GDP PER Capita in Europe: Time Trends and Persistence

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Abstract: This paper uses fractional integration techniques to show the existence of a negative correlation between the level of GDP per capita and its degree of persistence in a number of European countries. Weaker institutions and "shock absorbers" (financial markets to diversify risk and stabilization policies to counter shocks) might be the reason why countries with lower GDP per capita are characterized by a less effective management of the economy in response to shocks.

INTRODUCTION

GDP per capita is a key indicator of a country's economic performance and its success in improving living standards over time.In their seminal paper Nelson and Plosser (1982) modelled real macroeconomic variables by decomposing them into a secular (non-stationary) component associated with the long run and a cyclical one which is assumed to be stationary; they showed that most macroeconomic time series, such as GDP per capita, can be characterised as nonstationary processes, in contrast to traditional business cycle models in which aggregate output fluctuates around a deterministic trend and shocks have no long-run effects (see also Christiano and Eichenbaum, 1990). Instead real business cycle theories account for fluctuations in response to shocks at all frequencies and therefore there is no meaningful dichotomy between the short and the long run (Shapiro and Watson, 1988).King et al. (1987) concluded that economic fluctuations either arise from transitory shocks to production with persistent effects reflecting the propagation of disturbances over time, or represent the response of the economy to permanent changes in the underlying technology. Obviously the effects of shocks and the policy implications are very different in the trend stationary vis-à-vis the random walk or nonstationary approach.

Various studies such as Perron and Phillips (1987), Schwert (1987), Campbell and Mankiw (1987), Perron (1988), Rudebusch (1993), Diebold and Senhadji (1996), Cheung and Chinn (1997), Rothman (1997) and Darné (2009b) have focused on the nonstationary properties of real US GNP, with mixed results concerning the unit root hypothesis. Other contributions by Zelhorst and De Haan (1995), Ben-David and Papell (1998), Bradley and Jansen (1995), Ben-David, Lumsdaine, and Papell (2003), Darné and Diebolt (2004), Gaffeo, Gallegati, and Gallegati (2005) and Narayan (2007) have examined the properties of international aggregate output with mixed results.

Following a different approach, Hosking (1981, 1984), Granger and Joyeux (1980), Beran (1992, 1994), Baillie (1996), Robinson (1995a, 1995b), Caporale and Gil-Alana. (2008, 2009), Gil-Alana (2001, 2004), Candelon and Gil-Alana (2004), Škare and Stjepanović (2013),Caporale and Gil-Alana (2013) and Caporale and Skare (2014) suggest that real GDP may exhibit long-range dependence and should be modelled as a fractionally integrated process.According to Haubrich and Lo (2001), macroeconomic variables behave as a hybrid between random walk and white noise processes. Diebold and Rudebusch (1989), Sowell (1992), Gil-Alana and Robinson (1997) among others argue that fractionally integrated specifications are more appropriate than the I(0) and the I(1) models for describing real GDP.

The present paperalso estimates fractional integration models to examine the degree of persistence of GDP per capita in a number of European countries. Such models are much more general and flexible than those based on the classical I(0) vs. I(1) dichotomy, allow for much richer dynamics and provide information on the long-memory properties of the series. We show that fractional integration is a suitable framework to describe GDP per capita in Europe and find a significant negative correlation between its growth rate and its degree of persistence, i.e. richer countries are characterised by lower orders of integration and in some cases exhibit mean-reverting behaviour, whilst in poorer countries shocks have permanent effects.

The paper is structured as follows. Section 2 briefly reviews the methodology, Section 3 describes the data and presents the main empirical results, and Section 4 offers some concluding remarks.

TIME TRENDS AND PERSISTENCE

We analyse GDP per capita in various European countries using a fractional integration approach such that the differencing parameter for making a series stationary I(0) is

not necessarily an integer (usually 1) value, and can take instead any real value, including fractional ones. The model also includes a time trend to capture technologicalprogress and is specified as follows:

$$y_t = \beta_0 + \beta_1 t + x_t, \qquad (1)$$

$$(1 - L)^d x_t = u_t, \qquad t = 0, 1,..., \qquad (2)$$

where y_t stands for GPD per capita; β_0 and β_1 are unknown coefficients on an intercept and a linear time trend respectively, and the detrended process x_t is assumed to be I(d), where d is estimated along with the other parameters in the model.

This specification is more general than the classical one based on the I(0)/I(1) dichotomy, it produces more accurate estimates of the time trend coefficients since it allows for a much richer dynamic in the specification of the detrended process, including, for example, the case of nonstationary processesthat are nevertheless mean-reverting (i.e., $0.5 \le d < 1$).In addition, it includes the standard models examined in the literature such as the trend stationary one (i.e., (1) and (2) with d = 0) and the random walk with an intercept if d = 1. Note that both models can be extended by allowing for short-run dynamics in the form of autoregressive (AR) processes for u_t in (2).

Although several estimation and testing methods will be employed in this paper we will mainly focus on the results based on the Whittle function in the frequency domain (Dahlhaus, 1989), using a very general testing procedure derived by Robinson (1994) that is the most efficient one in the Pitman sense against local departures from the null. This method has the advantage that it remains valid even in non-stationary contexts (i.e., $d \ge 0.5$) unlike all the other procedures, and although there exist other more recent versions of this method (e.g., Lobato and Velasco, 2007) they require an efficient and consistent estimate of d, which

is not necessary when using Robinson's (1994) LM method. For the case of weak autocorrelation in the error term we apply the non-parametric approach of Bloomfield (1973), which has been widely used in the context of fractional integration (Gil-Alana, 2004, 2005).

DATA AND EMPIRICAL RESULTS

We use annual data on GDP per capita (current US dollars), from 1960 to 2016, obtainedfrom the World Development Indicators for the following countries: Austria, Belgium, Denmark, Finland, France, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden and the UK. Natural logs are taken before carrying out the statistical analysis. Figure 1 displays the series of interest. It can be seen that they are all upward trending.

We start the analysis by considering the model given by equations (1) and (2), i.e.

$$y_t = \beta_0 + \beta_1 t + x_t, \qquad (1 - L)^d x_t = u_t, \qquad t = 1, 2 \qquad (3)$$

Undertheassumptionthat u_t in (3) is an uncorrelated (whitenoise)process. We examine thethree standard cases of i) no deterministicterms (i.e., $\beta_0 = \beta_1 = 0$ in (3)), ii) anintercept ($\beta_1 = 0$), and iii)aninterceptwith a linear time trend, and report in Table 1 alongwiththeestimatedvaluesof d, the 95% confidencebands of the non-rejectionvalues of d, usingRobinson's (1994)Lagrange Multiplier (LM)tests, which are valideven in nonstationarycontexts. Thatis, we test thenullhypothesis:

$$H_o: d = d_o, \qquad (4)$$

in (3), where d_o can be any real value. Wechoose $d_o = 0$, 0.01, 0.02, …, (0.01), …, 1.99 and2; the non-rejectionvalues of d_o in(4)at the 5% level are reported in the tables in brackets.

Table 1: Estimates of d and 95% confidence bands with uncorrelated errors

Country	No terms	Anintercept	A linear trend
AUSTRIA	0.912 (0.731, 1.162)	1.324 (1.131, 1.618)	**1.286 (1.105, 1.578)**
BELGIUM	0.916 (0.739, 1.162)	**1.395 (1.173, 1.722)**	1.362 (1.145, 1.693)
DENMARK	0.921 (0.745, 1.165)	1.302 (1.098, 1.601)	**1.255 (1.072, 1.546)**
FINLAND	0.919 (0.739, 1.169)	1.318 (1.075, 1.714)	**1.281 (1.058, 1.675)**
FRANCE	0.919 (0.744, 1.163)	1.265 (1.064, 1.555)	**1.228 (1.046, 1.512)**
GREECE	0.914 (0.731, 1.166)	**1.444 (1.251, 1.733)**	1.401 (1.216, 1.675)
IRELAND	0.914 (0.725, 1.164)	1.229 (0.999, 1.538)	**1.189 (0.986, 1.501)**
ITALY	0.917 (0.737, 1.166)	1.273 (1.084, 1.562)	**1.231 (1.063, 1.504)**
LUXEMBOURG	0.899 (0.718, 1.147)	1.291 (1.056, 1.624)	**1.269 (1.035, 1.612)**
NETHERLANDS	0.918 (0.743, 1.162)	1.341 (1.149, 1.625)	**1.295 (1.117, 1.576)**
PORTUGAL	0.903 (0.714, 1.157)	1.365 (1.148, 1.684)	**1.325 (1.119, 1.648)**
SPAIN	0.929 (0.746, 1.178)	1.423 (1.186, 1.767)	**1.366 (1.151, 1.700)**
SWEDEN	0.923 (0.751, 1.166)	1.198 (0.965, 1.535)	**1.164 (0.965, 1.494)**
UK	0.901 (0.719, 1.146)	**1.359 (1.097, 1.780)**	1.339 (1.075, 1.785)

In bold, the significant deterministic terms.

Table 2: Estimated coefficients without autocorrelation

Country	d	Intercept	Time trend
AUSTRIA	1.286 (1.105, 1.578)	6.76436 (73.69)	0.06795 (1.96)
BELGIUM	1.395 (1.173, 1.722)	7.11737 (81.84)	---
DENMARK	1.255 (1.072, 1.546)	7.13912 (79.95)	0.06631 (2.19)
FINLAND	1.281 (1.058, 1.675)	6.99322 (69.10)	0.06491 (1.72)
FRANCE	1.228 (1.046, 1.512)	7.13056 (76.99)	0.05894 (2.07)
GREECE	1.444 (1.251, 1.733)	6.22933 (79.60)	---
IRELAND	1.189 (0.986, 1.501)	6.45112 (74.87)	0.07844 (3.42)
ITALY	1.231 (1.063, 1.504)	6.61104 (70.14)	0.06503 (2.22)
LUXEMBOURG	1.269 (1.035, 1.612)	7.66736 (76.47)	0.06143 (1.72)
NETHERLANDS	1.295 (1.117, 1.576)	6.89833 (76.27)	0.06781 (1.92)
PORTUGAL	1.325 (1.119, 1.648)	5.81776 (62.67)	0.06908 (2.22)
SPAIN	1.366 (1.151, 1.700)	5.87746 (59.18)	0.08446 (1.72)
SWEDEN	1.164 (0.965, 1.494)	7.52621 (73.97)	0.05788 (2.34)
UK	1.281 (1.058, 1.675)	7.20381 (83.63)	---

The values in parenthesis in the second column are the 95% confidence bands, while those in columns 3 and 4 are t-values for the deterministic terms.

The time trendcoefficient is found to be statistically significant in all countries exceptBelgium, Greece and the UK, where the intercept is the only significant deterministic term.Note thatthisselectionisbasedonthe t-valuesonthe d_o-differenced series, i.e.,

$$(1 - L)^{d_o} y_t = \beta_0 \tilde{1}_t + \beta_1 \tilde{t}_t + u_t, \qquad t = 1, 2, ..., \quad (5)$$

where $\tilde{1}_t = (1 - L)^{d_o} 1_t$ and 1_t is a vector of ones, and

$\tilde{t}_t = (1 - L)^{d_o} t$, and, since u_t is I(0) byconstruction,

standard t-testsare valid. Table 2 displaystheestimatedcoefficients in (3) foreach series;thehighest time trendcoefficients are found forSpain (0.08446),Ireland(0.07844) and Portugal (0.06908), i.e. some of the peripheral EU countries.One would expect such a finding, since those are the countries with the lowest initial levels of GDP per capita that have been catching up with the more developed ones.

Table 3: Estimates of d and 95% confidence bands with autocorrelatederrors

Country	No terms	Anintercept	A linear trend
AUSTRIA	0.725 (0.397, 1.164)	0.938 (0.751, 1.336)	**0.891 (0.625, 1.275)**
BELGIUM	0.749 (0.388, 1.173)	0.892 (0.690, 1.374)	**0.841 (0.541, 1.293)**
DENMARK	0.752 (0.374, 1.182)	0.893 (0.701, 1.324)	**0.862 (0.602, 1.239)**
FINLAND	0.734 (0.332, 1.207)	0.815 (0.681, 1.119)	**0.731 (0.482, 1.058)**
FRANCE	0.742 (0.329, 1.184)	0.903 (0.702 1.374)	**0.889 (0.622, 1.282)**
GREECE	0.684 (0.384, 1.172)	1.097 (0.812, 1.592)	**1.041 (0.704, 1.492)**
IRELAND	0.734 (0.349, 1.194)	0.879 (0.722, 1.396)	**0.853 (0.516, 1.301)**
ITALY	0.736 (0.356, 1.184)	0.965 (0.764, 1.308)	**0.938 (0.701, 1.264)**
LUXEMBOURG	0.729 (0.362, 1.184)	0.822 (0.686, 1.204)	**0.591 (0.191, 1.143)**
NETHERLANDS	0.764 (0.334, 1.179)	0.957 (0.721, 1.406)	**0.927 (0.655, 1.335)**
PORTUGAL	0.691 (0.417, 1.153)	0.924 (0.744, 1.376)	**0.858 (0.541, 1.282)**
SPAIN	0.760 (0.384, 1.202)	0.899 (0.671, 1.412)	**0.891 (0.623, 1.296)**
SWEDEN	0.754 (0.343, 1.206)	0.764 (0.613, 1.127)	**0.727 (0.479, 1.090)**
UK	0.722 (0.369, 1.179)	0.823 (0.696, 1.142)	**0.729 (0.474, 1.113)**

In bold, the significant deterministic terms.

Table 4: Estimatedcoefficients with autocorrelation (Bloomfield, 1973)

Country	d	Intercept	Time trend
AUSTRIA	0.891 (0.625, 1.275)	6.78203 (72.19)	0.07042 (8.32)
BELGIUM	0.841 (0.541, 1.293)	7.10222 (75.99)	0.06411 (8.99)
DENMARK	0.862 (0.602, 1.239)	7.17500 (78.43)	0.06708 (8.97)
FINLAND	0.731 (0.482, 1.058)	7.06047 (63.49)	0.06776 (11.18)
FRANCE	0.889 (0.622, 1.282)	7.15324 (76.20)	0.06051 (7.20)
GREECE	1.041 (0.704, 1.492)	6.21265 (71.39)	0.06242 (4.66)
IRELAND	0.853 (0.516, 1.301)	6.45216 (72.36)	0.08208 (11.60)
ITALY	0.938 (0.701, 1.264)	6.53343 (69.17)	0.06574 (6.46)
LUXEMBOURG	0.591 (0.191, 1.143)	7.63715 (52.32)	0.07453 (13.10)
NETHERLANDS	0.927 (0.655, 1.335)	6.91527 (74.49)	0.06773 (7.15)
PORTUGAL	0.858 (0.541, 1.282)	5.84470 (60.87)	0.07388 (9.57)
SPAIN	0.891 (0.623, 1.296)	5.93138 (57.66)	0.07622 (8.22)
SWEDEN	0.727 (0.479, 1.090)	7.58813 (70.70)	0.06071 (10.49)
UK	0.729 (0.474, 1.113)	7.17555 (78.96)	0.06471 (13.13)

The values in parenthesis in the second column are the 95% confidence band, while those in columns 3 and 4 are t-values for the deterministic terms.

The results based on the assumption of autocorrelated errors (as in the exponential spectral model of Bloomfield, 1973) are reported in Tables 3 and 4. Here the time trends coefficient is significant in all cases, the estimatesranging from 0.060 (France and Sweden) to 0.076 (Spain) and 0.082 (Ireland). As for the orders of integration, the I(1) hypothesis cannot be rejected in anyof the cases, with the values of d now ranging from 0.591 (Luxembourg), 0.720 (Sweden and the UK)and 0.731 (Finland) to 0.938 in Italy and 1.041 in Greece.

Given the differences in the results depending on the specificationof the error term, next we estimate d using a semiparametric method, no functionalform being imposed on the error term in this case. In particular, we use a "local" Whittle estimate, initiallyproposed by Robinson (1995b) and developed later by Velasco (1999), Shimotsu and Phillips(2005) and Abadir et al. (2007) among many others.[1]

Table 5: Estimates of d based on a semi parametric method

Country	5	6	7	8	9	10	AVG
AUSTRIA	1.192	**1.342**	1.137	1.207	1.273	**1.302**	1.242
BELGIUM	0.925	1.067	0.974	1.073	1.167	1.207	1.068
DENMARK	1.034	1.122	1.012	1.108	1.204	1.237	1.119
FINLAND	1.041	1.143	0.876	0.936	1.029	1.058	1.013
FRANCE	1.038	1.177	0.994	1.077	1.124	1.102	1.085
GREECE	0.996	1.202	1.141	**1.313**	**1.428**	**1.370**	1.241
IRELAND	1.114	0.959	0.821	0.883	0.960	1.019	0.959
ITALY	1.258	1.253	1.044	1.151	1.194	1.100	1.166
LUXEMBOURG	0.905	1.110	0.952	0.997	1.105	1.131	1.033
NETHERLANDS	1.130	1.294	1.138	1.211	**1.319**	**1.332**	1.237
PORTUGAL	1.095	1.290	1.100	1.156	1.173	1.122	1.156
SPAIN	0.840	1.008	0.938	1.059	1.136	1.104	1.014
SWEDEN	0.941	1.031	0.839	0.957	1.039	1.027	0.972
U. K.	**1.373**	1.115	0.810	0.861	0.928	0.977	1.010
Lower 95%	0.632	0.664	0.689	0.709	0.725	0.739	---
Upper 95%	1.367	1.335	1.310	1.290	1.274	1.260	---

In bold, evidence of I(d) behaviourwith d > 1.

The results produced by this semiparametric method, for a selected group of bandwidth parameters, m = 5, 6, ..., 9 and 10, are displayed in Table 5.[2]Most of the estimates are within the I(1) interval, the main exceptions being Austria (with m = 6 and 10), Greece (m = 8,9 and 10), theNetherlands (m = 9 and 10) and the UK (m = 5). In all these cases, the estimated value of d is significantly higher than 1.

Table 6: Ranking of the time trend coefficients

No autocorrelation (white noise)	Autocorrelation (Bloomfield)
SPAIN (0.08446)	IRELAND (0.08208)
IRELAND (0.07844)	SPAIN (0.07622)
PORTUGAL (0.06908)	LUXEMBOURG (0.07453)
AUSTRIA (0.06795)	PORTUGAL (0.07388)
NETHERLANDS (0.06781)	AUSTRIA (0.07042)
DENMARK (0.06631)	FINLAND (0.06776)
ITALY (0.06503)	NETHERLANDS (0.06773)
FINLAND (0.06491)	DENMARK (0.06708)
LUXEMBOURG (0.06143)	ITALY (0.06574)
FRANCE (0.05894)	UK (0.06471)
SWEDEN (0.05788)	BELGIUM (0.06411)
BELGIUM (---)	GREECE (0.06242)
UK (---)	SWEDEN (0.06071)
GREECE (---)	FRANCE (0.06051)

Table 7: Ranking of the estimates of d (degree of persistence)

Parametric estimation		Semiparametric estimation
No autocorrelation	Autocorrelation (Bloomfield)	
GREECE (1.444)	GREECE (1.041)	AUSTRIA (1.242)
BELGIUM (1.395)	ITALY (0.938)	GREECE (1.241)
SPAIN (1.366)	NETHERLANDS (0.927)	NETHERLANDS (1.237)
PORTUGAL (1.325)	AUSTRIA (0.891)	ITALY (1.166)
NETHERLANDS (1.295)	SPAIN (0.891)	PORTUGAL (1.156)
AUSTRIA (1.286)	FRANCE (0.889)	DENMARK (1.119)
FINLAND (1.281)	DENMARK (0.862)	FRANCE (1.085)
UK (1.281)	PORTUGAL (0.858)	BELGIUM (1.068)
LUXEMBOURG (1.269)	IRELAND (0.853)	LUXEMBOURG (1.033)
DENMARK (1.255)	BELGIUM (0.841)	SPAIN (1.014)
ITALY (1.231)	FINLAND (0.731)	FINLAND (1.013)
FRANCE (1.228)	UK (0.729)	UK (1.010)
IRELAND (1.189)	SWEDEN (0.727)	SWEDEN (0.972)
SWEDEN (1.164)	LUXEMBOURG (0.591)	IRELAND (0.959)

Table 6 and 7 display the ranking of the countries investigated on the basis of their time trend coefficients (usually associated with technological progress) and their degree of persistence respectively.Spain, Ireland and Portugal, namely the countries that experienced the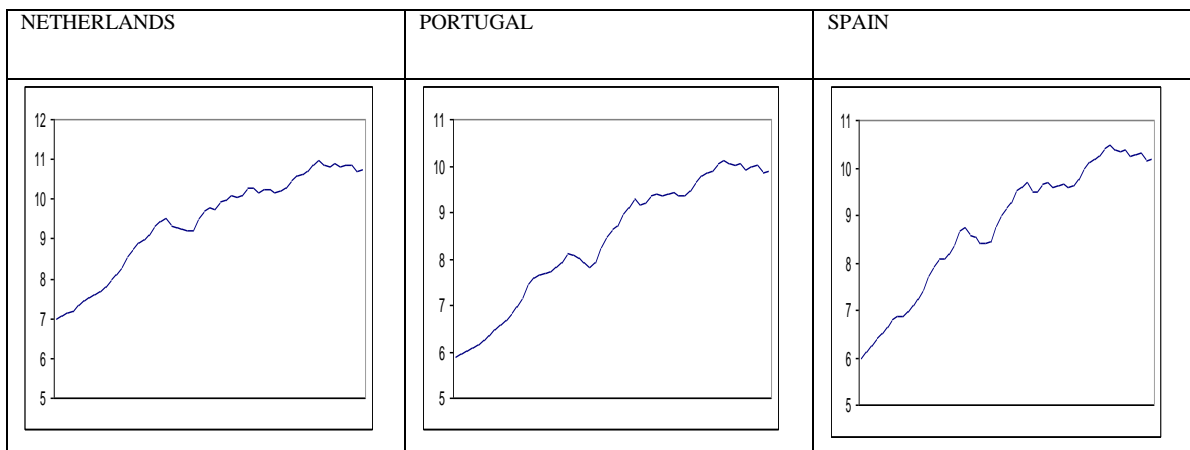 highest growth during the period examined, have the highest estimated time trend coefficients with both uncorrelated and aucorrelated errors. Finland, UK and Sweden, namely the countries with some of the highest initial income levels, exhibit the lowest degrees of integration. Next we investigate the nexus between the degree of dependence (i.e., the orders of integration) and growth.
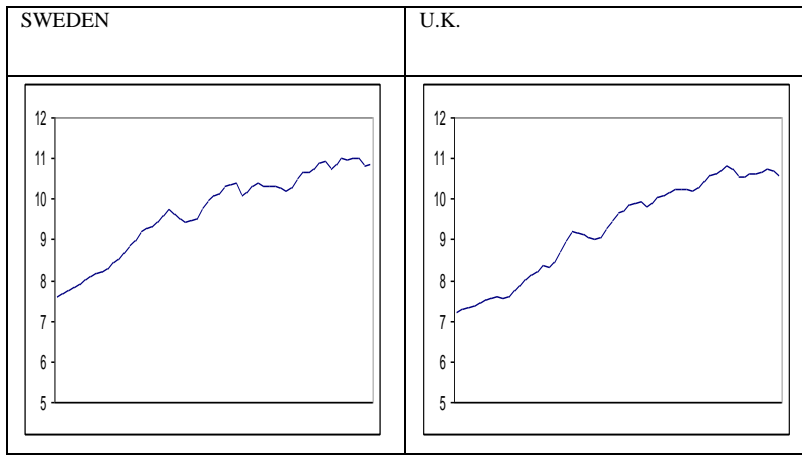
Figure 1: Time series plots

AUSTRIA	BELGIUM	DENMARK
FINLAND	FRANCE	GREECE
IRELAND	ITALY	LUXEMBOURG
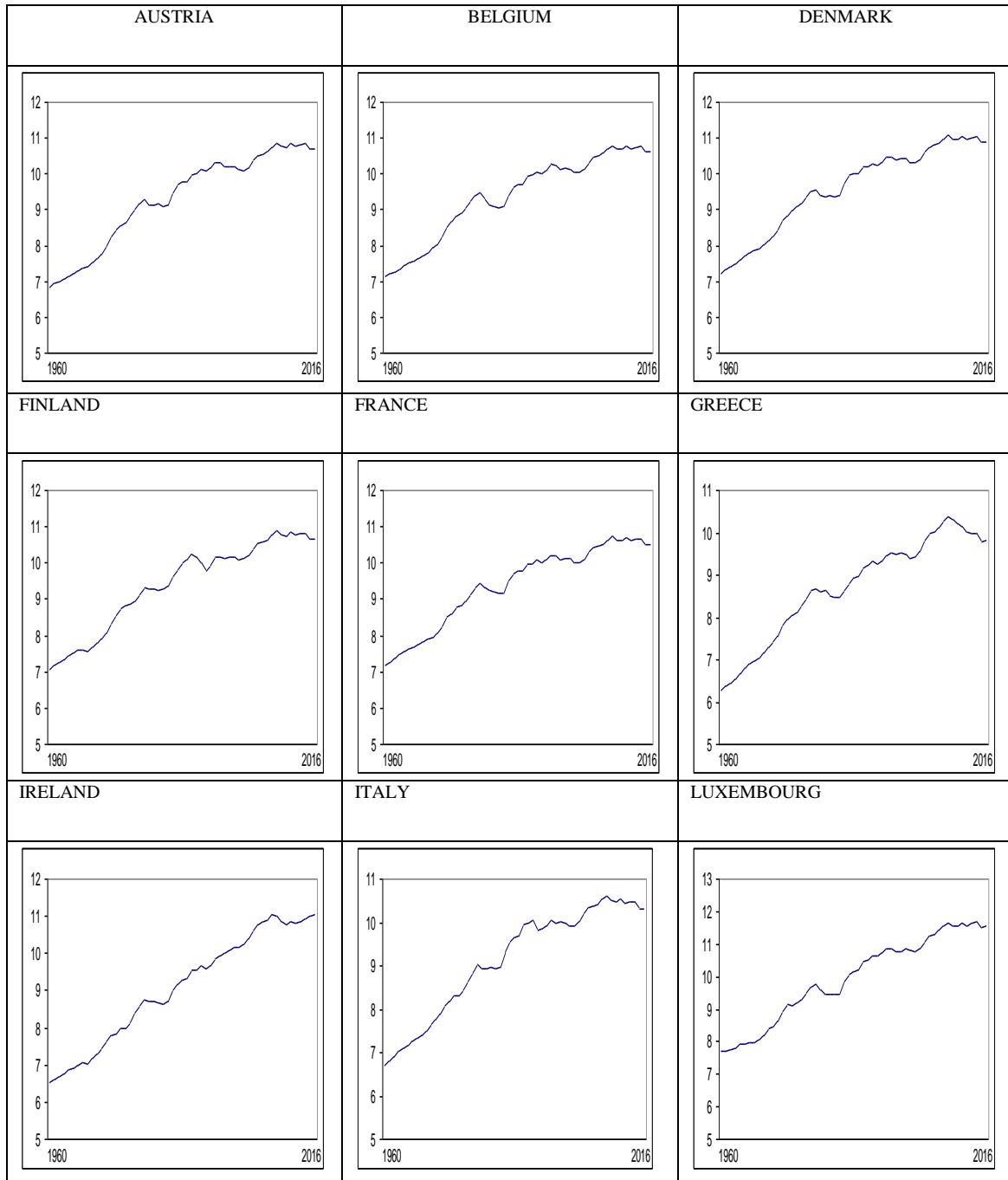
(cont.)

Figure 1: Time series plots (cont.)

NETHERLANDS	PORTUGAL	SPAIN

SWEDEN	U.K.

Figure 1: Correlation between the time trend coefficients and GDP per capita

i) Correlations using GDP per capita in 1960

a) No autocorrelation

b) Autocorrelation

ii) Correlations using GDP per capita in 2016

a) No autocorrelation
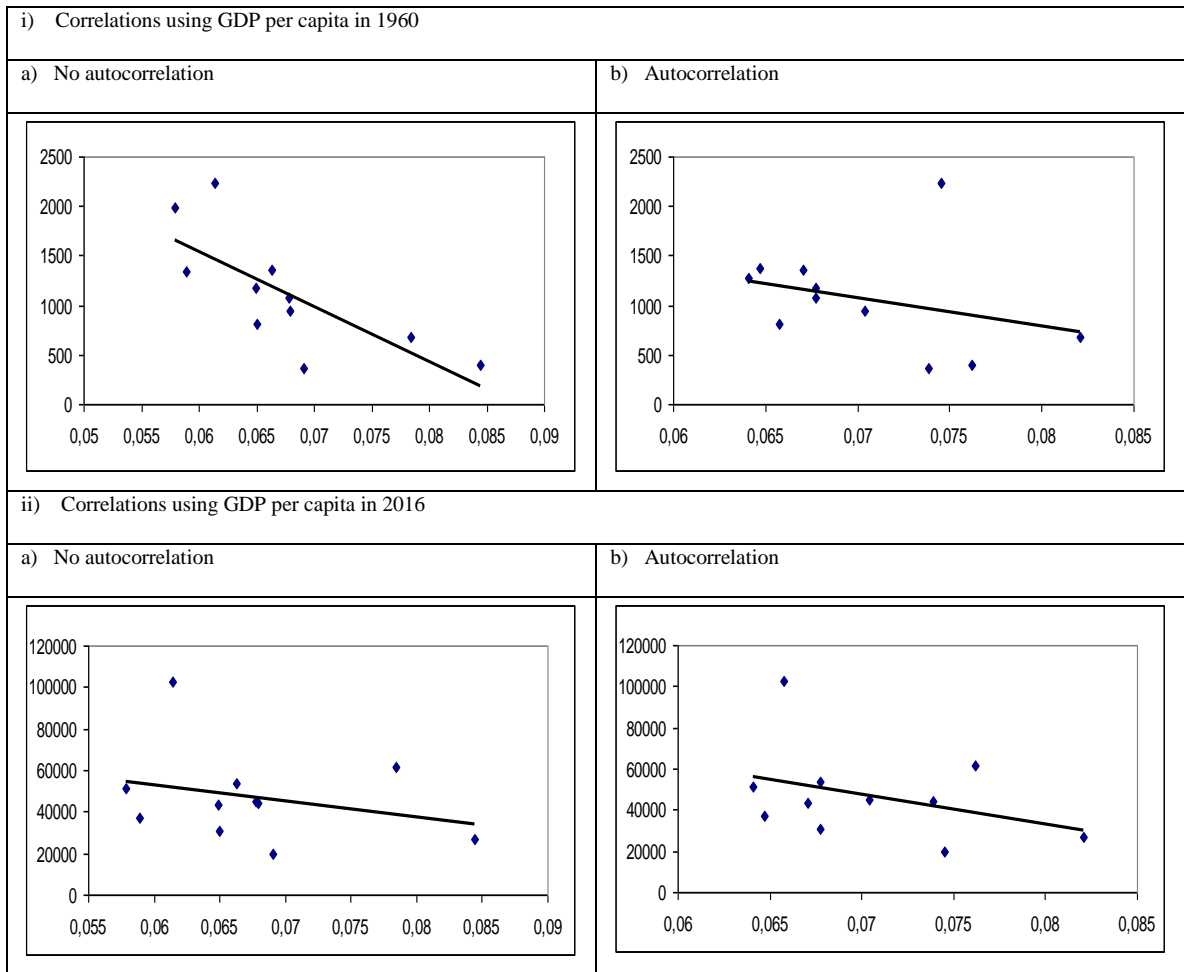
b) Autocorrelation

Figure 2: Correlation between the orders of integration and GDP per capita

i) Correlations using GDP per capita in 1960

a) White noise errors   b) Autocorrelated errors   c) Semiparametric method

ii) Correlations using GDP per capita in 2016

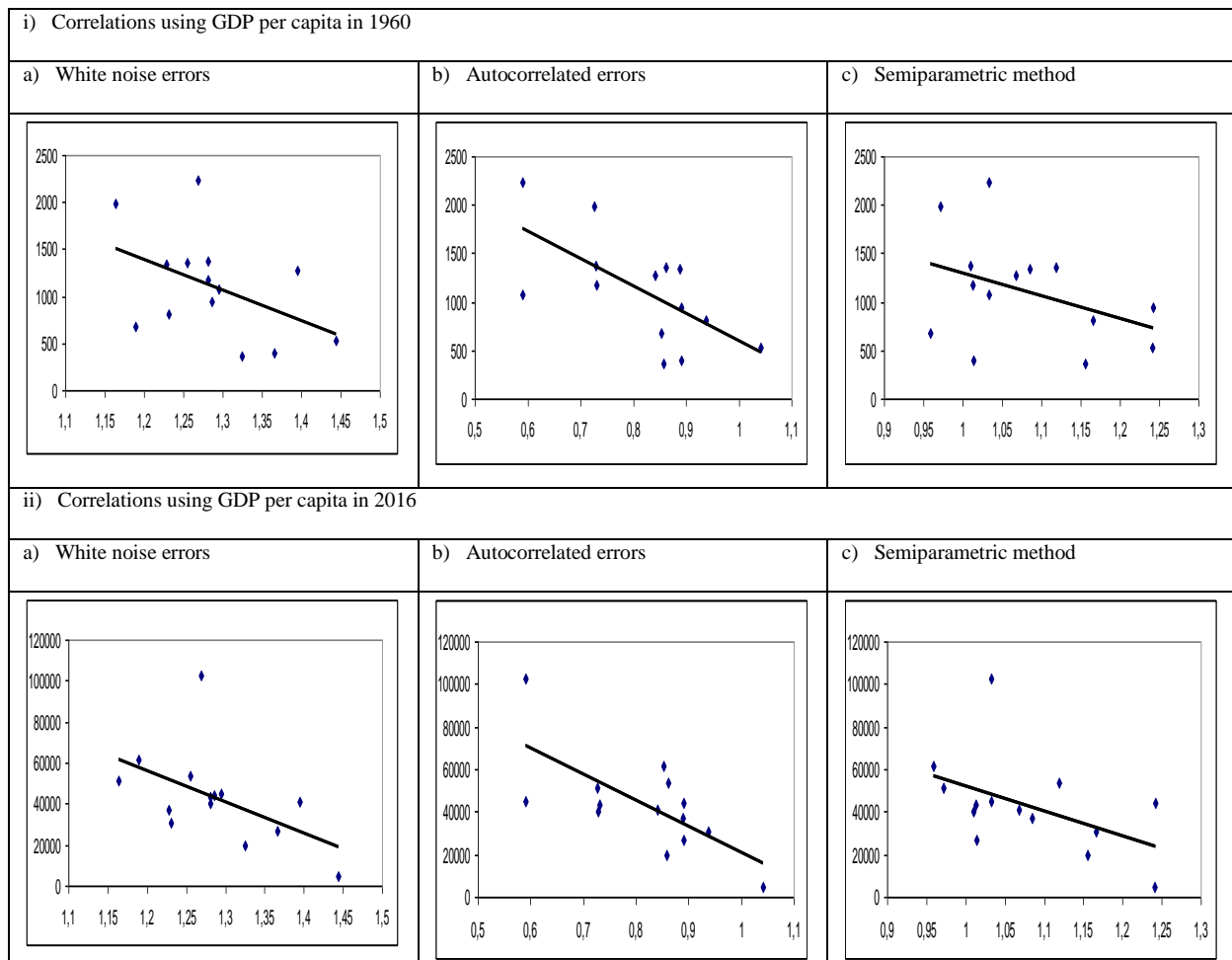a) White noise errors   b) Autocorrelated errors   c) Semiparametric method

Figure 2 shows the correlation between the time trend coefficients and the GDP per capita, focussing on the values of GDP per capita in 1960 in the upper half and those in 2016 in the bottom half. There is in all cases a significant negative correlation, implying that higher income countries are associated with lower time trend coefficients. Figure 3 displays instead the correlation between the degreeof persistence (i.e., the orderof integration) and GDP per capita.It is clear that there is a negative correlation between the two, i.e. higher orders of integration are found for countries with lower GDP per capita. In the case of developing economies institutional weakness is often thought of as a possible explanation for their lower ability to respond effectively to shocks and the higher persistence of their effects (see Fukuyama, 2014); in addition, higher macroeconomic volatility is also observed since the usual "shock absorbers" (financial markets to diversify risk and stabilization policies to counter shocks) are weaker (see Loayza et al., 2007). For European countries it is less obvious that the same reasons should apply. However, our evidence suggests that even in their case there still exist institutional, financial and policy differences leading to a less effective management of the economy in response to shocks in those with lower GDP per capita.

CONCLUSIONS

In this paper we have applied fractional integration methods to analyse the stochastic behaviour of GDP per capita in a group of fourteen European countries. For this purpose we have employed parametric, semiparametric and non-parametric techniques. We find in all cases orders of integration around 1, these being higher in less developed countries, which suggests a negative association with the level of GDP per capita. In other words, the empirical evidence points to a stylised fact, namely the existence of a negative correlation between the level of GDP per capita and its degree of persistence. This had already been observed in the case of developing countries and attributed to institutional weakness, a lower degree of financial development and less effective macro policies (see Loayza et al., 2007). Our analysis suggests that similar issues arise in the case of developed, European countries and that some of them are less capable of responding to shocks affecting the economy, and therefore are affected by them for a much longer period of time.

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[1] Unlike Robinson (1995b) these other methods require additional user-chosen parameters, and the results might be very sensitive to these values.

[2]The choice of the bandwidth (m) is important since it indicates the trade-off between bias and variance: the asymptotic variance is decreasing with m while the bias is growing with m. Some authors use m = $(T)^{0.5}$, in our case 7,54.