Modeling Dynamic Pies

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Overall Talk Plan

- Initial ideas
- Initial papers and software
- Substantive and methodological extensions
- Future directions

Figure 3 from "Through thick and thin? The dynamics of government support across income groups during economic crises." Palmer and Whitten, Electoral Studies 2011

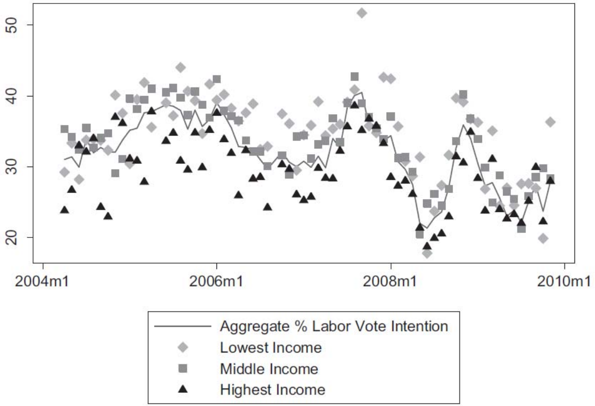


Figure 10 from "Booms and busts: how parliamentary governments and economic context influence welfare policy." Lipsmeyer, Christine S. International Studies Quarterly 55.4 (2011): 959-980.

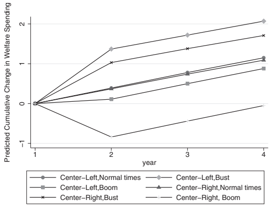
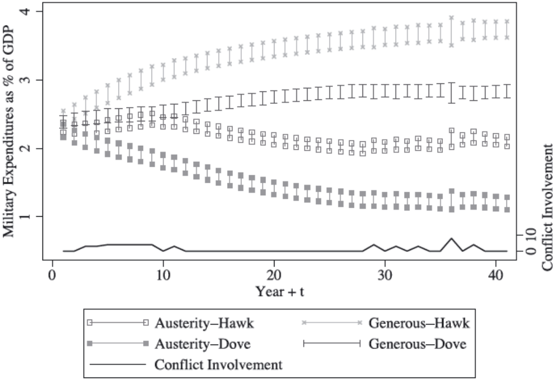


Fig 10. Predicted Changes in Welfare Spending across six different scenarios of Government Ideology and Economic Performance

simulations, I held all variables except boom duration, bust duration, and government ideology constant. For all scenarios, I started out with a two-party majority government that spent 22% of their nation's GDP on welfare in year 1. I then calculated the level of spending in years 2 through 4 for a center-left and a center-right government across three different economic scenarios: normal times throughout, a 1-year economic boom followed by normal times, and a 1-year economic bust followed by normal times. Figure 10 presents the long- and short-term effects estimated by the model in action. At the center of the figure, we can see the predicted spending by a center-left and a center-right government with normal times throughout. For both of these scenarios, the outcome is a slight increase in spending throughout the period, with this increase slightly higher for the center-left government. This upward trend is mostly due to the fact that both governments are a coalition of two parties. The top of the figure shows the predicted spending of a center-left and a center-right government when there is an economic bust in year 2 followed by normal economic times in years 3 and 4. Under these conditions, both the center-left and the center-right governments increase welfare spending substantially in year 2 and then increase spending less substantially thereafter. At the bottom of the figure, we can see the predicted spending of a center-left and a center-right government when there is

Figure 6 from "Buttery Guns and Welfare Hawks: The Politics of Defense Spending in Advanced Industrial Democracies." Whitten and Williams, AJPS 2011

FIGURE 6 Predicted Defense Spending by Four Government Types over 40 Years of Swedish Conflict Involvement



Note: Bars depict 95% confidence intervals.

*Heightening Comparativists' Concern for Model Choice: Voting Behavior in Great Britain and the Netherlands**

Guy D. Whitten, *Texas A&M University*
Harvey D. Palmer, *George Mason University*

Theory: As the research methodology more closely approximates the causal process being analyzed, the inferences and predictions derived from that methodology will better represent actual behavior. Statistical models were specified on the basis of accepted theories of voting behavior and political cleavages in the Netherlands and Great Britain.
Hypotheses: We hypothesize that multinomial models provide a more accurate characterization of voting behavior in countries with more than two political parties competing for votes.
Method: Binomial logit, multinomial logit, and nested multinomial logit models of voting behavior are estimated on Dutch and British National Election Study data.
Results: Compared to binomial methods, we find that multinomial models of voting behavior produce results that are more congruent with accepted theories of Dutch and British politics.

Whitten and Palmer, AJPS 1996

HEIGHTENING COMPARATIVISTS' CONCERN FOR MODEL CHOICE 23[?]

Table 1. Logit Model of Government Vote, 1986

	Parameter Estimate	Standard Error
Constant	−5.18***	0.75
Working Class	−0.45**	0.23
Upper Working Class	−0.14	0.28
Upper/Upper-Middle Class	0.07	0.26
Left-Right Self Placement	0.572***	0.051
Government Economic Evaluation	0.508***	0.067
Abortion	0.068*	0.049
Nuclear Power	−0.153***	0.046
Income Redistribution	−0.152***	0.049
Union Member	−0.31*	0.22
Unemployed	0.45*	0.30
Household Income	0.102***	0.033
Education	−0.040	0.041
Age	0.0006	0.0054
Married	0.02	0.19
Catholic*Church Attendance	0.465***	0.073
Protestant*Church Attendance	0.011	0.073
LR test statistic [16]	785.2	
Correctly predicted (%)	83.8	
Reduction in error (%)	67.6	
N	1230	

Note: The dependent variable is coded 1 if the respondent voted for either the Christian Democrats or the Liberals in the Netherlands. The LR test statistic is chi-squared with a 1% critical value of 32.0. The naive model that everyone votes opposition correctly predicts 50.1% of the cases.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ (one-tailed t-tests)

Whitten and Palmer, AJPS 1996

Figure 1. BNL Estimated Effect of Ideological Self Placement on Government Vote (Netherlands, 1986)

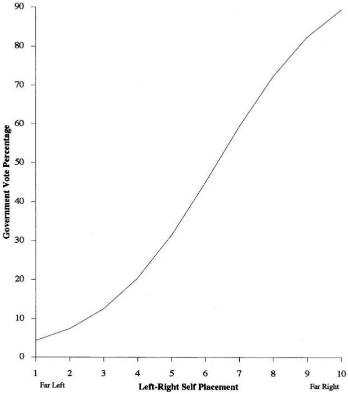


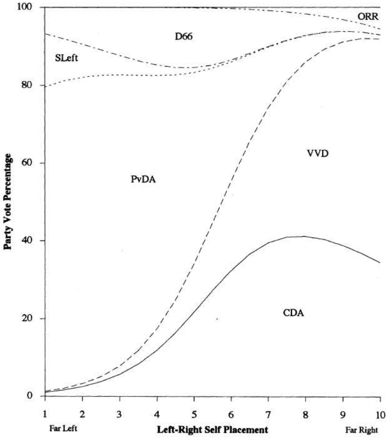
Table 2. Multinomial Logit Model of Dutch Vote, 1986

	ln[CDA/PvDA]	ln[VVD/PvDA]	ln[D66/PvDA]	ln[SLeft/PvDA]	ln[ORR/PvDA]	ln[CDA/VVD]
Constant	−6.45***	−10.87***	−6.40***	−0.37	−10.57***	4.41***
Working Class	−0.42*	−1.36***	−0.06	−0.36	−0.16	0.94**
Upper Working Class	−0.41	−0.39	−0.37	0.35	−0.38	−0.02
Upper/Upper-Middle Class	0.06	0.51*	0.40	−0.27	0.46	−0.45**
Left-Right Self Placement	0.874***	1.088***	0.320***	−0.479***	1.554***	−0.214***
Government Economic Evaluation	0.678***	0.976***	0.483***	0.071	0.563***	−0.298***
Abortion	−0.046	0.158**	0.292***	0.102	−0.760***	−0.204***
Nuclear Power	−0.234***	−0.266***	−0.195***	−0.037	−0.361***	0.032
Income Redistribution	−0.169***	−0.328***	−0.169***	−0.111	−0.077	0.159***
Union Member	−0.17	−0.38	0.17	0.16	0.59	0.21
Unemployed	0.05	0.60	−0.08	−0.22	−2.75**	−0.54
Household Income	0.118***	0.143***	0.088**	0.001	0.079	−0.025
Education	−0.049	0.155***	0.178***	0.198***	0.168*	−0.204***
Age	−0.0015	−0.0039	0.0010	−0.0244**	−0.0141	0.0024
Married	−0.05	0.31	0.36	−0.89***	−0.68	−0.37*
Catholic*Church Attendance	0.564***	−0.034	0.045	−0.231	−1.341*	0.598***
Protestant*Church Attendance	0.476***	−0.177	0.063	0.103	0.522***	0.653***
LR test statistic [80]			1594.3			
Correctly predicted (%)			68.2			
Reduction in error (%)			50.5			
N			1230			

Note: The dependent variable is party vote with six categories. The PvDA coefficients have been set to zero, so the first five columns represent a complete set of MNL coefficients. Coefficients for additional pairwise party comparisons, such as those in column six, are simple linear transformations of these coefficients (see note 9). The LR test statistic is chi-squared with a 1% critical value of 112.3. The naive model that everyone votes Labor (PvDA) correctly predicts 35.8% of the cases.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ (one-tailed t-tests)

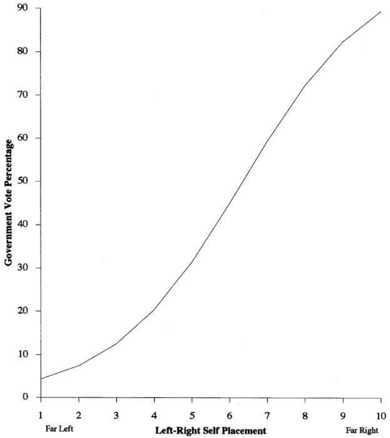
Whitten and Palmer, AJPS 1996

Figure 2. MNL Estimated Effect of Ideological Self Placement on Party Vote (Netherlands, 1986)



BNL vs. MNL

Figure 1. BNL Estimated Effect of Ideological Self Placement on Government Vote (Netherlands, 1986)



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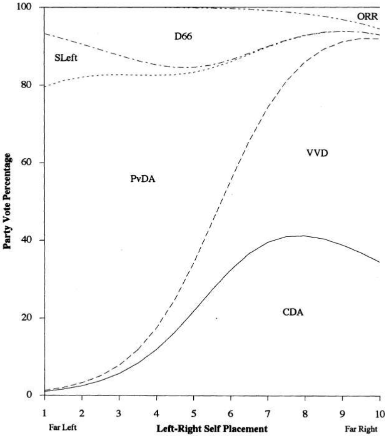
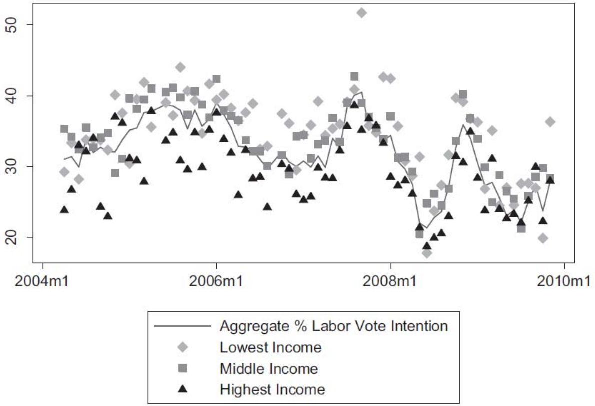
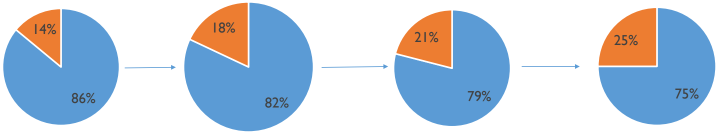


Figure 3 from "Through thick and thin? The dynamics of government support across income groups during economic crises." Palmer and Whitten, Electoral Studies 2011

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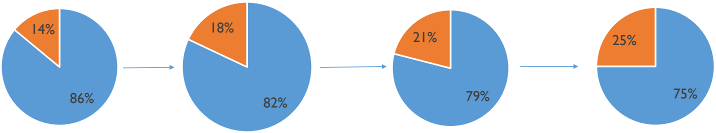
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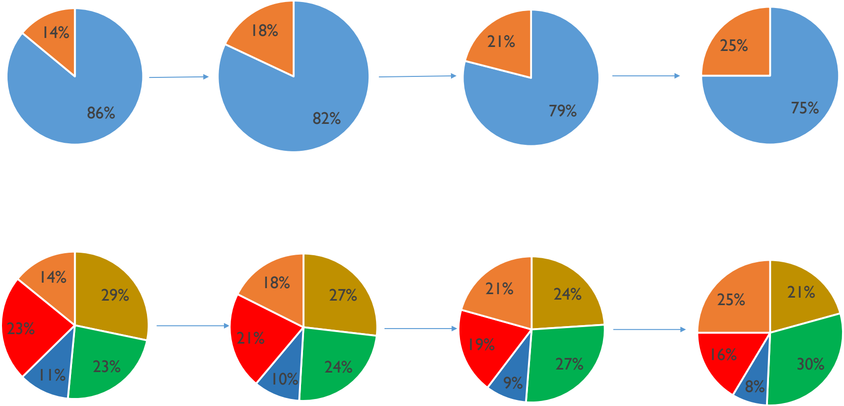
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Dynamically-interesting compositional variables are everywhere

- Public support for political parties/candidates
- Budget allocations
- Sources of revenue
- Issue attention
- Inequality

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The Dynamic Pie Project

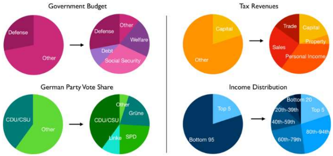
A Strategy for Modeling Trade-Offs in Compositional Variables Over Time

About **dynsimpie**

dynsimpie is a suite of Stata® commands for estimating, visualizing, and interpreting results from dynamic models of compositional dependent variables. Think here of dependent variables composed of multiple continuous categories that vary over time, such as government budgets, sources of tax revenue, party vote share, or compositions of the income distribution.

Scholars commonly collapse the many categories of these dependent variables into two distinct ones for ease of modeling. In **dynsimpie**, we allow for the estimation of all categories to occur simultaneously across time. This makes it easy to observe the trade-offs experienced by all distinct categories upon changes in the explanatory variables.

Two-Category Method *vs.* the **dynsimpie** Method



The Dynamic Pie Group

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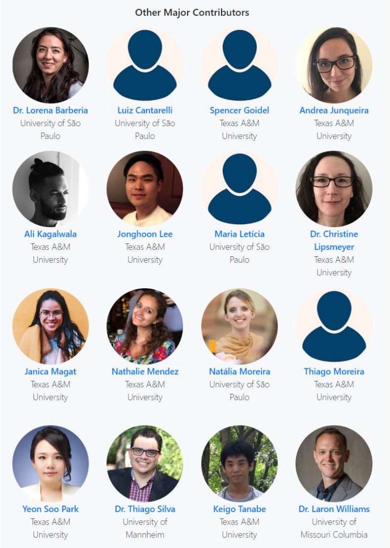
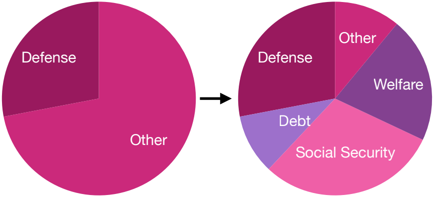
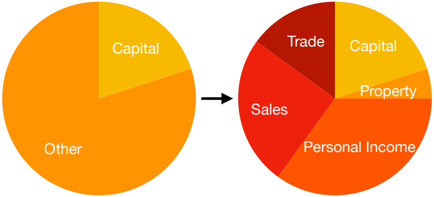


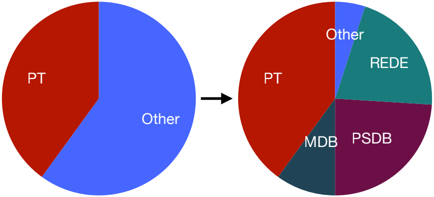
Government Budget



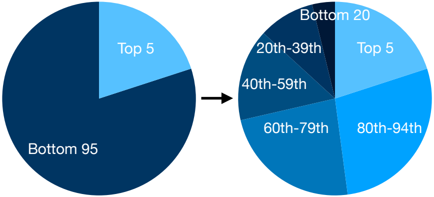
Tax Revenues



Party Vote Share



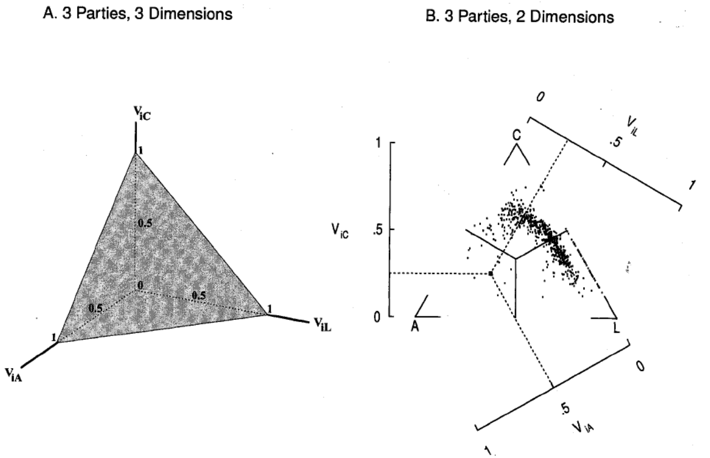
Income Distribution



Compositional Time Series

- A compositional variable, **V**, consists of a row of vectors of J components. If we label each individual observation in time for the value of a particular part of the same composition as V_{tj}, we can describe a compositional variable as having four defining characteristics:
  1. each component of the composition must have a value between zero and one, $0 < V_{tj} < 1$
  2. for each observation in time, t, the components must sum to one, $\sum_{j=1}^{J} V_{tj} = 1$
  3. from these properties, it follows that any change in a single component be bounded by -1 and 1, $-1 < \Delta V_{tj} < 1$
  4. and that all change among component parts at any single point in time must sum to zero, $\sum_{j=1}^{J} \Delta V_{tj} = 0$
- All of the component parts of variables like **V** cannot be handled in regression models.

FIGURE 2. The Simplex for Three Parties



Note: In a manner analogous to Figure 1, this figure reduces three vote variables to two dimensions. Graph A portrays the relationship among the votes for the Conservative (V_{iC}), Labour (V_{iL}), and Alliance (V_{iA}) parties; because of the constraints of equations 1 and 2, all points fall on an equilateral triangle that is the intersection of a plane with the three dimensional figure. Graph B portrays this more simply in two dimensions in a version of what is known as a "ternary diagram." Values of the three variables can be read by where the dots fall perpendicular to the three numbered axes. The little square point (with dotted lines referencing the axes) is the example discussed in the text.

Our Initial Modeling Strategy–Overview

1. We followed Aitchison's (1986) suggestion of a logratio transformation:
$$s_{tj} = ln(y_{tj}/y_{t1}) \forall j \neq 1.$$
2. Estimate the long-run and short-run dynamics using an error correction model.
3. When $J > 2$, we use a seemingly unrelated regression estimation approach (Zellner 1962; Tomz et al. 2002; Jackson 2002; Mikhailov et al. 2002).
4. Interpret the resulting rich parameterization using dynamic simulations built on Clarify (King, Tomz, Wittenberg 2000; Whitten and Williams 2011; Williams and Whitten 2011, 2012).

Our Initial Modeling Strategy–system of equations

$$\Delta s_{tj} = \beta_{0j} - \alpha_j s_{jt-1} + \boldsymbol{\beta}_{Lj}\mathbf{x}_{t-1} + \boldsymbol{\beta}_{Sj}\Delta\mathbf{x}_t + \varepsilon_{tj}$$

- where Δs_{tj} is the change in the logged ratio of dependent variable category "j" for $j > 1$ relative to baseline category $j = 1$ from time "t-1" to time "t",
- $\mathbf{x}_t$ is a vector of independent variable values at time "t",
- $-\alpha_j$ are adjustment parameters that measure the long-run error correction processes,
- $\boldsymbol{\beta}_{Sj}$ is a vector of short-run effects,
- $\boldsymbol{\beta}_{Lj}$, is a vector of parameters that can be combined with $-\alpha_j$ to calculate estimated long-run effects of changes in each independent variable,
- and ε_{tj} is the stochastic disturbance term that may be correlated across the "J" equations.

Results in $((J-1)((K \times 2) + 2))$ parameter estimates.

Initial Interpretation strategy

- "Un-transformation" equations

$$\hat{Y}_{tj} = \frac{e^{\hat{S}_{tj}}}{1 + \sum_{j=2}^{J} e^{\hat{S}_{tj}}} \forall j > 1$$

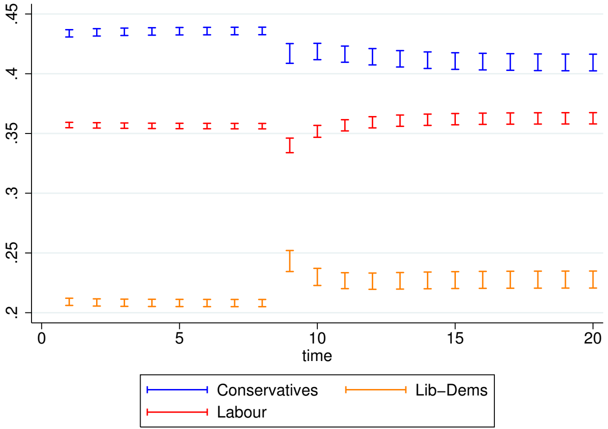
$$\hat{Y}_{t1} = \frac{1}{1 + \sum_{j=2}^{J} e^{\hat{S}_{tj}}} \text{ when } j = 1$$

- Graphic displays of model-based dynamic simulations.
- Initial assessments through "change from baseline simulations:"
  - set the lagged dependent variables to the sample mean for each category ($\bar{Y}_{tj}$)
  - set the lagged independent variables to their sample mean values
  - set the values for each of the differenced independent variable to zero
  - at a chosen point in each simulation, we change the value of one independent variable

Initial Interpretation strategy–A quick peak under the hood for what goes on during a change from baseline simulation

	$\Delta\hat{s}_{tj} = \hat{\beta}_{0j} - \hat{\alpha}_j s_{jt-1}$	$+ \hat{\beta}_{1j} x^*_{t-1}$	$+ \hat{\beta}_{2j} \Delta x^*_t$	$+ \hat{\boldsymbol{\beta}}_{Lj} \mathbf{x}_{t-1}$	$+ \hat{\boldsymbol{\beta}}_{Sj} \Delta \mathbf{x}_t + \hat{\epsilon}_{tj}$
$t = 1$	$\bar{s}_j$	$\bar{x}^*$	0	$\bar{\mathbf{x}}$	0
$t = 2$	s_{j1}	$\bar{x}^*$	0	$\bar{\mathbf{x}}$	0
$t = 3$	s_{j2}	$\bar{x}^*$	0	$\bar{\mathbf{x}}$	0
$t = 4$	s_{j3}	$\bar{x}^*$	$shock$	$\bar{\mathbf{x}}$	0
$t = 5$	s_{j4}	$\bar{x}^* + shock$	0	$\bar{\mathbf{x}}$	0
$\vdots$					

Initial Interpretation strategy–An example of a change from baseline figure



Before and After

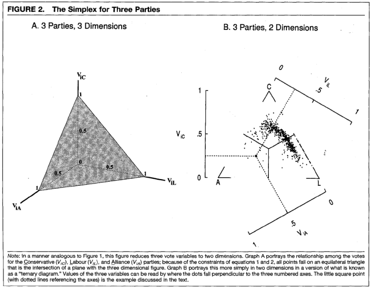


Figure: Katz and King

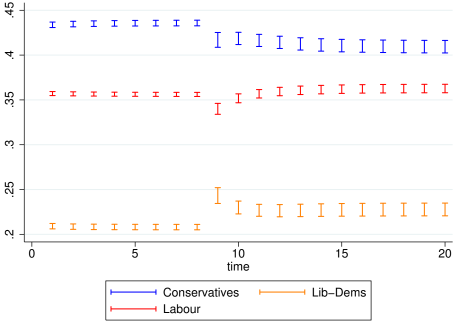
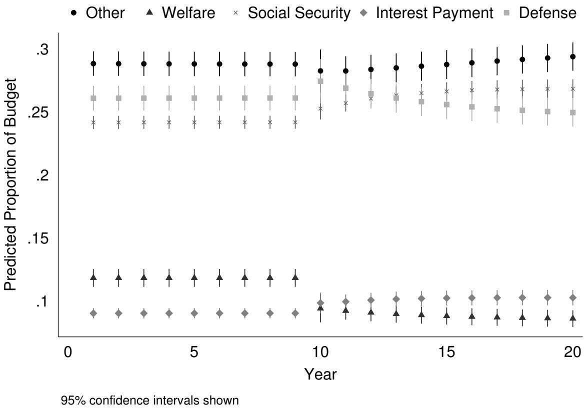


Figure: Dynamic Pie

Change from baseline figure with more than 3 categories–US budget response to a drop in unemployment



US Budget—Military spending as a percentage of federal budget

	$\frac{Defense}{AllOther}$
Population	-.049
Growth, Short	(0.037)
Population	-.080
Growth, Long	(0.126))
Hostility	-.0004
Level, Short	(0.001)
Hostility	.003
Level, Long	(0.004)
National	-.011
Unemployment, Short	(0.006)
National	.010
Unemployment, Long	(0.025)
Old Age	2.204
Dependency, Short	(5.011)
Old Age	-5.949**
Dependency, Long	(1.782)
Mood,	.001
Short	(0.002)
Mood,	.010
Long	(0.007)
% GDP	-.301
Change, Short	(0.170)
% GDP	-2.458
Change, Long	(2.191)
Democratic	-.016*
Congress	(0.008)
Democratic	-.007
President	(0.009)
$\hat{\alpha}$	-.181*
	(0.079)
Constant	.162
	(0.141)
N	48
R^2	0.50

Notes: * $p < .05$, ** $p < .01$

US Budget—Pie model of 5 category federal budget

Table S 4: Estimated short-run and long-run effects on US Budget Spending

	Other/Defense	Welfare/Defense	SocialSecurity/Defense	Interest/Defense	Other/Welfare	SocialSecurity/Welfare	Interest/Welfare	Other/SocialSecurity	Interest/SocialSecurity	Interest/Other
Population	0.288	0.050	0.247	0.583**	0.147	0.225	0.510*	-0.060	0.254	0.300
Growth, Short	(0.178)	(0.255)	(0.131)	(0.174)	(0.200)	(0.186)	(0.229)	(0.122)	(0.146)	(0.185)
Population	0.804	-0.739	0.584	1.560**	0.756*	1.124*	2.882**	-0.129	1.178*	1.334
Growth, Long	(0.880)	(0.937)	(0.340)	(0.482)	(0.351)	(0.495)	(1.114)	(0.216)	(0.721)	(0.723)
Hostility	-0.001	-0.004	0.0002	-0.002	0.002	0.004	0.002	-0.002	-0.003	-0.001
Level, Short	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.031)
Hostility	-0.007	-0.046	-0.008	0.004	0.015	0.027	0.057	-0.004	0.011	0.014
Level, Long	(0.031)	(0.037)	(0.012)	(0.016)	(0.013)	(0.018)	(0.038)	(0.008)	(0.027)	(0.027)
National	0.049	0.188**	0.003	-0.022	-0.146**	-0.186**	-0.222**	0.040*	-0.038	-0.083**
Unemployment, Short	(0.029)	(0.043)	(0.021)	(0.031)	(0.033)	(0.031)	(0.038)	(0.021)	(0.024)	(0.031)
National	-0.069	0.189	-0.107	-0.122	-0.165**	-0.277**	-0.416*	0.076	-0.043	-0.159
Unemployment, Long	(0.159)	(0.171)	(0.064)	(0.091)	(0.063)	(0.090)	(0.199)	(0.043)	(0.133)	(0.137)
Old Age	-33.33	-14.66	-15.672	55.061*	-26.748	6.068	68.137*	-32.206*	59.495**	91.819**
Dependency, Short	(23.74)	(34.16)	(17.57)	(23.001)	(26.312)	(25.558)	(30.433)	(15.944)	(19.271)	(24.451)
Old Age	34.30*	43.862**	35.615**	36.015**	-13.546**	-3.018	-13.682	-13.396**	-5.035	0.263
Dependency, Long	(14.120)	(14.723)	(4.825)	(6.695)	(4.926)	(7.210)	(15.187)	(4.452)	(11.086)	(12.952)
Mood,	0.006	-0.010	-0.013*	-0.017*	0.015	-0.003	-0.008	0.017**	-0.004	-0.023**
Short	(0.007)	(0.011)	(0.006)	(0.007)	(0.009)	(0.008)	(0.010)	(0.005)	(0.006)	(0.008)
Mood,	-0.033	-0.016	-0.056**	-0.110**	0.009	-0.032	-0.155*	0.028*	-0.102*	-0.133**
Long	(0.047)	(0.052)	(0.019)	(0.035)	(0.019)	(0.028)	(0.075)	(0.014)	(0.051)	(0.050)
% GDP	0.952	3.636**	0.872	0.550	-2.941**	-2.589**	-3.373**	-0.453	-0.702	-0.552
Change, Short	(0.818)	(1.184)	(0.601)	(0.826)	(0.923)	(0.867)	(1.078)	(0.616)	(0.674)	(0.871)
% GDP	14.510	32.354	4.212	5.426	-12.667*	-16.428*	-33.025	-0.943	-6.135	-6.520
Change, Long	(14.722)	(19.340)	(4.920)	(6.338)	(5.244)	(7.960)	(19.655)	(3.440)	(11.672)	(11.858)
Democratic	0.128**	0.078	0.048	0.041	-0.023	-0.038	-0.036	0.071**	-0.011	-0.085*
Congress	(0.037)	(0.054)	(0.028)	(0.037)	(0.043)	(0.040)	(0.049)	(0.026)	(0.030)	(0.039)
Democratic	-0.014	0.016	-0.056	-0.086*	-0.033	-0.081	-0.098	0.061	-0.034	-0.072
President	(0.043)	(0.062)	(0.032)	(0.042)	(0.049)	(0.047)	(0.056)	(0.033)	(0.035)	(0.044)
$\hat{\alpha}$	-0.127**	-0.164*	-0.235**	-0.241**	-0.353**	-0.251**	-0.143**	-0.331**	-0.119**	-0.151**
	(0.052)	(0.065)	(0.039)	(0.071)	(0.073)	(0.068)	(0.047)	(0.120)	(0.042)	(0.042)
Constant	-0.716	-1.532	-0.923*	-0.709	1.245*	0.943	1.638*	0.378	0.579	0.904
	(0.521)	(0.811)	(0.459)	(0.842)	(0.615)	(0.555)	(0.697)	(0.630)	(0.432)	(0.608)
N	48	48	48	48	48	48	48	48	48	48
R^2	0.48	0.55	0.54	0.55	0.58	0.63	0.67	0.51	0.58	0.57

Seemingly unrelated regression model with error correction specification. * $p < .05$, ** $p < .01$. One-tailed t-tests with standard errors in parentheses. Dependent variables are logged odds ratios relative to a baseline spending category.

Dynamic Pie Modeling Strategy–Initial Papers and Software

Dynamic Pie: A Strategy for Modeling Trade-Offs in Compositional Variables over Time

Andrew Q. Philips Texas A&M University
Amanda Rutherford Indiana University
Guy D. Whitten Texas A&M University

The substance of politics involves competition that evolves over time. While our theories about competition emphasize trade-offs across multiple categories, most empirical models tend to oversimplify them by considering trade-offs between one category and everything else. We propose a research strategy for testing theories about trade-off relationships that shape dynamic compositional variables. This approach improves current methods used to analyze compositional dependent variables by addressing two limitations. First, although scholars have considered compositional dependent variables, they have done so in contexts that were not dynamic. Second, current approaches toward graphical presentations become unwieldy when the compositional dependent variable has more than three categories. We demonstrate the utility of our strategy to expand current theories of party support and political budgeting. In both cases, we can extend trade-offs across pairs of alternatives (e.g., prime minister versus all other parties or spending on defense versus everything else) to competition across multiple alternatives.

Much of the substance of politics and policy-making involves trade-offs. These trade-offs reflect the competitive nature of the processes that political scientists study. For instance, when public support for one party increases, this usually comes from a corresponding decline in the support for other parties or in the proportion of the public that is undecided. Similarly, when policy makers increase spending in one area of their budget, this will typically be offset by spending cuts in other areas. In both situations, we can think about the dependent variable of interest as analogous to a pie that is repeatedly divided into portions. Although researchers have developed a wide range of theories about the processes that shape these types of zero-sum trade-off relationships over time, most have limited their analyses of this type of variable over time to models of the size of a single piece of the pie.

In this article, we propose a research strategy for testing theories about trade-off relationships that shape compositional variables over time. This approach improves on current methods used by political scientists to analyze compositional dependent variables by addressing two limitations in the extant literature. First, although political scientists have considered compositional dependent variables, they have done so either in contexts that are not dynamic or in contexts in which they ignore the dynamic nature of their data. Second, current approaches to graphical presentations become unwieldy when the

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Earlier versions of this article were presented at Texas A&M University, the University of Georgia, the Instituto de Estudos Socias e Politicos, Rio de Janeiro, the University of São Paulo, and the National University of Singapore. The authors thank these audiences for their helpful critiques and comments. The authors also thank Scott Ainsworth, Ryan Bakker, Lorena Barberia, Patrick Brandt, Ricardo Ceneviva, Bill Clark, Harold Clarke, Peter Enns, Rob Franzese, Christine Lipsmeyer, Jamie Monogan, and Laron Williams for their helpful critiques and comments. Despite this wealth of helpful advice, the authors take full responsibility for any errors that remain. The data and programming files needed to replicate the analyses presented in this article are available in the AJPS Data Archive on Dataverse at https://thedata.harvard.edu/dvn/(doi:10.7910/DVN/29316).

American Journal of Political Science, Vol. 00, No. 0, xxxx 2015, Pp. 1–16

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```
Title

    dynsimpie — A program to dynamically examine compositional dependent variables

Syntax

        dynsimpie indepvars [if] [in] [, options]

    options              Description
    ---------------------------------------------------------------------------------
    Required options
      dvs(varlist)         a list of the compositional dependent variables
      shockvar(varname)    independent variable not included in varlist that is to be shocked
      shock(#)             amount to shock shockvar(varname)
      time(#)              scenario time in which the shock occurs

    Additional options
      saving(string)       specifies the name of the output file (default is "dynsimpie_results.dta")
      range(#)             length of scenario to simulate (default is 20)
      sig(#)               significance level for confidence intervals (default is 95%)
      dummy(varlist)       list of dummy variables to include in the model
      dummyset(numlist)    list of values for each respective dummy variable in dummy(varlist) to take
                             on (default is to set all to 0)
      shockvar2(varname)   additional independent variable not included in varlist that is to be shocked
      shock2(numlist)      amount to shock shockvar2(varname)
      shockvar3(varname)   additional independent variable not included in varlist that is to be shocked
      shock3(numlist)      amount to shock shockvar3(varname)
    ---------------------------------------------------------------------------------

Description

    dynsimpie is a program to dynamically examine compositional dependent variables, as detailed in
    Philips, Rutherford, and Whitten (2015). Their modeling strategy is to use an error correction
```

Extensions to initial strategy

- First steps toward a mixed logit-type specification–including changing attributes of categories through interactive specifications (Philips, Andrew, Amanda Rutherford, and Guy D. Whitten. 2015. "The Dynamic Battle for Pieces of Pie–modeling party support in multi-party nations." *Electoral Studies*. 39:264-274.)

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

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A R T I C L E I N F O

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Party competition
Time series models
Compositional data

A B S T R A C T

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.

Food Safety and Spinach Demand: A Generalized Error Correction Model

Carlos Arnade, Fred Kuchler, and Linda Calvin

We estimate an error correction model representing demand for leafy green vegetables but generalize the structure to allow for adjustment to one conspicuous shock. We investigate whether the adjustment rate to the U.S. Food and Drug Administration's (FDA) 2006 warning that fresh spinach was contaminated with deadly bacteria was distinct from the overall adjustment rate. Our model allows consumers to correct both for past errors and for any errors in their reaction to the shock. This method yields an estimate of the adjustment rate to the policy shock and points to an improved estimate of the duration of policy impacts.

Key Words: error correction model, adjustment rates, AIDS demand model, retail food demand

error term equally influence the rate of adjustment to equilibrium" (p.251). Utilizing Arnade et al.'s time-dependent error decomposition (and adding a decomposition to the short-run parameters), we relax this assumption and change our model to:

$$\begin{aligned}\text{Party Support Share}_{tj} = f\big((&\text{Economic Evaluations}_t\\ &+ \text{CD Leader Evaluation}_t\\ &+ \text{SPD Leader Evaluation}_t\\ &+ \text{Average LR Self Placement}_t)\\ &\times (\text{Government Status}_{tjc})\big)\end{aligned} \tag{4}$$

where Government Status$_{tjc}$ for party j is an indicator of coalition c at time t and interacted with all other variables previously in the function. To derive this, we start with our initial ECM-SUR model from before:

$$\Delta s_{tj} = \beta_{0j} - \alpha_j s_{jt-1} + \mathbf{x}_{t-1}\boldsymbol{\beta}_{Lj} + \Delta\mathbf{x}_t\boldsymbol{\beta}_{Sj} + \boldsymbol{\Sigma}_{tj}. \tag{5}$$

Next, we collect the lagged dependent variable s_{jt-1} and the vector of parameters for the lagged independent variables as a function of the adjustment parameter α_j

$$\Delta s_{tj} = \beta_{0j} - \alpha_j\left(s_{jt-1} + \mathbf{x}_{t-1}\boldsymbol{\kappa}_{Lj}\right) + \Delta\mathbf{x}_t\boldsymbol{\beta}_{Sj} + \boldsymbol{\Sigma}_{tj} \tag{6}$$

since $\boldsymbol{\beta}_{Lj} = -\boldsymbol{\kappa}_{Lj}/\alpha_j$. Next we add a term $D_t\phi_j$ to the adjustment parameter α_j, and $D_t\zeta_j$ to the short-run parameters $\boldsymbol{\beta}_{Sj}$.

$$\begin{aligned}\Delta s_{tj} = \beta_{0j} - \alpha_j(1 + D_t\phi_j)\left(s_{jt-1} + \mathbf{x}_{t-1}\boldsymbol{\kappa}_{Lj}\right) + \Delta\mathbf{x}_t\boldsymbol{\beta}_{Sj}(1 + D_t\zeta_j)\\ + \boldsymbol{\Sigma}_{tj}\end{aligned} \tag{7}$$

$D_t\phi_j$ allows for a time-specific error correction, while $D_t\zeta_j$ relaxes the assumption that the effect of a short-run change in an independent variable is constant across coalitions. Because we remain agnostic as to whether both the short- and long-term effects of each parameter differ under the coalitions, we add the interaction to both the long-run adjustment parameter as well as the short-run 'shock'

Table 3
Germany–interaction results.

	$\frac{FDP}{CDU}$	$\frac{GRU}{CDU}$	$\frac{SDP}{CDU}$	$\frac{GRU}{FDP}$	$\frac{SDP}{FDP}$	$\frac{GRU}{SDP}$
Economy Thermometer, Short	−0.006	−0.006	0.006	−0.004	0.025	−0.014
	(0.035)	(0.025)	(0.019)	(0.038)	(0.033)	(0.027)
Economy Thermometer, Long	−0.155	−0.015	0.037	0.137	0.198	−0.055
	(0.167)	(0.103)	(0.113)	(0.218)	(0.123)	(0.142)
Economy Thermometer, Short Interaction	−0.002	−0.006	0.008	−0.008	0.052	−0.011
	(0.012)	(0.026)	(0.025)	(0.073)	(0.071)	(0.023)
Economy Thermometer, Long Interaction	−0.164	−0.012	0.046	0.150	0.213	−0.039
	(0.182)	(0.083)	(0.143)	(0.240)	(0.139)	(0.102)
CDU Chair Support, Short	−0.506	−0.214	-0.372^{*}	0.278	0.128	0.136
	(0.412)	(0.307)	(0.227)	(0.455)	(0.391)	(0.322)
CDU Chair Support, Long	−1.151	−0.580	−1.909	0.657	−0.346	0.831
	(3.275)	(1.980)	(2.314)	(4.225)	(2.377)	(2.761)
CDU Chair Support, Short Interaction	−1.676	−0.006	−0.286	−0.642	−0.252	0.134
	(1.748)	(0.026)	(0.399)	(1.255)	(0.838)	(0.312)
CDU Chair Support, Long Interaction	−1.922	−0.681	−1.166	−0.836	0.272	1.902
	(6.875)	(2.880)	(3.169)	(6.453)	(1.680)	(5.810)
Conservative Self-Placement, Short	-0.408^{**}	−0.160	-0.262^{***}	0.265	0.139	0.107
	(0.180)	(0.134)	(0.099)	(0.198)	(0.170)	(0.141)
Conservative Self-Placement, Long	0.041	−0.210	0.042	−0.073	−0.032	−0.109
	(0.320)	(0.225)	(0.220)	(0.434)	(0.235)	(0.294)
Conservative Lean, Short Interaction	-0.595^{*}	−0.189	-0.314^{**}	0.194^{**}	0.104	0.104
	(0.333)	(0.179)	(0.144)	(0.096)	(0.105)	(0.122)
Conservative Lean, Long Interaction	0.039	−0.227	0.041	−0.097	−0.029	−0.159
	(0.304)	(0.239)	0.214	(0.579)	(0.216)	(0.427)
SPD Support, Short	0.285	0.184	0.126	−0.059	−0.154	0.119
	(0.589)	(0.442)	(0.324)	(0.649)	(0.558)	(0.461)
SPD Support, Long	0.702	1.530	1.287	0.781	0.192	1.281
	(4.278)	(2.567)	(3.052)	(5.411)	(3.038)	(3.508)
SPD Support, Short	0.054	0.195	0.171	−0.127	−0.366	0.080
	(0.190)	(0.401)	(0.401)	(1.446)	(1.411)	(0.263)
SPD Support, Long	1.057	1.700	2.153	1.235	0.265	0.583
	(5.665)	(1.779)	(4.300)	(7.294)	(3.979)	(0.988)
Constant	−0.606	−0.114	−0.034	−0.243	0.774^{*}	−0.218
	(0.443)	(0.348)	(0.234)	(0.497)	(0.421)	(0.342)
$\widehat{\alpha}$	-0.282^{***}	-0.344^{***}	-0.231^{***}	-0.240^{***}	-0.365^{***}	-0.261^{***}
	(0.068)	(0.098)	(0.073)	(0.051)	(0.056)	(0.072)
$\widehat{\alpha}+\widehat{\alpha}\widehat{\phi}$	-0.290^{***}	-0.332^{***}	-0.214^{**}	-0.187^{***}	-0.369^{***}	-0.195^{**}
	(0.093)	(0.139)	(0.088)	(0.058)	(0.083)	(0.084)
N	130	130	130	130	130	130
R^2	0.22	0.24	0.26	0.20	0.26	0.26

Notes: Seemingly unrelated regression model with error correction specification. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Two-tailed t-tests with standard errors in parentheses. Dependent variables are logged ratios relative to a baseline category. Long-run effects are calculated $LR = \beta_{1j}/-\alpha_j$ or $LR = \beta_{1j}/-(\widehat{\alpha}_j + \widehat{\alpha}_j\widehat{\phi}_j)$ using the delta method.

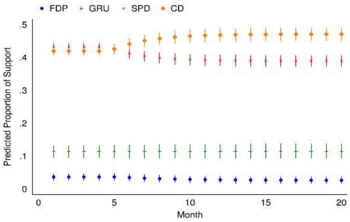

Fig. 5. Dynamic simulation of a one standard deviation decrease in SPD Leader Evaluation during SPD-GRU coalition government.

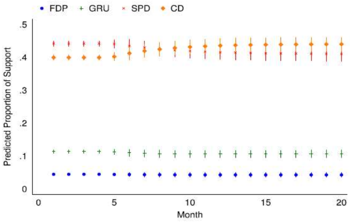

Fig. 6. Dynamic Simulation of a 1 std. dev. decrease in SPD Leader Evaluation during CD-FDP coalition government.

Extensions to initial strategy

- First steps toward a mixed logit-type specification–including changing attributes of categories through interactive specifications (Philips, Andrew, Amanda Rutherford, and Guy D. Whitten. 2015. "The Dynamic Battle for Pieces of Pie–modeling party support in multi-party nations." *Electoral Studies*. 39:264-274.)
- First extensions to TSCS data, Lagged DV specifications, other types of interactions, and effects plots. (Lipsmeyer, Christine S., Andrew Q. Philips, and Guy D. Whitten. 2017. "The Effects of Immigration and Integration on European Budgetary Trade-offs." *Journal of European Public Policy*. 24(6):912-930.)

Table: Theorized Expectations to Integrative Shocks

	Left	**Right**
General Priority	Labor (redistribution)	Capital and Business (efficiency)
Most Responsive To	Immigration	Labor Market Integration
Prioritized Budget Categories	Social Protection, Public Services, Housing, Health	Economic Policy, Health

JEPP paper model

$$s_{itj} = f((s_{it-1j} + \Delta Int_{it} + \Delta Imm_{it} + \mathbf{Controls})(1 + Right_{it}) + \varepsilon_{itj}) \qquad (1)$$

where

- s_{itj} is the log-ratio of dependent variable category "j" for $j > 1$ relative to baseline category $j = 1$ at time "t" for country i,
- s_{ijt-1} is a lagged dependent variable. We include this to take into account that the fact that budgets tend to shift incrementally. Another advantage of including a lagged dependent variable is the ability to obtain both short- and long-run effects of the independent variables,
- ΔInt_{it} is our measure of integration,
- ΔImm_{it} is our measure of immigration,
- $Right_{it}$ is a dummy variable equal to "1" if the party or coalition in government is right-leaning,
- and **Controls** is a vector of controls.

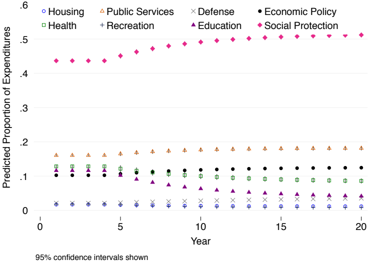

Figure 1a: Left Government Reaction to an Immigration Shock

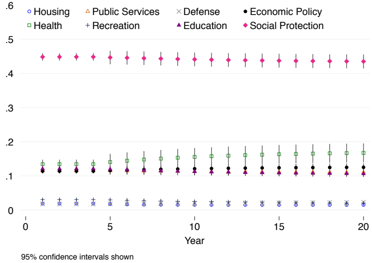

Figure 1b: Right Government Reaction to an Immigration Shock

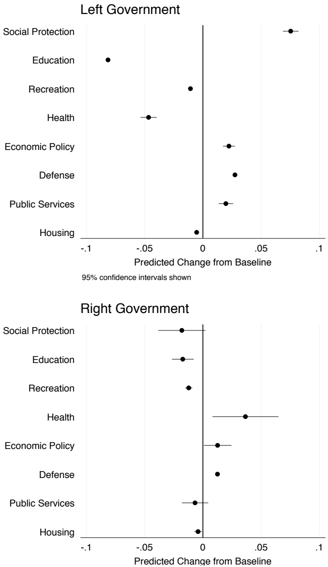

Figure 1c: Comparison of Governments' Long-Run Reactions to an Immigration Shock

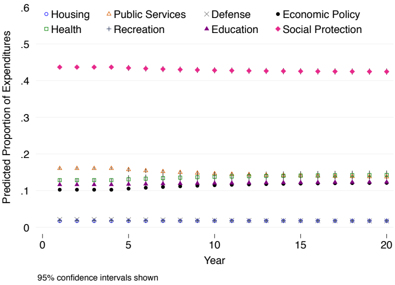

Figure 2a: Left Government Reaction to an Integration Shock

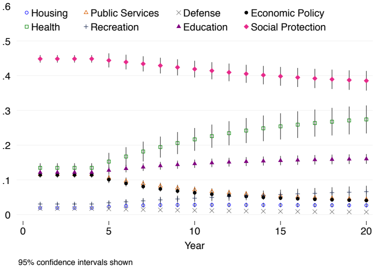

Figure 2b: Right Government Reaction to an Integration Shock

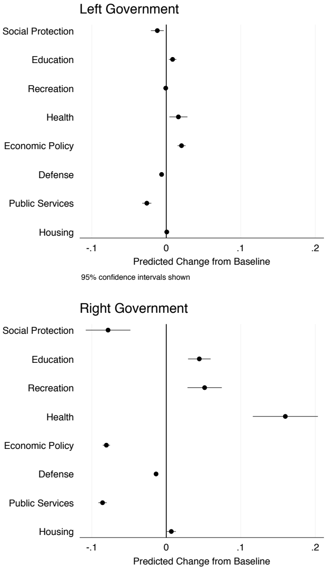

Figure 2c: Comparison of Governments' Reactions to an Integration Shock

Extensions to initial strategy (published and forthcoming)

- First steps toward a mixed logit-type specification–including changing attributes of categories through interactive specifications (Philips, Andrew, Amanda Rutherford, and Guy D. Whitten. 2015. "The Dynamic Battle for Pieces of Pie–modeling party support in multi-party nations." *Electoral Studies*. 39:264-274.)
- Lagged DV specifications, other types of interactions, and effects plots. (Lipsmeyer, Christine S., Andrew Q. Philips, and Guy D. Whitten. 2017. "The Effects of Immigration and Integration on European Budgetary Trade-offs." *Journal of European Public Policy*. 24(6):912-930.)
- Extending to TSCS data and including spatial econometric specifications. (Lipsmeyer, Christine S., Andrew Q. Philips, Amanda Rutherford, and Guy D. Whitten. 2019. "Comparing Dynamic Pies: A Strategy for Modeling Compositional Variables in Time and Space." *Political Science Research and Methods*.)

Political Science Research and Methods Page 1 of 18

doi:10.1017/psrm.2017.39

Comparing Dynamic Pies: A Strategy for Modeling Compositional Variables in Time and Space*

CHRISTINE S. LIPSMEYER, ANDREW Q. PHILIPS, AMANDA RUTHERFORD AND GUY D. WHITTEN

Across a broad range of fields in political science, there are many theoretically interesting dependent variables that can be characterized as compositions. We build on recent work that has developed strategies for modeling variation in such variables over time by extending them to models of time series cross-sectional data. We discuss how researchers can incorporate the influence of contextual variables and spatial relationships into such models. To demonstrate the utility of our proposed strategies, we present a methodological illustration using an analysis of budgetary expenditures in the US states.

Extensions to initial strategy (published and forthcoming)

- First steps toward a mixed logit-type specification–including changing attributes of categories through interactive specifications (Philips, Andrew, Amanda Rutherford, and Guy D. Whitten. 2015. "The Dynamic Battle for Pieces of Pie–modeling party support in multi-party nations." *Electoral Studies*. 39:264-274.)
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- Philips, Andrew Q., Flávio D. S. Souza, and Guy D. Whitten. Forthcoming. "Globalization and Comparative Compositional Inequality," *Political Science Research and Methods*.

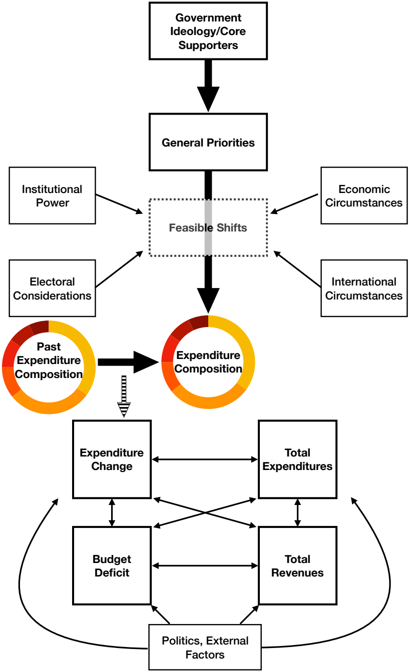
Projects in progress

Substantive:

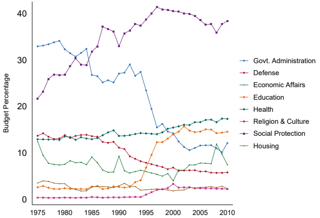
- Political economy of support for Brazilian parties
- Political economy of support for parties in Putin's Russia
- Political budgeting in the US states
- **Comparative political budgeting**

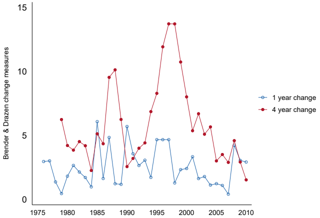
Methodological:

- **different modeling strategies for size of pie**
- **Compositional Volatility**


Government Ideology/Core Supporters
General Priorities
Institutional Power
Economic Circumstances
Feasible Shifts
Electoral Considerations
International Circumstances
Past Expenditure Composition
Expenditure Composition
Expenditure Change
Total Expenditures
Budget Deficit
Total Revenues
Politics, External Factors

Compositional Volatility models





Projects in progress

Substantive:

- Political economy of support for Brazilian parties
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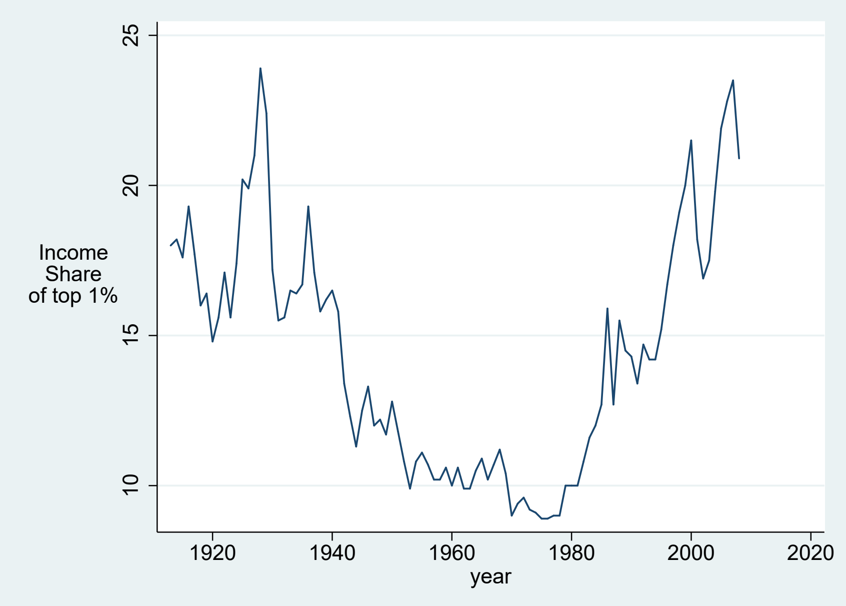
- Comparative political budgeting
- **Income inequality**

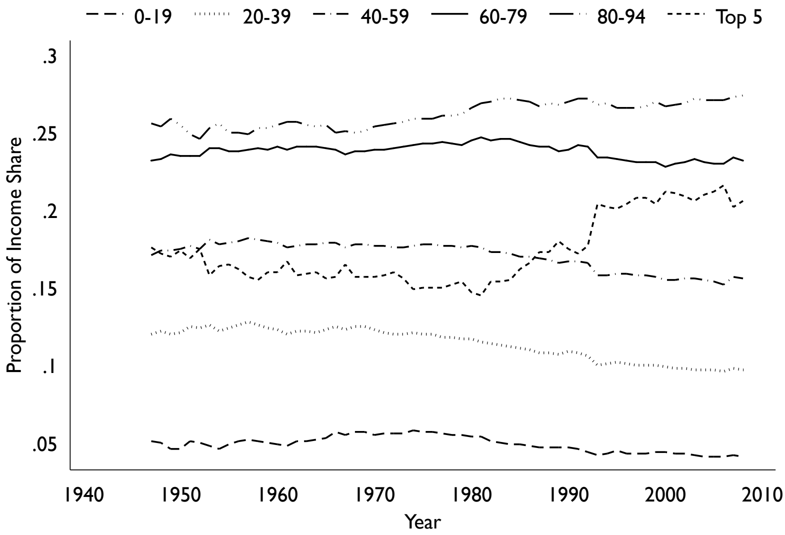
Methodological:

- different modeling strategies for size of pie
- Compositional volatility models
- **The continuous pie problem**

Picketty et al, multiple publications



The Proportion of Income in the US, 1947 to 2008



Projects in progress

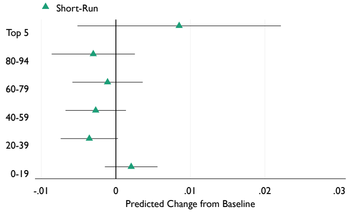
Substantive:

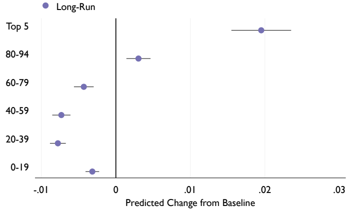
- Political economy of support for Brazilian parties
- Political economy of support for parties in Putin's Russia
- Political budgeting in the US states
- Comparative political budgeting
- **Income inequality**

Methodological:

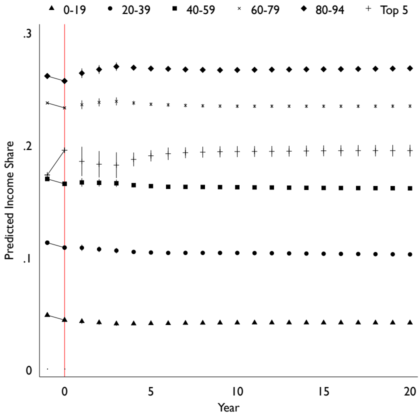
- different modeling strategies for size of pie
- Compositional volatility models
- The continuous pie problem
- **Endogenous pie**

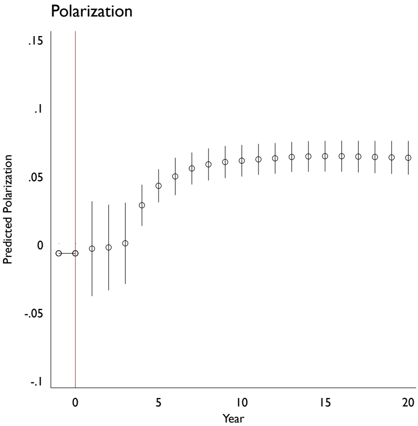
Effects of a 1 standard deviation increase in polarization in the US





Impulse-Response Plots for a 1 Standard Deviation Increase in Top 5%





Projects in progress

Substantive:

- Political economy of support for Brazilian parties
- Political economy of support for parties in Putin's Russia
- Political budgeting in the US states
- Comparative political budgeting
- Income inequality

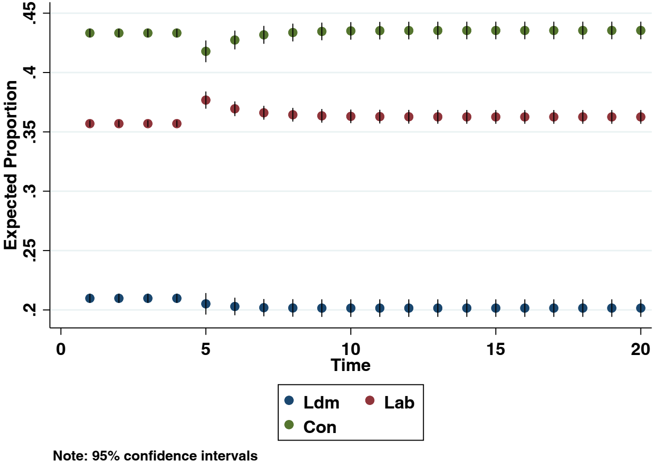
Methodological:

- different modeling strategies for size of pie
- Compositional ARCH and GARCH models
- The continuous pie problem
- Endogenous pie
- **full-blown mixed pie**
- **dynsimpie software update**

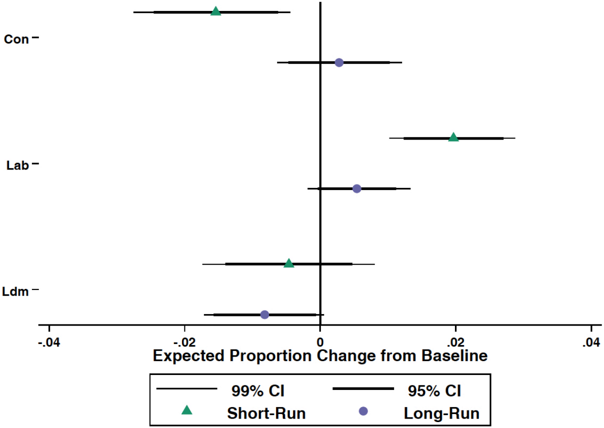
dynsimpie software updates

- Currently available in Stata, R version planned
- More flexible modeling options
  - ECM and ARDL versions
  - Interactive specifications
- Evolving scenarios for change from baseline plots (multiple shocks)
- Effects plots
- Coefficient plots

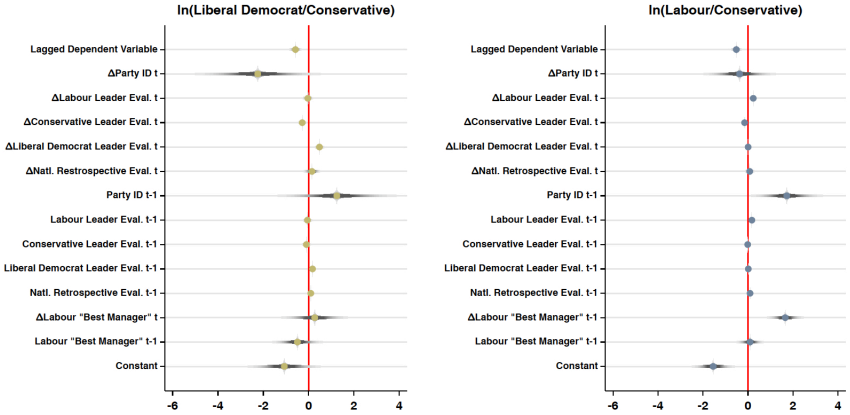
The simulated effect of a 1-SD increase in the percentage of those who think Labour is the best manager of the most important issue, created using the `cfbplot` option



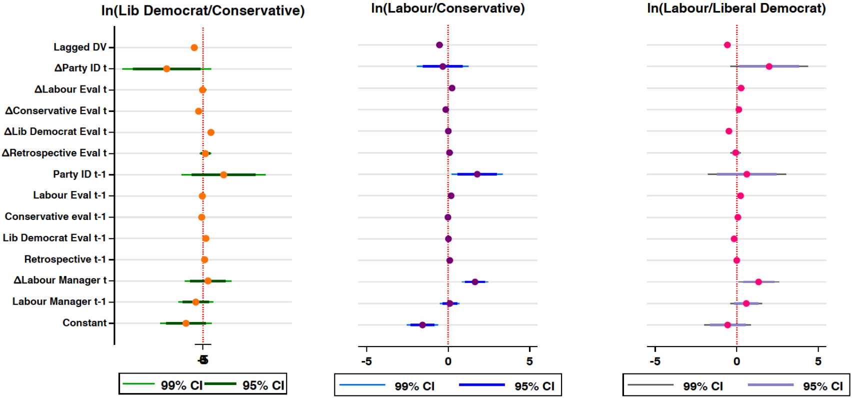
The simulated effect of a 1-SD increase in the percentage of those who think Labour is the best manager of the most important issue, created using the `sig(95)`, `sig2(99)` and `effectsplot` options



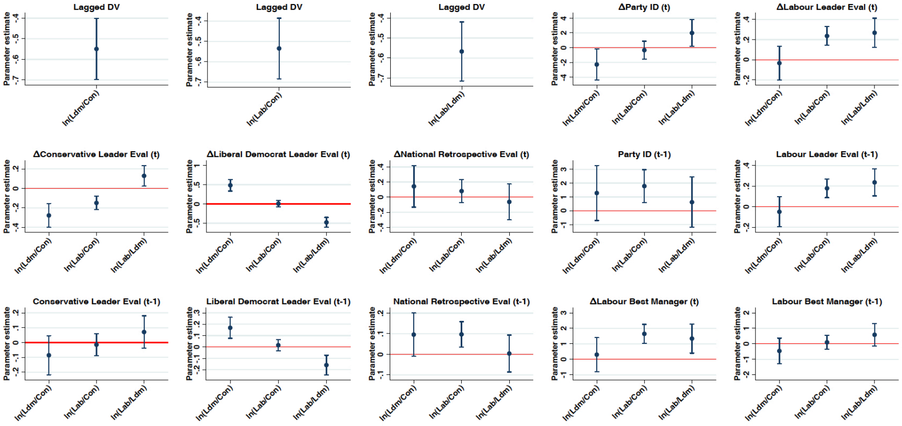
Coefficient plots from the dynsimpiecoef results, created using the smooth option



Coefficient plots from the dynsimpiecoef results, created using the sig(95), sig2(99), and all options



Coefficient plots from the `dynsimpiecoef` results, created using the `vertical` and `angle(45)` options



Thank you!