Survey Research Methods (2020)
Vol. 14, No. 5, pp. 461-476
doi:10.18148/srm/2020.v14i5.7628

© European Survey Research Association
ISSN 1864-3361
http://www.surveymethods.org

Integrating Large-Scale Online Surveys and Aggregate Data at the Constituency Level: The Estimation of Voter Transitions in the 2015 British General Elections

Paul. W. Thurner
Department of Political Science
LMU Munich, Germany

Ingrid Mauerer
Department of Political Science
LMU Munich, Germany

Maxim Bort
Statistical consulting unit StaBLab
Department of Statistics
LMU Munich, Germany

André Klima
Statistical consulting unit StaBLab
Department of Statistics
LMU Munich, Germany

Helmut Küchenhoff
Statistical consulting unit StaBLab
Department of Statistics
LMU Munich, Germany

What have been the underlying voter shifts that led to the victory of the Conservative Party in the 2015 British general election – against all predictions by pollsters? Analyses of voter transitions based on (online) surveys and recall questions are plagued by sampling and response biases, whereas aggregate data analyses are suspect of the well-known ecological fallacy. We propose a systematic statistical combination of individual-level survey and administrative data at the constituency level to identify regional electoral shifts between the 2010 to 2015 British general elections. The large-scale individual-level data collected by the British Election Study Internet Panel (BESIP) allow us to locate more than 28,000 respondents in their constituencies. We estimate voter transitions based on a recently developed Bayesian Hierarchical Hybrid Multinomial Dirichlet (HHMD) model. We discover substantial deviances from pure survey-based estimations of transition matrices.

Keywords: Voter Transitions; Individual Survey Data; Aggregate Data; Hybrid Models; British General Elections

1 Introduction

Exceptionally high landslides marked the 2015 British general election. It is an open question how these results came about. In this paper, we study the voter shifts that led to the unexpected victory of the Tories by drawing on a recently developed approach for the estimation of such transitions. In the run-up to the election, pollsters predicted a neck-to-neck rally between Labour and Conservatives, and the possibility of a hung parliament without clear majorities. It was, therefore, an utter surprise that the Conservatives achieved a clear majority of the seats (330 as compared to 232 seats for Labour). The Liberal Democrats, the junior coalition partner of the Conservatives since 2010, lost two-thirds of its all high share of 23 percent (57 seats) in 2010 and maintained only 7.9 percent of votes (8 seats) in 2015. Commentators characterized this as an "electoral meltdown" (Cutts & Russell, 2015) of UK's "third party" since 1921. The EU-critical UK Independence Party (UKIP) continued its successes, sparked at the second-order elections in 2013 (Local Elections) and especially at the European Parliament elections in May 2014[1] by more than quadrupling its 2010 vote share of 2.2 percent to 9.3 percent (from 919,471 to 3,881,099 votes). Despite becoming the third largest party in terms of votes, the party nevertheless received only one seat. The Scottish National Party (SNP) nearly tripled its votes from 491,386 in 2010 to 1,454,436 in 2015 but achieved 56

Contact information: Paul W. Thurner, Empirical Political Research and Policy Analysis, Department of Political Science, Ludwig-Maximilians-University Munich (LMU), Oettingenstr. 67, 80538 Munich Germany (E-Mail paul.thurner@gsi.uni-muenchen.de)

[1]Note that it received the majority of votes in the UK.

of 59 seats in Scotland—leading actually to a "meltdown" of Labour to 18 percent of votes in Scotland (Curtice, 2015, p. 35). The underlying volatility rendered the SNP the third largest party in terms of seats in the House, superseding thereby the Liberal Democrats for the first time as third party (Curtice, 2015). Experts considered the election at that time as leading to a fragmentation of the UK party system:

> "The sum of these changes was the most volatile election since 1931 (as measured by the Pedersen index) and the highest effective number of electoral parties since expansion of the franchise in 1918." (Green & Prosser, 2016, p. 1299)

Given this exceptionally high volatility, it is surprising that there are few scientific contributions studying only partial aspects of the underlying micro-transitions of voters switching from one party to another. E.g., Evans and Mellon (2016) provide a discussion of vote switching towards UKIP. They contest results by Ford and Goodwin (2014) according to which UKIP voters have been mainly attracted from the working class segment and former voters of Labour. This study, just as the one on voter flows between the elections 2015 to 2017 by Mellon, Evans, Fieldhouse, Green, and Prosser (2018), uses survey data, i.e. the British Election Study Internet Panel (BESIP). Survey data in general are often plagued by sampling and response biases,[2] despite they are often considered to be the objective gold standard for voter transition research. Which methodical approaches can be used in order to detect the complicated shifts appropriately? We resume anew the discussion on the proper identification of the direction and the extent of inter-election voter loyalty and voter transition. We exemplify this investigation with the 2015 British general election due to its remarkably high aggregate volatility. Additionally, the availability of an exceptionally large set of individual respondents enables the systematic comparison of different methods of estimations. We illustrate the superiority of the combination of survey with aggregate data based on the so-called Bayerian Hybrid Hierarchical Multionomial Dirichlet Model (HHMD, see Klima, Schlesinger, Thurner, & Küchenhoff, 2019). Our results show remarkable differences for turnout-related flows as compared to purely survey-based estimates. This corroborates insights from the "assessment of the causes of the errors in the 2015 UK General Election opinion polls" (Sturgis et al., 2017).

In the following, we first discuss research on voter transitions—with a special view on UK studies in this area. Second, we describe our methodical approach and propose to use BESIP data to locate panel participants in their respective constituencies. Then, we provide descriptive statistics on the distribution of surveyed respondents as compared to actual aggregate outcomes. In the next section, we compare our estimations for England, Wales and Scotland. We introduce convergence diagnostics, and for illustrative reasons we also present alternative, survey-based projections as an additional yardstick. Finally, we conclude with a discussion of the results and with an assessment of the potential of our approach.

2 Voter Transition Research

Voter transition research focuses on the number of individual voters switching parties (including the "abstain party") from one election to another.[3] This topic is of enormous theoretical and practical importance because party elites and whole party organizations, as well as governments, learn from these observable decisions whether and to which degree their policies—be they enacted, or promised—are accepted or refused, respectively. Just as Hirschman (1970) has outlined in his famous book "Exit, Voice and Loyalty. Responses to Decline in Firms, Organizations and States", voters and party members have three behavioral options: they can stay and remain loyal in the face of consistently provided good quality by the political supplier, or simply due to unquestioned habit. On the other hand, they may choose "exit" and move to another supplier because of a perceived degradation of policies and political personnel, or new and better offers by other or new party organizations (new entrants). There is also the possibility to "voice" within the organization, i.e., by trying to contribute communicatively to improve the organization and its offers.

Why then does voter transition analysis play a relatively minor role in electoral scientific research, at least as compared to the cross-sectional prediction and explanation of vote intentions and choices in elections? The underlying reason is a highly complicated problem: we simply do not have an external reference against which we can assess the quality of the estimates. This is different as compared to the forecasting of election results, where the final outcome on election day is the error-free and costless yardstick. Contrary, for voter transitions, we do not have true objective values.

There are three predominant approaches for the estimation of voter transitions: survey-based approaches and aggregate data-based approaches. The former distinguishes additionally between a panel-data approach and a recall-question approach.

The first approach relies on the identification of voter transitions using panel surveys where the party choices of the same individuals are surveyed in subsequent elections (see,

[2] See Sturgis et al. (2017); Mellon and Prosser (2017) for the case of the 2015 election; for the same problem in the US 2016 election, see Kennedy et al. (2018); more generally: see Selb and Munzert (2013) and Shirani-Mehr, Rothschild, Goel, and Gelman (2018); for the context of voter transitions, see Klima, Thurner, Molnar, Schlesinger, and Küchenhoff (2016).

[3] For overviews of the relevant literature see Achen and Shively (1995), Klima, Küchenhoff, Selzer, and Thurner (2017), Klima et al. (2019), Klima et al. (2016), Schoen (2003).

e.g., Butler & Stokes, 1969; Evans & Mellon, 2016; Schoen, 2003). The advantage is obvious: the declared behavior is measured close to the respective election. A major disadvantage of this procedure—beyond the well-known sampling and response biases—are the usually extremely high panel mortality and the enormous financial costs. The remaining samples are highly selective subpopulations, and how the selection into such samples impacts on specific research objectives is unknown. A cheaper procedure is the usage of the so-called recall question where the respondent is asked to provide the party choice in the previous election as well as in the follow-up election. The recall question can be integrated both into a cross-sectional design as well as in a panel design. A major difficulty with this approach is response biases induced by poor memorizing and rationalization (cognitive dissonance, social desirability). Many vote switchers seem to adjust their previous choices to the most recent one. And many previous abstainers feel themselves pressured to report participation and, therefore, report some imagined choice.[4] There is a meanwhile growing literature using the recall question embedded into panel designs. This allows the comparison between the declared retrospective vote and the actually stated vote (intention or behavior) in the earlier wave. E.g., investigating Norwegian elections Waldahl and Aardal (2000) find up to 40 percent of erroneous recalls in the case of voter switchers, and up to 70 percent of incorrect recalls in the case of former abstainers. Dassonneville and Hooghe (2017) investigate three recent elections in Belgium, Germany and The Netherlands. They find highly accurate recalls for stable voters (between 89 to 97 percent). Contrary for switchers, they find a range from approximately 34 to 79 percent of accuracy. Despite these valuable insights, assessing the accuracy of recalled votes by comparing them to the votes stated in an earlier wave implies the following: it is assumed that the stated votes in the respective previous waves reflect the true objective distributions. However, due to panel mortality, the remaining samples tend to be selective nonrandom sub-populations. Usually, it is unknown how selecting and remaining in such samples impacts on specific objectives, which makes it difficult to base the estimation of voter transitions on such a strong assumption.

Aggregate data are usually available at different administrative levels (e.g., national, regional, constituency, community). These data allow statements about inter-temporal aggregate differences in the shares of voters for specific parties (see e.g. Heath & Goodwin, 2017). It is, therefore, possible to identify losses and gains for parties in terms of percentages and percentage points. A measure for the aggregate volatility of gains and losses is, for example, the well-known Pedersen index (Pedersen, 1979). However, neither from the respective aggregation of percentage point gains and losses, nor from the inspection of the marginals of many tables at fine-grained levels is it possible to deduce micro-decisions (i.e., individual loyalty or the move to a specific other party).

This is a major result by Robinson (1950) who called the risk of such inappropriate cross-level inference "ecological fallacy" (see also Achen & Shively, 1995; King, 1997). Cho and Manski (2008) have shown this problem to be one of non-dissolvable indeterminacy because various possible underlying unobservable micro-shifts are leading to the same outcome at the macro level. Ecological inference models require therefore additional assumptions, often some kind of similarity between the different administrative regions, to allow an estimation. There has been an intense discussion about the validity of the proposed models (for an overview, see Klima et al., 2016).

In sum, there is no established gold standard of observable data for determining the performance of voter transition estimates, neither survey data nor aggregate data.[5]

Given these complicated preconditions, which directions have been taken in UK psephology in order to detect voter transitions in this specific electoral system? In the following, we provide a short outline.

The analysis of switch voters has a longstanding tradition in the UK context. One of the earliest concepts after World War II has been the so-called uniform national swing, a regularity observed by Butler (1952). Due to its simplicity, this swing concept is still propelled by the media, for instance, in the form of the swingometer.[6] For given poll results for the two major parties at the national level in the run-up to an election, this procedure assumes equal percentage point changes at each constituency level compared to the previous election results. Arithmetically, the swing is the average of the percentage point gains/losses of the two major parties. If correct, this simple relationship would allow calculating the resulting seats at the constituency level. Butler and Stokes (1969, pp. 135 et seqq. & 303 et seqq.) ascribed this national uniformity to processes of nationalization, i.e., reactions to national policies which are identical across the country. However, they already pointed to the paradox that such an interpretation would collide with the expectation that a swing rather should lead to proportional changes depending on the previous share for parties in $t-1$ (see already Berrington, 1965; Johnston & Hay, 1982). In order to maintain the idea of identical percentage point changes, the assumption that national information is processed differently in differently composed constituencies was introduced. Major deficits of the uniform swing concept and of the respective

[4]For recent comparative assessments, see Waldahl and Aardal (2000), and Dassonneville and Hooghe (2017).

[5]This might be the reason why some researchers resort to simulation-based assessments where the true values are known (see Greiner & Quinn, 2010; Klima et al., 2019).

[6]See BBC https://www.bbc.co.uk/news/av/election-2015-32502061/election-2015-the-swingometer-in-60-seconds, Retrieved June 2019.

analyses for the identification of voter transitions are clearly the focus on aggregate changes, thus being vulnerable to the mentioned ecological fallacy, and the non-consideration of the possibility of complex indirect voter flows.

Stokes (1969) applied Goodman's ecological regression approach (Goodman, 1953, 1959) to the 1964–1966 elections, but just to show that even under optimal conditions where the central assumption of constant transition rates are at least prima facie met, model estimates still violate the boundedness of transition probabilities, and that the estimated results are different as compared to those achieved from a panel survey. Achen and Shively (1995, pp. 121–133) provide explicit estimates for Stokes's analysis. Both contributions consider their results as a clear sign of the failure of ecological regression.

The implementation of a panel survey to UK elections has been the major invention of the classic Butler and Stokes (1969) study where the authors trace the changing British voter in the 1960–1966 elections. Taking a closer look at their database (see their Appendix), it turns out that they rely on a sample of N=2560 in order to determine the shares of respective stayers and movers. Note that the remaining number of respondents of the 1963–1964–1966 panel was N=1154 (see Butler & Stokes, 1969, p. 454). Given the fact that the authors determine values for 6x6 transition matrices, this is a quite small basis. Nevertheless, it was argued that such a panel design allowed not only the estimation of voter transitions at the national level, but at the same time it was assumed that the identified transition matrix also holds at the constituency levels.

Political geographers, however, showed this assumption to be invalid and accentuated the variability of context conditions in geographic space. Johnston and Pattie (1991b) and coauthors (Johnston & Hay, 1982, 1983) introduced a new procedure, the so-called entropy maximization approach in order to estimate local shift patterns both from national survey data and from aggregate data at the constituency level, the so-called "geography of the flow-of-the vote".[7] Based on national survey results, the results for each constituency where determined accounting for district level margins and the constraint that the summation of districts should equal the nation-wide survey result. This was achieved by the maximum entropy procedure which is equivalent to a multidimensional iterative proportional fitting (see Johnston & Pattie, 1991a) or to generalized raking procedures (see Deville, Särndal, & Sautory, 1993).

The already mentioned study by Evans and Mellon (2016, p. 464) uses "long-term panel data to examine the sequencing of vote switching from Labour to UKIP". The temporal design includes waves to the 2005 and 2010 elections, and a wave in 2014. The study is restricted to England and Wales combined. A major conclusion of the authors is "...that UKIP will hurt the Conservatives in the upcoming General Election."(Evans & Mellon, 2016, p. 477).

Mellon and Fieldhouse (2016) announced a "British Election Study 2015 General Election Constituency Forecast"[8] in the immediate run-up of the election, on 31/03/2015, i.e., about one month before the election day. The study relies on the large-scale BESIP panel. Their forecast is using a sophisticated procedure, i.e., they estimate a logit model generating voter transition probabilities at the national level. The original BESIP data were weighted by population data, and turnout probabilities were empirically estimated.

In face of the pollsters' mispredictions, i.e., the drastic overestimation of Labour and the underestimation of Conservatives, the British Polling Council initiated an inquiry. The resulting report[9] and its conclusions were published in Sturgis et al. (2017) and in Mellon and Prosser (2017), with a slightly different assessment in the latter. However, both identified as major problems the non-representativeness of the sample and the overestimation of turnout. Both articles refute the "late deciders" and "shy Tory voters" (a British variant of the "spiral of silence" (Noelle-Neumann, 1974)) conjectures as major reasons for misprediction.

3 The HHMD Model

The Bayesian Hybrid Hierarchical Multinomial-Dirichlet (HHMD) model (Klima et al., 2017; Klima et al., 2019) systematically combines individual survey data with aggregate data to overcome the described deficits in each separate approach. The combination of individual and aggregate data within hybrid models is expected to improve individual-data-only and aggregate-data-only approaches. Based on simulation studies, Greiner and Quinn (2010) showed that this to be the case. Klima et al. (2017), Klima et al. (2019) also assessed the performance of the HHMD model and the ecological inference model which underlays the hybrid model and found remarkable improvements, especially in the case of aggregation bias.

The HHMD model has its precursors in Brown and Payne (1986), King (1997), King, Rosen, and Tanner (1999), Rosen, Jiang, King, and Tanner (2001), and Wakefield (2004). King (1997) proposed a specific solution to the ecological inference problem by combining the ecological inference approach by Goodman (1953) with the methods of bounds approach by Duncan and Davis (1953). The major innovation here is the assumption of randomly distributed transition probabilities with the deterministic information of unit-specific bounds. In addition, he proposed a truncated bivariate normal model to avoid out-of-unit interval estimates,

[7] See Johnston and Pattie (2006, p. 78), for an overview of this literature, see also Elff, Gschwend, and Johnston (2008).

[8] See http://www.britishelectionstudy.com/bes-impact/british-election-study-2015-general-election-constituency-forecast/#.W2HL2bhCR-U, retrieved June 2019.

[9] See http://eprints.ncrm.ac.uk/3789/1/Report_final_revised.pdf

which are usually encountered by the Goodman regression. King et al. (1999) further developed this random parameters model to a hierarchical Bayesian approach, which assumes a binominal-beta distribution as the joint distribution for the transition probabilities across territorial units. The hierarchical binomial-beta model was still designed for the 2×2 case but estimated via Markov Chain Monte Carlo (MCMC) simulations. The multistage conception inherent in hierarchical models implies that the estimated coefficient vector capturing voter transitions itself follows a distribution that depends on a second parameter vector, which in turn is independent of territorial units i. Such a hierarchical structure has the advantage that relationships that do not follow a closed distribution can be estimated via Bayesian techniques.

Rosen et al. (2001) extended the binomial-beta model to the multinomial-Dirichlet model for the $R \times C$ case. Already Brown and Payne (1986) suggested the usage of a multinomial-Dirichlet structure. Wakefield (2004) proposed the hybrid approach where individual survey data are integrated into aggregate data. The HHMD model extends the 2×2 case in Wakefield (2004) to the $R \times C$ situation and underpins it with the hierarchical multinomial-Dirichlet model proposed by Brown and Payne (1986) and Rosen et al. (2001). Therefore, the HHMD model is tailor-made to determine voter transitions in multiparty contexts.[10]

To illustrate how the HHMD model integrates individual survey data into aggregate data for the $R \times C$ case, let us inspect a table capturing a transition matrix for the 2010 to 2015 British general elections. For simplicity, Table 1 displays the transition matrix for three parties only, the Conservatives (CON), Labour (LAB), and the Liberal Democrats (LD). We consider R parties for the 2010 election and C parties for the 2015 election. N_r describes the result of the 2010 election, T_c represents the result of the 2015 election, and $i = 1, \ldots, P$ indicates the territorial units, the constituencies we observe for both elections. As we see from Table 1, the marginals for each constituency i are known, whereas the inner cells are unknown.

Next, assume we have individual survey data at the constituency level at our disposal. Drawing on the same simplified transition matrix example, Table 2 illustrates the information contained in the individual data. $Y^{r,c}$ represents the absolute number of voters. M_r gives the row sum, and Z_c the column sum of individual data. We see that individual data are characterized by the feature that both the inner cells and the marginals of the transition table are known.

As usually only a subset of the electorate is surveyed, the marginals of the individual data are not identical to the marginals of the aggregate data. In such cases, Wakefield (2004) suggested subtracting individual data and aggregate data to avoid double counting of voters (see Table 3). After correcting the marginals of the aggregate data, only those eligible voters remain in the aggregate data for which there are no individual data. When there are no individual data available for constituency i, a correction of the marginals is neither possible nor necessary. Note that this kind of data preprocessing requires that the territorial affiliation of each surveyed individual is available. Without this information, the assignment of individuals to territorial units would not be possible.

Next, let us focus on the assumptions for the parameters describing the voter transitions. Wakefield (2004) assumes identical transitions within a territorial unit for individual and aggregate data. This assumption is plausible for surveys based on simple probability sampling but could be problematic in other cases. However, the assumption of equal transition probabilities is not mandatory. In any case, there should be a defined linkage of transition probabilities between the data types. Only if there are completely different structures of the transition probabilities in the individual and aggregate data, such that there is no definable linkage, a joint model is not reasonable. In such cases, an estimation improvement is not possible because the particular data type does not contain any real information for the parameters of the respective other data type.

As in the underlying ecological inference model, the HHMD model assumes that the aggregate data (i.e., the column marginals) in each constituency follow a multinomial distribution:

$$\begin{aligned}(N^*_{\text{CON'15},i}, N^*_{\text{LAB'15},i}, \ldots, N^*_{\text{Abstain'15},i})\\ \sim \text{MNL}(\theta_{\text{CON},i}, \theta_{\text{LAB},i}, \ldots, \theta_{\text{Abstain},i}, N^*_i) \quad , \end{aligned} \tag{1}$$

where

$$\begin{aligned} N^*_{\text{CON'15},i} &= T_{\text{CON},i} - Z_{\text{CON},i} \\ N^*_i &= N_i - M_i \quad , \end{aligned} \tag{2}$$

and, for example,

$$\theta_{\text{CON},i} = \sum_{r=1}^{R} \beta_{r,\text{CON'15},i} \times P^*_{r,2010,i} \quad , \tag{3}$$

where

$$P^*_{r,2010,i} = \frac{N_{r,i} - M_{r,i}}{N_i - M_i} \quad , \quad \forall\, r \in \{1, \ldots, R\} \quad . \tag{4}$$

Note that the outcome of the second election follows a multinomial distribution. Here, the parameters (i.e., the expected relative vote shares) are the weighted sum of the transition parameters. The way how the expected relative vote

[10]Greiner and Quinn (2010) proposed an alternative solution (multinomial normal model) to a hierarchical model. Klima et al. (2016) and Klima et al. (2019) show that this model is quite time consuming, requires the choice of a reference party, and has convergence problems in their German application context.

Table 1
Illustration of the known marginals for each constituency i in the 3×3 *case.*

2010 Election	2015 Election CON	LAB	LD	2010 Election Result
CON	-	-	-	$N_{\text{CON},i}$
LAB	-	-	-	$N_{\text{LAB},i}$
LD	-	-	-	$N_{\text{LD},i}$
2015 Election Result	$T_{\text{CON},i}$	$T_{\text{LAB},i}$	$T_{\text{LD},i}$	N_i

N_r gives the result of the 2010 election, T_c the result of the 2015 election, and $i = 1, \ldots, P$ indicates the constituency. Illustration is based on three parties: Conservatives (CON), Labour (LAB), and Liberal Democrats (LD).

Table 2
Illustration of the known individual data in the 3 × 3 *case.*

2010 Election	2015 Election CON	LAB	LD	2010 Election Result
CON	$Y_i^{1,1}$	$Y_i^{1,2}$	$Y_i^{1,3}$	$M_{\text{CON},i}$
LAB	$Y_i^{2,1}$	$Y_i^{2,2}$	$Y_i^{2,3}$	$M_{\text{LAB},i}$
LD	$Y_i^{3,1}$	$Y_i^{3,2}$	$Y_i^{3,3}$	$M_{\text{LD},i}$
2015 Election Result	$Z_{\text{CON},i}$	$Z_{\text{LAB},i}$	$Z_{\text{LD},i}$	M_i

$Y^{r,c}$: absolute number of voters. M_r: row sum, Z_c: column sum of individual data, and $i = 1, \ldots, P$ indicates the constituency. Illustration is based on three parties: Conservatives (CON), Labour (LAB), and Liberal Democrats (LD).

shares and the transition probabilities are related resembles the Goodman (1953) model. However, contrary to Goodman's regression, the HHMD model assumes constituency-specific transition probabilities.

Regarding the individual data, the HHMD model assumes for each row (i.e., party) a multinomial distribution for the inner cells. Separate multinomial distributions for each row are per assumption independent:

$$\left(Y_i^{\text{CON'10,CON'15}}, \ldots, Y_i^{\text{CON'10,Abstain'15}}\right) \sim \text{MNL}\left(\beta_{\text{CON'10,CON'15},i}, \ldots, \beta_{\text{CON'10,Abstain'15},i}, M_{\text{CON'10},i}\right). \tag{5}$$

As more information is available in the individual data, we can directly use the observed relation between the 2010 and 2015 election results. For each row (i.e., party choice in 2010), the model assumes a multinomial distribution of the party choice in 2015. Additionally, equal transition probabilities are assumed for both aggregate and individual data.

The HHMD model consists of three levels. At the first level, we have constituency-specific parameters. Without further restrictions, the number of parameters to be estimated here would be much larger than the number of constituencies. An additional restriction is necessary to estimate the transitions. Therefore, the model assumes a joint Dirichlet distribution for each row at the second level. Taking the first row in a constituency i, for example, we get:

$$(\beta_{\text{CON'10,CON'15},i}, \ldots, \beta_{\text{CON'10,Abstain'15},i}) \sim \text{Dirichlet}\left(\alpha_{\text{CON'10,CON'15}}, \ldots, \alpha_{\text{CON'10,Abstain'15}}\right) . \tag{6}$$

The specification of the Dirichlet distribution ensures that the transition probabilities in each row sum up to one. Contrary to constituency-specific transition parameters at the first level, the parameters of the Dirichlet distribution at the second level are global, i.e., they apply to all constituencies. Due to possible differences in the number of eligible voters in the constituencies, the expected values of the Dirichlet distribution are generally not identical to the global transition probabilities. However, the joint distributions of each row are a priori independent. The assumption of joint Dirichlet distributions implies some similarity between the constituencies while still allowing differences between the transitions at the constituency level. Note that the joint distribution only assumes similarity between the transition parameters of the constituencies; the election results themselves can strongly differ. The joint distribution has, however, some direct implication: It is not reasonable to estimate a single model for the whole of Great Britain, as the transitions towards regional parties in Scotland and Wales are fundamentally different

Table 3
Basic notation of a 3×3 *voter transition table in the HHMD model after preprocessing (A) aggregate and (B) individual data.*

	2015 Election			
2010 Election	CON	LAB	LD	Row Totals
(A) Aggregate Data				
CON	-	-	-	$N_{\mathrm{CON},i} - M_{\mathrm{CON},i}$
LAB	-	-	-	$N_{\mathrm{LAB},i} - M_{\mathrm{LAB},i}$
LD	-	-	-	$N_{\mathrm{LD},i} - M_{\mathrm{LD},i}$
Column Totals	$T_{\mathrm{CON},i} - Z_{\mathrm{CON},i}$	$T_{\mathrm{LAB},i} - Z_{\mathrm{LAB},i}$	$T_{\mathrm{LD},i} - Z_{\mathrm{LD},i}$	$N_i - M_i$
(B) Individual Data				
CON	$Y_i^{1,1}$	$Y_i^{1,2}$	$Y_i^{1,3}$	$M_{\mathrm{CON},i}$
LAB	$Y_i^{2,1}$	$Y_i^{2,2}$	$Y_i^{2,3}$	$M_{\mathrm{LAB},i}$
LD	$Y_i^{3,1}$	$Y_i^{3,2}$	$Y_i^{3,3}$	$M_{\mathrm{LD},i}$
Column Totals	$Z_{\mathrm{CON},i}$	$Z_{\mathrm{LAB},i}$	$Z_{\mathrm{LD},i}$	M_i

$Y_i^{r,c}$, $M_{r,i}$, $Z_{c,i}$, $N_{r,i}$, and $T_{c,i}$ are the observed counts, and $i = 1, ..., P$ indicates the constituency. Example is based on three parties: Conservatives (CON), Labour (LAB), and Liberal Democrats (LD).

from those in England where these parties do not compete.

The third level of the HHMD model relates to the hyperpriors of the parameters. In line with Lau, Moore, and Kellermann (2007), the model assumes here a gamma distribution

$$\alpha_{r,c} \sim \Gamma(\lambda_{r,c,1}, \lambda_{r,c,2}), \quad \forall\, r \in \{1, \ldots, R\}, c \in \{1, \ldots, C\}. \quad (7)$$

Note that it is also possible to implement cell-specific prior knowledge so that a different prior knowledge can be assumed for each voter transition. The technical implementation of the HHMD model is provided by Schlesinger (2014), based on Lau et al. (2007).

4 Data and Descriptive Statistics

We apply the HHMD model to study voter transitions in the 2010 to the 2015 general elections in the three countries of Great Britain (England, Scotland, Wales), thereby excluding Northern Ireland. Our analyses focus on the most important parties competing in the three countries and two regional parties, the Scottish National Party (SNP) for Scotland only, and Plaid Cymru (PC) for Wales only. We also account for nonvoters and a category "others", containing remaining candidates.[11] The aggregate data are the official results of the 2010 and 2015 British general elections at the constituency level provided by the Electoral Commission (U.K. Electoral Commission, n.d.). These results constitute the true known marginals in our voter transition tables. The individual data is obtained from the British Election Study (BES). We use rich survey data from the British Election Study Internet Panel (BESIP). We rely on Wave 5 of the BESIP (Fieldhouse et al., 2015), conducted before the 2015 election during the formal campaign. As respondents are assigned to their constituencies in the BESIP, the data can be linked to the respective administrative units.

Our voter transition analyses are based on 28,892 respondents in 631 constituencies.[12] Table 4 summarizes how the BESIP respondents are distributed among the constituencies in the countries. For example, 20,815 respondents are spread across the 532 constituencies in England, with a minimum of 17 and a maximum of 87 respondents in a constituency. On average, we have 39 respondents in a constituency in England, 88 in Scotland, and 71 in Wales. Note again that we assume equal electorates in both elections. We apply the Hawkes method (see Hawkes, 1969) so that the number of voters in 2010 is proportionally adjusted to the number of voters in 2015, i.e., the relative vote shares in 2010 do not change.

Next, we describe the voting behavior as represented by

[11] Note that, due to their small shares, model requirements made it necessary to subsume several parties under the category "others", depending on the country so that this category is defined differently in each case. We come back to this point in the next section.

[12] Wave 5 of the BESIP has a total sample size of 30,725 respondents. For both elections, we excluded respondents that reported a choice for a party that did not compete in their constituency or country of residence. We also had to drop respondents that had no constituency assigned. We excluded the respondents residing in constituency 108 because there only the Speaker, Greens, and UKIP competed. Finally, we lost respondents in those constituencies where the party shares in the individual data were larger than the corresponding ones in the aggregate data (see Table 3). In total, this results in a loss of 1,833 respondents and one constituency.

Table 4
Constituencies and BESIP respondents in England, Scotland and Wales.

Country	# Constituencies	# Respondents	Min.	Max.	Average
England	532	20815	17	87	39
Scotland	59	5210	18	159	88
Wales	40	2867	43	120	71

The Speaker's constituency (108) is excluded.
Source: Wave 5 in the BESIP (Fieldhouse et al., 2015).

Table 5
Vote shares in the 2010 and 2015 British general elections in England: Aggregate and individual data compared.

	(A) Aggregate Data		(B) Individual Data	
Parties	2010	2015	2010	2015
CON	26.0	27.0	34.2	32.3
LAB	18.4	20.9	24.0	30.2
LD	15.9	5.4	22.3	7.1
UKIP	2.2	9.3	3.3	13.9
Others	3.0	3.3	3.1	6.2
Abstain	34.5	34.0	13.1	10.4

(A) are the official results at the constituency level (U.K. Electoral Commission, n.d.), (B) are the observed shares in Wave 5 in the BESIP (Fieldhouse et al., 2015).

the true aggregate data and the individual survey data to assess the reliability of the latter. Here, we focus on England and provide the results for Scotland and Wales in Online Appendix A. The comparison of the shares in the individual survey data and the aggregate data shows partly substantial differences in the two data types (see Table 5). We observe especially large differences in the shares of nonvoters (ABSTAIN).[13] The numbers (13.1 percent in 2010, 10.4 percent in 2015) indicate an enormous overreporting of participation of more than 20 percentage points in the survey data. Consequently, actual abstention figures are greatly underestimated, and in turn, party shares are overestimated.[14] For example, the vote share of Labour is overestimated by nearly 10 percentage points in the 2015 election. As soon as one removes the abstention category and adjusts party shares accordingly, the proportions are much closer to the true aggregate data.

Figure 1 investigates the relationship between aggregate and individual data in each constituency in England separately. The y-axis presents the relative vote shares in the individual survey data and the x-axis the corresponding shares in the aggregate data. Such data presentation allows identifying systematic deviations at the constituency level. In case of an exact correspondence of both data types, all dots would be located on the diagonal. The further the dots are away from the diagonal, the larger the deviations. We again observe from Figure 1 that in nearly all constituencies the true aggregate vote shares of nonvoters are larger as the ones in the individual survey data. In addition, we see that there are also quite large deviations for the smaller parties, such as UKIP, whereas the dots for the Conservatives or Labour tend to be more symmetric around the diagonal. Similar patterns are detected for Scotland and Wales (see Figure A1 in Appendix A).

5 Voter Transition Estimations

In this section, we apply the HHMD model to estimate voter transitions between the 2010 and 2015 British general elections. As we have seen in the previous section, the individual survey data especially underestimate nonvoters. We expect that the HHMD model, which systematically integrates error-free aggregate data on both party shares and abstention, helps us to reduce such biases in the individual survey data. Before presenting the results, let us discuss a few important issues that need to be considered.

[13]The category abstention includes those respondents that stated "I would not vote" in the 2015 vote intention question or "I did not vote" in the 2010 recall question, respectively, and "Don't know" responses in each variable in Wave 5 of the BESIP.

[14]This is, of course, not an exclusive feature of the BESIP data. Similar patterns are for example observed in German online panel survey data (see Thurner et al., 2020).

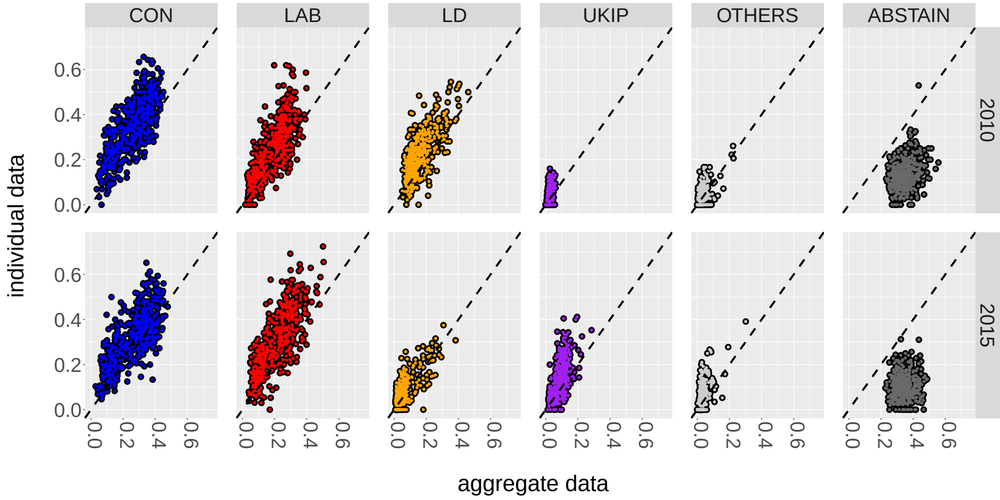


Figure 1. The relationship between aggregate and individual survey data at the constituency level, 2010 and 2015 British general elections in England. *Note:* The y-axis shows the relative vote shares in the individual survey data and the x-axis the corresponding shares in the aggregate data. Each dot represents one of the 532 constituencies in England.

First, the underreporting of abstention in the individual survey data indicates that one assumption of the HHMD model does not hold: There are probably structural differences in the constituency-specific transition rates between the aggregate and the individual survey data. In general, it is very difficult to make a precise assumption about the particular linkage of the transition rates between the two data types. However, simulation studies showed that the HHMD model provides reliable estimates even when there is no information on abstention in the individual data, such as in the case of exit polls where abstention in the current vote is missing by design (see Klima et al., 2019).

Second, the joint Dirichlet distribution at the second level (see Equation 6) implies estimating separate models for England, Scotland, and Wales because the transitions toward the SNP (Scotland) or Plaid Cymru (Wales) are distinct in the respective parts of Britain. Finally, there are some practical issues regarding parties gaining quite small vote shares. In such cases, it is not advisable to estimate transitions for all parties because the estimates for small parties become imprecise, while the number of parameters increases at the same time. We recommend subsuming several party options into the category "others" when this is the case. In our empirical application, we proceed like this and consider six choices in England (Conservatives, Labour, Liberal Democrats, UKIP, Others, Abstention) and five choices each in Scotland (Conservatives, Labour, SNP, Others, Abstention) and Wales (Conservatives, Labour, PC, Others, Abstention).

Table 6 summarizes the voter transition matrices obtained from the HHMD model without specifying prior knowledge. The left panel displays the absolute voter transitions (in 1000s) and the right panel the conditional transition probabilities. In each table, the main diagonal presents the loyalty rates (i.e., the same party was elected in both elections). Let us first focus on the results for England. We see that the loyalty probabilities are usually higher than the ones of switching. The probability of staying loyal to the Conservatives, Labour, UKIP, or abstaining is around 65–75 percent. By contrast, the "meltdown" of the Liberal Democrats can be seen in quite a small loyalty probability of 25.6 percent, which is similar to the probability of switching from the Liberal Democrats to Labour.

Inspecting the results for Scotland reveals that the SNP exhibits an extraordinary high loyalty probability of 83.9 percent. Whereas the loyalty rates for the Conservatives (62.9 percent) and abstaining (63.9 percent) are also comparatively high, the loyalty rate for Labour is only 44.5 percent. The results suggest that the SNP recruits to a large degree from previous Labour voters (37.5 percent, 413,104 in absolute numbers) and nonvoters (22.6 percent, 335,067 in absolute numbers). Particularly interesting is also the high probability of switching (39.5 percent) from 'Other' parties to the SNP.

The results for Wales suggest that the Liberal Democrats also suffered high losses here, whereas UKIP, the Greens (all three subsumed under the category "others") and Plaid Cymru (PC) slightly gained. Analogously to the models for England and Scotland, we see also in Wales high loyalty probabilities on the main diagonal. These are about 70 percent for Conservatives, Labour, and nonvoters, whereas PC exhibits a loyalty rate of 54.8 percent.

Figure 2 represents the model results in form of net flows. This perspective is especially important because it accounts for balances. The x-axis on the left scales the shares of net

Table 6
Estimation Results of the HHMD models without prior knowledge.
(a) England

	2015 Election											
	Absolute voter transitions (in 1000s)						Conditional transition probabilities					
2010 Election	CON	LAB	LD	UKIP	Others	Abstain	CON	LAB	LD	UKIP	Others	Abstain
CON	7518	280	193	1140	135	771	74.9	2.8	1.9	11.4	1.3	7.7
LAB	455	5140	88	431	177	825	6.4	72.2	1.2	6.1	2.5	11.6
LD	1050	1388	1576	520	547	1071	17.1	22.6	25.6	8.4	8.9	17.4
UKIP	112	51	21	560	21	102	12.9	5.9	2.5	64.6	2.4	11.8
Others	105	168	49	318	159	366	9.0	14.4	4.2	27.3	13.6	31.4
Abstain	1209	1062	172	630	245	10005	9.1	8.0	1.3	4.7	1.8	75.1

(b) Scotland

	2015 Election									
	Absolute voter transitions (in 1000s)					Conditional transition probabilities				
2010 Election	CON	LAB	SNP	Others	Abstain	CON	LAB	SNP	Others	Abstain
CON	274	38	50	42	32	62.9	8.8	11.7	9.7	7.3
LAB	40	490	413	39	119	3.6	44.5	37.5	3.5	10.8
SNP	24	19	436	17	23	4.6	3.6	83.9	3.4	4.5
Others	41	78	221	154	66	7.3	13.9	39.5	27.5	11.8
Abstain	56	83	335	62	949	3.8	5.7	22.6	4.2	63.9

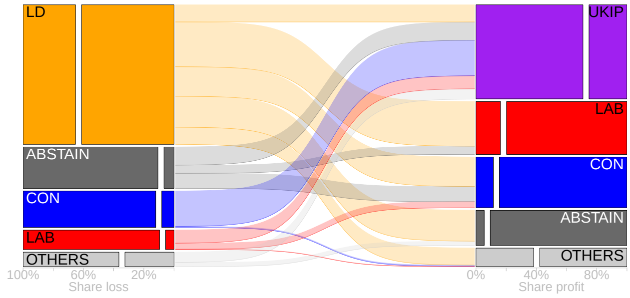
(c) Wales

	2015 Election									
	Absolute voter transitions (in 1000s)					Conditional transition probabilities				
2010 Election	CON	LAB	PC	Others	Abstain	CON	LAB	PC	Others	Abstain
CON	267	17	5	69	28	69.1	4.3	1.3	18.0	7.3
LAB	22	374	28	43	70	4.1	69.7	5.2	8.1	13.1
PC	11	18	91	22	24	6.6	10.6	54.8	13.4	14.6
Others	48	79	38	163	60	12.4	20.4	9.7	42.0	15.5
Abstain	60	65	20	58	601	7.5	8.0	2.5	7.2	74.7

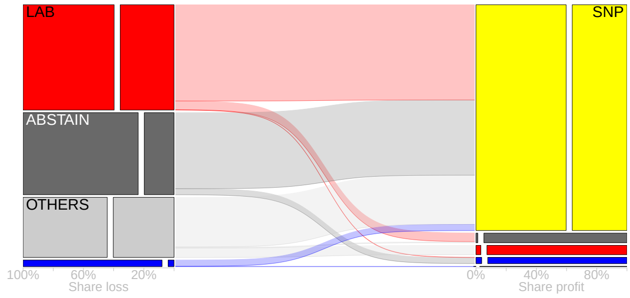
The rows represent the 2010 electoral choices, the columns the 2015 electoral choices. The main diagonals give the loyalty rates (i.e., the same party was elected both in 2010 and 2015). The values are to be read as follows: 7,518,000 voters (74.9 percent of the 2010 Convervative voters) in England voted for the Conservatives in both elections. 455,000 Labour voters in 2010 (6.4 percent) switched to the Conservatives in 2015.

losses in proportion to the number of voters in the 2010 election. The x-axis on the right presents the net gains. The net losses and gains between parties are scaled on the y-axis. In the middle panel of the figures, the summed net losses are separated. Such a visual result presentation allows identifying which target parties achieve the highest net losses of a sender party. Regarding England, the results suggest that the Liberal Democrats suffered the highest share of net losses (approximately 60 percent). This net loss is even more substantial as the sum of the net losses of nonvoters, Conservatives, and Labour together. The proportional net losses of nonvoters, Conservatives, and Labour are in the range of approximately 10 percent each. Especially remarkable is the net loss of the Conservatives, which mainly goes to UKIP. We also observe that the net losses of the Liberal Democrats nearly equally go to all considered parties. The plot for Scotland suggests that the SNP by far receives the highest net gains and exhibits no net loss. For the Conservatives, we only observe a small net loss toward SNP, but no net inflow. The most considerable net losses are detected for Labour and previous nonvoters. In Wales, nonvoters show the highest net losses. The Conservatives suffer the highest net losses to the

(a) England



(b) Scotland



(c) Wales

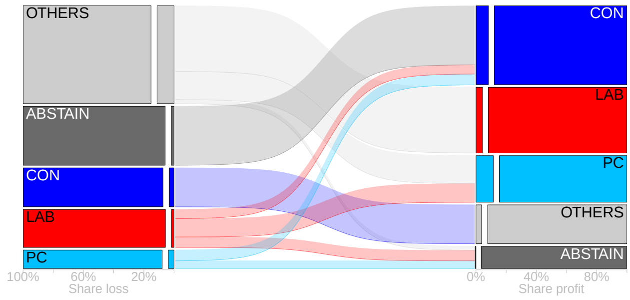


Figure 2. Net transition flows between the 2010 and 2015 British general elections. *Note:* Figures are based on the HHMD model estimates presented in Table 6.

category "others", which mostly consists of UKIP voters.

Relating these results to the described mispredictions and the results of Evans and Mellon (2016), it becomes clear which underlying processes drove the surprising electoral results. The Conservatives indeed heavily lost to UKIP and to SNP. However, they also attracted voters from previous abstainers and LD, at least in England and Wales. And high shares of Labour, Liberal Democrats and PC abstained in 2015. Given the first-past-the-post system, these latent shifts contributed to the success of the Conservatives' candidates. Without correct estimates of former and current abstainers a serious underestimation of the votes of the Conservatives is the consequence.

5.1 Convergence Diagnostics

Based on MCMC, a chain is generated that converges against the postulated posterior density. The chain ideally represents independent draws. However, it is well known that MCMC chains tend to be auto-correlated and adjacent values in a chain are not independent. There is a long discussion in the literature on whether chain thinning should be performed to obtain independent values. The current consensus is that in most cases thinning leads to lower overall efficiency, which should be avoided if possible (see, e.g., Link & Eaton, 2012), but there are also some cases where thinning can improve the efficiency of MCMC (see, e.g., Owen, 2017). We consider thinning as useful to obtain larger chains without heavily increasing the memory requirements for the hardware. This allows us to obtain larger chains and avoid an overly strong impact of the observed temporary deviations from the mean value in some chains. As improving efficiency is not our primary purpose here, we consider long chains with large thinning as appropriate.

We evaluated the global convergence of the models as follows. For each model, we generated two independent chains for one specific combination (e.g., CON – CON). Comparing independent chains is one of the approaches used in the literature on convergence diagnostics (see, e.g., Gelman & Rubin, 1992). The first step in our convergence analysis is based on a visual inspection of chain plots. We visually examined whether random values originate from a joint distribution. When there is a substantial overlap, we consider the estimates as converged. To avoid the risk of a visual misinterpretation and to further support the visual inspection, we additionally estimated different values, such as the mean values of the chains (not reported). We also used the visual inspection to identify still existing trends in the chains that would indicate an unsuitable burn-in value or chain length. This assessment step is performed for each chain separately.

In a second step, we evaluated the substantial convergence of the estimated voter transition tables by comparing the estimates obtained from the two independent chains based on the absolute distance (AD) index:

$$\mathrm{AD} = \sum_{r=1}^{R} \sum_{c=1}^{C} \left| T^{\mathrm{rel}}_{1,r,c} - T^{\mathrm{rel}}_{2,r,c} \right|.$$

The AD index compares two tables and quantifies their similarity. Cell by cell, we added up the absolute difference between two transition tables with relative frequencies. When the margins of both tables are identical, the AD index allows a straightforward interpretation of the difference. AD = 0 means that two tables are identical. AD = 2, which is the maximum value the index can take, meaning that two tables are completely different. In general, half of the absolute distance corresponds to the portion that must be assigned to another cell to obtain two identical tables.

We use the AD index as a measure of substantial convergence of the estimates. As a threshold for convergence, we use AD = 0.02, which means that at maximum one percent of all voters exhibit a difference in the two estimates. We consider this value to be low enough to assume that there are no longer substantial differences between two tables so that estimates can be considered as stable. Even though the AD index is less formal and strict than other established convergence criteria or tests (see, e.g., Cowles & Carlin, 1996; Roy, 2020), we believe it is suitable to evaluate the substantial convergence of the estimates in a straightforward way. As both the visual inspection of chain plots and the AD values must suggest convergence to assume convergence of the voter transition estimates, we are confident that the results are reliable. In the following, we discuss the result of our convergence diagnostic analyses. For each country, we assessed the ecological inference models, which rely only on the aggregate data at the constituency level, and the HHMD models, which use both aggregate and the individual survey data. For each model type, we ran the models without and with prior knowledge[15] and compared them based on the AD index (see Online Appendix B for chain plots and tabled results).

Let us first focus on the models for England. We observe a very good convergence behavior of the HHMD models here. The AD values for the model with prior knowledge (0.0010) and without (0.0012) are much below our postulated threshold for convergence. By contrast, the ecological inference models performed worse (without prior knowledge: 0.0090, with prior knowledge: 0.0070). It is also noticeable that prior knowledge does not lead to substantially different estimates for both model types. These differences are especially small in the HHMD models indicating that the models with and without prior knowledge converge against very similar voter transition estimates. However, the results show that there are large differences between the ecological inference and the HHMD model estimates. The AD value of approximately 0.35 suggests that about 17.5 percent of all voters exhibit a different voter decision in the HHMD model as compared to the ecological inference model, with the latter forgoing information from the survey. The models for Wales show a comparable convergence structure.

Regarding Scotland, the AD values for the ecological inference models without prior knowledge is much larger (0.1362) than our threshold of 0.02. The consideration of prior knowledge in the ecological inference models leads to an improvement, but also here convergence cannot be assumed with an AD = 0.0430. Inspecting the HHMD models for Scotland shows that both models (with and without prior knowledge) converged (0.0027 and 0.0014).

In sum, our combined approach to convergence diagnostics suggests that the HHMD model estimates are stable. By contrast, ecological inference models performed generally worse. Therefore, by integrating large-scale individual survey data at the constituency level, the HHMD model allows studying voter transitions in the countries of Great Britain, whereas it appears that there is not even sufficient information to perform ecological inference models in all countries.

5.2 Comparison with IPF-based Projections Based on Survey Data

To further evaluate the HHMD model estimates, we also estimated voter transitions based on a more classical survey data-orientated approach, using England as an illustrative example. As the BESIP individual survey data is sufficiently large at the constituency level, we use the 2010 and 2015 election results in every constituency as auxiliary information. For the projection, we apply the iterative proportional fitting (IPF) algorithm on the results from the survey data. The data is transformed at the constituency level to a voter transition table, which is in line with the marginal election results in the respective constituency. The IPF algorithm has been introduced and discussed in electoral research by Johnston and Pattie (1991a) and Johnston and Pattie (1993). The approach can be seen as a regression estimator or weighting correction similar to poststratification (Kolenikov, 2014).

The direct application of the IPF algorithm did not yield convergence in several constituencies (342 out of 532) in particular because of the occurrence of zeros in the cells. To overcome these difficulties, we added a small value to all cells of the transition table before applying the IPF. Such an adjustment ensures (i) convergence in those constituencies where it was not achieved, and (ii) that the difference between before and after the adjustment is close to zero in those constituencies where convergence was already given.

Table 7 compares the estimates obtained from the HHMD model to the IPF-based projection. We see that some IPF-based estimates resemble the ones in the HHMD model, but there are also notable differences. The estimates are relatively similar when one considers only the voter transitions between the parties, including the category "others" (AD = 0.0489). This result implies that both approaches identify similar relative voter transitions between parties. However, substantial differences are apparent when we additionally consider in the comparison the flows between the parties and nonvoters (AD = 0.1576). The HHMD model estimates much larger flows from or to nonvoters. Here, there are not only differences in magnitude but also structure. For example, the HHMD model estimates a larger flow—in absolute numbers—from Labour to nonvoters as compared to the Conservatives, while the survey-based projection estimates

[15] For the models with informative prior knowledge, a priori an higher expected loyality is assumed, and lower transitions to other parties. These different expectations are formulated by cell specific Γ-priors (equation (7), for more details see Klima et al. (2019)).

Table 7
Model comparisons, absolute voter transitions (in 1000s) between the 2010 and the 2015 British general elections in England.

(a) HHMD model without prior knowledge

	2015 Election					
2010 Election	CON	LAB	LD	UKIP	Others	Abstain
CON	7518	280	193	1140	135	771
LAB	455	5140	88	431	177	825
LD	1050	1388	1576	520	547	1071
UKIP	112	51	21	560	21	102
Others	105	168	49	318	159	366
Abstain	1209	1062	172	630	245	10005

(b) IPF-based projection

	2015 Election					
2010 Election	CON	LAB	LD	UKIP	Others	Abstain
CON	7015	238	202	1076	132	1375
LAB	526	4690	127	445	176	1136
LD	944	1365	1377	527	449	1487
UKIP	96	53	48	461	57	154
Others	120	137	83	287	201	338
Abstain	1748	1604	262	803	268	8651

suggest the opposite. Due to the fact that the HHMD accounts for the aggregate data-based objective information on nonvoters, it is obvious that its estimates are more reliable. The IPF procedure adjusts the inner cells to the marginals. When the initial conditions of the inner cells are biased - as has been the case especially for abstention, this adjustement might preserve this bias. Contrary, the hybrid model draws on a second data source thereby alleviating such biases.

6 Discussion and Concluding Remarks

For determining voter transitions at the occasion of the UK general election 2015, we applied a recently introduced estimation technique which combines survey data and aggregate data in a statistically systematic way. This so-called Hybrid Hierarchical Multinomial Dirichlet model alleviates well-known survey-related biases, and it mitigates the unsurmountable ecological fallacy problem. We find noticeable differences when exclusively processing survey data with the usual iterative proportional fitting technique – with underreporting of abstention being the obvious responsible reason. And our combined convergence diagnostics also demonstrate the superiority of data fusion over pure ecological inference. Insofar, we claim to provide completely new and more reliable insights into the occurrence of voter loyalty and voter shifts.

The application case has been highly challenging due to the specificities of the electoral system and due to the regionally varying composition of competing parties. First, the candidate-centric first-past-the-post system could aggravate the assumption of similarity across constituencies as compared to party-centric proportional systems. However, the flexibility of the distributional assumptions with regard to inter-constituency heterogeneity of the HHMD easily manages this variability. The models converged without problems. Second, the strong presence of local parties in Wales, Scotland and in England prevents to estimate one nationwide model for Great Britain. Actually, the disaggregation into three regional model allows more fine-grained insights into the complex system of loyal stocks and dissatisfied streams of voters in each country such that the integration of individual and aggregate data is optimized.

The accurate estimation of voter transitions is of particular theoretical and practical importance in the case of the 2015 British general election because third parties reached an all-time high proportion of votes. The underlying shifts have been partly conjectured, or selectively investigated (see Evans & Mellon, 2016), but there is no systematic Great Britain-wide study so far. Our results demonstrate, e.g., in England, the most dramatic party shifts occurred away from the Liberal Democrats. The party exhibited the smallest loyalty rate of only 26 percent, with major transitions to the Conservatives (17.1 percent) and Labour (22.7 percent). By contrast, 11.9 percent of former Conservative voters, 8.8 percent of Liberal Democrats voters and 6.6 percent of Labour voters moved to UKIP. In Scotland, we see a differentiated picture of flows of former Labour voters to the SNP, but also remarkable shares of former nonvoters to SNP. In Wales, the aggregate volatility is less dramatic, but we see that former LD voters in the majority went to PC and Labour, whereas the Conservatives gained from former abstainers and Labour. UKIP also profited from mobilizing former non-voters, but there were no major flows from Labour towards UKIP here.

Concerning the methodical conclusion, we plead for the combined usage of administrative data and survey data in voter transition research in the future. Well-known biases of surveys in this context cannot be ignored any longer. Only enriching them with aggregate data reduces these flaws. Next steps in our research will be to develop adequate survey designs for given electoral systems such that the integration of individual and aggregate data is optimized.

References

Achen, C. H., & Shively, W. P. (1995). *Cross-level inference*. Chicago, IL: University of Chicago Press.

Berrington, H. B. (1965). The General Election of 1964. *Journal of the Royal Statistical Society. Series A (General)*, *128*(1), 17–66.

Brown, P. J., & Payne, C. D. (1986). Aggregate data, ecological regression, and voting transitions. *Journal of the American Statistical Association*, *81*(394), 452–460.

Butler, D. E. (1952). *The British general election of 1951*. London, United Kingdom: Macmillan.

Butler, D. E., & Stokes, D. (1969). *Political change in Britain: Forces shaping electoral choice*. New York, NY: St. Martins Press.

Cho, W. T., & Manski, C. F. (2008). Cross-level/Ecological inference. In J. M. Box-Steffensmeier, H. E. Brady, & D. Collier (Eds.), *The oxford handbook of political methodology* (pp. 547–569). doi:10.1093/oxfordhb/9780199286546.003.0024

Cowles, M. K., & Carlin, B. P. (1996). Markov Chain Monte Carlo convergence diagnostics: A comparative review. *Journal of the American Statistical Association*, *91*(434), 883–904. doi:10.1080/01621459.1996.10476956

Curtice, J. (2015). A return to normality? How the electoral system operated. *Parliamentary Affairs*, *68*(suppl 1), 25–40. doi:10.1093/pa/gsv025

Cutts, D., & Russell, A. (2015). From coalition to catastrophe: The electoral meltdown of the Liberal Democrats. *Parliamentary Affairs*, *68*(1), 70–87. doi:10.1093/pa/gsv028

Dassonneville, R., & Hooghe, M. (2017). The noise of the vote recall question: The validity of the vote recall question in panel studies in Belgium, Germany, and the Netherlands. *International Journal of Public Opinion Research*, *29*(2), 316–338. doi:10.1093/ijpor/edv051

Deville, J.-C., Särndal, C.-E., & Sautory, O. (1993). Generalized raking procedures in survey sampling. *Journal of the American Statistical Association*, *88*(423), 1013–1020.

Duncan, O. D., & Davis, B. (1953). An alternative to ecological correlation. *American Sociological Review*, *18*(6), 665–666. doi:10.2307/2088122

Elff, M., Gschwend, T., & Johnston, R. J. (2008). Ignoramus, ignorabimus? On uncertainty in ecological inference. *Political Analysis*, *16*(1), 70–92. doi:10.1093/pan/mpm030

Evans, G., & Mellon, J. (2016). Working class votes and Conservative losses: Solving the UKIP puzzle. *Parliamentary Affairs*, *69*(2), 464–479. doi:10.1093/pa/gsv005

Fieldhouse, E., Green., J., Evans, G., Schmitt, H., van der Eijk, C., Mellon, J., & Prosser, C. (2015). British Election Study Internet Panel 2014-2015 (Waves 1-6). Data File Version 1.2. The University of Manchester. doi:10.15127/1.293723

Ford, R., & Goodwin, M. (2014). *Revolt on the right: Explaining support for the radical right in Britain*. doi:10.4324/9781315859057

Gelman, A., & Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. *Statistical Science*, *7*(4), 457–472. doi:10.1214/ss/1177011136

Goodman, L. A. (1953). Ecological regressions and behavior of individuals. *American Sociological Review*, *18*(6), 663–664. doi:10.2307/2088121

Goodman, L. A. (1959). Some alternatives to ecological correlation. *American Journal of Sociology*, *64*(6), 610–625.

Green, J., & Prosser, C. (2016). Party system fragmentation and single-party government: The British General Election of 2015. *West European Politics*, *39*(6), 1299–1310. doi:10.1080/01402382.2016.1173335

Greiner, D. J., & Quinn, K. M. (2010). Exit polling and racial bloc voting: Combining individual-level and RxC ecological data. *The Annals of Applied Statistics*, *4*(4), 1774–1796. doi:10.1214/10-aoas353

Hawkes, A. (1969). An approach to the analysis of electoral swing. *Journal of the Royal Statistical Society: Series A (General)*, *132*(1), 68–79.

Heath, O., & Goodwin, M. (2017). The 2017 General Election, Brexit and the return to two-party politics: An aggregate-level analysis of the result. *The Political Quarterly*, *88*(3), 345–358. doi:10.1111/1467-923x.12405

Hirschman, A. O. (1970). *Exit, voice, and loyality. responses to decline in firms, organizations and states*. Cambridge, MA: Harvard University Press.

Johnston, R. J., & Hay, A. M. (1982). On the parameters of uniform swing in single-member constituency electoral systems. *Environment and Planning A*, *14*(1), 61–74. doi:10.1068/a140061

Johnston, R. J., & Hay, A. M. (1983). Voter transition probability estimates: An entropy-maximizing approach. *European Journal of Political Research*, *11*(1), 93–98. doi:10.1111/j.1475-6765.1983.tb00045.x

Johnston, R. J., & Pattie, C. J. (1991a). Evaluating the use of entropy-maximising procedures in the study of voting patterns: Sampling and measurement error in the flow-of-the-vote matrix and the robustness of estimates. *Environment and Planning A*, *23*(3), 411–420.

Johnston, R. J., & Pattie, C. J. (1991b). Tactical voting in Great Britain in 1983 and 1987: An alternative approach. *British Journal of Political Science*, *21*(1), 95–128. doi:10.1017/s0007123400006049

Johnston, R. J., & Pattie, C. J. (2006). *Putting voters in their place. geography and elections in Great Britain*. New York, NY: Oxford University Press. Retrieved from %7B%7D

Johnston, R. J., & Pattie, C. (1993). Entropy-maximizing and the iterative proportional fitting procedure. *The Professional Geographer*, *45*(3), 317–322.

Kennedy, C., Blumenthal, M., Clement, S., Clinton, J. D., Durand, C., Franklin, C., … Wlezien, C. (2018). An evaluation of the 2016 election polls in the United States. *Public Opinion Quarterly*, *82*(1), 1–33. doi:10.1093/poq/nfx047

King, G. (1997). *A solution to the ecological inference problem: Reconstructing individual behavior from aggregate data*. Princeton, NJ: Princeton University Press.

King, G., Rosen, O., & Tanner, M. A. (1999). Binomial-beta hierarchical models for ecological inference. *Sociological Methods & Research*, *28*(1), 61–90. doi:10.1177/0049124199028001004

Klima, A., Küchenhoff, H., Selzer, M., & Thurner, P. W. (Eds.). (2017). *Exit Polls und Hybrid-Modelle. Ein neuer Ansatz zur Modellierung von Wählerwanderungen*. doi:10.1007/978-3-658-15674-9

Klima, A., Schlesinger, T., Thurner, P. W., & Küchenhoff, H. (2019). Combining aggregate data and exit polls for the estimation of voter transitions. *Sociological Methods & Research*, *48*(2), 296–325. doi:10.1177/0049124117701477

Klima, A., Thurner, P. W., Molnar, C., Schlesinger, T., & Küchenhoff, H. (2016). Estimation of voter transitions based on ecological inference: An empirical assessment of different approaches. *AStA Advances in Statistical Analysis*, *100*(2), 133–159. doi:10.1007/s10182-015-0254-8

Kolenikov, S. (2014). Calibrating survey data using iterative proportional fitting (raking). *The Stata Journal*, *14*(1), 22–59.

Lau, O., Moore, R. T., & Kellermann, M. (2007). eiPack: RxC ecological inference and higher dimension data management. *R News*, *7*(2), 43–47.

Link, W. A., & Eaton, M. J. (2012). On thinning of chains in MCMC. *Methods in Ecology and Evolution*, *3*(1), 112–115. doi:10.1111/j.2041-210x.2011.00131.x

Mellon, J., Evans, G., Fieldhouse, E., Green, J., & Prosser, C. (2018). Brexit or Corbyn? Campaign and inter-election vote switching in the 2017 UK General Election. *Parliamentary Affairs*, *71*(4), 719–737. doi:10.1093/pa/gsy001

Mellon, J., & Fieldhouse, E. (2016). The British Election Study 2015 General Election constituency forecast. *Electoral Studies*, *41*, 250–254. doi:10.1016/j.electstud.2015.11.009

Mellon, J., & Prosser, C. (2017). Missing nonvoters and misweighted samples. *Public Opinion Quarterly*, *81*(3), 661–687. doi:10.1093/poq/nfx015

Noelle-Neumann, E. (1974). The spiral of silence a theory of public opinion. *Journal of Communication*, *24*(2), 43–51. doi:10.1111/j.1460-2466.1974.tb00367.x

Owen, A. B. (2017). Statistically efficient thinning of a Markov Chain sampler. *Journal of Computational and Graphical Statistics*, *26*(3), 738–744. doi:10.1080/10618600.2017.1336446

Pedersen, M. N. (1979). The dynamics of European party systems: Changing patterns of electoral volatility. *European Journal of Political Research*, *7*(1), 1–26. doi:10.1111/j.1475-6765.1979.tb01267.x

Robinson, W. S. (1950). Ecological correlations and the behavior of individuals. *American Sociological Review*, *15*(3), 351–357. doi:10.2307/2087176

Rosen, O., Jiang, W., King, G., & Tanner, M. A. (2001). Bayesian and frequentist inference for ecological inference: The RxC case. *Statistica Neerlandica*, *55*(2), 134–156. doi:10.1111/1467-9574.00162

Roy, V. (2020). Convergence diagnostics for Markov Chain Monte Carlo. *Annual Review of Statistics and Its Application*, *7*(1), 387–412. doi:10.1146/annurev-statistics-031219-041300

Schlesinger, T. (2014). *Eiwild: Ecological inference with individual and aggregate data*. R package version 0.6.7.

Schoen, H. (2003). *Wählerwandel und Wechselwahl: Eine vergleichende Untersuchung*. Berlin, Heideberg: Springer VS.

Selb, P., & Munzert, S. (2013). Voter overrepresentation, vote misreporting, and turnout bias in postelection surveys. *Electoral Studies*, *32*(1), 186–196. doi:10.1016/j.electstud.2012.11.004

Shirani-Mehr, H., Rothschild, D., Goel, S., & Gelman, A. (2018). Disentangling bias and variance in election polls. *Journal of the American Statistical Association*, *113*(522), 607–614. doi:10.1080/01621459.2018.1448823

Stokes, D. E. (1969). Cross-level inference as a game against nature. In J. L. Bernd (Ed.), *Mathematical applications in political science, iv* (pp. 62–83). Charlottesville, VA: The University Press of Virginia.

Sturgis, P., Kuha, J., Baker, N., Callegaro, M., Fisher, S., Green, J., … Smith, P. (2017). An assessment of the causes of the errors in the 2015 UK General Election opinion polls. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *181*(3), 757–781. doi:10.1111/rssa.12329

Thurner, P. W., Kunz, F., Miclut, A., Mauerer, I., Klima, A., & Küchenhoff, H. (2020). Die Schätzung von Wählerwanderungen zwischen den Bundestagswahlen 2013–2017 mit Hilfe von Online-Paneldaten und Aggregatdaten in Hybridmodellen. In H. Schoen & B. Weßels (Eds.), *Wahlen und Wähler – Analysen aus Anlass der Bundestagswahl 2017.* In print. Springer VS.

U.K. Electoral Commission. (n.d.). Results of the 2010 and 2015 British General Elections at the constituency level.

Wakefield, J. (2004). Ecological inference for 2x2 tables. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *167*(3), 385–425. doi:10.1111/j.1467-985x.2004.02046_1.x

Waldahl, R., & Aardal, B. (2000). The accuracy of recalled previous voting: Evidence from Norwegian Election Study panels. *Scandinavian Political Studies*, *23*(4), 373–389.