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Editorial

Modelling memory and volatility: recent advances in the analysis of political time series. Editor's introduction

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Political scientists are fascinated by change — virtually all of them talk about it, and some spend their (professional) lives studying it. Over the past quarter-century, members of the latter group have employed an expanding toolkit of statistical procedures to study the dynamics of support for political parties and party leaders. In the 1970s and 1980s, Box-Jenkins ARIMA techniques (Box and Jenkins, 1970; see also Lebo, 1999; McCleary and Hay, 1980) and VAR models (Sims, 1980) challenged familiar OLS regression procedures (possibly with "corrections" for first-order autocorrelated errors) as the preferred methodology for analyzing time series data. Then, in the early 1990s, political researchers discovered the concept of cointegration and the utility of specifying error correction mechanisms to model the long-term dynamics of cointegrated series (Hendry, 1995). However, the recent introduction of the idea of "long memory" to political scientists necessitates reexamination not only of the conclusions derived from earlier studies but also of the data themselves and the estimation procedures used to analyze them. The papers in this special issue of *Electoral Studies* deal with some contemporary topics in the time series analysis of political data, especially the concept of long memory and the problems presented by fractionally integrated data.

The concept of fractional integration has prompted reconsideration of the conventional wisdom of time series analysis and the underlying micro-level foundations of aggregate time series data. Until very recently, researchers interested in modelling political phenomena over time confined themselves to the "knife-edged" decision

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whether their data were generated by an I=0 (stationary) or an I=1 (nonstationary, i.e., unit-root) process. Based on this decision, analysts would either difference their data (if they believed it was generated as a nonstationary process) or leave it in level form (if they believed it to be stationary). This decision is not merely a matter of taste or whimsy but, rather, it has serious analytic and theoretical consequences. Theoretically, classifying a variable as stationary implies that, ceteris paribus, its value at previous periods is forgotten at a consistent rate as it tends toward some long-term mean. However, classifying a variable as having a unit-root implies that it has the properties of a "random walk". Like the proverbial Bourbon kings of France, the series has perfect memory — its value at any time t is the same as its value at the previous period, $t-1$, plus any shock incurred at time t (see, e.g., Clarke et al., 1998).

Analytically, the researcher's decision that a variable manifests stationary or nonstationary behavior will influence the inferences that can be drawn from any model that includes the variable. Treating it as a unit-root process leads the researcher to transform it through the process of "first differencing", i.e., generating a new series based on differences between the value of the series at consecutive time points. However, this transformation is consequential because it prohibits the researcher from identifying any long-term relationships that might exist between the differenced variable and other variables in the model (Enders, 1995; Hamilton 1994; see also Lebo 1999 and Clarke et al., 1998). Eschewing differencing and leaving a variable in level form avoids this problem but can have negative consequences if the data generating process (DGP) does indeed possess some degree of long-memory. Specifically, *spurious regression* — finding a significant relationship between variables when none truly exists — is a likely result when variables with some degree of persistence are left in level form (Granger and Newbold, 1974; see also Lebo et al., this issue).

The concept of fractional dynamics provides political researchers with the opportunity to avoid this restrictive stationary versus nonstationary dichotomy (Box-Steffensmeier and Smith, 1996). Abandoning the assumption that time series variables must be either stationary processes or random walks has enabled political scientists to recognize that these variables need not be strictly classified as integrated or order zero ($I(0)$) or of order one ($I(1)$) (Box-Steffensmeier and Smith, 1996). Between these two extremes lies the possibility that a series may be fractionally integrated, i.e., $0<I<1$. Over an infinite time horizon a fractionally integrated series will be mean reverting, but over finite periods such as those characterizing the data available to political scientists a fractionally integrated series will mimic the properties of a unit-root series.

Entertaining the possibility that a series possesses fractional dynamics is best understood as a generalization of the familiar ARIMA models pioneered by Box and Jenkins (1970); for recent discussions, see Hamilton, 1994; Enders, 1995). In ARIMA notation, the DGP of series X is as follows:

$$\phi(B)(1-B)^d X_t=\theta(B)\varepsilon_t \text{ and: } \varepsilon_t\ N(0,\sigma^2) \quad (1)$$

where B is a backshift operator such that $B^k\varepsilon_t = \varepsilon_{t-k}$, $\phi(B)$ represents a stationary autoregressive process, $\theta(B)$ represents a stationary moving-average process, and the degree of integration of X is measured by the fractional differencing parameter, d.

Traditional approaches to analyzing ARIMA models assign integer values to d in Eq. (1). When d=0, the series will be characterized by mean reversion, finite variance and covariance stationarity, and it can be adequately modeled using combinations of autoregressive and moving-average parameters. This is an ARMA (p,0,q) model. The case of the random walk, where d=1, is characterized by mean, variance and covariance nonstationarity (Sims and Uhlig, 1991; Durr, 1993; Ostrom and Smith, 1993; Box-Steffensmeier and Smith, 1998). By first differencing, the random walk series can be modeled using stationary autoregressive and moving-average parameters in an ARIMA (p,1,q) format.

Understanding that the value of d may lie between 0 and 1 and realizing the diversity of characteristics in this middle ground motivates fractional integration methods. As with a series where d=0, a series where $0<d<1$ will be (ultimately) mean reverting. However, such a series will cease to be variance and covariance stationary where $0.5<d<1$ (Baillie, 1996). Of critical importance is the fact that a fractionally integrated series behaves in a distinctly different manner than a series where d holds some integer value. Specifically, the fractionally integrated series will be long-memoried with statistically significant — although not necessarily large — correlations between distant time points.

Political researchers also have been introduced to the long-memory properties of *near-integrated* series (DeBoef and Granato, 1997). A near-integrated series will possess such strong autoregressive tendencies that it will approach unit-root behavior in the short-term. Yet, over many periods, the memory of the near-integrated series will decay. When long memory is left unattended, near-integrated series pose many of the same threats to inference as do unit-root and fractionally integrated series (DeBoef and Granato, 1997). The key difference between these two types of long-memoried series is that the long memory of the near-integrated series declines steadily at a geometric rate while that of a fractionally integrated series declines more slowly. Memory for the fractionally integrated series may fade at a rate that is neither exponential nor constant. Rather, significant and very similar correlations at long lags will be visible in its autocorrelation function (ACF) and, thus, this pattern in an ACF has been designated as the characteristic signature of a fractionally integrated series (Lo, 1991).

The importance of understanding the implications of fractional integration has been highlighted as researchers, including contributors to this symposium, have demonstrated that many popular political variables exhibit fractional dynamics. These findings are consistent with those of Box-Steffensmeier and Smith (1996, 1998) who reported that the quarterly “macropartisanship” index developed by MacKuen et al. (1989), the percentages of Democrat and Republican identifiers in the quarterly Gallup Poll, and the University of Michigan’s index of consumer sentiment are integrated at some order between zero and one. The discovery that political variables often are fractionally integrated seems sensible when one considers the possible origins of fractional dynamics in aggregate time series data.

Granger (1980) demonstrates that fractional dynamics are built into an aggregate time series variable when it is created by combining data on heterogenous individual-level behavior. Heterogeneity here refers to individuals' possession of *varying* degrees of autoregressive and moving-average behavior. Granger considers a series x_{jt} consisting of individuals j=1,2,...,n each with their own autoregressive parameter, α_j, randomly generated from a beta distribution (0,1). Eq. (2) shows this series.

$$x_{jt}=\alpha_j x_{t-1}+\varepsilon_t \text{ and } \varepsilon_{jt}\sim N(0,\sigma^2) \quad (2)$$

Aggregating these varying autoregressive tendencies will create a series that is fractionally integrated, i.e., it will long remember the behavior of individuals for whom α approaches or equals unity but will quickly forget the past behavior of those with less pronounced autoregressive tendencies. DeBoef and Granato (1997) warn that fractional dynamics also become more likely when a variable is bounded at its upper and lower levels. Given that so many variables of interest to political scientists — such as approval levels and partisanship measures — are constructed by aggregating individual-level behavior and are bounded within a narrow range (often 0–1 or 0–100), we should expect fractional dynamics to be prevalent in political time series. The articles that follow diagnose the properties of a number of these time series and investigate various methods for including them in theoretically interesting models of political behavior. Although the articles vary in a number of respects, a common theme emerges — understanding the process creating the microfoundations of a time series contributes to a greater understanding of macro-level behavior.

The first article, Suzanna DeBoef's "Persistence and Aggregations of Survey Data over Time: From Microfoundations to Macropersistence", begins the task of fitting fractional integration methods within the framework of previous research. Examining three popular political time series, macropartisanship, presidential approval, and Stimson's (1991) public policy mood, DeBoef (1999) explains that the typical dichotomy of stationary versus unit-root behavior is incapable of capturing the full range of heterogenous micro-level behavior. Considering microfoundations, aggregation theorems, and macro theory, DeBoef finds persistence, in some cases strong persistence, in aggregated survey data.

The presence of persistence in aggregated data is supported by the findings of Lebo, Walker, and Clarke. In "You Must Remember This: Dealing with Long Memory in Political Analysis", these authors analyze several popular political time series including presidential approval, the index of consumer sentiment, and (United States) Supreme Court liberalism for the presence of long memory. In nearly every case, estimates of the fractional differencing parameter, d, indicate that these aggregated series are fractionally integrated, i.e., the value of d is significantly greater than 0 and significantly less than 1.0. In their analyses, evidence from Dickey-Fuller (1979) and other traditional tests of (non)stationarity are found to be contradictory in several cases, while different estimation procedures for d yield results quite similar to each other.

Lebo et al. also demonstrate the threats to inference posed by fractionally integrated data. As DeBoef and Granato (1997) did for the near-integrated case, Lebo et al. use Monte Carlo procedures to show the increased likelihood of spurious regressions when one fractionally integrated variable is regressed on another. Demonstrating that the chances of finding a significant relationship between two randomly generated fractionally integrated variables can be as high as 75%, these analyses provide strong impetus for researchers to confront the long-memoried characteristics of their data.

Byers et al. (1999) offer another inventory of political variables and again find fractional dynamics to be rampant. These authors analyze time series data on the popularity of 26 political parties in eight different democracies and find estimates of d in the 0.7 range. These estimates are similar to those found by Box-Steffensmeier and Smith (1996) for party identification in the United States and thereby support the argument that strong persistence characterizes aggregate measures of party support. Byers et al. hypothesize that their findings arise because electorates are composed of varying combinations of committed voters and “floating” voters, precisely the type of heterogeneity Granger (1980) suggests will create a fractionally integrated series when individual-level data are aggregated. Although Byers et al.’s conjecture requires testing with individual-level survey data (see, e.g., Clarke and McCutcheon, 1998), it illustrates the point that models of the genesis and dynamics of micro-level attitudes and behavior can facilitate the analysis and interpretation of macro-level processes.

An important step in the analysis of fractionally integrated political variables is taken by Box-Steffensmeier and Tomlinson (1999) who present the concept of fractional cointegration in their article, “Fractional Integration Methods in Political Science”. By relaxing the assumptions that for series to cointegrate they must each be ($I(1)$) independently and their linear combination must be ($I(0)$), fractional cointegration allows for diverse equilibriating mechanisms. Box-Steffensmeier and Tomlinson analyze the univariate properties of U.S. congressional approval and aggregated economic expectations and find each to be fractionally integrated. Further, they find evidence that the two variables may be fractionally cointegrated. Such a conclusion would mean that the two variables are in a long-run equilibrium relationship but that following a shock, the return to equilibrium is a long-memoried process. That is, the variables return to equilibrium at a non-exponential rate — a rate slower than that assumed in analyses positing standard $I(0)$ cointegrating relationships.

Wlezien’s article, “An Essay on ‘Combined’ Time Series Processes”, examines the implications of combining integrated and stationary series. Using Monte Carlo methods, Wlezien (1999) combines integrated series with stationary ones and assesses the properties of the resulting series. Further, he demonstrates that combined processes can be adequately modeled using error correction methodology where the equilibrium term is itself integrated. Doing so accounts for the fact that a part of any combined process is a unit-root and is therefore persistent. Thus, between the articles of Box-Steffensmeier and Tomlinson and Wlezien, this special issue offers political researchers new tools to deal with fractionally integrated variables.

The final article in the symposium is Maestas and Preuhs’ “Modelling Volatility in Political Time Series”. Maestas and Preuhs (1999) investigate another topic that deserves the attention of analysts of political time series, namely ARCH (autoregressive conditional heteroscedasticity) processes. Following pathbreaking work by Engle (1982), econometricians have developed techniques for modelling both the mean and the variance of time series (see, e.g., Enders, 1995ch. 3). Maestas and Preuhs use Monte Carlo procedures to demonstrate that in the presence of time-dependent variance, coefficient and standard error estimates from mean models become less trustworthy. Thus, modelling the conditional variance of time series data in addition to the mean can improve analyses of the dynamics of political phenomena. Since changes in political and economic contexts may affect the variance in public beliefs, attitudes and behavior, diagnostic tests for the presence of ARCH processes should be part of every political methodologists tool kit. Moreover, measuring and accounting for periods of unusually high or low volatility may add insight into the nature of a number of the processes of interest to political scientists.

In sum, the articles in this special issue of *Electoral Studies* address a range of issues that should be of concern to anyone who analyzes political dynamics. Many readers of *Electoral Studies* are in this category, and others will be as time series data of interest to them become available. Given the prevalence of fractionally integrated political time series, the topics discussed by contributors to this symposium deserve careful attention. Perhaps the most basic message is that many political time series are more like elephants than Bourbon kings — their memory is long, but not perfect. As a result, leaving variables in level form or first-differencing them because unit-root tests fail to reject a null hypothesis of (non)stationarity both create threats to inference. Although first threat is well-known, the second one has not received the attention it deserves. New techniques for dealing with fractionally integrated data that our contributors discuss are valuable because they enable analysts to address both threats. Models for ARCH processes also are useful — attending to forces driving the conditional variance of a series can be theoretically interesting in its own right, and doing so can strengthen the inferences one draws from a model of the mean of that series. By incorporating the techniques described in this symposium in their applied work, political scientists will be better equipped to analyze the dynamics of key political variables.

References

Baillie, R.T., 1996. Long memory processes and fractional integration in econometrics. Journal of Econometrics 73, 5–59.

Box, G.E.P., Jenkins, G.M., 1970. Time Series Analysis: Forecasting and Control. Holden Day, San Francisco.

Box-Steffensmeier, J.M., Smith, R.M., 1996. The dynamics of aggregate partisanship. American Political Science Review 90, 567–580.

Box-Steffensmeier, J.M., Smith, R.M., 1998. Investigating political dynamics using fractional integration methods. American Journal of Political Science 42, 661–689.

Box-Steffensmeier, J.M., Tomlinson, A.R., 1999. Fractional integration methods in political science. Electoral Studies, this issue.

Byers, D., Davidson, J., Peel, D., 1999. The dynamics of aggregate political popularity: evidence from eight countries. Electoral Studies, this issue.

Clarke, H.D., McCutcheon, A., 1998. Mixed Markov latent class models for the dynamics of party identification. Paper presented at the annual meeting of the Midwest Political Science Association, Chicago, Illinois, April 23rd.

Clarke, H.D., Norpoth, H., Whiteley, P., 1998. Modelling political and social dynamics: it's about time. In: Scarbrough, E., Tanenbaum, E. (Eds.), Research Strategies in the Social Sciences. Oxford University Press, Oxford, pp. 127–155.

DeBoef, S., 1999. Persistence and aggregations of survey data over time: from microfoundations to macropersistence. Electoral Studies, this issue.

DeBoef, S., Granato, J., 1997. Near-integrated data and the analysis of political relationships. American Journal of Political Science 41, 619–640.

Dickey, D.A., Fuller, W., 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association 74, 427–431.

Durr, R., 1993. An essay on cointegration and error correction models. Political Analysis 4, 185–228.

Enders, W., 1995. Applied Econometric Time Series. John Wiley and Sons, New York.

Engle, R., 1982. Estimates of the variance of U.S. inflation based on the ARCH model. Econometrica 50, 987–1002.

Granger, C.W.J., Newbold, P., 1974. Spurious regression in econometrics. Journal of Econometrics 2, 111–120.

Granger, C.W.J., 1980. Long memory relationships and the aggregation of dynamic models. Journal of Econometrics 14, 227–238.

Hamilton, J.D., 1994. Time Series Analysis. Princeton University Press, Princeton.

Hendry, D., 1995. Dynamic Econometrics. Oxford University Press, Oxford.

Lebo, M.J., 1999. Fractional integration and political modeling. Doctoral dissertation, University of North Texas.

Lebo, M., Walker, R.W., Clarke, H.D., 1999. You must remember this: dealing with long memory in political analysis. Electoral Studies, this issue.

Lo, A.W., 1991. Long term memory in stock market prices. Econometrica 59, 1279–1313.

MacKuen, M.B., Erikson, R.S., Stimson, R.A., 1989. Macropartisanship. American Political Science Review 83, 1125–1142.

Maestas, C., Preuhs, R.R., 1999. Modelling volatility in political time series. Electoral Studies, this issue.

McCleary, R., Hay, R.A., 1980. Applied Time Series Analysis. Sage, Beverly Hills.

Ostrom, C.W. Jr., Smith, R., 1993. Error correction, attitude persistence, and executive rewards and punishments: a behavioral theory of presidential approval. Political Analysis 4, 127–184.

Sims, C.A., 1980. Macroeconomics and reality. Econometrica 48, 1–49.

Sims, C.A., Uhlig, H., 1991. Understanding unit rooters: a helicopter tour. Econometrica 58, 113–144.

Stimson, J.A., 1991. Public Opinion in America: Mood, Cycles, and Swings. Westview Press, Boulder, CO.

Wlezien, C., 1999. An essay on "combined" time series processes. Electoral Studies, this issue.