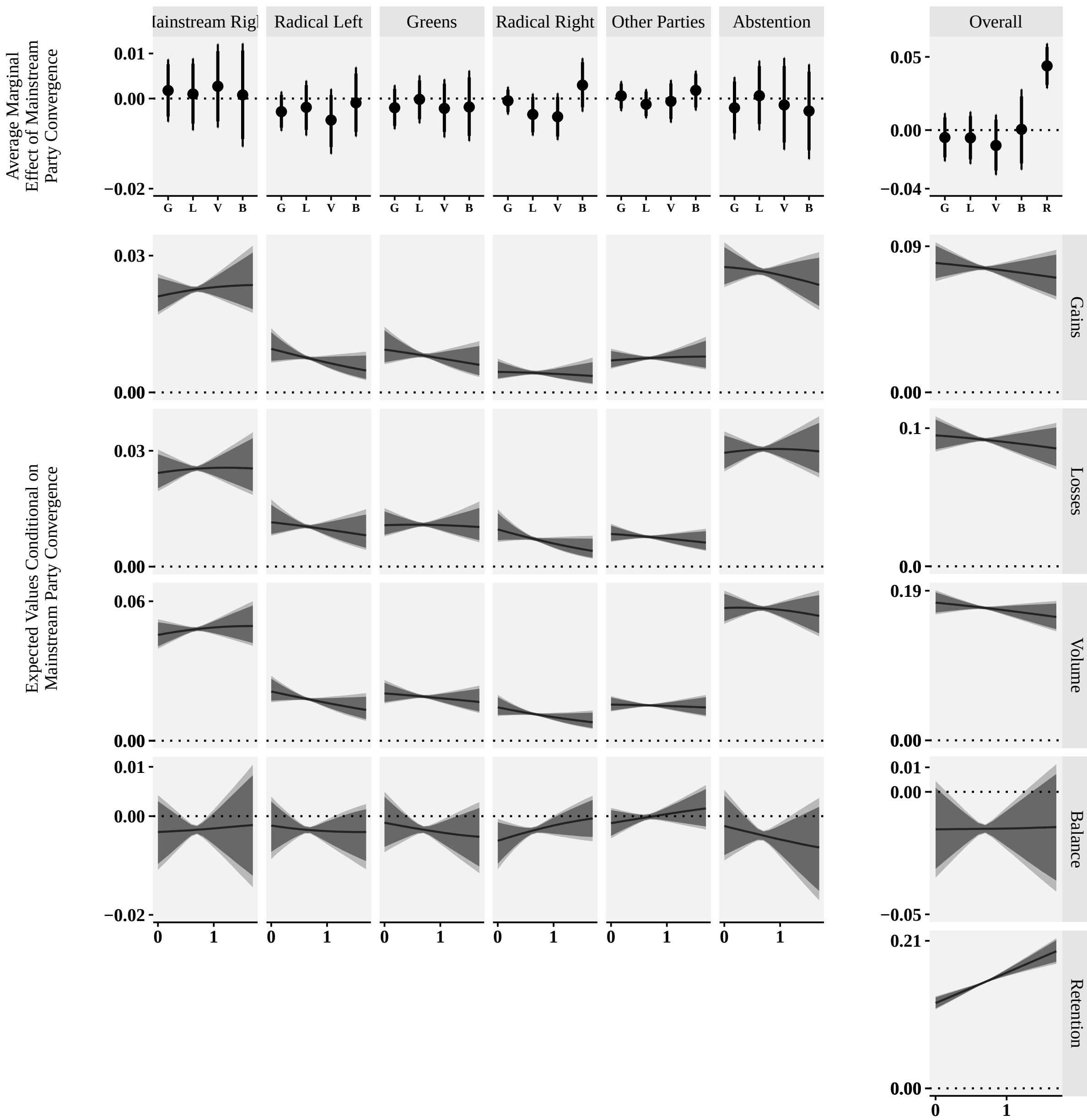

Figure A5.15: Vote switching quantities of interest as a function of mainstream party divergence (MPD). Mainstream left parties only.

A5.5 Robustness: No imputation

For the following analyses, we have foregone the imputation of respondents' vote choices at t and $t-1$ in our data-processing routine. As a result, the raw voter transition matrices only include those respondents with non-missing vote switching information. These are then raked and aggregated as usual. With only one set of rake-weighted cell counts per election, as opposed to M multiple imputations thereof, we then run one pair of Markov chains for a length of 3000 draws of which we discard the first 2000 as warmup, thin the remaining 1000 by a factor of two, and then process the resulting 1000 posterior samples. As we can see, the results are indistinguishable from those presented in the main text and in Figs. A5.5 and A5.6 above.

Main effects

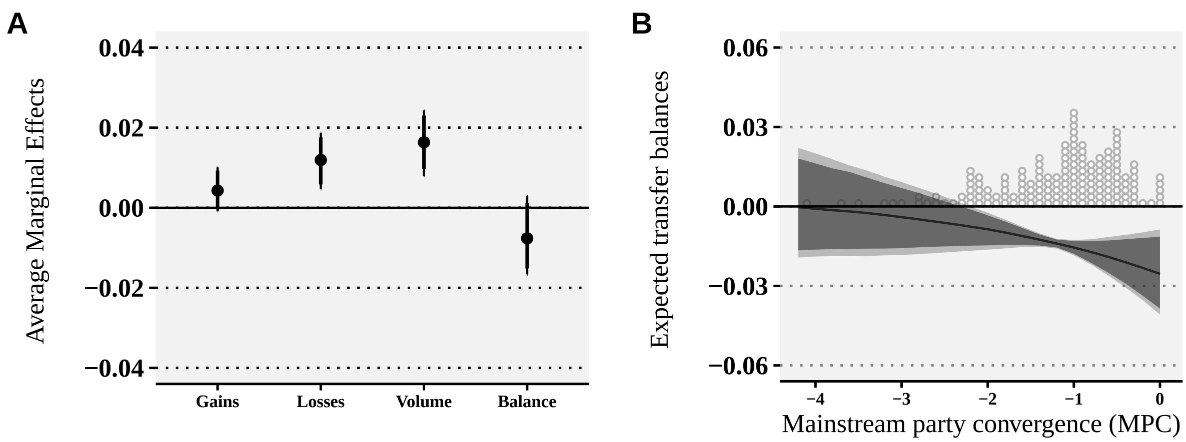

Figure A5.16: A: Average marginal effects of mainstream party convergence (MPC) on mainstream party gains, losses, volumes and balances with challenger parties. B: Expected mainstream party transfer balances with challenger parties as a function of MPC. Posterior medians with 90% and 95% credible intervals.

Secondary effects

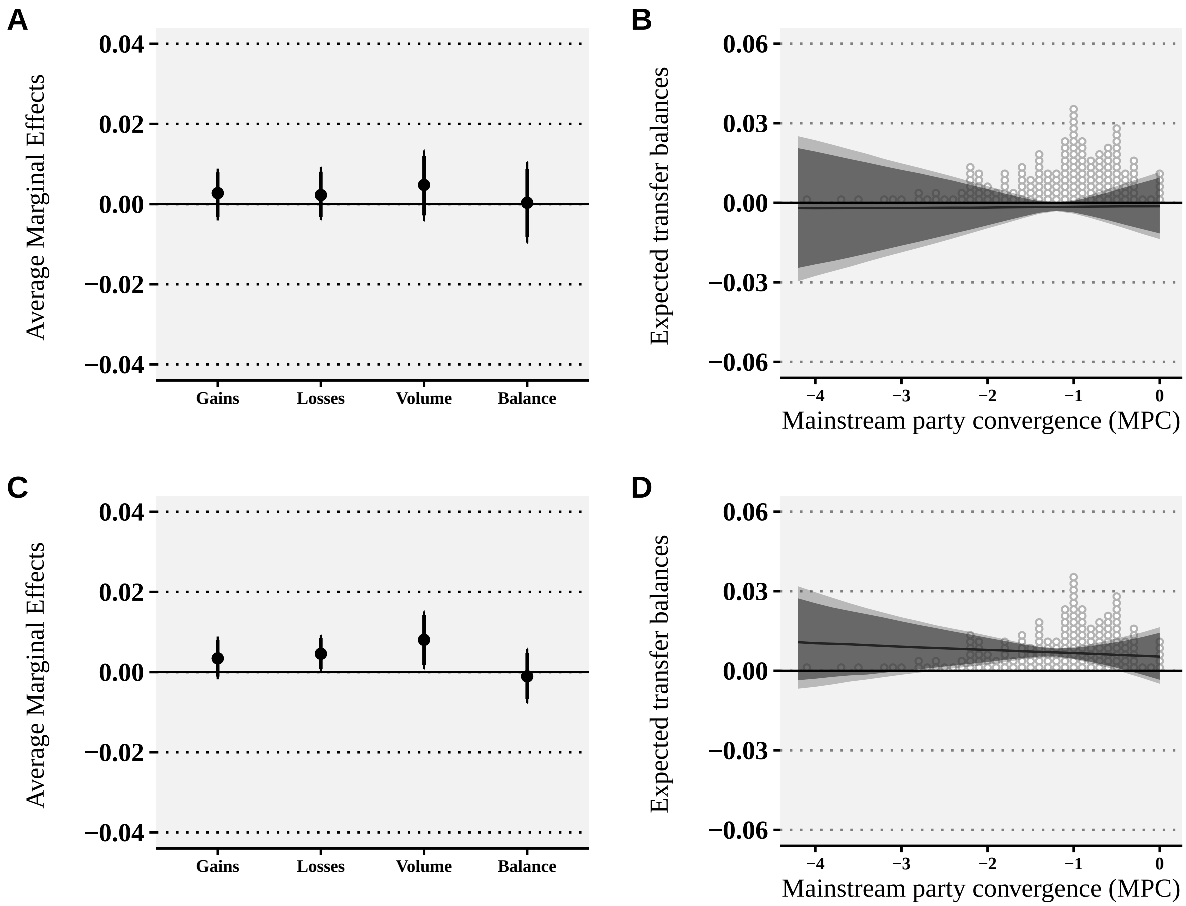

Figure A5.17: A: Average marginal effects of mainstream party convergence (MPC) on mainstream party gains, losses, volumes and balances with other parties and non-voters. B: Expected mainstream party transfer balances with other parties and non-voters as a function of MPC. C: Average marginal effects of mainstream party convergence (MPC) on challenger party gains, losses, volumes and balances with other parties and non-voters. D: Expected challenger party transfer balances with other parties and non-voters as a function of MPC. Posterior medians with 90% and 95% credible intervals.

Overall effects

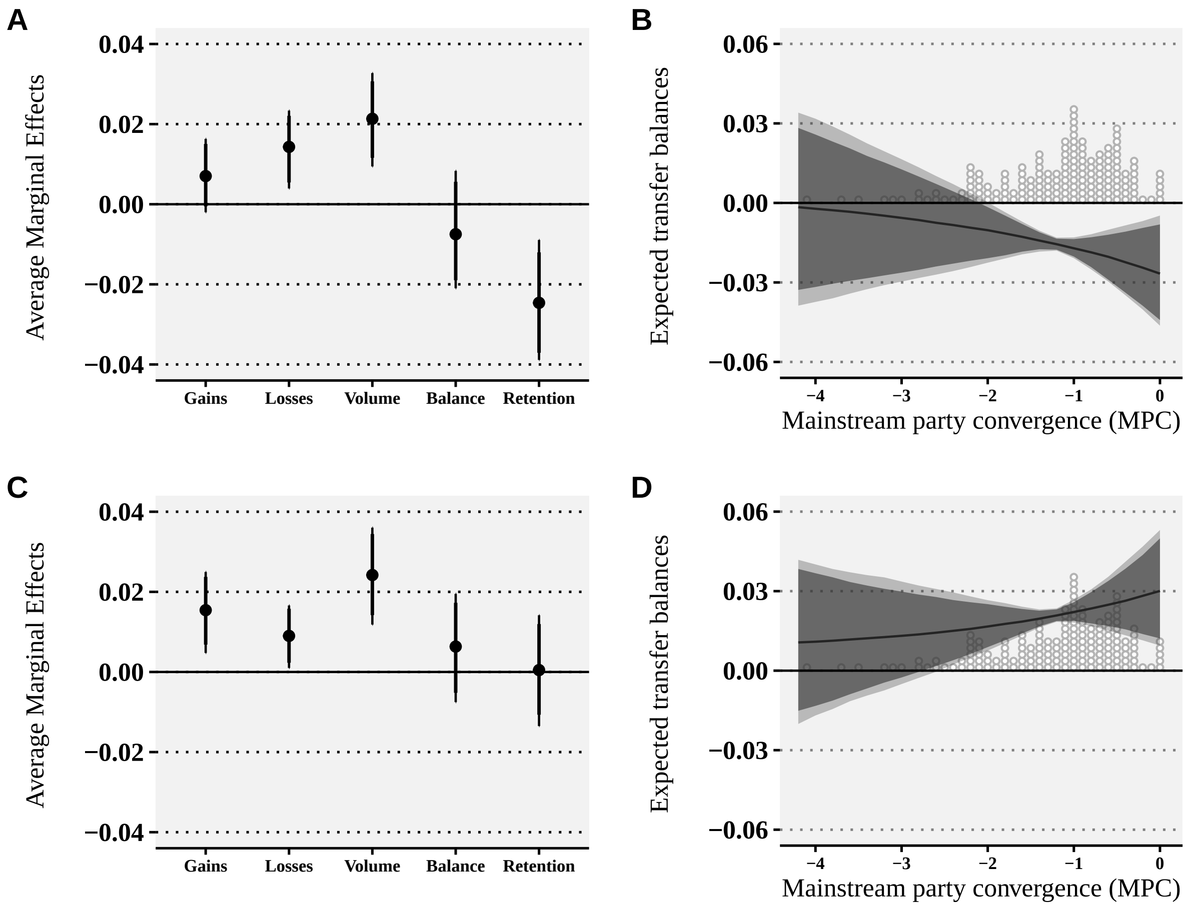

Figure A5.18: A: Average marginal effects of mainstream party convergence (MPC) on mainstream party overall gains, losses, volumes, balances, and retention. B: Expected overall mainstream party transfer balances as a function of MPC. C: Average marginal effects of mainstream party convergence (MPC) on challenger party overall gains, losses, volumes, balances, and retention. D: Expected overall challenger party transfer balances as a function of MPC. Posterior medians with 90% and 95% credible intervals.

Focal category: Mainstream right parties

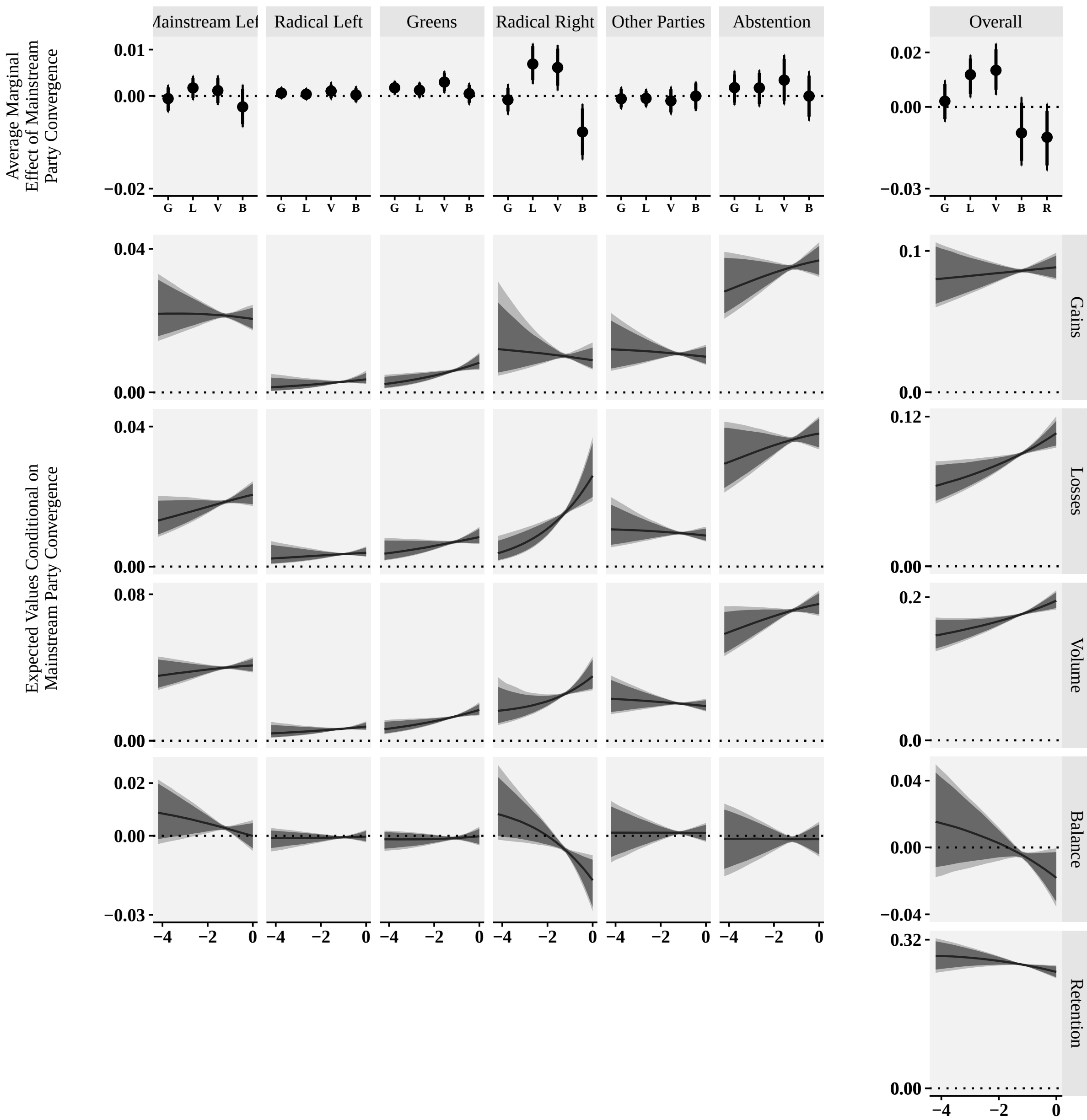

Figure A5.19: Vote switching quantities of interest as a function of positional convergence. Mainstream right parties only.

Focal category: Mainstream left parties

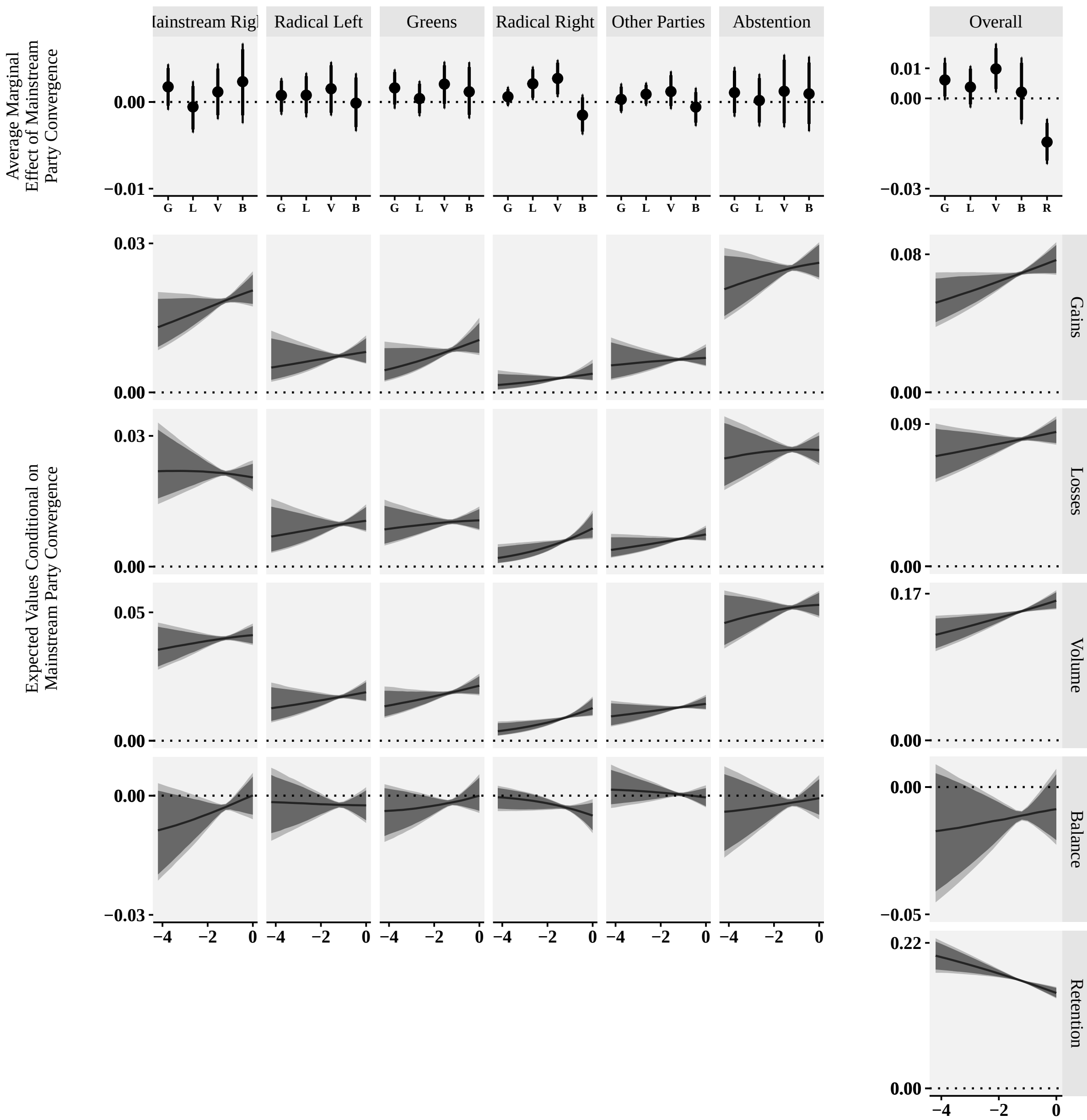

Figure A5.20: Vote switching quantities of interest as a function of positional convergence. Mainstream left parties only.

A6 Case study: Survey-based vote switching estimates in Germany, 2013-2017

Motivating problems

As we have explained in the main text, a key challenge in studying comparative vote switching is that we cannot directly observe voter transition matrices. While we know the true *marginal* distribution of a voter transition matrix per the official vote shares and abstention rates, we never know the true *joint* distribution. We must therefore rely on survey-based estimates.

Survey-based reports of vote switching are usually based on vote recall questions. The timing of the corresponding data collection can vary quite drastically between different types of surveys. *Post-election cross-sections* typically interview respondents a few days or week after an election at t, and prompt respondents to jointly recall their vote choices at t *and* $t-1$ – the latter of which may lie four or five years in the past. *Inter-election panels*, on the other hand, track the same individuals over time, which allows them to prompt respondents to recall their vote choices at t and $t-1$ on separate occasions, both of which usually happen in close temporal proximity to the respective election.

Regardless of the survey type, reports of voting behavior contains (usually unknown) levels of measurement error. In general, three groups of factors are assumed to explain respondents' incorrect reporting of past voting behavior (see, e.g., Dassonneville and Hooghe 2017):

1. social desirability
2. false memory
3. avoidance of cognitive dissonance

Social desirability bias, typically associated with overreporting of turnout and underreporting of vote choices for ostracized radical parties, is a general problem for survey-based electoral research that pertains to cross-sectional and longitudinal studies of vote switching alike. The other two factors, which we will jointly refer to as *recall bias*, may affect cross-sectional reports more severely than longitudinal reports: *False memory* is expected to increase with time, and the *avoidance of cognitive dissonance* (meaning that individuals want to streamline reports of past voting behavior with their current party preference) becomes more likely the more time passes during which individuals may update their party preferences.

However, panel data comes with its own disadvantages that might introduce other sources of bias. Most importantly, *(selective) panel attrition* can influence observed vote switching patterns. The direction of this bias is usually unknown and will be more consequential the less randomly distributed it is across respondents. In addition, collecting panel data is a costly approach. Inter-election panels are therefore comparatively rare, which makes the data type less eligible for comparative researchers.

Both post-election cross sectional surveys and inter-election panel surveys are thus prone to different types of measurement error. Combined with the problem that we never know the true voter transition matrix, comparisons between the two can therefore only uncover differences – not errors – in the joint distributions of vote choices at $t-1$ and t (though we can, of course, compare errors in the respective marginal distributions).

Case and empirical strategy
In the following, we conduct a case study that contrasts different data collections from which we can estimate vote switching patterns. We focus on the 2017 German general election, which is special in that it allows us to compare voter transition matrices across three different data sources:

1. An inter-election panel in the form of the GLES 2013-2017 long-term panel (GLES-LTP).
2. A large, general household panel in the form of the 2014 and 2018 waves of the German Socio-Economic Panel (GSOEP)
3. The same post-election cross-sectional data used in `voteswitchR`, the 2017 Post-Election Cross-Section of the German Longitudinal Election Study (GLES-PECS).

Inspecting the GSOEP is valuable in that we can introduce a third data set – an established, large, high-quality, and representative household panel – that can serve as an additional and reasonably credible benchmark for the post-election cross-section and the inter-election panel surveys. The GSOEP interviews approximately 30,000 respondents from 15,000 households. It has been in operation since 1984; its 2014 and 2018 waves are the first to include vote recall items for the 2013 and 2017 German *Bundestag* elections, respectively. While the GSOEP, of course, is also vulnerable to all the three types of measurement error discussed above, we think that it is the best estimate of the true voter transition matrix available.

	GLES-LTP	**GSOEP**	**GLES-PECS**
Type	inter-election panel	general household panel	post-election survey
Days since election at $t-1$	6 - 92	103 - 418	1465 - 1530
Days since election at t	1 - 75	101 - 452	2 - 67
Sample Size	865	13001	1805
Panel Attrition	65.2%	37.9%	
Error at $t-1$	6.37	4.06	3.8
Error at t	5.89	4.16	3.51
Error at $t-1$ with raking	1	0.02	0.02
Error at t with raking	1.52	0.03	0.03
Proportion of switchers	0.47	0.4	0.45
Proportion of switchers with raking	0.58	0.46	0.44
Eligibility for comparative research	medium	low	high

Table A6.9: Data overview

Table A6.9 gives an overview of the core characteristics of the three data sets and contrasts their respective advantages and disadvantages. Tables A6.10 and A6.11 yield additional, more nuanced insights by reporting both party-specific directional errors and attrition rates dependent on respondents' 2013 vote choice. Tables A6.12 and A6.13, lastly, show the estimates of the voter transition matrices based on the three data sets with and without application of raking, respectively.

Data	CDU/CSU	SPD	FDP	GREENS	LEFT	AfD	OTH	NON
GLES LTP	63.5	61.5	54.8	51.9	61.4	61.7	60	88.1
GSOEP	34.5	33.6	31.4	29.6	33.8	35.5	36	55.3

Table A6.10: Party-specific panel attrition rates based on 2013 vote choice.

Data	CDU/CSU	SPD	FDP	GREENS	LEFT	AfD	OTH	NON
GLES-LTP 2013	4.71	10.7	2.23	7.24	0.11	0.58	-1.12	-24.3
GLES-LTP 2017	4.67	7.24	2.73	6.06	2.9	-1.83	-0.37	-21.3
GSOEP 2013	5.61	7.26	-0.67	2.94	-1.19	-1.22	0.38	-13.2
GSOEP 2017	6.37	7.24	-0.37	2.86	-1	-2.13	0.23	-13.1
GLES-PECS 2013	3.21	5.06	-0.17	4.94	2.01	-2.12	-1.92	-11
GLES-PECS 2017	2.57	3.54	1.23	4.86	1.9	-0.93	-0.37	-12.7

Table A6.11: Party-specific directonal errors in vote proportions.

Results

We have assessed the three data sets and the resulting voter transition matrices using the following evaluation metrics:

- *Recency (days since election at $t-1$):* The **GLES-LTP** has clear advantages in terms of minimizing the duration between election day and the interview. Here, respondents were questioned directly after the two elections, respectively.[9] As a general household panel, the **GSOEP** is not timed around national elections; annual interviews are mostly conducted between January and September. Therefore, respondents' vote choices in the September 2013 and September 2017 elections were mostly reported between January and September of 2014 and 2018, respectively. As expected, timed shortly after the 2017 election, the **GLES-PECS** combines a short duration for the election at t with a very long duration since the election at $t-1$.
- *Sample size:* Unsurprisingly, as a large general household panel, the **GSOEP** has the largest number of respondents at 13001 observations with valid vote recall information for both 2013 and 2017. The cross-section of the **GLES-PECS** includes 1805 valid data points. Not least due the massive attrition rate, the **GLES-LTP** contains this information for only 865 respondents.

[9]Note that respondents who were interviewed before the 2013 German federal election were excluded from the following estimations.

- *Panel attrition:* To study a vulnerability to valid estimates of voter transition matrices that is unique to panel data, we report attrition rates for both the GSOEP and the GLES-LTP. These numbers reflect the percentage of respondents with valid 2013 vote choice information who are no longer part of the panel in the wave in which their 2017 vote choice would have been recorded. We note that both the GSOEP and the GLES-LTP contain individual time series that began before the wave in which their 2013 vote choice was recorded; we thus do not assess problems to representativeness caused by pre-2013 panel dropouts and provide a rather conservative estimate of the severity of panel attrition here. Even so, the numbers are worrying. The overall panel attrition rates based on all respondents with a valid (non-)vote in 2013 is 65.2% for the **GLES-LTP** and 37.9% for the **GSOEP**. Table A6.10 gives the attrition rates conditional on respondents' 2013 vote choice. Here, the attrition rates seem to be relatively equally distributed across voter groups, with one important exception: Non-voters drop out at excessive rates of 88% (**GLES-LTP**) and 55% (**GSOEP**).
- *Representativeness (pre-raking):* We assess the representativeness of the marginal distributions of the three voter transition matrices by reporting the mean absolute error of the weighted – but unraked – vote proportions relative to the actual election results of the 2013 ($t-1$) and 2017 (t) German federal elections. Remarkably, the **GLES-PECS** and the **GSOEP** estimates show substantially similar values of around four percentage points, while the **GLES-LTP** error is much larger at 6.4 and 5.9 percentage points, respectively. Table A6.11 digs a little deeper by showing the directional party-specific errors. Here, we learn that – although all three surveys drastically underestimate the share of non-voters and overestimate the shares of CDU/CSU, SPD, and Green voters – the **GLES-PECS** does so least, followed closely by the **GSOEP**, with the **GLES-LTP** in a distant third place.
- *Representativeness (post-raking):* In the next step, we calculated the same metrics after applying the raking routine to the voter transition matrices from three data sets. For comparability, we use non-imputed values and retain information from the sampling/post-stratification weights included in the different data sets. As can be seen in Table A6.9, the **GSOEP** and the **GLES-PECS** now perform equally well with a near-zero mean absolute error of about 0.2 percentage points. In addition, all cells in the transition matrices show only small differences in the party-specific transition patterns between the two data sets. Even after applying the raking procedure, the **GLES-LTP** data fails to give accurate estimates of the share of non-voters.
- *Estimated proportion of switchers (pre-raking)*: One of the frequently voiced caveats against the long-term vote recall questions in cross-sectional vote switching estimates is the under-estimation of switchers. As critics argue, false memory and the avoidance of cognitive dissonance lead respondents to report that they voted the same way at $t-1$ as they did at the more recent election t. Based on the unraked voter transition cells in Table A6.12 and the summary in Table A6.9, we do not find support for this argument. With an estimated pre-raking proportion of switchers and 95% confidence interval of 0.446 (0.422, 0.469), the cross-sectional **GLES-PECS** has a *higher* proportion of switchers than the **GSOEP** [0.405 (0.396, 0.413)] and only a marginally (and statistically insignificantly) lower proportion than the **GLES-LTP** [0.469 (0.434, 0.506)]. In terms of party-specific retention rates, the GLES-PECS yields notably *lower*

estimated retention rates for the major parties CDU/CSU and SPD than both GSOEP and GLES-LTP.

- *Estimated proportion of switchers (post-raking)*: Turning to the raked voter transition cells in Table A6.13, and the corresponding summary in Table A6.9, we find no major discrepancies between the **GLES-PECS** and the **GSOEP**. When comparing the two transition matrices, we find only small pairwise differences in the cell proportions. Post-raking, we no longer find a statistically significant difference in the proportion of switchers between the two data sets: The proportion is 0.443 (0.420, 0.467), for the **GLES-PECS** and 0.460 (0.452, 0.469) for the **GSOEP**. For most cells, the **GLES-LTP** is in the ballpark of the **GLES-PECS** and **GSOEP**. A systematic exception are the non-voter switching and retention cells: Due to the initial under-sampling of non-voters, the raking procedure produces much larger cell proportions for all non-voter switching rates and a much lower proportion for the non-voter retention rate vis-à-vis the **GLES-PECS** and the **GSOEP**. This artificially boosts the overall proportion of switchers to unreasonably high levels.
- *Eligibility for comparative research* is highest for post-election cross-sections. `voteswitchR` contains vote switching data for 260 elections, compared to several dozen inter-election panel surveys that could be used alterantively. High-quality household panels that contain vote choice items are rare; to the best of our knowledge, the only comparable alternatives are the BHPS-UKHLS in the UK (since 1992), the Swiss Household Panel (since 1999), and the more recent Dutch LISS panel (since 2006).

Conclusion

Conventional wisdom argues that inter-election panels yield more accurate estimates of voter transition matrices than cross-sectional post-election surveys due to a recency advantage in vote recall questions. This, so the argument goes, minimizes recall biases due to false memory and false reporting that results from avoiding cognitive dissonances in light of updated party preferences. In stark contrast to this, we find that large and selective panel mortality gravely jeopardizes the representativeness of the GLES-LTP and consequently diminishes the validity of the corresponding voter transition estimates. Additionally, we find that cross-sectional post-election surveys with contemporaneous recall questions for vote choices at $t-1$ and t like the GLES-PECS can perform on par with an exceptional high-quality household panel like the GSOEP.

More generally, as our analyses have shown, raking is no panacea for turning a bad survey data set into a good one. Contrary to initial concerns, this problem pertained to the GLES-LTP – not to the GLES-PECS. In other applications, however, the problem may apply to post-election cross-sections included as part of the `voteswitchR` data infrastructure. `voteswitchR` therefore provides the `calculate_meas_error()` function. This function allows users to compute party-election-specific directional errors and election-level mean absolute errors or root mean squared errors, using either nominal parties or a user-supplied comparative scheme to define the marginal categories of voter transition matrices. These metrics allow users to assess the quality of the underlying survey data. While this is by no means a perfect measure, it is the best available – and the only objective – criterion to assess the accuracy of (unraked) survey-based transition matrices in terms of their marginal vote proportions. These can then guide users in their decisions on context inclusion and robustness checks.

	Data	CDU/C '17	SPD '17	FDP '17	GREEN '17	LEFT '17	AfD '17	OTH '17	NON '17	2013
CDU/CSU '13	GLES-LTP	22	1.29	5.63	0.57	0.6	2.32	0.64	0.95	**34**
	GSOEP	24.62	1.76	2.89	0.85	0.5	2.06	0.87	1.35	**34.91**
	GLES-PECS	21.02	1.14	3.94	1.04	0.32	3.04	0.37	1.62	**32.5**
SPD '13	GLES-LTP	1.92	16.11	1.7	3.87	2.68	1.54	0.34	0.59	**28.75**
	GSOEP	2.37	16.1	1.2	1.74	1.2	0.86	0.48	1.42	**25.37**
	GLES-PECS	1.85	13.56	1	1.68	2.36	0.93	0.29	1.49	**23.16**
FDP '13	GLES-LTP	1.42	0.08	1.69	0.00	0.00	0.25	0.00	0.03	**3.47**
	GSOEP	0.54	0.12	1.22	0.07	0.04	0.11	0.05	0.11	**2.24**
	GLES-PECS	1.04	0.23	2.96	0.36	0.22	0.38	0.00	0.18	**5.36**
GREEN '13	GLES-LTP	1.52	2.31	0.71	7.03	0.74	0.12	0.63	0.18	**13.24**
	GSOEP	0.54	1.33	0.35	5.64	0.58	0.07	0.32	0.12	**8.94**
	GLES-PECS	0.44	1.21	1.01	6.41	0.89	0.06	0.49	0.4	**10.92**
LEFT '13	GLES-LTP	0.55	0.49	0.38	0.77	4.65	0.99	0.21	0.27	**8.32**
	GSOEP	0.28	0.55	0.15	0.14	2.87	0.8	0.23	0.4	**5.42**
	GLES-PECS	0.1	0.44	0.06	0.5	3.38	0.7	0.29	0.47	**5.94**
AfD '13	GLES-LTP	0.93	0.78	0.44	0.06	0.19	1.4	0.00	0.06	**3.86**
	GSOEP	0.15	0.15	0.26	0.04	0.03	1.05	0.24	0.15	**2.07**
	GLES-PECS	0.06	0.07	0.00	0.00	0.07	0.94	0.02	0.07	**1.23**
OTH '13	GLES-LTP	0.37	0.38	0.14	0.13	0.38	0.45	1.39	0.05	**3.3**
	GSOEP	0.49	0.86	0.24	0.52	0.42	0.75	1.07	0.45	**4.8**
	GLES-PECS	0.08	0.14	0.1	0.14	0.12	0.65	1.03	0.26	**2.53**
NON '13	GLES-LTP	0.8	1.27	0.28	0.36	0.41	0.66	0.14	1.15	**5.07**
	GSOEP	2.17	1.83	0.79	0.62	0.94	1.69	0.73	7.49	**16.25**
	GLES-PECS	2.81	2.19	0.95	1.42	0.89	1.85	0.89	7.37	**18.36**
2017	**GLES-LTP**	**29.49**	**22.72**	**10.99**	**12.78**	**9.67**	**7.73**	**3.35**	**3.27**	**100**
	GSOEP	**31.17**	**22.69**	**7.1**	**9.61**	**6.57**	**7.38**	**3.99**	**11.49**	**100**
	GLES-PECS	**27.41**	**18.97**	**10.02**	**11.55**	**8.24**	**8.55**	**3.4**	**11.86**	**100**

Table A6.12: Germany 2013-2017 transition matrix without raking.

	Data	CDU/C '17	SPD '17	FDP '17	GREEN '17	LEFT '17	AfD '17	OTH '17	NON '17	2013
CDU/CSU '13	GLES-LTP	19.37	0.65	3.64	0.3	0.24	2.26	0.44	4.05	**30.94**
	GSOEP	18.41	1.21	2.76	0.62	0.46	2.06	0.7	3.07	**29.29**
	GLES-PECS	18.51	0.96	3.43	0.68	0.25	2.45	0.3	2.72	**29.29**
SPD '13	GLES-LTP	1.8	8.72	1.18	2.17	1.13	1.6	0.25	2.31	**19.16**
	GSOEP	1.54	9.64	1	1.11	1	0.78	0.32	2.75	**18.14**
	GLES-PECS	1.46	10.19	0.78	0.98	1.63	0.67	0.21	2.23	**18.14**
FDP '13	GLES-LTP	1.41	0.04	1.26	0.00	0.00	0.28	0.00	0.58	**3.58**
	GSOEP	0.63	0.14	1.91	0.08	0.06	0.19	0.07	0.31	**3.39**
	GLES-PECS	0.66	0.14	1.86	0.17	0.12	0.22	0.00	0.22	**3.39**
GREEN '13	GLES-LTP	0.92	0.8	0.32	2.53	0.2	0.08	0.29	1.16	**6.3**
	GSOEP	0.35	0.78	0.28	3.53	0.47	0.06	0.22	0.28	**5.96**
	GLES-PECS	0.28	0.73	0.63	3.02	0.49	0.04	0.28	0.48	**5.96**
LEFT '13	GLES-LTP	0.46	0.23	0.23	0.38	1.74	0.91	0.14	2.31	**6.41**
	GSOEP	0.24	0.43	0.16	0.12	3.09	0.88	0.21	0.95	**6.07**
	GLES-PECS	0.11	0.45	0.06	0.39	3.15	0.68	0.28	0.96	**6.07**
AfD '13	GLES-LTP	0.8	0.39	0.28	0.03	0.08	1.35	0.00	0.58	**3.5**
	GSOEP	0.21	0.19	0.42	0.05	0.05	1.66	0.32	0.41	**3.32**
	GLES-PECS	0.18	0.19	0.00	0.00	0.16	2.35	0.06	0.37	**3.32**
OTH '13	GLES-LTP	0.6	0.36	0.17	0.12	0.28	0.81	1.75	0.58	**4.66**
	GSOEP	0.36	0.56	0.22	0.36	0.38	0.72	0.82	1	**4.42**
	GLES-PECS	0.15	0.22	0.18	0.19	0.19	1.02	1.63	0.84	**4.42**
NON '13	GLES-LTP	2.31	5.2	1.73	1.73	3.47	2.89	1.16	6.94	**25.43**
	GSOEP	3.1	2.52	1.37	0.87	1.44	3.18	1.12	15.82	**29.41**
	GLES-PECS	3.49	2.59	1.17	1.31	0.97	2.1	1.01	16.78	**29.41**
2017	**GLES-LTP**	**27.67**	**16.4**	**8.82**	**7.27**	**7.14**	**10.18**	**4.03**	**18.5**	**100**
	GSOEP	**24.83**	**15.46**	**8.1**	**6.74**	**6.97**	**9.53**	**3.77**	**24.6**	**100**
	GLES-PECS	**24.83**	**15.46**	**8.1**	**6.74**	**6.97**	**9.53**	**3.77**	**24.6**	**100**

Table A6.13: Germany 2013-2017 transition matrix with raking.

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