Long-Term Statistical Relationships in Political Science: An Analysis Based on Fractional Integration and Cointegration

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Abstract: In this paper we use new statistical methods to examine the connection between economic expectations and support for the government in the U.S.A. For this purpose, we analyse the order of integration for Congressional Approval and Economic Expectations from a fractional point of view. The results show that though both individual series can be specified in terms of fractional processes, the unit root cannot statistically be rejected, which is consistent with other empirical works in these variables. The possibility of cointegration is also examined from a fractional viewpoint, and the results strongly reject the hypothesis of cointegration. Thus, both series are nonstationary, and there is no linkage between them in the long run, according to an error correction equilibrium relationship.

JEL Classification: C22

Keywords: Fractional integration, Cointegration, Political time series.

1. INTRODUCTION

Over the last 15 years, the number of papers dealing with economics and government support has dramatically increased. Methodologically, there have been important advances, and there are now many time series available for different countries along with extensive public opinion polls. However, modelling time series in political science is a matter that still remains controversial. Thus, while some authors argue that most series are stationary around a deterministic trend, others assume that political time series are difference-stationary, that is, they contain a unit root. However, these two types of models (I(0) stationarity around a linear trend and I(1) or unit roots) are extremely specialised members of a wider class of processes, called fractionally integrated or I(d) processes. In this article we adopt the latter approach and assume that d can be a real value. In doing so, we allow for a much richer degree of flexibility in the dynamic behaviour of the series, not achieved when using these two classic representations.

It is widely accepted that economic factors play an important role in determining government popularity (see Lewis-Beck, 1988; Norpoth, Lewis-Beck and Lafay, 1991; and the VP-functions popularized by Nannestad and Paldam, 1994, and others). The idea behind this relationship is simple: if economic conditions are good, the electorate will reward incumbents, while it will punish them if economic conditions are less than satisfactory. Thus, the economic voting literature emphasizes indicators such as inflation or unemployment, but also subjective interpretations, captured *via* consumer sentiment, noting the utility of measures of voters' judgments about their own and their country's financial welfare (Sanders, 1991; Clarke and Steward, 1995)[1]. Forty years ago, Key (1968) articulated an argument that voters take their decisions guided by retrospective rather than prospective judgments of government performance. However, in recent years, prospective judgments have also been taken into account. Thus, for example, Sanders (1991) employed personal economic expectations in his study predicting the widely unanticipated Conservatory victory in the 1992 elections in Britain, while other authors such as MacKuen, Erikson and Stimson (1992, 1996) argue in favour of using national expectations rather than individual expectations.

Most of the time series employed in economics and political sciences are of a nonstationary nature. Traditionally, series which evolve or change over time have been modelled in terms of deterministic functions of time, which are fitted by linear regression techniques. Later on, and especially after the seminal paper of Nelson and Plosser (1982), it was shown that many time series were better described in terms of unit root models. That is, once a time series is differenced an appropriate number of times, it becomes stationary, and standard statistical techniques can be applied. However, in recent years, more complex statistical methods based on fractional integration have been proposed and, they permit us to consider these two previous representations as particular cases of the I(d) statistical models. Byers, Davidson and Peel (1997) examined political popularity in the UK from 1960 to 1995. Their work addressed a controversy over whether public opinion behaved as a unit root or as a stationary process, and they concluded that the opinion poll series follow an I(d) process with d around 0.7. Apart from the aforementioned work, there is a small but important body of literature using fractional integration in political science that includes among others the papers of Box-Steffensmeier and Smith (1996, 1998), DeBoef and Granato (1997), Box-Steffensmeier and De Boef (1997), Green, Palmquist and Schickler (1998), Box-Steffensmeier, Knight and Sigelman, (1998), DeBoef (2000), Wood (2000) and DeBoef and Kellstedt (2004). In most of these papers, the authors conclude that variables such as presidential approval and party identification are fractionally integrated (I(d)) variables.

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[1]Stock market information has been recently incorporated into the analysis of presidential approval. (Jackman, 1995; Alter and Goodhart, 2004).

1874-9496/08

In this paper we investigate if the unit root model is an adequate specification to describe the time series behaviour in political science even when we test this hypothesis within a fractional framework. In the context of I(d) processes, if d < 1, the series is mean reverting as opposed to the case of a unit root (d = 1) where the effects of the shocks persists forever. In the latter case, there will exist a stronger need of policy actions to bring the variable back to its original level, while in the former case the series will return to its level sometime in the future. Moreover, standard techniques used for testing unit roots (e.g., Dickey and Fuller, 1979; Phillips and Perron, 1988; etc.) have very low power in the context of fractional alternatives (Diebold and Rudebusch, 1991, Hassler and Wolters, 1994; Lee and Schmidt, 1996) and thus, a deeper examination in this context seems overdue.

The structure of the paper is as follows. Section 2 describes the concept of fractional integration and its implications in terms of political time series. In Section 3, we present some methods for estimating and testing the fractional differencing parameter. These methods have several distinguishing features compared with other procedures and they are highlighted also in Section 3. The procedures are then applied in Section 4 to some innovative data on Congressional Approval and Economic Expectations from Durr, Wolbrecht and Gilmour (1997). Section 5 concludes.

2. FRACTIONAL INTEGRATION AND POLITICAL SCIENCE

We say that a time series is integrated of order 0 (and denoted by I(0)) if it is covariance stationary, with a spectral density function that is positive and finite at the zero frequency. This is a broad class of models that include the classic white noise, stationary AutoRegressive (AR), Moving Average (MA), AutoRegressive-Moving Average (ARMA), etc. Avoiding technical definitions, we can say that a time series is integrated of order d (and denoted by I(d)) if it requires d-differences to achieve I(0). In other words, let us suppose that x_t is the observed time series and that:

$$(1 - L)^d x_t = u_t, \qquad t = 1, 2, \ldots, \qquad (1)$$

with $x_t = 0$ for $t \le 0$[2], where L is the lag operator (i.e. $Lx_t = x_{t-1}$) and u_t is I(0). Clearly, if d = 0, $x_t = u_t$, and a 'weakly autocorrelated' x_t is then allowed. If d > 0, the process is said to be long memory, so named because of the strong association between observations widely separated in time. Note that the polynomial in (1) can be expressed in terms of its Binomial expansion, such that for all real d,

$$(1 - L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - d\,L + \frac{d(d-1)}{2} L^2 - \ldots,$$

and (1) can be written as:

$$x_t = d\,x_{t-1} + \frac{d(d-1)}{2} x_{t-2} + \ldots + \varepsilon_t. \qquad (2)$$

If d is an integer value, x_t will be a function of a finite number of past observations, while if d is real, x_t depends strongly upon values of the time series far away in the past. (See, e.g., Granger and Ding, 1996; Dueker and Asea, 1998).

To correctly determine d is crucial from both economic and statistical viewpoints. Thus, if d ∈ (0, 0.5) in (1), x_t is covariance stationary and mean-reverting, with the effect of shocks disappearing in the long run; if d ∈ [0.5, 1), the series is no longer covariance stationary but it is still mean-reverting, while d ≥ 1 means nonstationarity and non-mean-reversion. This is relevant in the context of economic and political time series: if a series is mean reverting, in the event of an exogenous (negative) shock, there is less need of action than in the case of an I(1) (non-mean-reverting) process given that the series will return by itself to its original path in the future.

There exist different sources that might generate I(d) statistical models. Granger (1980) has shown that fractionally integrated data can be produced by two types of aggregation that are of interest to political scientists. Firstly, when data are aggregated across heterogeneous AR processes. In this context, for example, if the Congressional Approval, operationalized as a time series variable, shows a different pattern for highly political sophisticated respondents than for lesser sophisticated respondents, we would expect that the aggregate data would be fractionally integrated[3]. Another source of I(d) processes is obtained using data involving heterogeneous dynamic relationships at the individual level, which are then aggregated to form the time series. So that if different sets of individuals evaluate Congress in different ways, aggregating those individuals will also produce fractional integration. Theoretical discussion of how fractional integration can be useful in political science has been covered in great detail in Box-Steffensmeier and Tomlinson (2000); Lebo, Walker and Clarke (2000); Clarke and Lebo (2003); Dolado *et al.* (2003); etc. (See also first paragraph in Section 4).

On the other hand, earlier studies of the dynamics of government support (e.g. Goodhart and Bhansali, 1970; Miller and Mackie, 1973) focused exclusively on the effects of objective economic indicators such as inflation or unemployment rates. However, during the last 20 years or so, researchers have demonstrated that economic expectations play a significant role in determining party support (Sanders, 1991; Clarke and Stewart, 1995). In fact, it is now a well-known stylized fact that government support and economic expectations are highly correlated. This statistical relationship has motivated interest in the concept of cointegration, which enables us to capture possible long run relationships between the two variables. However, cointegration, at least in its classic bivariate sense, imposes the individual series to be I(1), while an I(0) process is assumed for the long run equilibrium relationship. In this paper, we first question the assumption of integer differentiation in our two variables (Congressional Approval and Economic Expectations), and instead of imposing the strict distinction between I(1)/I(0) processes, we allow for the possibility of fractional orders of integration. Then, the possibility of cointegration (and thus the existence of a long run equilibrium dynamic relationship between the two variables) will also be examined.

[2]For an alternative definition of fractionally integrated processes (the type I class), see Marinucci and Robinson (1999).

[3]Zaller (1992) examined the impact of political awareness and sophistication, though he does not use fractional integration. He argues that one might reasonably hypothesizes that the highly politically aware might use information from farther back in time to drive their evaluation of Congress, while those individuals low in political awareness might use their impressions of the current Congress or what the Congress has done in recent past.

3. ESTIMATION AND TESTING OF I(D) STATISTICAL MODELS

There are two main approaches to estimate the parameter d. The first approach is parametric, that is, the model is specified up to a finite number of parameters of which d is one. Here, we must specify the functional form of the underlying I(0) disturbances u_t in (1), and the analysis can be carried out in the time domain (e.g., Sowell, 1992) or in the frequency domain (e.g., Fox and Taqqu, 1986). However, in estimating with parametric approaches, the correct choice of the model is important; if it is misspecified, the estimates of d may be inconsistent. In fact, misspecification of the short-run components of the series may invalidate the estimation of its long run behaviour. Thus, there might be some advantages in estimating d on the basis of semiparametric approaches. Examples here are the procedures of Geweke and Porter-Hudak (1983), Robinson (1995a,b), Velasco (1999a,b), etc.

In this article we use both parametric and semiparametric methods. First, we present a parametric testing procedure of Robinson (1994a) that has several distinguishing features compared with other methods. Thus, it has standard null and local limit distributions, and this standard behaviour holds independently of the inclusion or not of deterministic components and of the different ways of modelling the I(0) disturbances. Moreover, it does not require gaussianity, with a moment condition of only 2 required, and it is the most efficient method when directed against the appropriate (fractional) alternatives. Then, a semiparametric procedure (Robinson, 1995a) will also be described.

3.1. A parametric Testing Procedure

Following Bhargava (1986), Schmidt and Phillips (1992) and others on the parameterization of unit-roots, Robinson (1994a) considers the regression model:

$$y_t \;=\; \beta' z_t \;+\; x_t \qquad t \;=\; 1, 2, ... \tag{3}$$

where y_t is a given raw time series; z_t is a (kx1) vector of exogenous variables; β is a (kx1) vector of unknown parameters; and the regression errors x_t are of form as in (1). He proposed a Lagrange Multiplier (LM) test of the null hypothesis:

$$H_o : d \;=\; d_o, \tag{4}$$

in (1) and (3) for any real value d_o. Thus, if $d_o = 1$, we are testing for a unit root, though other fractional values of d are also testable. The functional form of the test statistic (denoted by $\hat{r}$) is described in the Appendix. Based on the null hypothesis (4), Robinson (1994a) established that under some regularity conditions[4]:

$$\hat{r} \;\rightarrow_d\; N(0,1) \quad as \quad T \rightarrow \infty, \tag{5}$$

and also the Pitman efficiency of the test against local departures from the null[5]. Thus, we are in a classical large sample-testing situation by reasons described in Robinson (1994a): An approximate one-sided $100\alpha\%$ level test of H_o (4) against the alternative: H_a: $d > d_o$ ($d < d_o$) will be given by the rule "Reject H_o (4) if $\hat{r} > z_\alpha$ ($\hat{r} < - z_\alpha$)", where the probability that a standard normal variate exceeds z_α is α[6]. There exist other procedures for estimating and testing the fractionally differenced parameter in a parametric way, some of them also based on the likelihood function. We believe that as in other standard large-sample testing situations, Wald and LR test statistics against fractional alternatives will have the same null and local limit theory as the LM tests of Robinson (1994a). Sowell (1992) employed essentially such a Wald testing procedure but it requires an efficient estimate of d, and while such estimates can be obtained, no closed-form formulae are available and so the LM procedure of Robinson (1994a) seems computationally more attractive[7].

3.2. A Semiparametric Estimation Procedure

There exist several methods for estimating and testing the fractional differencing parameter in a semiparametric way. Examples are the Log-Periodogram regression Estimate (LPE), initially proposed by Geweke and Porter-Hudak (1983) and modified later by Künsch (1986) and Robinson (1995a), the Average Periodogram Estimate of Robinson (APE, 1994b) and a Whittle semiparametric approach (Robinson, 1995b) which we are now to describe. This method is basically a 'Whittle estimator' in the frequency domain, using a band of frequencies that degenerates to zero. The estimate is implicitly defined by:

$$\hat{d} = \arg\min_d \left(\log \overline{C(d)} \;-\; 2\,d\, \frac{1}{m}\sum_{j=1}^{m} \log\, \lambda_j \right), \tag{6}$$

$$\overline{C(d)} \;=\; \frac{1}{m}\sum_{j=1}^{m} I(\lambda_j)\, \lambda_j^{2d}, \qquad \lambda_j = \frac{2\,\pi\, j}{T}, \qquad \frac{m}{T} \rightarrow 0,$$

where m is a bandwidth parameter number, and $I(\lambda_j)$ is the periodogram of the time series, x_t, given by:

$$I(\lambda_j) \;=\; \frac{1}{2\pi T}\left|\sum_{t=1}^{T} x_t\, e^{i\lambda_j t}\right|^2 .$$

and $d \in (-0.5, 0.5)$[8]. Under finiteness of the fourth moment and other mild conditions, Robinson (1995a) proved that:

$$\sqrt{m}\,(\hat{d} \;-\; d_o) \;\rightarrow_d\; N(0, 1/4) \quad as\; T \rightarrow \infty,$$

where d_o is the true value of d and with the only additional requirement that $m \rightarrow \infty$ slower than T[9]. Robinson (1995a) showed that m must be smaller than T/2 to avoid aliasing

[4]These conditions are very mild, and concern technical assumptions to be satisfied by the model in (1) and (3).

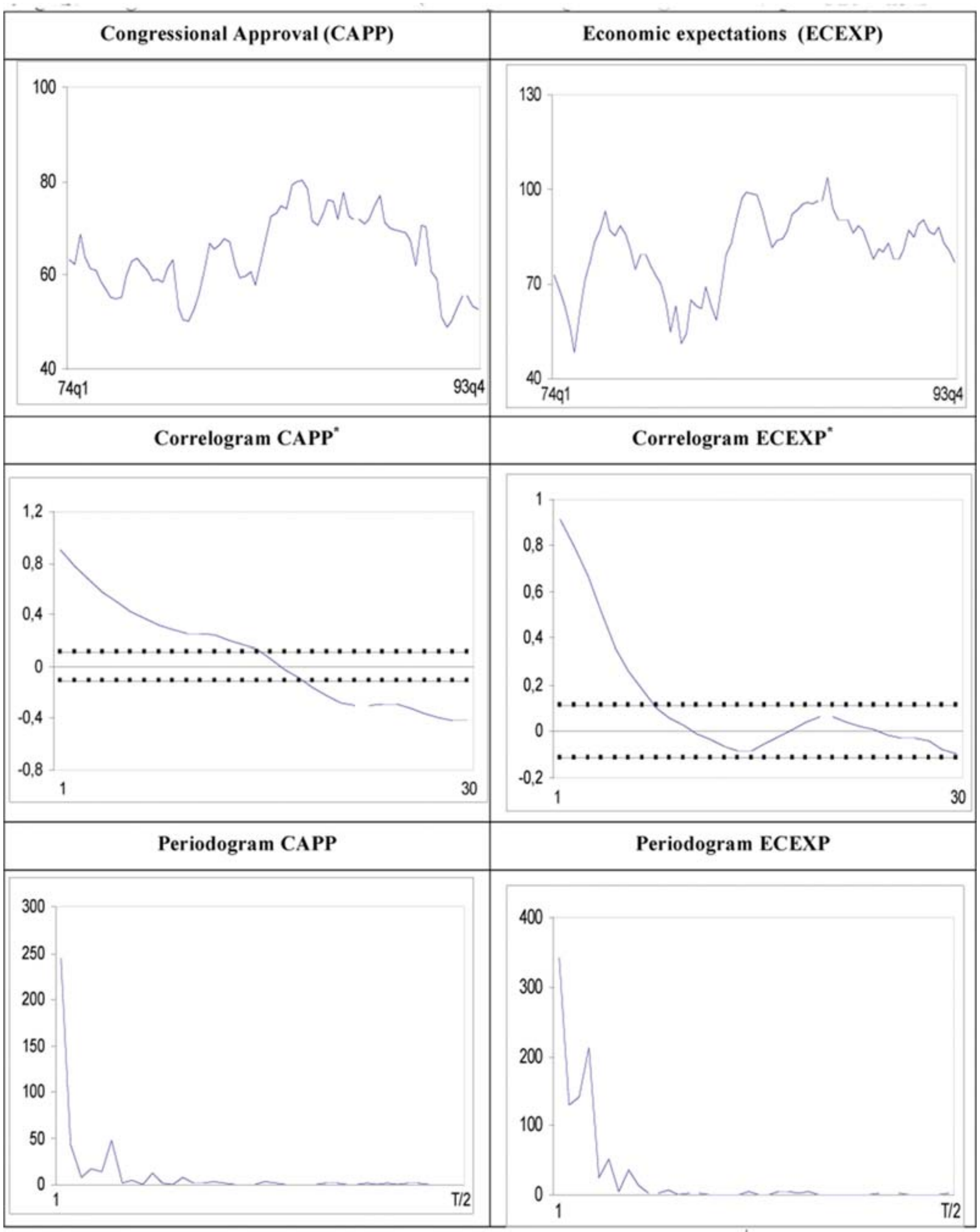
[5]This means that the test is the most efficient one when directed against local alternatives. In other words, if we direct the tests against the alternative: H_a: $d = d_o + \delta T^{-1/2}$, with $\delta \neq 0$, the limit distribution is normal, with variance 1 and mean that cannot be exceeded in absolute value by any rival regular statistic.

[6]This version of the tests of Robinson (1994a) was used in empirical applications in Gil-Alana and Robinson (1997) and Gil-Alana (2000b) and, other versions of his tests, based on seasonal, (quarterly and monthly), and cyclical data can be respectively found in Gil-Alana and Robinson (2001) and Gil-Alana (1999, 2001).

[7]There exists an OX-procedure with an ARFIMA-package that permits us to compute Sowell's (1992) procedure. This method, however, has the inconvenience that it requires d to be in the interval (-0.5, 0.5), so that the series may need first differences before proceeding with the estimation. Robinson's (1994a) method, described in Section 3.1, overcomes this problem by testing the null for any real value d_o.

[8]Velasco (1999a, b) has recently showed that the fractionally differencing parameter can also be consistently semiparametrically estimated in nonstationary contexts by means of tapering. See, also Phillips and Shimotsu (2004).

[9]The exact requirement is that $(1/m) + ((m^{1+2\alpha}(\log m)^2)/(T^{2\alpha})) \rightarrow 0$ as $T \rightarrow \infty$, where α is determined by the smoothness of the spectral density of the short run component. In case of a stationary and invertible ARMA, α may be set equal to 2 and the condition is $(1/m) + ((m^5(\log m)^2)/(T^4)) \rightarrow 0$ as $T \rightarrow \infty$.



* The large sample standard error under the null hypothesis of no autocorrelation is $1/\sqrt{T}$ or roughly 0.111.

Fig. (1). Original time series with their corresponding correlograms and periodograms.

effects. A multivariate extension of this estimation procedure can be found in Lobato (1999).

Other methods also based on semiparametric models (like the APE and the LPE) have been applied to economic time series (see, e.g. Gil-Alana, 2002). However, we have decided to use the Whittle method mainly because of its computational simplicity. Note that using it, we do not need to employ any additional user-chosen numbers in the estimation (as is the case with the LPE and the APE). Also, we do not have to assume Gaussianity in order to obtain an asymptotic normal distribution, the Whittle method being more efficient than the LPE.

The two above-mentioned procedures (Robinson, 1994a, 1995b) also allow us to test for unit roots. However, unlike other more classic methods (i.e., Dickey and Fuller, 1979; Phillips and Perron, 1988), the limit distribution is in both cases standard, in the sense that we do not have to calculate critical values numerically on a case by case simulation study. This is related with the smoothness in the asymptotic behaviour of the fractional processes around the unit root (d = 1), whilst in most of unit-root procedures, based on autoregressive alternatives, the limit distribution abruptly changes around the unit root[10]. Moreover, the standard limit behaviour in Robinson's (1994a) tests holds whether or not we include deterministic trends in the model, unlike what happens in most of other unit-root tests (Schmidt and Phillips, 1992).

[10]Note that in the classic unit root methods, we test H_o: $\rho = 1$ in the model $(1 - \rho L)x_t = u_t$, and a very different behaviour is obtained at $|\rho| < 1$, $\rho = 1$ or $|\rho| > 1$.

4. CONGRESSIONAL APPROVAL AND FRACTIONAL INTEGRATION

Granger's (1980) findings on the effects of aggregation on the nature of a time series should enlighten researchers to model political time series in terms of fractionally integrated processes. Congressional Approval is a good example. People use different strategies to form political opinions. Following Box-Steffensmeier and Tomlinson (2000): "ideologues use ideology (Converse, 1964); people who do not follow politics rely on cues from leaders or interest groups (Zaller, 1992; Lupia, 1994); others use heuristic shortcuts (Sniderman, Brody and Tetlock, 1991); elaborate schema (Conover and Feldman, 1984; Hastie, 1986), a memory based model (Kelley and Mirer, 1974), or an online process (Lodge, McGraw and Stroh, 1989)". So much heterogeneity in opinion formation exists that the aggregation of answers to the same question based on these different processes would permit according to Granger (1980) the existence of an I(d) process in the underlying series.

In this section we estimate d for the innovative measures of Congressional Approval and Economic Expectations used by Durr, Gilmour and Wolbrecht (1997). The data are quarterly from 1973 to 1993. Their measure of Congressional Approval (CAPP) was generated with Stimson's CALC algorithm (Stimson, 1991; Stimson, MacKuen and Erikson, 1994), which allows for aggregation of multiple survey items tapping a single phenomenon into a single time series. Stimson (1991) developed a "dyad ratios" algorithm for the purpose of constructing a single time series of public opinion data based upon individual series and survey marginals. This modelling process permits the identification of the shared movements over time across all individual series. By using the Stimson algorithm, Durr, Gilmour and Wolbrecth (1997) were able to use over 40 different survey items (listed in the Appendix in Durr *et al.* (1997)) administered nearly 300 times to produce a single, quarterly measure of Congressional Approval[11]. The scale of the measure is such that 100 represents a midpoint approval rating. The Economic Expectation (ECEXP) series was created starting from the long-term business conditions component of the University of Michigan's Index of Consumer Sentiment. In order to capture the portion of this series driven by economic considerations, Durr *et al.* (1997) regressed it on four measures of the objective economy, using the predicted values as the final time series[12, 13].

Fig. (**1**) displays plots of the time series, with their corresponding correlograms and periodograms. We observe that both series present a similar nonstationary behaviour, and this is substantiated by both the correlograms (with values decaying very slowly) and the periodograms (with large peaks at the smallest frequencies). Fig. (**2**) displays similar plots but based on the first differenced data. The series have now an appearance of stationarity, though we still observe significant values in the correlograms even at some lags relatively far away from zero, which might be an indication that other degrees of integration, greater than or smaller than 1 may be more appropriate than first differences. Also, the periodogram of the first differences in ECEXP shows a value close to zero at the smallest frequency, which may be an indication of overdifferencing with respect to such a frequency[14].

These two series were also examined in Box-Steffensmeier and Tomlinson (2000) from a fractional viewpoint. Using Sowell's (1992) procedure of estimating by maximum likelihood in the time domain, and based on the Akaike Information Criterion (AIC), these authors conclude that CAPP follows an AutoRegressive Fractionally Integrated Moving Average, ARFIMA(3, d, 3) model, with d = 0.72, while ECEXP is supposed to be an ARFIMA(0, d, 2) with d = 0.86. In both series, they reject the null hypothesis of I(0) stationarity (i.e. d = 0) but they are unable to reject the unit root (d = 1). It should be noted, however that the AIC and the BIC may not necessarily be the best criteria for applications involving fractional differences. They concentrate on the short-term forecasting ability of the fitted model and may not give sufficient attention to the long run properties of the ARFIMA models. (See, e.g. Hosking, 1981, 1984)[15].

Denoting each of the time series by y_t, we employ throughout the model given by (1) - (3), with $z_t = (1,t)'$, $t \geq 1$, $z_t = (0,0)'$ otherwise. Thus, under the null hypothesis (4):

$$y_t = \beta_0 + \beta_1 t + x_t, \qquad t = 1, 2, \ldots \tag{7}$$

$$(1 - L)^{d_o} x_t = u_t, \qquad t = 1, 2, \ldots., \tag{8}$$

and we treat separately the cases of $\beta_0 = \beta_1 = 0$ a priori, β_0 unknown and $\beta_1 = 0$ a priori, and β_0 and β_1 unknown, i.e., we consider respectively the cases of no regressors in the undifferenced regression (7), an intercept, and an intercept and a linear time trend. The reason for the inclusion of these deterministic regressors in (7) is the following: Suppose that u_t in (8) is white noise. Then, for example, when $d_o = 1$, the differences $(1 - L)y_t$ behave, for $t > 1$, like a random walk when $\beta_1 = 0$, and a random walk with a drift when $\beta_1 \neq 0$. However, we report throughout this section the test statistics not merely for the case of $d_o = 1$ but for $d_o = 0, (0.01), 2$, thus also including a test for stationarity ($d_o = 0.5$) as well as other fractionally integrated possibilities. With respect to the I(0) disturbances, we model u_t in terms of both white noise and weak autocorrelation. In the latter case, we tried first with AR(1) and AR(2) processes. However, we observe in such cases a lack of monotonicity in the value of the test statistic with respect to d. Such monotonicity is a characteristic of any reasonable statistic given correct specification and adequate sample size because, for example, we should expect that if H_o (4) is rejected with $d_o = 0.5$ against alternatives of form: $d > d_o$, an even more significant result in this

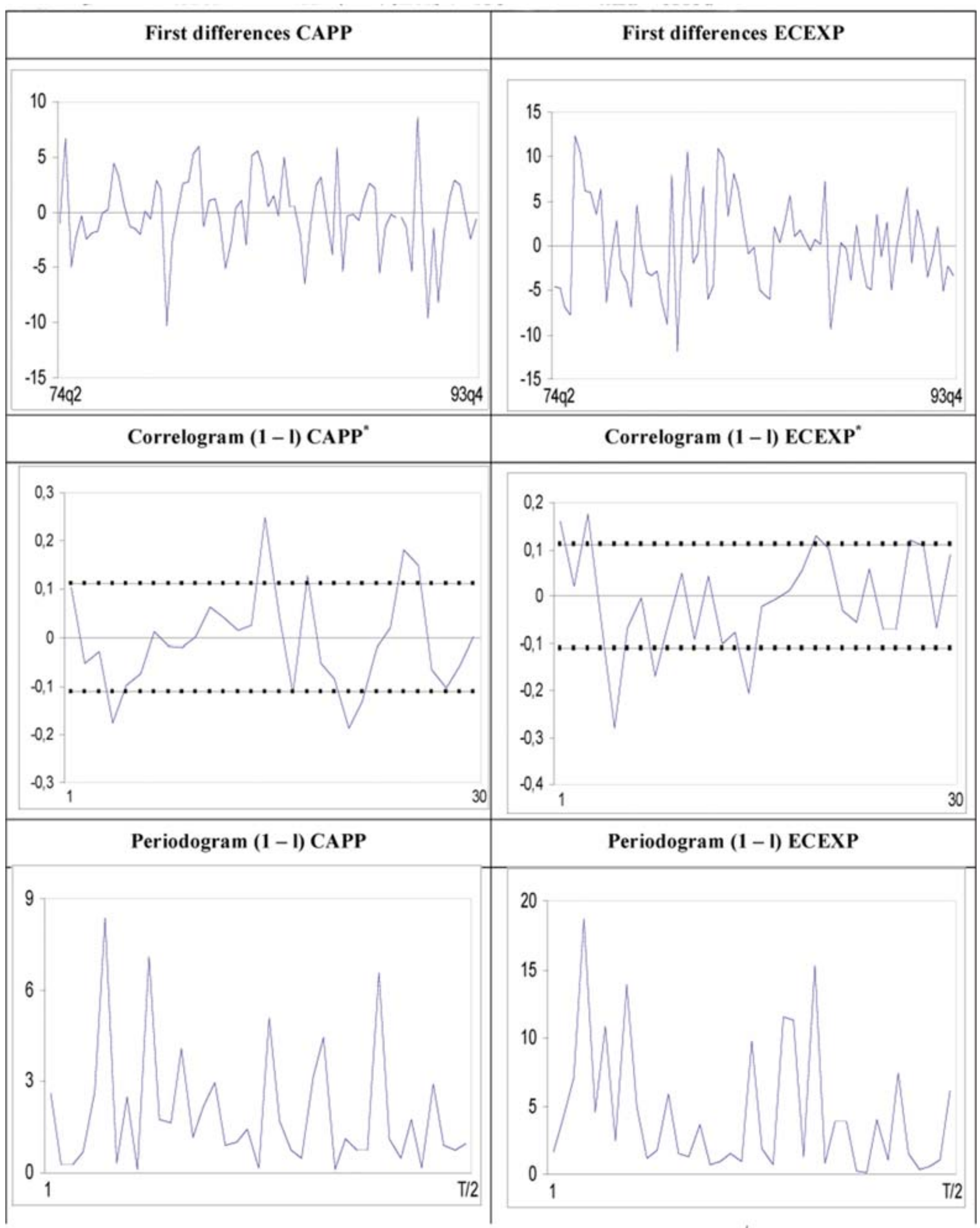
[11]The database of survey items is composed primarily of questions concerning the entire Congress. However, they include a number of survey questions that probe respondents' attitudes toward Congressional leadership in general, as well as particular leaders of Congress.

[12]Durr, Gilmour and Wolbrecht (1997) argue that the predicted values are devoid of political evaluations that contaminate other measures of consumer sentiment. (See, Durr, Gilmour and Wolbrecht, 1997, footnote 4).

[13]Longer time series data of these two variables are available. However, we have preferred to work with exactly the same dataset as in Durr, Gilmour and Wolbrecht (1997), and Box-Steffensmeier and Tomlinson (2000) in order to get better comparisons with these papers.

[14]The periodogram is an estimate of the spectral density function $f(\lambda)$. If a series is overdifferenced, $f(0) = 0$, so that we should expect a similar pattern in the periodogram.

[15]Another recent paper about model selection in the presence of long and short memory processes is Beran *et al.* (1998). They propose versions of the AIC, BIC and the HQ (Hannan and Quinn, 1979) in case of fractional autoregressions but do not consider MA components.



* The large sample standard error under the null hypothesis of no autocorrelation is $1/\sqrt{T}$ or roughly 0.111.

Fig. (2). First differenced series with their correlograms and periodograms.

direction should be expected when $d_o = 0.4$ or 0.3 are tested. Due to this lack of monotonicity, we also employ a non-parametric approach proposed by Bloomfield (1973). In his model, the disturbances are exclusively specified in terms of the spectral density function, which is given by:

$$f(\lambda;\sigma^2;\tau) = \frac{\sigma^2}{2\pi} \exp\left(2\sum_{r=1}^{m}\tau_r \cos(\lambda r)\right). \qquad (9)$$

Bloomfield (1973) showed that the logarithm of an estimated spectral density function is often found to be a fairly well-behaved function and can thus be approximated by a truncated Fourier series. He showed that (9) approximates to the spectral density of an ARMA(p, q) process well where p and q are small values, which usually happens in most of time series. Like the stationary AR(p) model, this has exponentially decaying autocorrelations and thus, using this specification, we do not need to rely on so many parameters as in the ARMA processes. In addition, the functional form of the test statistic greatly simplifies in this context, and we can replace $\hat{A}$ in the Appendix by the population quantity: $\sum_{l=r+1}^{\infty} l^{-2} = \frac{\pi^2}{6} - \sum_{l=1}^{m} l^{-2}$, which indeed is constant with respect to τ, (unlike the AR case). Finally, given the quarterly structure of the data, we also examine seasonal autoregressions of form:

$$u_t = \sum_{j=1}^{m} \phi_{4j}\, u_{t-4j} + \varepsilon_t, \quad t = 1, 2, \ldots,$$

Table 1. Testing H_o (4) in (1) and (3) with the Tests of Robinson (1994a) in CAPP

	No Regressors	An Intercept	A Linear Time Trend
White noise	[0.79 (0.94) 1.15]	[0.83 (1.00) 1.24]	[0.83 (1.00) 1.24]
Bloomfield (1)	[0.62 (0.79) 1.19]	[0.61 (0.74) 1.04]	[0.63 (0.75) 1.06]
Bloomfield (2)	[0.63 (0.80) 1.17]	[0.64 (0.79) 1.12]	[0.63 (0.80) 1.15]
Seasonal AR(1)	[0.79 (0.94) 1.14]	[0.87 (0.99) 1.22]	[0.87 (1.00) 1.22]
Seasonal AR(2)	[0.79 (0.96) 1.13]	[0.88 (1.00) 1.22]	[0.88 (1.00) 1.22]

The values refers to the 95%-confidence intervals of the values of d_o where H_o cannot be rejected.

Table 2. Testing H_o (4) in (1) and (3) with the Tests of Robinson (1994a) in ECEXP

	No Regressors	An Intercept	A Linear Time Trend
White noise	[0.74 (0.89) 1.08]	[0.92 (1.10) 1.34]	[0.92 (1.10) 1.34]
Bloomfield (1)	[0.63 (0.75) 1.07]	[0.57 (0.92) 1.38]	[0.59 (0.89) 1.39]
Bloomfield (2)	[0.67 (0.71) 1.11]	[0.59 (0.85) 1.35]	[0.66 (0.85) 1.34]
Seasonal AR(1)	[0.79 (0.97) 1.14]	[0.87 (1.01) 1.22]	[0.87 (1.00) 1.22]
Seasonal AR(2)	[0.72 (0.93) 1.09]	[0.93 (1.04) 1.32]	[0.93 (1.04) 1.32]

The values refers to the 95%-confidence intervals of the values of d_o where H_o cannot be rejected.

with m = 1 and 2 to describe the short run dynamics of the series.

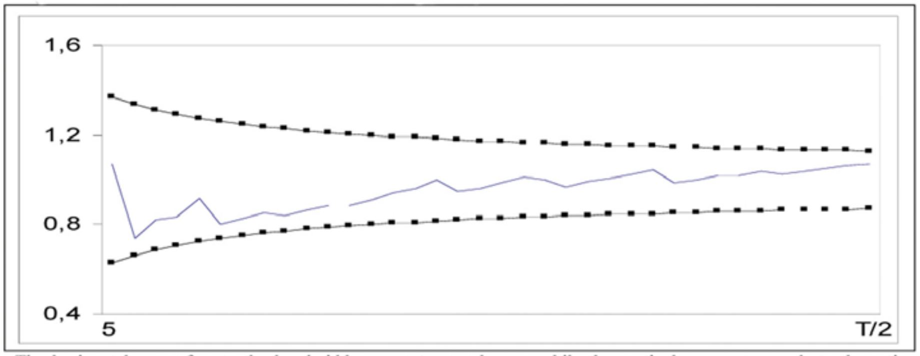
Tables **1** and **2** report respectively for CAPP and ECEXP the 95%-confidence intervals of those values of d_o where H_o (4) cannot be rejected for the three cases of no regressors, an intercept, and an intercept and a linear time trend[16]. We also report in the tables, (in parenthesis within the brackets), the value of d_o (d_o^*) which produces the lowest statistic in absolute value across d_o. That value is an approximation to the maximum likelihood estimate. We observe in both tables that all the intervals include the unit root (i.e. $d_o = 1$). In case of the CAPP the values range between 0.61 (Bloomfield (m = 1) u_t with an intercept) and 1.24 (white noise u_t and a linear trend). For ECEXP the values range between 0.57 (Bloomfield (m = 1) with an intercept) and 1.39 (with a linear time trend). We also observe that for the CAPP most of the estimated values of d are at 1 or are slightly smaller than 1, while for the ECEXP some of them are above 1. Thus, though fractional orders of integration seem to be plausible in both series, the unit root model cannot statistically be rejected, which is in line with the results reported in Box-Steffensmeir and Tomlinson (2000)[17].

Next, we perform the semiparametric procedure described in Section 3.2. Given that the series are clearly nonstationary the analysis is carried out based on the first differenced data, adding then 1 to the estimated values of d to obtain the proper orders of integration of the series. Fig. (**3**) displays the estimates of d for CAPP while Fig. (**4**) refers to ECEXP, and in both cases we report the results for the whole range of values of the bandwidth number m[18]. We also include in the figures the 95%-confidence intervals corresponding to the unit root case. Starting with CAPP, we see that all the estimates are within the unit root interval, supporting thus the results obtained above when using the parametric procedure. Similarly, for ECEXP most of the values are within the unit root interval, though here we observe some cases where d is above 1. We can therefore conclude this section by saying that both series seem to be nonstationary, and though some fractional degrees of integration might be plausible in some cases, the unit root null cannot statistically be rejected in any of the series. Moreover, we also performed some other classical unit-root tests (Dickey and Fuller, 1979; Phillips and Perron, 1990; Elliot *et al.* 1996), and the evidence here was also strongly in favour of the unit root hypothesis. The potential presence of structural breaks is another worry for practitioners in political time series, and in particular, in the context of Congressional approval. Note that the approval question changes every two years and structural breaks may occur when the majority party in Congress changes. We tried different types of breaks at different periods of time and in all cases, the coefficients associated to the dummy variables for the breaks were found to be insignificantly different from zero, finding strong evidence once more in favour of unit roots.

[16] The confidence intervals were built up according to the following strategy. First, choose a value of d from a grid. Then, form the test statistic testing the null for this value. If the null is rejected at the 5% level, discard this value of d. Otherwise, keep it. An interval is then obtained after considering all the values of d in the grid.

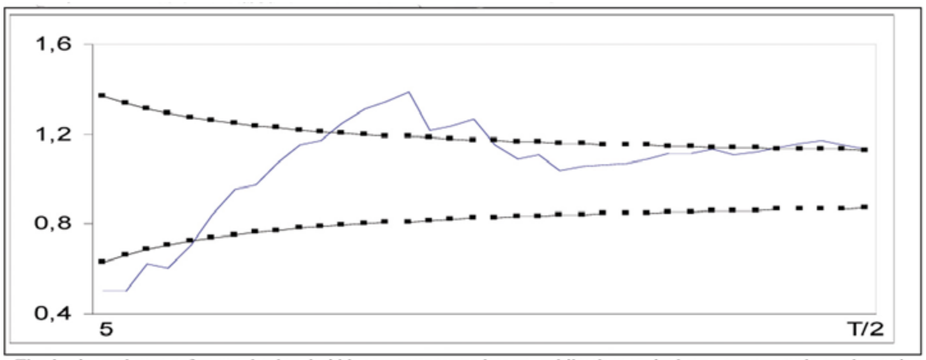
[17] Some authors may argue that since the CAPP is a bounded variable, it does not make sense to consider I(1) or I(d) (with $d \geq 0.5$) variables. Wallis (1988) suggests in this context the use of a logistic function. We tried with that transformation obtaining very similar results to those reported in the paper.

[18] Some attempts to calculate the optimal bandwidth numbers have been examined in Delgado and Robinson (1996) and Robinson and Henry (1996). However, in the case of the Whittle estimator, the use of optimal values has not been theoretically justified. Other authors, such as Lobato and Savin (1998) use an interval of values for m but we have preferred to report the results for the whole range of values of m.



The horizontal axe refers to the bandwidth parameter number m, while the vertical one corresponds to the estimated values of d.

Fig. (3). Estimates of d based on Robinson (1995a) for CAPP.



The horizontal axe refers to the bandwidth parameter number m, while the vertical one corresponds to the estimated values of d

Fig. (4). Estimates of d based on Robinson (1995a) for ECEXP.

5. CAPP AND ECEXP: A FRACTIONALLY COINTEGRATED APPROACH

Once we have shown that both series have a unit root, the follow-up step should be to examine if the two series are cointegrated. This is relevant in the context of our two series to determine if there exists a long run equilibrium relationship driving the joint dynamics of the series. Engle and Granger (1987) showed in a classic paper that two series are cointegrated if both are integrated of the same order and there exists a linear combination that is integrated of a smaller order. Practically all the empirical literature carried out after that paper assumed integer orders of integration, usually 1 for the individual series, and 0 for its cointegrating relationship. However, in the last few years, literature has moved to the case of fractional cointegration, allowing us to examine the relationship between the variables in a much more flexible way. Pioneering work in this area are the papers of Cheung and Lai (1993), Baillie and Bollerslev (1994) and Dueker and Startz (1998). More recently, Gil-Alana (2003) proposed a very simple procedure for testing the null hypothesis of no cointegration against the alternative of fractional cointegration, that follows the spirit of the idea represented in Engle and Granger (1987), that is, testing first the order of integration of the individual series, and then, if both series present the same degree of integration, performing Robinson's (1994a) tests, on the estimated residuals from the cointegration regression[19]. This is the approach employed in this section. A problem here occurs in that the residuals are not actually observed but obtained from minimizing the residual variance of the cointegrating regression and thus, a bias might appear in favour of stationary residuals. Note that this problem is similar to the one noticed by Engle and Granger (1987) when testing cointegration with the tests of Fuller (1976) and Dickey and Fuller (1979). (See, also Phillips and Ouliaris, 1991, and Kremers *et al.* 1992). In order to solve this problem, Gil-Alana (2003) computed finite-sample critical values to be employed in the applied work. Performing the OLS regression of one of the variables against the other, the estimated equation was:

$$CAPP_t = \underset{(5.56)}{44.784} + \underset{(0.07)}{0.245}\ ECEXP_t, \qquad (10)$$

with standard errors in parenthesis. Table **3** is analogous to Tables **1** and **2** but based on the estimated residuals from the cointegration regression (10). We see that the unit root null hypothesis cannot be rejected for any type of regressors and any type of disturbances, finding thus conclusive evidence against the hypothesis of cointegration.

The lack of cointegration is corroborated by the results in Fig. (**5**), where the Whittle semiparametric method is performed again on the estimated residuals from (10). We observe in that figure that for practically all values of m, the estimates are within the unit root interval, rejecting thus once more the hypothesis of cointegration of any degree between both variables.

The results presented in this paper suggest that both CAPP and ECEXP are nonstationary series with no linkage

[19]Other theoretical papers on fractional cointegration are Robinson and Marinucci, 2001, Robinson and Yajima, 2002, Robinson and Hualde, 2003, Chen and Hurvich, 2006, and Johansen, 2006.

Table 3. Testing H_o (4) in (1) and (3) with the Tests of Robinson (1994a) in the Estimated Residuals

	No regressors	An intercept	A linear time trend
White noise	[0.82 (1.00) 1.25]	[0.82 (1.00) 1.25]	[0.82 (1.00) 1.25]
Bloomfield (1)	[0.61 (0.87) 1.11]	[0.63 (0.89) 1.11]	[0.60 (0.88) 1.11]
Bloomfield (2)	[0.63 (0.89) 1.13]	[0.66 (0.88) 1.16]	[0.66 (0.89) 1.17]
Seasonal AR(1)	[0.85 (0.99) 1.23]	[0.85 (1.00) 1.23]	[0.85 (1.00) 1.23]
Seasonal AR(2)	[0.85 (1.00) 1.21]	[0.85 (0.99) 1.21]	[0.85 (1.01) 1.21]

The values refers to the 95%-confidence intervals of the values of d_o where H_o cannot be rejected.

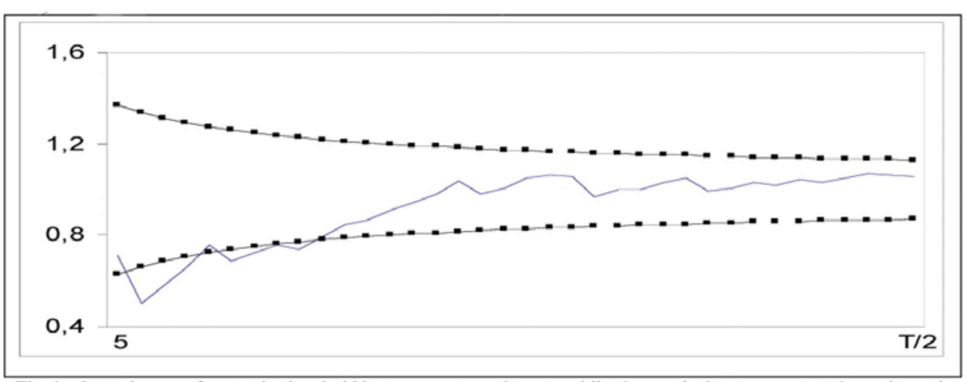
between them in the long run. These results are in sharp contrast with those reported in Box-Steffensmeier and Tomlinson (2000) where they found some evidence of fractional cointegration. In that paper they use the procedure of Dueker and Startz (1998), which is also based on a two-step strategy as in Gil-Alana (2003), and estimate d by maximum likelihood in the time domain on the estimated residuals, obtaining a value of d of 0.40. However, given the large standard errors, they were unable to reject the nulls of d = 0 and d = 1. The reason for this disparity in the results might be related with the different methods employed: Box-Steffensmeier and Tomlinson (2000), using Dueker and Startz's (1998) procedure, estimate d with Sowell's (1992) method, and use the AIC in OX to determine the structure of the short run dynamics. First, it is important to note that the AIC might not be a valid criterion in fractional contexts (see the comment in Section 4). Moreover, Sowell (1992) uses a likelihood function in the time domain, while Robinson's (1994a) method uses the frequency domain. Finally, Sowell's (1992) method of estimation employed in Box-Steffensmeier and Tomlinson (2000) may be biased in favour of stationarity because of the use of residuals instead of observed values. In that respect, the results presented here seem to be more robust in the sense that the null hypothesis of d = 0 is strongly rejected in favour of higher values of d. Finally, we should note that the lack of cointegration might be due to the existence of other nonstationary variables that are not captured by the model described in (10). Thus, the nonstationarity observed in the residuals in (10) might be the result of the omission of other relevant variables explaining the long run relationship between Congressional Approval and economic variables.

6. CONCLUDING COMMENTS

"Time series data have come to play an increasingly prominent role in political science in the last decade" (Bartels and Brady, 1993). This is the starting point of this paper, which attempts to use innovative techniques of integration and cointegration in political time series. In particular, we have used some recent developments on estimating and testing the order of integration of univariate series in the Congressional Approval and Economic Expectations series of Durr, Gilmour and Wolbretch (1997).

Testing of unit roots in political science usually rely on classic methods which are based on autoregressive alternatives, leading to a non-standard limit behaviour. On the other hand, fractional processes have become very popular in political sciences due to the aggregation of heterogeneous individual series. In that respect, we have employed some recent techniques for unit roots which are nested in fractional processes.

We use both parametric and semiparametric techniques. First, we employ the tests of Robinson (1994a). These tests are the most efficient ones when directed against the appropriate fractional alternatives. Moreover, they have standard null and local limit distributions, which hold independently of the inclusion or not of deterministic trends in the model, unlike the outcomes with other procedures for unit (and fractional) roots, where the limit distribution changes with features of the regressors. (See, Schmidt and Phillips, 1992). In the semiparametric approach, we use a "Whittle estimator" (Robinson, 1995a), given its computational simplicity and the fact that it just requires a single bandwidth parameter,



The horizontal axe refers to the bandwidth parameter number m, while the vertical one corresponds to the estimated values of d

Fig. (5). Estimates of d based on Robinson (1995a) for the estimated residuals.

unlike other procedures where a trimming number is also required. A FORTRAN code with the programs is available from the author upon request.

The results show that both individual series are nonstationary, with orders of integration ranging between 0.6 and 1.4. Moreover, the unit root null hypothesis cannot statistically be rejected, a result that is corroborated when using other more classic unit-root testing procedures. The possibility of both series being cointegrated was also examined from a fractional viewpoint. If the two series were cointegrated, there would be linked together, throughout a long run equilibrium relationship. We performed here a procedure of Gil-Alana (2003), which tests the null hypothesis of no cointegration against the alternative of fractional cointegration, and the results were very conclusive against the hypothesis of cointegration. Thus, the results in this paper are in apparent contradiction with other works in this area which found fractional integration in several political series (e.g., Byers, Davidson and Peel, 1997; Box-Steffensmeier and Smith, 1998; Lebo, Walker and Clarke, 2000). We show that, though fractional alternatives are plausible in some cases, the unit root is almost never rejected, with the implications that shocks affecting the series will persist forever, and thus requiring strong policy measures to bring the variables back to their original levels. On the other hand, there is no evidence that they are related in the long run. In other words, both series are persistent and they follow different paths.

A possible explanation for the lack of cointegration in this work is that the series used are very short, implying large standard errors and thus being unable to reject the existence of unit roots in the original series as well as in the cointegrating relationship. However, in spite of this small size, fractional integration and cointegration have been found in other time series using similar sizes with Robinson's techniques. Moreover, finite sample critical values of the tests were computed in Gil-Alana (2000b) and using these values, similar evidence of unit roots was found in all cases. As a conclusion we can summarize the results in this paper by saying that Congressional Approval and Economic Expectations are not related in the long run at least in terms of an error correction model. The use of other techniques like Granger causality tests or non-linear models can help us to explain the nature of the relationship between the two variables in a different way.

Finally, the fact that other authors have found fractional integration in political science suggests that this might also be the case for the variables analyzed in this paper, for example, if they were measured at other frequencies (e.g. monthly). However, if that were the case, the analysis of fractional cointegration should be conducted in a very detailed way. Note that in a bivariate context, a necessary condition for cointegration is that both individual series must share the same degree of integration and, in a fractional context, based on the real line, this might not always be the case. Recent techniques of fractional cointegration have been proposed by P.M. Robinson and his co-authors (e.g. Robinson and Marinucci, 2001; Robinson and Yajima, 2002, and Robinson and Hualde, 2002, 2003). Extensions of the multivariate version of the tests of Robinson (1994a) which permit us to test fractional cointegration in a system-based model are being developed. There exists a reduced-rank procedure suggested by Robinson and Yajima (2002); however, it is not directly applicable here since that method assumes I(d) stationarity ($d < 0.5$) for the individual series, while we consider I(1) nonstationary processes. The other above-mentioned approaches can be performed to further examine the relationship between economic indicators (and/or expectations) and government support.

APPENDIX

The test statistic proposed by Robinson (1994a) for testing H_o (4) in (1) and (3) is:

$$\hat{r} = \frac{T^{1/2}}{\hat{\sigma}^2} \hat{A}^{-1/2} \hat{a}$$

where T is the sample size and

$$\hat{a} = \frac{-2\pi}{T} \sum_{j=1}^{T-1} \psi(\lambda_j)\, g(\lambda_j;\hat{\tau})^{-1} I(\lambda_j);$$

$$\hat{\sigma}^2 = \sigma^2(\hat{\tau}) = \frac{2\pi}{T} \sum_{j=1}^{T-1} g(\lambda_j;\hat{\tau})^{-1} I(\lambda_j);$$

$$\hat{A} = \frac{2}{T}\left(\sum_{j=1}^{T-1} \psi(\lambda_j)^2 - \sum_{j=1}^{T-1} \psi(\lambda_j)\hat{\varepsilon}(\lambda_j)' \times \left(\sum_{j=1}^{T-1} \hat{\varepsilon}(\lambda_j)\hat{\varepsilon}(\lambda_j)' \right)^{-1} \times \sum_{j=1}^{T-1} \hat{\varepsilon}(\lambda_j)\psi(\lambda_j) \right)$$

$$\psi(\lambda_j) = \log\left| 2\sin\frac{\lambda_j}{2} \right|; \quad \hat{\varepsilon}(\lambda_j) = \frac{\partial}{\partial\tau} \log g(\lambda_j;\hat{\tau});$$

$$\lambda_j = \frac{2\pi\, j}{T}; \quad \hat{\tau} = \arg\min_{\tau \in T^*} \sigma^2(\tau).$$

where T^* is a compact subset of the R^q Euclidean space. $I(\lambda_j)$ is the periodogram of u_t evaluated under the null, i.e.,

$$\hat{u}_t = (1 - L)^{d_o} y_t - \hat{\beta}' w_t;$$

$$\hat{\beta} = \left(\sum_{t=1}^{T} w_t w_t' \right)^{-1} \sum_{t=1}^{T} w_t (1 - L)^{d_o} y_t; \quad w_t = (1 - L)^{d_o} z_t,$$

and the function g above is a known function coming from the spectral density of u_t,

$$f(\lambda;\sigma^2;\tau) = \frac{\sigma^2}{2\pi} g(\lambda;\tau), \quad -\pi < \lambda \le \pi.$$

These tests are purely parametric and require specific modelling assumptions regarding the short memory specification of u_t. Thus, if u_t is white noise, $g \equiv 1$, and if u_t is an AR process of form $\phi(L)u_t = \varepsilon_t$, $g = |\phi(e^{i\lambda})|^{-2}$, with $\sigma^2 = V(\varepsilon_t)$, so that the AR coefficients are a function of τ.

ACKNOWLEGMENTS

The author gratefully acknowledges financial support from the Minsterio de Ciencia y Tecnologia (SEJ2005-07657, Spain). Comments of two anonymous referees are also gratefully acknowledged.

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Received: December 18, 2007 Revised: February 11, 2008 Accepted: February 11, 2008