TIME TRENDS IN THE EUROPEAN AVERAGE TEMPERATURE ANOMALIES FOR THE PERIOD 1655-2017

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ABSTRACT

This paper deals with the analysis of the time trends for the European average temperature anomalies for the period from 1655 to 2017 using a dataset that is based on the Central England Temperatures (CET) and other meteorological stations. The results indicate that the series display long memory behavior and based on this and using recursive methods, we find that the time trend becomes statistically significant when incorporating the data from 2010 onwards suggesting the importance of the last few years in the claim for warming.

Keywords: European temperature anomalies; time trends; persistence; long memory

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1. Introduction

This paper deals with the analysis of the temperatures in Europe. More in particular, we focus on the analysis of the time trends to check if there has been an increase in the values across time. For the estimation of the time trends a usual requirement is that the errors in the regression model must be well behaved and it is here where we make our initial contribution by allowing the errors to be fractionally integrated, a feature that has been observed in many climatological data.

Some authors have analyzed the time trends in climatological data by classifying the global land into various climatic regions based on the climatological annual precipitation (Zhou et al. 2009). These authors analyze the spatial dependence of annual diurnal temperature range (DTR) trends from 1950–2004 on the annual climatology of three variables: precipitation, cloud cover, and leaf area index (LAI). It is found that the regional average trends for annual minimum temperature (T min) and DTR exhibit significant spatial correlations with the climatological values of these three variables, while such correlation for annual maximum temperature (T max) is very weak.

Focussing on Europe, there are other studies on time trends of climatological data. Klein & Können (2003), for example, studied the trends of extreme temperature indices on the basis of daily series of temperature and precipitation from more than 100 meteorological stations in Europe. The selected indices of daily temperature and precipitation extremes showed pronounced trends within the 1946–99 period. Europe-average trends in mean temperature are accompanied by "asymmetric" rather than "symmetric" changes in temperature extremes for two consecutive periods: 1946–75 and 1976–99. Luterbacher et al. (2004) argued that for the 21st-century European climate is very likely warmer than that of any other time during the past 500 years. Moberg & Jones (2005) analyzed 20th century trends in six indices for precipitation and four indices for temperature extremes, calculated from daily observational data for 80 European stations situated across central and western Europe. The selected indices reflected rather moderate extremes.

According to Mariani & Zavatti (2017) Europe is the world region with the longest time series of instrumental data due to the fact that the first meteorological instruments (thermometer, pluviometer, evaporimeter and barometer) were invented by some scientists of the Galilean school (Accademia del Cimento). In this paper we use the dataset gathered by these authors with the aim of organizing an easily updatable dataset which allows us to present an overview of the trend of European climate over the long time periods covered by instrumental data. The dataset includes information from 29 stations and starts in 1655 which is just the beginning of the Florentine Galileo series data (Camuffo & Bertolin 2012). The Central England Time Series, CET (MetOffice_Hadley Centre, 2016) was added from year 1659 and gradually other stations joined (MeteoFrance, ECA&D, MeteoSwiss), at first coming from historical observatories (Camuffo & Jones 2002) and then from current operational networks. The most recent data were obtained from either the website Rimfrost (2016) and from the above mentioned stations (Mariani & Zsavatti 2017). (See the Appendix for a description of the stations used).

Global air temperature has become the primary metric for judging global climate change. There are many studies on the temperature trend over time. Many of these studies explain the causes of global warming. Andronova & Schlesinger (2000) analyze two types of factors: "external" factors of human (anthropogenic) activity, volcanoes and putative variations in the irradiance of the sun, and the "internal" factor of natural variability. They show that temperature changes for different state-of-the-art radiative forcing models, “the anthropogenic effect has steadily increased in size during the entire 20th century such that it presently is the dominant external forcing of the climate system, there is a residual factor at work within the climate system, whether a natural oscillation or something else as yet unknown".

Kaufmann et al (2011) indicate that observed temperature after 1998 is consistent with the current understanding of the relationship among global surface temperature, internal variability, and radiative forcing, which includes anthropogenic factors but too must be considered and the changes in natural variables. Some studies on temperature in Europe show that "Europe's temperature rise of about 1°C since the 1980s is considerably larger than expected from anthropogenic greenhouse warming" (Philipona et al. 2009).

More in line with our work, Lovsletten and Rypdal (2016) use a model containing a linear deterministic trend along with a long memory process that is specified using various alternatives, including a Gaussian noise model. Their results indicate evidence of linear time trend and long memory in the majority of the regional temperature series examined.[1]

External and internal factors influence changes in temperature but although external factors are controlled, there are other factors that influence climate change. Our research focuses on studying whether temperature, with data coming back to 1655, have really increased without considering its causes.

We use the abovementioned dataset to examine two important features observed in the temperatures, such as the degree of persistence, measured in terms of the fractional differencing parameter, and the potential warming, measured by means of a (linear) time trend coefficient. We show in the following section that both issues are very much related since the estimation of the time trend coefficient clearly depends on

[1] A Bayesian approach of long memory (fractional Gaussian noise) with a linear trend can be found in Myrvoll-Nielsen et al. (2017).

the correct specification of the error term, which is allowed to be fractionally integrated to permit some degree of persistence. It might be argued that a linear trend may be unrealistic with a time horizon of about 400 years; nevertheless, it appears as a natural statistical instrument to measure warming. Our results can be summarized as follows: evidence of long memory behavior (with an order of integration in the stationary range (0, 0.5)) is observed in the European average temperature anomalies, and based on this pattern, a positive time trend is found to be statistically significant. This time trend coefficient is slightly higher than the one obtained under I(0) (or short memory) behavior. Testing if these two features, persistence and time trend, have changed across time, our results indicate that the degree of persistence has increased across time, especially after 1985. Similarly, the time trend coefficient has also increased and it becomes statistically significant during the last years of the sample. Other studies have also investigated the time trends in climatological data with shorter time series, including among others the works by Gil-Alana (2003) on the CET; Caballero et al. (2002) for the multidecadal daily time series from CET, Chicago and Los Angeles; Gil-Alana (2010), for the monthly data in specific locations in Spain and Portugal; Franzke (2012) in four stations: central England; Stockholm (Sweden); Faraday-Vernadsky (Antarctic Peninsula) and Alert (Canada); Percival et al. (2001) and Gil-Alana (2012), for monthly temperatures in Alaska; Kane & Usman (2013) for the Sokoto metropolis in Nigeria, or Franzke (2010), Bunde et al. (2014), and Ludescher et al. (2016), for monthly temperatures of different stations of Antarctica.

2. The model

Let us suppose that y_t is the time series we observe, in our case, the European average temperature anomalies, and, in order to test for a climate warming over time, we consider the following (linear) model,

$$y_t = \beta_0 + \beta_1 t + x_t; \qquad t = 0, 1, ..., \qquad (1)$$

where β_0 and β_1 are unknown coefficients referring respectively to the intercept and the time trend. Thus, β_1 measures the mean change in the temperatures by unit time (in our case, years), and, in order to test for warming, we can test the null hypothesis:

$$H_o = \beta_1 = 0, \qquad (2)$$

against the one-sided alternative: $\beta_1 > 0$. However, instead of assuming as in the standard cases, that the detrended process x_t in (1) is I(0) stationary, or alternatively, I(1) nonstationary, we estimate its order of integration from the data by means of the following model,

$$(1 - B)^d x_t = u_t, \quad t = 0, \pm 1, ..., \qquad (3)$$

where B refers to the backshift operator, i.e., $Bx_t = x_{t-1}$, d can be any integer or fractional value, and u_t is assumed to be I(0). Related with this latter component (u_t), we will suppose first that u_t in (3) is uncorrelated (white noise, i.e. $u_t = \varepsilon_t$); however, weak autocorrelation will also be permitted by using an autoregression of order 1 (AR(1), i.e., $u_t = \rho u_{t-1} + \varepsilon_t$) process, but also by using a non-parametric specification due to Bloomfield (1973), which approximates highly parameterized ARMA processes with very few parameters. (See Gil-Alana 2004 for a complete description of this model in the context of fractional integration). The estimation is carried out using the Whittle function in the frequency domain (Dahlhaus 1989, Robinson 1994 and others).

3. Data

We use the data collected by Mariani & Zavatti (2017), referring to the European average temperature anomalies for the time period 1655 – 2017. According to these authors, it was from the start of this period that the idea of spreading meteorological instruments at a European level to promote an observational network able to operate in a coordinated manner flourished for the first time (Iafrate 2008). The 29 data stations (reported in the Appendix) were chosen with the aim of organizing an easily updatable dataset which allows us to give an overview of the trend of European climate over the long time periods covered by instrumental data. In order to obtain a representative area average, the data of each station were converted into anomalies with respect to the average temperature 1961-1990 of the station itself. The final dataset, displayed in Figure 1, is the yearly average European temperature anomaly for the period 1655-2017, and it is available at: “http://www.climatemonitor.it/wp -content/uploads/2018/03/EUROPA_TD_da_1655_DATI-E-risultati.xls”

[Insert Figure 1 about here]

As a final remark here is important to note that these temperature series proposed in Mariani & Zavatti (2017) are negatively affected by changes in measurement units, observational standards (e.g., time of observation), location of instruments and by the intensity of urban effects (intensity of the urban heat island, UHI). Thus, results presented below should be taken with a bit of caution.

4. Results

We display in Table 1 the estimated coefficients in the model given by

$$y_t \;=\; \beta_0 \;+\; \beta_1 t \;+\; x_t, \qquad (1 \;-\; B)^d\, x_t \;=\; u_t, \quad t \;=\; 1, 2, \ldots, \tag{4}$$

under the three assumptions of uncorrelated, AR(1) and Bloomfield-type errors. As mentioned above the approach in Bloomfield (!973) is non-parametric in the sense that no explicit model is presented for u_t, and it is exclusively specified in terms of its spectral density function, which is given by:

$$f(\lambda;\sigma^2) = \frac{\sigma^2}{2\pi}\exp\left(2\sum_{r=1}^{m}\tau_r\cos(\lambda r)\right), \qquad (5)$$

where σ^2 is the variance of the error term, λ refers to the frequency constrained between 0 and π, and m indicates the last of the Fourier frequencies which is associated with the short run parameters. Bloomfield (1973) showed that the above equation can approximate extremely well the spectral density of any highly parameterized ARMA, since this model also produces autocorrelations decaying exponentially fast, and Gil-Alana (2004, 2008a) showed that this model is very suitable in the context of fractional integration, and more in particular with the version of the tests of Robinson (1994) used in this work; moreover, this model is stationary across all values of τ unlike what happens in the ARMA case.[2]

The first thing we observe in Table 1 is that the estimated value of d is found to be significantly positive in the three cases, being around 0.3 under no autocorrelation, and slightly higher (about 0.4) with autocorrelated disturbances. This is consistent with many other studies also reporting evidence of long memory in temperatures, e.g., Gil-Alana (2003), Lennartz & Bunde (2009), Rea et al. (2011), Bunde (2017), etc. On the other hand, the time trend coefficient is statistically positive in the three cases: 0.0029 with white noise errors, and 0.0028 with autocorrelation, being these values slightly higher than the one obtained under the assumption of I(0) errors (i.e., d = 0 in (4)) (0.0027). Figure 1 also displays the estimated time trend (for the autocorrelated model) along with the observed data.

[2] Alternatively, we could have used ARFIMA(p, d, q) models (Beran, 1995); however, in this context, we need to be extremely cautious about the orders p and q for the short run dynamics since misspecificiation of these components lead to an inconsistent estimate of the differencing parameter d.

We next examine the stability of the two parameters (persistence and time trend coefficient) across the sample period, and for this purpose we use recursive estimation of the parameters, starting with a subsample from 1655 to 1900, adding then successively five observations each time till completing the whole sample. That is, we consider again the model in (4), estimating the parameters β_0, β_1 and d, first for a subsample ending at 1900, and then, re-estimating the parameters adding five observations each time. The results in terms of the estimates of d (persistence) and β_1 (time trend) are displayed in Figure 2.

[Insert Figure 2 about here]

Starting with the degree of persistence, in the upper part of the figure, we observe that the estimate of the fractional differencing parameter has remained relatively stable during most subsamples, observing a slight increase especially when we incorporate data from 1985 onwards. This indicates that temperatures have become gradually more persistent, especially during the last years in the sample. Focusing on the time trend coefficient (lower part of Figure 2) we notice that the time trend has been successively increasing across the different subsamples, though it has become statistically significantly positive only during the last four subsamples, that is, incorporating the data from 2010 onwards.

[Insert Table 2 about here]

Table 2 reports the estimates of the differencing parameter and the time trend coefficient for the last 18 subsamples, starting from 2000. Both coefficients have increased across the subsamples, from 0.35 to 0.41 in case of the persistence parameter, and from 0.0019 to 0.0028 in case of the time trend coefficient. This last result indicates that the increase in the temperatures has become particularly relevant during the last ten years of the sample suggesting the relevance of the last period of the sample in the analysis of the global warming.

As a robustness method and in order to check if the beginning of the series has produced changes due to the artificial long term variability, we repeat the analysis of four different subsamples, the first three with 100 observations each (1655 – 1754; 1755 – 1854, and 1855 – 1954), and the final one with the last 62 observations (1955 – 2017). We estimate d for the three potential set-ups for the error term: white noise, AR(1) and Bloomfield-type disturbances, and the results are displayed in Table 3. We observe that if u_t is white noise, long memory takes place in the first two subsamples, but short memory (or I(0) behaviour) is found in the remaining two. The same happens under the exponential model of Bloomfield, and if u_t is AR(1), long memory only takes place during the first subsample. Focussing on the time trends, the coefficients are statistical significant in the last two subsamples in the three cases.

5. Discussion

Two features have been examined in this work in relation with the European temperatures: the degree of persistence in the data and the existence of time trends. Dealing with the first of these two issues, our results show evidence of long memory patterns in the temperatures, since the order of integration of the series is found to be significantly positive. This is consistent with other studies that find the same patter in global (Gil-Alana, 2005, 2008b; Hare and Mantua, 2000; Ivanov and Evtimov, 2010, Coggin, 2012; etc.) but also at specific locations all over the world (Caballero et al, 2002; Gil-Alana, 2003; Franzke, 2010; Bunde et al, 2014; Ludescher et al, 2016; etc.).

The fact that long memory is present in the data has also important implications for the estimation of the time trend. Thus, ignoring this feature produces bias in the estimate of the time trend coefficient reducing its magnitude and thus reducing the increase in the temperatures. Our results indicate that the European average temperatures increase about 0.2ºC every 100 years though this coefficient is slightly higher if we only consider data from the most recent past.

6. Concluding comments

We have examined in this work the persistence and the time trend in the European average temperature anomalies for the period from 1655 to 2017 using a new dataset gathered by Mariani & Zavtti (2017) and based on the information provided by 29 European stations. The results indicate that long memory is present in the data, with an order of integration in the stationary range (0, 0.5). On the other hand, the time trend coefficient is significantly positive, though using recursive estimation methods, we show that the significance in this parameter becomes relevant (statistically significant) when incorporating only the data from 2010 onwards. Separating the overall data in four subsamples, (the first three with 100 observations and the last one with the last 62 observations) we obtain evidence of long memory only during the first subsamples, which may be related with a potential artificial long term variability, and the time trend coefficients are only significant during the last two subsamples. Thus, these results provide further evidence supporting the increase in the temperatures in Europe in recent years.

With respect to the long memory property, this feature is observed when using the whole sample period, and it is consistent with many other works on climatological data (Percival et al. 2001; Gil-Alana, 2003, 2005, 2010; 2017; Lennartz & Bunde (2009), Rea et al. (2011), Franzke (2012), Yuan et al. (2013, 2015), Bunde et al., (2014), Ludescher et al. (2016), Bunde (2017), etc.). The fact that this property is not observed in some of the subsamples is clearly due to the wide confident intervals associated to the smaller sample sizes.

A drawback of the resent work is that it is based on raw observations and therefore potentially affected by changes in measurement conditions which may produces biases in the estimation of both the time trend coefficient and the fractional differencing parameter (see, e.g., Rust, Mestre & Venema, 2008). In this respect, the use of homogenization can solve this problem by comparing for example the results using both raw and homogenized data. In addition, the use of structural breaks and recursive estimation methods may also be helpful. Work in this direction is now in progress.

Appendix: List of the 29 stations

	Acronym	Latitude	Longitude
Central England Temperatures	CET	-1.00	52.00
Sonnblick	SBLI	12.95	47.05
Hamburg Fuhlsbuttel	HAMB	9.59	53.38
Navacerrada	NAVA	-3.59	40.46
Salamanca	SALA	-5.28	40.56
Bourges	BOUR	2.37	47.07
Mont-Aigoual	MAIG	3.35	44.07
Rennes Renn	RENN	1.44	48.04
Strasbourg	STRB	7.63	48.55
Toulouse (Blagnac)	TOUL	1.22	43.37
Uppsala	UPPS	17.38	59.51
Stockholm	STOC	18.04	59.19
Berlin Tempelhof	BERL	13.24	52.31
Paris Montsouris	PARI	2.34	48.82
St. Petersburg	SPIE	30.19	59.56
Frankfurt Am	FFUR	8.41	50.07
Kremsmuenster	KREM	14.08	48.03
CBT_Belgium-Bruxelles	BRUX	4.60	50.51
De-Bilt	DEBI	5.18	52.10
Poprad Tatry	POPR	20.25	49.07
Waddington (Lincoln)	WDD	0.52	53.17
Basel-Binningen	BASL	7.60	47.60
Verona Villafranca	VERO	10.52	45.23
Cagliari Elmas	CAGL	9.13	39.14
Brindisi	BRIN	17.56	40.38
Padova	PADO	11.52	45.24
Cadiz	CADI	-6.17	36.31
Col du Gran St_Bernard	CGSB	7.17	45.87
Florence	FIRE	11.20	43.81

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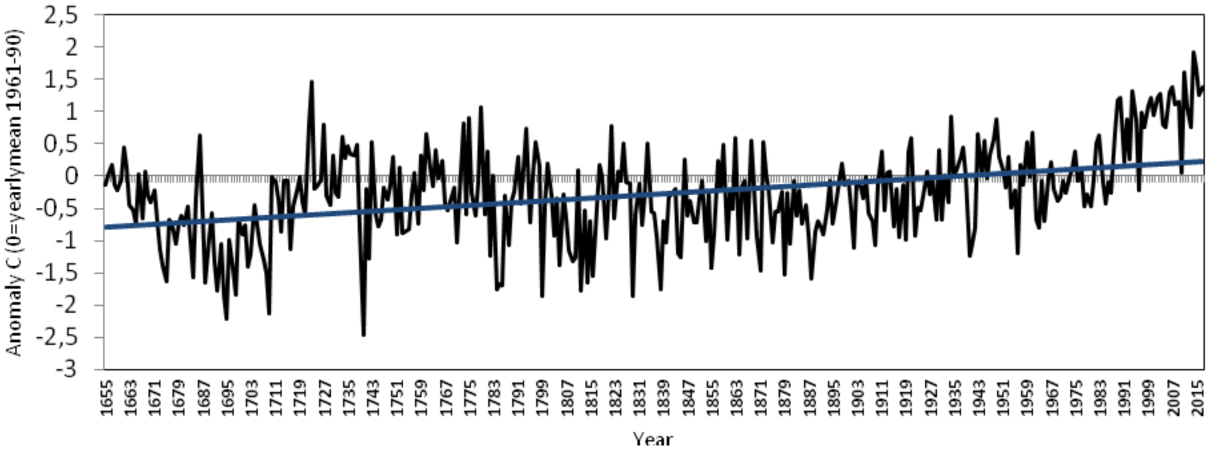


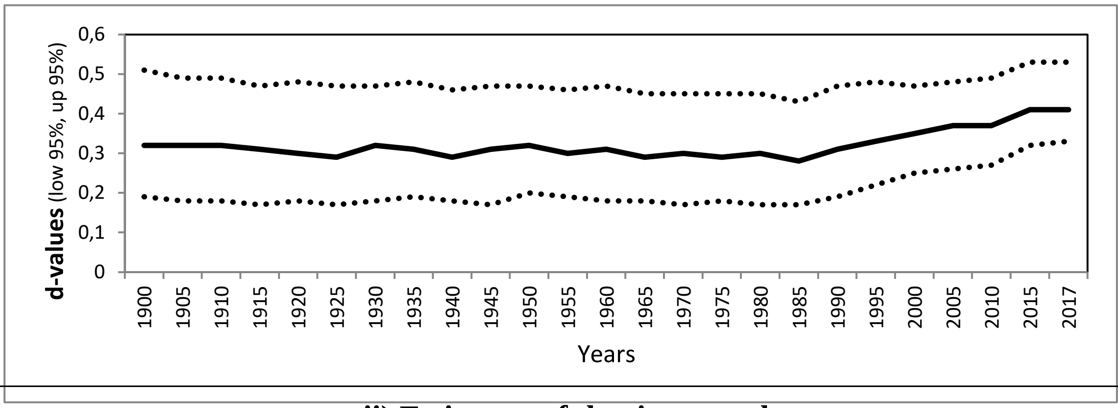
Figure 1: European average temperature anomalies and its estimated trend

Table 1: Estimated coefficients in the selected models

	d (95% band)	Intercept	Time trend	Autocorrelation
White noise	0.30 (0.25, 0.36)	-0.6739 (0.002)	0.0029 (0.002)	----
AR(1)	0.40 (0.32, 0.49)	-0.5584 (0.069)	0.0028 (0.034)	-0.178
Bloomfield	0.41 (0.33, 0.53)	-0.5448 (0.082)	0.0028 (0.038)	-0.190

The values in parenthesis in the 3rd and 4th columns refer to the corresponding p-values.

i) Estimates of persistence



ii) Estimates of the time trend

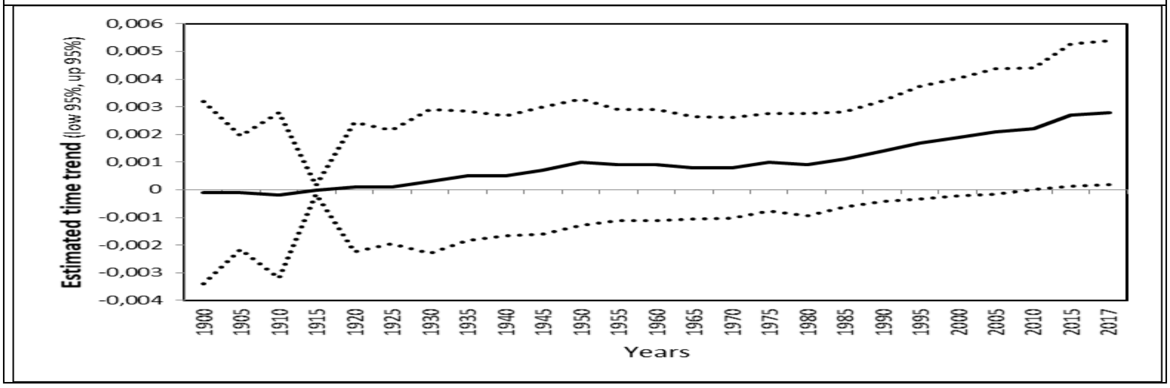


Figure 2: Persistence and trend recursive coefficients

Table 2: Estimated coefficients for persistence and trend from 2000 onwards

Sample period	Persistence d (95% band)	Time trend β_1 (p-value)
1655 – 2000	0.35 (0.25, 0.47)	0.0019 (0.071)
1655 – 2001	0.35 (0.25, 0.47)	0.0019 (0.067)
1655 – 2002	0.37 (0.27, 0.49)	0.0020 (0.075)
1655 – 2003	0.38 (0.26 0.50)	0.0021 (0.073)
1655 – 2004	0.37 (0.28, 0.49)	0.0021 (0.065)
1655 – 2005	0.37 (0.26, 0.48)	0.0021 (0.064)
1655 – 2006	0.38 (0.27, 0.50)	0.0022 (0.062)
1655 – 2007	0.38 (0.29, 0.52)	0.0023 (0.054)
1655 – 2008	0.38 (0.29, 0.51)	0.0023 (0.051)
1655 – 2009	0.39 (0.30, 0.51)	0.0024 (0.054)
1655 – 2010	0.37 (0.27, 0.49)	**0.0022 (0.049)**
1655 – 2011	0.39 (0.29, 0.50)	**0.0024 (0.049)**
1655 – 2012	0.39 (0.29, 0.50)	**0.0024 (0.047)**
1655 – 2013	0.39 (0.30, 0.50)	**0.0024 (0.048)**
1655 – 2014	0.40 (0.31, 0.52)	**0.0026 (0.042)**
1655 – 2015	0.41 (0.32, 0.53)	**0.0027 (0.043)**
1655 – 2016	0.40 (0.32, 0.52)	**0.0027 (0.036)**
1655 – 2017	0.41 (0.33, 0.53)	**0.0028 (0.038)**

In bold, the significant time trend coefficients at the 5% level.

Table 3: Estimated coefficients in the selected models

i) White noise				
	d (95% band)	Intercept	Time trend	Autocorrelation
1^{st} subsample	0.35 (0.25, 0.49)	-0.4257 (0.084)	----	----
2^{nd} subsample	0.14 (0.03, 0.28)	-0.4155 (0.000)	----	----
3^{rd} subsample	0.03 (-0.09, 0.20)	-0.6323 (0.000)	0.0064 (0.000)	----
4^{rd} subsample	0.05 (-0.10, 0.29)	-0.5389 (0.000)	0.0299 (0.000)	----
ii) AR(1)				
	d (95% band)	Intercept	Time trend	Autocorrelation
1^{st} subsample	0.32 (0.18, 0.50)	-0.4426 (0.046)	----	0.042
2^{nd} subsample	0.26 (-0.07, 0.53)	-0.4029 (0.032)	----	-0.171
3^{rd} subsample	0.00 (-0.31, 0.34)	-0.6337 (0.000)	0.0064 (0.000)	0.038
4^{rd} subsample	-0.17 (-0.33, 0.36)	-0.5609 (0.000)	0.0302 (0.000)	0.275
iii) Bloomfield				
	d (95% band)	Intercept	Time trend	Autocorrelation
1^{st} subsample	0.33 (0.14, 0.57)	-0.4372 (0.056)	----	0.029
2^{nd} subsample	0.25 (0.03, 0.67)	-0.4039 (0.023)	----	-0.170
3^{rd} subsample	-0.01 (-0.19, 0.23)	-0.6342 (0.000)	0.0064 (0.000)	0.059
4^{rd} subsample	-0.07 (-0.32, 0.30)	-0.5536 (0.000)	0.0301 (0.000)	0.160

The values in parenthesis in the 3^{rd} and 4^{th} columns refer to the corresponding p-values