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2 **TIME TRENDS AND PERSISTENCE IN EUROPEAN TEMPERATURE**
3 **ANOMALIES**

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16 **ABSTRACT**

17 This paper looks at the level of persistence in the temperature anomalies series of 114
18 European cities. Once this level of persistence has been identified, the time trend
19 coefficients are estimated and the results indicate that most of the series examined display
20 positive trends, supporting thus climate warming. Moreover, the results obtained confirm
21 the hypothesis that long-memory behaviour cannot be neglected in the study of
22 temperatures time series, changing therefore, the estimated effect of global warming.

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24 **Keywords:** Time trends; persistence; temperatures; Europe; long memory

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36 **1. Introduction**

37 It is a well-known fact that temperatures are increasing (Nicholls et al., 1996; Percival et
38 al., 2001; Caballero et al., 2002; Gil-Alana, 2003, 2005; Jones and Wigley, 2010; Franzke,
39 2012; Bunde et al., 2014; Ludescher et al., 2016; Folland et al., 2018; etc.). On a global
40 scale, organizations such as the National Oceanic and Atmospheric Administration
41 (NOAA) and NASA have shown that since 2010, we have had the warmest years on
42 record as compared to the baseline average of the 20th century and of 1951–1980
43 respectively. Authors such as Hansen et al. (2010) and Cahill et al. (2015) argue that this
44 trend is likely to continue in the long-term due to the continuous greenhouse gas
45 concentration increases.

46 In spite of the wide literature dealing with this problem, modelling climatological
47 time series is still a controversial topic that has no unique answer. In past years, it was
48 common to examine trends in global and regional mean temperatures over time assuming
49 temperatures time series were stationary $I(0)$ (Bloomfield and Nychka, 1992; Woodward
50 and Gray, 1993; etc.) or, alternatively, assuming nonstationary $I(1)$ models (Woodward
51 and Gray, 1995; Stern and Kaufmann, 2000; etc.), where in the $I(d)$ representation, d
52 indicates the number of differences required to get stationarity $I(0)$ ¹. However, the $I(0)$
53 and $I(1)$ models are only two particular cases of a wider class of $I(d)$ models, where d is
54 assumed to be a real number. These processes are said to be fractionally integrated or
55 integrated of order d , and if d is positive, the process belongs to a wider category of
56 models denominated long memory.

¹ A stationary process is said to be integrated of order 0, and denoted by $I(0)$ if the infinite sum of its autocovariances is finite. Examples are the white noise and the stationary and invertible ARMA-type of models. Another definition, this time in the frequency domain, is provided in Section 3. A nonstationary process is $I(1)$ if it requires first differences to render it stationary $I(0)$.

57 In recent years, with the development of new methods including spectral analysis
58 (Malamud and Turcotte, 1999; Weber and Talkner, 2001), the structure function method
59 (Lovejoy and Schertzer, 2012), wavelet analysis (Arneodo et al., 1995; Abry and Veitch,
60 1998), detrended fluctuation analysis (Peng et al., 1994; Kantelhardt et al., 2001), etc.,
61 the research on long-term memory has spread considerably, spanning many different
62 fields.

63 In previous research, long-term memory behavior has been observed in many
64 climate variables, such as precipitation (Kantelhardt et al., 2006; Jiang et al., 2017),
65 relative humidity (Chen et al., 2007), wind fields (Feng et al., 2009), atmospheric general
66 circulations (Vyushin and Kushner, 2009) and total ozone anomalies (Vyushin et al.,
67 2007).

68 In this paper we focus on the analysis of the temperature anomalies time series
69 across Europe, with monthly observations ranging over 45 years. We use 114 stations for
70 a time period starting in 1970 and ending in 2016. We are mainly interested in the analysis
71 of the degree of persistence of the data (measured by the order of integration of the series,
72 d) and its effect on the estimation of the time trends coefficients.

73 The paper is structured as follows. Section 2 deals with a review of the analysis of
74 the temperatures in Europe. Section 3 describes the methodology used in the paper, while
75 Section 4 presents the data and the empirical results. Section 5 concludes the paper.

76

77 **2. Temperatures in Europe**

78 Many recent studies have focused on the impact of global warming on a regional scale,
79 assessing that the trend of temperature anomalies is very different according to the
80 different locations and different time ranges. They all agree that during the last decades

81 there has been a large acceleration of warming, but they found different results for its rate
82 and about the period of highest interest.

83 To mention just a few of the more recent papers, Mikkonen et al. (2015) studied
84 long time series in Finland, finding a rapid increase of the warming after 1960s, with an
85 increase of $+0.14$ °C/decade between 1847 and 2013, and a rise of between 0.2 and 0.4
86 °C/decade after the 1960s; Delveux et al. (2019) examined the temperatures in Belgium
87 and found a warming of $+0.15$ °C/decade between 1880 and 2015, and $+0.3$ °C/decade
88 between 1954 and 2015, with an abrupt increase during the 1980s; Klingbjer and Moberg
89 (2003) focus on 200-year temperature time series in Sweden starting in 1802, and detect
90 an anomalous warming period in the last 3 decades. Brunet et al. (2007) studied time
91 series covering the period 1901-2005, concentrating on the geographical pattern of
92 warming across Spain, and found that the period 1973-2005 was the one with the highest
93 rate of change and the strongest acceleration of warming. Ribes et al. (2016) measured an
94 overall warming of $+1.5 \pm 0.5$ °C during the period 1959-2009 in France. Mamara et al.
95 (2015) explore temperature time series during the period 1960-2004 in 52 stations in
96 Greece, obtaining a negative trend before 1976 and an increasing one of 0.2-0.4
97 °C/decade between 1977 and 2004.

98 A large part of the most recent research is now studying the evolution of
99 temperatures taking into account the long-memory property of the series, both at a global
100 scale, Gil-Alana (2005), dealing with Northern Hemisphere temperatures, and at a local
101 scale, such as Franzke (2010), who explored eight stations in Antarctica, observing long-
102 range memory behavior. Jiang et al. (2015) also observed long-memory in the air
103 temperatures in 552 Chinese stations; Massah and Kantz (2016) and Yuan et al. (2014,
104 2015) used detrended fluctuation analysis (DFA) to detect long-memory behavior of

105 temperature series in Europe and in Antarctica respectively. Gil-Alana and Sauci (2019)
 106 compared the persistence across US states, obtaining a positive persistence parameter for
 107 all of the States, with an increase in the temperatures between 1.5 °F and 2.5 °F for most
 108 of them.

109

110 **3. Methodology**

111 Long memory is a feature in time series data that means that observations are highly
 112 dependent even if they are far apart in time. Within this category, widely observed in
 113 climatological data (Yuan et al., 2014; Jiang et al., 2015; Gil-Alana and Sauci, 2019), a
 114 well-known parametric model is the one based on fractional integration that means that
 115 the number of differences required in a series to render it stationary I(0) is a fractional
 116 value.

117 Since this paper deals with climate warming and time trends in the temperatures,
 118 the model examined will be the following one:

$$119 \quad y_t = \beta_0 + \beta_1 t + x_t, \quad t = 0, \pm 1, \dots, \quad (1)$$

120 where y_t refers to the temperature anomalies and x_t is an error term that is supposed to be
 121 integrated of order d , or I(d), and described as:

$$122 \quad (I - B)^d x_t = u_t, \quad (2)$$

123 where B is the backshift operator, i.e., $B^k x_t = x_{t-k}$ and u_t is I(0) defined as a process with
 124 a spectral density function that is positive and finite at all frequencies over the spectrum.

125 Based on (1) and (2), we test the null hypothesis:

$$126 \quad H_0 : d = d_0, \quad (3)$$

127 for any real value d_0 . Thus, under H_0 (3), the null model becomes:

$$128 \quad (I - B)^{d_0} y_t = \beta_0 \tilde{I}_t + \beta_1 \tilde{t}_t + u_t, \quad t = 0, 1, \dots, \quad (4)$$

129 where $\tilde{I}_t = (1 - B)^{d_0} I$, and $\tilde{t}_t = (1 - B)^{d_0} t$, and noting that u_t in (4) is I(0) by
130 construction, we can test the significance of β_1 by using standard methods.

131 In the empirical application carried out in the following section, we will display
132 the values of d_0 where H_0 (3) cannot be rejected along with the estimates of the
133 deterministic terms, β_0 and β_1 , the latter showing us if the temperatures have increased
134 across time. For this purpose, we use a simple version of a testing procedure developed
135 by Robinson (1994) and that has been widely used in the analysis of I(d) models (see,
136 e.g., Gil-Alana and Robinson, 1997). It is based on the Lagrange Multiplier (LM) method
137 and uses the Whittle function expressed in the frequency domain.

138

139 **4. Data and Empirical Results**

140 Monthly data anomalies of mean temperatures are obtained from free datasets from
141 KNMI Climate Explorer, ECA&D. Data span 114 stations across 29 different countries
142 in Europe, with starting points in January 1971 and ending points in November 2016. We
143 focused on these stations and this time range in order to have the most complete time
144 series. We have chosen the dataset in such a way that we have no more than 5 missing
145 data in each of the series, and no more than one consecutive missing data: in these cases
146 missing data were substituted with arithmetic mean of observations of the same month of
147 the previous and following years. The specific stations are displayed in Figure 1.² As we
148 can see from Figure 2, Germany is the country with the largest coverage, with 15 stations,
149 followed by other large countries such as France, Poland, Spain, Turkey and the United
150 Kingdom. Central Europe is the region with the highest density in terms of number of

² The distribution of the stations is quite heterogeneous, due to the difficulty in finding complete series from some countries like Italy, Albania and Bulgaria.

151 stations. 69 of the stations come from continental areas, while 45 are located next to the
152 sea. They are both from large metropolitan areas (15 stations from cities with more than
153 1 million inhabitants), from urban areas (71 of them are cities with a population greater
154 than 100.000 people), small towns (12 are cities with more than 10,000 inhabitants, and
155 rural area (16 stations are located in towns with fewer than 10,000 people); 12 stations
156 are located in mountain places, with an altitude higher than 600 metres; in particular the
157 stations of Saentis and Zugspitze are located at more than 2,000 metres above sea level,
158 so we can consider them as high mountain areas.

159 **[Insert Figures 1 and 2 about here]**

160 The increase of temperatures is evident in our dataset: focusing on the yearly
161 average temperatures, nine out of ten of the warmest years are after 2000. Winter months
162 are more influenced by these events, in fact, the top 15 months experiencing the largest
163 temperature increase during the period under consideration fell between December and
164 March; indeed, considering the average temperature anomalies among the 114 stations,
165 we observed that these months experiencing the largest temperature increase.

166 Table 1 displays the estimated coefficients under the assumption that u_t in equation
167 (2) is a white noise process. Thus, all the dependence between the observations is captured
168 by the differencing parameter d . The first thing we observe here is that the estimated
169 values of d are positive and statistically significant for all except two stations: Saentis
170 (CH) and Zugspitze (D), implying the existence of long memory, and thus being
171 consistent with most studies in this area. The highest levels of persistence are observed
172 in Alborg (DK) ($d = 0.30$); Kobenhavn (DK) (0.28) and Oslo and Stavanger (N) and
173 Visby (S) ($d = 0.27$), all corresponding to Scandinavian countries. We also observe that
174 in all cases the highest values at the confident bands are below 0.5, implying a stationary

175 though long memory pattern. Focusing now on the time trend coefficients, we observe
176 that they are significantly positive in 108 out of the 114 stations examined, being
177 insignificant only for Alborg (DK), Kopenhagen (DK), Tallin (EST), Linköping and
178 Visby (S), and Oslo (N), all them Northern European stations. On the other extreme, the
179 highest time trend coefficients correspond to Cuenca (E) (+0.59 °C/decade), and Graz (A)
180 and Belgrade (SRB) (+0.50 °C/decade), along with Sodankyla (FIN) (+0.48 °C/decade),
181 Burgos (E) (+0.47 °C/decade) and Wlodawa (PL) (+0.47 °C/decade).

182 **[Insert Tables 1 and 2 about here]**

183 Table 2 extends the results to the case of autocorrelated errors by using the
184 exponential spectral model of Bloomfield (1973). This is a non-parametric method that
185 approximates fairly well highly parameterized AR(MA) models.³ In addition it allows us
186 to describe the potential seasonality that might be present in the data. Under this
187 specification, the first thing we observe is that the estimated values of the differencing
188 parameter are smaller than in the previous case, clearly due to the competition between
189 the two structures (fractional integration and Bloomfield (1973)) in describing the time
190 dependence. In fact, the I(0) hypothesis of short memory behaviour, i.e., $d = 0$, cannot be
191 rejected in 76 stations, while long memory ($d > 0$) is found in the remaining 38, in all
192 cases displaying again a stationary ($d < 0.5$) pattern. Among these, the highest levels of
193 persistence are found in the cases of Vardo (N) ($d = 0.21$), Lerwick (UK) and Thorsnavn
194 (DK), both with estimated values of d equal to 0.20, and then, followed by Vishy (S) (d
195 $= 0.18$), Malinhead (IRE, $d = 0.16$), Greitswald (D) and Rostock (D) with $d = 0.15$, Alborg
196 and Kobenhavn (DK), Reykjavik (IS), Stavanger (N) and Linköping (S) with $d = 0.14$.

197 **[Insert Figure 3 about here]**

³ See Gil-Alana (2004) for the specification of this model in the context of fractional integration.

221 the table), and those based on estimated values of d , under both white noise (2nd column)
222 and autocorrelated (3rd column) errors.

223 **[Insert Table 3 about here]**

224 We observe in this table that imposing $d = 0$ produces a bias in the estimation of
225 the time trend in favor of higher coefficients for the time trend. Thus, comparing $d = 0$
226 with the case of estimated d and white noise errors, in 95 out of the 114 stations, the time
227 trend is higher under the (wrong) assumption of short memory or $I(0)$ behaviour. That
228 means that imposing a priori this restriction produces a higher increase in the temperatures
229 than the one obtained when we estimate this differencing parameter, being in many cases,
230 significantly higher than 0. Comparing now this case ($d = 0$) with the estimated d under
231 autocorrelation, the time trend parameter is lower in 72 stations under the estimation of d
232 with Bloomfield (1973) errors.

233 **[Insert Figure 7 here]**

234 In particular we can see that, as expected, the larger the persistence parameter is,
235 the higher the difference between the $I(0)$ scenario and the other two scenarios is. If we
236 call δ the difference between the slope under $d = 0$, and the slope under another estimation
237 of d , we obtain that the correlation between δ and d is 51% with white noise errors, and
238 60% with autocorrelated errors. Thus, long-memory has the effect of relaxing the increase
239 of temperatures in our model.

240 **[Insert Figure 8 here]**

241

242 **5. Concluding comments**

243 We have examined in this paper the temperature anomalies in 114 European stations,
244 examining the degree of persistence of the series by estimating the differencing parameter

245 d. Our results indicate that under the white noise specification for the error term, most of
246 the series display a long memory (stationary) pattern, presented in terms of a significantly
247 positive order of integration. Allowing autocorrelation in the error term, the degree of
248 persistence decreases, probably due to the competition between the $I(d)$ and the
249 autocorrelated $I(0)$ structures in describing the time dependence. Nevertheless, positive
250 values of d are found in most of the stations. This long memory feature also has an
251 influence on the estimation of the time trend coefficients, generally observing lower
252 values when the differencing parameter is estimated rather than imposed at zero. In other
253 words, not taking into account the long memory feature in the data produces a bias in
254 favor of higher coefficients in relation to the temperature warming. Even though the
255 memory parameters measured under the white noise specification for the error term are
256 higher than those based on the autocorrelation structure, the two models return similar
257 results concerning the warming, concluding that the overall average increase of
258 temperatures is about $0.35\text{ }^{\circ}\text{C}/\text{decade}$.

259 Dealing with the temperature trend, many people feel it is determined by the
260 change in temperature, regardless of the reasons for the change. Part of these changes
261 may be due to change in radiative forcing (global warming), while the other part may be
262 due to persistence. Therefore, the time trend may be non-linear, an issue of great interest,
263 noting that fractional integration and non-linear structures are intimately related (Diebold
264 and Inoue, 2001; Granger and Hyung, 2004). In this context, tests like those proposed in
265 Qu (2011) for testing spurious long memory can be implemented in the data, along with
266 the examination of potential nonlinear structures using, for instance, Chebyshev
267 polynomials in time (Cuestas and Gil-Alana, 2016), Fourier transform (Gil-Alana and
268 Yaya, 2020) or even neural network structures as in Yaya et al. (2021), still in the context

269 of fractional integration. Finally, the presence of inhomogeneities in the data, caused for
270 instance by station relocation or changes in the methods of observations, has not been
271 investigated in this paper. The analysis based on homogenized versions of the 114 series
272 examined would allow us to compare the results between the raw and the homogenized
273 series, and this would permit us to evaluate the uncertainty of the persistence and trends
274 due to the presence of non-climatic perturbations in the temperature series.

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278 **References**

279

280 Abry P., Veitch D., (1998). Wavelet analysis of long-range-dependent traffic. *IEEE Trans*
281 *Inf Theory* 44(1):2–15. DOI: 10.1109/18.650984.

282

283 Arneodo A., Bacry E., Graves P.V., Muzy J.F., (1995). Characterizing long-range
284 correlations in DNA sequences from wavelet analysis. *Physical Review Letters*,
285 *American Physical Society*, 74(16), 3293–3296. 10.1103/PhysRevLett.74.3293.

286

287 Blender R., Fraedrich K., (2006). Long-term memory of the hydrological cycle and river
288 runoffs in China in a high-resolution climate model. *International Journal of Climatology*
289 26(12):1547–1565. DOI:10.1002/joc.1325.

290

291 Bloomfield, P. (1973) An exponential model in the spectrum of a scalar time series,
292 *Biometrika* 60, 217-226.

293

294 Bloomfield P., Nychka D., (1992). Climate spectra and detecting climate change,
295 *Climatic Change* 21, 3, 275–287.

296

297 Bunde, A., J. Ludescher, C. L. E. Franzke, and U. Büntgen, (2014), How significant is
298 West Antarctic warming, *Nature Geoscience*, 7, 246–247.

299

300 Brunet M., Jones P. D., Sigró J., Saladié O., Aguilar E., Moberg A., Della-Marta P. M.,
301 Lister D., Walther A., López D., (2007). Temporal and spatial temperature variability and
302 change over Spain during 1850-2005. *Journal of Geophysical Research*, 112(12). DOI:
303 10.1029/2006JD008249.

304

305 Caballero, R., S. Jewson and A. Brix (2002), Long memory in surface air temperature:
306 detection, modeling, and application to weather derivative valuation, *Climate Research*
307 21(2), 127-140.

308

309 Cahill, N., S. Rahmstorf, and A. C Parnell (2015), Change points of global temperature,

310 Environmental Research Letters, 10, 084002, doi:10.1088/1748-9326/10/8/084002.
311
312 Chen X., Lin G.X., Fu Z., (2007). Long-range correlations in daily relative humidity
313 fluctuations: A new index to characterize the climate regions over China. *Geophysical*
314 *Research Letters* 34(7):L07804. DOI:10.1029/2006GL027755.
315
316 Cuestas, J.C. and L.A. Gil-Alana (2016). Testing for long memory in the presence of
317 non-linear deterministic trends with Chebyshev polynomials. *Studies in Nonlinear*
318 *Dynamics and Econometrics*, 20(1), 57–74.
319
320 Delveux C., Ingels R., Vrábel V., Journée M., Bertrand C., (2019). Quality control and
321 homogenization of the Belgian historical temperature data. *International Journal of*
322 *Climatology*, 2019; 39: 157-171. DOI: 10.1002/joc.5792.
323
324 Diebold F. X., and A. Inoue, A. (2001). Long memory and regime switching. *Journal of*
325 *Econometrics* 105, 131-159.
326
327 Eichner, J. F., Koscielny-Bunde E., Bunde A., Havlin S., and Schellnhuber H.-J., (2003).
328 Power-law persistence and trends in the atmosphere: A detailed study of long temperature
329 records. *Physical Reviews E*, 68. DOI:10.1103/PhysRevE.68.046133.
330
331 Feng T., Fu Z., Deng X., Mao J., (2009). A brief description to different multi-fractal
332 behaviors of daily wind speed records over China. *Physical Letters A*, 373(45): 4134-
333 4141. DOI:10.1016/j.physleta.2009.09.032.
334
335 Folland C.K., Boucher O., Colman A. and Parker D. E. (2018), Causes of irregularities
336 in trends of global mean surface temperature since the late 19th century. *Science*
337 *Advances* 4, eaao5297. DOI: 10.1126/sciadv.aao5297.
338
339 Fraedrich K., Blender R., (2003). Scaling of atmosphere and ocean temperature
340 correlations in observations and climate models. *Physical Review Letters*, 90(10):108501.
341 DOI:10.1103/PhysRevLett.90.108501.
342
343 Franzke C., (2010), Long-range dependence and climate noise characteristics of Antarctic
344 temperature data. *Journal of Climate*, 23, 6074–6081. DOI:10.1175/2010JCLI3654.1.
345
346 Franzke C. (2012), Nonlinear trends, long-range dependence, and climate noise
347 properties of surface temperature, *Journal of Climate*, 25(12), 4172–4183.
348
349 Gil-Alana, L.A. (2003), An application of fractional integration to a long temperature
350 series, *International Journal of Climatology* 23, 14, 1699-1710.
351
352 Gil-Alana, L.A. (2004), The use of the Bloomfield model as an approximation to ARMA
353 process in the context of fractional integration, *Mathematical and Computer Modelling*
354 39, 4, 429-436.
355

356 Gil-Alana, L.A. (2005), Statistical model for the temperatures in the Northern hemisphere
357 using fractional integration techniques, *Journal of Climate*, 18(24), 5537–5369.
358

359 Gil-Alana, L.A. and P.M. Robinson, (1997), Testing of unit roots and other nonstationary
360 hypothesis in macroeconomic time series, *Journal of Econometrics* 80, 2, 241-268.
361

362 Gil-Alana L. A., Sauci L., (2019). US Temperatures: Time trends and persistence.
363 *International Journal of Climatology*, 39(13): DOI: 10.1002/joc.6128.
364

365 Gil-Alana, L.A. and O. Yaya (2020) esting fractional unit roots with non-linear smooth
366 break approximations using Fourier functions, *Journal of Applied Statistics*,
367 forthcoming.
368

369 Granger, C. W. J., and Hyung, N. (2004). Occasional structural breaks and long memory
370 with an application to the S&P 500 absolute stock returns. *Journal of Empirical Finance*
371 11, 399-421.
372

373 Hansen, J., R. Ruedy, M. Sato, and K. Lo (2010), Global surface temperature change,
374 *Reviews of Geophysics*, 48(4), RG4004, doi:10.1029/2010RG000345.
375

376 Jiang L., Li N., Fu Z., Zhang J., (2015). Long-range correlation behaviors for the 0-cm
377 average ground surface temperature and average air temperature over China. *Theoretical*
378 *and Applied Climatology*, 119(1-2):25–31. DOI:10.1007/s00704-013-1080-0.
379

380 Jiang L., Li N., Zhao X., (2017). Scaling behaviors of precipitation over China.
381 *Theoretical and Applied Climatology*, 128(1-2):63–70. DOI:10.1007/s00704-015-1689-
382 2.
383

384 Jones, P. D., and T. M. L. Wigley, (2010). Estimation of global temperature trends:
385 What’s important and what isn’t. *Climatic Change*, 100, 59–69.
386

387 Kantelhardt J.W., Koscielny-Bunde E., Rego H.H.A., Havlin S., Bunde A., (2001).
388 Detecting long-range correlations with detrended fluctuation analysis. *Physica A* 295(3-
389 4): 441–454. DOI: 10.1016/S0378-4371(01)00144-3.
390

391 Kantelhardt J.W., Koscielny-Bunde E., Rybski D., Braun P., Bunde A., Havlin S., (2006).
392 Long-term persistence and multifractality of precipitation and river runoff records.
393 *Journal of Geophysical Research*, 111(01), D01106. DOI: 10.1029/2005JD005881.
394

395 Kaufmann R. K., Stern D. I., (2002). Cointegration analysis of hemispheric temperature
396 relations, *Journal of Geophysical Research* 107, no. D2. DOI: 10.1029/2002JD002080.
397

398 Klingbjer P., Moberg A., (2003). A composite monthly temperature record from
399 Tornedalen in northern Sweden, 1802-2002. *International Journal of Climatology* 23(12):
400 1465-1494. DOI: 10.1002/joc.946.
401

402 Lovejoy S., Schertzer D. (2012). Extreme events and natural hazards: the complexity
403 perspective, low frequency weather and the emergence of the climate. AGU monographs,
404 Washington, pp 231–254. DOI:10.1029/2011GM001087.
405

406 Ludescher, J., A. Bunde, C.L. Franzke and H. J. Schellnhuber (2016). Long-term
407 persistence enhances uncertainty about anthropogenic warming of Antarctica, *Climate*
408 *Dynamics*, 46(1–2), 263–271. DOI: 10.1007/s00382-015-2582-5.
409

410 Malamud B.D., Turcotte D.L. (1999). Advances in geophysics: long range persistence in
411 geophysical time series, self-affine time series: I. generation and analyses. Academic
412 Press, San Diego, 1–87. DOI: 10.1016/S00652687(08)60293-9.
413

414 Mamara A., Argiriou A. A., Anadranistakis M., (2015). Recent trend analysis of mean air
415 temperature in Greece based on homogenized data. *Theoretical and Applied Climatology*,
416 126, 543–573, DOI: 10.1007/s00704-015-1592-x.
417

418 Massah M., Kantz H., (2016). Confidence intervals for time averages in the presence of
419 long-range correlations, a case study on Earth surface temperature anomalies.
420 *Geophysical Research Letters*, 43(17):9243–9249. DOI: 10.1002/2016GL069555.
421

422 Mikkonen S., Laine M., Mäkelä H. M., Gregow H., Tuomenvirta H., Lahtinen M.,
423 Laaksonen A., (2015). Trends in the average temperature in Finland, 1847-2013. *Stoch*
424 *Environ Res Risk Assess* 29: 1521-1529, DOI: 10.1007/s00477-014-0992-2.
425

426 Monetti, R. A., S. Havlin, and A. Bunde, 2003: Long-term persistence in the sea surface
427 temperature fluctuations. *Physica A*, 320, 581–589, DOI:10.1016/S03784371(02)01662-
428 X.
429

430 Nicholls, N., G. V. Gruza, J. Jouzel, T. R. Karl, L. A. Ogallo, and D. E. Parker, (1996).
431 Observed climate variability and change. *Climate Change 1995: The Science of Climate*
432 *Change*, J. T. Houghton et al., Eds., Cambridge University Press, 133–192.
433

434 Peng C.-K., Buldyrev S.V., Havlin S., Simon M., Stanley H.E., Ary L.G. (1994). Mosaic
435 organization of DNA nucleotides. *Physical Review E*, 49(2):1685–1689. DOI:
436 10.1103/PhysRevE.49.1685.
437

438 Percival, D. B., J. E. Overland, and H. O. Mofjeld (2001), Interpretation of North Pacific
439 variability as a short- and long-memory process, *Journal of Climate*, 14(24), 4545–4559.
440

441 Qu, Z. (2011), A tests against spurious long memory, *Jornal of Business Economic and*
442 *Statistics* 29, 3, 423-438.
443

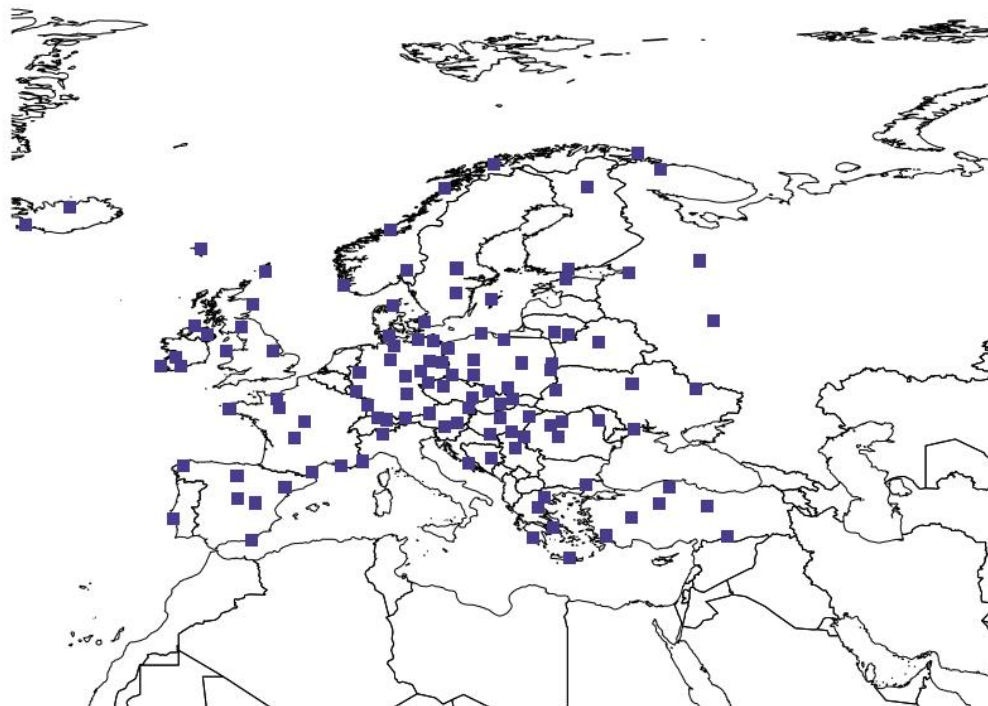
444 Ribes A., Corre L., Gibelin A., Dubuisson B., (2016). Issues in estimating observed
445 change at the local scale – a case study: the recent warming over France. *International*
446 *Journal of Climatology*, 2016: 36(11): 3794-3806. DOI: 10.1002/joc.4593.
447

448 Robinson, P.M. (1994) Efficient tests of nonstationary hypotheses, *Journal of the*
449 *American Statistical Association* 89, 1420-1437.

450
451 Stern, D. I., and R. K. Kaufmann (2000), Detecting a global warming signal in
452 hemispheric temperature series: a structural time series analysis, *Climatic Change*, 47(4),
453 411–438.
454
455 Vyushin D.I., Fioletov V.E., Shepherd T.G., (2007). Impact of long-range correlations on
456 trend detection in total ozone. *Journal of Geophysical Research*, 112(D14): D14307. DOI:
457 10.1029/2006JD008168.
458
459 Vyushin D.I., Kushner P.J., (2009). Power-law and long-memory characteristics of the
460 atmospheric general circulation. *Journal of Climate*, 22(11): 2890–2904.
461 DOI:10.1175/2008jcli2528.1.
462
463 Weber R.O., Talkner P. (2001). Spectra and correlations of climate data from days to
464 decades. *Journal of Geophysical Research* 106, D17. DOI: 10.1029/2001jd000548.
465
466 Woodward W. A., Gray H. L., (1993). Global warming and the problem of testing for
467 trend in time series data, *Journal of Climate* 6, 5, 953–962.
468
469 Woodward W. A., Gray H. L., (1995). Selecting a model for detecting the presence of a
470 trend, *Journal of Climate* 8, 8, 1929–1937.
471
472 Yaya, O., A.E. Ogbonna, L.A. Gil-Alana and F. Furuoka, (2021), A new unit root
473 analysis for testing hystereis in unemployment, *Oxford Bulletin of Economics and*
474 *Statistics*, forthcoming.
475
476 Yuan N., Fu Z., Liu S., (2014). Extracting climate memory using fractional integrated
477 statistical model: a new perspective on climate prediction. *Sci Rep* 4:6577. DOI:
478 10.1038/srep06577.
479
480 Yuan N., Ding M., Huang Y., Fu Z., Xoplaki E., Luterbacher J., (2015). On the Long-
481 Term Climate Memory in the Surface Air Temperature Records over Antarctica: A
482 Nonnegligible Factor for Trend Evaluation. *Journal of Climate*, 28(15): DOI:
483 10.1175/JCLI-D-14-00733.1.
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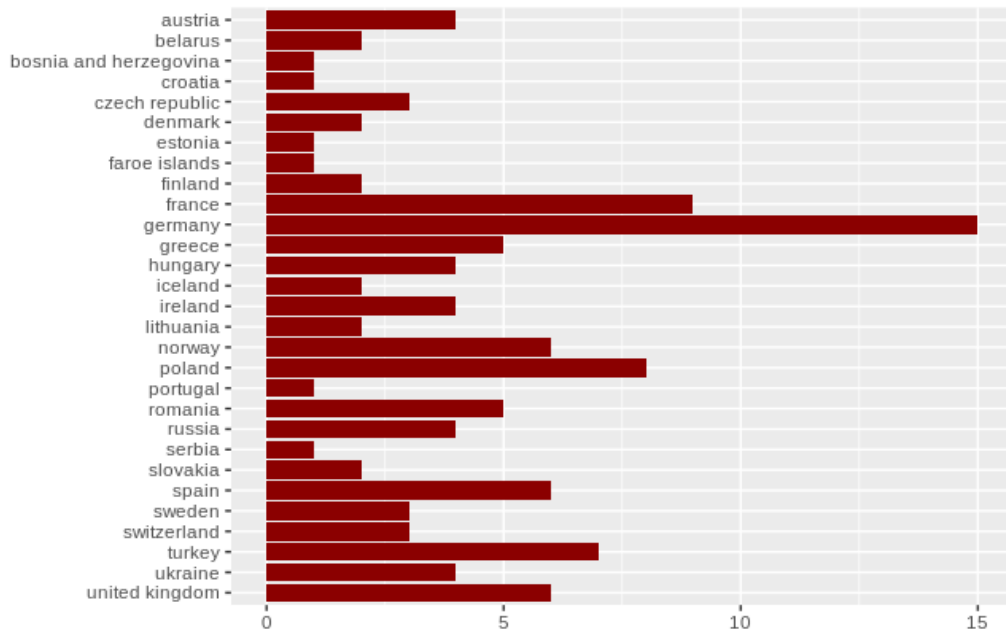
Figure 1: Distribution of the stations



490 The distribution of the stations is quite heterogeneous, with a higher density in Central Europe and a
491 lower density in Southern Europe and poor-inhabited areas in Northern Europe.
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495 **Figure 2: Number of stations displayed by country.**

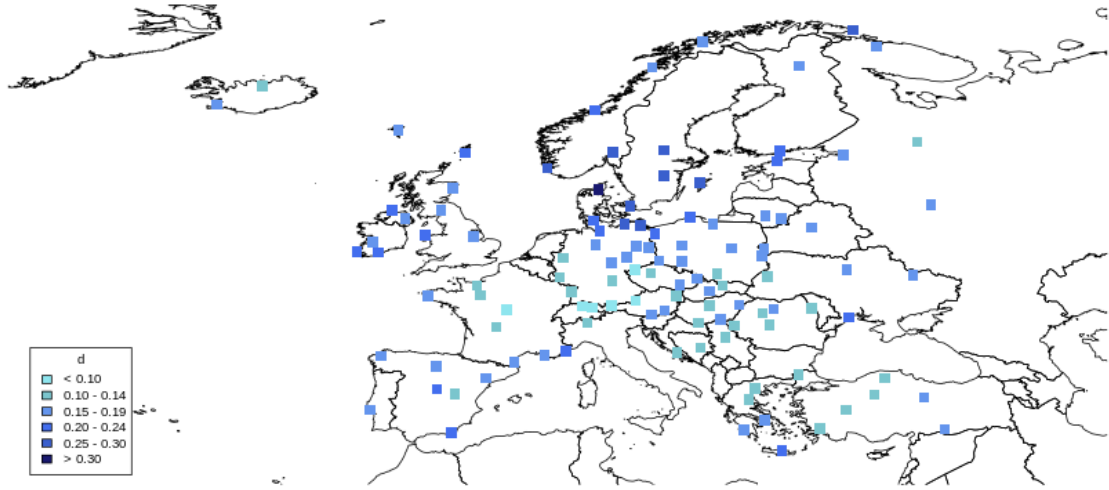
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The bar chart depicts the number of stations by country. 29 countries are represented in our study. The country with the highest number of stations is Germany (15).

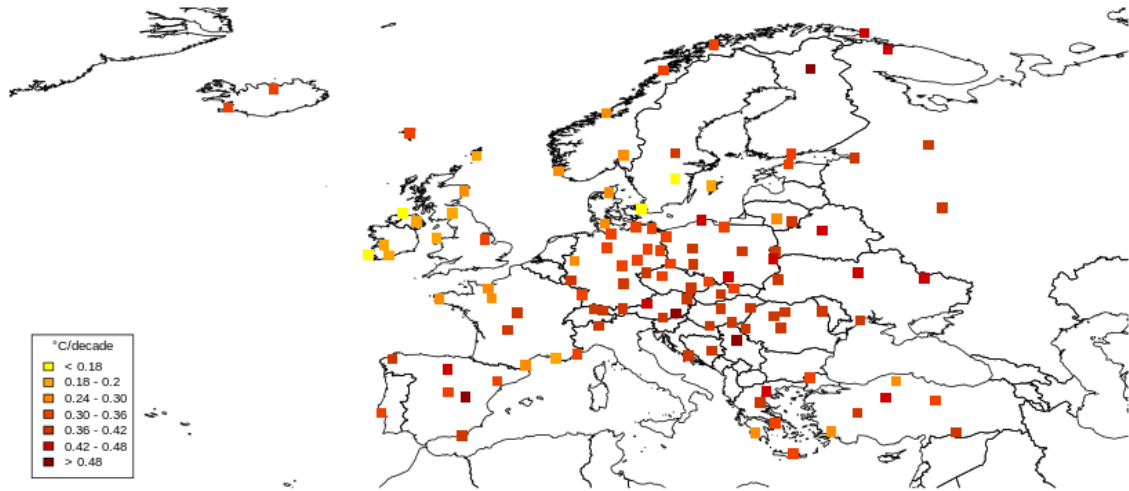
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Figure 3: Persistence in Europe.



525 Darker stations represent stations with stronger long-memory behavior. Darker points are located
526 especially next to Baltic Sea and Atlantic Ocean. Continental stations are characterized by weaker long-
527 memory behavior

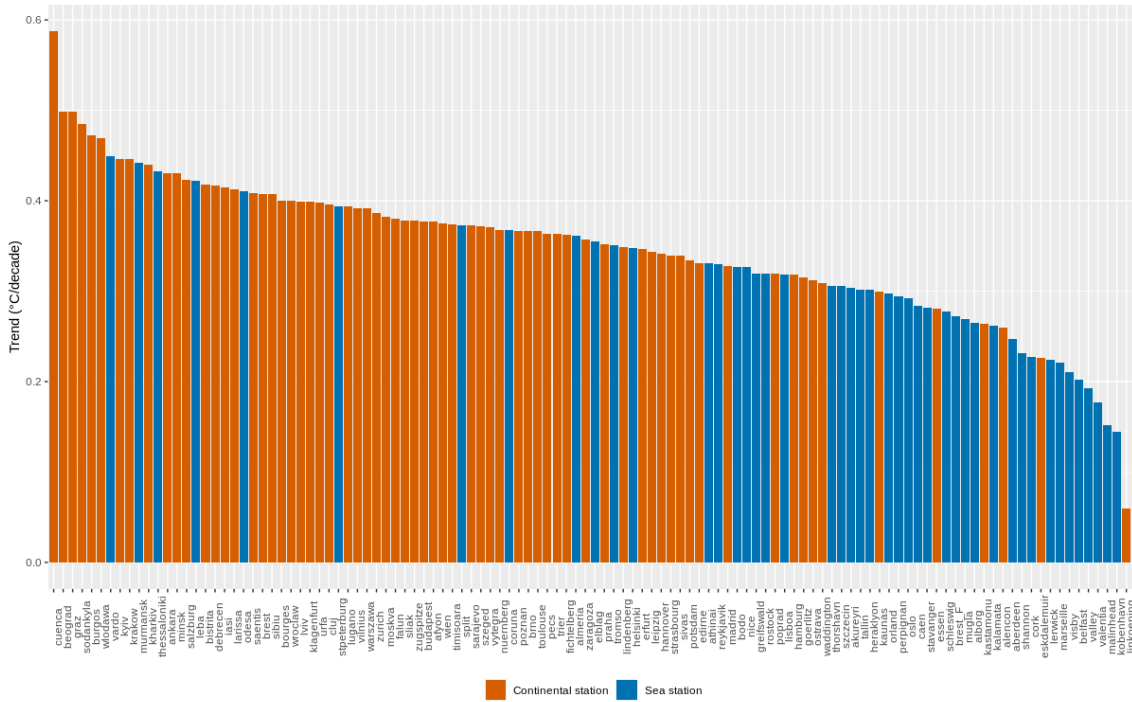
528 **Figure 4: Trends in Europe**
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530 Darker points represent stations with higher trend parameter. The increment of the temperatures is more
531 prominent in continental regions, while it is less severe in sea stations, Great Britain and Ireland.
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534 **Figure 5: Trends and sea proximity.**



535 Comparison of the trend parameter of the temperatures between sea stations (blue) and continental
536 stations (brown). Most of the highest positions are occupied by continental stations. The pattern is the
537 opposite of the persistence parameter.

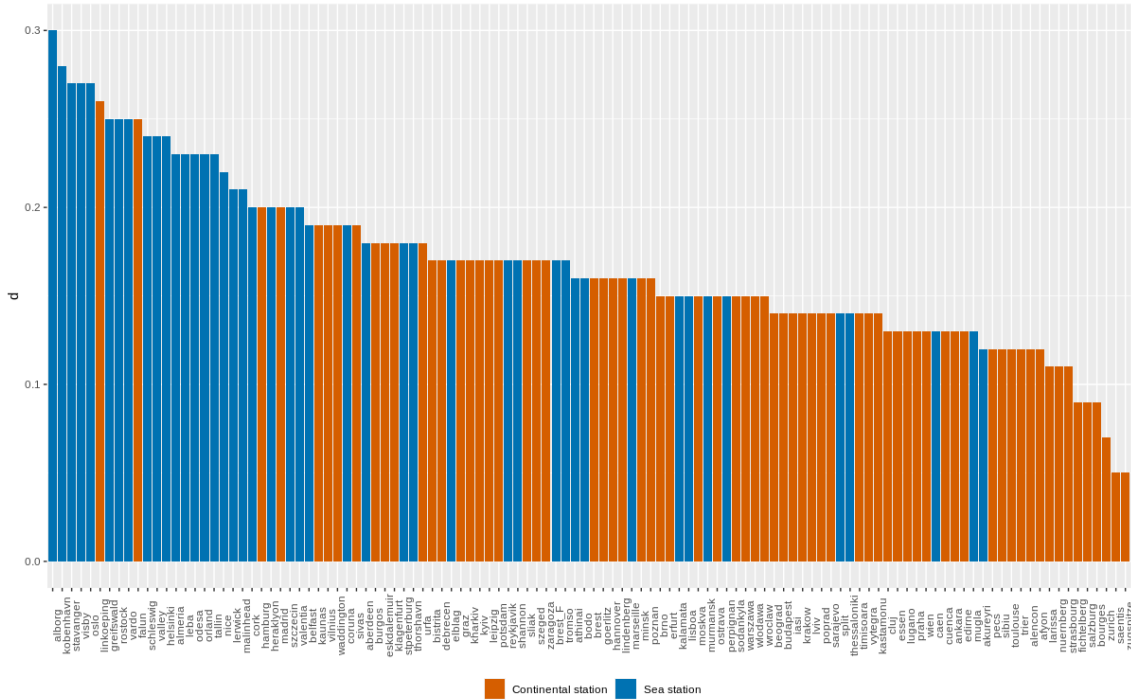
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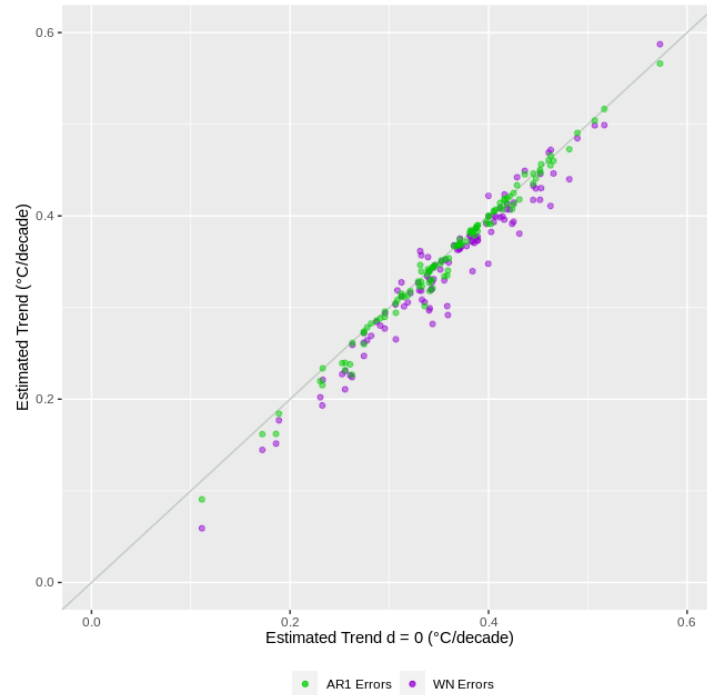
542 **Figure 6: Persistence and sea proximity**



543 Comparison of d parameter (that characterize $I(d)$) between sea stations and continental stations. In
 544 agreement with previous research, the strength of long-memory is higher in temperature time series for
 545 stations close to oceans and seas.

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571 **Figure 7: Models comparison**

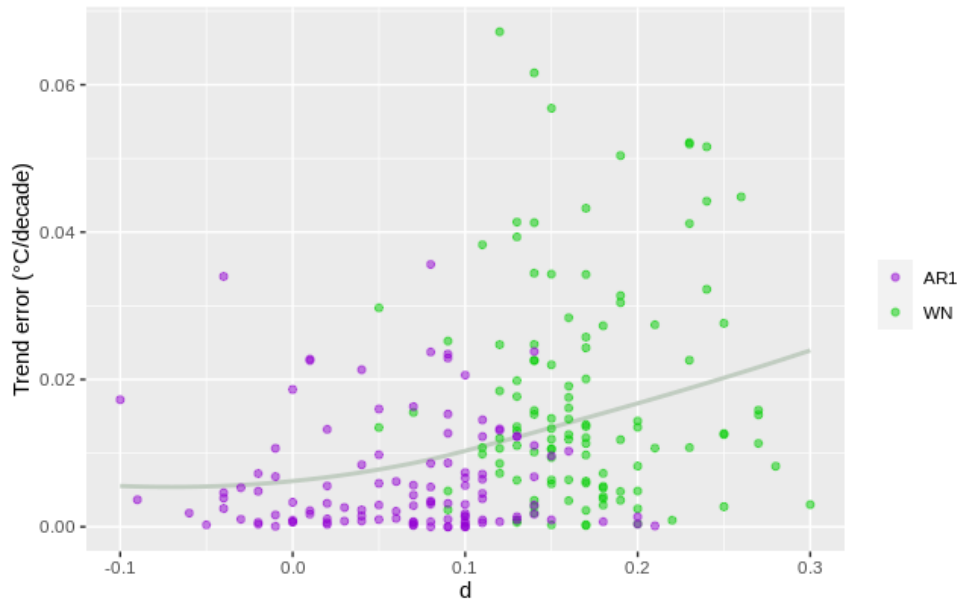


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In the plot, the trend estimates obtained are compared: for each station, the x axis represents the trend under short memory assumption and the y axis the trend under the two models. Most of the observations fall below the bisector, meaning that the $d = 0$ assumption overestimates the trend.

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Figure 8: Trends errors



623 Comparison of the absolute values of the differences between trends estimates under the assumption $d=0$,
624 and under long-memory assumption. As we can observe, the increment of d has significant consequences
625 on the estimation of the trend. The white noise assumption leads to higher estimates of d (on average,
626 $d=0.17$ under white noise and $d=0.06$ with autocorrelated errors).
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652 **Table 1: Estimated coefficients: White noise errors**

City	d (95% band)	Intercept (t-value)	Time trend ⁴ (t-value)
Aberdeen (UK)	0.18 (0.12, 0.27)	-0.73885 (-3.34)	0.2472 (3.09)
Afyon (TK)	0.12 (0.05, 0.20)	-1.09225 (-3.99)	0.3766 (3.77)
Akureyri (IS)	0.12 (0.05, 0.21)	-0.77300 (-3.04)	0.3032 (3.27)
Alborg (DK)	0.30 (0.22, 0.40)	-0.71536 (-1.32)	0.2654 (1.33)
Alencon (F)	0.12 (0.05, 0.20)	-0.82984 (-3.74)	0.2592 (3.21)
Almeria (E)	0.23 (0.17, 0.32)	-1.27293 (-5.30)	0.3616 (4.16)
Ankara (TK)	0.13 (0.05, 0.22)	-1.22732 (-4.20)	0.3766 (4.04)
Athens (GR)	0.16 (0.09, 0.26)	-1.12073 (-4.90)	0.3308 (3.99)
Belfast (UK)	0.19 (0.12, 0.28)	-0.64199 (-2.79)	0.2020 (2.43)
Belgrade (SRB)	0.14 (0.06, 0.24)	-1.39786 (-4.47)	0.4990 (4.39)
Bistrita (RO)	0.17 (0.09, 0.27)	-1.08282 (-3.06)	0.4175 (3.25)
Bodo (N)	0.16 (0.09, 0.26)	-0.83926 (-2.83)	0.3270 (3.05)
Bourges (F)	0.09 (0.02, 0.18)	-1.17550 (-5.61)	0.4003 (5.20)
Brest (BY)	0.16 (0.09, 0.24)	-1.09978 (-2.86)	0.4072 (2.92)
Brest (F)	0.17 (0.10, 0.25)	-0.87223 (-3.88)	0.2721 (3.34)
Brno (CZ)	0.15 (0.09, 0.24)	-1.03105 (-3.37)	0.3665 (3.30)
Budapest (H)	0.14 (0.07, 0.24)	-1.09231 (-3.78)	0.3775 (3.59)
Burgos (E)	0.18 (0.11, 0.23)	-1.35656 (-4.78)	0.4720 (4.59)
Caen (F)	0.13 (0.07, 0.22)	-0.90114 (-4.26)	0.2842 (3.69)
Cluj (RO)	0.13 (0.06, 0.23)	-1.08124 (-3.78)	0.3960 (3.80)
Cork (IRE)	0.20 (0.13, 0.29)	-0.71542 (-3.05)	0.2272 (2.67)
Coruna (E)	0.19 (0.12, 0.28)	-1.18437 (-6.07)	0.3677 (5.21)
Cuenca (E)	0.13 (0.04, 0.24)	-1.60427 (-7.47)	0.5873 (7.35)
Debrecen (H)	0.17 (0.10, 0.26)	-1.13413 (-3.32)	0.4173 (3.37)
Edirne (TK)	0.13 (0.06, 0.22)	-1.03946 (-4.16)	0.3311 (3.64)
Elblag (PL)	0.17 (0.10, 0.26)	-0.99661 (-2.48)	0.3551 (2.44)
Erfurt (D)	0.15 (0.08, 0.23)	-0.97915 (-2.96)	0.3464 (2.88)
Eskdalemuir (UK)	0.18 (0.11, 0.26)	-0.66889 (-2.72)	0.2261 (2.54)
Essen (D)	0.13 (0.07, 0.22)	-0.85376 (-3.05)	0.2803 (2.75)
Falun (S)	0.25 (0.17, 0.35)	-0.91001 (-1.57)	0.3806 (1.80)
Fichtelberg (D)	0.09 (0.03, 0.18)	-0.90584 (-3.65)	0.3627 (3.99)
Goerlitz (D)	0.16 (0.09, 0.24)	-0.89994 (-2.60)	0.3157 (2.51)
Graz (A)	0.17 (0.10, 0.25)	-1.34253 (-4.51)	0.4988 (4.63)
Greifswald (D)	0.25 (0.18, 0.34)	-0.91138 (-2.13)	0.3197 (2.06)
Hamburg (D)	0.20 (0.13, 0.29)	-0.91196 (-2.39)	0.3183 (2.31)

Hannover (D)	0.16 (0.09, 0.25)	-0.98406 (2.93)	0.3415 (2.80)
Helsinki (FIN)	0.24 (0.16, 0.34)	-0.86899 (-1.59)	0.3478 (1.76)
Heraklyon (GR)	0.20 (0.13, 0.30)	-1.04605 (-5.17)	0.3013 (4.12)
Iasi (RO)	0.14 (0.06, 0.23)	-1.15611 (-3.35)	0.4146 (3.30)
Kalamata (GR)	0.15 (0.08, 0.25)	-0.94868 (-5.68)	0.2616 (4.32)
Kastamonu (TK)	0.14 (0.06, 0.24)	-0.80206 (-3.01)	0.2643 (2.73)
Kaunas (LT)	0.19 (0.13, 0.28)	-0.82186 (-1.85)	0.2993 (1.86)
Kharkiv (UA)	0.17 (0.10, 0.27)	-1.14450 (2.54)	0.4401 (2.70)
Klagenfurt (A)	0.18 (0.10, 0.28)	-1.09318 (-3.59)	0.3991 (3.62)
Kobenhavn (DK)	0.28 (0.20, 0.37)	-0.49393 (-1.04)	0.1447 (0.83)
Krakov (PL)	0.14 (0.08, 0.23)	-1.19842 (-3.81)	0.4458 (3.00)
Kyiv (UA)	0.17 (0.10, 0.26)	-1.18052 (-2.84)	0.4463 (2.96)
Larissa (GR)	0.11 (0.03, 0.21)	-1.27952 (-6.45)	0.4130 (5.70)
Leba (PL)	0.23 (0.14, 0.33)	-1.18031 (-2.25)	0.4219 (2.22)
Leipzig (D)	0.17 (0.10, 0.25)	-0.98446 (-2.76)	0.3435 (2.66)
Lerwick (UK)	0.21 (0.15, 0.29)	-0.63429 (-3.08)	0.2241 (3.00)
Lindenberg (D)	0.16 (0.10, 0.25)	-0.98526 (-2.84)	0.3941 (2.78)
Linkoeping (S)	0.26 (0.19, 0.36)	-0.16821 (-0.30)	0.0591 (0.29)
Lisboa (P)	0.15 (0.07, 0.25)	-1.10520 (-5.85)	0.3187 (4.65)
Lugano (CH)	0.13 (0.06, 0.22)	-1.16079 (-6.02)	0.3933 (5.60)
Lviv (UA)	0.14 (0.07, 0.22)	-1.06354 (-3.27)	0.3994 (3.38)
Madrid (E)	0.20 (0.13, 0.30)	-1.13171 (-3.87)	0.3275 (3.10)
Malinhead (IRE)	0.21 (0.14, 0.30)	-0.53641 (-2.50)	0.1516 (1.95)
Marseille (F)	0.16 (0.08, 0.26)	-0.81883 (-3.27)	0.2211 (2.44)
Minsk (BY)	0.16 (0.09, 0.24)	-1.11263 (-2.73)	0.4299 (2.91)
Moscu (RUS)	0.15 (0.09, 0.24)	-0.98484 (-2.33)	0.3824 (2.49)
Mugla (TK)	0.13 (0.06, 0.23)	-0.92469 (-4.46)	0.2691 (3.57)
Murmansk (RUS)	0.15 (0.08, 0.23)	-1.024452 (-2.47)	0.4422 (2.95)
Nice (F)	0.22 (0.13, 0.34)	-1.06964 (-4.35)	0.3269 (3.67)
Nurenberg (D)	0.11 (0.05, 0.19)	-1.03969 (-4.09)	0.3679 (3.96)
Odesa (UA)	0.23 (0.15, 0.33)	-1.11663 (-2.52)	0.4109 (2.56)
Orland (N)	0.23 (0.16, 0.32)	-0.75230 (-1.94)	0.2969 (2.11)
Oslo (N)	0.27 (0.19, 0.37)	-0.73585 (-1.36)	0.2918 (1.47)
Ostrava (CZ)	0.15 (0.08, 0.23)	-0.88525 (-2.70)	0.3121 (2.63)
Pecs (H)	0.12 (0.05, 0.21)	-1.06034 (-3.85)	0.3638 (3.62)
Perpignan (F)	0.15 (0.07, 0.25)	-1.00115 (-4.77)	0.2938 (3.85)

Poprad (SK)	0.14 (0.07, 0.22)	-0.84625 (-2.81)	0.3189 (2.91)
Postdam (D)	0.17 (0.11, 0.26)	-0.95606 (-2.70)	0.3342 (2.62)
Poznan (PL)	0.16 (0.10, 0.24)	-1.01505 (-2.87)	0.3671 (2.86)
Praha (CZ)	0.13 (0.07, 0.21)	-0.97528 (-3.34)	0.3518 (3.31)
Reykjavik (IS)	0.17 (0.11, 0.25)	-0.82488 (-3.37)	0.3296 (3.72)
Rostock (D)	0.25 (0.18, 0.34)	-0.91138 (-2.14)	0.3197 (2.06)
Saentis (CH)	0.05 (-0.02, 0.13)	-0.92004 (-4.44)	0.4080 (5.31)
Salzburg (A)	0.09 (0.03, 0.18)	-1.17615 (-5.01)	0.4233 (4.91)
Sarajevo (BH)	0.14 (0.05, 0.24)	-1.05884 (-3.51)	0.3725 (3.40)
Schleswig (D)	0.24 (0.16, 0.33)	-0.79083 (-1.89)	0.2770 (1.83)
Shannon (IRE)	0.17 (0.10, 0.26)	-0.73769 (-3.30)	0.2309 (2.85)
Sibiu (RO)	0.12 (0.05, 0.21)	-1.10310 (-3.90)	0.4069 (3.95)
Sivas (TK)	0.19 (0.11, 0.30)	-0.93265 (-2.13)	0.3397 (2.14)
Sliak (SK)	0.17 (0.10, 0.26)	-1.02840 (-3.08)	0.3784 (3.13)
Sodankyla (FIN)	0.15 (0.08, 0.24)	-1.09408 (-2.21)	0.4847 (2.70)
Split (HR)	0.14 (0.06, 0.24)	-1.18599 (-5.11)	0.3731 (4.42)
Stavanger (N)	0.27 (0.19, 0.36)	-0.70342 (-1.52)	0.2820 (1.67)
S.Petersburg	0.18 (0.11, 0.26)	-1.00006 (-2.08)	0.3938 (2.27)
Strasbourg (F)	0.11 (0.05, 0.20)	-1.01213 (-4.16)	0.3398 (3.82)
Szczecin (PL)	0.20 (0.13, 0.29)	-0.87732 (-2.18)	0.3055 (2.10)
Szeged (H)	0.17 (0.09, 0.26)	-1.06187 (-3.06)	0.3719 (2.96)
Tallin (EST)	0.23 (0.16, 0.33)	-0.76665 (-1.47)	0.3015 (1.59)
Tessalonica (GR)	0.14 (0.06, 0.24)	-1.32416 (-6.08)	0.4329 (5.47)
Thorshavn (DK)	0.18 (0.13, 0.25)	-0.80754 (-4.14)	0.3058 (4.43)
Timisoara (RO)	0.14 (0.06, 0.24)	-1.07717 (-3.62)	0.3736 (3.46)
Toulouse (F)	0.12 (0.05, 0.21)	-1.125810 (-4.89)	0.3661 (4.35)
Trier (D)	0.12 (0.06, 0.20)	-1.04497 (-4.02)	0.3636 (3.83)
Tromso (N)	0.17 (0.10, 0.26)	-0.85765 (-2.86)	0.3504 (3.22)
Urfa (TK)	0.18 (0.11, 0.27)	-1.28170 (-4.46)	0.3982 (3.83)
Valentia (IRE)	0.20 (0.13, 0.30)	-0.62299 (-2.89)	0.1769 (2.27)
Valley (UK)	0.24 (0.17, 0.33)	-0.62755 (-2.27)	0.1931 (1.93)
Vardo (N)	0.25 (0.19, 0.32)	-1.03911 (-2.97)	0.4492 (3.54)
Vilnius (LT)	0.19 (0.12, 0.28)	-1.04937 (-2.33)	0.3914 (2.40)
Visby (S)	0.27 (0.20, 0.36)	-0.58310 (-1.27)	0.2107 (1.26)
Vytegra (RUS)	0.14 (0.07, 0.23)	-0.91294 (-1.92)	0.3705 (2.14)
Waddington (UK)	0.19 (0.12, 0.28)	-0.90617 (-3.39)	0.3086 (3.19)

Warsaw (PL)	0.15 (0.09, 0.23)	-1.05587 (-2.99)	0.3914 (3.05)
Wien (A)	0.13 (0.06, 0.21)	-1.08121 (-3.98)	0.3752 (3.79)
Wlodawa (PL)	0.15 (0.07, 0.24)	-1.26161 (-3.27)	0.4691 (3.34)
Wroclaw (PL)	0.15 (0.09, 0.23)	-1.11910 (-3.39)	0.3996 (3.34)
Zaragoza (E)	0.17 (0.10, 0.26)	-1.19749 (-4.53)	0.3570 (3.73)
Zugspitze (D)	0.05 (-0.02, 0.13)	-0.78448 (-3.80)	0.3781 (4.94)
Zurich (CH)	0.07 (0.00, 0.16)	-1.09273 (-5.35)	0.3866 (5.14)

All of the trend coefficients in the following tables have °C/decade as unit.

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Table 2: Estimated coefficients: Autocorrelated errors

City	d (95% band)	Intercept (t-value)	Time trend ⁴ (t-value)
Aberdeen (UK)	0.11 (0.01, 0.25)	-0.77439 (-4.84)	0.2530 (4.45)
Afyon (TK)	0.02 (-0.07, 0.16)	-1.113508 (-6.71)	0.3864 (6.10)
Akureyri (IS)	0.04 (-0.06, 0.17)	-0.78368 (-4.53)	0.3045 (4.73)
Alborg (DK)	0.14 (0.04, 0.28)	-0.82598 (-3.09)	0.2942 (3.03)
Alencon (F)	0.05 (-0.03, 0.19)	-0.83451 (-5.25)	0.2613 (4.44)
Almeria (E)	0.13 (0.07, 0.23)	-1.21308 (-7.97)	0.3464 (6.25)
Ankara (Turkey)	-0.04 (-0.13, 0.10)	-1.31722 (-10.31)	0.4562 (9.35)
Athens (GR)	0.04 (-0.08, 0.18)	-1.16228 (-9.01)	0.3395 (7.07)
Belfast (UK)	0.09 (-0.01, 0.26)	-0.69884 (-4.83)	0.2198 (4.14)
Belgrade (SRB)	0.00 (-0.12, 0.15)	-1.46170 (-9.18)	0.5166 (8.61)
Bistrita (RO)	0.02 (-0.06, 0.14)	-1.22661 (-7.10)	0.4500 (6.96)
Bodo (N)	-0.01 (-0.09, 0.12)	-0.90486 (-6.95)	0.3435 (6.98)
Bourges(F)	0.00 (-0.10, 0.15)	-1.18197 (-8.72)	0.4055 (7.94)
Brest (BY)	0.09 (-0.01, 0.24)	-1.12339 (-4.05)	0.4129 (4.05)
Brest (F)	0.09 (-0.01, 0.24)	-0.87349 (-5.63)	0.2739 (4.81)
Brno (CZ)	0.10 (-0.01, 0.23)	-1.04648 (-4.33)	0.3692 (4.17)
Budapest (H)	0.08 (-0.04, 0.22)	-1.11484 (-5.12)	0.3832 (4.79)
Burgos (E)	0.10 (0.01, 0.23)	-1.31764 (-6.74)	0.4658 (6.51)
Caen (F)	0.06 (-0.02, 0.18)	-0.89779 (-5.92)	0.2858 (5.10)
Cluj (RO)	-0.03 (-0.11, 0.11)	-1.16831 (-8.90)	0.4181 (8.36)
Cork (IRE)	0.12 (0.02, 0.26)	-0.74792 (-4.60)	0.2392 (4.03)
Coruna (E)	0.11 (0.01, 0.24)	-1.16604 (-8.66)	0.3673 (7.47)
Cuenca (E)	-0.10 (-0.22, 0.07)	-1.57835 (-22.2)	0.5662 (20.44)
Debrecen (H)	0.08 (-0.02, 0.21)	-1.20996 (-5.41)	0.4353 (5.29)
Edirne (TK)	0.00 (-0.08, 0.11)	-1.10186 (-8.28)	0.3446 (6.88)
Elblag (PL)	0.07 (-0.05, 0.22)	-0.94885 (-3.78)	0.3418 (3.69)
Erfurt (D)	0.09 (-0.01, 0.24)	-0.98042 (-3.93)	0.3461 (3.78)
Eskdalemuir (UK)	0.13 (0.03, 0.26)	-0.70220 (-3.60)	0.2380 (3.35)
Essen (D)	0.04 (-0.05, 0.19)	-0.87943 (-4.83)	0.2882 (4.25)
Falun (S)	0.09 (0.01, 0.23)	-1.06364 (-3.81)	0.4180 (4.08)
Fichtelberg (D)	0.02 (-0.07, 0.17)	-0.92699 (-5.25)	0.3677 (5.56)
Goerlitz (D)	0.11 (0.01, 0.26)	-0.91266 (-3.30)	0.3180 (3.17)
Graz (A)	0.07 (-0.02, 0.20)	-1.35905 (-7.32)	0.5041 (7.36)
Greifswald (D)	0.15 (0.05, 0.29)	-0.94731 (-3.47)	0.3300 (3.33)

Hamburg (D)	0.08 (-0.02, 0.23)	-0.94544 (-4.33)	0.3279 (4.08)
Hannover (D)	0.07 (-0.03, 0.20)	-1.00368 (-4.56)	0.3477 (4.28)
Helsinki (FIN)	0.07 (-0.04, 0.20)	-1.02552 (-4.12)	0.3913 (4.26)
Heraklyon (GR)	0.10 (0.00, 0.24)	-1.09710 (-8.62)	0.3115 (6.68)
Iasi (RO)	0.01 (-0.09, 0.18)	-1.19964 (-6.49)	0.4249 (6.12)
Kalamata (GR)	0.03 (-0.08, 0.16)	-0.99482 (-10.60)	0.2727 (7.78)
Kastamonu (TK)	-0.02 (-0.11, 0.11)	-0.85969 (7.00)	0.2783 (5.98)
Kaunas (LT)	0.12 (0.03, 0.24)	-0.87984 (-2.74)	0.3179 (2.71)
Kharkiv (UA)	0.05 (-0.05, 0.16)	-1.26205 (-4.95)	0.4727 (5.00)
Klagenfurt (A)	0.02 (-0.08, 0.17)	-1.13217 (-7.97)	0.4068 (7.65)
Kobenhavn (DK)	0.14 (0.03, 0.28)	-0.56054 (-2.20)	0.1618 (1.75)
Krakow (PL)	0.11 (-0.02, 0.26)	-1.20536 (-4.41)	0.4474 (4.48)
Kyiv (UA)	0.07 (-0.04, 0.19)	-1.23743 (-4.77)	0.4600 (4.81)
Larissa (GR)	-0.09 (-0.18, 0.03)	-1.31156 (-17.76)	0.4193(14.60)
Leba (PL)	0.04 (-0.07, 0.18)	-1.09484 (-5.09)	0.4002 (5.01)
Leipzig (D)	0.08 (-0.02, 0.23)	-0.99275 (-4.25)	0.3442 (4.00)
Lerwick (UK)	0.20 (0.10, 0.34)	-0.64388 (-3.26)	0.2268 (3.18)
Lindenberg (D)	0.10 (0.00, 0.24)	-1.00472 (-3.84)	0.3537 (3.69)
Linkoeping (S)	0.14 (0.05, 0.26)	-0.31497 (-0.96)	0.0909 (0.76)
Lisboa (P)	0.00 (-0.09, 0.13)	-1.06063 (-11.58)	0.3082 (8.93)
Lugano (CH)	0.01 (-0.07, 0.14)	-1.19865 (-11.08)	0.4045 (9.96)
Lviv (UA)	0.08 (-0.02, 0.23)	-1.09746 (-4.47)	0.4073 (4.51)
Madrid (E)	0.07 (-0.02, 0.21)	-1.05927 (-6.66)	0.3153 (5.38)
Malinhead (IRE)	0.16 (0.05, 0.34)	-0.56831 (-3.32)	0.1622 (2.61)
Marseille (F)	-0.02 (-0.12, 0.12)	-0.86519 (-8.27)	0.2337 (5.89)
Minsk (BY)	0.08 (-0.02, 0.25)	-1.15552 (-4.13)	0.4410 (4.28)
Moscu (RUS)	0.10 (-0.01, 0.25)	-1.01909 (-3.05)	0.3915 (3.20)
Mugla (TK)	-0.02 (-0.11, 0.13)	-0.97434 (9.73)	0.2826 (7.44)
Murmansk (RUS)	0.07 (-0.02, 0.20)	-1.01459 (-3.57)	0.4333 (4.14)
Nice (F)	-0.05 (-0.18, 0.13)	-1.08842 (-16.11)	0.3286 (12.69)
Nuernberg (D)	0.08 (-0.03, 0.22)	-1.03955 (-4.71)	0.3670 (4.52)
Odesa (UA)	0.06 (-0.03, 0.22)	-1.27359 (-6.34)	0.4551 (6.12)
Orland (N)	0.10 (0.02, 0.22)	-0.87047 (-4.09)	0.3269 (4.19)
Oslo (N)	0.11 (0.02, 0.24)	-0.91611 (-3.47)	0.3403 (3.53)
Ostrava (CZ)	0.09 (-0.01, 0.25)	-0.89872 (-3.64)	0.3125 (3.45)
Pecs (H)	0.03 (-0.09, 0.17)	-1.08692 (-6.07)	0.3692 (5.53)

Perpignan (F)	-0.01 (-0.11,	-1.00921 (-9.90)	0.2958 (7.70)
Poprad (SK)	0.10 (0.00, 0.23)	-0.86890 (-3.48)	0.3234 (3.54)
Postdam (D)	0.08 (-0.02, 0.23)	-0.96887 (-4.19)	0.3366 (3.96)
Poznan (PL)	0.10 (0.00, 0.26)	-1.03684 (-3.87)	0.3719 (3.79)
Praha (CZ)	0.10 (0.01, 0.24)	-0.98295 (-3.88)	0.3529 (3.80)
Reykjavik (IS)	0.14 (0.06, 0.24)	-0.84983 (-4.18)	0.3341 (4.53)
Rostock (D)	0.15 (0.05, 0.29)	-0.94731 (-3.47)	0.3300 (3.33)
Saentis (CH)	-0.04 (-0.13,	-0.93448 (-7.03)	0.4140 (8.15)
Salzburg (A)	0.02 (-0.10, 0.15)	-1.15956 (-6.93)	0.4174 (6.67)
Sarajevo (BH)	-0.06 (-0.17,	-1.11002 (-9.77)	0.3842 (8.80)
Schleswig (D)	0.10 (0.01, 0.26)	-0.84334 (-3.83)	0.2899 (3.59)
Shannon (IRE)	0.12 (0.01, 0.26)	-0.76214 (-4.30)	0.2396 (3.71)
Sibiu (RO)	0.00 (-0.07, 0.12)	-1.17143 (-7.41)	0.4213 (7.08)
Sivas (Turkey)	0.01 (-0.09, 0.13)	-1.08552 (-5.84)	0.3829 (5.48)
Sliak (SK)	0.07 (-0.02, 0.21)	-1.05760 (-5.08)	0.3812 (4.96)
Sodankyla (FIN)	-0.03 (-0.11, 0.08)	-1.14716 (-5.57)	0.4904 (6.25)
Split (HR)	-0.01 (-0.12, 0.15)	-1.24172 (-10.51)	0.3896 (8.74)
Stavanger (N)	0.14 (0.05, 0.27)	-0.86224 (-3.32)	0.3207 (3.40)
S.Petersburg (RUS)	0.10 (0.00, 0.25)	-1.06645 (-3.22)	0.4125 (3.40)
Strasbourg (F)	0.05 (-0.03, 0.19)	-1.01267 (-5.54)	0.3395 (5.01)
Szczecin (PL)	0.11 (0.01, 0.25)	-0.90775 (-3.41)	0.3130 (3.22)
Szeged (H)	0.04 (-0.07, 0.17)	-1.11388 (-5.96)	0.3821 (5.49)
Tallin (EST)	0.13 (0.01, 0.27)	-0.88178 (-2.66)	0.3349 (2.77)
Tessalonica (GR)	-0.04 (-0.14, 0.10)	-1.13725 (-15.12)	0.4462 (12.87)
Thorsnavn (DK)	0.20 (0.10, 0.32)	-0.79118 (-3.71)	0.3015 (3.91)
Timisoara (RO)	-0.01 (-0.12, 0.12)	-1.14408 (-7.95)	0.3897 (7.17)
Toulouse (F)	0.02 (-0.07, 0.15)	-1.13918 (-7.99)	0.3702 (6.94)
Trier (D)	0.05 (-0.04, 0.19)	-1.05694 (-5.68)	0.3679 (5.33)
Tromso (N)	0.05 (-0.05, 0.16)	-0.87675 (-5.16)	0.3516 (5.58)
Urfa (TK)	0.08 (-0.04, 0.23)	-1.33183 (-7.39)	0.4097 (6.18)
Valentia (IRE)	0.10 (-0.01, 0.27)	-0.64254 (-4.73)	0.1842 (3.70)
Valley (UK)	0.13 (0.04, 0.26)	-0.70083 (-4.17)	0.2152 (3.52)
Vardo (N)	0.21 (0.12, 0.33)	-1.03660 (-3.53)	0.4452 (4.19)
Vilnius (LT)	0.11 (0.01, 0.23)	-1.09032 (-3.51)	0.4074 (3.59)
Visby (S)	0.18 (0.08, 0.33)	-0.66390 (-2.15)	0.2317 (2.07)
Vytegra (RUS)	0.09 (-0.03, 0.24)	-0.94392 (-2.51)	0.3786 (2.74)

Waddington (UK)	0.09 (0.00, 0.22)	-0.94932 (-5.65)	0.3231 (5.24)
Warsaw (PL)	0.11 (0.01, 0.24)	-1.07177 (-3.66)	0.3938 (3.68)
Wien (A)	0.10 (-0.02, 0.23)	-1.08164 (-4.58)	0.3741 (4.33)
Wlodawa (PL)	0.01 (-0.11, 0.16)	-1.23510 (-6.26)	0.4608 (6.22)
Wroclaw (PL)	0.09 (-0.01, 0.25)	-1.12137 (-4.51)	0.3993 (4.37)
Zaragoza (E)	0.06 (0.01, 0.16)	-1.12648 (-7.19)	0.3395 (5.86)
Zugspitze (D)	-0.04 (-0.13, 0.11)	-0.80452 (-6.07)	0.3838 (7.58)
Zurich (CH)	-0.02 (-0.12, 0.14)	-1.09537 (-8.33)	0.3878 (7.78)

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663 **Table 3: Estimated coefficients for the time trend under different assumptions**

City	d estimated (WN)	d estimated (BL)	d = 0
Aberdeen (UK)	0.2472 (3.09)	0.2530 (4.45)	0.2745 (7.49)
Afyon (TK)	0.3766 (3.77)	0.3864 (6.10)	0.3872 (6.60)
Akureyri (IS)	0.3032 (3.27)	0.3045 (4.73)	0.3062 (5.62)
Alborg (DK)	----	0.2942 (3.03)	0.3065 (5.48)
Alencon (F)	0.2592 (3.21)	0.2613 (4.44)	0.2628 (5.53)
Almeria (E)	0.3616 (4.16)	0.3464 (6.25)	0.3311 (10.14)
Ankara (TK)	0.3766 (4.04)	0.4562 (9.35)	0.4529 (7.57)
Athens (GR)	0.3308 (3.99)	0.3395 (7.07)	0.3406 (8.30)
Belfast (UK)	0.2020 (2.43)	0.2198 (4.14)	0.2304 (6.33)
Belgrade (SRB)	0.4990 (4.39)	0.5166 (8.61)	0.5166 (8.43)
Bistrita (RO)	0.4175 (3.25)	0.4500 (6.96)	0.4518 (7.42)
Bodo (N)	0.3270 (3.05)	0.3435 (6.98)	0.3428 (6.46)
Bourges (F)	0.4003 (5.20)	0.4055 (7.94)	0.4055 (7.88)
Brest (BY)	0.4072 (2.92)	0.4129 (4.05)	0.4182 (6.05)
Brest (F)	0.2721 (3.34)	0.2739 (4.81)	0.2745 (7.09)
Brno (CZ)	0.3665 (3.30)	0.3692 (4.17)	0.3727 (6.48)
Budapest (H)	0.3775 (3.59)	0.3832 (4.79)	0.3888 (6.86)
Burgos (E)	0.4720 (4.59)	0.4658 (6.51)	0.4627 (9.86)
Caen (F)	0.2842 (3.69)	0.2858 (5.10)	0.2871 (6.61)
Cluj (RO)	0.3960 (3.80)	0.4181 (8.36)	0.4158 (7.10)
Cork (IRE)	0.2272 (2.67)	0.2392 (4.03)	0.2524 (7.07)
Coruna (E)	0.3677 (5.21)	0.3673 (7.47)	0.3680 (11.92)
Cuenca (E)	0.5873 (7.35)	0.5662 (20.44)	0.5717 (12.77)
Debrecen (H)	0.4173 (3.37)	0.4353 (5.29)	0.4450 (7.55)
Edirne (TK)	0.3311 (3.64)	0.3446 (6.88)	0.3446 (6.74)
Elblag (PL)	0.3551 (2.44)	0.3418 (3.69)	0.3389 (4.92)
Erfurt (D)	0.3464 (2.88)	0.3461 (3.78)	0.3460 (5.57)
Eskdalemuir (UK)	0.2261 (2.54)	0.2380 (3.35)	0.2605 (6.42)
Essen (D)	0.2803 (2.75)	0.2882 (4.25)	0.2909 (5.06)
Falun (S)	0.3806 (1.80)	0.4180 (4.08)	0.4310 (5.96)
Fichtelberg (D)	0.3627 (3.99)	0.3677 (5.56)	0.3687 (6.06)
Goerlitz (D)	0.3157 (2.51)	0.3180 (3.17)	0.3211 (5.16)
Graz (A)	0.4988 (4.63)	0.5041 (7.36)	0.5070 (9.91)
Greitswald (D)	0.3197 (2.06)	0.3300 (3.33)	0.3423 (6.4)
Hamburg (D)	0.3183 (2.31)	0.3279 (4.08)	0.3322 (5.74)

Hannover (D)	0.3415 (2.80)	0.3477 (4.28)	0.3514 (5.82)
Helsinki (FIN)	0.3478 (1.76)	0.3913 (4.26)	0.3997 (5.68)
Heraklyon (GR)	0.3013 (4.12)	0.3115 (6.68)	0.3149 (10.25)
Iasi (RO)	0.4146 (3.30)	0.4249 (6.12)	0.4253 (6.30)
Kalamata (GR)	0.2616 (4.32)	0.2727 (7.78)	0.2741 (8.76)
Kastamonu (TK)	0.2643 (2.73)	0.2783 (5.98)	0.2777 (5.32)
Kaunas (LT)	0.2993 (1.86)	0.3179 (2.71)	0.3407 (4.84)
Kharkiv (UA)	0.4401 (2.70)	0.4727 (5.00)	0.4813 (6.20)
Klagenfurt (A)	0.3991 (3.62)	0.4068 (7.65)	0.4073 (8.14)
Kobenhavn (DK)	----	0.1618 (1.75)	0.1721 (3.27)
Krakov (PL)	0.4458 (3.00)	0.4474 (4.48)	0.4522 (7.32)
Kyiv (UA)	0.4463 (2.96)	0.4600 (4.81)	0.4654 (6.51)
Larissa (GR)	0.4130 (5.70)	0.4193(14.60)	0.4188 (9.44)
Leba (PL)	0.4219 (2.22)	0.4002 (5.01)	0.3999 (5.72)
Leipzig (D)	0.3435 (2.66)	0.3442 (4.00)	0.3444 (5.62)
Lerwick (UK)	0.2241 (3.00)	0.2268 (3.18)	0.2623 (8.65)
Lindenberg (D)	0.3941 (2.78)	0.3537 (3.69)	0.3598 (5.77)
Linkoeping (S)	----	----	----
Lisboa (P)	0.3187 (4.65)	0.3082 (8.93)	0.3082 (8.71)
Lugano (CH)	0.3933 (5.60)	0.4045 (9.96)	0.4053 (10.25)
Lviv (UA)	0.3994 (3.38)	0.4073 (4.51)	0.4141 (6.49)
Madrid (E)	0.3275 (3.10)	0.3153 (5.38)	0.3122 (7.05)
Malinhead (IRE)	0.1516 (1.95)	0.1622 (2.61)	0.1859 (5.93)
Marseille (F)	0.2211 (2.44)	0.2337 (5.89)	0.2329 (5.20)
Minsk (BY)	0.4299 (2.91)	0.4410 (4.28)	0.4476 (6.12)
Moscu (RUS)	0.3824 (2.49)	0.3915 (3.20)	0.4025 (5.07)
Mugla (TK)	0.2691 (3.57)	0.2826 (7.44)	0.2816 (6.64)
Murmansk (RUS)	0.4422 (2.95)	0.4333 (4.14)	0.4287 (5.51)
Nice (F)	0.3269 (3.67)	0.3286 (12.69)	0.3292 (9.65)
Nuernberg (D)	0.3679 (3.96)	0.3670 (4.52)	0.3651 (6.40)
Odesa (UA)	0.4109 (2.56)	0.4551 (6.12)	0.4624 (7.80)
Orland (N)	0.2969 (2.11)	0.3269 (4.19)	0.3402 (6.50)
Oslo (N)	----	0.3403 (3.53)	0.3590 (5.73)
Ostrava (CZ)	0.3121 (2.63)	0.3125 (3.45)	0.3123 (5.08)
Pecs (H)	0.3638 (3.62)	0.3692 (5.53)	0.3702 (6.27)
Perpignan (F)	0.2938 (3.85)	0.2958 (7.70)	0.2957 (7.53)

Poprad (SK)	0.3189 (2.91)	0.3234 (3.54)	0.3302 (5.59)
Postdam (D)	0.3342 (2.62)	0.3366 (3.96)	0.3380 (5.57)
Poznan (PL)	0.3671 (2.86)	0.3719 (3.79)	0.3778 (5.93)
Praha (CZ)	0.3518 (3.31)	0.3529 (3.80)	0.3567 (5.95)
Reykjavik (IS)	0.3296 (3.72)	0.3341 (4.53)	0.3553 (8.38)
Rostock (D)	0.2472 (3.09)	0.3300 (3.33)	0.3423 (6.43)

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Saentis (CH)	0.3197 (2.06)	0.4140 (8.15)	0.4116 (6.71)
Salzburg (A)	0.4080 (5.31)	0.4174 (6.67)	0.4161 (7.22)
Sarajevo (BH)	0.4233 (4.91)	0.3842 (8.80)	0.3826 (6.50)
Schleswig (D)	0.3725 (3.40)	0.2899 (3.59)	0.2954 (5.48)
Shannon (IRE)	0.2770 (1.83)	0.2396 (3.71)	0.2556 (6.64)
Sibiu (RO)	0.2309 (2.85)	0.4213 (7.08)	0.4213 (6.96)
Sivas (TK)			0.3839 (5.54)
Sliak (SK)	0.4069 (3.95)	0.3829 (5.48)	0.3811 (6.65)
Sodankyla (FIN)	0.3397 (2.14)	0.3812 (4.96)	0.4895 (5.28)
Split (HR)	0.3784 (3.13)	0.4904 (6.25)	0.3889 (8.56)
Stavanger (N)	0.4847 (2.70)	0.3896 (8.74)	0.3436 (6.42)
S.Petersburg (RUS)	0.3731 (4.42)	0.3207 (3.40)	0.4252 (5.37)
Strasbourg (F)	0.2820 (1.67)	0.4125 (3.40)	0.3400 (6.22)
Szczecin (PL)	0.3938 (2.27)	0.3395 (5.01)	0.3186 (5.21)
Szeged (H)	0.3398 (3.82)	0.3130 (3.22)	0.3838 (6.44)
Tallin (EST)	0.3055 (2.10)	0.3821 (5.49)	0.3586 (5.09)
Tessalonica (GR)	0.3719 (2.96)	0.3349 (2.77)	0.4451 (10.45)
Thorsnavn (DK)	----	0.4462 (12.87)	0.3355 (10.34)
Timisoara (RO)	0.4329 (5.47)	0.3015 (3.91)	0.3891 (6.69)
Toulouse (F)	0.3058 (4.43)	0.3897 (7.17)	0.3709 (7.50)
Trier (D)	0.3736 (3.46)	0.3702 (6.94)	0.3709 (6.65)
Tromso (N)			0.3526 (6.83)
Urfa (TK)			0.4118 (8.69)
Valentia (IRE)	0.3661 (4.35)	0.3679 (5.33)	0.1887 (5.77)
Valley (UK)	0.3636 (3.83)	0.3516 (5.58)	0.2325 (6.49)
Vardo (N)	0.3504 (3.22)	0.4097 (6.18)	0.4365 (9.91)
Vilnius (LT)	0.3982 (3.83)	0.1842 (3.70)	0.42327 (5.94)
Visby (S)	0.1769 (2.27)	0.2152 (3.52)	0.2555 (4.81)
Vytegra (RUS)	0.1931 (1.93)	0.4452 (4.19)	0.3857 (4.13)

Waddington (UK)	0.4492 (3.54)	0.4074 (3.59)	0.3329 (7.87)
Warsaw (PL)	0.3914 (2.40)	0.2317 (2.07)	0.3977 (5.99)
Wien (A)	----	0.3786 (2.74)	0.3711 (6.66)
Wlodawa (PL)	0.3705 (2.14)	0.3231 (5.24)	0.4605 (6.37)
Wroclaw (PL)	0.3086 (3.19)	0.3938 (3.68)	0.4002 (6.47)
Zaragoza (E)	0.3914 (3.05)	0.3741 (4.33)	0.3322 (7.31)
Zugspitze (D)	0.3752 (3.79)	0.4608 (6.22)	0.3817 (6.25)
Zurich (CH)	0.4691 (3.34)	0.3993 (4.37)	0.3875 (7.05)

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