Pergamon

Electoral Studies 19 (2000) 63–76

Electoral Studies

www.elsevier.com/locate/electstud

Fractional integration methods in political science

Janet M. Box-Steffensmeier *, Andrew R. Tomlinson

The Ohio State University, Department of Political Science, 2140 Derby Hall, 154 N. Oval Mall, Columbus, OH 43210-1373, USA

Abstract

We argue that fractional integration methods have the potential to unify and simplify time series analysis. Estimation of the *d* parameter in an ARFIMA (*p*, *d*, *q*) model is no longer difficult and multivariate extensions are proving useful. In particular, we discuss and illustrate the most promising route, fractional cointegration and the innovation of relaxing the assumption that the parent series are I(1). We illustrate the technique with an analysis of congressional approval, a topic of great interest to institutional scholars, and its relationship with economic expectations. © 1999 Elsevier Science Ltd. All rights reserved.

Keywords: Fractional integration; Fractional cointegration; Time series; Congressional approval

Over the course of the last two decades, social scientists have made large strides in modeling time series data. One of the central areas that has made important developments is the study of long memory, in particular, the study of fractional integration. Fractional integration gives researchers more precise tools with which to characterize their time series. By appropriately treating data as fractionally integrated when modeling time series data, substantial insight may be gained into the nature of political change.

In this article, we present a basic description of fractional integration and its applications in political science as well as an updated assessment of the technique. We discuss more thoroughly why applied analysts should use fractional integration methods in political science and the potential of fractional integration to unify and

* Corresponding author. Tel.: +1-614-292-9642; fax: +1-614-292-1146.
E-mail address: jboxstef+@osu.edu (J.M. Box-Steffensmeier)

PII: S0261-3794(99)00036-0

simply the approach to time series analysis. We consider both univariate fractional integration and multivariate fractional integration, highlighting recent advances in fractional cointegration. To illustrate our substantive and methodological points, we use innovative data on congressional approval from Durr et al. (1997).

1. What is fractional integration?

As noted above, fractional integration is part of a larger classification of time series, commonly referred to as "long memory" models.[1] Long memory models address the degree of persistence in data. In their review of long memory models,[2] Granger and Ding (1996) define a series as a long memory series based on a slowly declining autocorrelation structure. "Such autocorrelation structure suggests that the process mucst depend strongly upon values of the time series far away in the past" (Dueker and Asea, 1998).

Fractional integration addresses a shortcoming that commonly used Auto-Regressive Integrated Moving Average (ARIMA) models have with modeling the degree and type of persistence in a time series. ARIMA models have three parameters: *p*, *d*, and *q*. The parameter corresponding to the number of lags involved in the auto-regressive portion of the series is *p*. The parameter for the moving average lags is *q*. Finally, *d* is a dichotomous variable indicating whether the series is integrated or not. If the series is integrated, *d* takes a value of 1. Otherwise, *d* equals 0, and the model is referred to as an ARMA model. ARFIMA (Auto-Regressive Fractionally Integrated Moving Average) models allow *d* to take any value, not just 0 or 1. Fractionally integrated series are modeled with an ARFIMA model of the form:

$$\varphi(L)(1-L)^d x_t = \Theta(L)\epsilon_t \tag{1}$$

where the parameter *d* is a real number, ε_t is distributed normally with mean 0 and variance σ^2, and $\phi(L)$ and $\theta(L)$ represent AR and MA components with lag *L*, respectively (Box-Steffensmeier and Smith, 1998).

Instead of being forced into modeling (often incorrectly) data as either stationary, i.e., I(0) or as integrated, i.e., I(1), we can more accurately model the dynamics of the series with fractional integration, I(*d*), where *d* can still be 0 or 1, but any fraction as well. If data are stationary, external shocks can have a short-term impact, but little long-term effects, as the data revert to the mean of the series at an exponential rate. In contrast, integrated data do not decay, i.e., do not return to the previous mean after an external shock has been felt. ARIMA models do not account for the possibility that data can be mean-reverting while still exhibiting effects of shocks

[1] See Beran (1994) and Granger and Ding (1996) for a discussion of the broader class of long memory models, including how the basic model discussed in this paper can be extended.

[2] See Baillie (1996) for an excellent survey and review of fractional integration. Baillie's article is the lead piece in volume 73 of the Journal of Econometrics, which is devoted exclusively to the topic of fractional differencing and long memory processes.

long since passed. By allowing *d* to take fractional values, we allow data to be mean-reverting and to still have long memory in the process.

2. Why fractional integration is important

Granger (1980) has shown that fractionally integrated data can be produced by two types of aggregation that are of interest to political scientists. First, when data are aggregated across heterogeneous auto-regressive processes, the resulting series will be fractionally integrated. So, for example, if the Congressional approval time series shows a different pattern for highly politically sophisticated respondents than for lesser sophisticated respondents, we would expect that the aggregated data would be fractionally integrated. Zaller (1992) has shown in detail the impact of political awareness and sophistication, and one might reasonably hypothesize that the highly politically aware might use information from farther back in time to drive their evaluations of Congress, while those individuals low in political awareness might use their impressions of the current Congress, or of what the Congress has done in the last month, to inform their overall evaluation. Modeling such data as stationary or integrated without testing for fractional integration would lead one to draw incorrect conclusions about the nature of the political process.[3]

Byers and Peel (1997) examine political popularity in the United Kingdom from 1960 to 1995. Their work addresses a controversy over whether public opinion behaved as a random walk or as a stationary process. Byers and Peel, hypothesize that if voters are thought of as “committed” or “uncommitted,” then, following the reasoning of Granger, the data will be fractionally integrated. The “committed,” who have stronger partisan attachments than the “uncommitted,” will base their political opinions on partisanship, while the “uncommitted” will base their opinions on performance. The aggregation of these different types of observations leads to a fractionally integrated series of data. Based on Granger’s (1980) aggregation theory, Maddala and Kim (1998) conclude that “it makes sense to consider I(*d*) processes while analyzing aggregate data” (1998, 273). De Boef (1999) extends this research agenda by focusing on the important topic of how microfoundations relate to aggregation theorems and to the persistence of aggregate series.

Second, if the data involve heterogeneous dynamic relationships at the individual level, which are then aggregated to form a time series, that series will be fractionally integrated (Granger, 1980; Lebo et al., 1998). So if different *sets* of individuals evaluate Congress in different ways, aggregating those individuals will produce fractional integration. One might expect partisans to react one way to new information about Congress, and independents might react differently. Zaller (1992) has shown that when elites are polarized on an issue, the public becomes polarized as well, usually along partisan lines. Zaller attributes this effect to cueing information from

[3] Lanier et al. (1998) make a similar argument for why one would suspect that a time series on Supreme Court liberalism would be fractionally integrated.

elites. Yet independents would not be likely to react to cueing information, because they do not identify with the partisan labels that elites use, so their process of opinion formation is different from that of partisans, and aggregation of these groups would cause fractional integration in the data.

Besides the insight gained between linking macro and micro-level processes, fractional integration is important because we should model the data generating processes as precisely as possible (Lanier et al., 1998). Box-Steffensmeier and Smith (1998) have shown that modeling a fractionally integrated series with an ARIMA, ARMA, or ARFIMA model will produce strikingly different estimates of the persistence of the series (see Figure 2 in their article). Using transfer function models to compare models of macropartisanship that assume different values of *d* for the dependent variable, they find that the different models come to starkly different conclusions about the impact of the independent variables. This analysis brings to light the risks one takes when ignoring the possibility of fractional integration.

Avoiding the "knife-edged" decision between treating a series as stationary or integrated, ARFIMA models grant social scientists greater freedom and flexibility in modeling long memory processes. For example, modeling data as fractionally integrated allows the researcher to model slower rates of decay than with other common modeling techniques, such as ARMA or ARIMA models (Box-Steffensmeier and Smith, 1998; Baillie, 1996). If one were to set *d* equal to 1 and difference the series instead of checking for the appropriate value of *d* with fractional integration, the result would be an over-differenced series. Subsequently, models of the over-differenced series would produce inflated estimates of the moving average component in the model (Box-Steffensmeier and Smith, 1998). The alternative solution to this dilemma would be to test for fractional integration, and if found, to fractionally difference the data.

The estimate of *d* will allow a researcher to test whether a series is an I(0) or an I(1) process. The estimate of *d* addresses a concern of critics of Box–Jenkins time series analysis, specifically, that the "art" of interpreting autocorrelation functions (acfs) and partial autocorrelation functions (pacfs) to determine the characterization of the series is too casual a method of analysis. The maximum likelihood estimate of *d* (Sowell, 1992a,b) jointly estimates *p*, *d*, and *q* and the associated standard errors for *d* to determine whether the series is stationary or integrated. Indeed, Beran (1994) calls these models "a unified approach to Box–Jenkins modeling" (1994, 115). Fractional integration estimates also simplify the analysis of time series data by ending debates over the best way to test for unit roots, where one needs to choose among many different tests, such as Dickey–Fuller, Augmented Dickey–Fuller, variance ratio, or KPSS, and by assumption choose the null hypotheses of d=1 or d=0 (see Maddala and Kim, 1998, p. 124). That is, instead of running multiple tests and looking for patterns suggesting stationarity, one can instead rely upon the point estimates of *d* and the associated *t*-ratios (Barkoulas et al., 1999; Box-Steffensmeier and Smith, 1998)

Lanier et al. (1998) and Lebo (1998) argue that modeling data with fractional integration reduces spuriousness. Fractionally differenced data will produce more precise regression results and predictions. Lebo et al. (1998) provide Monte Carlo evidence that demonstrates the likelihood of spurious regressions when researchers fail to account for fractional dynamics. In addition, Lanier et al. (1998) argue that including the fractionally differenced dependent variable improves parsimony, because irrelevant AR and MA components are dropped. Fractionally integrated series are being found with increasing frequency (Hassler and Wolters, 1995). Importantly, Lebo et al. (1998) show that most of the series of interest to political scientists characterized by fractional dynamics, including presidential approval, consumer sentiment, macropartisanship, and ideology of the Supreme Court. Finally, thinking of a series as fractionally integrated may lead to richer theory about the data generating process.

3. Congressional approval and univariate fractional integration analysis

Granger's findings on the effects of aggregation on the nature of a time series should enlighten researchers seeking to model political processes. Since many political variables involve heterogeneous processes, one need not look far for a good example. Public opinion scholars as far back as Converse (1964) have shown differences in attitude formation based on political sophistication. Suspecting, then, that attitudes toward political elites would be different across different levels of political sophistication is reasonable. Furthermore, one could suspect that highly sophisticated persons have more stable opinions about political elites than those who are not very politically sophisticated.

Alternatively, one could suspect the opposite, that those who are the most sophisticated are subject to the most fluctuation, because they will understand both sides of an issue. Voters with low levels of political sophistication might not be exposed to new information about a politician's performance in office, and may adopt the same positive or negative attitude every time their opinions are asked. Finally, one could suspect, as Zaller (1992) has shown, that people who are on either extreme of sophistication would be most stable in their opinions, while those in the middle — those with some exposure to new information, but without the cognitive capability to counterargue messages that contradict their previous opinion — would be the least stable in their attitudes. Any of these three hypotheses would suggest that voters may exhibit different auto-regressive patterns in their opinions based on their level of political sophistication. A series that aggregates such voters would be fractionally integrated.

We expect congressional approval, operationalized as a time series variable, to be fractionally integrated. People use different strategies to form political opinions — ideologues use ideology (Converse, 1964), people who do not follow politics rely on cues from leaders or interest groups (Lupia, 1994; Zaller, 1992), others use heuristic shortcuts (Sniderman et al., 1991), elaborate schema (Conover and Feldman, 1984; Hastie, 1986), a memory based model (Kelley and Mirer, 1974), or an online process (Lodge et al., 1989). Which type of opinion formation model is used depends on the person's cognitive abilities, his or her interest in politics, access to information, and motivation to form an opinion. So much heterogeneity in opinion formation exists that the aggregation of answers to the same question based on these different processes would meet Granger's second condition for fractional integration, if not his first.

As an example of testing for fractional integration, we estimate *d* for the innovative measures of congressional approval and economic expectations used by Durr et al. (1997), which are displayed in Fig. 1. The data are quarterly from 1974 to 1993. Their measure of Congressional Approval was generated with Stimson's CALC algorithm (Stimson 1991, 1994), which allows for aggregation of multiple survey items tapping a single phenomenon into one time series.[4] The scale of their new quarterly measure of congressional approval is such that 100 represents a midpoint approval rating. Fig. 1 shows that, as an institution, Congress suffers from a negative bias (see also Parker, 1981; Patterson and Caldeira, 1990). The economic expectations series was created by regressing the Michigan Index of Consumer Sentiment on four measures of the objective economy, and then creating predicted values. Durr et al. (1997) argue that the predicted values are devoid of political evaluations that contaminate other measures of consumer sentiment (1997[4]).

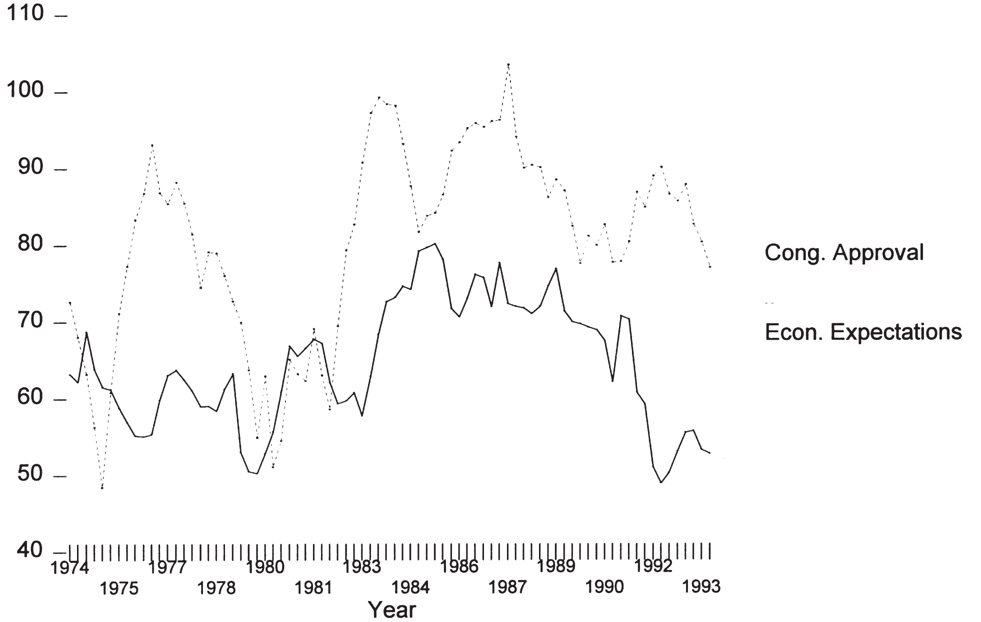

Fig. 1. Congressional approval and economic expectations.

[4] See Durr et al. (1997) for a detailed explanation of this technique for these series; see Stimson (1991) for explanation of the original algorithm.

Table 1 presents the fractional integration estimates for congressional approval and economic expectations.[5] Using the Akaike Information Criterion (AIC), a (3,d,3) model is chosen for congressional approval where d=0.72 and the standard error is 0.23. The null hypothesis that d=0 is rejected (t=3.13) but the null hypothesis that d=1 is cannot be rejected (t=−1.22). Thus, we can conclude that the congressional approval series may be fractionally integrated or integrated. The same pattern holds for economic expectations. A (0,d,2)model is selected with d=0.86 and based on the t-ratios for the null hypotheses shown in Table 1, we can conclude that the economic expectations series may be fractionally integrated or integrated. So, although Dueker and Startz (1998) make the important innovation of relaxing the requirement that the parent series be I(1) in a cointegration study, their innovation is not needed in our particular empirical study.

Beyond drawing conclusions about whether the series is stationary, integrated, or fractionally integrated, scholars have used and applied univariate estimates of d in a number of ways.[6] The concept of fractional integration has been incorporated into many areas of time series analysis, including forecasting and seasonality, with a general advantage of more precise answers (Frances and Ooms, 1997). Granger and Ding (1996) discuss generalizations of fractional integration to regime switching, time varying parameter models, and nonlinear models. In this symposium, Maestas and Preuhs (1999) persuasively argue why modeling the variance of time series is substantively interesting and highlight the consequences if one does not test and control for underlying autoregressive conditional heteroskedasticity (ARCH) processes. Gleditsch and Maestas (1998) extend this to the analysis of a fractionally integrated ARCH model of macropartisanship. Other scholars examining the combination of fractional integration and heterogeneity include Baillie et al. (1996a,b), Breidt et al. (1998) and Duan and Jacobs (1996). Diebold and Rudebusch (1989) and Box-Steffensmeier and Smith (1996) incorporate d into an impulse response function to assess the degree of persistence. By modeling macropartisanship as a fractionally integrated series and using an impulse response function, Box-Stef-

Table 1
Maximum likelihood estimates of d

	Parameter estimates[a]	H_0: d=1[b]	H_0: d=0[b]
Congressional approval	0.72 (0.23)	−1.22	3.13
Economic expectations	0.86 (0.21)	−0.67	4.10

[a] The standard errors of the estimates are shown in parentheses.
[b] These are the ML "t-ratios" for tests of the null hypothesis that d=1 and d=0.

[5] One of the easiest ways to estimate d is with OX, which is part of the PcGive 9.0 package and is also available free (DOS version) from http://www.eur.nl/few/ei/faculty/ooms/index.html#programs (November 25, 1998).

[6] There is a large economics literature on univariate fractional integration analyses (see Baillie, 1996 for a review).

fensmeier and Smith (1996) are able show the rate of decay after an exogenous shock.

4. Fractional cointegration

The next stage in the advancement of fractional integration modeling techniques is the ability to model multivariate fractionally integrated processes. Ravishanker and Ray (1997) present a Bayesian analysis of vector ARFIMA processes. Box-Steffensmeier et al. (1998) incorporate fractional integration into a Granger causality analysis. Importantly, Lebo (1998) studies the vital question of how and when to include ARFIMA specifications in bivariate and multivariate models. One of the most fruitful areas in multivariate analysis is fractional cointegration, most notably the work of Baillie and Bollerslev (1994), Cheung and Lai (1993) and Dueker and Startz (1998).

If two series are cointegrated, there is a long-term equilibrium relationship between the series. "Cointegrated series are in a dynamic equilibrium in the sense that they tend to move together in the long run. Shocks that persist over a single period are 'reequilibrated' or adjusted by this cointegrating relationship" (Clarke et al., 1998, p. 562). Typically, the two parent series are tested and if found to be I(1), the cointegrating regression is estimated. The residuals of the cointegrating regression are tested to see if they are I(0). If so, the parent series are said to be cointegrated and a relationship exists.[7]

Cheung and Lai (1993) relaxed the assumption that the residuals needed to be I(0), introducing the idea that the residuals could be fractionally integrated. Cheung and Lai point out the theoretical relevance of fractional cointegration; if one finds fractional cointegration in the two parent series, there is a long-term equilibrium relationship between them. The relationship responds to exogenous shocks, but then returns to equilibrium. Univariate fractionally integrated series are mean-reverting, but show short-run persistence and tell us how those data react to exogenous shocks. Finding fractional cointegration between two variables gives us insight into how the equilibrium relationship between those two variables reacts to exogenous shocks. Just as fractional integration methods avoid the knife-edged distinction between a series being I(0) and I(1), fractional cointegration methods avoid making the same claim about the residual series of a cointegrating regression.

The rate of mean reversion of equilibrium error is of key importance. As Cheung and Lai (1993) illustrate, the mean-reverting properties of the equilibrium relationship between two variables determine how those variables stay cointegrated in response to exogenous shocks. For example, if the equilibrium error is not mean-reverting, a shock can cause permanent disequilibrium (Cheung and Lai, 1993). To

---

[7] For exemplary work on cointegration in political science, see Beck, 1993; Clarke et al., 1998; Durr, 1993; Eisinga and Franses, 1996; Ostrom and Smith, 1993; Smith, 1993; Williams, 1993; and on near-integration, De Boef and Granato 1997, 1999.

test for cointegration between two series x_{1t} and x_{2t}, Cheung and Lai (1993) follow the method proposed by Engle and Granger (1987) by regressing one series on the other, and then estimating the *d* parameter of the residual series.[8] Cheung and Lai (1993) show that if the estimated *d* for the residual series is not an integer, then the parent series are fractionally cointegrated. While the previous literature has assumed that the parent series are I(1), we follow Dueker and Startz (1998) in theory by relaxing this assumption and by extending Cheung and Lai's work by allowing the estimates for the parent and residual series to all be I(*d*), where $d \epsilon [0,1]$.

Dueker and Startz (1998) provide an important innovation by invoking Granger's (1986) broader notion of cointegration, noting that only a lower order of integration for the residuals compared to the parent series is required (1998, 420). That is, they relax the assumption that the parent series be I(1). We follow Dueker and Startz (1998) by allowing the estimate for the order of the parent series (*d*) and the residuals (*d*') to take any value of *d* in our investigation into the relationship of congressional approval and economic expectations.[9] If $d' < d$, then the series are cointegrated.

Our results in the previous section show that the two parent series are both I(*d*), where *d* is the same within a one standard deviation, and quite likely the two series are both I(1). Thus, given on our estimates of *d* for the two parent series, relaxing the I(1) assumption is not critical to our particular empirical example. Based on the large literature about the effect of the economy on presidential approval (MacKuen et al., 1992), and about the effect of the economy on congressional elections (Jacobson, 1992; Kinder and Kiewiet, 1979; Tufte, 1978), it is reasonable to expect congressional approval and economic expectations to be related. Looking again at Fig. 1, it is reasonable to expect that the series are cointegrated. That is, the series appear to be trending together, particularly since around 1980. In any case, testing for fractional integration relieves one from reliance on debatable ocular testing.

We proceed by testing for fractional cointegration, which is more general than testing for cointegration. In traditional cointegration analyses one would simply test whether or not the residuals are stationary. Depending upon which test was chosen, the null hypothesis would be either that the residuals are I(0), for example, if the KPSS test was used, or are I(1), for example, if the Dickey–Fuller test was used. The problem is that these diagnostic tests often do not give the same conclusion.

There is a large literature examining congressional approval, (e.g., Durr et al., 1997; Hibbing and Theiss-Morse, 1995; Kimball and Patterson, 1997; Mockabee and Monson, 1999; Parker and Davidson, 1979; Patterson and Magleby, 1992; Patterson

[8] Cheung and Lai (1993) use the GPH estimate for *d* (see Geweke and Porter-Hudak, 1983). Agiakloglou et al. (1993) and Hurvich and Ray (1995) have recently shown that the GPH has serious biases. We use Sowell's maximum likelihood estimate of *d*.

[9] Dueker and Startz (1998) is also noteworthy for the innovation of jointly estimating the value of *d* and *d*'. We replicated their results and consider their method a promising route for future research because of the efficiency aspects of jointly estimating *d* and *d*'. However, we do not carry out such an analysis for the congressional approval data for two reasons. First, the model selection procedure for their approach is unsettlingly ad hoc. Second, the program is extremely sensitive to the starting values and at this time tends to get stuck in local minima.

and Barr, 1995; Patterson and Caldeira, 1990; Patterson and Monson, 1998). We contribute to this literature by looking at the relationship between congressional approval and economic expectations; the regression results are in Table 2. The results show classic spurious regression concerns. The regression results look great; the R^2 and *t*-ratio for economic expectations are very high and the effect of economic expectations is in the right direction. As people are more optimistic about the economy, approval of Congress increases. One clue that there may be a problem is that the Durbin–Watson statistic is low. Granger and Newbold (1974) point out that if the R^2 is greater than the Durbin–Watson statistic, one should suspect that the estimated regression is spurious and should test for cointegration.

A (3,*d*,3) model is chosen for the residuals according to the AIC. The estimate of d'=0.40. This suggests that we do have fractional cointegration between congressional approval and economic expectations. However, when taking into account the standard error of 0.45, we cannot reject the null hypothesis that $d'=1$ ($t=-1.33$). Similarly, we cannot reject the null that $d'=0$ ($t=0.89$). This later null is not problematic, since if we could reject the null that the residuals were I(1) but not the null that they were I(0), we could still conclude that the series were cointegrated. Conclusions about fractional cointegration only require that $d'=d-b$ where $b>0$, i.e., that the order of the cointegrating residuals be less than the order of the parent series. Unfortunately, the standard errors are large, which leads to less definitive hypothesis testing than is desirable. The large standard errors are not unexpected since there are only 80 observations.[10]

Table 2
Cointegrating regression on congressional approval and maximum likelihood estimate of d' for the residuals

	Parameter estimate[a]	*P*-value	
Constant	44.78 (5.56)	0.00	
Economic expectations	0.24 (0.07)	0.00	
R^2=0.987			
Durbin–Watson statistic=0.245			
	Parameter estimate[a]	H_0: d=1[b]	H_0: d=0[b]
Residuals from the cointegrating regression	0.40 (0.45)	−1.33	0.89

[a] The standard errors of the estimates are shown in parentheses.
[b] These are the ML "*t*-ratios" for tests of the null hypothesis that d=1 and d=0.

[10] When looking into the stability of the point estimate of *d* and the associated standard errors, we found that the point estimates of *d* were quite similar whether the series had 150 or 70 observations. What changed dramatically, not surprisingly, was the precision of the standard errors.

5. Conclusion

In their assessment of the state of quantitative political methodology, Bartels and Brady (1993) point out that "time series data have come to play an increasingly prominent role in political science in the last decade" (1993, 125). Fractional integration methods offer many advantages and the promise of a more straightforward implementation of time series methods. Less reliance on the "art" of time series and the unification of the literature on modeling the characteristics of one's time series, in contrast to the recent myriad of typically contradictory tests for stationarity and unit roots, are benefits that are already realized. Fractional integration has already been incorporated into univariate time series analysis, for example, in the interpretation of impulse response functions or the modeling of heterogeneity. On-going work incorporates this important concept into bivariate or multivariate analyses, such as fractional cointegration or examining how and when to incorporate ARFIMA specifications. In the five years since Bartels and Brady (1993) wrote their assessment, we have benefitted from even more methodological progress in time series and there is no indication that the pace will slow down any time soon.

Acknowledgements

The authors thank the anonymous referees, Suzanna De Boef, Matthew Lebo, Robert Walker, Elaine Willey, and Chris Wlezien for helpful comments and discussion, Christina Wolbrecht for the data on Congressional Approval, and Harold Clarke for putting this issue together. All data and related files will be archived at ICPSR upon publication.

References

Agiakloglou, C., Newbold, P., Wohar, M., 1993. Bias in an Estimator of the Fractional Differencing Parameter. Journal of Time Series Analysis 14, 233–246.

Baillie, R.T., 1996. Long Memory Processes and Fractional Integration in Econometrics. Journal of Econometrics 73, 5–59.

Baillie, R.T., Bollerslev, T., 1994. Cointegration, Fractional Cointegration, and Exchange Rate Dynamics. The Journal of Finance 79, 737–745.

Baillie, R.T., Bollerslev, T., Ole Mikkelsen, H., 1996a. Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity. Journal of Econometrics 74, 3–30.

Baillie, R.T., Chung, C.-F., Tieslau, M.A., 1996b. Analyzing Inflation by the Fractionally Integrated ARFIMA-GARCH Model. Journal of Applied Econometrics 11, 23–40.

Barkoulas, J.T., Baum, C.F., Caglayan, M., 1999. Fractional Monetary Dynamics. Applied Economics (in press).

Bartels, L.M., Brady, H.E., 1993. The State of Quantitative Political Methodology. In: Finifter, A. (Ed.), Political Science: The State of the Discipline. American Political Science Association, Washington, DC.

Beck, N., 1993. The Methodology of Cointegration. Political Analysis 4, 237–248.

Beran, J., 1994. Statistics for Long-Memory Processes. Chapman and Hall, New York.

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., Knight, K., Sigelman, L., 1998. The Interplay of Partisanship and Ideology: A Time-Series Analysis. Journal of Politics 60, 1044–1062.

Breidt, F.J., Crato, N., De Lima, P., 1998. The Detection and Estimation of Long Memory in Stochastic Volatility. Journal of Econometrics 83, 325–348.

Byers, D., Peel, D., 1997. Modeling Political Popularity: An Analysis of Long-range Dependence in Opinion Poll Series. Journal of the Royal Statistical Society 160, 471–490.

Cheung, Y.-W., Lai, K.S., 1993. A Fractional Cointegration Analysis of Purchasing Power Parity. Journal of Business and Economic Statistics 11, 103–112.

Clarke, H.D., Stewart, M.C., Whiteley, P.F., 1998. New Models for New Labour: The Political Economy of Labour Party Support, January 1992-April, 1997. American Political Science Review 92, 559–575.

Conover, P.J., Feldman, S., 1984. How People Organize the Political World: A Schematic Model. American Journal of Political Science 28, 95–126.

Converse, P., 1964. The Nature of Belief Systems in Mass Publics. In: Apter, D.E. (Ed.), Ideology and Discontent. Free Press, New York.

De Boef, S., 1999. Persistence and Aggregations of Survey Data over Time: From Microfoundations to Macropersistence. Electoral Studies (in press).

De Boef, S., Granato, J., 1997. Near-integrated Data and the Analysis of Political Relationships. American Journal of Political Science 41, 619–640.

De Boef, S., Granato, J., 1999. Testing for Cointegrating Relationships With Near-integrated Data. Political Analysis (in press).

Diebold, F.X., Rudebusch, G.D., 1989. Long Memory & Persistence in aggregate output. Journal of Monetary Economics 24, 189–209.

Duan, J.-C., Jacobs, K., 1996. A Simple Long-Memory Equilibrium Interest Rate Model. Economics Letters 53, 317–321.

Dueker, M.J., Asea, P.K., 1998. Non-Monotonic Long Memory Dynamics in Black-Market Premia. Typescript: The Federal Reserve Bank of St. Louis.

Dueker, M., Startz, R., 1998. Maximum-Likelihood Estimation of Fractional Cointegration with an Application to U.S. and Canadian Bond Rates. The Review of Economics and Statistics 420–426.

Durr, R., 1993. An Essay on Cointegration and Error Correction Models. Political Analysis 4, 185–228.

Durr, R., Gilmour, J.B., Wolbrecht, C., 1997. Explaining Congressional Approval. American Journal of Political Science 41, 175–207.

Eisinga, R., Franses, P., 1996. Testing for Convergence in Left-Right Ideological Positions. Quality and Quantity 30, 345–359.

Engle, R.F., Granger, C.W.J., 1987. Cointegration and Error Correction: Representation, Estimation, and Testing. Econometrica 55, 251–276.

Frances, P.H., Ooms, M., 1997. A Periodic Long-memory Model for Quarterly UK Inflation. International Journal of Forecasting 13, 117–126.

Geweke, J., Porter-Hudak, S., 1983. The Estimation and Application of Long Memory Time Series Models. Journal of Time Series Analysis 4, 221–238.

Gleditsch, K., Maestas, C., 1998. Sensitivity of GARCH Estimates: Effects of Model Specification on Estimates of Macropartisan Volatility. Presented at the annual meeting of the Midwest Political Science Association, Chicago.

Granger, C.W.J., 1980. Long Memory Relationships and the Aggregation of Dynamic Models. Journal of Econometrics 14, 227–238.

Granger, C.W.J., 1986. Developments in the Study of Cointegrated Economic Variables. Oxford Bulletin of Economics and Statistics 48, 213–228.

Granger, C.W.J., Ding, Z., 1996. Varieties of Long Memory Models. Journal of Econometrics 73, 61–77.

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

Hassler, U., Wolters, J., 1995. Long Memory in Inflation Rates — International Evidence. Journal of Business and Economic Statistics 13, 37–45.
Hastie, R., 1986. A Primer of Information-processing Theory for the Political Scientist. In: Lau, R.R., Sears, D.O. (Eds.), Political Cognition. Erlbaum, Hillsdale, NJ.
Hibbing, J., Theiss-Morse, E., 1995. Congress as Public Enemy: Public Attitudes Toward American Political Institutions. Cambridge University Press, Cambridge.
Hurvich, C.M., Ray, B.K., 1995. Estimation of the Memory Parameter for Nonstationary or Noninvertible Fractionally Integrated Processes. Journal of Time Series Analysis 16, 17–41.
Jacobson, G.C., 1992. The Politics of Congressional Elections. 3rd ed. Harper Collins Publishers, New York.
Kelley, S. Jr., Mirer, T.W., 1974. The Simple Act of Voting. American Political Science Review 68, 572–591.
Kimball, D., Patterson, S., 1997. Living Up to Expectations: Public Attitudes Toward Congress. Journal of Politics 59, 701–728.
Kinder, D.R., Kiewiet, D.R., 1979. Economic Discontent and Political Behavior: The Role of Personal Grievances and Collective Economic Judgments in Congressional Voting. American Journal of Political Science 23, 495–527.
Lanier, D.N., Lebo, M.J., Walker, R.W., 1998. The Long Memory of the Supreme Court. Presented at the annual meeting of the Southern Political Science Association, Atlanta.
Lebo, M.J., 1998. Fractional Integration: Dissertation Proposal. University of North Texas, Denton, TX, Unpublished manuscript.
Lebo, M.J., Walker, R.W., Clarke, H.D., 1998. You Must Remember This: Dealing with Long Memory in Political Analyses. Presented at the annual meeting of the American Political Science Association.
Lodge, M., McGraw, K.M., Stroh, P., 1989. An Impression-Driven Model of Candidate Evaluation. American Political Science Review 83, 399–419.
Lupia, A., 1994. Shortcuts Versus Encyclopedias: Information and Voting Behavior in California Insurance Reform Elections. American Political Science Review 88, 63–76.
MacKuen, M.B., Erikson, R.S., Stimson, J.A., 1992. Peasants or Bankers? The American Electorate and the US Economy. American Political Science Review 86, 597–611.
Maddala, G.S., Kim, I.-M., 1998. Unit Roots, Cointegration, and Structural Change, draft copy. Cambridge University Press, Cambridge.
Maestas, C., Preuhs, R.R., 1999. Modeling Volatility in Political Time Series. Electoral Studies, (in press).
Mockabee, S.T., Monson, Q., 1999. Public Approval of Congress, Legislative Action, and Representation. Presented at the annual meeting of the Midwest Political Science Association, Chicago.
Ostrom, C.W. Jr., Smith, R.M., 1993. Error Correction, Attitude Persistence, and Executive Rewards and Punishments: A Behavioral Theory of Presidential Approval. Political Analysis 4, 127–184.
Parker, G.R., 1981. Can Congress Ever Be a Popular Institution? In: Cooper, J., Mackenzie, G.C. (Eds.), The House at Work. University of Texas Press, Austin.
Parker, G., Davidson, R., 1979. Why Do Americans Love their Congressmen so much more than their Congress? Legislative Studies Quarterly 4, 53–61.
Patterson, K.D., Magleby, D., 1992. The Polls - Poll Trends: Public Support for Congress. Public Opinion Quarterly 56, 539–551.
Patterson, S.C., Barr, M., 1995. Congress Bashing and the 1992 Congressional Election. In: Weisberg, H. (Ed.), Democracy's Feast. Chatham House, Chatham, NJ.
Patterson, S.C., Caldeira, G.A., 1990. Standing Up for Congress: Variations in Public Esteem since the 1960s. Legislative Studies Quarterly 15, 25–47.
Patterson, S.C., Monson, Q., 1998. Two More Years: Reelecting the Republican Congress. In: Weisberg, F.H., Box-Steffensmeier, J.M. (Eds.), Reelection 1996: How Americans Voted. Chatham House, Chatham, NJ.
Ravishanker, N., Ray, B.K., 1997. Bayesian Analysis of Vector ARFIMA Processes. Australian Journal of Statistics 39, 295–311.
Smith, R.M., 1993. Error Correction, Attractors, and Cointegration: Substantive and Methodological Issues. Political Analysis 4, 249–254.

Sniderman, P.M., Brody, R.A., Tetlock, P.E., 1991. Reasoning and Choice: Explorations in Political Psychology. Cambridge University Press, New York.

Sowell, F.B., 1992a. Maximum Likelihood Estimation of Stationary Univariate Fractionally Integrated Time Series Models. Journal of Econometrics 53, 165–188.

Sowell, F.B., 1992b. Modeling Long Run Behavior with the Fractional ARIMA Model. Journal of Monetary Economics 29, 277–302.

Stimson, J.A., 1991. Public opinion in America: moods, cycles, and swings. Westview Press, Boulder, CO.

Stimson, J.A., 1994. Using CALC and Dyad Ratios Algorithm. University of Minnesota. Typescript.

Tufte, E.R., 1978. Political Control of the Economy. Princeton University Press, Princeton.

Williams, J.T., 1993. What goes around comes around: unit root tests and cointegration. Political Analysis 4, 229–236.

Zaller, J., 1992. The Nature and Origins of Mass Opinion. Cambridge University Press, Cambridge.