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ON THE RELATIONSHIP BETWEEN GHGS AND GLOBAL TEMPERATURE ANOMALIES: MULTI-LEVEL ROLLING ANALYSIS AND COPULA CALIBRATION

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On the relationship between GHGs and Global Temperature Anomalies:

Multi-level rolling analysis and Copula calibration

Abstract

The relationship between GHG emissions and global warming is studied through multi-level rolling analysis to assess whether or not there are increasing rates in global change as a result of higher levels of anthropogenic emissions, as we move forward in time. Furthermore, in order to assess whether we observe tail-dependence, representing simultaneous occurrence of extreme events, we employ copula methods. Our main findings do not support views of increasing rates in global climate change as a result of higher levels of emissions. On the contrary, they suggest a constant or even a decreasing effect of emissions on temperature anomalies especially from 2005 onward. At the same time, our copula calibration shows that the Frank copula achieves the best fit. Since the Frank copula is a copula that assigns a low probability to joint extreme events, our analysis does not show tail dependence.

Keywords: GHGs; Global temperature anomalies; Rolling analysis; Copulas.

JEL Classification: Q54; Q51; C53; C69.

1. Introduction

For more than a decade the question of mankind's effects, through anthropogenic emissions, on global warming has become a deeply polarized one among politicians, scientists, or simple citizens (Witt et al. 2016, Barr et al. 2011, Anderson et al. 2016, Hook et Tang, 2013,). There are controversial views which in many cases are biased by various factors out of any relative science¹. Attributing trends to a single influence is difficult to establish unequivocally because the climate system can often respond in unexpected ways to external influences and has a strong natural variability. At the same time, results from new risk/uncertainty based assessments suggest that “there is a significant chance that the climate system is more sensitive than was originally thought” (Stern, 2008, page 11). Hence, there is scope for further examining the relationship between anthropogenic greenhouse gas (GHG) emissions and global warming on renovated scientific grounds, rather than subjective estimations with personal beliefs, and climate sensitivity remains an area of active research.

The purpose of this paper is to study again the relationship between GHG emissions and global warming and to assess whether or not there are increasing rates in global change as a result of higher levels of anthropogenic emissions. This valuation will have interesting policy implications as well, which call for different degrees in the urgency of precautionary policy interventions which are required to contrast global warming² (see, f.e., Taleb et al, 2014).

In most simulations (see, f.e., Gillett, Arora, Matthews and Allen, 2013, and references there) global warming has been shown to be almost proportional to cumulative carbon dioxide (CO_2) emissions, which makes the climate response to CO_2 emissions (the so-called “carbon-climate response”, CCR) a measure which can be used to calculate the cumulative emissions compatible with a 2°C (or 1.5°C)

¹ US government now seems to embrace conservative views about climate change and plans its environmental agenda with less sensitivity on the matter. An example is the recent executive orders by the US President reviving controversial oil Pipelines which had been stalled by his predecessor.

² Several world-wide organizations appealed to a precautionary principle in policy measures. For example, the Rio Declaration on Environment and Development states: “In order to protect the environment, the precautionary approach shall be widely applied by states according to their capabilities. Where there are threats of serious or irreversible damage, lack of full scientific certainty shall not be used as a reason for postponing cost-effective measures to prevent environmental degradation”.

warming target (Matthews, Gillett, Stott and Zickfeld, 2009; from now onwards, Matthews et al.) - that is, the target representing the (estimated) threshold beyond which climate change would determine dangerous anthropogenic interference³.

Matthews et al. (2009) were the first to ascertain a proportionality between global warming, measured as the global mean temperature change over some period of time, and the total cumulative carbon dioxide emitted over that period, and they firstly proposed the CCR measure. In most simulation models, they showed that CCR is approximately constant with respect to time and CO_2 emission scenario, implying that “the CCR, when evaluated from climate-carbon models under idealized conditions, represents a simple yet robust metric for comparing models, which aggregates both climate feedbacks and carbon cycle feedbacks” (Matthews et al. 2009, page 1).

However, although such results are useful concepts for climate change “mitigation” policies - that is, policies directed at reducing GHGs emissions (Tol, 2005) -, the presence of large uncertainties in climate and carbon sensitivities⁴ prevent confident estimates of the CO_2 stabilization level necessary to avoid the 2°C (or 1.5°C) warming target. At the same time, the CCR refers only to cumulative CO_2 emissions, and is not applicable to emissions of other non- CO_2 greenhouse gases.

In this paper we study the relationship between GHG emissions and global warming following a more practical and observationally-based approach. While the simulation models and the carbon-climate model experiments provide important

³ The main objective of climate policies is to reduce the amount of anthropogenic greenhouse gas (GHG) emissions to achieve “stabilization of GHG concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system” (UN Framework Convention on CC, art.2). Most of the ‘unburnable carbon’ debate has recently recognized the need of limiting the global mean temperature increase to 2°C relative to preindustrial times - and even a relatively more ambitious target of 1.5°C was reached in the Paris Agreement in December 2015.

⁴ For example, Allen, Stott, Mitchell, Schnur, and Delworth (2000) claim that the predicted response of climate change to a given emission scenario is inevitably uncertain. Recent observed changes appear to be attributable to human influence. Substantial changes in the current balance of GHG warming and sulphate aerosol cooling could increase the uncertainty. Allen et al (2000) try to assess the range of warming rates that are consistent with the observed temperature as well as with the overall patterns of response, which is relatively robust to errors in models’ climate sensitivity, global response to sulphate aerosols, etc.

insights describing the climate response to CO_2 cumulative emissions, a relevant measure for policy makers is the response of the real climate system. Thus, historical carbon emissions and observed temperature changes have to be computed. The most direct application of Matthews et al (2009) results is to use surface temperature observations to derive an estimate of CO_2 -attributable warming to the present. Here we study the relation between GHG emissions (both in levels and cumulative emissions) and temperature changes from historical observations.

The data set used in this paper consists of GHG emissions for (almost) all countries in various years, in particular, carbon dioxide, methane, nitrous oxide and other GHG emissions. As for the temperature changes, we take the global surface temperature anomalies index, which has been elaborated by the NASA GISS analysis, as developed in Hansen, Ruedy, Sato and Lo (2010). For our study, we employ a multi-level rolling analysis. Our methods, that is, standard rolling correlation, structural breaks, rolling regressions and forecasting analysis, enable us to identify the dynamics, if any, in the relationship between emissions and global temperature anomalies, as we move forward in time. Furthermore, in order to assess whether we observe tail-dependence, representing simultaneous occurrence of extreme events, we employ copula methods. To the best of our knowledge, this is the first paper employing such methods in climate research.

Our main findings show that our rolling analysis does not support views of increasing rates in global climate change as a result of higher levels of emissions. On the contrary, our results suggest a constant or even a decreasing effect of emissions on temperature anomalies especially from 2005 onward. At the same time, our copula calibration shows that the Frank copula achieves the best fit. Since the Frank copula is a copula that assigns a low probability to joint extreme events, our analysis does not show tail dependence. Overall, our findings seem to provide arguments in favour of a skeptical view of global warming.

The rest of the paper is structured as follows: in Section 2 we present our methodology and the data used in the paper; in Section 3 our empirical results are discussed; Section 4 develops a copula approach and presents the main result under this approach; finally Section 5 concludes and offers some extensions of the current work. All our tables and figures are found in the Appendix.

2. Data and methodology

2.1 Data

We employ annual data for our analysis, covering a period from 1960 until 2012 for the main part of our work. Notwithstanding the fact that some time series, e.g. the global temperature anomalies, are extended within larger time samples, due to reasons of common overlapping we restrict our sample within this period only. Our two main data categories concern global temperature and emissions. For the first, we have used Nasa's global mean estimates (GISTEMP, 2016) based on Land-Surface air temperature anomalies (Meteorological Station Data), which we abbreviate with T_dts, as developed in Hansen, Ruedy, Sato and Lo (2010). The GISTEMP analysis gives the global surface temperature anomalies over many years (from 1880 to 2015), relative to the 1951-1980 base period⁵.

According to Hansen and Lebedeff (1987), the best estimate for absolute global mean for 1951-1980 is 14 degrees of Celsius, and is used as the conversion factor from absolute scale to temperature anomalies. Except the GISSTEMP analysis, other data suppliers for global temperature are the National Centers for Environmental Information (NOAA) Global Analysis (NOAA, 2016) which uses also absolute values and values in time series, and Berkeley Earth (BERKLEY, 2016) who has released data for two global land and ocean surface temperature products. Both GISTEMP and NOAA describe that absolute estimates of global mean surface temperature are difficult to compile for a number of reasons, for instance in areas with few temperature stations, etc. Regarding temperature anomalies, as shown in Figure 1 below, the data source selection is of minor importance, since in all three cases temperature anomalies are very close to each other.

[Insert Figure 1, about here]

⁵ Alternatively, we could use the global land-ocean temperature index, which still employs the GISS analysis, combining available sea surface temperature records with meteorological station measurements. It is shown that, on average, warming in the recent four decades was larger over land than over ocean, in part because of the ocean's larger thermal inertia.

The data for emissions are also annual, both in levels and cumulative emissions for (almost) all countries. We have used total GHG emissions and emissions per different types of gases. Carbon dioxide (CO₂) emissions consist of annual data from 1960 to 2012, whereas methane (CH₄) and nitrous oxides (N₂O) and other GHG emissions consist of annual data from 1973 to 2012. The latter three emission types are measured in terms of CO₂ equivalent levels, which allow us to conduct comparisons over time. The annual national estimates for the total fossil-fuel CO₂ emissions - and respective fossil-fuel CO₂ emissions from solid (coal), liquid (oil) and gas (natural gas) consumption - come from Carbon Dioxide Information Analysis Center (CDIAC) of the U.S. Oak Ridge National Laboratory (see Boden et al. 2013). In their work, the total fossil-fuel CO₂ emission estimates are obtained by using the energy statistics of the United Nations (2013), following the methodology of Marland and Rotty (1984). Methane, nitrous oxide and other GHG emissions are from the International Energy Agency (IEA).

All the data sets are categorized and taken from the World Bank's World Development Indicators (<http://www.worldbank.org/indicators>).

2.2 Methodology

As already mentioned, the focus of this paper is to consider whether there is a changing effect of emissions on global temperature anomalies when different levels of emissions are tested. To do that, we apply a multi-level rolling analysis in several steps. The main idea of using a rolling analysis lies in the identification of a potential dynamic relationship between our examined variables or not. As we move forward in time, new data inputs are considered for examination, and different outputs in terms of estimated coefficients and variables are produced. A strong difference in these coefficients could be regarded as a difference in the causal relationship among the examined variables.

Hence, we first estimate a standard smoothed rolling correlation between each of the GHGs and global temperature anomalies using a 10-year rolling window for the correlation and a 5-year moving average filter to reject unnecessary noise.

Hence:

$$\text{Correlation}(X_i, T_dts_i)_{\text{Rolling, Smoothed}} = \frac{1}{5} \sum_{k=j}^{j+5} \text{Corr}_j(X_i, Y_i) \quad (1)$$

where $i = j, \dots, j+10$ & $j = \text{year}_1, \dots, \text{year}_{n-15}$ & $X_i = \{\text{GHGs}_i, \text{CO}_2_i, \text{N}_2\text{O}_i, \text{CH}_4_i\}$

A trend existence in the above estimated time series of rolling correlations could be considered as a sign of changing effect with an upward trend as a stronger relationship and a downward trend as a looser one.

Since correlation does not necessarily imply causation, we further apply a 1-step rolling regression of the logs of cumulative GHGs and cumulative CO₂ emissions on the logs of global temperature anomalies, after having tested for stationarity and applied standard specification tests for the full sample (see Table 1). All our time series are stationary and all the specification tests do not reject their Null Hypotheses. Hence, the estimated equation is:

$$LT_dts_{t,i} = C_{1,i} + C_{2,i} \cdot LX_{t,i} + \epsilon_{t,i} \quad (2)$$

where $LT_dts_{t,i}$ stands for the log of the global temperature anomalies and $X_{t,i}$ stands for the log of either total cumulative GHGs or cumulative CO₂ emissions. Subscript i sets the starting point of the estimated subsample each time, while t stands for the time inside the fixed window of the 30 annual observations.

[Insert Table 1, about here]

Furthermore, to make the interpretation more sound, besides the estimated rolling coefficients $C_{2,i}$, we present additional rolling statistics for rolling P-values, rolling adjusted R-squared, and the AIC rolling information criterion.

After that, we test for the existence of any structural change in equation (2) for the full sample. Hence, we perform two stability diagnostics; namely, the Quandt-Andrews test and the Bai-Perron test. We first apply the Quandt-Andrews breakpoint test for one or more unknown structural breakpoints in the sample and test whether there has been a structural change in a subset of the parameters. We use the Quandt-Likelihood Ratio (QLR) statistic as shown in equation (3), after trimming the first and the last 15 percent of observations. Thus, QLR statistic has the following form:

$$QLR = \max[F(\tau_o), F(\tau_o + 1), \dots, F(\tau_1 - 1), F(\tau_1)] \quad (3)$$

Secondly, we apply the Bai-Perron approach for m potential breaks, producing $m+1$ regimes within the sample. Hence, for the observations $T_j, T_{j+1}, \dots, T_{j+1} - 1$ in regime j we estimate the following regression model:

$$y_t = L_t \beta + Z_t \delta_j + \epsilon_t \quad (4)$$

for $j = 0, \dots, m$; where L variables are those whose parameters do not vary across regimes, while Z variables have coefficients that are regime specific. Since equation (2) is a bivariate model, L is a scalar with the unit value and Z represents either total cumulative GHGs or cumulative CO₂ emissions.

Last, we apply a 1-step ahead rolling forecast of LT_dts in equation (2) but we use emissions lagged by one year, and taking annual emissions as well. Therefore, the adjusted equation (2) for forecasting becomes as follows:

$$LT_dts_{f,i,w} = C_{1,i,w} + C_{2,i,w} \cdot LX_{t_{end},i,w} + \epsilon_{f,i,w} \quad (5)$$

where subscript f equals $t_{end} + 1$, and stands for the 1-step ahead forecasted value, subscript w is for the length of the variable rolling window and t_{end} is always the last value of the estimation subsample. The explanatory variables are:

$$LX_{t-1,i} = \{LGHGs_{t_{end},i,w,cum}, LCO_2_{t_{end},i,w,cum}, LGHGs_{t_{end},i,w,annual}, LCO_2_{t_{end},i,w,annual}\}$$

Hence, equation (5) produces four different forecasting models depending on the selected $LX_{t-1,i}$ variable each time.

Instead of a fixed rolling window as before, we have now chosen a variable rolling window. The forecasting objective here is not to go through all the time sample sequentially by using a fixed window and observe any changes in different segments of time as with the rolling regression before, but to remark the changes in the forecasting performance of $LT_dts_{f,i,w}$ from equation (5), as new and more recent data enter for estimation and, in parallel, when more contemporaneous values of global temperature anomalies have to be forecasted. If forecasting performance, in terms of forecasting errors, becomes better when we approach the present, and conditional on that, emissions keep increasing, this might be interpreted in the

following way: at higher levels of emissions, changes in global temperature are better predicted with changes in emissions, which implies, although indirectly, an increasing effect of emissions on temperature changes at higher levels. If this not true and the forecasting performance of equation (5) is constant or even becomes worse, then this could be interpreted as a constant or decreasing effect of emissions on temperature changes and might give credit to a skeptic view about global warming.

The full sample starts from 1973 and ends in 2013, while the forecasted period f lies in between: $T_{window+1} \leq f \leq T_{end}$, where $T_{window+1}$ refers to the first period in the sample after the model's estimation window. As mentioned before, we use a rolling window with different time-lengths in order to examine the forecasting performance of emissions when more recent values of it are included in the estimation sample.

The time-length of the variable rolling window is selected from the following set N :
 $N = \{25, 29, 32, 35\}$

Hence, the output of this iterative procedure is a series of 1 step-ahead forecasts of $LT - dts_{f,i,w}$ over the remaining observations

To evaluate the forecasted performance of the four models of equation (5), we compare it with an appropriate ARIMA model that is used as a benchmark. Since the benchmark does not include emissions in its right hand side, it enables us to cross-compare the forecast accuracy of our models by using the forecast error measures of Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and the scale invariant measure of Theil's inequality coefficient (Theil IC)

[Insert Table 2, about here]

After applying the standard Box-Jenkins methodology and testing for significance and stationarity (see Table 2 above), we conclude to the following ARIMA model:

$$(1 - \varphi_1 B - \varphi_2 B^2) LT - dts_{f,i,w} = c + (1 + \theta_1 B^3 + \theta_2 B^4) \epsilon_{f,i,w} \quad (6)$$

The ARIMA model in equation (6) is stationary, invertible and properly specified since all its AR and MA roots lies inside the unit circle, the residuals are close to the estimated theoretical correlations and autocorrelations and its response tends to zero when ± 2 S.E. impulses are applied (data are available upon request).

Apart from the standard forecast error metrics, we test our models for equal predictive accuracy by applying the Diebold-Mariano test. For the loss function $g(\square)$, we use both the squared and the absolute error as shown below:

$$g_1(e_{jiw}) = e_{jiw}^2 \quad \& \quad g_2(e_{jiw}) = |e_{jiw}|,$$

where $e_{jiw} = LT_dts_{f,i,w} - LT_dts_{real_t_{end},i,w}$ and $j = 1, \dots, 5$ indicating the four forecasting models and the benchmark.

Thus, the Null Hypothesis of equal predictive accuracy is:

$$H_0 : E[g_k(e_{j,i,w}) - g_k(e_{5,i,w})] = 0 \quad \forall i, w \quad \begin{array}{l} \text{where } k=1,2 \text{ depending on the loss function} \\ \text{and } j=1,2,3,4 \text{ depending on the model} \end{array}$$

The results from all our methods, that is the standard rolling correlation, the structural breaks, the rolling regression and the forecasting analysis, enable us to identify the dynamics, if any, in the relationship between emissions and global temperature anomalies, as we move forward in time.

3. Empirical results and discussion

The results are rather neat and supportive of a critical view about increasing changing rates of global temperature anomalies as a result of higher cumulative (or annual) emissions levels. To begin with, the rolling correlations between temperature anomalies and total GHGs in aggregate level, but also in disaggregation with carbon dioxide, methane and nitrous oxide emissions, have a seasonal component only, without any trend-like characteristics (Figures 2 and 3). There may be a slight decreasing trend in the correlations between temperatures and methane or nitrous oxides, especially if smoothed series are used, but certainly there is no evidence for an upward trend in any of the examined emissions. These first findings roughly suggest a constant relationship among our tested variables, free of time dependence.

[Insert Figures 2 and 3, about here]

Moving to the results from the rolling regression of equation (2) we see, both with cumulative GHGs and cumulative CO2 emissions, that when our fixed window shifts more to the right, meaning closer to the present, the respective rolling coefficients are decreasing at the same time when the adjusted coefficient of determination is increasing. Also there is a decrease in the values of the Akaike information criterion

(AIC). To be more specific, we observe two potential thresholds approximately before and after 2005 (see Figures 4 and 5). Before this year, emissions have on average a bigger effect on temperature anomalies with an elasticity of 1.5% for CGHGs and 1.1% for CCO₂ emissions respectively and an explanatory power well below 55%. After 2005, elasticities are decreasing on average in 1% and 0.9% respectively with $\bar{R}^2$ on average at 65%. Besides that, the elasticities were significant for the whole sample with p-values lower than 0.02. The same case is with AIC, where less information is passed from emissions to temperature anomalies before 2005 than after it. In other words, not only the effect of emissions becomes smaller but this smaller effect interprets better temperatures fluctuations as well.

[Insert Figures 4 and 5, about here]

Stability diagnostics in Table 3 enhance the argument of one structural regime in which emissions affect temperature anomalies, as both Quandt-Andrews and Bai-Perron tests do not reject the null hypothesis of no breakpoints in the coefficients of equation (2). Despite the fact that the stability diagnostics results might abate the results from the rolling regression which revealed two threshold effects, still and under no circumstances none of them suggest an increase in the effect of emissions on temperature over time.

[Insert Table 3, about here]

Last, in examining the forecast performance of the four models of equation (5), we find considerable results that are in line with all the prior produced results, making our analysis more robust and its interpretation more complete. MAE and RMSE forecast error measures in Table 4 and Figure 6, suggest a constant or a decreasing forecasting power of our models compared to the benchmark. Because these metrics are not scale invariant to different variables or to different time ranges which is our case here due to variable rolling windows, we cannot compare their forecast performance along the horizontal x-axis of window lengths but we can make comparisons across all models for each window.

[Insert Table 4, about here]

Considering this, we observe that both RMSE and MAE become bigger compared to the benchmark as we move forward in time and more recent temperature values have

to be forecasted. This applies to equations (1), (3) and (4) when annual GHGs, annual CO₂ emissions and cumulative CO₂ emissions are used. The forecast performance of equation (2) with cumulative GHGs is better than the benchmark's performance but their difference is decreasing when more recent values are used. In order to overcome different scaling issues with time we have estimated Theil's IC. The results are again supportive of the main argument of the paper. In all the cases, including that of equation (2), our models forecast performance becomes worse over time compared to the benchmark's or to their initial past performance.

[Insert Figure 6, about here]

As a final evaluation step, we have tested the models for equal predictive accuracy (see Table 5) by applying a Diebold-Mariano test in pair-wise mode with each of them compared to the benchmark. The results validate our forecast analysis, as they reject the null hypothesis of equal predictive accuracy with the benchmark when the larger estimation window is used or in other words when the most recent values have included in the estimation of the forecast model. Furthermore, DM-stats for the models (1) and (3) with a window length of 35 observations, are positive and higher compared with the respective statistics when the window length includes 29 observations. This means that the spread between the significant unequal forecasts becomes larger, which in turn means lower forecast performance of models (1) and (3) when more recent values are forecasted. For the models (2) and (4), the DM-stats which reject the null hypothesis, show an increase in terms of forecast accuracy which nevertheless decreases in the last window, reaching approximately the forecast accuracy levels of the first examined window with 25 observations. In a nutshell, this suggests a rather constant forecast performance over time when we use cumulative levels of emissions. In both cases, we see either a decreasing or a constant forecasting performance of the four models of equation (5) as we move forward in time and newer data are considered.

[Insert Table 5, about here]

All in all, the results are clear and highly indicative: there are no signs of a positively accelerating changing rate of temperature anomalies as we move forward in time, or, in other words, our rolling analysis doesn't support views of increasing rates in global climate change as a result of higher levels of emissions. On the contrary, the results

suggest a constant or even a decreasing effect of emissions on temperature anomalies especially from 2005 onward. Similar conclusions, albeit in different framework, have been reached in the literature⁶, treating it as a phenomenon worthy of further explanation in the mainstream scientific discourse.

4. A Copula Analysis

In this section we complement the previous analysis employing a copula approach to study the structure of dependence between GHGs and global temperature anomalies. Copula based methodology is particularly useful to analyse the connection with multivariate extremes and to distinguish between different classes of probability distributions of events, that is, “those in which events are accompanied by well behaved, mild variations (e.g., Gaussian or thin tails), and those where small probabilities are associated with large variations that have no characteristic scale (fat tails)” (Taleb et al, 2014).

Different copulas that model dependence are calibrated on the data. Here we focus on five types of copulas, that is, the Gaussian, the Student, the Clayton, the Gumbel and the Frank copulas (for copula methods, see Nelsen, 2006). Figure 8 shows scatterplots of simulated standard normal marginal distributions that are combined with (i) a Gaussian copula, (ii) a Student t copula, (iii) a Clayton copula, (iv) a Gumbel copula and (v) a Frank copula. While all simulated bivariate samples in this example have a similar correlation measure and all marginal distributions are standard normal, the scatterplots look quite different for different copulas.

[Insert Figure 8, about here]

The Gaussian copula is the copula that is implied by a Gaussian distribution. The Student t copula is the copula that is implied by a Student t distribution. In contrast to the Gaussian copula it displays tail dependence. This implies that it assigns a higher probability to joint extreme events than does the Gaussian copula. The lower the degree of freedom ν the higher the tail dependence. If ν is large, the Student t copula resembles a Gaussian copula. In fact, the Gaussian copula is a special case of the Student t copula, where $\nu \rightarrow \infty$. The Clayton copula displays lower tail dependence but no upper tail dependence. Loosely speaking this means that there is a comparably

⁶ Florides et Christodoulides, 2008; Allan et al., 2014; Brown et al., 2014; ^aBoykoff, 2014; ^bBoykoff et al., 2004; Laepple and Huybers, 2014; Tollefson, 2014.

high probability of joint extreme low realisations and a comparably low probability of joint extreme high realisations. The Gumbel copula displays upper tail dependence but no lower tail dependence. The Frank copula does not display tail dependence. Actually, the Frank copula assigns a lower probability to joint extreme events than does the Gaussian copula.

We perform copula calibration with the pseudo-log-likelihood method introduced by Genest and Rivest (1993) that does not make any assumptions on the specific functional forms of the marginal distributions. Rather, this method is based on the size of the observation in comparison to the other observations of the sample of the marginal distributions. More specifically it is based on the ranks of the observation. To calibrate a copula we first have to transform our empirical observations $x_{i,t}$ into so-called pseudo-observations $u_{i,t}$:⁷

$$u_{i,t} = \frac{1}{T+1} \sum_{s=1}^T \mathbf{1}_{x_{i,s} \leq x_{i,t}}$$

where T is the number of joint observations and $\mathbf{1}_{x_{i,s} \leq x_{i,t}}$ is an indicator function that takes a value of 1 if $x_{i,s} \leq x_{i,t}$ and a value of 0 otherwise. In other words, the pseudo-observations are calculated as the rank of the observation, divided by $(T+1)$.

Once the pseudo observations are calculated, the copula parameter are estimated with a maximum (log-) likelihood estimation (see Nelsen, 2006). Denoting the (vector⁸ of) estimated copula parameters as $\hat{\theta}$,

$$\hat{\theta} = \arg \max_{\theta} \sum_{t=1}^T \ln c_{\theta}(u_{1,t}, u_{2,t}) ,$$

where $\ln$ is the natural logarithm and $c_{\theta}(u_{1,t}, u_{2,t})$ is the density function of the copula to be calibrated with parameter(s) θ , evaluated at $(u_{1,t}, u_{2,t})$. That is, the copula parameters are calibrated in such a manner that the log likelihood – the term $\sum_{t=1}^T \ln c_{\theta}(u_{1,t}, u_{2,t})$ – is maximised.

⁷ In their article, Genest and Rivest (1993) divide by T rather than by $(T+1)$. Dividing by $(T+1)$ has the advantage that it keeps the pseudo-observations away from the boundaries of the unit cube where the densities of many copulas take infinite values.

⁸ Here only for the Student t copula two parameters have to be estimated, while the other bivariate copulas have only one parameter.

Let us analyse the dependence between temperature levels and emissions by calibrating copulas to the data and analysing which of the copulas has the best fit. Because the calibration of a Student t copula does not converge in any of the cases, when both parameters, ρ and ν , were calibrated, we calibrate four different Student t copulas in each of the case, where the degrees of freedom are fixed at $\nu \in (3, 10, 100, 1000)$. A Student t copula with $\nu = 100$ is already very close to a Gaussian copula, while a Student t copula with $\nu = 1000$ almost returns identical results as a Gaussian copula.

Table 6 displays the log-likelihood that is achieved when fitting the different copulas on temperature levels and levels of emissions. The values can be interpreted as a goodness-of-fit measure: the higher the log-likelihood the better the fit of the copula.

[Insert Table 6, about here]

We first look at the values for the levels of CO₂- and other GHG-emissions. We find that in both cases, the Frank copula achieved the best fit. This result is interesting as the Frank copula assigns a lower probability to joint extreme events than the Gaussian copula (the “benchmark” copula). For other GHG-emissions the Gaussian copula is the one with the second-best fit. Its log-likelihood is higher than any of the Student t copulas. Hence for other GHG-emissions and temperature, there is no indication that tail dependence (a high probability of joint extreme events) is prevalent for the data sample at hand. Also for CO₂-emissions and temperature there is little indication that tail dependence might be prevalent, as the best fit is achieved by a Frank copula. The second-best fit is achieved by a Gumbel copula that displays upper tail dependence but the log-likelihood is not very different from that of the Gaussian copula. A further indicator that it is unlikely that there is (strong) tail-dependence is the slightly lower log-likelihood of Student t copulas with $\nu \in (3, 10)$ that model a relatively strong tail-dependence.

For methane emissions and temperature levels the Clayton survival copula (Clayton C^-) and the Gumbel copula achieved the highest log-likelihood. These two copulas display upper tail dependence, i. e. they assign a higher probability of joint extreme large values. Because the log-likelihoods for the survival Clayton and the Gumbel copula (upper tail dependence) are considerably higher than that for the Clayton and survival Gumbel (lower tail dependence) it seems unlikely that lower tail dependence

is prevalent while upper tail dependence is not. Still it remains ambiguous whether tail dependence exists at all: comparing the log-likelihoods of the Gaussian and the Student t copulas, we see that the Gaussian copula has achieved a higher log-likelihood than any of the Student t copulas. This is interesting as the Gaussian copula does not model tail dependence while the Student t copula does (identical upper and lower tail dependence).

Finally, Table 7 displays the log-likelihoods achieved when fitting copulas on temperature levels and cumulative emissions. Interestingly, in all cases the Frank copula achieved the best fit. The Frank copula is a copula that assigns a low probability to joint extreme events. Also, in all cases the Gaussian copula (no tail dependence) achieved a better fit than the Student t copulas (positive tail dependence).

[Insert Table 7, about here]

In conclusion, our copula analysis does not show tail dependence. Thus, our findings seem to provide arguments less in favour of a strong view of global warming, which opens the path to further questioning.

5. Conclusions

The focus of the paper is to examine the time dependent relationship between global temperature anomalies and levels of GHGs, either annual or cumulative. Moreover, we tried to verify whether this relationship becomes stronger over time as emission levels increase. If this is the case, then over-stressed environmental concerns about climate change should be regarded as the main scenario and appropriate additional measures should be implemented, while those already imposed should be reconsidered to avoid extreme negative outcomes. To examine this, we applied a multi-level rolling analysis. Our results seem to reply in the negative; no changing effect is observed between our variables when we move forward in time and in some cases even a relaxation is apparent with lower threshold effects.

Future global temperature is the product of very complex dynamic ecosystems with multiple underlying and interacting factors; furthermore, if combined with all the driving forces of new inputs of GHGs, such as demographic development, socio-

economic development and technological change, future global temperature values become even more ambiguous⁹. Nevertheless, this research is based on a time series analysis which is subject to various limitations. Hence a negative answer now cannot assure a negative answer in the future as well. Our research identifies analytically the relationship between emissions and temperature, and argues in favor of a potential constant effect of emissions on temperature changes regardless of the level of emissions and given the socio-economic characteristics and environmental factors that existed until now. Moreover, we have focused our research exclusively on the relationship between temperature anomalies and emissions, without considering the relationship between extreme natural events and temperature anomalies. However, the number of realized extreme events of natural disasters may follow, say, a polynomial relationship with temperature anomalies, even if temperature and emissions change at the same rate. This can potentially be translated in disproportional consequences, albeit proportional changing in temperature anomalies but at different levels. Therefore, the highly important nexus between the level of emissions and the frequency and the magnitude of extreme events needs further analysis and remains a question for future research.

⁹ IPCC, 2014; Latif, 2010; Barr et al, 2011; Nazarenko et al. 2015, Hansen et al, 2005.

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Appendix I – Figures

Figure 1. Global surface temperature anomalies based on conversion factors provided by, GISTEMP (continuous line), NOAA (dotted line) and Berkley (dashed line)

Figure 2. Rolling correlations between temperature anomalies and GHGs, CO₂, CH₄, and N₂O emissions respectively with a 10-year correlation window.

Figure 3. Smoothed rolling correlations between temperature anomalies and GHGs, CO₂, CH₄, and N₂O emissions respectively with a 5-year moving average window.

Figure 4. Rolling regression results of the log of cumulative CO₂ emissions on the log of temperature anomalies using a fixed window of 30 annual observations.

Figure 5. Rolling regression results of the log of cumulative GHGs emissions on the log of temperature anomalies using a fixed window of 30 annual observations.

Figure 6. MAE, RMSE and THEIL IC forecast error measures of our examined models (EQ1-EQ4) with cumulative and annual levels of GHGs and CO2 emissions and the benchmark's (EQ5), across all estimation windows.

Figure 7. 1-step ahead rolling forecasts of the four models of eq.(5), of the ARIMA model and actual values of global temperature anomalies for all the examined windows

Figure 8

Scatterplots of marginal standard normal distributions that are combined with (i) a Gaussian copula, (ii) a Student t copula, (iii) a Clayton copula, (iv) a Gumbel copula and (v) a Frank copula (from left to right). All bivariate distributions have a Kendall's tau correlation measure of roughly 0.6.

Appendix II – Tables

Table 1. Stationarity and specification Tests for the full sample of eq. (2)

Phillips-Perron Unit Root Test			
Variable	Test statistic	Prob.	
LT_dts	-3.54	0.05	
LGHGs	-14.29	0.00	
LCO ₂	-16.18	0.00	
Breusch-Godfrey Serial Correlation LM Test:			
Model	Test statistic	Prob.	
$LT_dts_{t,i} = C_{1,i} + C_{2,i} \cdot LCGHGs_{t,i} + \epsilon_{t,i}$	0.07	0.80	
$LT_dts_{t,i} = C_{1,i} + C_{2,i} \cdot LCCO_{2t,i} + \epsilon_{t,i}$	0.12	0.73	
Residuals Normality Test			
Model	Test statistic	Prob.	
$LT_dts_{t,i} = C_{1,i} + C_{2,i} \cdot LCGHGs_{t,i} + \epsilon_{t,i}$	1.09	0.57	
$LT_dts_{t,i} = C_{1,i} + C_{2,i} \cdot LCCO_{2t,i} + \epsilon_{t,i}$	0.79	0.67	
Ramsey Reset Test			
Model	Test statistic	Prob.	
$LT_dts_{t,i} = C_{1,i} + C_{2,i} \cdot LCGHGs_{t,i} + \epsilon_{t,i}$	0.31	0.58	
$LT_dts_{t,i} = C_{1,i} + C_{2,i} \cdot LCCO_{2t,i} + \epsilon_{t,i}$	0.21	0.65	
Coefficient			
Model	C _{1,i}	C _{2,i}	$\bar{R}^2$
$LT_dts_{t,i} = C_{1,i} + C_{2,i} \cdot LCGHGs_{t,i} + \epsilon_{t,i}$ ¹⁰	-12.29	0.85	0.73
$LT_dts_{t,i} = C_{1,i} + C_{2,i} \cdot LCCO_{2t,i} + \epsilon_{t,i}$ ¹¹	-14.89	1.06	0.75

Table 2. Stationarity and Estimation results for the ARIMA model of eq. (6)

Variable	Coefficient	Prob.
C	-0.51	0.05
AR(1)	0.40	0.01
AR(2)	0.32	0.03
MA(3)	0.56	0.00
MA(4)	-0.38	0.00
Coefficient of Determination, R^2		0.70
Inverted AR Roots		Inverted MA Roots
1	0.81	0.54
2	-0.4	-0.98
3	-	0.22+0.82i
4	-	0.22-0.82i

¹⁰ All coefficients are statistically significant at 1% confidence level

¹¹ All coefficients are statistically significant at 1% confidence level

Table 3. Stability diagnostics results for eq. (2)

Model	Quandt-Andrews unknown breakpoint test			
	Ave LR F-statistic	Prob*	Ave Wald F-statistic	Prob*
$LT_dts_{t,i} = C_{1,i} + C_{2,i} \cdot LCGHG_{t,i} + \epsilon_{t,i}$	0.61	0.68	1.22	0.68
$LT_dts_{t,i} = C_{1,i} + C_{2,i} \cdot LCCO_{2t,i} + \epsilon_{t,i}$	0.72	0.57	1.45	0.57
Model	Bai-Perron tests of L+1 vs. L sequentially determined breaks**			Critical Value***
	F-statistic	Scaled F-statistic		
$LT_dts_{t,i} = C_{1,i} + C_{2,i} \cdot LCGHG_{t,i} + \epsilon_{t,i}$	3.35	6.70		11.47
$LT_dts_{t,i} = C_{1,i} + C_{2,i} \cdot LCCO_{2t,i} + \epsilon_{t,i}$	1.61	3.22		11.47

Note:

Null Hypothesis: No breakpoints within 15% trimmed data

* Probabilities calculated using Hansen's (1997) method

** Bai-Perron breakpoint Test: 0 vs. 1

*** significant at the 0.05 level

Table 4. RMSE, MAE and TEIL IC forecast error measures for Equations 1-4 and the benchmark's, across all estimation windows.

	Estimation window											
	window = 25			window = 29			window = 32			window = 35		
	RMSE	MAE	THEIL IC	RMSE	MAE	THEIL IC	RMSE	MAE	THEIL IC	RMSE	MAE	THEIL IC
Equation 1	0.28	0.22	0.48	0.29	0.29	0.69	0.38	0.33	0.90	0.44	0.40	0.99
Equation 2	0.19	0.15	0.30	0.15	0.13	0.31	0.13	0.12	0.32	0.16	0.14	0.42
Equation 3	0.27	0.23	0.50	0.37	0.33	0.92	0.50	0.46	0.95	0.56	0.53	0.98
Equation 4	0.18	0.15	0.31	0.16	0.14	0.38	0.16	0.14	0.47	0.23	0.22	0.74
Benchmark	0.26	0.21	0.32	0.23	0.20	0.34	0.20	0.19	0.35	0.19	0.19	0.33

Table 5. Diebold-Mariano test results for Equations 1-4.

Loss Function	Window Length=25		Window Length=29		Window length=32		Window length=35	
	$g_1(e_{it}) = e_{it}^2$	$g_2(e_{it}) = e_{it} $	$g_1(e_{it}) = e_{it}^2$	$g_2(e_{it}) = e_{it} $	$g_1(e_{it}) = e_{it}^2$	$g_2(e_{it}) = e_{it} $	$g_1(e_{it}) = e_{it}^2$	$g_2(e_{it}) = e_{it} $
Equation (1) vs. Equation (5)								
DM-Test Statistic	-1.01	-1.17	+1.97	+1.68	-1.58	-1.54	+2.05	+1.76
Probability	0.39	0.26	0.05	0.09	0.10	0.11	0.04	0.08
Equation (2) vs. Equation (5)								
DM-Test Statistic	-1.87	-2.12	0.55	0.40	-2.91	-2.88	-2.42	-2.06
Probability	0.06	0.03	0.57	0.68	0.00	0.00	0.02	0.00
Equation (3) vs. Equation (5)								
DM-Test Statistic	-0.50	-0.62	+2.45	+1.88	-1.34	-1.29	+2.73	+1.91
Probability	0.613	0.53	0.01	0.05	0.17	0.19	0.00	0.05
Equation (4) vs. Equation (5)								
DM-Test Statistic	-1.71	-1.95	+0.95	+0.66	-2.74	-2.62	-1.52	-1.77
Probability	0.08	0.05	0.34	0.50	0.00	0.00	0.11	0.09

Notes: A negative DM-Test Statistic means larger forecasting errors for equation (5) compared with these of Eq.(1)-Eq.(4), while a positive DM- Test statistic indicates the opposite.

Table 6: Log-likelihood achieved when calibrating copulas on temperature levels and levels of emissions. The two highest values are highlighted.

Copula	level.CO2	level.GH	level.NIT	level.MET
Gaussian	35.58907	25.10817	0.003079	6.154866
Student t ($\nu=3$)	34.07031	21.85309	0.134705	4.027596
Student t ($\nu=10$)	35.56345	24.16319	0.107569	5.644866
Student t ($\nu=100$)	35.61811	25.0173	0.013659	6.108593
Student t ($\nu=1,000$)	35.59237	25.09914	0.00413	6.15029
Clayton	20.12282	18.75326	0.020867	1.374209
Clayton C^-	34.25629	16.98314	0.079952	9.969721
Clayton C^{+-}	-	-	0.421483	-
Clayton C^{++}	-	-	0.434279	-
Gumbel	37.41816	21.16278	-	7.981741
Gumbel C^-	28.86561	22.74216	0.001806	2.770918
Frank	42.657	27.72293	0.002742	6.124983

Table 7: Log-likelihood achieved when calibrating copulas on temperature levels and cumulative emissions. The two highest values are highlighted.

Copula	level.cumCO2	level.cumGH/NIT/MET
Gaussian	36.31334	32.69776
Student t ($\nu=3$)	34.18391	30.64534
Student t ($\nu=10$)	35.94368	32.20682
Student t ($\nu=100$)	36.29439	32.65901
Student t ($\nu=1,000$)	36.31167	32.69402
Clayton	20.19954	23.98978
Clayton C^-	34.7597	25.04407
Gumbel	37.92833	30.38185
Gumbel C^-	28.99038	29.5827
Frank	43.30515	34.57172