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Trends and Persistence in the Number of Hot Days: Some Multi-Country Evidence

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Abstract

This paper uses fractional integration methods to obtain comprehensive evidence on the evolution of the number of hot days, defined as those with temperatures above 35 °C, in 54 countries from various regions of the world over the period from 1950 to 2022. The variable analysed is a key indicator of global warming, and the chosen modelling approach is most informative about the behaviour of the series as it provides evidence on the possible presence of time trends, on whether or not mean reversion occurs, and on the degree of persistence. In brief, the findings indicate the presence of considerable heterogeneity among the countries studied and highlight the importance of tailored climate policies based on both global and local factors.

Keywords: Number of hot days; climate change; persistence; fractional integration

JEL Code: C22; Q54

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1. Introduction

Analysing the evolution of maximum temperatures and the frequency of hot days is crucial to understand the impact of climate change. Existing studies point to a significant increase in average maximum temperature in several regions of the world (Yan et al., 2020; Francis and Fonseca, 2024; Ogunrinde et al., 2024; etc.). This increase, combined with more frequent heat waves, is transforming weather patterns dramatically. The regions most affected include North Africa, sub-Saharan Africa, Central and West Asia, the Mediterranean and parts of the Americas. These changes are exacerbating aridity over vast tracts of land, with profound implications for food security, water resource availability, and both local and transnational migration patterns (Sun et al., 2018; Linares et al., 2020; Issa et al., 2023).

In particular, in Central Asia, North Africa and West Africa there has been a marked increase in maximum temperatures from previous ranges of 36-39 °C to new ones of 39-42 °C in several areas (Ogunrinde et al., 2024). In sub-Saharan Africa and the Sahel, models project even more extreme temperature increases between 3 and 6 °C by the end of the 21st century (Weber et al., 2018; Ofori et al., 2021).

Heat waves, a climatic phenomenon associated with significant risks to public health and the economy, are also on the rise. In West and Central Africa, a considerable increase in both their frequency and duration is expected, especially in the most arid and vulnerable areas (Diedhiou et al., 2018). Similarly, in North Africa and West Asia, extreme temperatures not only affect the quality of life, but are also closely linked to an increase in the likelihood of socio-political conflicts and forced migrations (Abdel, 2024).

In East Africa, climate records highlight concerning upward trends in both maximum and minimum temperatures, underscoring the urgent need to implement sustainable, local-scale adaptation measures. These strategies must be based on a thorough understanding of the specific needs of the affected communities (Gebrechorkos et al., 2019).

The Mediterranean and the Middle East, regions which are particularly vulnerable to climate change, are also experiencing warming at an increasing rate. This phenomenon is more pronounced during the spring and summer seasons (Hadjinicolaou et al., 2023; Francis and Fonseca, 2024). These trends affect local ecosystems, agricultural production and water resources, aggravating living conditions in communities already facing climate challenges.

In China, there has also been a sharp increase in maximum temperatures and the frequency of hot days, especially since the 1990s (Yan et al., 2020; Zhou and Lu, 2021). In Australia, positive trends of more than 0.6 °C per decade have been detected in the highest temperatures of the year, and heat waves are becoming more intense, prolonged and frequent, affecting human health, agriculture and urban systems (Papari et al., 2020). The same is happening in the US, where the frequency of extreme heat events is also increasing (Ombadi and Risser., 2022; Ibebuchi et al., 2024).

This context requires the development and implementation of region-specific adaptation strategies. These should consider the characteristics of agricultural, water and social systems, as well as the intrinsic vulnerability of each area to projected climate changes. Therefore, there is a need for studies evaluating the evolution and long-term patterns of maximum temperatures and extreme events. These are essential to identify trends, validate climate models and design informed and sustainable adaptation policies.

The present study contributes to this area of the literature by analysing annual data on the evolution of days with temperatures above 35 °C over the period from 1950 to 2022 in 54 countries from different regions of the world, including sub-Saharan Africa (Benin, Burkina Faso, Cameroon, Chad, Eritrea, Ethiopia, Gambia, Ghana, Mali, Mauritania, Mozambique, Niger, Nigeria, Senegal, South Africa, Somalia, South Sudan, Sudan, Sudan and Togo), Central Asia (Kazakhstan, Tajikistan, Uzbekistan), South Asia (Afghanistan, Bangladesh, India, Nepal, Pakistan), North Africa (Algeria, Djibouti, Egypt, Libya, Morocco and Tunisia), West Asia and the Middle East (Bahrain, Iran, Iraq, Syria, Jordan, Kuwait, Oman, Qatar, Saudi Arabia, Turkey, United Arab Emirates and Yemen), East Asia and Pacific (Australia, China, Myanmar and Thailand), as well as parts of the Americas (Argentina, Mexico, Paraguay and the United States). The analysis uses fractional integration methods, which are ideally suited to our purposes. Note that most of the existing literature on this topic is based on the classical dichotomy between stationary (or integrated of order 0, denoted as I(0)) and non-stationary (or I(1)) series (see, e.g., Woodward and Gray, 1993; Stern and Kaufmann, 2000; Kaufmann et al., 2006, 2010; etc.). Such studies are based on standard unit roots tests that are now known to have very low power against fractional integration alternatives (see, e.g., Diebold and Rudebusch, 1991; Hassler and Wolters, 1994; Lee and Schmidt, 1996; etc.). By contrast, a fractional integration framework (see Granger, 1980; Granger and Joyeux, 1980, and Hosking, 1981) is much more general and flexible, since the differencing parameter d is allowed to take any real value, including fractional ones. Consequently, it encompasses a much wider range of stochastic processes, including the unit root case, and provides key information about whether or not the series of interest are mean-reverting (and thus on whether exogenous shocks have permanent or transitory effects) and on their degree of persistence, with crucial implications for climate change policies.

The remainder of the paper is structured as follows: Section 2 briefly reviews the relevant literature; Section 3 introduces the modelling framework; Section 4 describes the data and presents the empirical results; Section 5 offers some concluding remarks.

2. Literature Review

Understanding the evolution of temperatures and climatic conditions and their long-term trends, as well as changes in the frequency and intensity of extreme events, is essential to develop models generating reliable forecasts (Papacharalampous et al., 2018; Bahari and Hamid, 2019, Liu et al., 2021; Domonkos et al., 2021; etc.). For this purpose, various methods have been used.

Classical models, such as the autoregression integrated moving average (ARIMA) one, are widely employed due to their versatility in analysing and modelling stationary and non-stationary series. ARIMA specifications allow to decompose time series into trend, seasonal and noise components, providing a useful framework for making short-term temperature forecasts (Lai and Dzombak, 2020; Dimri et al., 2020). However, this approach has limitations in the presence of long-range dependence between the observations, as in the case of temperature data, since past weather events may have persistent effects on future conditions (Chen et al., 2023).

Other common methods include exponential smoothing techniques (Taylor, 2004), which prioritise recent observations to capture dynamic changes, and decomposition-based approaches such as seasonal or Fourier analysis (Yang, 2013). These methods are useful for identifying periodic or cyclical patterns in the series, such as seasonal temperature variations. However, they are less suitable for capturing long-term trends and for distinguishing between stationary and non-stationary components in the series.

Regression analysis is another common tool, which is often used for exploring relationships between temperatures and variables such as greenhouse gas emissions, land use or geographic factors. However, this approach assumes linearity in the relationships, which may not be appropriate for climate data that exhibit complex and nonlinear behaviour (Deb and Jana, 2021).

As already mentioned, a framework which is ideally suited to model the behaviour of temperature series is the autoregressive fractional integrated fractional moving average (ARFIMA) model (Granger and Joyeux, 1980; Hosking, 1981); this allows the differencing parameter d to be any real number, including fractional ones as opposed to integers only, and thus provides a more accurate description of both short- and long-range dependence (Huang et al., 2022), and it also yields more efficient estimates (Bhardwaj et al., 2020). Its generality and flexibility are particularly useful to distinguish between stationary and non-stationary processes, which is crucial to avoid erroneous conclusions about the evolution of weather patterns, and to capture the long-range dependence or long memory typically exhibited by temperatures (Caporale et al., 2024, 2025; Gil Alana et al., 2022, 2024, 2025). Climate series are often influenced by long-term phenomena, such as global warming, climate cycle variability or the cumulative impact of anthropogenic changes (Twaróg, 2024), and therefore fractional integration techniques can shed light on their degree of persistence. Finally, these methods are a powerful tool for long-term forecasting of temperatures (Lenti and Gil-Alana, 2021; Gil-Alana et al., 2022, 2024, 2025; Chibuzor and Gil-Alana, 2024; Vyushin and Kushner, 2009; Yuan et al., 2013) as they integrate system memory, and thus generate more accurate predictions reflecting underlying trends and persistence dynamics. The main features of this approach are described in the next section.

3. Fractional Integration

Fractional integration can be defined in terms of the degree of differencing required to produce stationary I(0) behaviour in a series. Specifically, a process x(t), t = 0, 1, 2 … is said to be integrated of order d, and denoted as I(d), if it can be written as:

$$(1 - L)^{d} x(t) \; = \; u(t), \quad t \; = 1, 2, \ldots, \qquad (1)$$

where L stands for the lag operator; d is a real positive value, and u(t) is an I(0) process that can be assumed to be a white noise process or alternatively a weakly autocorrelated one as in the stationary AutoRegressive Moving Average class of models.

The parameter d is called the differencing parameter; for non-integer values of d, one can use the following Binomial expansion of L, such that

$$(1 - L)^{d} \; = \; \sum_{j=1}^{\infty} \frac{\Gamma(\mathrm{d}-1)\,(-L)^{j}}{\Gamma(\mathrm{d}-\mathrm{j}+1)\,\Gamma(\mathrm{j}+1)},$$

where Γ is the gamma function, which is defined as:

$$\Gamma(\mathrm{z}) = \int_{0}^{\infty} t^{z-1} e^{-t}\, d(t).$$

Alternatively, $(1-L)^d$ can be expressed as

$$(1-L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - \dots$$

and thus equation (1) becomes:

$$x(t) = d\, x(t-1) - \frac{d(d-1)}{2} x(t-2) + \dots + u(t).$$

Several cases can occur depending on the value of d, namely:

i) short memory, if d = 0,

iii) stationary long memory, if 0 < d < 0.5,

ii) nonstationary mean reversion, if 0.5 ≤ d < 1,

iv) I(1) behaviour, if d = 1, etc.

In the empirical application carried out in the following section, we assume that x(t) are the errors in a regression model including a linear time trend, i.e.,

$$y(t) = \alpha + \beta t + x(t), \quad t = 1, 2, \dots, \qquad (2)$$

where y(t) is the observed series.

The estimation of d (and of the coefficients of the deterministic terms, i.e., α and β) is based on a maximum likelihood function expressed in the time domain.

4. Data and Empirical Results

Data on the number of days per year with maximum temperature above 35 °C are taken from the World Bank Climate Change Knowledge Portal (2024), https://climateknowledgeportal.worldbank.org/); they are based on a heat index, which is a measure of temperature including the influence of atmospheric humidity and is constructed as explained in World Bank Group (2025).

The selected countries are all those for which data are available for the entire period from 1950 to 2022; the sample covers sub-Saharan Africa (Benin, Burkina Faso, Cameroon, Chad, Eritrea, Ethiopia, Gambia, Ghana, Mali, Mauritania, Mozambique, Niger, Nigeria, Senegal, South Africa, Somalia, South Sudan, Sudan and Togo), Central Asia (Kazakhstan, Tajikistan and Uzbekistan), South Asia (Afghanistan, Bangladesh, India, Nepal, Pakistan), North Africa (Algeria, Djibouti, Egypt, Libya, Morocco and Tunisia), West Asia and Middle East (Bahrain, Iran, Iraq, Syria, Jordan, Kuwait, Oman, Qatar, Saudi Arabia, Turkey, United Arab Emirates and Yemen), East Asia and Pacific (Australia, China, Myanmar and Thailand), as well as parts of the Americas (Argentina, Mexico, Paraguay and the United States).

Table 1 reports the estimates of d in equations (1) and (2) under the assumption of white noise errors and for three different model specifications. The estimation is carried out using a general to specific approach. Column 4 shows the estimates of d (and the corresponding 95% confidence bands) from the most general model including both an intercept and a linear time trend. If the latter is found to be statistically insignificant, it is dropped from the regression, namely β is set equal to 0 in equation (2) and the model is re-estimated including only an intercept as the deterministic component; the corresponding estimates of d with their 95% confidence bands are displayed in column 3. Finally, if the intercept is also found to be insignificant, the model is re-estimated setting $\alpha = \beta = 0$; column 2 reports the results obtained in this case.

Table 1 shows the estimates of d, with those corresponding to the selected models in bold. It can be seen that only in five countries, namely Mozambique, India, Nepal, China and Paraguay, the time trend is not statistically significant and is not included in the preferred specification. The entire set of estimated coefficients corresponding to the latter is instead shown for each country in Table 2.

[Insert Tables 1 and 2 about here]

Concerning the estimates of d, it can be seen that the highest degrees of persistence are found in the cases of Tajikistan (d=0.48), Qatar (0.46), Yemen (0.46), UAE (0.43) and Saudi Arabia (0.37). This parameter is significantly positive in 24 countries in total, the additional 19 being Chad and China (0.36), Iran and Kuwait (0.34), Sudan (0.33), Iraq (0.31), Eritrea (0.29), Mozambique (0.28), USA (0.27), Ethiopia (0.26), Bahrain (0.24), Egypt (0.20), Algeria (0.19), Uzbekistan (0.18), Kazakhstan (0.17), Tunisia (0.16), Morocco, Syria and Turkey (0.15). In another 24 countries the estimated values of d are either positive or negative and the I(0) hypothesis of short memory cannot be rejected – these are Mali (0.31), Australia (0.14), Djibouti and Mexico (0.13), South Sudan (0.12), Niger (0.11), Argentina and Somalia (0.08), Afghanistan (0.07), Ghana (0.04), Pakistan (0.02), Bangladesh (-0.01), Paraguay (-0.02), Cameroon and Mauritania (-0.04), Jordan (-0.06), Burkina Faso and Afghanistan (-0.07), Benin and Senegal (-0.09), Oman (-0.10), India (-0.11), Syria and Nepal (-0.12), Gambia (-0.14), Togo (-0.17), Thailand (-0.24) and Myanmar (-0.29). Finally, two countries exhibit significant anti-persistent patterns, specifically Libya (-0.27) and Nigeria (-0.42). The time trend is significant in 49 countries, the highest coefficients being those corresponding to Kuwait (0.8274), Saudi Arabia (0.7463), Qatar (0.6784), UAE (0.6339), Iraq (0.6325), Mali (0.6218), Mauritania (0.5061) and Algeria (0.4739), while it is insignificant in five countries, namely Morocco, India, Pakistan, China and Paraguay.

[Insert Tables 3 and 4 about here]

Tables 3 and 4 have the same layout as Tables 1 and 2 but report the results under the assumption of autocorrelation in the error term modelled as in Bloomfield (1973). It can be seen from Table 3 that the time trend is now statistically insignificant in Tajikistan, Uzbekistan, Pakistan, China and Paraguay, in the latter three just as in the the previous case of white noise errors. Concerning the differencing parameter d, statistical evidence of a long memory pattern, i.e., d > 0, is now found in 19 countries, namely Tajikistan (d = 0.84), Uzbekistan (0.68), Tunisia, Kuwait and UAE (0.54), Saudi Arabia (0.49), Kazakhstan (0.48), Iraq (0.42), Chad and Qatar (0.41), Iran (0.40), Algeria (0.36), Afghanistan (0.34), Syria (0.30), Eritrea (0.24), Turkey (0.23), Pakistan and Egypt (0.22) and Sudan (0.17). Short memory or I(0) behaviour is found in 27 countries, namely China (0.30), Yemen (0.27), Morocco and Jordania (0.13), Mozambique and Argentina (0.08), Paraguay (0.06), USA (0.05), South Sudan (0.03), Niger (-0.3), Syria and Bahrain (-0.05), Mexico (-0.06), Cameron and Ghana (-0.09), Somalia (-0.14) Gambia (-0.19), Djibouti (-0.21), Bangladesh and Australia (-0.24), Oman (-0.30), Burkina Faso (-0.32), Senegal (-0.33), Nepal and South Africa (-0.42), Togo (-0.53), and Eritrea and Ethiopia (-0.67). Further, 8 countries exhibit anti-persistence (d < 0), namely Benin (-0.42), Libya (-0.52), India and Mauritania (-0.54), Thailand (-0.55), Nigeria (-0.69), Myanmar (-1.09) and Mali (-1.21). Finally, the countries with the highest time trend coefficients are Kuwait (0.8714), Saudi Arabia (0.7323), Qatar (0.6844), Iraq (0.6428), U.A.E. (0.6182), Mali (0.6122), Mauritania (0.5006) and Algeria (0.4693). Tables 5 and 6 provide a summary of the results concerning the time trends and the degree of persistence respectively.

[Insert Tables 5 and 6 about here]

5. Conclusions

The number of hot days, namely those with temperatures above 35 °C, is often used as a measure of global warming and as the basis to design appropriate policies to tackle climate change. This paper uses fractional integration methods to obtain comprehensive evidence on how this variable has evolved in 54 countries from various regions of the world over the period from 1950 to 2022. The chosen modelling approach is most informative about the behaviour of the series as it provides evidence on the possible presence of time trends, on whether or not mean reversion occurs, and on the degree of persistence, with important implications for the design of effective climate policies. In brief, the findings indicate considerable heterogeneity among the countries studied.

More specifically, the results show that the Middle Eastern countries (in particular Kuwait, Saudi Arabia and Qatar) are those with the most pronounced upward trends. Warming in this region is driven by a combination of global factors such as increased greenhouse gases and local factors such as desertification, vegetation decrease and the urban heat island effect in densely populated cities. Since this geographical area is characterised by arid and semi-arid climates, it is particularly vulnerable to small variations in temperature due to the limited capacity of the ecosystem to buffer climatic changes (Malik et al., 2024; Zittis et. al. 2022).

Worrying positive trends are also found in the case of sub-Saharan Africa, where climatic conditions already severely limit water availability and agricultural productivity. In this region, global warming not only intensifies droughts, but also increases the frequency and intensity of heat waves, with direct effects on public health and food security (Ahmed, 2020).

By contrast, there is less evidence of concerning trends in countries such as Morocco, China, India and Paraguay, which appear to be characterised by a more stable climate. This is likely to reflect local factors, such as effective environmental policies, higher levels of vegetation or natural climate variability, which counteract the effects of global warming. In particular, in India and China efforts to reduce emissions through climate policies and reforestation programmes could be contributing to this behaviour (Yu et al., 2020, Li et al., 2022).

As for persistence, the results based on white noise errors indicate that Tajikistan, Qatar, Yemen, UAE and Saudi Arabia are the countries where long-range dependence is most apparent. This could reflect reduced rainfall, increased greenhouse gas emissions and the retreat of resilient ecosystems. Under the assumption of autocorrelated errors an even higher degree of persistence is estimated in countries such as Tajikistan, Uzbekistan and Kuwait. In Central Asia this evidence could be linked to increasing aridity and altered atmospheric patterns resulting from both human activity and natural phenomena (Alahmad et al. 2022; Zong et al., 2020).

In other countries the estimates instead imply the presence of anti-persistence. These include Nigeria, Libya, Ethiopia, Mauritania, Myanmar, Thailand and India, with the coefficients being even bigger in absolute terms under the assumption of autocorrelated errors, for instance in Mali and Myanmar. The anti-persistence identified in these cases reflects climate patterns determined by extreme events counteracting each other over time and resulting in more pronounced and less predictable fluctuations. This feature may be associated with local factors such as massive deforestation, abrupt land-use changes, seasonal variability and socio-political instabilities, that limit the capacity of ecosystems and social systems to respond to climate change. In the case of Nigeria, for example, thermal fluctuations could be related to the impact of massive deforestation (Zaccheaus, 2015), while in Myanmar and Libya, political and social instabilities have resulted in less effective climate change monitoring. In terms of climate change such patterns imply that these regions are highly vulnerable to sudden and variable weather changes. This phenomenon requires further analysis to develop adaptive strategies aimed at mitigating the risks inherent in this unusual thermal behaviour.

To sum up, the findings in this study indicate diverse climate patterns in different regions of the world, some of them, such as the Middle East and Sub-Saharan Africa, being characterised by pronounced upward trends and high persistence in the number of hot days, whilst in others there is less evidence of sustained warming. The observed differences reflect the interaction between the global phenomenon of climate change and local factors affecting warming. This evidence underscores the importance of adopting differentiated approaches to mitigate the effects of climate change, prioritising strategies that address both global factors and specific local dynamics.

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Table 1: Estimates of d under three deterministic specifications. White noise errors

Country	No terms	A constant	A constant and a linear trend
North Africa			
ALGERIA	0.39 (0.30, 0.56)	0.45 (0.38, 0.54)	**0.19 (0.08, 0.35)**
DJIBOUTI	0.33 (0.23, 0.48)	0.39 (0.29, 0.53)	**0.13 (-0.05, 0.39)**
EGYPT	0.34 (0.26, 0.46)	0.39 (0.31, 0.51)	**0.20 (0.09, 0.37)**
LIBYA	0.14 (0.07, 0.24)	0.19 (0.10, 0.32)	**-0.27 (-0.44, -0.02)**
MOROCCO	0.35 (0.27, 0.48)	0.41 (0.33, 0.52)	**0.15 (0.02, 0.34)**
TUNISIA	0.30 (0.22, 0.41)	0.34 (0.25, 0.44)	**0.16 (0.02, 0.33)**
Sub-Saharian Africa			
BENIN	0.27 (0.19, 0.40)	0.33 (0.24, 0.46)	**-0.09 (-0.28, 0.46)**
BURKINA FASO	0.29 (0.22, 0.40)	0.36 (0.28, 0.47)	**-0.07 (-0.24, 0.47)**
CAMEROON	0.23 (0.16, 0.35)	0.28 (0.19, 0.40)	**-0.05 (-0.18, 0.40)**
CHAD	0.49 (0.49, 0.60)	0.52 (0.45, 0.61)	**0.36 (0.25, 0.61)**
ERITREA	0.48 (0.39, 0.59)	0.52 (0.45, 0.64)	**0.29 (0.16, 0.64)**
ETHIOPIA	0.36 (0.27, 0.57)	0.47 (0.37, 0.62)	**0.26 (0.00, 0.62)**
GAMBIA	0.21 (0.13, 0.31)	0.24 (0.15, 0.35)	**-0.14 (-0.28, 0.35)**
GHANA	0.19 (0.09, 0.35)	0.21 (0.10, 0.38)	**0.04 (-0.12, 0.25)**
MALI	0.30 (0.24, 0.38)	0.45 (0.38, 0.55)	**0.31 (-0.54, 0.03)**
MAURITANIA	0.30 (0.24, 0.42)	0.47 (0.39, 0.59)	**-0.04 (-0.23, 0.25)**
MOZAMBIQUE	0.28 (0.14, 0.47)	**0.28 (0.14, 0.48)**	0.25 (0.12, 0.46)
NIGER	0.41 (0.34, 0.52)	0.48 (0.41, 0.58)	**0.11 (-0.02, 0.31)**
NIGERIA	0.21 (0.14, 0.30)	0.26 (0.18, 0.36)	**-0.42 (-0.57, -0.17)**
SENEGAL	0.30 (0.23, 0.40)	0.37 (0.30, 0.47)	**-0.09 (-0.27, 0.14)**
SOUTH AFRICA	-0.01 (-0.12, 0.16)	-0.01 (-0.14, 0.18)	**-0.15 (-0.32, 0.09)**
SOMALIA	0.32 (0.24, 0.45)	0.40 (0.31, 0.52)	**0.08 (-0.11, 0.35)**
SOUTH SUDAN	0.26 (0.16, 0.41)	0.28 (0.18, 0.42)	**0.12 (-0.01, 0.32)**
SUDAN	0.47 (0.38, 0.63)	0.51 (0.43, 0.64)	**0.33 (0.17, 0.57)**
TOGO	0.08 (-0.01, 0.23)	0.10 (-0.01, 0.26)	**-0.17 (-0.37, 0.09)**
Central Asia			
KAZAKHSTAN	0.25 (0.15, 0.38)	0.26 (0.16, 0.39)	**0.17 (0.04, 0.33)**
TAJIKISTAN	0.49 (0.38, 0.64)	0.48 (0.37, 0.63)	**0.48 (0.37, 0.63)**

UZBEKISTAN	0.23 (0.13, 0.37)	0.25 (0.14, 0.38)	**0.18 (0.05, 0.33)**
South Asia			
AFGHANISTAN	0.24 (0.17, 0.34)	0.31 (0.23, 0.40)	**0.07 (-0.03, 0.21)**
BANGLADESH	0.13 (-0.01, 0.32)	0.11 (-0.01, 0.30)	**-0.01 (-0.18, 0.23)**
INDIA	-0.04 (-0.09, 0.34)	**-0.11 (-0.29, 0.16)**	-0.14 (-0.32, 0.14)
NEPAL	0.05 (-0.12, 0.26)	0.04 (-0.09, 0.20)	**-0.12 (-0.32, 0.15)**
PAKISTAN	0.43 (-0.04, 0.62)	**0.02 (-0.08, 0.16)**	-0.01 (-0.11, 0.14)
West Asia and Middle East			
BAHRAIN	0.31 (0.17, 0.52)	0.33 (0.19, 0.54)	**0.24 (0.06, 0.50)**
IRAN	0.47 (0.38, 0.61)	0.53 (0.46, 0.63)	**0.34 (0.23, 0.49)**
IRAQ	0.42 (0.32, 0.60)	0.46 (0.38, 0.56)	**0.31 (0.17, 0.50)**
SYRIA	0.05 (-0.04, 0.17)	0.06 (-0.04, 0.19)	**-0.12 (-0.24, 0.06)**
JORDAN	0.09 (-0.01, 0.20)	0.10 (-0.01, 0.22)	**-0.06 (-0.18, 0.10)**
KUWAIT	0.50 (0.36, 0.75)	0.45 (0.36, 0.55)	**0.34 (0.20, 0.53)**
OMAN	0.17 (0.12, 0.36)	0.36 (0.28, 0.49)	**-0.10 (-0.26, 0.18)**
QATAR	0.54 (0.42, 0.73)	0.54 (0.45, 0.69)	**0.46 (0.34, 0.66)**
SAUDI ARABIA	0.50 (0.43, 0.62)	0.56 (0.50, 0.65)	**0.37 (0.26, 0.54)**
SYRIA	0.25 (0.17, 0.37)	0.28 (0.19, 0.40)	**0.15 (0.04, 0.30)**
TURKEY	0.22 (0.13, 0.36)	0.24 (0.14, 0.38)	**0.15 (0.03, 0.32)**
U.A.E.	0.51 (0.41, 0.67)	0.52 (0.44, 0.64)	**0.43 (0.32, 0.59)**
YEMEN	0.54 (0.45, 0.70)	0.62 (0.53, 0.76)	**0.46 (0.28, 0.71)**
East Asia and Pacific			
AUSTRALIA	0.20 (0.06, 0.48)	0.25 (0.10, 0.48)	**0.14 (-0.06, 0.44)**
CHINA	0.45 (0.28, 0.70)	**0.36 (0.23, 0.55)**	0.36 (0.23, 0.55)
MYANMAR	0.03 (-0.06, 0.17)	0.04 (-0.08, 0.21)	**-0.29 (-0.52, 0.02)**
THAILAND	-0.06 (-0.16, 0.10)	-0.07 (-0.20, 0.12)	**-0.24 (-0.42, 0.01)**
America			
ARGENTINA	0.11 (-0.02, 0.33)	0.12 (-0.01, 0.32)	**0.08 (-0.10, 0.38)**
MEXICO	0.24 (0.14, 0.42)	0.31 (0.20, 0.47)	**0.13 (-0.03, 0.37)**
PARAGUAY	-0.02 (-0.14, 0.17)	**-0.02 (-0.15, 0.16)**	-0.01 (-0.15, 0.17)
U.S.A.	0.35 (0.24, 0.55)	0.41 (0.30, 0.57)	**0.27 (0.10, 0.50)**

Note: In bold the selected specification on the basis of the statistical significance of the deterministic components. The reported values are the estimates of d, and in brackets the corresponding 95% confidence intervals.

Table 2: Estimated coefficients from the selected models. White noise errors

North Africa			
Country	diff. par. (95% band)	Intercept (t-value)	Time trend (t-value)
ALGERIA	0.19 (0.08, 0.35)	19.1234 (8.46)	0.4739 (9.31)
DJIBOUTI	0.13 (-0.05, 0.39)	-0.7466 (-0.46)	0.2413 (6.58)
EGYPT	0.20 (0.09, 0.37)	0.3750 (0.41)	0.1073 (5.30)
LIBYA	-0.27 (-0.44, -0.02)	0.2672 (2.28)	0.0687 (12.68)
MOROCCO	0.15 (0.02, 0.34)	1.3111 (2.97)	0.0848 (8.50)
TUNISIA	0.16 (0.02, 0.33)	-0.2058 (-2.21)	0.1334 (6.27
Sub-Saharian Africa			
BENIN	-0.09 (-0.28, 0.46)	-0.3268 (-1.99)	0.0448 (11.29)
BURKINA FASO	-0.07 (-0.24, 0.47)	-0.7746 (-1.71)	0.1574 (12.79)
CAMEROON	-0.05 (-0.18, 0.40)	-0.1669 (-1.94)	0.0181 (8.84)
CHAD	0.36 (0.25, 0.61)	-1.8865 (-1.09)	0.2409 (6.00)
ERITREA	0.29 (0.16, 0.64)	-0.5539 (-0.81)	0.1166 (7.56)
ETHIOPIA	0.26 (0.00, 0.62)	0.5729 (2.11)	0.0436 (7.14)
GAMBIA	-0.14 (-0.28, 0.35)	-0.4767 (-3.49)	0.0362 (10.74)
GHANA	0.04 (-0.12, 0.25)	-0.0906 (-1.98)	0.0074 (4.19)
MALI	0.31 (-0.54, 0.03)	14.9884 (25.38)	0.6218 (39.82)
MAURITANIA	-0.04 (-0.23, 0.25)	15.4798 (12.34)	0.5061 (16.95)
MOZAMBIQUE	0.28 (0.14, 0.48)	0.0419 (1.76)	------
NIGER	0.11 (-0.02, 0.31)	-1.5606 (-1.07)	0.4072 (12.35)
NIGERIA	-0.42 (-0.57, -0.17)	-0.3132 (-6.08)	0.0384 (27.02)
SENEGAL	-0.09 (-0.27, 0.14)	-0.2115 (-0.35)	0.2294 (16.03)
SOUTH AFRICA	-0.15 (-0.32, 0.09)	-0.0047 (-1.94)	0.0003 (3.18)
SOMALIA	0.08 (-0.11, 0.35)	0.0069 (0.20)	0.0062 (8.10)
SOUTH SUDAN	0.12 (-0.01, 0.32)	-0.8026 (-1.66)	0.0466 (4.24)
SUDAN	0.33 (0.17, 0.57)	0.5948 (0.32)	0.2848 (6.82)
TOGO	-0.17 (-0.37, 0.09)	-0.0731 (-1.80)	0.0058 (5.74)
Central Asia			
KAZAKHSTAN	0.17 (0.04, 0.33)	-0.0136 (-0.19)	0.0058 (3.77)
TAJIKISTAN	0.48 (0.37, 0.63)	-0.0324 (-2.23)	0.0095 (2.72)

UZBEKISTAN	0.18 (0.05, 0.33)	0.0828 (0.15)	0.0433 (3.84)
South Asia			
AFGHANISTAN	0.07 (-0.03, 0.21)	3.0462 (5.66)	0.0938 (7.59)
BANGLADESH	-0.01 (-0.18, 0.23)	0.2836 (3.73)	-0.0046 (-2.60)
INDIA	-0.11 (-0.29, 0.16)	0.7991 (42.00)	------
NEPAL	-0.12 (-0.32, 0.15)	0.2355 (6.90)	-0.0026 (-3.08)
PAKISTAN	0.02 (-0.08, 0.16)	22.3880 (54.49)	-----
West Asia and Middle East			
BAHRAIN	0.24 (0.06, 0.50)	0.1026 (0.04)	0.1257 (2.49)
IRAN	0.34 (0.23, 0.49)	6.9583 (6.78)	0.1636 (6.91)
IRAQ	0.31 (0.17, 0.50)	19.6346 (4.44)	0.6325 (6.28)
SYRIA	-0.12 (-0.24, 0.06)	-0.0125 (-1.27)	0.0010 (4.11)
JORDAN	-0.06 (-0.18, 0.10)	-0.1473 (-2.81)	0.0188 (4.56)
KUWAIT	0.34 (0.20, 0.53)	51.8854 (7.81)	0.8274 (5.40)
OMAN	-0.10 (-0.26, 0.18)	26.7653 (25.71)	0.3002 (11.85)
QATAR	0.46 (0.34, 0.66)	24.0736 (3.05)	0.6784 (3.39)
SAUDI ARABIA	0.37 (0.26, 0.54)	12.7233 (3.03)	0.7463 (7.84)
SYRIA	0.15 (0.04, 0.30)	0.6866 (2.74)	0.0820 (3.93)
TURKEY	0.15 (0.03, 0.32)	0.0666 (1.61)	0.0022 (2.36)
U.A.E.	0.43 (0.32, 0.59)	30.68761 (3.99)	0.6339 (3.36)
YEMEN	0.46 (0.28, 0.71)	1.8171 (2.30)	0.1815 (5.14)
East Asia and Pacific			
AUSTRALIA	0.14 (-0.06, 0.44)	3.5900 (4.74)	0.0406 (2.35)
CHINA	0.36 (0.23, 0.55)	0.1342 (2.63)	------
MYANMAR	-0.29 (-0.52, 0.02)	0.0091 (2.42)	0.0038 (6.82)
THAILAND	-0.24 (-0.42, 0.01)	-0.0085 (-0.39)	0.0020 (3.68)
America			
ARGENTINA	0.08 (-0.10, 0.38)	0.0134 (2.26)	0.0039 (3.48)
MEXICO	0.13 (-0.03, 0.37)	0.1212 (3.11)	0.0041 (4.72)
PARAGUAY	-0.02 (-0.15, 0.16)	0.4142 (4.47)	------
U.S.A.	0.27 (0.10, 0.50)	0.0988 (2.06)	0.0054 (5.04)

Note: Column 2 reports the estimate of d and in brackets the corresponding 95% confidence intervals, whilst column 3 and 4 report the estimates of the intercept and of the coefficient on the time trend respectively as well as the corresponding t-values in brackets; --- indicates lack of statistical significance.

Table 3: Estimates of d under three deterministic specifications. Autocorrelated errors

North Africa			
Country	No terms	A constant	A constant and a linear trend
ALGERIA	0.73 (0.47, 1.06)	0.55 (0.40, 0.74)	**0.36 (0.13, 0.65)**
DJIBOUTI	0.28 (0.12, 0.51)	0.35 (0.17, 0.58)	**-0.21 (-0.73, 0.24)**
EGYPT	0.42 (0.28, 0.61)	0.47 (0.30, 0.66)	**0.22 (0.04, 0.50)**
LIBYA	0.19 (0.08, 0.37)	0.28 (0.11, 0.46)	**-0.52 (-1.08, -0.11)**
MOROCCO	0.39 (0.27, 0.60)	0.45 (0.32, 0.59)	**0.13 (-0.06, 0.40)**
TUNISIA	0.59 (0.35, 0.95)	0.55 (0.34, 0.93)	**0.54 (0.14, 0.94)**
Sub-Saharian Africa			
BENIN	0.28 (0.15, 0.44)	0.34 (0.18, 0.51)	**-0.42 (-0.75, -0.03)**
BURKINA FASO	0.35 (0.21, 0.54)	0.42 (0.27, 0.61)	**-0.32 (-0.71, 0.21)**
CAMEROON	0.29 (0.13, 0.46)	0.34 (0.18, 0.51)	**-0.09 (-0.38, 0.17)**
CHAD	0.58 (0.44, 0.75)	0.61 (0.48, 0.76)	**0.41 (0.20, 0.64)**
ERITREA	0.52 (0.40, 0.72)	0.57 (0.45, 0.74)	**0.24 (0.03, 0.57)**
ETHIOPIA	0.23 (0.12, 0.39)	0.36 (0.20, 0.53)	**-0.67 (-1.04, 0.11)**
GAMBIA	0.30 (0.18, 0.47)	0.35 (0.21, 0.51)	**-0.19 (-0.44, 0.12)**
GHANA	0.16 (-0.02, 0.42)	0.19 (-0.05, 0.45)	**-0.09 (-0.60, 0.29)**
MALI	0.28 (0.19, 0.38)	0.42 (0.28, 0.55)	**-1.21 (-1.86, -0.58)**
MAURITANIA	0.25 (0.16, 0.37)	0.40 (0.25, 0.53)	**-0.54 (-0.95, -0.13)**
MOZAMBIQUE	0.12 (-0.15, 0.37)	0.12 (-0.12, 0.38)	**0.08 (-0.15, 0.34)**
NIGER	0.41 (0.30, 0.56)	0.48 (0.36, 0.62)	**-0.03 (-0.27, 0.25)**
NIGERIA	0.28 (0.17, 0.40)	0.35 (0.22, 0.49)	**-0.69 (-0.87, -0.39)**
SENEGAL	0.36 (0.23, 0.51)	0.43 (0.30, 0.57)	**-0.33 (-0.75, 0.17)**
SOUTH AFRICA	-0.05 (-0.24, 0.21)	-0.06 (-0.32, 0.26)	**-0.42 (-0.88, 0.05)**
SOMALIA	0.41 (0.24, 0.96)	0.51 (0.34, 0.97)	**-0.14 (-0.49, 0.98)**
SOUTH SUDAN	0.25 (0.07, 0.49)	0.28 (0.08, 0.49)	**0.03 (-0.22, 0.34)**
SUDAN	0.45 (0.33, 0.64)	0.51 (0.38, 0.68)	**0.17 (0.04, 0.49)**
TOGO	0.09 (-0.07, 0.32)	0.12 (-0.09, 0.39)	**-0.53 (-1.06, 0.04)**
Central Asia			
KAZAKHSTAN	0.54 (0.21, 0.85)	0.49 (0.20, 0.83)	**0.48 (0.16, 0.83)**
TAJIKISTAN	**0.84 (0.55, 1.13)**	0.84 (0.48, 1.13)	0.83 (0.57, 1.14)

UZBEKISTAN	**0.68 (0.25, 1.00)**	0.59 (0.18, 1.00)	0.68 (0.30, 1.01)
South Asia			
AFGHANISTAN	0.55 (0.37, 0.79)	0.52 (0.39, 0.68)	**0.34 (0.15, 0.56)**
BANGLADESH	0.11 (-0.17, 0.43)	0.07 (-0.12, 0.37)	**-0.24 (-0.51, 0.17)**
INDIA	-0.11 (-0.19, 0.35)	-0.48 (-0.80, -0.08)	**-0.54 (-0.82, -0.15)**
NEPAL	0.01 (-0.29, 0.40)	0.01 (-0.34, 0.31)	**-0.42 (-0.74, 0.09)**
PAKISTAN	0.70 (0.40, 0.99)	**0.22 (0.03, 0.49)**	0.18 (-0.01, 0.48)
West Asia and Middle East			
BAHRAIN	0.15 (-0.04, 0.47)	0.17 (-0.04, 0.47)	**-0.05 (-0.41, 0.41)**
IRAN	0.61 (0.45, 0.83)	0.59 (0.45, 0.75)	**0.40 (0.25, 0.63)**
IRAQ	0.60 (0.36, 1.03)	0.58 (0.44, 0.89)	**0.42 (0.11, 0.90)**
SYRIA	0.18 (0.02, 0.42)	0.21 (0.03, 0.46)	**-0.05 (-0.29, 0.32)**
JORDAN	0.28 (0.10, 0.54)	0.31 (0.12, 0.56)	**0.13 (-0.10, 0.47)**
KUWAIT	0.73 (0.38, 1.08)	0.62 (0.44, 1.07)	**0.54 (0.09, 1.06)**
OMAN	0.18 (0.12, 0.40)	0.40 (0.27, 0.59)	**-0.30 (-0.47, 0.02)**
QATAR	0.52 (0.37, 0.80)	0.57 (0.42, 0.78)	**0.41 (0.21, 0.71)**
SAUDI ARABIA	0.63 (0.50, 0.90)	0.70 (0.58, 0.90)	**0.49 (0.28, 0.83)**
SYRIA	0.42 (0.26, 0.64)	0.44 (0.29, 0.64)	**0.30 (0.11, 0.57)**
TURKEY	0.33 (0.17, 0.57)	0.37 (0.21, 0.58)	**0.23 (0.01, 0.56)**
U.A.E.	0.59 (0.43, 0.87)	0.65 (0.51, 0.88)	**0.54 (0.34, 0.84)**
YEMEN	0.53 (0.42, 0.71)	0.63 (0.51, 1.23)	**0.27 (-0.01, 0.77)**
East Asia and Pacific			
AUSTRALIA	0.03 (-0.08, 0.26)	0.06 (-0.18, 0.34)	**-0.24 (-0.60, 0.14)**
CHINA	0.35 (-0.01, 1.04)	**0.30 (-0.03, 0.71)**	0.35 (0.01, 0.69)
MYANMAR	-0.02 (-0.15, 0.17)	-0.03 (-0.22, 0.21)	**-1.03 (-1.69, -0.32)**
THAILAND	-0.11 (-0.28, 0.14)	-0.15 (-0.41, 0.17)	**-0.55 (-1.17, -0.08)**
America			
ARGENTINA	0.10 (-0.09, 0.64)	0.13 (-0.13, 0.51)	**0.08 (-0.29, 0.86)**
MEXICO	0.19 (0.06, 0.48)	0.28 (0.08, 0.52)	**-0.06 (-0.39, 0.33)**
PARAGUAY	0.06 (-0.25, 0.53)	**0.06 (-0.23, 0.48)**	0.10 (-0.20, 0.57)
U.S.A.	0.25 (0.07, 0.54)	0.30 (0.11, 0.50)	**0.05 (-0.29, 0.41)**

Note: In bold the selected specification on the basis of the statistical significance of the deterministic components. The reported values are the estimates of d, and in brackets the corresponding 95% confidence intervals.

Table 4: Estimated coefficients from the selected models. Autocorrelated errors

North Africa			
Country	diff. par. (95% band)	Intercept (t-value)	Time trend (t-value)
ALGERIA	0.36 (0.13, 0.65)	20.3542 (6.10)	0.4693 (6.04)
DJIBOUTI	-0.21 (-0.73, 0.24)	-0.7076 (-1.19)	0.2368 (15.80)
EGYPT	0.22 (0.04, 0.50)	0.4061 (0.43)	0.1069 (5.03)
LIBYA	-0.52 (-1.08, -0.11)	0.2828 (-1.08)	0.0681 (24.87)
MOROCCO	0.13 (-0.06, 0.40)	1.2932 (-0.06)	0.0849 (8.95)
TUNISIA	0.54 (0.14, 0.94)	0.1199 (0.05)	0.1442 (2.53)
Sub-Saharian Africa			
BENIN	-0.42 (-0.75, -0.03)	-0.3207 (-5.66)	0.0443 (28.22)
BURKINA FASO	-0.32 (-0.71, 0.21)	-0.7488 (-3.14)	0.1559 (24.69)
CAMEROON	-0.09 (-0.38, 0.17)	-0.1676 (-2.20)	0.0181 (9.80)
CHAD	0.41 (0.20, 0.64)	-1.6176 (-0.85)	0.2388 (5.22)
ERITREA	0.24 (0.03, 0.57)	-0.6227 (-1.03)	0.1176 (8.64)
ETHIOPIA	-0.67 (-1.04, 0.11)	0.7013 (42.74)	0.0409 (81.60)
GAMBIA	-0.19 (-0.44, 0.12)	-0.4760 (-4.06)	0.0361 (12.23)
GHANA	-0.09 (-0.60, 0.29)	-0.0912 (-0.60)	0.0073 (5.78)
MALI	-1.21 (-1.86, -0.58)	15.2272 (446.99)	0.6133 (485.57)
MAURITANIA	-0.54 (-0.95, -0.13)	15.5827 (60.43)	0.5006 (66.88)
MOZAMBIQUE	0.08 (-0.15, 0.34)	0.0028 (0.12)	0.0009 (1.71)
NIGER	-0.03 (-0.27, 0.25)	-1.7392 (-1.80)	0.4081 (17.80)
NIGERIA	-0.69 (-0.87, -0.39)	-0.3105 (-13.76)	0.0384 (55.49)
SENEGAL	-0.33 (-0.75, 0.17)	0.0233 (1.24)	0.2259 (5.37)
SOUTH AFRICA	-0.42 (-0.88, 0.05)	-0.0044 (-2.26)	0.0003 (6.36)
SOMALIA	-0.14 (-0.49, 0.98)	0.0045 (00.25)	0.0063 (14.53)
SOUTH SUDAN	0.03 (-0.22, 0.34)	-0.8439 (-2.25)	0.0466 (5.35)
SUDAN	0.17 (0.04, 0.49)	0.2383 (0.19)	0.2875 (10.36)
TOGO	-0.53 (-1.06, 0.04)	-0.0658 (-5.00)	0.0055 (14.53)
Central Asia			
KAZAKHSTAN	0.48 (0.16, 0.83)	0.0183 (0.14)	0.0064 (1.87)
TAJIKISTAN	0.84 (0.55, 1.13)	------	------

UZBEKISTAN	0.68 (0.25, 1.00)	------	------
South Asia			
AFGHANISTAN	0.34 (0.15, 0.56)	3.2783 (3.19)	0.0940 (3.96)
BANGLADESH	-0.24 (-0.51, 0.17)	0.2914 (7.70)	-0.0049 (-5.08)
INDIA	-0.54 (-0.82, -0.15)	8.2815 (61.02)	0.0132 (3.36)
NEPAL	-0.42 (-0.74, 0.09)	0.2361 (17.65)	-0.0025 (-6.91)
PAKISTAN	0.22 (0.03, 0.49)	22.5716 (27.01)	------
West Asia and Middle East			
BAHRAIN	-0.05 (-0.41, 0.41)	-0.2843 (-0.28)	0.1259 (5.29)
IRAN	0.40 (0.25, 0.63)	7.1588 (6.21)	0.1621 (5.88)
IRAQ	0.42 (0.11, 0.90)	19.2862 (3.51)	0.6428 (4.81)
SYRIA	-0.05 (-0.29, 0.32)	-0.0119 (-0.98)	0.0009 (3.39)
JORDAN	0.13 (-0.10, 0.47)	-0.1355 (-0.46)	0.0192 (2.90)
KUWAIT	0.54 (0.09, 1.06)	48.2138 (5.18)	0.8714 (3.29)
OMAN	-0.30 (-0.47, 0.02)	26.4727 (46.62)	0.3088 (20.65)
QATAR	0.41 (0.21, 0.71)	23.2478 (3.21)	0.6844 (3.93)
SAUDI ARABIA	0.49 (0.28, 0.83)	14.0864 (2.82)	0.7323 (5.59)
SYRIA	0.30 (0.11, 0.57)	0.9216 (0.69)	0.0804 (2.67)
TURKEY	0.23 (0.01, 0.56)	0.0741 (1.47)	0.0021 (1.82)
U.A.E.	0.54 (0.34, 0.84)	32.3177 (3.57)	0.6182 (2.40)
YEMEN	0.27 (-0.01, 0.77)	1.1794 (1.23)	0.1962 (9.10)
East Asia and Pacific			
AUSTRALIA	-0.24 (-0.60, 0.14)	3.5276 (14.55)	0.0396 (6.36)
CHINA	0.30 (-0.03, 0.71)	0.1312 (2.65)	------
MYANMAR	-1.03 (-1.69, -0.32)	-0.0148 (7.01)	0.0037 (49.63)
THAILAND	-0.55 (-1.17, -0.08)	-0.0551 (-0.67)	0.0019 (8.08)
America			
ARGENTINA	0.08 (-0.29, 0.86)	0.0134 (0.26)	0.0039 (3.48)
MEXICO	-0.06 (-0.39, 0.33)	0.1226 (5.44)	0.0040 (7.51)
PARAGUAY	0.06 (-0.23, 0.48)	0.4202 (2.98)	------
U.S.A.	0.05 (-0.29, 0.41)	0.10004 (3.75)	0.0052 (8.41)

Note: Column 2 reports the estimate of d and in brackets the corresponding 95% confidence intervals, whilst column 3 and 4 report the estimates of the intercept and of the coefficient on the time trend respectively as well as the corresponding t-values in brackets; --- indicates lack of statistical significance.

Table 5: Summary results. Time trends

No autocorrelation		With autocorrelation	
Highest time trends	No time trends	Highest time trends	No time trends
Kuwait (0.8274)	Morocco	Kuwait (0.8714)	Tajikistan
Saudi Arabia (0.7463)	India	Saudi Arabia (0.7323)	Uzbekistan
Qatar (0.6784)	Pakistan	Qatar (0.6844)	Pakistan
U.A.E. (0.6339)	China	Iraq (0.6428)	China
Iraq (0.6325)	Paraguay	U.A.E. (0.6182)	Paraguay
Mali (0.6218)		Mali (0.6122)	
Mauritania (0.5061)		Mauritania (0.5006)	
Algeria (0.4739)		Algeria (0.4693)	

Table 6: Summary results. Persistence

No autocorrelation		With autocorrelation	
Highest d	Lowest d	Highest d	Lowest d
Tajkistan (0.48)	Nigeria (-0.42)	Tajkistan (0.84)	Mali (-1.21)
Qatar (0.46)	Myanmar (-0.29)	Uzbekistan (0.68)	Myanmar (-1.03)
Yemen (0.46)	Libya (-0.27)	Kuwait (0.53)	Nigeria (-0.69)
U.A.E. (0.43)	Thailand (-0.24)	U.A.E. (0.54)	Ethiopia (-0.67)
Saudi Arabia (0.37)	Togo (-0.17)	Tunisia (0.54)	Thailand (-0.55)
Chad (0.36)	South Africa (-0.15)	Saudi Arabia (0.49)	India (-0.54)
China (0.36)	Gambia (-0.14)	Kazakhstan (0.48)	Mauritania (-0.54)
Iran (0.34)	Nepal (-0.12)	Iraq (0.42)	Togo (-0.53)
Kuwait (0.34)	Syria (-0.12)	Qatar (0.41)	Libya (-0.52)
Sudan (0.33)	India (-0.11)	Chad (0.40)	Benin (-0.42)
Mali (0.31)	Oman (-0.10)	Iran (0.40)	Nepal (-0.42)
Iraq (0.31)		Algeria (0.36)	South Africa (-0.42)
		Afghanistan (0.34)	