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.

Keywords: GDP per capita; Europe; time trends; persistence; long memory

JEL Classification: C22; E02; E69

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 non-stationary 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 non-stationary 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 non-stationary 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), Skare 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 paper also 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 technological progress and is specified as follows:

\[ y_t = \beta_0 + \beta_1 t + x_t, \quad (1) \]

\[(1 - L)^d x_t = u_t, \quad t = 0, 1, \ldots, \quad (2)\]

where \( y_t \) stands for GDP per capita; \( \beta_0 \) and \( \beta_1 \) 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 processes that are nevertheless mean-reverting (i.e., \( 0.5 \leq d < 1 \)). 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 nonstationary contexts. That is, we test the null hypothesis:

\[ H_0 : d = d_o , \quad (4) \]

Under the assumption that \( u_t \) in (3) is an uncorrelated (white noise) process. We examine the three standard cases of i) no deterministic terms (i.e., \( \beta_0 = \beta_1 = 0 \) in (3)), ii) an intercept (\( \beta_1 = 0 \)), and iii) an intercept with a linear time trend, and report in Table 1 along with the estimated values of \( d \), the 95% confidence bands of the non-rejection values of \( d \), using Robinson’s (1994) Lagrange Multiplier (LM) tests, which are validated in nonstationary contexts. That is, we test the null hypothesis:

\[ H_0 : d = d_o , \quad (4) \]

in (3), where \( d_o \) can be any real value. We choose \( d_o = 0, 0.01, 0.02, \ldots, (0.01), \ldots, 1.99 \) and 2; the non-rejection values of \( d \), in (4) at the 5% level are reported in the tables in brackets.

**DATA AND EMPIRICAL RESULTS**

We use annual data on GDP per capita (current US dollars), from 1960 to 2016, obtained from 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.

\[ y_t = \beta_0 + \beta_1 t + x_t, \quad (1 - L)^d x_t = u_t, \quad t = 1, 2, 3, \ldots \]

Under the assumption that \( u_t \) in (3) is an uncorrelated (white noise) process. We examine the three standard cases of i) no deterministic terms (i.e., \( \beta_0 = \beta_1 = 0 \) in (3)), ii) an intercept (\( \beta_1 = 0 \)), and iii) an intercept with a linear time trend, and report in Table 1 along with the estimated values of \( d \), the 95% confidence bands of the non-rejection values of \( d \), using Robinson’s (1994) Lagrange Multiplier (LM) tests, which are validated in nonstationary contexts. That is, we test the null hypothesis:

\[ H_0 : d = d_o , \quad (4) \]

in (3), where \( d_o \) can be any real value. We choose \( d_o = 0, 0.01, 0.02, \ldots, (0.01), \ldots, 1.99 \) and 2; the non-rejection values of \( d \), 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        | An intercept | 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)     |
| BELGIUM     | 1.395   | (1.173, 1.722)     | 7.11737 (81.84)     |
| DENMARK     | 1.255   | (1.072, 1.546)     | 7.13912 (79.95)     |
| FINLAND     | 1.281   | (1.058, 1.675)     | 6.99322 (69.10)     |
| FRANCE      | 1.228   | (1.046, 1.512)     | 7.13056 (76.99)     |
| GREECE      | 1.444   | (1.251, 1.733)     | 6.22933 (79.60)     |
| IRELAND     | 1.189   | (0.986, 1.501)     | 6.45112 (74.87)     |
| ITALY       | 1.231   | (1.063, 1.504)     | 6.6104 (70.14)      |
| LUXEMBOURG  | 1.269   | (1.035, 1.612)     | 7.07363 (76.47)     |
| NETHERLANDS | 1.295   | (1.117, 1.576)     | 6.89833 (72.27)     |
| PORTUGAL    | 1.325   | (1.046, 1.512)     | 7.13056 (76.99)     |
| SWEDEN      | 1.164   | (0.965, 1.494)     | 7.52621 (73.97)     |
| 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 trend coefficient is found to be statistically significant in all countries except Belgium, Greece and the UK, where the intercept is the only significant deterministic term. Note that his is selection is based on the t-values on the differenced series, i.e.,

\[(1 - L)^d y_t = \beta_0 + \beta_1 \tilde{t}_t + u_t, \quad t = 1, 2, ..., \tag{5}\]

where \(\tilde{t}_t = (1 - L)^d 1_t\) and 1, is a vector of ones, and \(\tilde{t}_t = (1 - L)^d 1_t\) and, since \(u_t \sim I(0)\) by construction.

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

| Country     | No terms | An intercept | 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    | (0.321, 1.217)| 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)| 0.865 (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)|
| SWEDEN      | 0.754    | (0.343, 1.206)| 0.764 (0.613, 1.172)| 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.
The results based on the assumption of autoregressed 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 estimates ranging from 0.060 (France and Sweden) to 0.076 (Spain). As for the orders of integration, the I(1) hypothesis cannot be rejected in any of 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 specification of the error term, next we estimate d using a semiparametric method, no functional form being imposed on the error term in this case. In particular, we use a “local” Whittle estimate, initially proposed by Robinson (1995b) and developed later by Velasco (1999), Shimotsu and Phillips (2005) and Abadir et al. (2007) among many others.1

### Table 4: Estimated coefficients 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 (78.20) | 0.06051 (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 (72.36) | 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 (69.17) | 0.07453 (13.10) |
| SWEDEN   | 0.727    | (0.479, 1.109) | 7.58813 (78.96) | 0.06471 (13.13) |
| 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.

### 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(1) behaviour with d > 1.
The results produced by this semiparametric method, for a selected group of bandwidth parameters, \( m = 5, 6, \ldots, 9 \) and \( 10 \), are displayed in Table 5. 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 \( 10 \)), the Netherlands (\( m = 9 \) and \( 10 \)) and the UK (\( m = 5 \)). In all these cases, the estimated value of \( d \) is significantly higher than 1.

| 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 6: Ranking of the time trend coefficients

| Parametric estimation | Autocorrelation (Bloomfield) | Semiparametric estimation |
|-----------------------|------------------------------|----------------------------|
| No autocorrelation    |                              |                            |
| 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 (1.251)         | 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 7: Ranking of the estimates of \( d \) (degree of persistence)

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 autocorrelated 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.
| AUSTRIA | BELGIUM | DENMARK |
|---------|---------|---------|
| ![Time series plot for Austria](image1) | ![Time series plot for Belgium](image2) | ![Time series plot for Denmark](image3) |
| FINLAND | FRANCE | GREECE |
| ![Time series plot for Finland](image4) | ![Time series plot for France](image5) | ![Time series plot for Greece](image6) |
| IRELAND | ITALY | LUXEMBOURG |
| ![Time series plot for Ireland](image7) | ![Time series plot for Italy](image8) | ![Time series plot for Luxembourg](image9) |

(cont.)

| NETHERLANDS | PORTUGAL | SPAIN |
|--------------|----------|-------|
| ![Time series plot for Netherlands](image10) | ![Time series plot for Portugal](image11) | ![Time series plot for Spain](image12) |

Figure 1: Time series plots (cont.)
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

table

ii) Correlations using GDP per capita in 2016
a) No autocorrelation
b) Autocorrelation

chart
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, focusing 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 degree of persistence (i.e., the order of 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 \( m = \left(T^{1/4}\right) \), in our case 7,54.