Online Appendix[1]

Filtering public opinion for short- and long-run dependence

The standard approach to obtaining stationary data is to difference (and de-trend) as appropriate. However, aggregate public opinion data pose a challenge in this regard. Granger (1980) has demonstrated that aggregation can produce series that have long-term memory, without being fully integrated, $I(1)$. Rather, the series may be *fractionally integrated* (FI). Such a series would be stationary (i.e. mean reverting), but its autocorrelation function would decay more slowly than that of an auto-regressive (AR) process (Granger and Joyeux, 1980). While the autocorrelations of an AR process decay exponentally, and thus quickly, those of a fractionally integrated process decay at a slower, hyperbolic rate. AR and FI processes thus offer alternative parameterizations of a variable's autocorrelation function, with the latter capturing processes with longer memory than the former.

Fractional integration could arise, for example, when aggregating heterogeneous auto-regressive processes, which is almost inevitably the case with public opinion data. In general, citizens' political attitudes must be expected to depend at least to some positive degree on their previous attitudes. Furthermore, heterogeneity in public opinion formation is widely documented, by scholars such as Zaller (1992), making it very likely that some types of voters show greater stability in their attitudes than others. Thus, Box-Steffensmeier and Smith (1998) view macropartisanship as a fractionally integrated series, while Box-Steffensmeier and Tomlinson (2000) make the same case for Congressional approval. In the present case, aggregate support for the EU may be fractionally integrated, not fully reflecting an integrated level of support, $I(1)$, nor pure changes.

Accordingly, testing the series for stationarity using the Augmented Dickey-Fuller (ADF) test gives ambivalent results, as some series yield results that allow rejection of the $I(1)$ hypothesis, while others do not. The relevant p-values are shown in the ADF-column, under 'Pre' in table A1. To obtain stationary series of pure innovations, the series have been filtered. As already mentioned, while auto-regressive models are suited for capturing short-run serial dependence, fractional integration components are suited for capturing long-run dependence in stationary series. How quickly the autocorrelations decay is essentially an empirical question, and models incorporating both AR and FI components may facilitate estimation and interpretation (Sowell, 1992). However, in this case, with a limited number of observations, there is also a risk of over-fitting. Thus, the following approach has been applied for each opinion series: Three models have been estimated, including (a) an FI-component, (b) FI- and AR(1)-components, and (c) only an AR(1)-component. In addition, because the series are measured twice a year, a binary indicator

[1] This material belongs to the following article: Bølstad, J (2015), Dynamics of European integration: Public opinion in the core and periphery. *European Union Politics* 16(1).

separating spring from autumn has been included in each model to remove any seasonal differences. Likelihood-ratio (LR) tests have been used for model selection. Where model b fits significantly better than a, b has been preferred to a, but if b does not also fit better than c, c has been preferred to b.

The models are reported in table A1, where columns under 'Pre', report standard deviations (SD) and ADF tests for the pre-filtered series, while those under 'Post' refer to the filtered series. 'L1/AR' refers to the first-order AR component (a lagged dependent variable), while fractional integration is captured by the d-parameter, which can take on values between $-.5$ and $+.5$ (the boundaries distinguishing an FI-series from an $I(1)$-series). None of the series are found to need an ARFI-model, but about half get an FI-model, the other half an AR-model. In practice, the innovations predicted by these models are virtually identical, but at least one series (the British) would show signs of remaining serial dependency if it were fit using a pure FI-model. The reported models avoid this problem. Furthermore, the standard deviations are notably smaller for all the filtered series, and the ADF-test allows an unequivocal rejection of the $I(1)$-hypothesis after filtering.

Table A1: Auto-regressive frac. integrated (ARFI) filtering of public opinion

	ARFI				Pre		Post	
	Const.	Spring	L1/AR	d	SD	ADF, p	SD	ADF, p
France	72.907	−.820	.	.487	6.753	.042	3.543	.000
Belgium	79.202	−.148	.	.467	5.565	.016	3.852	.000
Netherlands	85.965	−.428	.	.468	4.237	.005	2.739	.000
W. Germany	75.900	−1.852	.703	.	5.348	.003	3.754	.000
Italy	76.794	−.016	.975	.	8.381	.866	3.535	.000
Luxembourg	86.945	−.499	.	.232	3.391	.000	3.225	.000
Denmark	63.198	−.912	.857	.	9.048	.001	4.964	.000
Ireland	77.004	−.936	.927	.	9.822	.646	4.114	.000
U.K.	54.322	−1.050	.838	.	8.147	.428	4.444	.000

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