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Modeling Equilibrium Relationships: Error Correction Models with Strongly Autoregressive Data

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Political scientists often argue that political processes move together in the long run. Examples include partisanship and government approval, conflict and cooperation among countries, public policy sentiment and policy activity, economic evaluations and economic conditions, and taxing and spending. Error correction models and cointegrating relationships are often used to characterize these equilibrium relationships and to test hypotheses about political change. Typically the techniques used to estimate equilibrium relationships are based on the statistical assumption that the processes have permanent memory, implying that political experiences cumulate. Yet many analysts have argued that this is not a reasonable theoretical or statistical assumption for most political time series. In this paper I examine the consequences of assuming permanent memory when data have long but not permanent memory. I focus on two commonly used estimators: the Engle–Granger two-step estimator and generalized error correction. In my analysis I consider the important role of simultaneity and discuss implications for the conclusions political scientists have drawn about the nature, even the existence, of equilibrium relationships between political processes. I find that even small violations of the permanent memory assumption can present substantial problems for inference on long-run relationships in situations that are likely to be common in applied work in all fields and suggest ways that analysts should proceed.

1 Introduction

POLITICAL SCIENTISTS IN all empirical fields are interested in understanding the causes and consequences of political change over time. Testing theories about political dynamics requires analysts to make critical statistical assumptions about the nature of the responsiveness of political time-series to new information. Elections, for example, present politicians, economic actors, and ordinary citizens with new information about the course of government. This information may produce quick and irreversible changes, exert effects that characterize a political era, or register only as temporary blips in attitudes or outcomes. The rate at which the effects of shocks, such as the effect of elections on streams of policy

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outputs or attitudes, dissipate characterizes the memory of the process. Memory may take many forms, but typically applied analysts consider only *permanent memory* (integrated processes), in which the stream of outputs or attitudes is permanently altered, or *short memory* (stationary processes), in which it is briefly interrupted and quickly returns to preelection levels. Assumptions about memory lie at the heart of our theories about political processes and they affect both the models we choose and the inferences we draw from them.

Short and permanent memory are consistent with the assumptions of the statistical models political scientists typically use to test hypotheses. But often, neither permanent nor short memory characterizes political time-series data well. In other cases, *long memory* represents a plausible alternative to short or permanent memory. Either way, it may make sense to consider strongly autoregressive, near-integrated alternatives to permanent and short memory processes. Near-integrated processes—those with long but not permanent memory—are consistent with the theoretical and statistical features of many political time series processes. Consider some examples.

- Analysts often fail to reject permanent memory null hypotheses with regard to presidential approval. While this suggests that the process has permanent memory, this characterization seems highly unlikely given the rapid changes in approval ratings in response to international crises and the small historical range of approval ratings, for example. Instead, the analyst might argue that economic recession would affect presidential approval ratings for a long time. In fact, approval ratings for any given president might not recover from the effects of a recession that occurred early in an administration. This suggests that long, rather than permanent memory may characterize presidential approval.[1]
- Theories of macropartisanship suggest that partisanship is highly inertial, but the extent of the inertia is hotly debated (Green et al. 1998; Abramson and Ostrom 1992). MacKuen et al. (1998) argue that political and economic conditions exert cumulative effects on macropartisanship so that the process has permanent memory. Yet as the electorate turns over, the experience of the body politic changes and the effects of shocks such as the Great Depression may disappear entirely so that long memory may better match our understanding of the party system.
- Modernization theories of economic development imply that development unfolds slowly as domestic or foreign investment or levels of education in the population increase (Todaro 1994). Shocks such as a drought or a civil war will likely affect development levels for many years, but it seems unreasonable to argue that it will do so generations down the road. Theory suggests that long memory may be a reasonable characterization of economic development and that policy makers and citizens alike must be patient with efforts to modernize.
- Levels of cooperation or conflict between countries may have long memory. Rajmaira and Ward (1990) have argued that they have permanent memory, but it may make sense to think of reciprocity in terms of long memory. The effects of World War II, for example, may appear to affect conflict between the superpowers yet today. But the tensions brought about by war ease over time and the likelihood of further conflict decreases so that the memory of war recedes and levels of cooperation may return to some prewar norm. Indeed, the prospect of a return to peace underlies the motivation for political dialogue.

[1] At a statistical level, this example and others that follow cannot be exact unit roots: the statistical model implies that approval rates *will* go below zero and grow without bound (De Boef and Granato 1997; Alvarez and Katz 1996; Williams 1992; Beck 1992). In addition, these concepts are bounded conceptually so that scale changes in measurement do not solve the problem (Stock and Watson 1996).

Theories about political dynamics seldom distinguish long memory from permanent memory. Statistical tests often do no better. Typically short memory is a default alternative to permanent memory, but long memory represents a reasonable theoretical and statistical characterization of memory in these and many other political time series that have been hypothesized to exhibit permanent memory.

The presence of long memory presents problems for applied analysis. Available estimators assume either stationary or integrated processes and are not consistent with the statistical features of long memory processes. Preliminary work in economics suggests that using a statistical model that imposes permanent memory *or* adopting models for stationary time series will typically lead to systematic errors in inference when the processes are long-memoried (Elliott 1995, 1998; Cavangh et al. 1995; Stock 1997). The purpose of this paper is to extend the work in economics to cover two estimation strategies often used to test dynamic hypotheses in political science when analysts posit an error correction behavioral relationship and assume data to be permanent memoried. Specifically, I test the performance of the Engle–Granger two-step estimator and the generalized error correction model (GECM) when the data may be long-memoried and specifically near-integrated: I focus on strongly autoregressive, near-integrated long memory processes.[2]

I proceed with a formal discussion of time series persistence and the theoretical dynamics implied by univariate characterizations of persistence. I follow this with a discussion of the modeling strategies associated with each characterization and a statement of the general problem I am investigating. Next, I discuss error correction as a behavioral model and outline Engle and Granger's two-step error correction method and the generalized one-step error correction model. Then I outline the problem and extend the experimental work conducted in economics. This is followed by the analyses and a discussion of the implications for applied work.

2 Persistence in Political Time Series

Applied analysts typically assume, implicitly or explicitly, that their time series are either permanent or short-term memory processes. But theoretical considerations like those above suggest that long, but not permanent, memory may be a more appropriate assumption in many cases and a reasonable alternative in others. In this section, I define permanent memory (integrated), short memory (stationary), and near-integrated, long memory characterizations of the persistence in political time series and consider the theoretical and statistical implications of each.

2.1 *Definitions*

Presidential approval, macropartisanship, public policy mood, per capita GNP, and many other political time series have been described as first-order autoregressive processes such that the current value of the process is a function of its own past value and some random error

$$y_t = \rho y_{t-1} + \mu_t \tag{1}$$

where the magnitude of ρ determines the strength of time dependence (the memory of the process). Any shocks to the system are incorporated in μ, an iid random variable.

[2]Fractional (Box-Steffensmeier and Smith 1996) and other long memory processes may also be consistent with these kinds of political processes. The mathematical and theoretical issues involved with fractional processes are beyond the scope of this paper.

In the autoregressive representation, values of $|\rho| < 1$ produce a short memory, stationary process. Any shocks to the process, represented by μ, will exert a transient effect on y. More generally the process has no inherent tendency to move from its mean or equilibrium value.

In contrast, the process is integrated and contains a unit root, denoted $I(1)$, for values of $|\rho| = 1$. In this case, the series exhibits permanent memory so that shocks to the process have a cumulative effect. As a direct result, the process does not converge to a stable equilibrium value; both the mean and the variance of the series depend on time (Banerjee et al. 1993).

If long memory is a reasonable theoretical and statistical alternative to short and permanent memory, analysts should consider strongly autoregressive, near-integrated processes. These processes have a root close to, but not quite unity. In the autoregressive representation, $|\rho| = 1 + c$, where c is small and negative.[3] Near-integrated processes are strongly persistent, but shocks to them die out given long enough time spans. The underlying distinction between near-integrated and integrated processes is thus the existence of an equilibrium in the former case and the absence of an equilibrium in the latter.[4] The difficulty is that we often observe too few time points to know whether the process has a meaningful equilibrium value.[5]

2.2 *Theoretical and Statistical Implications*

Characterizations of single time series provide important information about the persistence of the effects of shocks to political processes. Often, this information is in itself informative about the meaning of a given political process—whether shocks to these processes dissipate quickly, slowly, or not at all. The characterization also has statistical implications. We are generally interested in testing hypotheses about the relationships between political processes. To do so we need to choose an appropriate estimator and the characterization of persistence matters in this case as well. Short memory, stationary characterizations lead analysts to choose regression techniques to test hypotheses. Permanent memory characterizations lead analysts to cointegration techniques, ARIMA (autoregressive, integrated, moving average) models, or regressions in differences. In these cases, the characterization of the memory process of the time series and the statistical assumptions are consistent. However, if the data are near-integrated, we are on unfamiliar ground, where statistical assumptions of our models do not match those of the data generating process.

Theories about political dynamics often predict or are consistent with long memory. Statistical tests can seldom rule out this possibility (Blough 1994; Banerjee et al. 1993). But we do not know much about the statistical properties of multivariate analysis when the data are individually near-integrated. We do know that near-integrated processes are prone to the spurious regression problem (De Boef and Granato 1997) and that tests for cointegration cannot distinguish long-run relationships from spurious relationships at acceptable rates when the series are individually near-integrated (De Boef and Granato 1999; Kremers et al. 1992). We also know that for some models, near-integration introduces bias and inefficiency in analyses adopting methods for *either* stationary or unit root processes (Stock 1997; Elliott 1995, 1998). But many questions remain. In this paper I ask, When theories about political processes predict long memory or when statistical tests about the dynamics of single series

[3] c may take a range of values including 0 (unit root case) and positive values (explosive case). I do not consider explosive processes.

[4] The variance of a near-integrated time series depends on time in finite samples (Phillips 1987a, b; DeBoef and Grananto 1997) but, in the limiting case, reduces to $\sigma^2/(1 - \rho^2)$ so that the series is mean reverting.

[5] For an expanded discussion of the statistical and theoretical issues associated with near-integration, see De Boef and Granato (1997).

cannot reject unit root null hypotheses and we proceed to estimate error correction models, what are the consequences for our understanding of the dynamics of politics given strongly autoregressive, near-integrated processes? Alternatively put, what are the consequences of departures from a unit process for inferences about political dynamics based on error correction models?

I consider the properties of two commonly used estimators of long-run relationships when the component series are near-integrated. Specifically, I consider two methods of estimating error correction models, those due to Engle and Granger (1987) and designed for permanent memory and cointegrated time series and the generalized error correction method suggested by Banerjee et al. (1993) in the context of stationary time series. I show under what conditions applied analysts can use the Engle–Granger (1987) two-step method to estimate long-run relationships between political processes, as well as short-run dynamics, if the data are near-integrated and when dynamic regressions, specifically generalized error correction models, can be used to estimate these relationships.

3 Error Correction Models

Error correction models are based on the behavioral assumption that two or more time series exhibit an equilibrium relationship that determines both short- and long-run behavior.[6] Political scientists in all empirical subfields are increasingly positing theories of political dynamics that are consistent with this behavioral model.[7] Analysts have argued that presidential approval and economic conditions are tied together such that positive support cannot be maintained over periods of recession (Ostrom and Smith 1992; Clarke and Stewart 1994). Others have argued that diplomatic relationships are conditional upon a long-run equilibrium: cooperative overtures of one country cannot continue when a neighbor is repeatedly antagonistic (Rajmaira and Ward 1990). Still others contend that policy sentiment is tied in the long run to economic conditions and government spending (Durr 1993; Wlezien 1996, 1995), that taxes and benefits are tied by "actuarial soundness" (Mebane 1994), that economic evaluations are linked to economic conditions (Krause 1997), and that political forces and seat distributions in legislatures are linked in the long run to form an equilibrium relationship (Simon et al. 1991). Finally, party support, some argue, is sustained by positive political and economic experience (MacKuen et al. 1998; Green et al. 1998). If these kinds of long-run relationships describe behavior, ECMs present a nice fit with theory.

Equilibrium relationships in turn have implications for short-run behavior; one or more series move to restore equilibrium. Government support falls with poor economic conditions and improves with economic booms, adverserial behavior is matched by increasingly confrontational responses, increases in spending produce decreases in liberal policy preferences, and periods of sustained economic growth produce increases in party support. In each case, short-run change is necessary to maintain the long-run relationship.[8] The error correction model tells us the degree to which the equilibrium behavior drives short-run dynamics.

[6] This long-run equilibrium is assumed in virtually all dynamic models involving levels data but is trivial in the stationary case. The equilibrium can be modeled in many ways when the data are stationary, including autoregressive distributed lag models, generalized error correction models, and other dynamic regressions. See Beck (1991) and Banerjee et al. (1993) for a discussion.

[7] For a nice discussion of ECMs in political science, see Ostrom and Smith (1992) or Durr (1993). For an introduction to ECMs more generally, see Banerjee et al. (1993).

[8] In some cases the changes will come exclusively from changes in one process. Attitudes change in response to exogenous conditions, for example. In other cases, both processes may respond to disequilibrium. Depending on the nature of error correction, different estimators of the relationship must be used.

In practice, many models of equilibrium relationships are premised on permanent memory and rely on the Engle–Granger two-step method (Ostrom and Smith 1992; Clarke and Stewart 1994; Rajmaira and Ward 1990; Wlezien 1995). A smaller number estimate generalized error correction models in one step (Durr 1993; Green et al. 1998; MacKuen et al. 1998), and fewer yet adopt alternative (generally systems) estimators such as Johansen's (1988) vector ECM, but the theoretical argument is the same in all cases: the processes move together over time in the long run, and short-run behavior is determined by how far out of equilibrium the processes currently are. The choice of estimator rides on the characterization of the persistence of the individual time series (and in the case of integrated series, on the persistence in the linear combination as well) and assumptions about exogeneity. We have a good understanding of the properties of these estimators when data are stationary or cointegrated, but the costs of using these estimators when the data are near-integrated is unclear.

3.1 *Engle and Granger Two-Step Method*

Since Engle and Granger (1987) published their seminal article on cointegration, political scientists have borrowed the Engle–Granger two-step methodology from economics and applied it to political time series and questions about the dynamics of politics. The Engle–Granger two-step method proceeds as follows. In the first step, theory and econometric evidence are used to determine whether the data contain unit roots in the individual time series. If so, the analyst estimates the long-run relationship, $\hat{\beta}$, in a first-step static cointegrating regression of y on x, where x may be a vector:

$$y_t = \alpha + \beta x_t + \mu_t \tag{2}$$

If the residuals from the cointegrating regression exhibit short memory,[9] then the time series are said to be cointegrated and we may proceed with the second-step regression. In the second step, changes in y are regressed on changes in x and the previous period's equilibrium error (the residuals from the cointegrating regression) to estimate the equilibrium rate, $\hat{\gamma}$, and short-run dynamics, $\hat{\lambda}_2$:

$$\Delta y_t = \lambda_1 + \lambda_2 \Delta x_t - \gamma \hat{\mu}_{t-1} + \eta_t \tag{3}$$

Additional or alternative lags (and deterministic terms) may be included as well.

We know that estimates of the long-run relationship and inferences drawn from these estimates using the Engle–Granger two-step estimator perform well only under limited conditions: permanent memory, or unit roots, and a cointegrating regression without serially correlated errors and without simultaneity. If the processes are short memory or stationary, the cointegrating regression will not be superconsistent and the bias due to contemporaneously correlated errors in the static regression will not decrease as the sample size increases (Stock 1987). If our data exhibit long, but not permanent, memory, these limited conditions do not hold and our understanding of the dynamics of political processes is likely to be compromised.

These results suggest that the first-stage regression may be biased, inefficient, and inconsistent if the data are near-integrated. However, since near-integrated processes behave as integrated processes in finite samples, the extent to which the first-stage estimates are

[9] See De Boef (2000b) on the power of tests for cointegration.

consistent, unbiased, and efficient in applied work depends on specific assumptions about the underlying data generating process. Further, the nature of the estimates from the first-stage cointegrating regression affects the second-stage error correction model estimates. Often in applied work in political science, the second-stage estimates are the basis for inference. To test hypotheses about the responsiveness of y to deviations from its long-run relationship with x, we need to estimate the second-stage error correction model. Analysis of the properties of the estimates of the error correction coefficient are also necessary.

3.2 *Generalized One-Step Error Correction Method*

The generalized one-step error correction model is a transformation of an autoregressive distributed lag (ADL) model (Banerjee et al. 1993). As such, the model may be used to estimate relationships among stationary processes as well as unit root processes. It requires no restrictions on the ADL so that the same information is available from the ADL as from the ECM representation (Banerjee et al. 1990). The ECM representation is thus used when information about reequilibration is the focus of our inquiry and when weak exogeneity is an appropriate assumption.[10]

The generalized error correction model is estimated in one step and may be written in its simplest form as follows:

$$\Delta y_t = \lambda_1 + \lambda_2 \Delta x_t - \gamma(y_{t-1} - x_{t-1}) + \pi x_{t-1} + \eta_t \tag{4}$$

The error correction term in the GECM is given by $(y_{t-1} - x_{t-1})$. The (implied) coefficient on x_{t-1} of one in this term suggests a proportional (or one-to-one) long-run relationship between y and x. The validity of this assumption does not affect the estimated error correction rate, γ (Banerjee et al. 1993). However, to estimate the long-run relationship accurately, a second x_{t-1} term is included in the GECM to "break homogeneity," i.e, to allow the equilibrium relationship to deviate from one-to-one. The true long-run relationship is then given by $1 - (\hat{\pi}/\hat{\gamma})$.[11] All other variables in the GECM are defined and may be interpreted as for the second-stage ECM above. Unlike the two-step method, using the dynamic single-equation GECM, the analyst simultaneously estimates the long-run relationship, the disequilibrium, and the short-run dynamics.

The single-equation GECM is both theoretically appealing and also statistically superior to the two-step estimator in many cases. Banerjee et al. (1993) show that dynamic regressions will be asymptotically equivalent to more complex full-information maximum-likelihood and fully modified estimators when the processes are weakly exogenous. Thus the single-equation GECM will be efficient and unbiased, as well as consistent. Importantly, if weak exogeneity is not a reasonable assumption, the single-equation GECM will be both biased and inefficient and t tests based on the model parameters will be highly misleading. The implications of near-integration in this context are not clear.

[10] The one-step error correction model was popularized in economics by Davidson et al. (1978). They advocated the general error correction model for theoretical and empirical reasons. In particular, they wished to estimate the error correction coefficient directly, rather than deriving it from alternative specifications. As for all ADL models, weak exogeneity is an important assumption for the ECM representation.

[11] The standard error for the long-run effect cannot be calculated analytically, as it involves the ratio of estimated parameters. One solution is to use simulations from the estimated data to calculate the correct standard errors or to reformulate the regression so that the long-run relationship is estimated directly (Banerjee et al. 1993). Alternatively, we can approximate the standard error by $J_f' \text{var}(\hat{\pi}, \hat{\gamma}) J_f$, where J_f is the Jacobian of the transformation given by f, here $1 - (\hat{\pi}/\hat{\gamma})$, and $\text{var}(\hat{\pi}, \hat{\gamma})$ is the variance–covariance matrix of the component parameters. The trade-off with other dynamics regressions is that the error correction coefficient will not be directly estimated.

3.3 *The Problem: One- Versus Two-Step ECMs Under Near-Integration*

Let us assume that error correction is a reasonable behavioral assumption. If theory and statistical evidence regarding the memory of the processes we care about is mixed so that $|\rho|$ may be 1 or less than 1, what happens if we use either of these methods to estimate an error correction model?

Evidence from economics suggests that inferences from either static or dynamic regressions will be systematically biased. The work of Elliott (1995, 1998) is particularly relevant.[12] He investigated the properties of alternative efficient estimators of long-run relationships under near-integration of x. He assumed a static data generating process identical to the static regression estimated in step 1 of the Engle–Granger estimator and allowed for a very general error structure in the data generating processes (DGPs), including both serial correlation and cross-equation residual correlations. Elliott summarized the analytical evidence in two main results.

1. Efficient estimators such as those used by Saikkonen (1992) or Johansen (1988) or full-information maximum-likelihood estimators and fully modified estimators will be biased (but consistent) under general conditions when the x data generating process is near-integrated.[13] This bias increases as the covariance of the DGPs increases (as simultaneity increases).
2. The coverage of the confidence intervals on the estimate of the long-run relationship will be very poor; the confidence intervals will not include the true value at acceptable rates. Specifically, analytical results suggest that the size of the test will go to 0 asymptotically but in sample will go to 1.0 as simultaneity increases *if* the data are near-integrated. Bias is smaller as the variance of y increases. The mean bias is nonnegative, leading to overrejection of the null hypothesis that the data contain no long-run relationships.[14]

The key to the problem is that we need to "quasi-difference" near-integrated data rather than including first differences or additional lagged levels in our models. The problem is that we do not know the true value of ρ needed to quasi-difference appropriately, and it *cannot* be consistently estimated.[15] This is the reason that estimators that take into account contemporaneous correlations, like SUR, and correlations at leads and lags, like dynamic regressions such as DOLS (Saikkonen 1991), ECMs, or systems estimators like Johansen (1988) will not solve the problem; the properties of these estimators depend critically on a known value of ρ. If we assume that $\rho = 1$ and we are right, these procedures will provide unbiased estimates. If the assumption is incorrect and we have simultaneity (in addition to serial correlation), our estimates will be biased and inefficient; weak exogeneity will fail and conditioning on the marginal process will be invalid.

[12] In a similar analysis of FMVAR, Kauppi (1998) shows that FMVAR is also vulnerable to the problems raised by Elliott when roots are close to but not quite 1.0.

[13] While Elliott did not consider single-equation GECMs, he argues that these results are likely to generalize to the class of efficient estimators. Further, Banerjee et al. (1993) note that the generalized ECM is asymptotically equivalent to FIML, provided that weak exogeneity is an accurate assumption.

[14] Elliott identifies two key parameters in the distributions of the estimated long-run relationship and its t statistic: σ_{12} (the covariance) and c. If either σ_{12} or c is equal to zero, the nonstandard part of the distributions disappears, but when *either* the processes are near-integrated ($c \neq 0$) *or* there is simultaneity ($\sigma_{12} \neq 0$), the distribution of the t statistic estimating the long-run relationship is a mixture of normals with random mean. The distribution for the estimate of the long-run relationship is also nonstandard in this case.

[15] Static regressions, which omit all dynamics, can only do worse in this case.

If there is no simultaneity in the long run, the problems cited here disappear, even under near-integration. This is important. The problems associated with imposing unit roots on the data generating process occur only if the errors in the x and y DGP are correlated, that is, $\sigma_{12} \neq 0$. The lower the correlation, the smaller the bias and efficiency problems introduced by departures from a unit root. Combinations of high correlations and large departures from unit roots increase the likelihood of both problems and thus of incorrect inference.

It is important to remember that the costs of adopting methods for short memory processes are also high, particularly if permanent memory is a reasonable characterization of the data (Stock 1997). Stock shows, for example, that for large ρ, regressors in dynamic regressions will be inefficient. This result, and those like it, motivates the use of cointegration methods, which have received so much attention in the literature.

This evidence suggests that near-unit roots present substantial cause for concern when using cointegration methodology or when using methods for short memory processes to estimate long-run relationships, even when using efficient estimators. I show how bad the problem can be in theory and how prevalent it may be in applied work. Then I discuss some potential solutions and alternatives.

4 Analysis

Elliott's analytical and experimental work provides a starting point for the analyses that follow.[16] In this section I extend his experimental work using Monte Carlo analysis in two ways. First, I generalize from the simple static data generating process analyzed in Elliott's work to allow for dynamic relationships. Second, I cover estimators of error correction models that have been widely used in applied literature in political science. In the next section I try to gain a sense of the extent to which this problem plagues applied work in political science.

Given our interest in error correction as a behavioral model, the Y data generation process (DGP) is the error correction model. The X DGP is a simple autoregressive process.

$$\Delta Y_t = \lambda_1 + \lambda_2 \Delta X_t + \gamma(Y_{t-1} - \beta X_{t-1}) + \epsilon_{1t} \tag{5}$$

$$X_t = \rho X_{t-1} + \epsilon_{2t} \tag{6}$$

where $\rho = 1 + c$, $\epsilon_t \sim MN(0, \Omega)$, and

$$\Omega = \begin{pmatrix} 1 & \sigma_{12} \\ \sigma_{12} & 1 \end{pmatrix}$$

where X may be integrated, near-integrated, or stationary, depending on the value of ρ; and Y is a conditional process and is consistent with the model to be estimated.

I set the parameter values for the Y DGP as follows: $\lambda_1 = 0$, $\lambda_2 = 0.1$, $\gamma = -0.5$, and $\beta = 1$. These values are similar to those in much applied work. Rho will take values from 1.0, for a unit root process, down to 0.80, by increments of 0.01. These values of ρ encompass a range of values often estimated for political time series and produce near-integrated time series in certain samples (De Boef and Granato 1997). I consider samples

[16] Elliott conducted Monte Carlo experiments using static data generating processes and estimated long-run equilibria using both dynamic and static (cointegrating) regressions. He did not, however, consider dynamic data generating processes, nor did he estimate the generalized error correction model or the second-stage cointegrating regression.

of size 100.[17] As it is unclear what values the covariance typically takes in applied work, I vary the covariance of the errors, σ_{12}, from 0.00 to 0.90, by increments of 0.10. The models to be estimated are the Engle–Granger two-step and GECM models defined above.

A variety of information will be obtained from the Monte Carlo experiments. Of particular interest are the inferences regarding the long-run relationship, β, and the error correction coefficient, γ. Many analyses draw inference about both these parameters, others are concerned primarily with the long-run relationship or the error correction rate. I consider the bias in estimates of these coefficients and the coverage rates—the percentage of times the confidence interval includes the true parameter value—for the hypothesis $\hat{\beta} = 1$ and relate these results to applied work in political science.

5 Results

5.1 *Coverage Rates for* $\hat{\beta}$

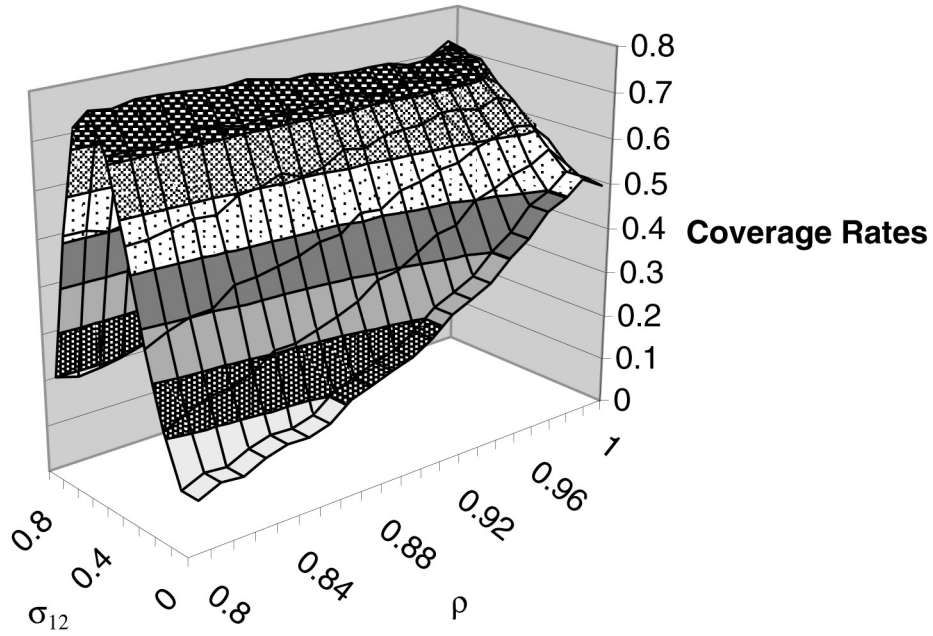
When the true data generating process contains a unit root, the DGPs imply cointegration and our expectations about the results follow the literature on cointegration. In particular, for all efficient estimators, the estimated confidence intervals should include the true value so that $\hat{\beta} = 1$, the long-run relationship, an average of 95% of the time, regardless of the degree of simultaneity between X and Y. In other words, the asymptotic coverage rates of the confidence intervals should be approximately 95%. In finite samples, we know that the Engle–Granger estimator is not efficient, however, so we expect coverage rates to drop for this estimator (Kremers et al. 1992; Stock 1987). As simultaneity increases and the degree of autocorrelation decreases, Elliott's results suggest a decrease in coverage rates for the true long-run relationship. Figures 1a and b summarize the results in response surfaces: that is, coverage rates are given as a function of σ_{12} and ρ.

Coverage rates using the two-step estimator are poor, even when the data are cointegrated. The rightmost portion of the response surface shows coverage rates of only about 50% with $\rho = 1$. As ρ drops, so, too, does the coverage rate, reaching as low as 20%. Coverage rates peak just under 80%, with moderate ranges of simultaneity for each value of ρ. These results are consistent with the evidence cited above: the static cointegrating regression is both biased and inefficient when the true DGP is dynamic.[18] The message from the coverage rates is clear: confidence intervals do not include the true value of β, the long-run parameter, in large proportions of the samples in any circumstance when the DGP is dynamic and the regression is static.

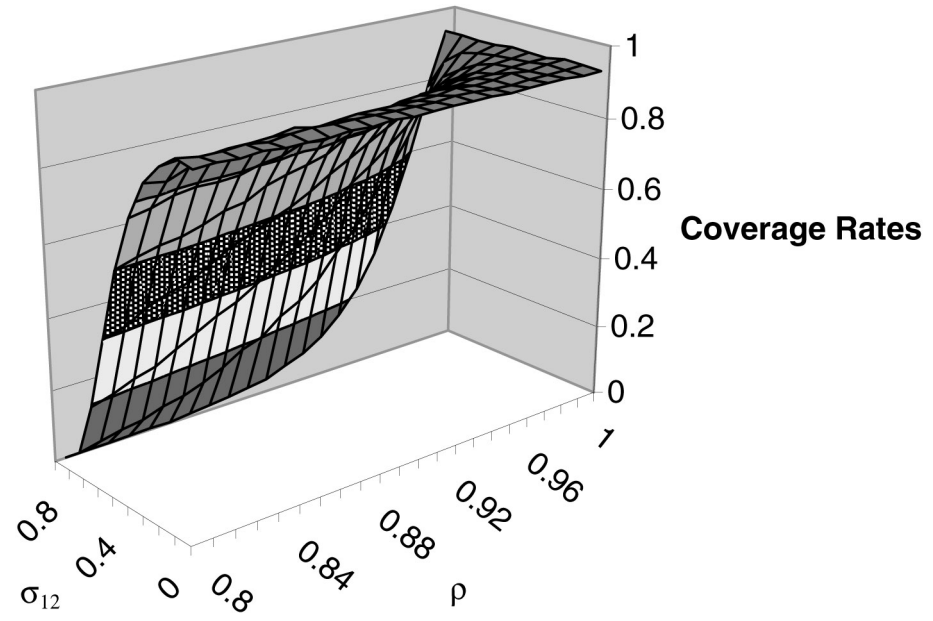
Coverage rates for $\hat{\beta} = 1$ using the GECM are consistent with Elliott's findings for alternative forms of dynamic regressions. In samples as small as 100, coverage rates hover just below the expected long-run rate of 95% for permanent memoried processes. Coverage rates are maintained even when ρ drops to 0.90, as long as simultaneity remains minimal. In these cases, the response surface is very flat. As simultaneity increases, coverage rates begin to drop with departures from a unit root, falling off gradually with departures from permanent memory and absent simultaneity. As ρ goes to 0.90 and σ_{12} goes to 0.90, coverage rates drop quickly, reaching as low as 20%, and inference becomes very hazardous.

[17] Changes in the sample size have predictable effects. The problem are compounded in smaller samples and improve with longer samples.

[18] For a static DGP, the patterns in the coverage rate response surface follow those from the GECM, with departures from a unit root and increases in simultaneity causing decreases in coverage rates. The introduction of dynamics in the DGP causes the simultaneity and departures from a unit root to interact in ways that depend very much on the nature of the dynamics.



(a) Two-Step Estimates



(b) Generalized ECM Estimates

Fig. 1 Coverage rates for the estimated long-run relationship as a function of σ_{12} and ρ.

5.2 *Bias in* $\hat{\beta}$

In addition to the poor general performance of standard confidence intervals, estimates of the long-run relationship are biased with departures from a unit root. Bias in long-run estimates using the GECM estimates follows the predicted patterns of the estimators analyzed by

Table 1 Bias in $\hat{\beta}$, the estimated long-run relationship[a]

	Long-run covariance, σ_{12}									
ρ	*0*	*0.1*	*0.2*	*0.3*	*0.4*	*0.5*	*0.6*	*0.7*	*0.8*	*0.9*
					a. Two-step estimator					
0.80	0.33	0.269	0.206	0.142	0.083	0.019	−0.043	−0.104	−0.164	−0.228
0.85	0.271	0.217	0.166	0.116	0.067	0.014	−0.037	−0.09	−0.139	−0.188
0.90	0.205	0.164	0.125	0.088	0.054	0.013	−0.026	−0.063	−0.102	−0.139
0.91	0.191	0.154	0.121	0.086	0.049	0.014	−0.021	−0.058	−0.093	−0.128
0.92	0.175	0.144	0.109	0.08	0.049	0.013	−0.02	−0.051	−0.084	−0.116
0.93	0.162	0.133	0.103	0.074	0.045	0.016	−0.016	−0.044	−0.074	−0.103
0.94	0.148	0.122	0.096	0.072	0.04	0.016	−0.011	−0.039	−0.064	−0.09
0.95	0.134	0.109	0.086	0.063	0.042	0.016	−0.006	−0.03	−0.053	−0.077
0.96	0.12	0.1	0.078	0.058	0.039	0.018	−0.003	−0.022	−0.042	−0.063
0.97	0.103	0.089	0.07	0.054	0.036	0.02	0.002	−0.014	−0.031	−0.048
0.98	0.088	0.078	0.062	0.048	0.036	0.022	0.007	−0.007	−0.018	−0.032
0.99	0.075	0.067	0.055	0.044	0.035	0.025	0.015	0.004	−0.007	−0.016
1.0	0.064	0.058	0.05	0.044	0.036	0.029	0.023	0.014	0.008	0
					b. GECM estimator					
0.80	0.007	−0.041	−0.079	−0.122	−0.162	−0.2	−0.24	−0.279	−0.319	−0.359
0.85	0.002	−0.027	−0.057	−0.088	−0.122	−0.149	−0.179	−0.208	−0.238	−0.27
0.90	0.002	−0.019	−0.039	−0.062	−0.078	−0.101	−0.119	−0.14	−0.158	−0.18
0.91	0.002	−0.018	−0.032	−0.054	−0.07	−0.088	−0.106	−0.126	−0.144	−0.162
0.92	0.001	−0.016	−0.031	−0.045	−0.062	−0.08	−0.095	−0.111	−0.129	−0.144
0.93	0.003	−0.014	−0.026	−0.041	−0.054	−0.071	−0.082	−0.096	−0.111	−0.126
0.94	0.002	−0.012	−0.022	−0.035	−0.048	−0.057	−0.071	−0.084	−0.095	−0.108
0.95	0.003	−0.01	−0.019	−0.029	−0.04	−0.05	−0.059	−0.069	−0.079	−0.09
0.96	0.001	−0.008	−0.015	−0.02	−0.029	−0.04	−0.049	−0.057	−0.065	−0.073
0.97	0.001	−0.004	−0.01	−0.018	−0.025	−0.03	−0.035	−0.042	−0.048	−0.054
0.98	0.001	−0.002	−0.007	−0.009	−0.015	−0.02	−0.025	−0.028	−0.033	−0.036
0.99	0.001	−0.001	−0.003	−0.006	−0.007	−0.01	−0.011	−0.013	−0.016	−0.019
1.0	−0.002	0.001	0.001	0	0.001	0.001	0	0	0	0

[a]Cell entries contain mean biases of estimated long-run relationships for given ρ and σ_{12}. In part a, estimates are based on a static cointegrating regression ($y_t = \alpha + \beta x_t + \mu_t$). In part b, estimates are based on the generalized error correction model ($\Delta y_t = \lambda_1 + \lambda_2 \Delta x_t - \gamma(y_{t-1} - x_{t-1}) + \pi x_{t-1} + \eta_t$), where $\hat{\beta} = 1 - (\hat{\pi}/\hat{\gamma})$. Results are based on 5000 Monte Carlo replications.

Elliott and Kauppi in the context of static data generating processes (Table 1). Bias grows with departures from a unit root and with increases in the degree of simultaneity. The biases are not large, however, in many of these experiments.

The biases in the estimates using the two-step ECM vary in what appears to be a rather haphazard manner. Often the bias is smaller than from the GECM under the same experimental parameters. If σ_{12} is at least 0.40, for example, the biases are smaller using the two-step method. The strange behavior of the bias results from an interaction between the omitted dynamics in the static regression and the problems introduced by simultaneity in combination with departures from a unit root.[19]

[19]Once again, this is due to the omission of dynamics in the first stage of the two-step method. Depending on the nature of these (their strength and direction) dynamics and the relative variances of X and Y, the biases may be larger or smaller in the GECM.

Table 2 Bias in $\hat{\gamma}$, the estimated error correction rate[a]

	Long-run covariance, σ_{12}									
ρ	*0*	*0.1*	*0.2*	*0.3*	*0.4*	*0.5*	*0.6*	*0.7*	*0.8*	*0.9*
					a. Two-step estimator					
0.80	0.015	0.017	0.016	0.016	0.016	0.016	0.017	0.015	0.015	0.014
0.85	0.015	0.015	0.015	0.015	0.015	0.018	0.018	0.018	0.019	0.019
0.90	0.016	0.015	0.015	0.015	0.017	0.02	0.021	0.018	0.021	0.019
0.91	0.016	0.018	0.018	0.017	0.018	0.019	0.021	0.022	0.018	0.02
0.92	0.015	0.014	0.016	0.018	0.017	0.021	0.018	0.02	0.02	0.021
0.93	0.016	0.015	0.017	0.018	0.021	0.019	0.018	0.023	0.024	0.023
0.94	0.015	0.017	0.016	0.018	0.017	0.021	0.02	0.02	0.023	0.025
0.95	0.014	0.014	0.017	0.018	0.021	0.02	0.02	0.021	0.022	0.023
0.96	0.014	0.018	0.017	0.017	0.017	0.021	0.02	0.022	0.024	0.023
0.97	0.015	0.016	0.016	0.019	0.019	0.02	0.019	0.026	0.022	0.024
0.98	0.015	0.016	0.016	0.021	0.019	0.02	0.02	0.025	0.024	0.025
0.99	0.014	0.014	0.019	0.017	0.019	0.019	0.024	0.025	0.024	0.026
1.0	0.014	0.017	0.018	0.019	0.019	0.019	0.027	0.023	0.025	0.024
					b. GECM estimator					
0.80	0.015	0.013	0.015	0.014	0.014	0.016	0.016	0.017	0.016	0.014
0.85	0.014	0.013	0.015	0.016	0.016	0.017	0.017	0.019	0.019	0.016
0.90	0.017	0.015	0.015	0.015	0.017	0.016	0.018	0.017	0.021	0.02
0.91	0.014	0.016	0.018	0.018	0.019	0.016	0.019	0.019	0.021	0.02
0.92	0.013	0.015	0.014	0.017	0.017	0.02	0.018	0.019	0.021	0.021
0.93	0.012	0.015	0.016	0.015	0.02	0.017	0.018	0.02	0.023	0.022
0.94	0.014	0.014	0.014	0.016	0.017	0.02	0.02	0.021	0.022	0.024
0.95	0.014	0.014	0.019	0.018	0.019	0.021	0.021	0.021	0.022	0.024
0.96	0.014	0.014	0.018	0.018	0.02	0.02	0.02	0.024	0.024	0.023
0.97	0.013	0.017	0.017	0.018	0.017	0.02	0.02	0.021	0.022	0.024
0.98	0.015	0.016	0.016	0.019	0.019	0.022	0.022	0.023	0.024	0.026
0.99	0.015	0.015	0.018	0.018	0.018	0.02	0.021	0.025	0.022	0.025
1.0	0.016	0.016	0.018	0.018	0.022	0.019	0.023	0.024	0.023	0.024

[a]Cell entries contain mean biases of estimated error correction rates, $\hat{\gamma}$, for given ρ and σ_{12}. In part a, estimates are based on the Engle–Granger second-step regression ($\Delta y_t = \lambda_1 + \lambda_2 \Delta x_t - \gamma \hat{\mu}_{t-1} + \eta_t$). In part b, estimates are based on the generalized error correction model ($\Delta y_t = \lambda_1 + \lambda_2 \Delta x_t - \gamma(y_{t-1} - x_{t-1}) + \pi x_{t-1} + \eta_t$). Results are based on 5000 Monte Carlo replications.

5.3 *Bias in Error Correction Rates, $\hat{\gamma}$*

Often tests of dynamic hypotheses focus on the rate at which political processes respond to disequilibrium. When this is the case, the error correction coefficient is the basis for inference. The experimental evidence suggests that the estimated rate of reequilibration is unaffected by departures from a unit root or degree of simultaneity: the error correction coefficients exhibit small biases in all cases for both estimators (Table 2). In both estimators, the error correction term is clearly stationary and its coefficient, like that of all stationary short-term effects in the ECM, is unaffected by problems associated with near-unit roots.

6 Implications for Applied Work

Theories about political dynamics seldom distinguish long memory from permanent memory. Much debate surrounds the decision to characterize political time series from modernization and GNP per capita, to budgets and spending, to attitudes about the president,

the economy, and the parties as either permanent, long, or short memoried. While theories suggest that persistence is an important feature of much of our data, the degree of persistence is often unclear. Statistical tests designed to help with these decisions do not provide the additional leverage needed to make these decisions. Often we cannot know which characterization is accurate.

Recently, analysts have thought more about unit root assumptions. More sophisticated unit root tests are used in applied work and more often analysts are willing to concede the possibility that the processes they care about are strongly autoregressive. Analysts have thought very little about simultaneity in this context. We need to ask, Do the shocks to the processes that generate presidential approval or consumer sentiment, for example, share patterns with the shocks that generate partisanship? If the answer is yes, then inferences about the long-run relationship need to be considered with caution. If the degree of simultaneity is large, empirical analyses like this one suggest that we need to consider hypotheses in ways that allow us to focus on short-run dynamics.

If the data are not permanent memoried, using single-equation GECMs will produce inefficient and biased estimates of the long-run relationship in the presence of simultaneity. In the case of the two-step estimator, problems with the estimates of the long-run relationship are often worse and may be unpredictable. The problems grow with either departures from permanent memory or increases in simultaneity. This is an important finding and suggests that many of the long-run relationships estimated in a cointegration framework in applied work are tenuous at best.

Importantly, departures from unit roots in the absence of simultaneity do not introduce bias or inefficiency. And small departures from $\sigma_{12} = 0$ and $|\rho| = 1$ exact a small cost. Long-run relationships can be estimated reasonably well with $\rho > 0.90$ as long as simultaneity is not too high (say $\sigma_{12} < 0.30$). As ρ grows, more simultaneity may be tolerated. But as ρ drops further, inferences about long-run relationships become more fragile. These findings suggest that if theory tells us that simultaneity is low and persistence quite strong, we may be fairly confident in estimates of long-run relationships. However, our confidence does not extend to nominal test levels.

If simultaneity is suspected, the analyst should consider ways to remove or diminish the correlations between the errors of the processes.[20] Two possibilities exist. First, better specifications of our models may minimize the correlations in the errors. Second, we may be able to use instrumental variables to remove or reduce simultaneity. Suitable instruments are, however, difficult to find when the data are strongly autoregressive. Neither strategy offers a general solution.

At a minimum, knowing something about both memory and simultaneity in our data can help us to know something about the potential scope of the problem. I consider a few examples and suggest that analysts provide readers with information about simultaneity as well as presenting pretests for unit roots.

MacKuen et al. (1998) offered a theoretical argument for permanent memory in macropartisanship, while Green et al. (1998) have argued that the process is strongly autoregressive. Point estimates of the degree of autocorrelation in Gallup macropartisanship produce estimates of around 0.95 with 90% confidence intervals that dip as low as 0.90 and as high 1.008, so that statistical evidence is consistent with both characterizations of the memory of partisanship (De Boef 2000a). Estimates of the degree of simultaneity or contemporaneous error correlations between the residuals of the model of partisanship estimated by MacKuen

[20] Tests for weak exogeneity may give us some idea of the extent of the problem (Engle, Hendry and Richard 1983, Charemza and Deadman 1997).

et al. and those from simple AR(1) models of cumulative presidential approval and cumulative consumer sentiment—the marginal processes—are of a relatively small magnitude, between 0.18 and 0.20, respectively. This information suggests that the standard errors may be too small. Given the relatively minimal simultaneity indicated, however, the problem is likely to be relatively small as well. Further, the estimated long-run coefficients are in both cases over four times their standard errors using Gallup partisanship and almost six times their standard errors using CBS/NYT partisanship. If error correction is an appropriate behavioral relationship, we can be quite confident that macropartisanship responds positively to both presidential approval and consumer sentiment in the long run.

Like partisanship, analyses of presidential approval have often been conducted using error correction models. I find that evidence of simultaneity in error correction models of presidential approval depends heavily upon the specification of both the final ECM (the number and kind of short-run variables, events, and administration effects) and the processes that are included in the long-run component of the model. Models similar to those estimated by Clarke and Stewart (1994) produce correlations that range from near-zero to about 0.40. Models similar to those produced by Ostrom and Smith (1992) suggest that the correlations of the residuals from these models is about -0.30. These correlations are enough to affect the level of the test so that standard errors are likely to be too small.

If the contemporaneous correlations estimated in these models of presidential approval are representative, we might feel some reason for optimism. It is important to note, however, that these estimates do not consider the additional complication of more general dynamics in the errors of the data generating processes or of incomplete specification of the marginal models, both of which are likely to affect these correlations. Thus, our optimism should be guarded.

Even when long-run relationships cannot be estimated with precision or efficiency due to either departures from unit roots or moderate to large simultaneity, there is much that analysts *can* do. In particular, analysts can continue to estimate the effect of deviations from the long-run relationship on short-run behavior. This is true in spite of the fact that the estimated long-run relationship is itself biased and inefficient. Estimated rates of error correction remain unbiased even when the regressors that structure the long-run relationship are not permanent memoried processes and simultaneity exists. Thus inferences about error correction rates in either the Engle–Granger two-step method or the GECM should be unaffected by the debates over permanent and long memory. When hypotheses do not involve tests on the long-run relationship, the problems highlighted here may matter little.

Political scientists are often concerned primarily with the effect of the disequilibrium and not the nature of the long-run equilibrium relationship itself. Krause (1997), for example, chose not to present the estimated long-run relationships between economic expectations and economic conditions. He focused instead on the second-stage ECM coefficients, which are unaffected by the problems highlighted here. While inferences about the long-run relationship between economic expectations and conditions and also presidential approval and economic conditions may be tenuous and depend critically on the degree of simultaneity and autocorrelation, inferences about the rate at which changes in presidential approval or partisanship adjust to correct equilibrium error should be unaffected by the dilemma over permanent and long memory.

More generally, we can test hypotheses on the short-run dynamics in error correction models. Departures from unit roots coupled with simultaneity have a minimal affect on all short-run parameters, i.e., on all variables measured as changes or first differences, not just the error correction rate. If hypotheses can be tested in terms of short-run dynamics, concerns about the persistence and simultaneity characterizing the levels of the processes are less relevant.

7 Conclusion

Long memory processes can present serious problems for testing dynamic hypotheses about politics. While there is much that we can do, there is no general solution to the problems raised here when inference on long-run relationships is our goal. Alternative estimators of ECMs or other dynamic regression models (including FMVAR) fare no better than the generalized ECM.

It is worth repeating that it is *not* the case that the analyst can argue that political time series cannot be unit roots and simply adopt methods for stationary time series *if* the data are near-integrated. Spurious relationships are likely to occur in this case. But, as this work shows, neither can we simply adopt cointegration methods whenever unit root tests cannot reject the null hypothesis. The costs of estimating long-run relationships with either methodology may be high if long memory characterizes political time series.

Much work remains to be done. In the interim, analysts should think carefully about the possibility that unit root assumptions may not hold. In these cases, further care should be taken to consider the degree of simultaneity in the data. Where there is reason to believe that the degree of simultaneity is large, extra caution should be exercised and ways to minimize simultaneity should be considered before estimating long-run relationships. In all cases, analysts should use methods that are efficient for unit root processes and avoid inefficient methods like the Engle–Granger two-step estimator. If hypotheses can be stated in terms of short-run dynamics, then this should be the focus of applied work.

Long-run equilibrium relationships often make sense. Political theories are often consistent with an error correction behavioral model. The introduction of cointegration methods and, particularly, the Engle–Granger methodology to political science has been invaluable. The virtue comes at least as much from suggesting a way to think about behavioral models as a way to estimate relationships among unit root processes. As such, it has been an aid to theory building in all the empirical subfields of the discipline. It is, however, time to question the simple transference of the Engle–Granger methodology to political science.

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