

Appendix for “How Does the Ideological Composition of the Electorate Influence Attack Advertising Strategies?”

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Error Correction Model Specification

To capture the dynamic effects of mood on judges’ voting behavior, we test our hypotheses using single-equation error correction models (ECM) with judge-level random effects. Our use of ECMs provide a strong link between our theoretical expectations and our empirical model. The ECM estimates a coefficient for both the differenced and lagged values of each predictor.¹ This allows us to examine both short-run effects, in which a change in public preferences produces an immediate change in judges’ voting behavior, and long-run effects, in which the past value of public preferences influences current and future voting behavior through an equilibrium relationship (DeBoef and Keele 2008). Allowing for separate estimation of short- and long-run effects accounts for the fact that the judiciary is a reactive branch of government. While a court can have substantial influence on policy, it cannot exert such influence until a relevant case is argued before it. Thus, while immediate responses to public preferences are possible, our strategy also allows for the possibility that a change in the public’s preferences may take several years to influence judges’ behavior.

In recent years, much attention has been given to the proper or improper use of the General Error Correction Model (GECM). Much of this debate focuses on (1) the appropriateness of the models based on the types of series in an analysis, and (2) Type I error due to the use of the model. Here we work through numerous points of contention in the current debate and outline evidence that we are estimating and interpreting the model correctly.

Grant and Lebo (2016) outline many issues that researchers often ignore when working with the GECM, including situations that arise where scholars misspecify the ECM, which leads to spurious results.

1. The dependent variable is a unit root, $I(1)$.

¹A lagged independent variable in an ECM is a re-parameterized estimate of the error term from regressing Y on X . Consequently, the ECM models the extent to which the disequilibrium between X and Y is adjusted or corrected through changes in Y .

2. The dependent variable is a *bounded* unit root.
3. The dependent variable and all independent variables are stationary.
4. The dependent variable is strongly autoregressive/near integrated.
5. The dependent variable is fractionally integrated.
6. The dependent variable is explosive, $d \geq 1$.

We can dismiss a number of these instances given the nature of our two series of interest (state mood and judicial ideal points) with a unit root test. In Table A1, we present results from a Fisher Test for Panel Unit Roots using an Augmented Dickey-Fuller for each of our models. The test statistics in Table A1 both reject the null hypothesis that either of our series contain a unit root. The panel test for a unit root, however, is a broadsword where a scalpel may be needed. The null hypothesis is that *all series contain a unit root*. An alternative to this would be to split out each panel and run individual Dickey-Fuller tests for each one. This is problematic for our data given the short nature of each series within the panel. The Dickey-Fuller test is based on an ordinary least squares (OLS) regression. We would have at the most 28 observations per regression due to the inclusion of the lags and differenced variables. The mean length of the series is 7.6 weeks and the median is 6 weeks. This would make statistical significance difficult to ascertain. This same issue would prevent us from estimating panel specific tests of cointegration. We take the information in Table A1 as supporting evidence that the two series in our data are in fact stationary and the dependent variable is not explosive. An explosive dependent variable would be indicative in the unit root test.

The biggest potential for concern raised by Grant and Lebo is perhaps case 3, that both series are stationary. De Boef and Keele (2008) contend that one highlight of the ECM model is the ability to use two stationary time series in the model framework. They outline the algebraic equivalence of the ECM and the Autoregressive Distributed Lag (ADL) model, and applaud the flexibility of the ECM. In fact, many scholars have interpreted this as freedom to use the ECM in any situation. This is a flawed approach. Both Keele, Linn, and Webb (2016) and Enns et al. (2016) stress the importance of understanding the types of series used in the ECM framework.

Enns et al. note the haphazard nature in which scholars have been using the ECM framework and emphasize that spurious results in ECMs with two series are most likely a result of not testing for cointegration between the series. We fully agree with this sentiment and encourage the recommendations the authors outline in their manuscript. The data we utilize in this manuscript, however, are not as easily suited for traditional tests of cointegration. To begin, we have panel data. Complicating matters is the unbalanced length of the series within our panels. We have series ranging from 3 to 28 weeks. Existing panel cointegration tests require balanced series with no

Table A1: Fisher Test for Panel Unit Root Using an Augmented Dickey-Fuller Test

	Democratic Attacks	Republican Attacks
χ^2	856.5973	832.1681
Prob $\geq \chi^2$	0.000	0.000

gaps in the data to execute the test given the nature of the necessary matrix used in the estimations. Below, we discuss how we examine cointegration in combination with other concerns regarding stationary times series.

Grant and Lebo argue the ECM framework will all but ensure statistically significant results for the error correction parameter and that although the two models are algebraically equivalent, “the reorganization of the parameters is not benign.” We point to Keele, Linn, and Webb (2016) to support the appropriateness of our model selection. To begin, the algebraic equivalence of the ADL and ECM cannot be stressed enough. In equation A2, we note the functional form of the ADL framework and in equation 2, the ECM model.

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \beta_0 X_t + \beta_1 X_{t-1} + \varepsilon_t \quad (1)$$

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \beta_0 \Delta X_t + \beta_1 X_{t-1} + \varepsilon_t \quad (2)$$

We argue that given the equivalence of the ADL and ECM, we are appropriately modeling the dynamic relationship of two stationary series. Either the ADL or the ECM would be an appropriate model for our series.

In the ADL model, the short run effect is the β parameter, the long run effect is noted by $\frac{\beta_0 + \beta_1}{1 - \alpha_1}$, and the error correction rate is $\alpha_1 - 1$. We present interaction terms in our models, which slightly alters this formula. The long run effect in the ADL is extended to include the interaction term and constitutive term when $Z \neq 0$ and simply the estimate of X when $Z = 0$. Thus, when $Z \neq 0$, $\frac{(\beta X_{t-1} + \beta X_{t-1} * Z) + (\beta X_t + \beta X_t * Z)}{1 - \beta Y_1}$.

To show this equivalence, we estimate our ECM model with the ADL framework. Table A2 reports the results of the ADL and indicates the algebraic equivalence of the ECM results in Table 1 of the main text. Note that the estimates generated for the lagged dependent variables are equal to one another once they are properly transformed. In other words, they are identical to one another when you subtract 1 from the values presented in the table. For example, the estimated coefficient for the lagged value of Democratic attacks is -0.387 in the ECM and 0.613 in the ADL. By subtracting 1 from 0.613, we calculate a value of -0.387. This suggests that the two forms of models produce equivalent results.

In addition, we can also reproduce the LRMs reported in the main text. In the ECM Democratic attacks equation, these values are 1.244 for the Republican attacks LRM and -0.020 for the interaction term. Using a few minor transformations, we produce the same values from the estimates generated by the ADL version of our model. The equations $\frac{(\beta X_{t-1}) + (\beta X_t)}{1 - \beta Y_1}$ and $\frac{(\beta X_{t-1} * Z) + (\beta X_t * Z)}{1 - \beta Y_1}$ allow us to do so, the former for the Democratic/Republican attacks and the latter for the interaction term. Thus, the values for the parts of the LRM for Republican attacks are $\frac{(-.2022794) + (.6830399)}{1 - .6133883} = 1.2435229$ and $\frac{((.0015978) + (-.0091715))}{1 - .6133883} = -0.01958994$, both of which round to the correct values. Thus we are confident that we have not erred by using an ECM in this research.

Keele et al. note the results replicated in the Grant and Lebo piece are caused by a low number of observations and the use of unbalanced equations—meaning, using a stationary dependent variable and an integrated independent variable. We do not suffer from either of these potential pitfalls in our analysis.

The results noted in Table A2 should also help assuage concern 4 in Grant and Lebo’s (2016) critique. They conclude “the ADL should be preferred over the GECM with either stationary,

strongly autoregressive, or near-integrated data.” Our ADL model shows we do not return a spurious result based solely on the model choice. If our data is either strong autoregressive or near integrated, our results stand.

The final point we have not addressed in Grant and Lebo’s work is fractional integration. This is a difficult response in the context of our data due to its panel structure. Fractional Integration is much easier to assess when there is not panel data. An Autoregressive Fractionally Integrated Moving Average (ARFIMA) model would suffice. We simply can not find a model selection for a fractionally integrated analysis of panel data. Finally, Esarey (2016) concludes, “I find evidence that the simple autodistributed lag model (ADL) or equivalent error correction model (ECM) can, without first testing or correcting for fractional integration, provide a useful estimate of the immediate and long-run effects of weakly exogenous variables in fractionally integrated (but stationary) data” (42).

Table A2: Negative Advertising and Ideological Composition of the Electorate in Gubernatorial and Campaigns, 2000 - 2004, 2008

	Democratic Attacks	Republican Attacks
Democratic attacks		0.452 (0.297)
Democratic attacks _{t-1}	0.613* (0.022)	-0.648* (0.307)
Republican attacks	0.683* (0.259)	
Republican attacks _{t-1}	-0.202 (0.259)	0.632* (0.021)
% state moderates	-0.372 (0.310)	0.183 (0.322)
% state moderates × Democratic attacks		-0.004 (0.007)
% state moderates × Democratic attacks _{t-1}		0.012† (0.007)
% state moderates × Republican attacks	-0.009 (0.006)	
% state moderates × Republican attacks _{t-1}	0.002 (0.006)	
Year: 2002	-0.406 (2.393)	0.239 (2.493)
Year: 2003	1.761 (6.428)	0.202 (6.689)
Year: 2004	0.047 (2.352)	-1.302 (2.450)
Year: 2008	-3.722 (3.443)	0.165 (3.587)
Intercept	21.873 (15.524)	-4.421 (16.149)
R ²	0.4181	0.4466
N	1,465	1,465

Estimated ordinary least squares coefficients are reported along with standard errors in parentheses from Seemingly Unrelated Autoregressive Distributed Lag Model.

* = $p \leq 0.05$ (two tailed)

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