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The dynamic battle for pieces of pie—Modeling party support in multi-party nations

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ABSTRACT

When teams of rival politicians compete for public support, they are essentially playing a zero sum game where one party's gains tend to come from the losses of one or more of their opponents. Despite this, most analyses of party support across time model the dynamics associated with a single party's support. In nations where only two parties are competing for votes, this approach is fine. But in nations with more than two parties, much of the substance of what is going on in party competition is lost. In this paper we illustrate the usefulness of a modeling strategy proposed by Philips et al. (2015) for estimating and interpreting the causal relationships that shape trade-offs in party support as they evolve over time. We extend their work by modeling public support for four parties instead of three and by developing the ability to model dynamic changes in party characteristics. We estimate our models on monthly data from the United Kingdom and Germany.

When teams of rival politicians compete for public support, they are essentially playing a zero sum game where one party's gains tend to come from the losses of one or more of their opponents. Despite this, most analyses of party support across time model the dynamics associated with a single party's support. In nations where only two parties are competing for votes, this approach is fine. But in nations with more than two parties competing, much of the substance of what is going on in party competition is lost.

Although panel designs and experiments have become more prevalent in recent years, the two most popular research designs for studying party support are cross-sectional surveys and time series collections of aggregated public opinion. In the 1990s, individual-level models of party support across more than two parties moved from two-category (i.e., binomial logit or probit) to multi-category models (e.g., Alvarez and Nagler, 1995; Whitten and Palmer, 1996). Despite the increased complexity of these models and some early confusion over the differences across them, they have now become the industry standard for anyone interested in modeling individual-level support across more than two alternatives.[1]

Models of aggregate-level party support across time have maintained a two-category focus. The dependent variable in these analyses is usually measured as the level of support for the party of the President or Prime Minister. Such analyses implicitly lump multiple categories of the dependent variable together, modeling support for the chief executive versus all other options. While these models can provide interesting insights into the dynamics of party competition, they are unable to answer a series of theoretically interesting questions about politics. When support for the party of the chief executive goes up, does the corresponding decrease in support come equally from all other parties, or are some affected more than others? Are there some variables that matter only for parties that

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[1] Dow and Endersby (2004) provide a summary of these debates and an authoritative discussion of the relative merits of commonly-used models.

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have a shot at being the largest party? Are the variables that drive support across coalition partners different from the variables that drive support between parties in the government and parties in the opposition?

In an earlier paper (Philips et al., 2015), we provided a preliminary demonstration of the utility of a strategy for modeling support across three different political parties over time. In this paper, we build on this approach in two ways. First, we expand from modeling support for three different parties to modeling support for four different parties. Second, we propose an extension of our modeling strategy to include measures of the changing characteristics of parties. As we discussed in our earlier paper, the parameterization of the resulting models from our modeling strategy is closely analogous to that of multinomial logit models with the added complication of short- and long-run dynamic interpretations. In our current extension of this work, we produce a more complicated model specification in which we allow the characteristics of political parties to vary across time. We believe that this type of model, which is analogous to a mixed logit model, has considerable promise for the study of the dynamics of party support. In the next section of this paper we provide a discussion of the use of compositional models in political science. We then provide a brief summary of our proposed approach followed by three empirical applications. In the final section, we offer some conclusions and discuss a number of possibilities for future work.

1. Compositional dependent variables in political science

The work of John Aitchison (in particular Aitchison, 1986) on the analysis of compositional variables has been influential across a broad range of substantive applications. The recommendations of Aitchison for dealing with compositional dependent variables were first introduced to political science by Katz and King (1999) in a discussion of the size and trend of the electoral advantage for incumbents in the United Kingdom. One of the contributions of the study was to address the tendency of researchers to analyze multiparty elections in a two dimensional space by comparing the electoral performance of one party to all other parties. The authors show that simplifying multiple parties into two categories (termed by the authors as an “amalgamation” of multiple categories into a single category) creates both bias and information loss. Bias occurs when the “other category” to which the party of interest is compared varies across time and/or space, as would be the case when a party runs a candidate in some elections but not others. Second, information about the dynamics among parties is lost when they are grouped together in a single “other” category such that dynamics between parties cannot be accurately assessed. To address the constraints of compositional data present in multiparty elections, Katz and King recommend overcoming the limitations of OLS by first transforming the data and then maximizing the likelihood of a multivariate *t* distribution (as opposed to an additive normal distribution which the authors argue is inappropriate for multiparty data) to produce an additive logistic Student's *t* (LT) distribution. The authors calculate a predicted vote, an expected vote, and a causal effect using Monte Carlo simulation.

While the contribution of Katz and King (1999) is substantial, there are limitations to their method. These include the complexity of computation, the difficulty of illustrating the substantive meaning of their results, and the limited number of parties that can be included in these models. The plots provided through their approach cannot extend to more than four parties without becoming increasingly multidimensional and requiring the use of various coloring or shading techniques (p. 30). Further, while Katz and King are able to provide a time-series analysis for a single component of a larger composition, they do not consider the many dynamics that occur within the compositions over time. For instance, how does a shift in the average voter towards a more conservative stance affect vote shares of the parties in the short-run as well as in the long-run?

Tomz et al. (2002) argued that the compositional problems addressed by Katz and King could be solved through an approach that was less statistically complicated and less demanding on compositions of more than three categories (see also Jackson, 2002; Mikhailov et al., 2002). Tomz et al. proposed the evaluation of compositional data through the use of seemingly unrelated regressions (SUR), demonstrating that this method is more convenient to use and no less efficient than the Katz-King approach (p.68). The SUR approach, further, takes advantage of correlated errors across equations that are estimated on data from the same election. They do not use the LT distribution, relying instead on a multivariate normal to enhance the ease of use of their method without compromising model accuracy (p.71). Tucker (2006) developed this approach in a cross-national study of regional, post-communist economic voting. In exploring the contingencies of traditional hypotheses on the relationship between economic health and support for governing parties, Tucker modeled logged ratio compositional dependent variables in SUR models to produce predicted values and stochastic simulations of vote shares when economic variables are manipulated. Despite these impressive efforts to accurately estimate and interpret models with compositional dependent variables, Tucker is largely silent on how to address dynamic changes that occur within compositions over time.

When considering how to best model the dynamic changes of compositions, it is important to address each of the limitations of this type of data. A compositional dependent variable, *V*, consists of a row of *J* components. As described in Philips et al. (2015), each individual observation in time for the value of a single component of a composition can be labeled as V_{tj}. Each component also has four defining characteristics. First, at any point in time, each component must have a value that is between zero and one ($0 < V_{tj} < 1$). Second, at each point in time, the individual components of the composition must sum to one ($\sum_{j=1}^{J} V_{tj} = 1$). From these two characteristics, it is also the case that any change in the composition from one time period to another will necessarily be bounded by -1 and 1 ($-1 < \Delta V_{tj} < 1$) and that all changes will sum to zero ($\sum_{j=1}^{J} \Delta V_{tj} = 0$).