PERSISTENCE OF ECONOMIC COMPLEXITY IN OECD COUNTRIES

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ABSTRACT

Economic complexity refers to the level at which a country is able to mobilize its productive knowledge. Economic complexity is a vital predictive factor of variations in income, economic growth, emissions and income inequality Despite its importance, several aspects of economic complexity have not been explored in the literature including its persistence, which is important for policy modelling purpose. This article investigates the statistical properties of the economic complexity data in a group of 29 OECD countries, testing for their degree of persistence by looking at the order of integration of the series from a fractional integration viewpoint. The results vary substantially depending on the assumptions made on the error term; in particular, mean reversion is only found in the case of Chile if the errors are uncorrelated; however, if autocorrelation is permitted, mean reversion is found in a group of ten countries, namely, Australia, Canada, Colombia, France, Greece, Ireland, Israel, Norway, New Zealand and South Korea. Robust estimation is also conducted by means of non-parametric methods and non-linear structures are also incorporated in the model. Policy implications are derived at the end of the article.

Keywords: Economic complexity; long range dependence; persistence; fractional integration

JEL Classification: C22; C32

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1. Introduction

Economic complexity is a term that can be used to gauge the level at which a country is able to mobilize its productive knowledge. According to Hausmann et al. (2014), economic complexity measures a nation's productive output and it also indicates the arrangements that are in place to hold and integrate knowledge. Therefore, what countries know is reflected in what they make. Complex nations are the countries that can connect huge amounts of relevant knowledge together, among several networks of individuals, to create an assorted mixture of knowledge-intensive goods. On the other hand, simpler economies, only possess a smaller base of knowledge capacity and consequently, they generate simpler and fewer goods, that only requires finite networks of interaction. Enlarging economic complexity is essential for a country to be able to retain as well as adopt a higher level of productive knowledge (Hausmann et al., 2014).

The importance of economic complexity cannot be overemphasised. First, it measures the level and usage of knowledge in an economy. Secondly, it is associated with several macroeconomic variables. Productive capabilities are important to be able to understand economic development. Economic complexity is important as it provides explanation on the dissimilarities in the level of economic development of countries. The economic complexity measure comprises more information correlating to a nation's potential economic growth than the standard series utilised to compute human capital, including the level of formal schooling attainment by the working age population (Hausmann et al., 2014). Economic complexity contains more growth-related statistics than the six World Governance Indicators (including control of corruption, government effectiveness, regulatory quality, voice and accountability, political stability and rule of law), either individually or combined. (Hausmann et al., 2014). Thirdly, it reflects the level of infrastructure, quality of institutions, and research and development (R&D) expenditures (Hausmann and Hidalgo, 2011) in the production process. It has also been shown that complexity may affect the correlation between population growth and economic growth (Bucci et al., 2019).

There are several other economic insights of economic complexity. It has been argued that increases in economic complexity generate job opportunities and the production of wider range of sophisticated products (Vu, 2020). Besides, consumption of energy and emissions rise as a result of diversifying and refining of exporting goods. Therefore, economic complexity can be regarded as a vital contributor to environmental degradation (Li et al. 2021). The level of knowledge entrenched in the productive structure of complex economies encapsulates the needed knowledge for technologies aimed at cleaner production (Romero and Gramkow, 2021).

Due to the importance of economic complexity, several aspects of the subject-matter have been examined including its economic impacts. It has been shown that an increase in economic complexity in a country leads to an expansion in the real gross domestic product (GDP) of that country (Hausmann and Hidalgo, 2011). Expansion in economic complexity leads to a decrease in income inequality (Hartmann et al., 2017). Can and Gozgor (2017) show that economic complexity reduces CO_2 emissions. The trend of economic complexity has also been studied in the extant literature (Hausmann et al., 2014). Few empirical papers have also examined the economic determinants of economic complexity. For instance, Nguyen et al. (2020) showed that patents have a significantly positive effect on the economic complexity. Dung and Thanh (2021) demonstrated that institutional quality has a significant impact on economic complexity. Avom et al. (2021) demonstrated that volatility in both output and trade adversely impact economic complexity. Kamguia et al. (2021) observed that expansion in foreign generates a negative impact on economic complexity.

One of the aspects that has not been sufficiently explored in the existing literature is the persistence of economic complexity. Recent research such as the Tenreiro-Machado et al. (2020) used the fractional calculus (FC) and pseudo-phase space (PPS) techniques for the dynamics of world economies. David et al (2021) used the Auto-Regressive Integrated Moving Average (ARIMA), Auto-Regressive Fractionally Integrated Moving Average (ARFIMA), and Detrendd Fluctuation Analysis (DFA) methods to assess the price dynamics of cryptocurrencies (David et al., 2021). On the other hand, Tarasov (2020) used the fractional econophysics approach for the dynamics of market prices and the results show that when effects of memory are taken into account, developing better pricing strategies is possible.

The aim of the present article is to extend the existing literature on economic complexity by examining the time-series properties of the series. Our main contribution is that we investigate the persistence of economic complexities in 29 Organization for Economic Cooperation and Development (OECD) countries during the period 1964-2017. The importance of testing for persistence of economic complexity are numerous. Firstly, the existence of nonstationarity indicates that shocks arising from the policies aimed at increasing economic complexity will be permanent (Sidneva and Zivot, 2014). These are usually connected with improved infrastructure, improving institutional quality and investment in education and vocational training. Conversely, stationarity of economic complexity implies that policy shocks to economic complexity will have transient impacts. In this case, rolling short term and medium policies will be more relevant with regard to improving economic complexity. Moreover, the existence of nonstationarity in economic complexity series has vital consequences from an econometric viewpoint. Econometric methods such as ordinary least squares (OLS) approach are premised on the assumption of stationarity of the series being examined. Otherwise, spurious results can be yielded if economic complexity (which is part of the analysis) is actually nonstationary (Hendry and Juselius, 2000). Thirdly, testing for persistence is also essential for the purpose of forecasting economic complexity. The long-term forecasts are the extrapolated deterministic trend for both nonstationary and stationary series. Nevertheless, forecast uncertainty increases for a persistent series as the forecast horizon increases, while on the other hand, it is bounded for a mean-reverting series.

We adopt a fractional integration, which is a more flexible technique than the common approaches based on integer differentiation, using ARMA (d = 0)-ARIMA (d = 1) models. We have considered the OECD countries as a result of several reasons. OECD countries accounted for 63% of the global GDP (which amounted to gross domestic product of US$52 trillion (in 2010 prices)) in 2018 (World Bank, 2020). Secondly, OECD countries form a cluster of complex economies that produce diverse mix of knowledge-intensive products. Thirdly, OECD countries are armed with the best set of policies with which to improve their economic complexities. Many non-OECD countries look towards OECD countries when formulating policies to enhance their complexities.

There are three main contributions of the paper: 1) the analysis of the economic complexity from a different approach based on historical ttime series data; 2) the use of fractional integration methods, which is a relatively new technique that is more general and flexible than the classical approaches based on integer degrees of differentiation, and 3) the inclusion of non-linear models still within a long memory context with the advantagte that introduces a degree of smoothness in the treatment of potential breaks in the data. The paper is organized as follows. First, the methodology and data are presented in the next section. The third section discusses the empirical findings. Finally, the conclusions of this research are presented in the last section.

2. Methodology and data

2.1 Method

To know the statistical properties of a time series is important from various viewpoints. Starting from a statistical viewpoint, to know if it is covariance stationary is important if we need to make statistical inference. The classical approach focuses on distinguishing between series which are stationary I(0) or nonstationary I(1), ignoring potential fractional degrees of differentiation. If the latter is allowed, a greater degree of flexibility is permitted, and covariance stationarity holds if the order of integration, say d, is smaller than 0.5. Values of d equal to or above 0.5 indicate nonstationarity and the higher the value of d is, the higher the level of nonstationarity is in the sense that the variance of the partial sums increases in magnitude with d. From a policy perspective, d also plays a crucial role. Thus, if $d < 1$, the series displays mean reversion and shocks will have a transitory nature, disappearing in the long run. In this context we can have series which are nonstationary though mean reverting, with shocks having temporary but long lasting effects. In other words, we can classify the time series processes depending on the values of the differencing parameter d as follows:

$d < 0$: anti-persistence,

$d = 0$: I(0) or short memory behaviour,

$0 < d < 0.5$: stationary and long memory pattern,

$0.5 \leq d < 1$: nonstationarity and mean reversion, and

$d \geq 1$: lack of mean reversion.

In the empirical section, we consider the following two equations,

$$y_t = \alpha + \beta t + x_t; \qquad (1 - L)^d x_t = u_t, \qquad t = 0, 1, \ldots, \qquad (1)$$

where α and β are unknown coefficients associated to a constant and a linear time trend respectively; y_t refers to the economic complexity data, and the regression errors x_t are supposed to be I(d) where d is also estimated from the data.

The estimation of the fractional integration parameter d is based on the Whittle function, presented in the frequency domain as in Dahlhaus (1989) and using a testing approach developed in Robinson (1994) and widely used in empirical applications of fractional integration (see, e.g., Gil-Alana and Robinson, 1997). This method is based on testing the null hypothesis:

$$H_o \; : \; d \; = \; d_0, \tag{2}$$

for any real value d0 in Eq. (1). The testing procedure has a limiting standard Normal distribution, which holds indepently of the asumptions made on the deterministic terms in (1) and the assumptions made on the I(0) error term u_t. Moreover, it is very flexible and allows us consider nonstationary ($d \geq 0.5$) with no need of prior differentiation of the data and has an asymptotical stardand N(0,1) distribution unlike most unit root methods proposed in the literature.

2.2 Computation of economic complexity index

In order to successfully compute economic complexity, there is a need to determine both the complexity of locations and the economic activities taking place in such locations. This is because of the sophisticated nature of the subject-matter (Tenreiro Machado and Lopes, 2015; Lopes et al. 2019). The general notion is that the activities taking place, exported or produced from a place, convey information about such location's complexity. Moreover, the places where an activity is taking place convey information about the complexity needed to execute such activity (Hausmann et al. 2014). This foregoing idea can be converted into a cluster of equations that can be employed to compute economic complexities.

We assume that K_c is the complexity *K* of a location c (i.e., city or country) and K_p is the complexity *K* of an activity *p* (i.e., industry or product). Besides, we also assume

M_{cp} is a matrix capturing the activities, p, taking place in location, c. Generally, M_{cp} is defined as $M_{cp} = 1$ when the output arising from an activity in a location is greater than what is anticipated for an activity with the similar total output and a location of similar size. This is done via the use of the Revealed Comparative Advantage (RCA) of the location, Hausmann et al. 2014). The following mathematical expressions can be constructed:

$$K_c = f(M_{cp}, K_p), \tag{3}$$

$$K_p = g(M_{cp}, K_c), \tag{4}$$

where f and g are the parameters of functions. The assumption in equation (3) is that location's complexity is determined by the complexity, K_p, of the activities taking place in it, M_{cp}. The assumption in equation (4) is that complexity of an activity is determined by the complexity, K_c, of the locations where the activity is taking place, M_{cp}. The foregoing equations can be respectively expressed as:

$$K_c = f(M_{cp}, g(M_{cp}, K_c)), \tag{5}$$

$$K_p = g(M_{cp}, f(M_{cp}, K_p)), \tag{6}$$

The reduced form (or the linear equation equivalents) of the foregoing equations is respectively:

$$K_c = \tilde{M}_{cc}{}' K_c, \tag{7}$$

$$K_p = \tilde{M}_{pp}{}' K_p, \tag{8}$$

These linear equations suggests that the complexity of nations, or of the activities taking place in these nations, are eigenvectors of matrices linking countries that are related ($M_{cc}{}'$) or products that are related ($M_{pp}{}'$).

Based on the foregoing context, economic complexity index of a place can be regarded as the mean of the product complexity index of the activities taking place in such place (Hausmann and Hidalgo, 2011; Hausmann et al. 2014). Formally, the mean of economic complexity index formula is the solution to the following cluster of equations:

$$K_c = \frac{1}{M_c}\sum_p M_{cp}K_p, \tag{9}$$

$$K_p = \frac{1}{M_p}\sum_c M_{cp}K_c, \tag{10}$$

Inserting equation (10) in equation (9) is tantamount to diagonalizing the matrix below:

$$\tilde{M}_{cc}' = \sum_p \frac{M_{cp}M_{C'p}}{M_c M_p}' K_c, \tag{11}$$

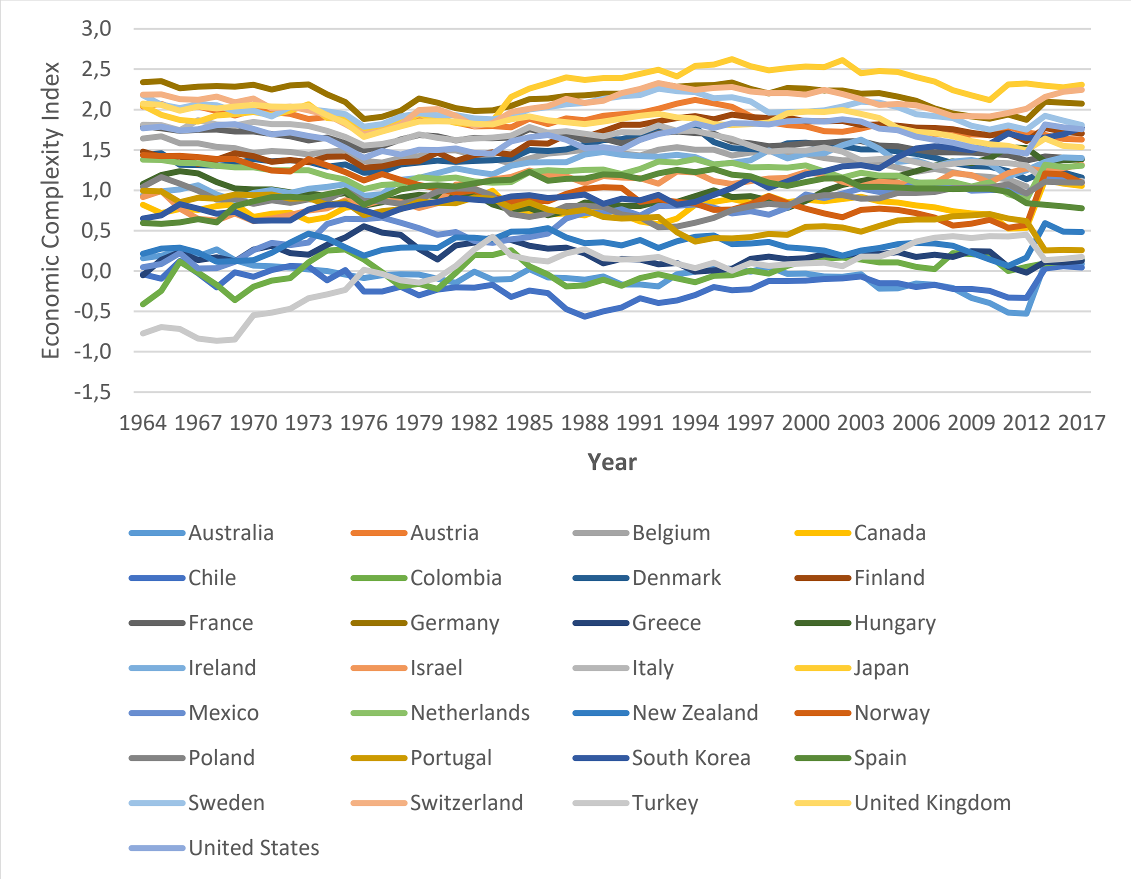
where $M_c = \sum_p M_{cp}$ is diversity or the number of activities taking place in a particular location and $M_p = \sum_c M_{cp}$ is the ubiquity or the number of locations that an activity is taking place. The results are then normalized using a Z-transform because economic complexity is a relative metric. Thus the following expression is obtained:

$$ECI = \frac{K_c - \tilde{K}_c}{\sigma(K_c)}, \tag{12}$$

where ECI is economic complexity index, $\tilde{K}_c$ is the mean of K_c and $\sigma(K_c)$ is the standard deviation of K_c.

2.3 Data description

Figure 1: Economic Complexity Index by country (1964-2017)



The data for the economic complexity index (see Figure 1), which has been used as a proxy for economic complexity, has been obtained from the Atlas of Economic Complexity that belongs to Hausmann et al. (2014). According to the index, a country that experiences higher level of economic complexity has become more complex. The economic complexity index is a measure that is premised on the scale for the "complexity" of goods in the export basket as well as covering a higher number of products. Economic complexity is a measure that takes into consideration the elements of "diversity" and "ubiquity" of the products that are exported by a country, these two characteristics being connected to each other (Hausmann et al., 2014). Diversity, in a country is the number of unique products that the country can make. Ubiquity is associated with the amount of knowledge that is needed for the production of each of these products. Therefore, the volume of knowledge that a nation possesses is reflected in the ubiquity and diversity of the products that such a nation produces (Hausmann et al., 2014). The economic complexity index is based on a unit variance and usually ranges between -2 and 2. A country's economic complexity level equals the world average if the country's economic complexity value in a year is zero. The data is for 1964-2017 for all the countries and the exception is Belgium with a dataset for 1964-2012. Other OECD countries which are not included do not have sufficient datasets for analysis.

The descriptive analysis is displayed in Table 1 and the mean statistics shows that Japan is the most complex country. This is not surprising given that Japan produces and exports several complex products including machines and appliances for specialized particular industries. The production of these products often requires specialised knowledge and skills. Coincidentally, Japan has the biggest real GDP after the USA and China (World Bank, 2020). Apart from Japan and the USA, the top 10 most complex economies are European countries. This is not unexpected as this continent has the largest number of countries with high productive knowledge in the world. Colombia has an average economic complexity level equal to the world average. The countries with an average of economic complexity level less than the world average include Australia, Chile and Turkey. It is also shown that Norway has the least skewed economic complexity index, while Turkey has the highest skewed economic complexity index. **PLEASE REVISE THIS SENTENCE. SOMETHING SEEMS TO BE WRONG.**

Table 1: Descriptive statistics

Country	Starting	Ending	Max. value	Min. value	Mean	Std. Dev.	Kurtosiss	Skewness
AUSTRIA	2.04	1.63	2.12	1.63	1.86	0.13	1.52	-0.77
AUSTRALIA	0.16	0.09	0.27	-0.53	-0.05	0.16	-0.94	0.16

BELGIUM	1.64	1.05	1.67	1.05	1.42	0.13	1.02	-0.90
CANADA	0.82	1.06	1.13	0.53	0.80	0.13	0.48	0.27
CHILE	-0.04	0.04	0.12	-0.57	-0.18	0.15	-0.14	-0.22
COLOMBIA	-0.41	0.14	0.27	-0.41	0.00	0.16	-0.40	-0.39
DENMARK	1.44	1.16	1.78	1.14	1.43	0.15	-0.35	0.39
FRANCE	1.79	1.39	1.79	1.37	1.61	0.11	-1.55	-0.13
FINLAND	1.48	1.71	1.94	1.28	1.63	0.21	-0.58	-0.48
GERMANY	2.34	2.08	2.35	1.87	2.16	0.14	-0.85	-0.55
GREECE	-0.05	0.13	0.56	-0.05	0.21	0.13	0.36	0.46
HUNGARY	1.08	1.38	1.53	0.69	1.03	0.21	-0.42	0.71
ITALY	1.81	1.12	1.87	1.11	1.59	0.20	-0.98	-0.43
IRELAND	0.94	1.40	1.63	0.88	1.26	0.19	-0.69	-0.76
ISRAEL	0.91	1.31	1.31	0.62	1.03	0.20	-0.27	-0.78
JAPAN	2.05	2.31	2.62	1.72	2.21	0.27	-1.44	-0.20
MEXICO	0.05	1.10	1.16	0.03	0.66	0.32	-0.82	-0.37
NETHERLAND	1.38	1.30	1.39	0.89	1.21	0.11	0.14	-0.68
NORWAY	1.44	1.09	1.44	0.54	0.98	0.26	-0.14	0.03
NEW ZEALAND	0.21	0.48	0.59	0.06	0.32	0.11	-1.02	0.22
PORTUGAL	0.99	0.26	0.99	0.26	0.69	0.20	-0.22	-0.46
POLAND	1.04	1.09	1.16	0.54	0.89	0.15	-0.59	-0.48
SPAIN	0.59	0.78	1.26	0.58	1	0.18	-0.63	0.80
SOUTH KOREA	0.65	1.78	1.78	0.62	1.04	0.33	0.08	-0.85
SWEDEN	2.18	1.81	2.26	1.75	1.99	0.12	-0.48	0.08
SWITZERLAND	2.19	2.24	2.33	1.69	2.07	0.15	-0.34	-0.54
TURKEY	-0.77	0.18	0.45	-0.86	-0.01	0.36	0.26	-1.07
U.K.	2.07	1.53	2.07	1.49	1.85	0.15	-0.29	-0.62
U.S.A.	1.77	1.76	1.88	1.40	1.67	0.14	-1.31	-0.25

4. Empirical results

We consider the model given by the equations in (1). We estimate the differencing parameter d under three characterizations: i) when α and β are assumed to be 0 a priori. that is. imposing no deterministic components in the model in (1). ii) with β = 0 a priori.

that is. allowing for a constant. and iii) allowing for a linear time trend by estimating α and β freely from the data. The results in terms of the estimation of d for each of these three cases are reported across Tables 2 – 5. In Tables 2 and 3 we suppose u_t in (1) is a white noise process. while in Tables 4 and 5 weak autocorrelation is permitted throughout the spectral modelling approximation of Bloomfield (1973). The latter is an approximation to the AutoRegressive (AR) structure. requiring fewer parameters and it being stationary for all its values.

Table 2: Estimates of d: White noise errors

Country	No terms	Intercept	Intercept + time trend
AUSTRIA	0.91 (0.72. 1.19)	**0.93 (0.70. 1.22)**	0.93 (0.72. 1.22)
AUSTRALIA	**0.85 (0.60. 1.16)**	0.78 (0.54. 1.13)	0.78 (0.54. 1.13)
BELGIUM	0.83 (0.60. 1.17)	**1.00 (0.82. 1.23)**	1.00 (0.82. 1.23)
CANADA	0.86 (0.68. 1.09)	**0.65 (0.32. 1.04)**	0.65 (0.32. 1.04)
CHILE	**0.70 (0.53. 0.95)**	0.72 (0.55. 0.96)	0.72 (0.55. 0.96)
COLOMBIA	0.69 (0.33. 1.23)	**0.95 (0.32. 1.53)**	0.95 (0.32. 1.53)
DENMARK	0.87 (0.68. 1.14)	**1.06 (0.91. 1.28)**	1.06 (0.91. 1.28)
FRANCE	0.91 (0.73. 1.17)	0.87 (0.63. 1.25)	**0.88 (0.65. 1.25)**
FINLAND	0.84 (0.63. 1.10)	**0.89 (0.78. 1.04)**	0.88 (0.77. 1.04)
GERMANY	0.94 (0.75. 1.20)	**0.99 (0.78. 1.30)**	0.99 (0.78. 1.30)
GREECE	**0.84 (0.64. 1.19)**	0.85 (0.57. 1.28)	0.86 (0.59. 1.27)
HUNGARY	0.99 (0.80. 1.30)	**1.06 (0.89. 1.37)**	1.06 (0.89. 1.38)
ITALY	0.92 (0.75. 1.19)	0.90 (0.75. 1.16)	**0.90 (0.72. 1.17)**
IRELAND	0.94 (0.71. 1.22)	0.81 (0.63. 1.16)	**0.82 (0.62. 1.16)**
ISRAEL	0.84 (0.54. 1.21)	**0.84 (0.68. 1.12)**	0.83 (0.62. 1.12)
JAPAN	0.86 (0.66. 1.14)	**1.03 (0.86. 1.29)**	1.03 (0.85. 1.29)
MEXICO	0.83 (0.58. 1.17)	0.84 (0.64. 1.18)	**0.85 (0.60. 1.17)**
NETHERLAND	0.94 (0.77. 1.19)	**0.74 (0.54. 1.01)**	0.74 (0.54. 1.01)
NORWAY	0.96 (0.81. 1.17)	**0.87 (0.67. 1.19)**	0.87 (0.65. 1.19)
NEW ZEALAND	0.88 (0.59. 1.27)	**0.76 (0.36. 1.25)**	0.78 (0.43. 1.25)
PORTUGAL	0.84 (0.65. 1.13)	0.88 (0.62. 1.17)	**0.90 (0.67. 1.17)**
POLAND	0.98 (0.76. 1.29)	**0.98 (0.79. 1.31)**	0.98 (0.79. 1.31)

SPAIN	0.92 (0.77. 1.13)	**0.98 (0.86. 1.17)**	0.98 (0.85. 1.17)
SOUTH KOREA	0.97 (0.79. 1.26)	0.86 (0.74. 1.08)	**0.83 (0.69. 1.09)**
SWEDEN	0.87 (0.69. 1.11)	**0.98 (0.76. 1.29)**	0.98 (0.78. 1.29)
SWITZERLAND	0.96 (0.77. 1.22)	**1.18 (0.94. 1.55)**	1.18 (0.94. 1.55)
TURKEY	0.98 (0.82. 1.22)	**0.98 (0.78. 1.27)**	0.98 (0.79. 1.27)
U.K.	0.91 (0.63. 1.18)	**1.05 (0.81. 1.37)**	1.05 (0.82. 1.37)
U.S.A.	0.95 (0.76. 1.20)	**0.95 (0.75. 1.23)**	0.95 (0.75. 1.23)

The values in parenthesis refer to the 95% confidence intervals. In bold. the specification selected based on the t-values of the deterministic terms.

We have marked in bold in Table 2 for each series the most appropriate specification in relation with the deterministic terms. This has been made based on the t-values of the estimated coefficients in the d-differenced processes.

Table 3: Estimated coefficients: White noise errors

Country	No terms	Intercept	Intercept + time trend
AUSTRIA	0.93 (0.70. 1.22)	2.0359 (36.03)	---
AUSTRALIA	0.85 (0.60. 1.16)	---	---
BELGIUM	1.00 (0.82. 1.23)	1.6402 (11.04)	---
CANADA	0.65 (0.32. 1.04)	0.8009 (8.91)	---
CHILE	0.70 (0.53. 0.95)	---	---
COLOMBIA	0.95 (0.32. 1.53)	-0.4031 (-3.47)	---
DENMARK	1.06 (0.91. 1.28)	1.4373 (25.48)	---
FRANCE	0.88 (0.65. 1.25)	1.7946 (43.08)	-0.0075 (-1.96)
FINLAND	0.89 (0.78. 1.04)	1.4721 (25.08)	---
GERMANY	0.99 (0.78. 1.30)	2.3393 (34.44)	
GREECE	0.84 (0.64. 1.19)	---	---
HUNGARY	1.06 (0.89. 1.37)	1.0753 (15.77)	---
ITALY	0.90 (0.72. 1.17)	1.8299 (32.11)	-0.0133 (-2.46)
IRELAND	0.82 (0.62. 1.16)	0.9336 (13.28)	0.0091 (1.68)
ISRAEL	0.84 (0.68. 1.12)	0.9083 (12.21)	---
JAPAN	1.03 (0.86. 1.29)	2.0552 (24.30)	---
MEXICO	0.85 (0.60. 1.17)	0.0362 (0.44)	0.0207 (3.06)
NETHERLAND	0.74 (0.54. 1.01)	1.3509 (19.10)	---

NORWAY	0.87 (0.67. 1.19)	1.4225 (13.21)	---
NEW ZEALAND	0.76 (0.36. 1.25)	0.2327 (2.79)	---
PORTUGAL	0.90 (0.67. 1.17)	1.0064 (12.92)	-0.0136 (-1.78)
POLAND	0.98 (0.79. 1.31)	1.0416 (14.63)	---
SPAIN	0.98 (0.86. 1.17)	0.5949 (9.71)	---
SOUTH KOREA	0.83 (0.69. 1.09)	0.6282 (9.46)	0.0212 (4.08)
SWEDEN	0.98 (0.76. 1.29)	2.1722 (34.98)	---
SWITZERLAND	1.18 (0.94. 1.55)	2.1910 (33.32)	---
TURKEY	0.98 (0.78. 1.27)	-0.7683 (-7.51)	---
U.K.	1.05 (0.81. 1.37)	2.0766 (36.49)	---
U.S.A.	0.95 (0.75. 1.23)	1.7668 (23.36)	---

The t-values on columns 3 and 4 are the corresponding t-values.

We start presenting the results under the assumption of white noise errors. We observe that except for Chile. all the other series support the I(1) hypothesis. the values of d ranging from 0.65 (Canada) and 0.70 (Chile) to 1.18 (Switzerland). Note that in the case of Canada. in spite of presenting the lowest value of d. the null hypothesis of a unit root (i.e.. d = 1) cannot be rejected since the 95% confidence interval includes the value 1. Focussing on the linear trend coefficients. displayed in Table 3. we notice that for three series (Ireland. Mexico and South Korea) the coefficient is significantly positive. while for another three countries (France. Italy and Portugal). it is significantly negative.

Table 4: Estimates of d: Autocorrelated errors

Country	No terms	Intercept	Intercept + time trend
AUSTRIA	0.71 (0.22. 1.18)	0.53 (-0.04. 1.21)	**0.69 (0.25. 1.21)**
AUSTRALIA	0.27 (-0.08. 1.09)	0.30 (-0.11. 0.80)	**-0.15 (-0.56. 0.77)**
BELGIUM	0.31 (-0.06. 0.79)	0.75 (-0.84. 1.28)	**0.89 (-0.37. 1.28)**
CANADA	0.91 (0.35. 1.58)	-0.42 (-0.82. 0.44)	**-0.56 (-1.31. 0.54)**
CHILE	**0.57 (0.21. 1.10)**	0.64 (0.29. 1.13)	0.64 (0.27. 1.13)
COLOMBIA	-0.23 (-0.62. 0.24)	-0.23 (-0.58. 0.23)	**-0.46 (-0.94. 0.23)**
DENMARK	0.60 (0.06. 1.10)	**1.07 (0.77. 1.46)**	1.08 (0.79. 1.48)

FRANCE	0.73 (0.30. 1.23)	0.44 (0.06. 0.91)	**0.45 (0.03. 0.91)**
FINLAND	0.65 (0.17. 1.22)	**1.33 (1.08. 1.64)**	1.33 (1.08. 1.68)
GERMANY	0.77 (0.22. 1.24)	**0.66 (0.04. 1.18)**	0.71 (0.34. 1.19)
GREECE	0.45 (0.11. 0.84)	**0.38 (0.08. 0.85)**	0.32 (-0.17. 0.85)
HUNGARY	0.74 (0.50. 1.16)	**0.80 (0.57. 1.09)**	0.78 (0.51. 1.08)
ITALY	0.71 (0.34. 1.17)	0.72 (0.38. 1.11)	**0.70 (0.39. 1.13)**
IRELAND	0.51 (0.11. 1.26)	0.53 (0.37. 0.78)	**0.47 (0.22. 0.79)**
ISRAEL	0.16 (0.09. 0.78)	0.59 (0.39. 0.94)	**0.37 (0.03. 0.93)**
JAPAN	0.62 (0.12. 1.15)	**0.92 (0.66. 1.30)**	0.92 (0.60. 1.31)
MEXICO	0.41 (0.22. 1.07)	0.49 (0.27. 1.08)	**0.14 (-0.63. 1.05)**
NETHERLAND	0.82 (-0.02. 0.41)	**0.45 (-0.10. 1.03)**	0.48 (0.04. 1.02)
NORWAY	1.05 (0.61. 1.57)	0.54 (0.34. 0.89)	**0.29 (-0.32. 0.83)**
NEW ZEALAND	-0.02 (-0.15. 0.72)	**-0.04 (-0.30. 0.38)**	0.01 (-0.29. 0.51)
PORTUGAL	0.57 (0.28. 1.26)	0.44 (0.20. 1.41)	**0.59 (-0.10. 1.42)**
POLAND	0.64 (0.33. 0.78)	**0.75 (0.45. 1.13)**	0.75 (0.45. 1.13)
SPAIN	0.88 (0.54. 1.21)	**1.01 (0.75. 1.30)**	1.01 (0.77. 1.29)
SOUTH KOREA	0.80 (0.57. 1.25)	0.78 (0.60. 0.99)	**0.70 (0.45. 1.00)**
SWEDEN	0.75 (0.02. 1.26)	**0.81 (0.28 1.27)**	0.82 (0.45 1.26)
SWITZERLAND	0.79 (0.10. 1.33)	**0.69 (0.30. 1.15)**	0.69 (0.26. 1.15)
TURKEY	1.00 (0.50. 1.54)	0.73 (0.46. 1.12)	**0.74 (0.44. 1.11)**
U.K.	0.73 (0.19. 1.22)	0.48 (-0.22. 1.29)	**0.69 (0.20. 1.28)**
U.S.A.	0.83 (0.17. 1.47)	**0.74 (0.28. 1.31)**	0.74 (0.28. 1.31)

The values in parenthesis refer to the 95% confidence intervals. In bold. the specification selected based on the t-values of the deterministic terms.

Table 5: Estimated coefficients: Autocorrelated errors

Country	No terms	Intercept	Intercept + time trend
AUSTRIA	0.69 (0.25. 1.21)	2.0421 (39.03)	-0.0071 (-2.59)
AUSTRALIA	-0.15 (-0.56. 0.77)	0.1070 (5.44)	-0.0062 (-9.10)
BELGIUM	0.89 (-0.37. 1.28)	1.6790 (11.28)	-0.0292 (-2.06)
CANADA	-0.56 (-1.31. 0.54)	0.7581 (123.45)	0.0013 (5.15)
CHILE	0.57 (0.21. 1.10)	---	---
COLOMBIA	-0.46 (-0.94. 0.23)	-0.1132 (-13.13)	0.0043 (12.89)
DENMARK	1.07 (0.77. 1.46)	2.3014 (38.21)	---
FRANCE	0.45 (0.03. 0.91)	1.7756 (60.72)	-0.0065 (-6.44)

FINLAND	1.33 (1.08. 1.64)	1.4951 (28.06)	---
GERMANY	0.66 (0.04. 1.18)	0.1683 (4.13)	---
GREECE	0.38 (0.08. 0.85)	1.0927 (16.98)	---
HUNGARY	0.80 (0.57. 1.09)	1.0927 (16.98)	---
ITALY	0.70 (0.39. 1.13)	1.8426 (35.97)	-0.0126 (-4.59)
IRELAND	0.47 (0.22. 0.79)	0.9686 (18.76)	0.0094 (5.19)
ISRAEL	0.37 (0.03. 0.93)	0.7846 (16.56)	0.0096 (6.23)
JAPAN	0.92 (0.66. 1.30)	2.0428 (24.35)	---
MEXICO	0.14 (-0.63. 1.05)	0.1306 (4.21)	0.0199 (20.32)
NETHERLAND	0.45 (-0.10. 1.03)	1.2696 (28.46)	---
NORWAY	0.29 (-0.32. 0.83)	1.3573 (23.63)	-0.0126 (-6.97)
NEW ZEALAND	-0.04 (-0.30. 0.38)	0.3200 (30.87)	---
PORTUGAL	0.59 (-0.10. 1.42)	0.9945 (14.97)	-0.0119 (-4.27)
POLAND	0.75 (0.45. 1.13)	1.0315 (15.81)	---
SPAIN	1.01 (0.75. 1.30)	0.5927 (9.67)	---
SOUTH KOREA	0.70 (0.45. 1.00)	0.6189 (9.91)	0.0206 (6.14)
SWEDEN	0.81 (0.28 1.27)	2.1410 (35.72)	---
SWITZERLAND	0.69 (0.30. 1.15)	2.1534 (37.88)	---
TURKEY	0.74 (0.44. 1.11)	-0.7628 (-7.87)	0.0202 (3.49)
U.K.	0.69 (0.20. 1.28)	2.0763 (39.87)	-0.0094 (-3.44)
U.S.A.	0.74 (0.28. 1.31)	1.7544 (25.27)	---

The t-values on columns 3 and 4 are the corresponding t-values.

Allowing for autocorrelation (Tables 4 and 5) there are more significant time coefficients (positive in 7 cases and negative in 8). Looking at the orders of integration. the values of d are now smaller than in the previous case. and we observe that 10 out of the 28 series examined display reversion to the mean (i.e., estimates of d significantly below 1); half of them include the I(0) (short memory) hypothesis (Australia. Canada. Colombia. Norway and New Zealand); the other 5 series displaying mean reversion present a long memory (d > 0) pattern. They are France. Greece. Ireland. Israel and South Korea. For Austria. Chile. Denmark. Germany. Hungary. Italy. Poland. Spain. Sweden

Switzerland. Turkey. the UK and the USA. the I(1) hypothesis cannot be rejected. while d > 1 is statistically supported in the case of Finland. For the remaining four countries. Belgium. Mexico. Netherlands and Portugal. the confidence intervals are so wide that neither the I(0) and the I(1) hypotheses can be rejected.

Since there are no similar studies in the literature. it will be difficult to compare the comparative analysis of the results of this paper. However, the empirical findings can be compared with previous thoughts. The results are in tandem with Hsu et al. (2008)'s hypothesis that posits that bigger series will be more persistent. Shocks to a bigger series will generate in a larger departure from the long-run equilibrium route. as it is harder for complex countries to quickly go back to long-run equilibrium (Hsu et al., 2008). Japan. Germany. Switzerland. Sweden and Austria are the most complex countries and they are all very persistent. The results are not generally consistent with the notion of Narayan et al. (2008) which posits that high volatile series will be more persistent. South Korea. Mexico and Norway are among the top 5 countries with the most volatile economic complexities; however, the series are mean reverting. showing lower degrees of persistence.

As a robustness method in relation with the differencing parameter, we also employ a non-parametric approach. In particular, we employ a version of the Hurst exponent (Hurst, 1951), testing the hypothesis of short memory (H= 0.5 or d = 0) against long memory (H > 0.5, $d > 0$) or anti-persistence (H < 0.5) $d < 0$). Note that H is the Hurst exponent and is related with d through the following relationship,

$$H = d + 0.5.$$

We use the modified R/S statistic (Lo, 1991) that is described as:

$$Q_T(q) = \frac{1}{\hat{\sigma}_T(q)} \left(\max_{1 \le k \le T} \sum_{j=1}^{k} (y_t - \bar{y}) - \min_{1 \le k \le T} \sum_{j=1}^{k} (y_t - \bar{y}) \right), \tag{13}$$

where

$$\hat{\sigma}_T^2(q) = \hat{\sigma}_y^2 + 2\sum_{j=1}^{q}\omega_j(q)\hat{\gamma}_j; \qquad \omega_j = 1 - \frac{j}{q+1}, \quad 1 \leq j > T, \tag{14}$$

$$\hat{\sigma}_T^2(q) = \hat{\sigma}_x^2 + 2\sum_{j=1}^{q}\omega_j(q)\hat{\gamma}_j \quad \text{and} \quad \omega_j(q) = 1 - \frac{j}{q+1}, \quad 1 \leq j < T,$$

where y_t is a stationary series ($-0.5 < d < 0.5$) of sample size T, with sample mean $\bar{y}$ and simple variance $\hat{\sigma}_y^2$, and simple autocovariance at lag j given by $\hat{\gamma}_j$. The test statistic is further normalized as

$$V_T(q) = \frac{Q_T(q)}{\sqrt{T}}. \tag{15}$$

An advantage of this statistic is that it allows us to obtain a simple formula for the differencing parameter *d*, since

$$d = \frac{\log Q_T(q)}{\log T}, \tag{16}$$

Thus, if $q = 0$, it corresponds to the classic Hurst–Mandelbrot R/S statistic (Hurst, 1951). The null hypothesis of I(0) behaviour includes weakly autocorrelated (e.g., ARMA) strucutres, though, as pointed out by Haubrich and Lo (2001), it does not contain a trend-stationary model. The limit distribution of $V_T(q)$ is derived in Lo (1991) and the 95% confidence interval with equal probabilities in both tails is [0.809, 1.862]. Several Monte Carlo experiments conducted, for example, by Teverovsky et al. (1999) showed that this method is biased in favor of accepting the null of no long memory when the bandwidth parameter *q* increases. Thus, using Lo's modified method in isolation can distort the results. Thus, we report the results for a selected number of the bandwidth parameter q = 1, 2, 3, 5 and 7. The results are reported in Table 6. The upper parameter refers to the test statistic while the lower part refers to the estimated value of d. We observe a higher level of persistence in all cases with the estimates of d being close to 1 in the majority of the cases and evidence of mean reversion is only found in the cases of Mexico and the US for some specific bandwidth numbers.

Table 6: Estimates of d based on the non-parametric R/S approach

Series	q = 0 (modified Lo)	q = 1	q = 2	q = 3	q = 5	q = 7
AUSTRIA	1.357 (1.07)	1.345 (1.07)	1.316 (1.06)	1.372 (1.08)	1.450 (1.09)	1.585 (1.11)
AUSTRALIA	0.928 (0.98)	0.937 (0.98)	0.993 (0.99)	1.040 (1.01)	1.167 (1.04)	1.364 (1.07)
BELGIUM	1.291 (1.06)	1.255 (1.05)	1.298 (1.06)	1.352 (1.07)	1.506 (1.10)	1.263 (1.06)
CANADA	0.923 (0.98)	0.960 (0.99)	0.960 (0.99)	0.987 (0.99)	1.050 (1.01)	1.067 (1.01)
CHILE	0.886 (0.96)	1.051 (1.01)	1.171 (1.04)	1.142 (1.03)	1.215 (1.05)	1.334 (1.07)
COLOMBIA	1.256 (1.05)	1.100 (1.02)	1.056 (1.01)	1.179 (1.02)	1.112 (1.02)	1.083 (1.02)
DENMARK	1.607 (1.12)	1.560 (1.11)	1.521 (1.10)	1.468 (1.09)	1.472 (1.10)	1.372 (1.08)
FRANCE	1.213 (1.05)	1.178 (1.04)	1.192 (1.04)	1.262 (1.06)	1.722 (1.13)	1.677 (1.13)
FINLAND	1.307 (1.06)	1.570 (1.11)	1.582 (1.11)	1.524 (1.10)	1.359 (1.09)	1.241 (1.05)
GERMANY	1.138 (1.03)	1.091 (1.02)	1.060 (1.01)	1.099 (1.02)	1.156 (1.04)	1.219 (1.05)
GREECE	1.164 (1.03)	1.178 (1.04)	1.187 (1.04)	1.290 (1.06)	1.466 (1.09)	1.448 (1.09)
HUNGARY	1.404 (1.08)	1.124 (1.03)	1.329 (1.07)	1.328 (1.07)	1.365 (1.08)	1.314 (1.06)
ITALY	1.169 (1.04)	1.180 (1.04)	1.191 (1.04)	1.223 (1.05)	1.336 (1.07)	1.401 (1.08)
IRELAND	1.005 (1.00)	0.991 (0.99)	1.092 (1.02)	1.224 (1.05)	1.314 (1.07)	1.436 (1.09)
ISRAEL	0.910 (0.97)	0.918 (0.97)	1.000 (1.00)	1.054 (1.01)	1.040 (1.01)	1.124 (1.02)
JAPAN	1.319 (1.07)	1.276 (1.06)	1.229 (1.05)	1.262 (1.06)	1.304 (1.06)	1.258 (1.05)
MEXICO	**0.787 (0.94)**	**0.792 (0.94)**	**0.802 (0.95)**	0.814 (0.95)	0.844 (0.95)	1.197 (1.04)
NETHERLAND	0.833 (0.95)	0.898 (0.97)	0.970 (0.99)	1.006 (1.01)	1.080 (1.01)	1.084 (1.02)
NORWAY	0.867 (0.96)	0.850 (0.95)	0.918 (0.97)	0.967 (0.99)	1.016 (1.00)	1.119 (1.03)
NEW ZEALAND	0.929 (0.98)	0.895 (0.97)	0.932 (0.98)	1.011 (1.00)	1.242 (1.05)	1.625 (1.12)
PORTUGAL	1.018 (1.00)	1.049 (1.01)	1.035 (1.00)	1.043 (1.01)	1.055 (1.01)	1.178 (1.04)
POLAND	1.264 (1.06)	1.208 (1.04)	1.161 (1.03)	1.226 (1.05)	1.429 (1.09)	1.401 (1.08)
SPAIN	1.294 (1.06)	1.313 (1.07)	1.319 (1.07)	1.312 (1.07)	1.263 (1.06)	1.148 (1.03)
SOUTH KOREA	1.232	1.265	1.359	1.506	1.613	1.545

	(1.05)	(1.05)	(1.07)	(1.10)	(1.12)	(1.11)
SWEDEN	1.312 (1.07)	1.284 (1.06)	1.273 (1.06)	1.284 (1.06)	1.356 (1.07)	1.455 (1.09)
SWITZERLAND	1.256 (1.05)	1.100 (1.02)	1.056 (1.01)	1.079 (1.02)	1.112 (1.02)	1.083 (1.02)
TURKEY	1.372 (1.08)	1.321 (1.07)	1.334 (1.07)	1.394 (1.08)	1.455 (1.09)	1.444 (1.09)
U.K.	1.483 (1.10)	1.386 (1.08)	1.332 (1.07)	1.340 (1.07)	1.462 (1.09)	1.734 (1.14)
U.S.A.	0.882 (0.96)	0.877 (0.96)	0.860 (0.96)	**0.803** **(0.96)**	0.899 (0.97)	**0.784** **(0.98)**

The 95% confidence interval with equal probabilities in both tails is [0.809, 1.862]. The values in parenthesis refer to the estimates of d. In bold, evidence of mean reversion

As a final approach, the possibility of breaks in the data must also be taken into account. However, rather than using structural breaks that produced abrupt changes in the behaviour of the models (in particular, in relation with the degree of persistence d) we use a non-linear approach based on Chebyshev polynomials in time and that was developed in Cuestas and Gil-Alana (2016). Using this approach, we consider a model of form:

$$y_t \;=\; \sum_{i=0}^{m} \theta_i \, P_{iT}(t) \;+\; x_t\,; \qquad (1 - L)^d x_t \;=\; u_t, \qquad t \;=\; 1,\, 2,\, \dots, \qquad (17)$$

with m indicating the order of the Chebyshev polynomial in time $P_{i,T}(t)$ defined as:

$$P_{0,T}(t) \;=\; 1,$$

$$P_{i,T}(t) \;=\; \sqrt{2}\cos\big(i\,\pi\,(t - 0.5)/T\big), \qquad t \;=\; 1,\, 2,\, \dots,\, T; \quad i \;=\; 1,\, 2,\, \dots \qquad (18)$$

According to Bierens (1997) and Tomasevic and Stanivuk (2009) it is possible to approximate highly non-linear trends with rather low degree polynomials. If $m = 0$ the model contains an intercept; if $m = 1$ it also includes a linear trend, and if $m > 1$ it becomes non-linear - the higher m is the less linear the approximated deterministic component becomes.[1] Specifically, we use the method developed in Cuestas and Gil-Alana (2016)

[1] See Hamming (1973) and Smyth (1998) for a detailed description of these polynomials.

which is essentially an extension to the non-linear case of the Robinson's (1994) fractional integration (linear) approach.

The first thing we observe is that there are five countries where mean reversion is observed, i.e., with estimates of d significantly smaller than 1. They are Chile (with d = 0.52), Finland (0.26), Netherlands (0.60), Spain (0.67) and South Korea (0.29), and in the latter case the null hypothesis of I(0) behaviour (i.e., d = 0) cannot be rejected. For the rest of the countries, the confidence intervals are wide and the unit root null hypothesis (d = 1) cannot be rejected. Focussing on the coefficients for the deterministic terms, the intercept (θ_0) is significant in the majority of the cases; also the time trend coefficient (θ_1) is significant in many cases; strong evidence of non-linearities (i.e., with both θ_2 and θ_3 statistically significant) is found in the cases of Belgium, Finland, Italy, Japan, South Korea and Turkey. For another group of fourteen countries (Chile, Denmark, France, Germany, Greece, Hungary, Ireland, Norway, Poland, Spain, Sweden, Switzerland, UK and USA) only one of the two non-linear coefficients is found to be statistically significant, while for the remaining 9 countries (Austria, Australia, Canada, Colombia, Israel, Mexico, Netherlands, New Zeeland and Portugal) both coefficients are insignificant and thus, no evidence of non-linear structures.

Table 7: Estimates of d using the non-linear Chebyshev polynomials in time

Series	d	θ_0	θ_1	θ_2	θ_3
AUSTRIA	0.80 (0.53, 1.16)	**0.00172** **(5.38)**	0.00029 (1.04)	-0.00017 (-0.65)	-0.00005 (-0.15)
AUSTRALIA	0.71 (0.26, 1.08)	-0.00302 (-0.18)	0.06411 (0.69)	0.03110 (0.49)	0.04843 (1.01)
BELGIUM	0.36 (0.34, 1.11)	**1.42229** **(70.83)**	**0.08911** **(8.68)**	**-0.03381** **(-2.95)**	**0.07903** **(7.81)**
CANADA	0.65 (0.33, 1.04)	**0.82984** **(6.19)**	-0.03269 (-0.43)	0.01709 (0.31)	0.01315 (-0.31)
CHILE	0.52 (0.21, 0.87)	**0.19328** **(2.39)**	0.00845 (0.17)	**0.10247** **(2.73)**	0.02813 (0.64)

COLOMBIA	0.94 (0.33, 1.52)	-0.23841 (-0.63)	-0.07762 (-0.35)	0.01014 (0.08)	-0.04371 (-0.05)
DENMARK	0.65 (0.30, 1.09)	**1.44985** **(22.17)**	-0.01142 (-0.31)	**-0.10440** **(-3.95)**	0.08951 (-0.29)
FRANCE	0.73 (0.36, 1.20)	**1.63712** **(24.38)**	**0.08580** **(2.28)**	-0.03022 (-1.20)	**0.04337** **(2.29)**
FINLAND	0.26 (0.07, 0.51)	**1.63039** **(102.30)**	**-0.17048** **(-14.56)**	**-0.06544** **(-6.23)**	**0.08695** **(9.03)**
GERMANY	0.75 (0.35, 1.16)	**2.17025** **(19.25)**	0.02918 (0.46)	-0.01245 (-0.30)	**0.10328** **(3.35)**
GREECE	0.71 (0.39, 1.23)	0.10722 (0.85)	0.03309 (0.49)	-0.02842 (-0.59)	**-0.06534** **(-1.79)**
HUNGARY	0.70 (0.31, 1.24)	**1.02556** **(10.73)**	**-0.09475** **(-1.77)**	**0.16995** **(4.62)**	-0.01789 (-0.63)
ITALY	0.71 (0.41, 1.10)	**1.58403** **(19.35)**	**0.17278** **(3.77)**	**-0.06934** **(-2.22)**	**0.05927** **(2.50)**
IRELAND	0.51 (0.13, 1.05)	**1.27000** **(23.28)**	**-0.15396** **(-4.76)**	**-0.08935** **(-3.48)**	0.01771 (0.83)
ISRAEL	0.75 (0.49, 1.07)	**1.17418** **(8.85)**	**-0.13837** **(-1.86)**	-0.05426 (-1.11)	-0.02053 (-0.56)
JAPAN	0.67 (0.32, 1.11)	**2.24930** **(21.15)**	**-0.20024** **(-3.35)**	**-0.06851** **(-2.10)**	**0.11623** **(3.56)**
MEXICO	0.87 (0.62, 1.18)	**0.57103** **(2.70)**	**-0.30050** **(-2.50)**	-0.01632 (-0.23)	-0.04538 (-0.92)
NETHERLAND	0.60 (0.32, 0.93)	**1.24959** **(15.62)**	**0.18865** **(1.67)**	0.09386 (1.29)	0.00301 (0.05)
NORWAY	0.77 (0.45, 1.14)	**1.02967** **(5.11)**	0.01465 (0.32)	-0.00093 (-0.02)	**0.06530** **(2.40)**
NEW ZEALAND	0.70 (0.18, 1.22)	**0.35132** **(2.69)**	-0.02071 (-0.28)	-0.03773 (-0.75)	-0.03665 (-0.95)
PORTUGAL	0.91 (0.67, 1.16)	**0.73200** **(3.18)**	0.17669 (1.34)	0.02587 (0.35)	-0.02104 (-0.41)
POLAND	0.82 (0.47, 1.26)	**0.93365** **(6.15)**	-0.00504 (-0.05)	**0.11378** **(2.17)**	-0.03092 (-0.82)
SPAIN	0.67 (0.41, 0.99)	**0.95048** **(12.42)**	**-0.07137** **(-1.66)**	**-0.16036** **(-5.29)**	-0.00688 (-0.29)
SOUTH KOREA	0.29 (-0.06, 0.85)	**1.0446** **(45.76)**	**-0.30228** **(-18.61)**	**0.10873** **(7.49)**	**-0.06589** **(-5.05)**
SWEDEN	0.73 (0.41, 1.18)	**2.05238** **(20.97)**	0.02858 (0.52)	-0.05171 (1.41)	**0.08198** **(2.97)**
SWITZERLAND	1.08 (0.77, 1.43)	**2.11449** **(6.38)**	-0.02440 (-0.12)	-0.02757 (-0.30)	**0.10390** **(1.77)**
TURKEY	0.67 (0.22, 1.08)	-0.01127 (-0.08)	**0.26299** **(3.64)**	**-0.14586** **(-2.86)**	**-0.13509** **(-3.42)**
U.K.	0.87 (0.50, 1.31)	**1.84219** **(12.95)**	0.09735 (1.20)	-0.02455 (-0.52)	**0.09003** **(2.72)**
U.S.A.	0.76 (0.38, 1.10)	**1.66305** **(12.71)**	-0.04065 (-0.55)	0.02314 (0.48)	**0.09888** **(2.80)**

5. Conclusions

In this article we have investigated the level of persistence in the series corresponding to the economic complexity data of 29 OECD countries. For this purpose, I(d) or fractional integration techniques have been employed. The results are very heterogeneous depending on what specification we make for the error term. Thus, if no autocorrelation is permitted, mean reversion (i.e. evidence of d statistically smaller than 1) is only obtained for the case of Chile. However, if autocorrelation is allowed, this hypothesis cannot be rejected in ten countries, namely, Australia, Canada, Colombia, France, Greece, Ireland, Israel, Norway, New Zealand and South Korea. As a robustness method, non-parametric approaches were also conducted and the results further supported the hypothesis of lack of mean reversion with shocks having permanent effects in the majority of the cases. If non-linear trends are permitted some evidence of it is found in a number of cases (in all except in nine of the series examined) which tends to support the hypothesis of overestimation in the degree of persistence if non-linear structures are not considered.

The implication of the foregoing results is that long term policies aimed at promoting economic complexity in 13 countries might be effective. Hence, there might a need for long term policies that improve economic complexity, which include better infrastructure, improving institutional quality and investment in education and vocational training. Better infrastructure could create innovative potential for light manufacturers, which will increase the productive capacity of a country. Improving institutional quality may generate an atmosphere in which a broader array of creative and, moreover, more complex activities can flourish. Investment in education and vocational training may lead to innovation through the creation of new knowledge. A skilled profession requires specific vocational training.

For the countries with mean reverting economic complexities, there might be a need for rolling short term and medium-term policies to improve economic complexities in these countries. These policies include tax policies and reduction in regulatory barriers. Tax policies include the introduction of tax incentives that enhance productive capacities, while phasing out taxes and reforming the costly subsidies that give rise to resource misallocation and foster brain drain. There might also be a need to reduce regulatory barriers because an economy characterised by state controls is likely to restrain creativity from individuals and entrepreneurs. An atmosphere that inspires self-employment and business creation might foster greater productive output in an economy, since these policies are short-term and medium-term policies in nature, they should be rolling in nature. Although most of these variables are already high within the OECD, further improvements in these series might have the desirable impact on economic complexity. For instance, there are several Vocational Education and Training (VET) schemes in OECD countries.

From a methodological viewpoint this paper can be extended in several directions. Thus, for example the dimensionality issue (dimensionality measures) can be examined in future papers. Focussing on the statistical properties of the series under examination and following the line of research “ Let the data speak by themselves “, alternative non-linear trends like those based on Fourier functions (Gil-Alana and Yaya, 2021) or neural networks (Yaya et al., 2021) can also be employed. In addition, the examination of structural breaks in these long series will be investigated.

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