PERSISTENCE AND NON-STATIONARITY IN THE BUILT-UP LAND FOOTPRINT ACROSS 89 COUNTRIES

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ABSTRACT

This paper deals with the analysis of the degree of persistence and nonstationarity in the built-up land footprint time series referring to 89 countries all over the world. Using long memory and fractional integration methods the results indicate the existence of positive trends in 57 of the countries examined, while 7 series display negative trends. Dealing with persistence we observe a large of degree of heterogeneity across countries, with some countries displaying short memory patterns, while others showing orders of integration significantly higher than 1.

Keywords: built up footprint, long memory; persistence; fractional integration

JEL Classification: C22; Q57

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1. Introduction

The importance of the built-up land footprint -which captures the demand for biologically productive areas used for infrastructures, such as roads, carparks, houses and buildings and industrial structures- continues to rise over time. Although the built up footprint is the smallest of all the six components of the ecological footprint, it has experienced the highest growth rate of the six[1]. It has increased from about 81 million global hectares in 1961 to about 473 million global hectares in 2016 (Global Footprint Network, 2019). Built-up areas which chiefly determine the built up footprint continue to encroach on areas meant for agriculture and grazing land. Since human settlements historically congregated on the most arable land, several of the present built-up areas are occupying former cropland (York et al., 2003; National Footprint Accounts, 2018).

Commercial and residential expansions in hitherto agricultural zones frequently result in harmful impacts on agro-ecological areas, which further act as pull factors for extra facilities, more degradation as well as more population (Yar and Huafu, 2019; Yuan et al., 2019). Since fertile lands are more productive than other categories of land, a level of consumption that requires one hectare of fertile land would have an ecological footprint greater than one hectare (York et al., 2003). Built-up areas have both direct and indirect adverse effects on the natural habitat. The direct effect of the expansion of built-up areas on natural habitat loss is triggered by the conversion of natural habitat into built-up areas, while the indirect impacts arise from changing agricultural land into built-up area and the consequent change of natural habitat into agricultural land elsewhere as a compensation (Ke et al., 2018).

Due to the growing importance of the built up footprint, several aspects of the environmental indicator have been investigated in the literature including its trend (Fu et

[1] The remaining components are cropland, grazing land, carbon footprint, forest products and fishing grounds footprints.

al. 2015). The determinants of the built up footprint have also been investigated in the extant literature and the factors are urban population (Jorgenson and Rice, 2005; Marquart-Pyatt, 2010; Denny and Marquart-Pyatt, 2018), income inequality, land area, and world-system status (Marquart-Pyatt, 2010), GDP, total population, population density, and the length of coastline of a country (Denny and Marquart-Pyatt, 2018). The economic and environmental impacts of the built up footprint have also been investigated and it has been shown that the built up footprint increases land surface temperature (Morabito et al., 2016). One of the aspects that has been largely overlooked in the literature is the persistence of the built up footprint as the papers on the subject-matter are limited (Ulucak and Lin, 2017; Yilanci et al., 2019). Persistence happens in a series when the mean of the series changes with time. When a series is persistent, the series is also considered to be nonstaionary because a non-stationary series also has different mean values over time. The literature on persistence of pollution indicators is dominated by the papers on the persistence of CO_2 emissions (Christidou et al., 2013; Barros et al., 2016; Belbute and Pereira, 2017) and the ecological footprint (Solarin and Bello, 2018; and Ozcan et al., 2019). Much research has been conducted on the stationarity / non-stationarity of the ecological footprint, as well as some of its six components. Thus, for example, Solarin and Bello (2018) and Ozcan et al. (2019) tested the stationarity of the ecological footprint in a significant number of countries. The former study concludes that most of the 128 countries examined (96) have a nonstationary behaviour. The empirical results in Ozcan et al. (2019) show nonstationarity for low-middle-income countries and stationarity for most other high-income, middle-high, and low-income economies.

The carbon footprint is the component with the greatest weight in the ecological footprint. Perhaps for this reason CO_2 emissions have been widely analysed as an environmental indicator benchmark. In this context we can mention the work by

Christidou et al. (2013) which, using a non-linear panel unit root test, showed the stationarity of CO_2 emissions from 33 countries. Using other statistical methods, Lee et al. (2008) noted that relative CO_2 emissions per capita from 21 OECD countries were stationary and stochastically converged. The results in Belbute and Pereira (2017), with fractional integration techniques indicated that the global CO_2 emissions were stationary. On the other hand, there are many studies that show the nonstationarity of CO_2 emissions (Criado and Grether, 2011; Herrerías, 2013; Li and Lin, 2013; Presno et al., 2018; Jaunky, 2011; Yamazaki et al., 2014; etc.). Barros (2016) also concluded the nonstationarity of CO_2 emissions, but unlike previous authors, this is the only one that uses fractional integration methods.

Solarin et al. (2019) focused its study on the stationarity or nonstationarity properties of the carbon footprint. These authors, using fractional integration, rejected the stationarity hypothesis in the 92 countries analyzed. In addition, they showed that the highest degrees of persistence occur in the carbon footprint series of high-income level countries.

Finally, we have only found very few papers that specifically analyse the other components of the ecological footprint. Ulucak and Lin (2017) and Yilanci et al. (2019) examined the stationarity of the ecological footprint as well as its six elements. In the first of these two papers the authors show the nonstationarity character of the carbon footprint, the grazing land footprint, the forest footprint, the built-up land footprint and the fishing footprint. Yilanci et al. (2019) used a panel stationary test with both smooth and sharp breaks to show that all the components of the ecological footprint display stationarity with the exception of fishing grounds.

The trend that the ecological footprint has followed over the years is quite different from the trend that has been observed for the built-up footprint (Global Footprint

Network, 2019). The policy aimed at addressing each type of footprint differs. For instance, policies associated with urban centers can be applied to address the built-up footprint, policies associated with agriculture can be applied for both cropland and forest footprints. The dimension of each component differs across countries (Marquart-Pyatt, 2010) and their determinants also differ (Denny and Marquart-Pyatt, 2018). Therefore, the results obtained for the aggregate footprint might not be relevant for all the components including the built-up footprint[2].

There are several benefits of finding out whether the built up footprint treads a nonstationary path or a stationary pattern. Firstly, the existence of a non-stationary built-up footprint connotes that policy shocks to the built-up footprint resulting from the utilization of technologies and innovations (including the use of recyclable building materials and the use of the state-of-the-art lighting and optimizing daylighting) that lower the impact of built-up activities on nature will be permanent (McKitrick, 2007). An example of such technologies is the aerogel based on the high silica content precursor, which provides an innovative option for improved thermal performance for the existing building infrastructure (Buildup, 2016). Secondly, the existence of unit roots in the built-up footprint series has significant implications for the environmental Kuznets curve (EKC) papers that have used (or will use) the built-up footprint as an indicator of environmental degradation. Some of these studies including the work of Marquart-Pyatt (2010) have assumed that there is trend stationarity in the pollution indicators. Using a non-stationary built-up footprint series at levels in a regression, while the other variables including income and demographic variables are nonstationary, is likely to yield spurious inference. In other words, statistical methods such as the ordinary least squares (OLS)

[2] Besides, there are differences in the ways that each component of the footprint is calculated. Unlike most of the other components of the ecological footprint, the National Footprint Accounts (2018) do not track imports and exports of built-up land, although built-up land is embodied in goods that are traded internationally.

that are premised on the assumption that all the variables under investigation do not contain unit roots could produce spurious regression inferences, if the time series for pollution indices have stochastic trends.[3] Thus, the classical diagnostic tests which are usually employed to assess the reliability of the OLS estimates will suggest a statistically significant relationship in the series when there is no actual relationship between the data-generating processes (Hendry and Juselius, 2000). The dynamic ordinary least squares (DOLS) of Stock and Watson (1993) operates under the premise that all variables in the analysis including pollution indicators should achieve stationarity at first differences.

Thirdly, distinguishing between trend and difference stationary processes is vital for gauging the likely long-term effect of environmental blueprints as they depend on the projection of future pollution figures and evaluating the precision of these projections. For both nonstationary and stationary series, the long-term projections are the inferred deterministic trend. Uncertainty in forecasting nonstationary variables increases as the time horizon of the forecasts increases. On the other hand, series that are mean-reverting are not affected by forecast uncertainty. Thus, the long-term effects of a policy are more certain when the series are stationary than when they are persistent (Gil-Alana and Solarin, 2018). Fourthly, if the built-up footprint series of several countries or regions are difference stationary at level, there is very limited chance of convergence between them and thus any conclusion of convergence on the relative built-up footprint is, at best, weak (Nieswiadomy and Strazicich, 2004).

The objective of this research is to add to the literature on the nonstationarity of pollution indicators in two distinct ways. It first investigates the stationarity of the built-up footprint in 89 nations, which is likely to provide new information on a series that has

[3] OLS is among the methods that was utilised in the study of Marquart-Pyatt (2010), and it was the only method used in Morabito et al. (2016).

been virtually overlooked in the extant literature. The characteristics of the built-up footprint differ across nations, and thus blueprints that are suitable for OECD countries or the US may not essentially be appropriate for other nations. Therefore, the empirical findings from the present exercise are likely to serve as direction for several nations on whether their officials should introduce new environmental blueprints aimed at decreasing their built-up footprint or let the domestic dynamics of these nations mechanically tackle any upsurge in the built-up footprint. The other contribution of this study is the utilization of fractional integration methods which, according to the information available to the authors, has not been sufficiently utilized in the extant literature to investigate stationarity of the ecological footprint or its components. The only exception is the paper of Solarin et al. (2019) but that paper focussed on the carbon footprint. Fractional integration is a novel technique that outperforms standard unit root methods in the sense that they are merely particular cases of the I(d) case where d can be any integer or fractional value. Thus, these classical methods consider stationarity if d = 0 and nonstationarity if d = 1. In the fractional case, this flexibility allows us to consider a wide variety of alternatives that include long memory stationarity (if $0 < d < 0.5$), nonstationarity and mean reversion though with long lasting effects (if $0.5 \leq d < 1$), and nonstationarity and non-mean-reversion if $d \geq 1$.

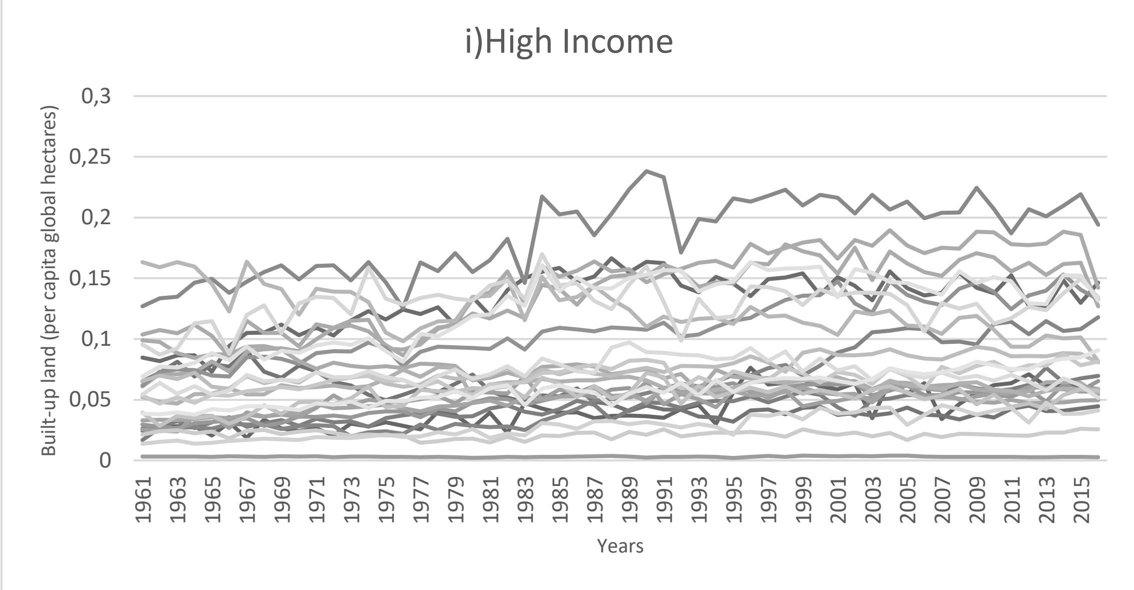
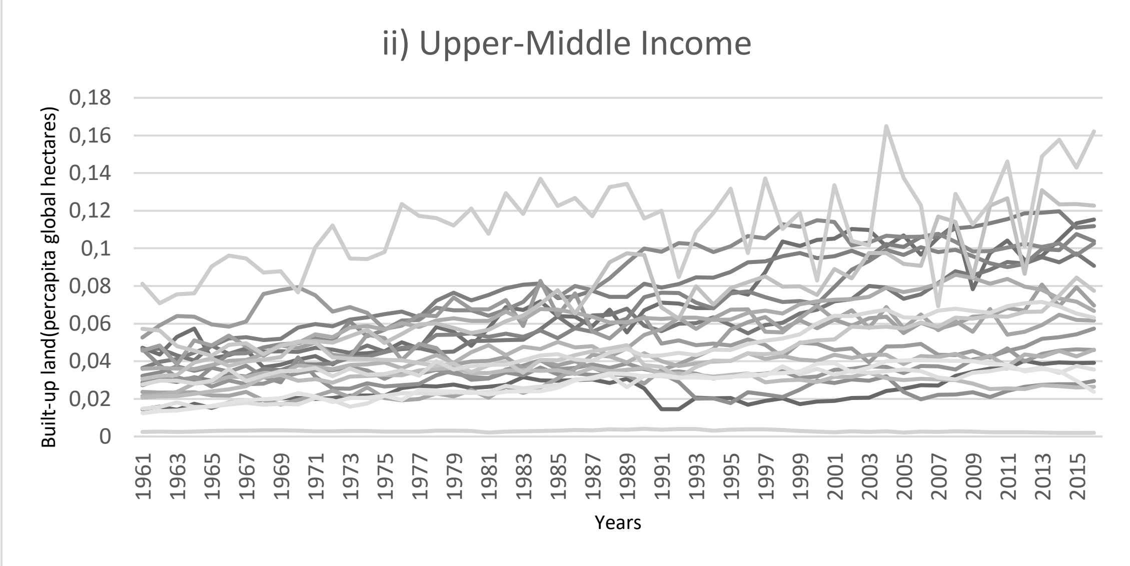
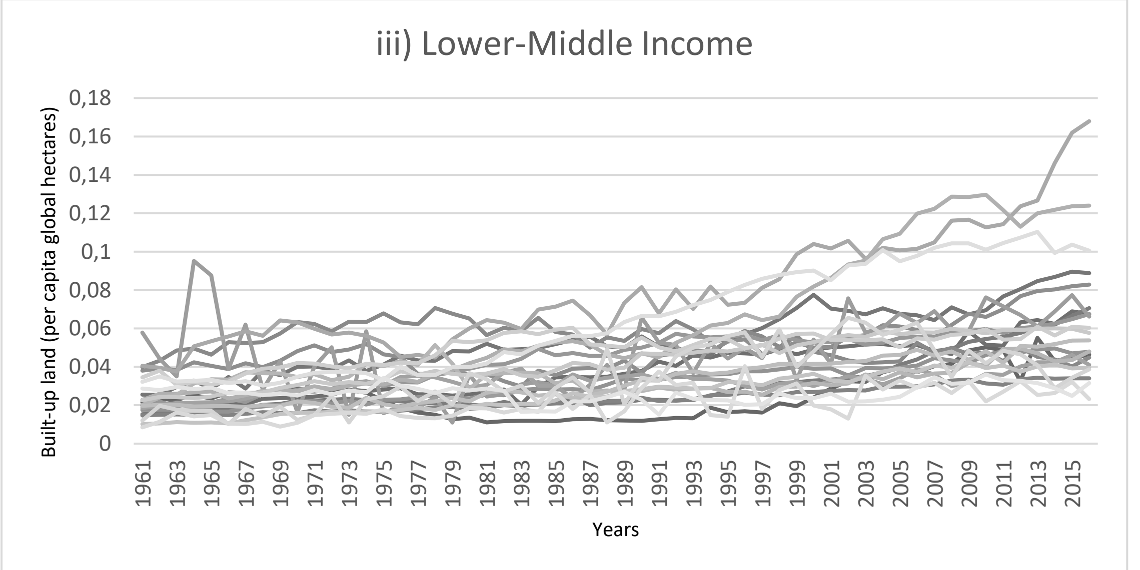
~~The objetives of this study are …. **Solarin ?????**~~ **(Please check line 157)**

The other parts of this paper are arranged as follows: Section 2 provides the data and the methodology adopted in this study. Section 3 reports the results; Section 4 present the discussion of the results, and Section 5 concludes the paper.

2. Material and Methods

We generated the annual dataset of built up footprint in per capita global hectares from the website of the Global Footprint Network (2019)[4]. We have included 89 countries and the global-level dataset for the 1961 to 2016 period due to data availability. Table 1 contains countries' names abbreviations. The trend of the series has been displayed in Figure 1 and an increase in built up footprint is shown to be widespread across different countries. It is noted that most countries in each of the groups have growth in built up footprint over the period considered. In all groups there is positive average growth. The highest average growth rate (1.74%) occurs in the lower middle-income group of countries.

[4] The details on how the built-up footprint footprint is computed can be found in Global Footprint Network (2019).

Maximum: 0.23817251 Minimum: 0.00203361 Average growth rate (%): 0.80817838	
Maximum: 0.16494226 Minimum: 0.0019212 Average growth rate (%): 1.20487459	
Maximum: 0.1619424 Minimum: 0.00850281 Average growth rate (%): 1.74447189	

Maximum: 0,11284443

Minimum: 0,00658281

Average growth rate (%): 0,91237949

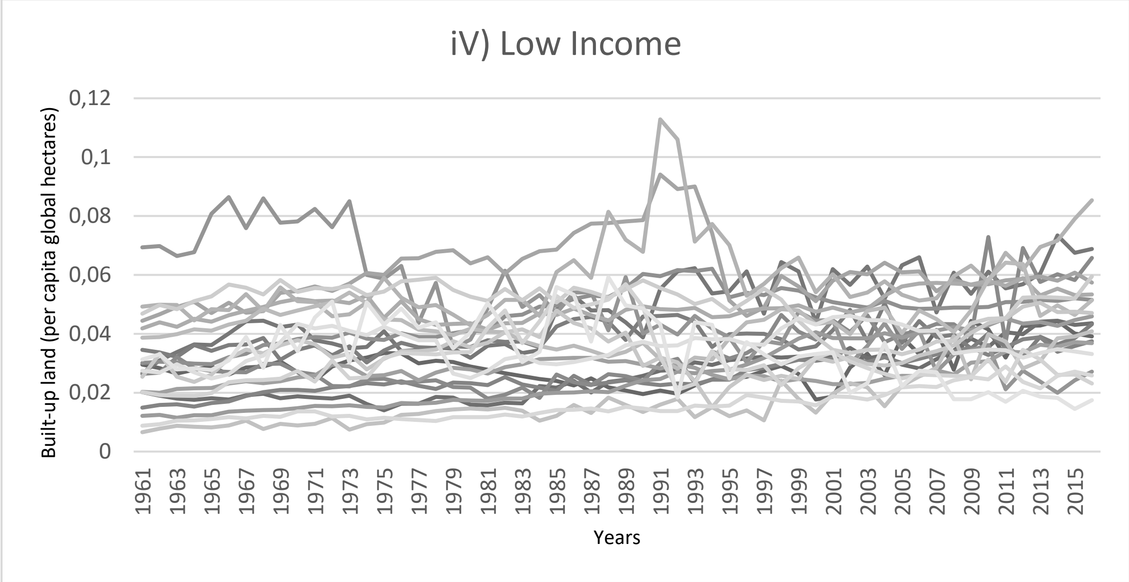


Figure 1: Built-up land according countries income (1961-2016, per capita global hectares)

Carmen, what should we do with figure 1 according to Reviewer 4?

Table 1: Countries and abbrevations

Abbrev.	Country	Abbrev.	Country	Abbrev.	Country
AFG	Afghanistan	GAM	Gambia	NOR	Norway
ALB	Albania	GER	Germany	PAK	Pakistan
ANG	Angola	GHA	Ghana	PAN	Panama
ARG	Argentina	GRE	Greece	PAR	Paraguay
AUS	Australia	GUA	Guadeloupe	PER	Peru
AUST	Austria	GUI	Guinea	PHI	Philippines
BAR	Barbados	GUY	Guyana	POL	Poland
BEL	Belgium	HAI	Haiti	POR	Portugal
BEN	Benin	IND	India	ROM	Romania
BOL	Bolivia	INDO	Indonesia	RWA	Rwanda
BRA	Brazil	ISR	Israel	SAI	Saint Lucia
BUR	Burkina Faso	ITA	Italy	SIE	Sierra Leone
BURU	Burundi	JAP	Japan	SOM	Somalia
CAD	Côte d'Ivoire	JOR	Jordan	SPA	Spain
CAM	Cameroon	KEN	Kenya	SRI	Sri Lanka
CAN	Canada	KOR	North Korea	SWE	Sweden
CEN	Central Af. Rep.	KORE	South Korea	SWI	Switzerland

CHA	Chad	LAO	Lao People R.	SYR	Syrian Arab R.
CHI	Chile	LEB	Lebanon	THA	Thailand
CHIN	China	LUX	Luxembourg	TOG	Togo
COL	Colombia	MAD	Madagascar	TUN	Tunisia
CONGO	Congo	MAL	Malaysia	TUR	Turkey
CONGOD	Congo Dem. R.	MALI	Mali	UGA	Uganda
COS	Costa Rica	MEX	Mexico	UNI	United Kingdom
CUB	Cuba	MOZ	Mozambique	UNIT	U. S. A.
DEN	Denmark	MYA	Myanmar	VEN	Venezuela,
DOM	Dominican R.	NET	Netherlands	VIE	Viet Nam
ELS	El Salvador	NIC	Nicaragua	WORLD	World
FIJ	Fiji	NIG	Niger	YEM	Yemen
FRA	FRANCE	NIGE	Nigeria	ZIM	Zimbabwe

Similarly to Belbute and Pereira (2017) and Solarin et al. (2019), we also use fractional integration. In particular, we implement a simple version of the tests of Robinson (1994), which is based on the Whittle function in the frequency domain (Dahlhaus, 1989). This method tests the null hypothesis:

$$H_o : \ d = d_o \tag{1}$$

for any real value d_o, in the model given by:

$$(1 - B)^d x_t = u_t , \qquad t = 1, 2, ..., \tag{2}$$

where u_t is supposed to be I(0) (in particular, white noise), and where x_t can be the errors in a regression model of form:

$$y_t = \beta^T z_t + x_t ; \qquad t = 1, 2, ..., \tag{3}$$

where z_t is a vector of deterministic terms (that might include an intercept, a linear rend or any other deterministic terms), and y_t is the series under investigation.

Remember that in this context of fractional integration or I(d) processes, if d = 0 in (2), x_t is said to be short memory, in the sense that the dependence across time between the observation is small, and the autocorrelations decay exponentially fast; however, if $d > 0$, x_t is long memory, the time dependence is higher and the autocorrelations decay hyperbolically slow; also, second order stationary is satisfied if $d < 0.5$ and nonstationarity takes place if $d \geq 0.5$, in fact, the series is said to be "more nonstationarity" as we depart above from 0.5 in the sense that the variance of the partial sums increase in magnitude with d; finally, if d is smaller than 1, x_t is mean reverting, with shocks having a temporary effect and disappearing faster as lower is the value of d; on the other hand, if $d \geq 1$, x_t is non-mean-reverting.

Robinson's (1994) tests have various advantages with respect to other approaches. First, it can be computed for any real value d_o, and thus, it is not constrained to the stationary region ($d < 0.5$) as is the case in most other procedures. Moreover, it has a standard null limit distribution (N(0,1)) and this limit behaviour is unaffected by the inclusion of deterministic terms like those in (3). Finally, from a statistical viewpoint, it is the most efficient method in the Pitman sense against local departures from the null. (See Gil-Alana and Robinson, 1997, for the specific functional form of this method).

3. Results

Across Table 2 we display the estimates of d (and the 95% confidence intervals of the non-rejection values of d using the tests of Robinson, 1994), in the model given by the equations (2) and (3) with $z_t = (1, t)^T$, i.e.,

$$y_t = \beta_1 + \beta_2 t + x_t, \qquad (1 - B)^d x_t = u_t, \qquad t = 1, 2, ..., \qquad (4)$$

where β_1 and β_2 are unknown coefficients to be estimated from the data along with the differencing parameter d. We report the results for the three classical cases of i) no deterministic terms, i.e., $\beta_1 = \beta_2 = 0$ a priori in (4); ii) an intercept (β_1 estimated and $\beta_2 = 0$ a priori); and with an intercept and a linear time trend (both coefficients unknown and estimated from the data), and reported in the table in bold, the selected cases among these three specifications.

We observe in Table 2 that the time trend is required in 65 out of the 89 countries examined and the estimated values of d widely range from -0.12 (Tunisia) and 1.21 (Cameroon). Table 3 displays the estimated coefficients for each country.

Table 2: Estimates of d for each country

	No terms	An intercept	A linear time trend
AFG	0.67 (0.54, 0.85)	**0.56 (0.45, 0.70)**	0.54 (0.43, 0.69)
ALB	0.98 (0.84, 1.20)	**0.97 (0.82, 1.20)**	0.97 (0.82, 1.20)
ANG	0.81 (0.71, 0.96)	**0.77 (0.69, 0.89)**	0.76 (0.67, 0.88)
ARG	0.68 (0.51, 0.94)	0.67 (0.58, 0.81)	**0.57 (0.41, 0.78)**
AUS	0.32 (0.24, 0.48)	0.45 (0.37, 0.57)	**0.17 (-0.01, 0.42)**
AUST	0.75 (0.56, 0.99)	0.56 (0.47, 0.69)	**0.58 (0.48, 0.72)**
BAR	0.99 (0.83, 1.22)	0.69 (0.58, 0.90)	**0.62 (0.44, 0.89)**
BEL	0.34 (0.26, 0.71)	0.69 (0.58, 0.86)	**0.55 (0.36, 0.84)**
BEN	0.80 (0.66, 1.02)	0.84 (0.75, 0.99)	**0.80 (0.66, 0.99)**
BOL	0.72 (0.58, 0.93)	0.69 (0.62, 0.82)	**0.55 (0.41, 0.76)**
BRA	0.75 (0.60, 0.97)	0.81 (0.72, 0.97)	**0.73 (0.58, 0.95)**
BUR	0.56 (0.32, 0.81)	0.45 (0.36, 0.75)	**0.29 (0.13, 0.51)**
BURU	0.76 (0.57, 0.98)	0.33 (0.22, 0.48)	**0.30 (0.17, 0.48)**
CAD	0.85 (0.68, 1.05)	0.73 (0.61, 0.95)	**0.71 (0.51, 0.95)**
CAM	1.19 (1.07, 1.36)	1.20 (1.11, 1.33)	**1.21 (1.09, 1.35)**
CAN	0.67 (0.36, 1.00)	0.49 (0.41, 0.62)	**0.22 (-0.04, 0.62)**
CEN	0.85 (0.67, 1.12)	0.66 (0.58, 0.80)	**0.58 (0.43, 0.80)**
CHA	0.52 (0.42, 0.66)	0.49 (0.41, 0.58)	**0.40 (0.31, 0.51)**
CHI	0.88 (0.75, 1.11)	0.89 (0.79, 1.04)	**0.86 (0.73, 1.05)**
CHIN	0.80 (0.53, 1.09)	0.76 (0.67, 0.94)	**0.68 (0.48, 0.94)**
COL	0.83 (0.61, 1.12)	0.87 (0.73, 1.16)	**0.82 (0.53, 1.16)**
CONGO	0.82 (0.63, 1.09)	0.78 (0.71, 0.90)	**0.56 (0.42, 0.80)**
CONGOD	0.93 (0.76, 1.15)	**1.00 (0.86, 1.18)**	1.00 (0.87, 1.18)
COS	0.86 (0.62, 1.14)	0.85 (0.74, 1.02)	**0.86 (0.75, 1.02)**

CUB	0.76 (0.59, 1.01)	0.57 (0.38, 1.01)	**0.63 (0.34, 1.01)**
DEN	0.63 (0.38, 0.86)	0.50 (0.42, 0.62)	**0.41 (0.28, 0.62)**
DOM	1.02 (0.87, 1.15)	0.89 (0.74, 1.08)	**0.90 (0.76, 1.10)**
ELS	0.96 (0.82, 1.18)	**0.73 (0.60, 0.91)**	0.73 (0.59, 0.91)
FIJ	0.87 (0.74, 1.05)	0.57 (0.46, 0.72)	**0.46 (0.27, 0.69)**
FRA	0.35 (0.28, 0.74)	0.68 (0.60, 0.84)	**0.64 (0.50, 0.83)**
GAM	0.82 (0.69, 1.01)	0.56 (0.47, 0.68)	**0.36 (0.19, 0.59)**
GER	0.67 (0.29, 0.97)	0.59 (0.52, 0.71)	**0.28 (0.04, 0.61)**
GHA	0.95 (0.81, 1.15)	0.90 (0.78, 1.07)	**0.89 (0.77, 1.08)**
GRE	0.65 (0.27, 0.94)	0.54 (0.47, 0.64)	**0.49 (0.38, 0.64)**
GUA	0.75 (0.56, 1.01)	**0.42 (0.23, 0.69)**	0.43 (0.23, 0.69)
GUI	0.92 (0.77, 1.20)	1.01 (0.90, 1.21)	**1.02 (0.87, 1.22)**
GUY	0.76 (0.63, 0.93)7	0.69 (0.59, 0.83)	**0.66 (0.55, 0.82)**
HAI	0.97 (0.84, 1.15)	**0.96 (0.82, 1.13)**	0.96 (0.83, 1.13)
IND	0.69 (0.52, 1.00)	0.77 (0.70, 0.89)	**0.48 (0.26, 0.79)**
INDO	0.94 (0.71, 1.21)	0.79 (0.68, 1.00)	**0.82 (0.68, 1.01)**
ISR	0.50 (0.15, 0.73)	0.44 (0.34, 0.56)	**0.44 (0.32, 0.60)**
ITA	0.81 (0.63, 1.02)	0.61 (0.52, 0.74)	**0.63 (0.53, 0.76)**
JAP	0.82 (0.67, 1.03)	0.47 (0.39, 0.59)	**0.35 (0.13, 0.69)**
JOR	0.41 (0.29, 0.58)	**0.39 (0.29, 0.52)**	0.34 (0.22, 0.50)
KEN	0.81 (0.66, 1.00)	0.59 (0.42, 0.90)	**0.65 (0.47, 0.90)**
KOR	0.98 (0.81, 1.24)	**1.03 (0.81, 1.37)**	1.03 (0.81, 1.37)
KORE	0.82 (0.68, 1.04)	**0.54 (0.39, 0.78)**	0.57 (0.41, 0.79)
LAO	1.01 (0.87, 1.20)	0.91 (0.73, 1.12)	**0.91 (0.75, 1.14)**
LEB	0.67 (0.56, 0.85)	0.75 (0.66, 0.87)	**0.71 (0.59, 0.85)**
LUX	0.76 (0.60, 0.97)	0.39 (0.27, 0.57)	**0.36 (0.15, 0.64)**
MAD	0.91 (0.75, 1.14)	0.70 (0.57, 0.89)	**0.70 (0.55, 0.89)**
MAL	0.77 (0.52, 1.00)	**1.01 (0.86, 1.19)**	1.00 (0.85, 1.19)
MALI	0.81 (0.62, 1.06)	**0.61 (0.44, 0.88)**	0.62 (0.44, 0.88)
MEX	0.89 (0.75, 1.07)	0.57 (0.44, 0.79)	**0.69 (0.58, 0.84)**
MOZ	0.93 (0.75, 1.21)	**0.79 (0.60, 1.09)**	0.79 (0.61, 1.09)
MYA	1.07 (0.92, 1.32)	1.16 (1.03, 1.38)	**1.18 (1.03, 1.39)**
NET	0.76 (0.55, 1.01)	0.55 (0.47, 0.68)	**0.28 (0.09, 0.55)**
NIC	0.98 (0.83, 1.20)	**0.77 (0.57, 1.02)**	0.81 (0.65, 1.02)
NIG	0.53 (0.43, 0.67)	0.54 (0.46, 0.66)	**0.44 (0.33, 0.60)**

NIGE	0.75 (0.60, 0.96)	0.75 (0.68, 0.84)	**0.61 (0.49, 0.78)**
NOR	0.57 (0.32, 0.78)	0.42 (0.32, 0.55)	**0.43 (0.32, 0.58)**
PAK	0.55 (0.48, 0.73)	0.74 (0.68, 0.85)	**0.45 (0.22, 0.74)**
PAR	0.37 (0.30, 0.52)	0.50 (0.43, 0.60)	**0.11 (-0.07, 0.36)**
PER	0.86 (0.72, 1.06)	**0.92 (0.80, 1.12)**	0.91 (0.78, 1.12)
PHI	0.63 (0.41, 0.99)	0.75 (0.67, 0.89)	**0.52 (0.31, 0.83)**
POL	0.73 (0.56, 0.93)	0.47 (0.35, 0.64)	**0.41 (0.24, 0.63)**
POR	0.78 (0.63, 0.98)	**0.34 (0.20, 0.51)**	0.34 (0.20, 0.51)
ROM	0.09 (0.03, 0.68)	0.23 (0.11, 0.38)	**0.12 (-0.03, 0.34)**
RWA	0.95 (0.80, 1.16)	**0.86 (0.70, 1.06)**	0.86 (0.71, 1.06)
SAI	0.91 (0.75, 1.14)	**0.79 (0.65, 1.00)**	0.79 (0.64, 1.00)
SIE	1.11 (0.95, 1.37)	**1.02 (0.85, 1.25)**	1.02 (0.86, 1.25)
SOM	0.81 (0.65, 1.05)	**0.82 (0.66, 1.09)**	0.82 (0.66, 1.09)
SPA	0.31 (0.26, 0.40)	0.48 (0.41, 0.57)	**0.02 (-0.18, 0.27)**
SRI	0.87 (0.67, 1.13)	0.71 (0.58, 0.95)	**0.73 (0.56, 0.96)**
SWE	0.70 (0.55, 0.88)	0.34 (0.20, 0.54)	**0.39 (0.24, 0.59)**
SWI	0.73 (0.58, 0.92)	**0.61 (0.50, 0.75)**	0.61 (0.50, 0.75)
SYR	0.45 (0.35, 0.63)	0.54 (0.46, 0.66)	**0.48 (0.35, 0.65)**
THA	0.69 (0.53, 0.96)	0.80 (0.71, 0.95)	**0.70 (0.53, 0.93)**
TOG	0.76 (0.62, 0.96)	0.69 (0.60, 0.84)	**0.61 (0.47, 0.81)**
TUN	0.19 (0.13, 0.29)	0.32 (0.23, 0.46)	**-0.09 (-0.31, 0.22)**
TUR	0.39 (0.30, 0.85)	0.60 (0.53, 0.69)	**0.45 (0.33, 0.61)**
UGA	0.95 (0.78, 1.20)	**1.05 (0.85, 1.33)**	1.05 (0.85, 1.33)
UNI	0.63 (0.38, 0.86)	0.62 (0.56, 0.78)	**0.63 (0.52, 0.78)**
UNIT	0.71 (0.48, 0.96)	0.52 (0.45, 0.60)	**0.12 (-0.05, 0.36)**
VEN	0.73 (0.44, 1.02)	**1.07 (0.88, 1.35)**	1.07 (0.86, 1.35)
VIE	0.72 (0.62, 0.94)	0.91 (0.83, 1.02)	**0.86 (0.73, 1.02)**
WORLD	0.90 (0.71, 1.14)	0.73 (0.67, 0.79)	**0.26 (0.09, 0.48)**
YEM	0.84 (0.64, 1.14)	**0.59 (0.44, 0.83)**	0.60 (0.43, 0.83)
ZIM	0.56 (0.44, 0.73)	0.43 (0.34, 0.56)	**0.38 (0.27, 0.55)**

In bold, the selected deterministic cases. In parenthesis, 95% confidence bands for d.

Table 3: Estimates of d for each country

	No terms	An intercept	A linear time trend
AFG	**0.56 (0.45, 0.70)**	0.0294 (9.25)	---
ALB	**0.97 (0.82, 1.20)**	0.0145 (5.69)	---
ANG	**0.77 (0.69, 0.89)**	0.0226 (5.39)	---
ARG	**0.57 (0.41, 0.78)**	0.0412 (6.25)	**0.0012 (5.08)**
AUS	**0.17 (-0.01, 0.42)**	0.0206 (5.69)	**0.0007 (7.29)**
AUST	**0.58 (0.48, 0.72)**	0.0879 (9.60)	**0.0011 (3.13)**
BAR	**0.62 (0.44, 0.89)**	0.0702 (13.67)	**-0.0006 (-2.74)**
BEL	**0.55 (0.36, 0.84)**	0.1000 (10.40)	**0.0014 (3.99)**
BEN	**0.80 (0.66, 0.99)**	0.0188 (9.50)	**0.0004 (3.23)**
BOL	**0.55 (0.41, 0.76)**	0.0171 (6.72)	**0.0008 (8.82)**
BRA	**0.73 (0.58, 0.95)**	0.0436 (12.31)	**0.0008 (4.43)**
BUR	**0.29 (0.13, 0.51)**	0.0301 (8.97)	**0.0006 (6.36)**
BURU	**0.30 (0.17, 0.48)**	0.0347 (16.72)	**0.0001 (1.84)**
CAD	**0.71 (0.51, 0.95)**	0.0245 (6.97)	**0.0011 (5.94)**
CAM	**1.21 (1.09, 1.35)**	0.0144 (10.23)	**0.0010 (2.51)**
CAN	**0.22 (-0.04, 0.62)**	0.0236 (10.78)	**0.0007 (11.43)**
CEN	**0.58 (0.43, 0.80)**	0.0148 (11.63)	**0.0004 (7.84)**
CHA	**0.40 (0.31, 0.51)**	0.0205 (4.41)	**0.0006 (4.10)**
CHI	**0.86 (0.73, 1.05)**	0.0236 (4.45)	**0.0017 (3.85)**
CHIN	**0.68 (0.48, 0.94)**	0.0369 (12.97)	**0.0014 (10.29)**
COL	**0.82 (0.53, 1.16)**	0.0258 (6.97)	**0.0014 (5.27)**
CONGO	**0.56 (0.42, 0.80)**	0.0136 (19.20)	**0.0003 (13.69)**
CONGOD	**1.00 (0.86, 1.18)**	0.0301 (14.67)	---
COS	**0.86 (0.75, 1.02)**	0.0314 (7.22)	**0.0013 (3.66)**
CUB	**0.63 (0.34, 1.01)**	0.0413 (11.44)	**-0.0002 (-1.72)**
DEN	**0.41 (0.28, 0.62)**	0.1365 (12.51)	**0.0015 (4.42)**
DOM	**0.90 (0.76, 1.10)**	0.0203 (11.77)	**0.0005 (2.12)**
ELS	**0.73 (0.60, 0.91)**	0.0434 (10.75)	---
FIJ	**0.46 (0.27, 0.69)**	0.0634 (13.48)	**-0.0003 (-2.27)**
FRA	**0.64 (0.50, 0.83)**	0.0665 (6.82)	**0.0016 (3.86)**

GAM	**0.36 (0.19, 0.59)**	0.0762 (15.51)	**-0.0009 (-6.39)**
GER	**0.28 (0.04, 0.61)**	0.0679 (17.74)	**0.0014 (12.42)**
GHA	**0.89 (0.77, 1.08)**	0.0371 (10.13)	**0.0008 (2.35)**
GRE	**0.49 (0.38, 0.64)**	0.0292 (8.99)	**0.0006 (5.64)**
GUA	**0.42 (0.23, 0.69)**	0.0030 (15.59)	----
GUI	**1.02 (0.87, 1.22)**	0.0115 (9.99)	**0.0006 (3.68)**
GUY	**0.66 (0.55, 0.82)**	0.0440 (8.69)	**0.0004 (1.94)**
HAI	**0.96 (0.82, 1.13)**	0.0404 (13.38)	---
IND	**0.48 (0.26, 0.79)**	0.0155 (14.68)	**0.0005 (16.71)**
INDO	**0.82 (0.68, 1.01)**	0.0191 (10.24)	**0.0008 (6.28)**
ISR	**0.44 (0.32, 0.60)**	0.0313 (7.31)	**0.0005 (3.86)**
ITA	**0.63 (0.53, 0.76)**	0.0341 (12.09)	**0.0003 (2.71)**
JAP	**0.35 (0.13, 0.69)**	0.0924 (33.57)	**-0.0006 (-7.89)**
JOR	**0.39 (0.29, 0.52)**	0.0503 (6.41)	---
KEN	**0.65 (0.47, 0.90)**	0.0195 (7.89)	**0.0004 (3.40)**
KOR	**1.03 (0.81, 1.37)**	0.0442 (8.10)	---
KORE	**0.54 (0.39, 0.78)**	0.0558 (16.91)	---
LAO	**0.91 (0.75, 1.14)**	0.0379 (5.29)	**0.0022 (3.17)**
LEB	**0.71 (0.59, 0.85)**	0.0214 (4.36)	**0.0007 (3.02)**
LUX	**0.36 (0.15, 0.64)**	0.1545 (21.27)	**-0.0010 (-4.75)**
MAD	**0.70 (0.55, 0.89)**	0.0424 (19.74)	**0.0002 (1.86)**
MAL	**1.01 (0.86, 1.19)**	0.0359 (13.21)	---
MALI	**0.61 (0.44, 0.88)**	0.0523 (6.91)	---
MEX	**0.69 (0.58, 0.84)**	0.0232 (8.56)	**0.0004 (2.88)**
MOZ	**0.79 (0.60, 1.09)**	0.0395 (9.45)	---
MYA	**1.18 (1.03, 1.39)**	0.0211 (5.72)	**0.0017 (1.81)**
NET	**0.28 (0.09, 0.55)**	0.0628 (27.71)	**0.0004 (6.98)**
NIC	**0.77 (0.57, 1.02)**	0.0232 (6.42)	---
NIG	**0.44 (0.33, 0.60)**	0.0044 (1.91)	**0.0005 (5.62)**
NIGE	**0.61 (0.49, 0.78)**	0.0175 (9.29)	**0.0006 (8.12)**
NOR	**0.43 (0.32, 0.58)**	0.0397 (8.41)	**0.0003 (2.19)**
PAK	**0.45 (0.22, 0.74)**	0.0091 (8.48)	**0.0006 (17.10)**
PAR	**0.11 (-0.07, 0.36)**	0.0299 (8.52)	**0.0015 (15.04)**
PER	**0.92 (0.80, 1.12)**	0.0566 (14.18)	---
PHI	**0.52 (0.31, 0.83)**	0.0222 (15.35)	**0.0007 (13.86)**

POL	**0.41 (0.24, 0.63)**	0.0528 (13.76)	**0.0005 (4.13)**
POR	**0.34 (0.20, 0.51)**	0.0218 (20.28)	---
ROM	**0.12 (-0.03, 0.34)**	0.0864 (13.12)	**0.0009 (4.77)**
RWA	**0.86 (0.70, 1.06)**	0.0264 (14.18)	---
SAI	**0.79 (0.65, 1.00)**	0.0025 (14.18)	---
SIE	**1.02 (0.85, 1.25)**	0.0467 (14.18)	---
SOM	**0.82 (0.66, 1.09)**	0.0206 (4.08)	---
SPA	**0.02 (-0.18, 0.27)**	0.0127 (11.16)	**0.0005 (16.21)**
SRI	**0.73 (0.56, 0.96)**	0.0341 (11.61)	**0.0004 (2.91)**
SWE	**0.39 (0.24, 0.59)**	0.1085 (11.79)	**0.0005 (1.86)**
SWI	**0.61 (0.50, 0.75)**	0.0605 (11.24)	---
SYR	**0.48 (0.35, 0.65)**	0.0143 (2.33)	**0.0006 (3.00)**
THA	**0.70 (0.53, 0.93)**	0.0268 (10.63)	**0.0007 (5.66)**
TOG	**0.61 (0.47, 0.81)**	0.0084 (6.77)	**0.0003 (5.79)**
TUN	**-0.09 (-0.31, 0.22)**	0.0104 (8.44)	**0.0003 (9.55)**
TUR	**0.45 (0.33, 0.61)**	0.0151 (10.71)	**0.0004 (8.99)**
UGA	**1.05 (0.85, 1.33)**	0.0274 (9.68)	---
UNI	**0.63 (0.52, 0.78)**	0.0736 (7.92)	**0.0014 (3.44)**
UNIT	**0.12 (-0.05, 0.36)**	0.0360 (23.40)	**0.0008 (17.87)**
VEN	**1.07 (0.88, 1.35)**	0.0122 (5.93)	---
VIE	**0.86 (0.73, 1.02)**	0.0304 (9.22)	**0.0013 (4.87)**
WORLD	**0.26 (0.09, 0.48)**	0.0261 (56.76)	**0.0006 (48.34)**
YEM	**0.59 (0.44, 0.83)**	0.0279 (10.78)	---
ZIM	**0.38 (0.27, 0.55)**	0.0388 (7.15)	**-0.0002 (-1.97)**

Table 4 shows the list of the countries with a significant positive time trend. We observe that the highest coefficients correspond to Lao People Republic, Chile, Myanmar, France, Paraguay and Denmark. In this list of countries, 28.1% correspond to high income level countries, to 23,6% to upper-middle income countries, 24,7% to lower-middle income and 23,6% to low income countries.

Table 4: Countries with significant positive time trend coefficients

Country	Time trend coeff.	Country	Time trend coeff.
LAO (3)	0.0022 (3.17)	GRE (1)	0.0006 (5.64)
CHI (1)	0.0017 (3.85)	GUI (4)	0.0006 (3.68)
MYA (3)	0.0017 (1.81)	NIGE (3)	0.0006 (8.12)
FRA (1)	0.0016 (3.86)	PAK (3)	0.0006 (17.10)
PAR (2)	0.0015 (15.04)	SYR (3)	0.0006 (3.00)
DEN (1)	0.0015 (4.42)	WORLD	0.0006 (48.34)
BEL (1)	0.0014 (3.99)	DOM (2)	0.0005 (2.12)
CHIN (2)	0.0014 (10.29)	IND (3)	0.0005 (16.71)
COL (2)	0.0014 (5.27)	ISR (1)	0.0005 (3.86)
GER (1)	0.0014 (12.42)	NIG (4)	0.0005 (5.62)
UNI (1)	0.0014 (3.44)	POL (1)	0.0005 (4.13)
COS (2)	0.0013 (3.66)	SPA (1)	0.0005 (16.21)
VIE	0.0013 (4.87)	SWE (1)	0.0005 (1.86)
ARG (2)	0.0012 (5.08)	BEN (4)	0.0004 (3.23)
AUST (1)	0.0011 (3.13)	CEN (4)	0.0004 (7.84)
CAD (3)	0.0011 (5.94)	GUY (2)	0.0004 (1.94)
CAM (3)	0.0010 (2.51)	KEN (3)	0.0004 (3.40)
BOL (3)	0.0008 (8.82)	MEX (2)	0.0004 (2.88)
BRA (2)	0.0008 (4.43)	NET (1)	0.0004 (6.98)
GHA (3)	0.0008 (2.35)	SRI (3)	0.0004 (2.91)
INDO (3)	0.0008 (6.28)	TUR (2)	0.0004 (8.99)
UNIT (1)	0.0008 (17.87)	CONGO (3)	0.0003 (13.69)
AUS (1)	0.0007 (7.29)	ITA (1)	0.0003 (2.71)
CAN (1)	0.0007 (11.43)	NOR (1)	0.0003 (2.19)
LEB (2)	0.0007 (3.02)	TOG (4)	0.0003 (5.79)
PHI (3)	0.0007 (13.86)	TUN (3)	0.0003 (9.55)
THA (2)	0.0007 (5.66)	MAD (4)	0.0002 (1.86)
BUR (4)	0.0006 (6.36)	BURU (4)	0.0001 (1.84)
CHA (4)	0.0006 (4.10)		

(1) High income; (2): Upper-middle income; (3): Lower-middle income, and (4): Low income.

Table 5: Countries with significant negative time trend coefficients

Country	Time trend coeff.	Country	Time trend coeff.
LUX (1)	-0.0010 (-4.75)	FIJ (2)	-0.0003 (-2.27)
GAM (4)	-0.0009 (-6.39)	CUB (2)	-0.0002 (-1.72)
BAR (1)	-0.0006 (-2.74)	ZIM (4)	-0.0002 (-1.97)
JAP (1)	-0.0006 (-7.89)		

(1) High income; (2): Upper-middle income; (3): Lower-middle income, and (4): Low income.

Table 5 displays the seven countries with a negative time trend. They are Luxembourg, Gambia, Barbados, Japan, Fiji, Cuba and Zimbawe, and three out of the four countries with the highest coefficients belong to group (1), corresponding to the high income level countries.

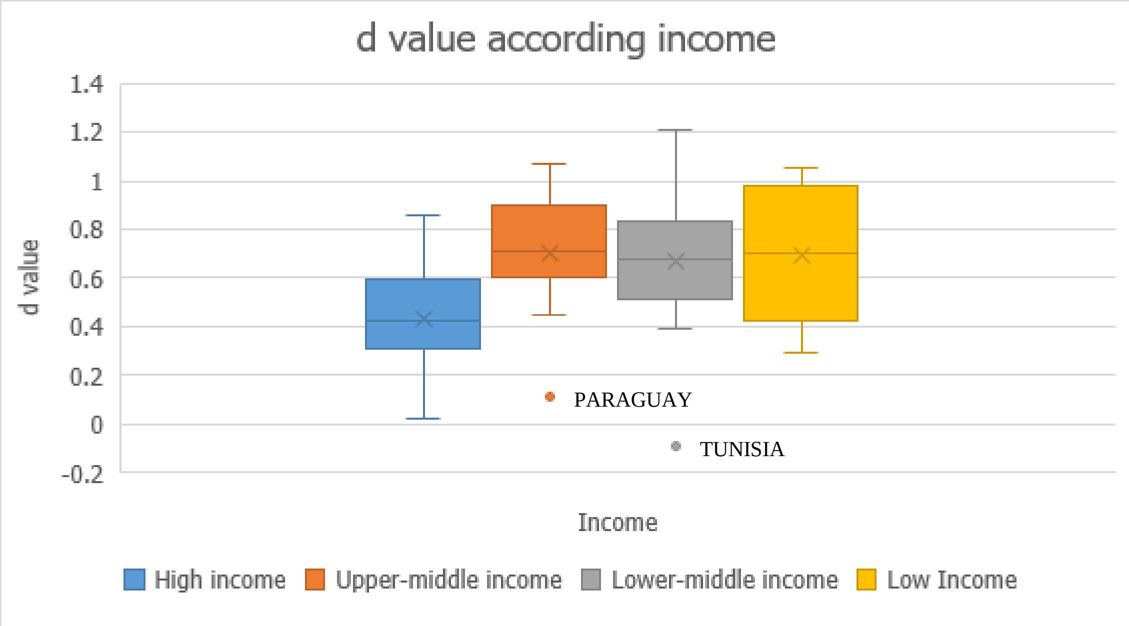
Table 6: Classification of countries according to the order of integration

<table>
<tr><th>I(0)</th><th>0 < d < 0.5</th><th>0.5 ≤ d < 1</th><th>I(1)</th><th>d >1</th></tr>
<tr><td rowspan="4">TUN (-0.12)
SPA (0.02)
PAR (0.11)
ROM (0.12)
UNIT (0.12)
AUS (0.17)
CAN (0.22)</td><td>WORLD (0.26)
BURU (0.30)</td><td>SWI (0.61)
UNI (0.63)
ITA (0.63
FRA (0.64)
GUY (0.66)
MEX (0.69)
THA (0.70)
MAD (0.70)
LEB (0.71)
CAD (0.71)
SRI (0.73)
ELS (0.73)
BRA (0.73)
ANG (0.77)
BEN (0.80)</td><td rowspan="4">CUB (0.63)
NIC (0.77)
SAI (0.79)
MOZ (0.79)
COL (0.82)
SOM (0.82)
INDO (0.82)
CHI (0.86)
COS (0.86)
VIE (0.86)
RWA (0.86)
GHA (0.89)
DOM (0.90)
LAO (0.91)
PER (0.92)
HAI (0.96)
ALB (0.97)
CONGOD (1.00)
MAL (1.01)
SIE (1.02)
GUI (1.02)
KORE (1.03)</td><td rowspan="4">MYA (1.18)
CAM (1.21)</td></tr>
<tr><td colspan="2">0 < d < 1</td></tr>
<tr><td>d < 0.5</td><td>d > 0.5</td></tr>
<tr><td>GER (0.28)
NET (0.28)
BUR (0.29)
POR (0.34)</td><td>PHI (0.52)
KORE (0.54)
BEL (0.55)
BOL (0.55)</td></tr>
</table>

	JAP (0.35)	AFG (0.56)	UGA (1.05)	
	GAM (0.36)	CONGO (0.56)	VEN (1.07)	
	LUX (0.36)	ARG (0.57)		
	ZIM (0.38)	AUST (0.58)		
	JOR (0.39)	CEN (0.58)		
	SWE (0.39)	YEM (0.59)		
	CHA (0.40)	TOG (0.61)		
	DEN (0.41)	MALI (0.61)		
	POL (0.41)	NIG (0.61)		
	GUA (0.42)	BAR (0.62)		
	NOR (0.43)	KEN (0.65)		
	NIG (0.44)	CHIN (0.68)		
	ISR (0.44)			
	PAK (0.45)			
	TUR (0.45)			
	FIJ (0.46)			
	IND (0.48)			
	SYR (0.48)			
	GRE (0.49)			

Table 6 classifies the countries according to their degree of persistence, measured in terms of the estimated values of d. We distinguish the cases of $d = 0$ (or short memory); stationary long memory ($0 < d < 0.5$); nonstationary though mean reverting behaviour ($0.5 \leq d$ 1); unit roots ($d = 1$) and explosive patterns ($d > 1$).

In the first group, referring to short memory we have countries such as Tunisia (-0.12), Spain (0.02), Paraguay (0.11), Romania and USA (0.12), Australia (0.17) and Canada (0.22). In the second group, dealing with stationary long memory, we have data for WORLD (0.26) and Burundi (0.30). There are 15 countries in the third group ($0.5 \leq d < 1$) with values of d ranging from 0.61 (Switzerland) to 0.80 (Benin). Within these last two groups, there are many countries with values constrained between 0 and 1 but not belonging to the second or third category. The unit root null hypothesis (i.e., $d = 1$) cannot be rejected in another group of 24 countries, while two countries display an explosive behaviour (Myanmar, 1.18, and Cameroon, 1.21).



	High income	Upper-middle income	Lower-middle income	Low Income
Maximum	0,86	1,07	1,21	1,05
Minimum	0,02	0,11	-0,09	0,29
Median	0,42	0,71	0,68	0,7

Figure 2: d value according to countries income levels

Figure 2 relates income levels with persistence (d). We observe that generally there are no atypical patterns in any of the four groups of countries according to income. All countries display values of d within the standard confidence bands to the group they belong to. There are only two atypical values of d: on the one hand, Paraguay (d = 0.11) within the upper-middle income group, and on the other hand, Tunisia (d = -0.12) in the lower-middle income countries. Apart from that, we also observe that more than 50% of the countries belonging to low income countries, lower-middle income and upper-middle income display nonstationary patterns, with values of d higher than 0.5. This is contrary to what happens to high income countries where more than 50% of them display stationary patterns. Finally, we also observe that all the countries with high income levels and nonstationary patterns display mean reversion ($d < 1$), while for the remaining three income groups, the nonstationary series displays values of d equal to or significantly higher than 1.

4. Discussion of the results

The foregoing results generally suggest that built-up land footprint in most of the countries have positive (and significant) trends and are mean reverting. The evidence for mean reversion of the series is consistent with the results of Yilanci et al. (2019) but contrary to the output of Ulucak and Lin (2017). Focussing on the USA (as it is the only country that is common to the three studies), our results and that of Yilanci et al. (2019) provide evidence for mean reverting built-up land footprint in the country, while the study of Ulucak and Lin (2017) showed that built-up land footprint is not mean reverting in the country. Apart from the use of different methods, the disparity in the results may be due to the use of different datasets. While our paper and that of Yilanci et al. (2019) have used the revised (and the latest) version of the dataset provided by *Global Footprint Network*, the old version of the dataset has been used in the work of Ulucak and Lin (2017).

The evidence for positive and significant trends found in this paper can be ascribed to the rising level of built-up land footprint being witnessed in several countries. For instance, Denmark, which has the largest average built-up land footprint, experienced a around 53% growth rate in built-up land footprint over the 1961-2016 period. Majority of the countries examined experienced expansion in built-up land footprint in most the years under observation. It has to be noted that the results do not support the hypothesis of Hsu et al. (2008) posits that larger series are likely to be more persistent. For instance, Denmark, Belgium, France, Austria and Sweden are the top five countries in terms of the average built-up land footprint per capita. The results suggest that there are at least 26 countries with more persistent built-up land footprint per capita than these countries.

The findings supporting mean reversion of the built-up land footprint can be attributed to most of determinants of built-up land footprint (including urban population, population density and GDP) being mean reverting. For instance, Yang et al. (2015) has shown that population density and GDP are mean reverting, while Mishra et al. (2009) provided evidence for mean reverting GDP. According to Smyth (2013), a series related to another variable, which is nonstatonary (stationary) will inherit such nonstationarity (stationarity), and transmit it to the other related variable in economic system. Therefore, these determinants have transmitted mean reversion tendencies to built-up land footprint.

5. Conclusion

In this paper we have tested the stationarity ($d < 0.5$) / nonstationarity ($d \geq 0.5$) nature of the built-up land footprint in the time series referring to 89 countries by using fractional integration. In doing so, we allow for a large degree of flexibility in the modelling of the degree of persistence of the data.

Our results indicate first evidence of positive significant trends in 57 out of the 89 countries examined. In all the other cases, the time trend coefficients are found to be statistically insignificantly different from zero. On the other hand, we find seven countries with significant negative trends (Luxembourg, Gambia, Barbados, Japan, Fiji, Cuba and Zimbabwe**).** Dealing with the degree of persistence, the results are very heterogeneous across countries finding evidence of short memory in a group of seven countries **(**Tunisia, Spain, Paraguay, Romania, USA, Australia and Canada); stationary long memory in two series (WORLD and Burundi); nonstationary long memory though still with a mean reverting pattern in 15 countries (Switzerland, United Kingdom, Italy, France, Guyana, Mexico, Thailand, Madagascar, Lebanon, Côte d´Ivoire, Sri Lanka, El Salvador, Brazil, Angola and Benin)**;** (for another group of 37 countries the orders of integration are constrained between 0 and 1 but the intervals are so wide that we cannot distinguish between stationarity and nonstationarity); for 24 countries, the unit root hypothesis cannot be rejected and for Myanmar and Cameroom the order of integration is found to be significantly higher than 1. Thus, mean reversion is detected in 63 countries (70.78% of the countries examined) while lack of it is identified in the remaining 26 (29.12%) countries.

That mean reversion is found in most of these economies connotes that shocks to the built-up land footprint are momentary. The built-up land footprint will gravitate back to its initial trend or mean in the aftermath of an economic or natural shock. Therefore, authorities should not introduce excessive targets (through series of building policies or urban policies and programmes) when the built-up land footprint temporarily departs from the trend path as environmental conservation and management blueprints designed to mitigate the built-up land footprint will not yield long-lasting effects. The internal economic conditions of these nations will tend to force the built-up land footprint to its original trend path. Therefore, undue interventions by the governments might not be the best solution in this situation.

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