Long Memory and Structural Breaks in Finnish and Swedish Party Popularity Series*

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Abstract

A time series with a unit root or fractional unit root can be miscategorized in stationarity tests if the series has structural breaks. This finding is tested on Finnish and Swedish party popularity series. The composition and nature of popularity series provide reasons to assume fractional dynamics. The years included, 1987-2001, offer several reasons for the existence of structural breaks. Three series have breaks and in two cases control of the structural breaks changes the unit root assumption to a fractional unit root. Popularity series have either long or perfect memory, but this property cannot be removed by controlling structural breaks.

Keywords: political party popularity, fractional unit root, structural breaks

JEL Classification: D72, C22

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1 Introduction

This study asks whether we can completely ignore fundamental changes in society in analyzing the stationarity of party popularity ratings. As time series data is nowadays an acceptable way to explore voting behavior and factors affecting election results, the stationarity of popularity series has come under intense scrutiny (Box-Steffensmeier and Smith, 1996, 1998, Byers et al., 1997, 2000, Clarke and Lebo, 2002, Lebo et al., 2000). Correct information on stationarity has consequences for econometric modeling if the series are used in further econometric analysis. Incorrect assumptions may cause problems for statistical inference, the forecasting performance of the model and lag structure specification. Good forecasting performance is especially important in countries where the government can decide on the timing of elections and economic policy measures. Incumbents also have a tendency to create politically induced business cycles. In that case it is useful to have information on behavior with respect to economic policy changes. Whether the influence of a change is positive or negative is quite trivial, but a more challenging task is to find out how long the influence lasts. Anticipating the persistence of a shock in political popularity has been of interest to political scientists and politicians for a long time, but until now we have not had proper methods of capturing this effect.

Stationarity analysis is mostly about finding out how a series reacts to a shock. There are three options for shock persistence: it lasts either for ever or long or short. When the series has perfect memory the series has a unit root, when the shock effect lasts long we say that the series has long memory or a fractional unit root, and when the effect of the shock dies out quickly the series has short memory. The composition of popularity series gives us reason to assume that such series have long memory but neither short nor perfect memory. The popularity series is a sum of the survey answers of heterogenous respondents. It is reasonable to assume that popularity ratings have long memory since, after experiencing a shock, the rating changes smoothly as some supporters are slow to change their opinion of the party if they are doing it at all (Byers and Peel, 1997). Other respondents/supporters change their opinions quickly. This division in the respondent group creates a smooth change over time in the popularity series. In addition, voters react to different events; some react mainly to political events and others only to economic events (Zaller, 1992).

Another important issue in time series analysis we have to be aware of is structural breaks. Since, several macro-level time series have structural breaks because of exogenous shocks and major institutional changes (Perron, 1989), the occurrence of such breaks in party popularity ratings is also highly probable. In general, poll results are assumed to project the state of the society and changes in society should be reflected in the polls. Elections can cause structural breaks in popularity series by various means. Before the elections the information level of voters increases as the media concentrate on campaigns and the achievements of the incumbents. After elections the actors behind institutions change and this may cause a break as well. Other possible causes of structural breaks are changes in parliamentary status (from government to opposition, and vice versa; from the prime minister's party to an incumbent or opposition party), changes in the poll sampling method and the wording of survey questions. Party popularity ratings may also reflect changes in the economy and economic policy. We may thus confidently assume that there may be several unknown break points in a popularity series.

When there is a reason to doubt that a series has both of these properties, we have to be especially careful in time series property analysis. In the usual stationarity tests, ignoring structural breaks leads us to conclude that the series has a unit root when in reality it does not (Perron, 1989). The same problem applies to a series with long memory. This is still a potential problem as stationarity tests have not yet been developed to distinguish long memory from structural breaks. When we have classified a series as having long memory, i.e. the effect of a shock lasts long, there is a chance that we have confused long memory and a structural break (Diebold and Inoue, 2001). The nature and composition of party popularity series supports the assumptions of structural breaks and long memory. We approach the problem by first separately seeking long memory and unknown multiple structural breaks. If both are found, then we control the structural breaks in the series and test whether a unit root or long memory still exists. This particular approach has not been applied to popularity series before.

This reasoning applies to the popularity series of Finnish and Swedish parties. The four biggest parties in each country have been chosen as targets of the analysis. The Finnish parties included are the Left Alliance (LA), the Social Democratic Party (SDP), the Centre Party (CENT) and the National Coalition Party (NC). The corresponding Swedish parties are the Left Party (LP), the Social Democratic Party (SDP), the Centre Party (CENT) and the Moderate Party (MP). Finnish popularity ratings have been obtained by Taloustutkimus and the Swedish ratings are from SIFO. Monthly data is from September 1987 to October 2001. Large fluctuation in economic circumstances, changes in the economic policy regime and political paradigms make it reasonable to assume that these series will exhibit multiple break points in this period. Both countries experienced the deepest peace-time depression ever in the 1990s. Other changes affecting these countries and related to the first mentioned are overall liberalization in the economy (from a controlled market economy to a more pure form of market economy), an increase in general market-orientation, regime change in economic and monetary policy (EMU convergence criteria, inflation targets), EU membership, the collapse of Soviet Union and changes in industrial structure, not to mention elections and events within parties and politics.

In the following, I first describe the statistical differences between unit root, fractional unit root and stationary series. In chapter 3, we test which of these characterizations best fits the popularity series. As is already clear, there is a serious threat of misinterpretation of those tests if we do not pay proper attention to the possible existence of structural breaks. Section 4 applies a sequential test in the search for multiple unknown break points. The last procedure is to test whether the break points cause stationarity properties in Finnish and Swedish party popularity series.

2 Integer vs. Fractional Integration

This section defines different memory lengths using statistical terms. As is usual (see e.g. Maddala and Kim, 1998) we see how close to each other these nonstationary and stationary series are in theory, noting their behavior of variance and autocorrelation structure. Finally, I explain why it is reasonable to assume that popularity series have each of these structures.

To clarify the differences between integer and fractional integration, let us consider a series with the following formulation $\phi(L)(1-L)^d X_t = \theta(L)\varepsilon_t$, $\varepsilon_t \sim N(0,\sigma^2)$, where $\theta(L)$ is a stationary MA process. Obviously, many properties depend on d, the order of integration.

If d=0, the series has short memory, which means that correlation between consecutive observations fades out quickly and the series returns to its constant mean. Its variance is finite and independent of time and the covariance is stationary. This series is modeled by combining an autoregressive and a moving average parameter as in ARMA (p,0,q).

If d=1, the series is a unit root process[1] and its mean, variance and covariance are non-stationary. Variance is time-dependent and infinite. This series is a function of its previous value and current error. The effect of a shock grows (cumulates) over time and the series does not revert to a constant mean level. Modeling involves differencing the unit root process and then applying stationary autoregressive moving average parameters in the form of ARIMA (p,1,q).

If 0<d<1, the series has a fractional unit root (or long memory). This series has properties of both stationary and nonstationary series. All the series with d in this range are similar as to memory and mean reversion, but differ in variance behavior depending on whether d is above or below 0.5. When d lies between 0 and 0.5 (0<d<0.5) the variance of the series is finite, and stationary, covariance is stationary and the series is stationary. When d belongs to 0.5≤d<1 variance is infinite and non-stationary, covariance is non-stationary and the series is non-stationary. Here we concentrate mainly on the case where d is 0.5≤d<1. It is said that in stationary processes autocorrelation decays at an exponential rate, but in fractional unit root processes it decays at a hyperbolic rate. In other words, autocorrelation decays more slowly the greater the value d has. The series is modeled by ARFIMA (p,d,q), a general approach to testing autoregressive and moving average properties which includes estimating ARMA (p,0,q) and ARIMA (p,1,q) models as its special cases. The general properties of I(d) are discussed in reviews by Baillie et al. (1996) and Sowell (1992).

In general, macro-level time series are assumed to have unit roots (Nelson and Plosser, 1982). In popularity series the assumption of stationarity means

[1] Also known as a random-walk process or a series integrated of order 1.

very stable popularity shares because of mean reversion. If the assumption of stationarity is strictly followed, it blocks the emergence of new parties, which is not a very plausible assumption in normal democracies. In unit root processes there are sudden changes of unlimited volume, but in the normal situation large and sudden popularity changes are not likely. The interest in understanding why popularity series could be characterized by fractional dynamics has increased recently (e.g. Granger, 1980, Granger and Joyeux, 1980, Box-Steffensmeier and Smith, 1996, 1998). Popularity series are created by aggregating heterogenous individual-level behavior. Heterogenous in this context means differences in a persons's autoregressive behavior. Heterogenous memory properties may arise from differences in the information level of voters, the persistence of party identification, myopia, rationality and reaction speed[2]. If one survey respondent's behavior has a fractional unit root then the whole aggregated data set has it. The fact that the series has clearly defined upper and lower limits (0-100) also supports the assumption about fractional dynamics.

As we have seen, the description of I(0), I(1) and I(d) is quite simple in statistical theory. The crucial differences between the actual series are caused by one parameter.

3 Detecting Fractional Integration

Our strategy in testing stationarity is to move from autocorrelation plots to more sophisticated test formulas. In this phase we exclude the possibility of bias in test results caused by structural breaks. There are several easily applied and widely used tests to detect whether a series is either I(0) or I(1). We start with one of them, the Augmented Dickey-Fuller (ADF) test. If the results are inconclusive, we move on to a more sophisticated method to ascertain whether the results differ from each other.

The first approach to exploring the length of memory in a time series is to examine the correlation structure of consecutive observations. In the following figures (Figures 1-2), actual party popularity ratings are plotted with corresponding autocorrelation functions in Finland and Sweden. The more slowly

[2] There are several empirical studies showing the influence of information level differences on the pattern of party approvals, such as Zaller (1992).

decreasing an autocorrelation structure a series has, the longer the memory.

There are two more precise ways to find out whether a series is fractionally integrated or not: diagnostic tests and point estimation of d, the decay rate. The H_0 hypothesis (I(0) or I(1)) has to be chosen in a diagnostic test and fractional integration is then tested against it.

Among the widely applied stationarity tests which include an option for fractional unit roots are the variance ratio test (Cochrane, 1988) and the KPSS test (Kwiatkowski et al., 1992). In the variance ratio test, H_0 is a unit root with drift and H_1 fractional integration. In the KPSS test, H_0 assumes that the time series is a stationary process and H_1 assumes a unit root. This test also has power against a fractional unit root. These two last tests share the severely limiting weakness that a long time series ($n \geq 1000$) is needed to distinguish long memory from short memory reliably.[3]

An adaptable stationarity test for a series with less than 200 observations is the Augmented Dickey-Fuller test (ADF). The H_0 hypothesis of ADF is a pure random walk or a random walk with drift. The ADF test has been criticized for its low power in seeking fractional integration (Diebold and Rudebusch, 1991). It does not directly indicate whether the series has a fractional unit root but this weakness can be covered if we can conclude that a series possibly has a fractional unit root when both alternatives are excluded. Table 1 shows ADF test results. The Augmented Dickey-Fuller test does not reject the assumption of I(1) for any series. The ADF test sheds some light on the question of long against short memory but, as we recall, the ADF test is biased if there are breaks in the trend.

The most exact information on the memory decay process is obtained by estimating the decay rate, d. There are three methods of doing this: semiparametric estimation (Geweke and Porter-Hudak, 1983), the approximate maximum likelihood in the frequency domain (Li and McLeod, 1986, Fox and Taqqu, 1986) and the exact maximum likelihood in the time domain (Sowell, 1992). Since the first two do not perform well in small samples (Sowell, 1992), the following results are computed with ARFIMA 1.0 (Ooms and Doornik, 1998) which uses Ox (Sowell) and GiveWin frameworks[4].

[3] Papers discussing test properties: Sowell (1992), Lebo et al. (2000).

[4] Sowell's Exact Maximum Likelihood estimator for OX. The ARFIMA package is down-

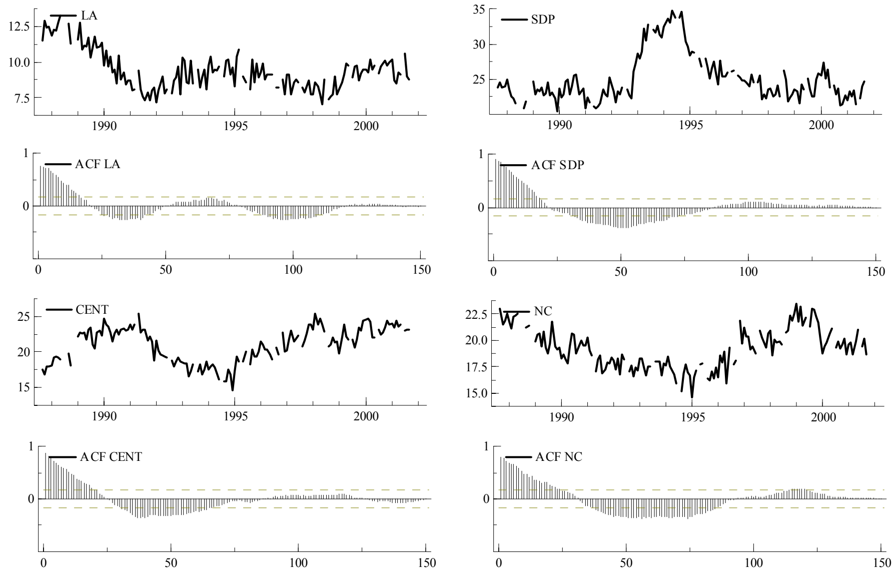

Figure 1. Time series plots and autocorrelation functions of Finnish party popularities.

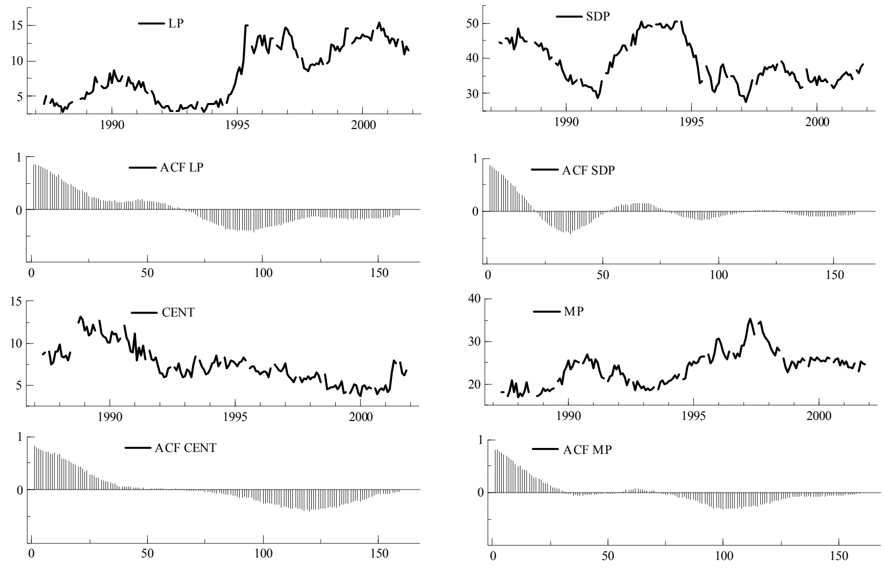

Figure 2. Time series plots and autocorrelation functions of Swedish party popularities.

loadable from Doornik's homepage (www.nuff.ox.ac.uk/users/doornik).

Table 1. Significance of ADF tests with lag length 4, Ho: unit root.

	Finland	Sweden
LA/LP	-2.54	-1.16
SDP	-1.831	-1.82
CENT	-1.92	-1.38
NC/MP	-2.1	-1.66

LA - Left Alliance, SDP - Social Democratic Party,

CENT -Centre Party, NC - National Coalition Party

LP - Left Party, MP - Moderate Party

Before applying Sowell's method, the data is first-differenced to ensure stationarity. ARFIMA models with different p's and q's are estimated and the most suitable ARFIMA model chosen using Akaike's Information Criteria. The AIC depends on the number of parameters estimated, the residual sum of squares and the sample size. Simplifying to some extent, the smaller the AIC value gets, the better the model fits the data. The AIC values are reported in the Appendix (Table 1). The AIC shows that ARFIMA (0,d,0) describes every Swedish party popularity series best. There is more variation in the Finnish results. ARFIMA (0,d,1) performs best in the SDP's and NC's popularity series, ARFIMA (3,d,0) in the LA's and ARFIMA (2,d,0) in the CENT's popularity series. In previous studies AIC has in most cases chosen the ARFIMA (0,d,0) model to best describe the properties of party or presidential popularity (Byers et al., 2000, Lebo et al., 2000, Box-Steffensmeier and Smith, 1996). The ARFIMA model selected has been estimated and a combination of diagnostic test and point estimate used in categorizing a series as a unit root, fractional unit root or short memory series. A series is assumed to have a fractional unit root when d falls within $0.5 \leq d < 1$. In addition, the t-test determines whether d differs from 0 or 1. There is reason to suspect fractional integration if diagnostic tests reject both stationarity and a unit root (Baillie et al., 1996). In tables 2-3 $\widehat{d}$'s and their standard errors are reported as well as t-test values for two different H_0 hypotheses (d=0 and d=1). Normal distribution is used for critical values in the t-test.

Table 2. $\widehat{d}$'s, standard errors and t-tests for Finnish parties.

Finland			t-test	
	$\widehat{d}$	s.e.	H_0:d=0	H_0: d=1
LA	0.982	0.088	11.59***	-0.204
SDP	1.00	0.161	6.21***	-0.001
CENT	0.954	0.115	8.29***	-0.402
NC	0.962	0.39	2.466***	-0.09

LA - Left Alliance, SDP - Social Democratic Party,

CENT -Centre Party, NC - National Coalition Party

Rejection levels: *** = 0.01, ** = 0.05, * = 0.1

In general, the assumptions of I(0) are rejected in favor of I(1). Fractional integration is not suspected in any instance. Because Finnish party popularities have not been tested before for fractional integration, there is no comparable evidence for these results. In this phase we conclude that these series seem to be I(1). This result leaves the possibility of confusion between long/perfect memory and structural break still open.

Table 3. $\widehat{d}$'s, standard errors and t-tests for Swedish parties.

Sweden			t-test	
	$\widehat{d}$	s.e.	H_0: d=0	H_0: d=1
LP	0.875	0.064	13.67***	-1.95*
SDP	0.972	0.061	15.93***	-0.,46
CENT	0.685	0.066	10.38***	-4.77***
MP	0.856	0.064	13.38***	-2.25**

LP - Left Party, SDP - Social Democratic Party,

CENT - Centre Party, MP - Moderate Party

Rejection levels: *** = 0.01, ** = 0.05, * = 0.1

Results for Swedish parties are different. In all but the Social Democratic Party popularity series both hypotheses, I(0) and I(1), are rejected. This leads us to assume fractional integration in those series. The magnitude of estimated d also supports the assumption of a fractional unit root. In the Social Democratic Party series only I(0) is rejected which signals that the series is I(1). There are previous results on stationarity in Swedish party popularity series in Byers et al. (2000). In their study Swedish parties have somewhat higher estimated d's than those reported here, but the sample period also differs. Byers et al. (2000) found that the popularity series of 26 parties possess very similar properties. In large samples d gets values from 0.65 to 0.85.

These results suggests that it is possible to conclude confidently that in any case these series are not I(0). There is some discrepancy between the ADF and ARFIMA results. In 3 of 8 cases, ADF classifies the series differently than ARFIMA does. It is also interesting that all the differently classified series are Swedish. There are several possible explanations for these inconsistent results. Firstly, the ADF test has low power against I(d). Secondly, the small number of observations (<200) may make it difficult to tell a stationary from a non-stationary process. We can also question the assumption of long memory in a series which covers only 14 years. If we find long memory, can we really speak about long-term time dependence? One reason for alternating classification is that a person's current behavior depends largely on his past behavior, a dependence which may be short-term, long-term or permanent. In various situations the length of persistence is best characterized by either a stationary, unit root, strongly autoregressive near integrated or fractionally integrated process[5]. Thirdly, it has been shown in theory that I(1) can mistakenly be classified as I(d) when there is a structural change in the series (Diebold and Inoue, 2001). Let us illustrate this chance of confusion with a random walk process. As we recall, in a random walk series the observation for this period is a sum of its previous value and a shock. These shocks can be large and thus may be confused with structural changes. It is thus very likely that such confusion occurs, especially in short series. As to a series having a fractional unit root, the effect of the shock term (ε_t) is downsized by the coefficient of the autoregressive term (<1), but the shock can still be large in value. Thus, it is obvious that in short series mistakes are also made in the case of long memory series.

[5] As is the case for the US President's approval ratings. The time series properties of the US President's popularity have been studied in DeBoef (2000), Ostrom and Smith (1992), Durr (1993) and Wlezien (1996).

4 Detecting Structural Changes

Domingo and Tonella (2002) have described the nature of structural changes very well "Structural changes appear when some part or properties are lost or added to the object, some relations appear, disappear or change their form. In other words, structural changes imply changes in the object identity. Of course, this may happen in such a small degree that the change is unnoticeable, or in such a degree that the system becomes practically a new one."

It is essential to test the potential existence of structural breaks in these series, as they might be the reason for controversial results in the stationarity tests discussed above. There is already textbook-like literature on unit roots and structural breaks (see e.g. Maddala and Kim, 1998) but when the unit root assumption is replaced by a fractional unit root there is not much literature to which to refer. The latest attempt to provide both theoretical proof and Monte Carlo evidence for this possibility of misunderstanding is by Diebold and Inoue (2001). In this paper structural change is considered as one cause of long memory. In the Monte Carlo part of their study, Diebold and Inoue stress the importance of testing both I(0) and I(1), as these two classifications have contrary memory properties. They conclude that they have clear theoretical and empirical evidence for confusing long memory and structural change. Before Diebold and Inoue, Granger and Hyung (1999) dealt with the same problem and I approach the question as they do.

It has already been shown that our series have long or perfect memory. In other words, they are either I(d) or I(1). We start by testing the existence of structural breaks with the method developed by Bai (1997), which is suitable for seeking multiple unknown structural break points in autoregressive models. This method finds one break point at a time. Besides finding an unknown break point, this test indicates its timing as well. Basically, the test procedure goes as follows. An autoregressive model, like $y_t = \rho y_{t-t} + \varepsilon_t$, $\varepsilon_t \sim IN(0,1)$, t=1,2,...,T, is estimated by OLS. The appropriate number of lags is chosen by AIC, reported in Appendix (Table 2). Let us assume that a break point is found at time point m.

The data is then divided into two sub-samples

$y_t = \rho_1 y_{t-t} + \varepsilon_{1t}$, t=1,2,...,m

and

$y_t = \rho_2 y_{t-t} + \varepsilon_{2t}$, t=m+1,...,T.

These autoregressive models are estimated by OLS and parameter constancy in the sub-samples is examined by a test presented in Bai and Perron (1998, pp. 60), where critical values are also found[6]. This procedure is repeated until parameter constancy is not rejected for all sub-samples.

Structural break tests were performed for every Finnish series, though the ADF and ARFIMA results were not controversial. The plot of the SDP's series, however, reveals the need for a structural break test. Appendix (Table 3) lists these break points with their significance and timing[7]. Of the Finnish series only the SDP's popularity has structural breaks. Two Swedish series have structural breaks, the SDP and the LP. There are 1-3 break points in the series. All these series have one break time in common, 6/1994. The dates of the break points coincide with closeness of an election, the deepest phase of the economic crisis and a turning point in unemployment.

The next phase is to find out whether these breaks are the source of long memory. Our way to approach this question is to estimate an autoregressive model in which the breaks are controlled by step-dummies. If step-dummies remove or reduce long memory properties in the series (i.e. decrease the value of d), then the breaks can be suspected of being the cause of long memory. The exact AR(1) model estimated here is $y_t = \alpha_1 + \beta_1 y_{t-1} + D_1(\alpha_2 + \beta_2 y_{t-1}) + D_2(\alpha_3 + \beta_3 y_{t-1}) + \varepsilon$. D_1 equals 1 starting from the first break date and D_2 equals 1 starting from the second break date, otherwise they are 0. The residuals of this AR(1) model are saved and the order of integration d is estimated by Sowell's ARFIMA method. In other words, the existence of unit roots in these series, which are "cleansed" of structural breaks, is estimated. If there is long or perfect memory left then it should be of pure form, not to be confused with structural breaks. This testing is done for the series with breaks.

[6] The critical values in Bai and Perron (1998) recognize how many breaks have already been found.

[7] Here we applied Hansen's (2000) GAUSS code for estimating the break points.

Table 4. $\widehat{d}$'s, standard errors and t-tests for residuals. Critical values from normal distribution.

	party	ARFIMA			t-test	
	residuals	model	$\widehat{d}$	s.e.	H_0:d=0	H_0: d=1
Finland	SDP	(0,d,0)	0.808	0.064	12.6***	-2.98***
Sweden	SDP	(0,d,0)	0.827	0.072	11.48***	-2.40**
	LP	(0,d,0)	0.904	0.064	14.12***	-1.50

SDP- Social Democratic Party, LP - Left Party

Rejection levels: *** = 0.01, ** = 0.05, * = 0.1

Controlling structural breaks seems to alternate classifications I(1) and I(d). In the case of the Finnish and Swedish SDP it looks as if controlling for structural breaks removes the unit root property. The value of d declines and the t-test rejects both options, I(0) and I(1). There is thus a possibility that these party series could have been classified as I(1) when in fact they had structural breaks and long memory. For the Finnish SDP this should not be a surprise since a quick look at the time series plot reveals the existence of structural change. The Left Party results do not support the hypothesis, although the change in the value of d is very small. As the Bai and Perron test (1998) is not consistent, we have performed checks for robustness. We included breaks that are close to being significant in d estimations and checked whether their inclusion changes the value of $\widehat{d}$. The result is that this does not occur.

5 Conclusions

The results reported in this paper categorize party popularity series into perfect and long memory series, but a chance of miscategorizing in the presence of structural breaks is also apparent. After different stationarity tests, we examined whether the same series have structural breaks. If they did, their influence on the series was removed by estimating an autoregressive model with step-dummies at break points. The residuals of the regression were tested for stationarity.

The weakest form of stationarity test applied here, the ADF test, categorizes all the series as having a unit root. A slightly more elaborate way to explore stationarity in time series is to estimate the order of integration. Sowell's estimation method recognizes 5 series with unit root and 3 with fractional unit root. When the influence of structural breaks is removed and the order of integration is reestimated, the classification changes in two of the three series. In both cases it changes from a unit root to a fractional unit root.

After these exercises we can conclude that of the Finnish parties the Left Alliance, the Centre Party and the National Coalition Party have series with a unit root. In Swedish parties only the Left Party popularity has a unit root. Parties with a fractional unit root in popularity series are the Swedish Centre Party and the Moderate Party and the Social Democratic Parties in both countries.

If these series are applied in popularity function estimation, which is often the case, the same kind of procedure should be conducted for the explanatory variables, since there is an obvious risk of co-integration. Apart from that, combined examination might give some indication of the occurrence of (partisan) political business cycles. The logic is that if popularity and economic variables have structural breaks at the same time and if this happens around elections then we could conclude that the party in power affects the nature of unemployment and/or inflation series.

Appendix

Table 1. AIC's for different ARFIMA models, * marks the lowest value.

	Finland				Sweden			
	LA	SDP	CENT	NC	LP	SDP	CENT	MP
0,d,0	2.396	3.491	3.094	2.944	2.779*	3.932*	2.454*	3.391*
1,d,0	2.337	3.483	3.099	2.914	2.792	3.938	2.466	3.402
2,d,0	2.309	3.483	3.084*	2.928	2.789	2.949	2.474	3.415
3,d,0	2.261*	3.496	3.091	2.939	2.791	3.962	2.482	3.426
0,d,1	2.283	3.478*	3.093	2.912*	2.792	3.937	2.466	3.402
0,d,2	2.27	3.491	3.10	2.925	2.791	3.949	2.473	3.415
0,d,3	2.265	3.489	3.093	2.927	2.804	3.962	2.479	3.426
1,d,1	2.83	3.491	3.104	2.925	2.802	3.949	2.475	3.415

Table 2. Number of lags used in AR models for seeking a break point. Number of lags determined by AIC.

	Finland	Sweden
LA/LP	4	3
SDP	2	1
CENT	3	2
NC/MP	5	2

Table 3. List of break points in Finnish and Swedish series.

	var	obs.	time	test value	significance level
Finland	SDP	53.	8/1992	23.94	0.000
		74.	6/1994	13.78	0.1
Sweden	LP	78.	6/1994	26.11	0.000
		89/90	6/95	12.49	robustness check
	SDP	17.	12/1988	12.54	robustness check
		42.	3/1991	14.12	0.1
		78.	6/1994	13.89	0.05

References

[1] Bai, J., 1997. Estimating multiple breaks one at a time. Econometric Theory, 13, 315-352.

[2] Bai, J., Perron, P., 1998. Estimating and testing linear models with multiple structural changes. Econometrica, 66, 47-78.

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

[4] Baillie, R. T., Chung, C-F., Tieslau, M. A., 1996. Analyzing inflation by the fractionally integrated ARIMFA-GARCH model. Journal of Applied Econometrics, 11, 23-40.

[5] Box-Steffensmeier, J.M., Smith, R.M., 1998. Investigating political dynamics using fractional integration methods. American Journal of Political Science 42(2), 661-689.

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

[7] Byers, D., Davidson, J., Peel, D., 2000. The dynamics of aggregate political popularity: Evidence from eight countries. Electoral Studies 19, 49-62.

[8] Byers, D., Davidson, J., Peel, D., 1997. Modelling political popularity. An analysis of long-range dependence in opinion poll series. Journal of the Royal Statistical Society Series A 160, 471-490.

[9] Clarke, H.D., Lebo, M., 2002. Fractional (co)integration and governing party support in Britain: A methodological research note. Paper submitted to the British Journal of Political Science.

[10] Cochrane, J.H., 1988. How big is the random walk in GNP? Journal of Political Economy 96, 893-920.

[11] DeBoef, S., 2000. Persistence and aggregations of survey data over time: from micro-foundations to macro-persistence. Electoral Studies 19, 9-29.

[12] Diebold, F.X., Inoue, A., 2001. Long memory and regime switching. Journal of Econometrics 105, 131-159.

[13] Domingo, C., Tonella, G., 2002. Towards a theory of structural change. Structural Change and Economic Dynamics 11, 209-225.

[14] Durr, R., 1993. What moves policy sentiment? American Political Science Review, 87, 158-170.

[15] Fox, R.,Taqqu, M.S., 1986. Large sample properties of parameter estimates for strongly dependent stationary Gaussian time series. Annals of Statistics 14, 517-532.

[16] Geweke, J., Porter-Hudak, S., 1983. The estimation and application of long memory time series models. Journal of Time Series Analysis 4, 221-238.

[17] Granger, Clive W.J., 1980. Long memory relationships and the aggregation of dynamic models. Journal of Econometrics 14, 227-238.

[18] Granger, Clive W.J., Hyung, N., 1999. Occasional structural breaks and long memory. Discussion Paper 14/1999. Department of Economics. University of California San Diego.

[19] Hansen, B., 2000. Testing for structural change in conditional models. Journal of Econometrics 97. 93-115.

[20] Kwiatkowski, D., Phillips, P.C.B., Schmidt, P., Shin, Y., 1992. Testing the null hypothesis of stationary against the alternative of a unit root. Journal of Econometrics 54, 159-178.

[21] Lebo, M.J., Walker, R.W., Clarke, H.D., 2000. You must remember this: Dealing with long memory in political analyses. Electoral Studies 19, 31-48.

[22] Li, W.K.- McLeod, A.I., 1986. Fractional Time Series Modeling. Biometrika 73, 217-221.

[23] Maddala, G.S., Kim, I-M., 1998. Unit Roots, Cointegration and Structural Change. Cambridge University Press. Cambridge.

[24] Nelson, C.R., Plosser, C.I., 1982. Trends and random walks in macroeconomic time series. Journal of Monetary Economics 10, 139-162.

[25] Ooms, M., Doornik, J.A., 1998. Estimation, simulation, and forecasting for fractional autoregressive integrated moving average models. Discussion Paper, Econometric Institute, Erasmus University Rotterdam. Presented at the fourth annual meeting of the Society for Computational Economics, June 30, 1998, Cambridge, UK.

[26] Ostrom, C.W. Jr., Smith, R., 1992. Error correction, attitude persistence, and executive rewards and punishments: A behavioral theory of presidential approval. Political Analysis 4, 127-184.

[27] Perron, P., 1989. The great crash, the oil price shock, and the unit root hypothesis. Econometrica 57(6), 1361-1401.

[28] Sowell, F., 1992. Maximum likelihood estimation of fractionally integrated time series models. Journal of Econometrics 52, 165-188.

[29] Wlezien, C., 2000. An essay on 'combined' time series processes. Electoral Studies 19, 77-93.

[30] Zaller, J., 1999. The Nature and Origins of Mass Opionion. Cambridge University Press.