Appendix for "Negative Advertising and the Dynamics of Candidate Support"

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Model Tests

Grant and Lebo (2016) argue that ECMs are appropriate with both stationary and integrated series, but only if all of the series are of the same degree of integration. This is an excellent point and one of contention right now in the methods community. Grant and Lebo's paper outlines many issues that researchers often ignore when working with the generalized error correction model. The authors point out numerous situations that arise where scholars misspecify the ECM, which can lead to spurious results:

1. the dependent variable is a unit root, I(1)
2. the dependent variable is a *bounded* unit root
3. the dependent variable and all independent variables are stationary
4. the dependent variable is strong 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 points given the nature of our two series of interest with a unit root test. In Table A-1, we present results from a Fisher Test for Panel Unit Roots using an Augmented Dickey Fuller. The two test statistics in Table A-1, both reject the null hypothesis that either of our series contain a unit root. The panel test for 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 contest. 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 Regression. We would have at the most 12 observations per regression. This would make statistical significance difficult to ascertain. We however, have done this for each series to simply look at the value of the coefficient for the lagged value of the dependent variable. We do not report the results of the 160 regressions in the memo, but not a single coefficient in the Augmented Dickey Fuller test has a coefficient approaching 0 that would indicate a unit root. We are confident both 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.

Table A-1: Fisher Test for Panel Unit Root Using an Augmented Dickey-Fuller Test

	Democratic polling advantage	Democratic attack advantage
χ^2	203.3272	498.1251
Prob $\geq \chi^2$	0.0116	0.000

Neither of our dependent variables are bounded unit roots. Bounded time series are those that can be limited with an upper or lower bound. Grant and Lebo (2015, 13) note that "A bounded series is an odd case. For one, it cannot meet the textbook definition of a unit root since its asymptotic properties include mean reversion and finite variance (Williams 1992)." They note however, that over long series, bounded series can appear integrated. This problem is only persistent however as the series approaches the extreme upper and lower bounds of the series. The Democratic polling advantage variable has a bounded range of 0% to 100%. The range of observed data is between 15% and 80%. The Democratic attack advantage variable is bounded between -100 and 100, but does not contain a unit root. We are confident we are not viewing spurious results as we 1) do not have a unit root in either variable, 2) the Democratic vote share does not push the extremes of their bounds, 3) the Democratic attack advantage does not push the extremes of their bounds, as the mean is -3.63 with a standard deviation of 34.19.

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 two models and applaud the flexibility of the model. In fact, many scholars have interpreted this as essential freedom to use the ECM in any framework. This is a flawed approach. Both Keele, Linn, and Webb (2016) and Enns, Masaki, and Kelly (N.d.) stress the importance of understanding the types of series used in the ECM framework. The Enns, Masaki, and Kelly (N.d.) paper is linked below:

`http://takaakimasaki.com/wp-content/uploads/2014/08/EnnsMasakiKelly_ECM_9.25.14.pdf`

Enns, Masaki, and Kelly note the haphazard nature in which scholars have been using

the ECM framework and note that *"spurious regression results emerge close to 20 percent of the time when integrated data that are not cointegrated are analyzed with an ECM."* In table A-2, we present the results from four types of Panel Cointegration tests developed by Westerlund (2007). In this table, 3 of the 4 cointegration tests indicate that our two series are not cointegrated. The G_t test null hypothesis is that one panel has cointegrated series. It is the least rigorous of the 4 tests outlined by Westerlund. We argue that since we have both stationary series that are not cointegrated, we are not drawing spurious inferences from our results.

Table A-2: Westerlund Error Correction Based Panel Cointegration Test

Statistic	Value	Z-value	P-value
G_t	-3.571	-17.2	0.000
G_a	$-.00003$	$-.00047$	1.000
P_t	-10.719	-2.474	0.993
P_a	-4.405	$-.093$	0.463

The concern, however, that poses the most potential trouble for our manuscript is the claim that two stationary series used in a ECM framework lead to spurious results. 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 the Keele, Linn, and Webb manuscript to support the appropriateness of our model selection. To begin, the algebraic equivalence of the ADL and ECM cannot be stressed enough. In equation 1, we note the functional form of the Autoregressive Distributed lag framework and in equation 2, the ECM model. 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 $\alpha_1 - 1$.

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \beta_0 X_t + \beta_1 X_{t-1} + \epsilon_t \tag{1}$$

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \beta_0 \Delta X_t + \beta_1 X_{t-1} + \epsilon_t \tag{2}$$

To show this equivalence, we estimate our ECM model with the ADL framework. Table A-3 reports the results of the Autoregressive Distributed Lag Model (ADL). This table indicates the algebraic equivalence of Table 3 in the main text. To begin, we point out the variables that are significant in Table 3 of the text remain significant in Table A-3. Furthermore, the standard errors of these models are nearly identical. Recall the result of interest in the main text is the Long Run Multiplier of Democratic attack advantage in the model predicting Democratic support. This value is -.101. In the ADL model, as noted above, the formula is $\frac{\beta_0+\beta_1}{1-\alpha_1}$. Plugging in the values from Table A-3, we get an identical -.101111226 value. Our results are identical across model choice.

Keele, Linn, and Webb note the results replicated in the Grant and Lebo piece are caused by a low number of observations and utilizing 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.

Table A-3: ADL Model Predicting Negative Advertising and Candidate Support in Gubernatorial and Campaigns, 2000 - 2004

	Democratic polling advantage		Democratic attack advantage	
Democratic attack advantage	0.008*	(0.003)		
Democratic attack advantage$_{t-1}$	-0.011*	(0.003)	0.552*	(0.034)
Democratic polling advantage			1.050*	(0.439)
Democratic polling advantage$_{t-1}$	0.970*	(0.013)	-1.314*	(0.449)
Gubernatorial election	-0.148	(0.196)	-2.328	(2.294)
Democratic Incumbent	0.476†	(0.255)	1.371	(2.999)
Republican Incumbent	-0.337	(0.240)	-1.807	(2.818)
Intercept	1.501*	(0.653)	13.033†	(7.676)
BIC	10,322.13			
N	714			

* = p $\leq$ 0.05 (two tailed) † = p $\leq$ 0.1 (two tailed)

The results noted in Table A-3 should also help assuage concern 4 in Grant and Lebo (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.

Alternate Measurement Strategies

We present the results of two additional models in which we used different measurement strategies to capture Democratic attack advantage. In the first, reported in Table A-4, we calculate the Democratic attack advantage by subtracting the number of negative ads aired by Republicans from the number of Democratic-sponsored negative spots that aired in a given week and contest. In the second, reported in Table A-5, we do the same and

then divide this value by the population of the state (in 100,000s) in which each contest occurred.[1] The former measure seeks to capture Democratic attack advantage in terms of pure advertising volume while the latter does the same and accounts for the population of the state in which the contest takes place. We include this standardization because candidates contesting states with larger populations, especially those that are spread out across many media markets, are likely to air more ads in order to reach more potential voters than are candidates contesting elections in states with smaller populations.

As shown below, both measurement strategies produce results that are substantively similar to those presented in the main paper in terms of the effects of Democratic attack advantage on candidate support. Note, however, that neither of the below models produce a significant effect of candidate support on Democratic attack advantage.

Table A-4: Raw Volume of Negative Advertising

	Democratic polling advantage		Democratic attack advantage	
Long run multipliers				
Democratic attack advantage	-0.015*	(0.001)		
Democratic polling advantage			-0.791	(1.027)
ΔDemocratic attack advantage	0.001	(0.001)		
Democratic attack advantage$_{t-1}$	-0.001	(0.001)	-0.514*	(0.034)
ΔDemocratic polling advantage			4.261	(3.085)
Democratic polling advantage$_{t-1}$	-0.030*	(0.012)	-0.406	(1.028)
Gubernatorial election	-0.140	(0.195)	-9.908	(16.109)
Democratic incumbent	0.512*	(0.257)	29.320	(21.263)
Republican incumbent	-0.332	(0.241)	-29.151	(19.845)
Intercept	1.507*	(0.650)	20.053	(53.853)
BIC	13,118.07			
N	714			

Estimated ordinary least squares coefficients are reported along with standard errors in parentheses. Long-run multipliers and their standard errors were generated using the Bewley (1979) transformation.
* = p $\leq$ 0.05 (two tailed) † = p $\leq$ 0.1 (two tailed)

[1]We use state population estimates calculated by the U.S. Census taken from July of each election year.

Table A-5: Volume of Negative Advertising Adjusted for State Population

	Democratic polling advantage		Democratic attack advantage	
Long run multipliers				
Democratic attack advantage	-0.472*	(0.030)		
Democratic polling advantage			-0.014	(0.019)
ΔDemocratic attack advantage	0.044†	(0.024)		
Democratic attack advantage$_{t-1}$	-0.014	(0.029)	-0.662*	(0.037)
ΔDemocratic polling advantage			0.103†	(0.057)
Democratic polling advantage$_{t-1}$	-0.030*	(0.012)	-0.009	(0.019)
Gubernatorial election	-0.139	(0.196)	-0.340	(0.300)
Democratic incumbent	0.478†	(0.255)	0.082	(0.392)
Republican incumbent	-0.323	(0.241)	-0.696†	(0.369)
Intercept	1.494*	(0.651)	0.786	(1.000)
BIC	7,422.28			
N	714			

Estimated ordinary least squares coefficients are reported along with standard errors in parentheses. Long-run multipliers and their standard errors were generated using the Bewley (1979) transformation.
* = p $\leq$ 0.05 (two tailed) † = p $\leq$ 0.1 (two tailed)

References

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