Estimating European Temperature Trends

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ABSTRACT

This paper presents estimates for common trends in European temperature panels using new estimators. The analyzed data contains 4000 Eurasian weather stations. A sampling algorithm robust against inherent geographical biases is developed, and appropriate estimators are evaluated. The estimations based on this evaluation show that commonalities in temperature movements disappear with growing geographical scope. They also reveal that European mean temperature increased by 1.8°C over the past 130 years, but estimates differ by region. A particularly pronounced increase has taken place since the 1980s. Further, a 20-year cycle is discovered, and a fractal structure of temperature trends is proposed.

Keywords
Temperature trend, Climate Change, deterministic trends, cross-sectional dependence, econometrics, panel data.

INTRODUCTION

Climate change is often estimated fitting deterministic trends of specified functional form. Linear trends are usually assumed (see, e.g., Yue, T. X., Zhao, N., Ramsey, D. R., et al., 2013). Despite of this being common practice in climatological sciences, it is well-known that misspecified models with deterministic trends give rise to spurious regressions. First to address this issue in panels by proposing kernel methods are Atak, Linton, and Xiao (2011). Since then, a branch of econometric research has focused on this estimation approach, as it does not restrict the functional form of the trend. For the panel case, the method is extended to a two-step procedure by Robinson (2012). Chen, Gao, and Li (2012) further adapt it to semiparametric analysis. The underlying model for estimations following this approach is the general semiparametric panel of form

$$y_{it} = \alpha_i + x_{it}\beta + f(t/T) + \epsilon_{it}, \qquad (1)$$
$$i = 1,2, \dots N; \quad t = 1,2, \dots, T.$$

Where α_i is the individual fixed effect of cross-sectional unit i, x_{it} are the regressors measured for individual i at time t. The trend function f in this model defines a mapping $f: [0,1] \to R$ and is twice continuously differentiable. The residual variance term ϵ_{it} is allowed to be cross-sectionally dependent, with $E(\epsilon_{it}\epsilon_{jt}) = \sigma_{ij}$ for individuals i, j. If one imposes $\beta = 0$, the model reduces to the one proposed by Robinson (2012) and is estimated with purely nonparametric methods.

DATA

All data analyzed in this paper are taken from http://www.ecad.eu/. A blended panel with 4000 stations recording as early as 1880 is used. The variables studied from this set are primarily mean temperature (TAVG), but also minimum temperature (TMIN), and maximum temperature (TMAX). The data is adjusted seasonally by taking monthly dummies. Fourier expansion was also investigated, but did not yield noticeable differences in the trend estimations.

A major challenge guiding the data selection and the sampling procedure are the inherent geographical biases. The top panel of Figure 1 reveals one such bias for European weather stations recording prior to 1901: The spatial density of stations in Germany is much higher than in any other region. Consequently, a sampling algorithm geared at minimizing sample bias and achieving constant spatial density is proposed: First, the recording stations are clustered using longitude and latitude with a standard K-Means algorithm (e.g., Han, Kamber, & Pei, 2011). In the second step, stratification is achieved by drawing random sampling of each. An exemplary outcome of this procedure is illustrated in Figure 1. In total, eight samples are generated using the algorithm, comprising different regions and time periods.

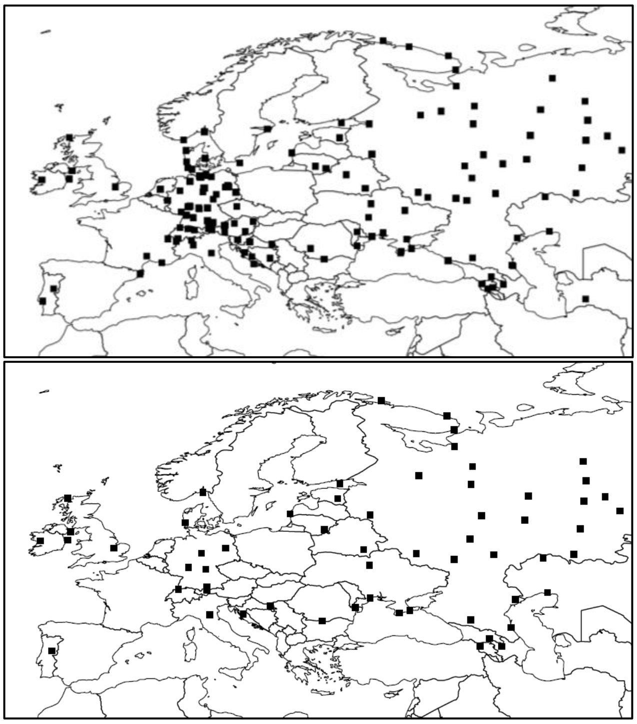

Figure 1. *Top: All European stations measuring TAVG prior to 1901. Bottom: A constant spatial density sample of these stations.*

KERNEL REGRESSION CHOICES

The estimators proposed in Robinson (2012) and Chen et al. (2012) necessitate kernel regression. Their kernel regressions use a weight function K_h built from K as $K_h(\tau, t/T) = K((\tau - t/T)/h)$ to construct weighted local averages or weighted local linear regressions. The kernel function input for constructing the weight of an observation at time point t when estimating the trend at relative time point $\tau \in [0,1]$ is $(\tau - t/T)/h$, where h is the bandwidth. One can rewrite this as $(\tau T - t)/Th$ and interpret it as the time distance between two observations at time points τT and t, adjusted for the bandwidth. Most kernel functions used for the analysis have support of $[-1,1]$ and are symmetric around zero, i.e. $K(z) = K(-z)$ and $z \notin [-1,1] \rightarrow K(z) = 0$. Hence, it is easy to see that smaller bandwidths h cause the kernel function to smooth over a smaller time period when estimating the trend at τ.

Before running any kernel regression, three issues have to be addressed: Firstly, which kernel function to use for weight assignment. Secondly, which bandwidth selection procedure to apply for determination of the smoothing interval. Thirdly, which kernel estimator to employ.

Kernel Function

Thirteen different kernel functions are investigated and compared. Particular attention is paid to boundary kernels constructed using a variety of adjustment schemes. The *boundary problem* is a bias arising because the effective support of any kernel function is reduced at the boundary. In the setting at hand, τ lies in the boundary if $\tau \in [0, h] \cup [1 - h, 1]$ (see e.g., Fan & Gijbels, 1996). In this region, the kernel function tries to assign positive values to observations whose relative time point (i.e., t/T) lies outside of $[0,1]$.

An important discovery of this paper is that for bandwidth selection using Generalized Cross-Validation (GCV), the kernel function greatly impacts whether or not meaningful minima are found. In particular, kernels that are not treated at the boundary do not produce a global minimum in Estimated Prediction Error (EPE). Boundary kernels change this, and clear cut global minima arise. Amongst all examined boundary kernels, the IMSE-optimal modification proposed by Müller (1991) does best in this regard. Figure 2 illustrates this by comparing the EPE curves one finds for Epanechnikov's unmodified and the IMSE-optimal boundary kernel of first order.

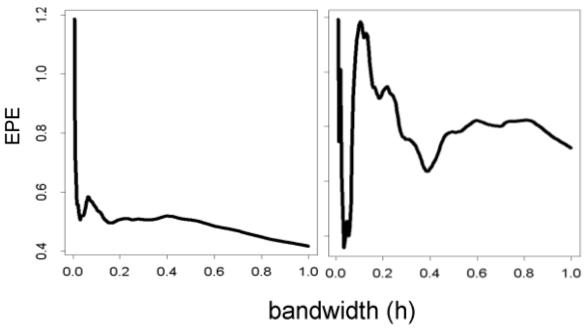

Figure 2. *Exemplary EPE-function for GCV. Left: Epanechnikov's kernel. Right: IMSE-optimal boundary kernel of first order.*

Bandwidth Selection

For bandwidth selection, Generalized Cross Validation (GCV) and an iterative Plug-In (IPI) method proposed by Gasser, Kneip, and Köhler (1991) are compared. The IPI method is found to choose extremely small values for h, and implies highly fluctuating trend estimations. This is most likely the case because homoscedasticity in the errors is required for the method to work. GCV selection schemes are investigated and prove to be robust, delivering reasonable bandwidths: Varying leave-out schemes and penalty functions are found to not alter the results. The most notable finding is the strong interaction effect between GCV and the kernel choice depicted in Figure 2 and described in the previous paragraph.

Lastly, the bandwidths found for the eight analyzed data sets using GCV and IMSE-optimal boundary kernels imply nonzero weight assignment to observations roughly 10-20 years around the time point τT for which the trend is estimated.

Kernel Estimator

Following Fan and Gijbels (1998), and adopting notation, any nonparametric regression estimator can be written as

$$\widehat{f(\tau)} = \frac{\sum_{t=1}^{T} w_t(\tau, h,) y_{At}^{v*}}{\sum_{t=1}^{T} w_t(\tau, h)} \qquad (2)$$

With bandwidth h, cross-sectional average y_{At}^{v*} weighted using a vector v^*, and a weight function $w_t(\tau, h)$ whose functional form depends on the chosen kernel estimator and the kernel function K_h. Three kernel estimators are investigated: The Nadaraya-Watson Estimator (NWE), the Gasser-Müller Estimator (GME), and the Local Linear Regression (LLR). NWE and GME use local weighted averages; LLR fits a weighted local linear regression. Defining $S_{T,l} := \left(\sum_{j=1}^{T} K_h(\tau, j/T)(\tau, j/T)^l\right)$, equations (3) – (5) give their weight functions.

$$w_t^{NWE}(\tau, h) = K_h(\tau, t/T) \qquad (3)$$

$$w_t^{GME}(\tau, h) = \int_{t-0.5}^{t+0.5} K_h(\tau, u/T)\, du \qquad (4)$$

$$w_t^{LLR}(\tau, h) = K_h(\tau, t/T)\{S_{T,2} - (\tau - t/T) S_{T,1}\} \qquad (5)$$

Intuitively, the NWE uses the discrete kernel values for weight assignment. The GME bases the weights on an integration of K_h around the time point t. Lastly, LLR performs a weighted local linear regression around $(\tau - t/T)$ and assigns weight to the produced fit using K_h.

The NWE is suggested by Robinson (2012) for a two-step procedure which finds the Mean Square Error (MSE) optimal weight vector v^*. It is found that the GME and the NWE deliver near identical results for this estimator, with LLR capturing slightly more cyclical movement, but affecting the trend estimate only negligibly. Because LLR needs twice as many parameters, the NWE and GME are preferred. On the other hand, for the method proposed by Chen et al. (2012), LLR is found to be the best estimator of all three in practice. This is in line with theory, as the authors show that it is more efficient than any local constant fit. However, LLR is unable to smooth cycles at the boundary. This suggests that higher order polynomials would be even more suitable for temperature data.

NON- & SEMIPARAMETRIC ESTIMATORS

Estimator choice

Semiparametric estimation

Whether it is better to use Cross-sectional averages (CSA), the estimator proposed by Robinson (2012) (RE), or the estimator proposed by Chen et al. (2012) (CGLE) depends on the data and estimation characteristics. CGLE is the only feasible choice for semiparametric estimations. For nonparametric settings, CSA or RE are preferred. In general, CGLE is found to perform extremely poorly at the boundary. The reason is that the estimator is based on local linear regression and that temperature moves in 20-year cycles (see Figure 3). Because said cycle will either slope upwards or downwards at the boundaries, CGLE fits a local linear trend and produces extremely steep boundary estimates.

Nonparametric estimation

Given that the assumptions of common trend and stable long-run correlation between the stations hold, the best choice for a nonparametric estimator depends on two factors: Firstly, the magnitude of N. Secondly, the presence and significance of outliers. Ideally, it should hold that N is either very small (i.e., $2 \leq N \leq 5$) or moderately large (i.e., $N > 25$). In this case, no problems arise. For moderate N (i.e., $6 \leq N \leq 24$), RE only performs reasonably well if the common trend is very strong and there are *no outliers*. The reason for this behavior is the Mean Square Error (MSE) optimal reweighting scheme used by RE. The method fits a preliminary trend and estimates residuals based on this preliminary estimate. These residuals are used for construction of a heteroscedasticity-consistent covariance matrix estimate. This matrix is used to calculate MSE-optimal weights for the cross-sectional units. These weights are then used to construct an optimally weighted cross-sectional average for a second trend estimation. While this reweighting process generally improves the estimation, it does not do so in the presence of extreme outliers for moderate magnitudes of N. Under these circumstances, too much weight is put on the outliers, and the trend estimates become nonsensical. In this case, CSA is preferred. If N is moderately large (i.e., $N > 25$), enough random correlation is typically introduced to make RE robust against outliers. For very small N (i.e., $2 \leq N \leq 5$), every station effectively becomes an outlier, and so the problem disappears again.

Common Trend Specification

The model in equation (1) makes a strong assumption on the commonality of the time trend: The deterministic trend function has to be shared by all cross-sectional units. Misspecification and thereby biased estimations are potential dangers when estimating models described by equation (1). Hence, the common trend assumption requires careful evaluation. Zhang, Su, and Phillips (2012) propose a residual-based specification test which is based on an asymptotically pivotal distribution Yet, the convergence rate of the asymptotic test is extremely slow, and a small scale Monte Carlo study conducted as part of the research reveals that it can only be used in its bootstrapped form. A bootstrapped version of the test exceeds the computer resources available for the analysis, however.[1] Consequently, one has to evaluate the assumption using visual inspection of the trend plots. LLR is used for smoothing an individual station's trend, and the trends are expressed in mean-deviation terms. Figure 3 illustrates this approach: The individual stations' TAVG trends are estimated, demeaned and plotted for all of Scandinavia after 1952. The plot reveals that the common trend assumption for Scandinavia is reasonable.

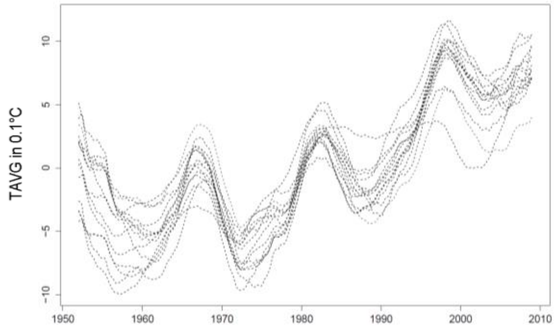

Figure 3. *Estimated individual TAVG trends of all Scandinavian stations recording prior to 1952 and expressed in mean-deviation units.*

RESULTS

Common Trend Assumption

In total, eight data sets are analyzed. The pattern across these data sets is consistent, and reveals that the common trend assumption is inappropriate for panels of Eurasian dimension. For panels of European data, the individual trends exhibit much clearer similarities. Because N is large enough in the data sets of European scale, RE performs reasonably well and does not introduce a bias when compared to CSA. Yet, a common trend in the mathematical sense of equation (1) remains questionable, especially before 1900. That being said, one should keep in mind that before the 1910s, temperature was commonly measured with mercury-based thermometers. These appliances are far less precise than thermometers based on alcohol, which were widely introduced in the 1920s. In contrast, for regions within Europe (e.g., Germany, Scandinavia, and Spain/Portugal), a common trend is a reasonable assumption (see Figure 3).

Estimated Increases In Mean Temperature

Generally, between 1880 and 2010, an increase in mean temperature of around 1.8°C is found for the common trend within Europe. The strongest increase takes place from 1975 onwards until 2010, where temperature strongly increases by around 1°C. For the Eurasian samples, a common trend is clearly absent. For the German weather stations recording prior to 1901, the estimated increase in TAVG until 2010 is around 0.5°C, and thus below European average. Mean temperature in Portugal and Spain, on the other hand, increased by around 0.6°C in the last 60 years alone. Scandinavia has seen an even bigger increase of nearly 1.3°C since 1952. Two semiparametric estimations are also performed, using minimum (TMIN) and maximum (TMAX)

[1] On a 64-bit operating system with an Intel i5 2x2.67GHz processor and 4 GHz DDR4-RAM, the bootstrapped test with 1.000 bootstrap samples is estimated to take up to 2 weeks of computation time.

temperature as regressors. One finds that European mean temperature has risen around 0.5°C between 1901 and 2010 relative to both the minimum and the maximum.

Cycles and fractal dimension of temperature

A perhaps more interesting discovery than its increase is a 20-year cycle in TAVG. The oscillation of this cycle has an amplitude of around 1 – 1.5°C, and is thus bigger than most estimated increases. It is stronger in regions with maritime climate (e.g., Scandinavia), indicating a link with sea currents (Hurrell & Van Loon, 1997). The cycle's periodicity and onset differs across regions, but the general movement remains. Consequently, it would be interesting to adjust for this 20-year seasonality and re-evaluate the common trend assumption for Eurasia. Whilst on the topic of cycles, it is further noteworthy that one finds common trend movements suggesting a cycle of even lower frequency (i.e., 150 – 200 years). Fractal organization in natural phenomena is not uncommon (see Mandelbrot, 1977), and low frequency temperature cycles are well-known in the literature, see for instance Velichko, Borisova, Zelikson, et al., 1992.

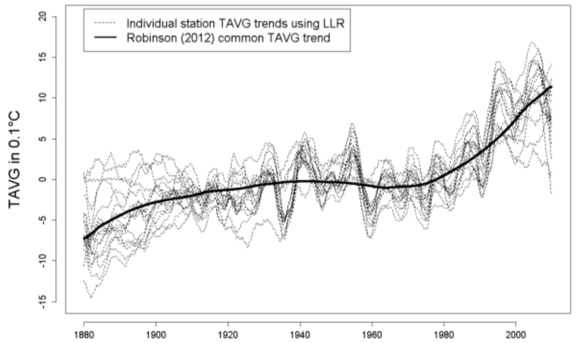

Figure 4. *Common European trend in TAVG using Robinson (2012), GCV, the NWE, and an IMSE-optimal boundary kernel of first order.*

CONCLUSION

Analyzing different kernel regression choices, this study concludes that the iterative plug-in method proposed by Gasser et al. (1991) is not robust to heteroscedastic data. Furthermore, one finds a strong interaction effect between kernel function and GCV if the NWE is used, suggesting usage of IMSE-optimal boundary kernels.

For the estimator proposed by Chen et al. (2012) (CGLE), extreme boundary effects are found. This is due to cyclical behaviour that LLR cannot capture appropriately at the boundary. While one can treat the estimate by cutting off the boundary, a fit of higher order is a better solution. The findings for Robinson's estimator (RE) suggest that the method is robust towards outliers for very small N (i.e., $2 \leq N \leq 5$) or moderately large N (i.e., $N > 25$). For moderately sized N (i.e., $6 \leq N > 24$), the method can only be used for very homogenously behaved panels without outliers. On a sidenote, the specification test proposed by Zhang et al. (2012) is shown to have poor asymptotics, necessitating a bootstrapped approach.

Common trends are found in Germany, Scandinavia, and Spain/Portugal. Increases in the last 60 years range from 0.6°C (Spain/Portugal) to 1.3°C (Scandinavia). Estimating a common trend across Europe, one finds mean temperature to have increased by around 1.8°C since 1880. Regardless of the exact geographical area, a stable 20 year cycle in mean temperature is observed, and it is speculated that cycles of longer wavelengths could be found due to low-frequency dynamics in temperature.

ROLE OF THE STUDENT

Jeremias Knoblauch was an undergraduate student working under the supervision of Prof. Dr. Stephan Smeekes and Prof. Dr. Jean-Pierre Urbain. The topic was proposed by the supervisors. The research as well as the writing was done by the student.

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