After which threshold do anthropogenic greenhouse gas emissions have an effect on global temperature?

Abstract

We employ a Smooth Transition Conditional Correlation (STCC) model and the latest available data to examine for a non-linear relationship between changes in global temperature and anthropogenic emissions of greenhouse gases. Controlling for natural factors which also affect global temperature, we find that anthropogenic climate forcings and global temperature have practically zero correlation before a certain threshold value is reached. In contrast, correlation rises strongly after anthropogenic emissions exceed this threshold. The value of this threshold can be traced back in the mid-1960's, during the years of the post-WWII economic boom, when a substantial amount of additional greenhouse gases (compared to the pre-industrial era) had started accumulating in the atmosphere due to the burning of fossil fuels from human activities.

Keywords: global temperature; anthropogenic emissions; conditional correlation
JEL Classification: C12, C32, C51, Q50, Q54

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Introduction

In the post-1990’s world, there has probably been no other environmental issue which has attracted more attention than the anthropogenic effect on climate change, and more specifically on temperature increases. In recent years, a growing number of scholars examine the causes of global warming using econometric methods.[1] In general, these studies produced mixed results: some document that human activities merely cause a temporary effect on temperature (Beenstock et al, 2012), others that this effect is less significant than usually considered (Stern and Kaufmann, 2014), while a third strand documents a stronger effect (Pretis and Hendry, 2013; Estrada et al, 2013; Dergiades et al, 2016; Stips et al, 2016; Leggett and Ball, 2015; Chevillion, 2015, Pretis and Allen, 2013).

In an attempt to examine whether climate forcings (and more specifically anthropogenic forcings) are related to global temperature changes, the common methodology employed by the majority of these studies is a variation of Granger-causality and co-integration techniques.[2] Therefore, the goal of these studies is primarily to investigate the determinants and the behaviour of a long run relationship.

Focusing on the long-run effects, the literature has thus far not investigated the nature of the short-run relationship between anthropogenic forcings and temperature. Given that changes in the former are expected to have a contemporaneous effect on the evolution of the latter, this knowledge should be valuable to climate scientists. In

[1] Econometric methods are used to explore several aspects of climate change, such as the relationship between anthropogenic emissions and climate, the effects of climate change on the output of different economic sectors, the impact of climate on mortality etc. See an overview of these approaches in Hsiang (2016).

[2] A climate forcing is defined as an imposed perturbation of the Earth's energy balance, which can be the result of natural phenomena (natural forcings) or human activities (anthropogenic forcings). A positive or negative forcing tends to make Earth warmer or cooler respectively (NRC, 2001).

addition, the findings of the above studies could potentially be influenced by the non-linearity of the relationship as the correlation between temperature and anthropogenic forcings is not necessarily linear in its parameters. Intuitively, this suggests that anthropogenic forcings may have an influence on temperature only after a threshold value, or more generally that the correlation between the two is not constant over time. Such a hypothesis is in line with the fact that global temperature increases have only become a pressing issue in the recent past, which may be linked to the fact that a substantial amount of greenhouse gases has accumulated in the atmosphere.

Figure 1, obtained from Marland et al (2016) the Carbon Dioxide Information Analysis Center (CDIAC), shows the global carbon emissions from 1751 to 2013. The red solid line is the total effect which consists of various sources of carbon emissions. The grey dashed line corresponds to emissions from combustion of gas fuels such as natural gas, with the dotted green line and the blue (dense) dashed line signifying the emissions from liquid and solid fossil-fuel burning respectively. The black dash-and-dot line are the emissions coming from cement production which are on the rise the last few years. It is evident from the graph that carbon emissions responsible for green house effects have been stable for more than a decade but have been surging since the 1960s.

In order to formally test the hypothesis of a change in the correlation between anthropogenic forcings and temperature, this paper employs a time-varying conditional correlation model for the examination of the temperature-anthropogenic forcing relationship. To our knowledge, this is the first attempt to apply such a model to examine whether these correlations change over time. In addition, our work differs from the existing literature in an essential way since it examines the drives of short-run variation in the relationship between anthropogenic forcings and global temperature changes.

The main findings of this study suggest that correlation between the two variables is essentially zero up to a specific level of anthropogenic forcings while it jumps to 0.54 after this level is exceeded. The changing point in correlation lies in the 1960’s, during the years of the post-WWII economic boom, when a substantial amount of additional greenhouse gases (compared to the pre-industrial era) had started accumulating in the atmosphere due to the burning of fossil fuels from human activities which is also evident in figure 1.

The findings underline the importance of economic activity on anthropogenic forcings. At the same time, they confirm the view that is widely shared among climate scientists and declared by the United Nations Intergovernmental Panel on Climate Change, that humans are the main cause of current global warming (IPCC, 2014).

The rest of the paper is organized as follows: Section 2 presents the econometric methodology. Section 3 presents the empirical findings. The paper ends with a summary and conclusions.

Econometric Methodology

As already discussed, the literature investigating the effects of the anthropogenic interpretation of global warming (i.e. whether increases in atmospheric anthropogenic forgings have raised global temperature), focuses solely on long-run relationships. Furthermore, an important caveat of the analyses is that they do not allow for the possibility of a non-linear relationship between anthropogenic forcings and global temperature, after controlling for non-anthropogenic factors. In addition, to our knowledge there is no study to examine whether these correlations change over time, a feature that standard regression models fail to accommodate.

To address this, we propose the use of the Smooth Transition Conditional Correlation (STCC) model (see Berben and Jansen, 2005; Silvennoinen and Teräsvirta, 2005) to test whether correlations between global temperature and anthropogenic forgings change.

Consider a time series of two variables $\{y_t\}$, $t = 1, \ldots, n$, namely $temp_t$ and z_t (i.e. $y_t = [temp_t, z_t]'$), the stochastic properties of which are assumed to be described by the following model:

$$temp_t = \beta_0 + \sum_{k=1}^{p} \beta_{1,\kappa} temp_{t-k} + \sum_{l=1}^{q} \beta_{2,l} x_{t-l} + \sum_{b=1}^{r} \beta_{3,b} z_{t-b} + \varepsilon_{1t} \qquad (1)$$

where $temp_t$ refers to the first difference of the global mean temperature anomaly (sea and land combined, as in Beenstock et al, 2012) at time t, x_t refers to non-anthropogenic forcings and z_t refer to the change in anthropogenic forcings.[3, 4]

The second equation follows a similar process such that:

$$z_t = \delta_0 + \sum_{k=1}^{p} \delta_{1,\kappa} z_{t-k} + \sum_{l=1}^{q} \delta_{2,l} temp_{t-l}$$
$$+ \sum_{b=1}^{r} \delta_{3,b} \left(1 - G\left(time; \gamma_g; c_g\right)\right) growth_{t-b} \qquad (2)$$
$$+ \sum_{b=1}^{r} \delta_{4,b} G\left(time; \gamma_g; c_g\right) growth_{t-b} + \varepsilon_{2t}$$

where $temp_t$, x_t and z_t are defined as in (1) and $growth_t$ refers to world GDP growth at time t. Based on SIC criterion and without any loss of generality, the lag order is set to one for all variables.

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[3] Data definitions and sources can be found in the appendix.

[4] Since changes are employed in econometric methodology, the estimates represent short-run variations.

To capture possible temporal changes in the effects of growth on the change in anthropogenic forcings we let $G(time;\gamma_g,c_g)$ be a logistic function, where time is a variable that measures time, γ_g a coefficient that accounts for the speed of adjustment from one regime to the other, while c_g determines the point of the change in time.[5]

In order to capture any temporal effects in the error volatilities and correlations, the error process of equations (1) and (2) is assumed to follow the process

$$\varepsilon_t \mid \Psi_{t-1} \sim N(0,\Sigma_t), \tag{3}$$

where $\varepsilon_t = [\varepsilon_{1t}, \varepsilon_{2t}]'$, Ψ_{t-1} is the information set consisting of all relevant information up to and including time $t-1$, and N denotes the bivariate normal distribution. The conditional covariance matrix of ε_t, Σ_t, is assumed to follow a time-varying structure given by

$$\Sigma_t = E[\varepsilon_t\varepsilon_t' \mid \Psi_{t-1}], \tag{4}$$

$$\sigma_{1t} = \omega_1 + \alpha_1\varepsilon^2_{1t-1} + \xi_1\sigma_{1t-1}, \tag{5}$$

$$\sigma_{2t} = \omega_2 + \alpha_2\varepsilon^2_{2t-1} + \xi_2\sigma_{2t-1}, \tag{6}$$

$$\sigma_{12,t} = \rho_t(\sigma_{1t}\,\sigma_{2t})^{1/2}, \tag{7}$$

$$\rho_t = \rho_0(1-G(s_t;\gamma,c)) + \rho_1 G(s_t;\gamma,c), \tag{8}$$

where the conditional variances σ_{1t} and σ_{2t} both follow a GARCH(1,1) specification which is able to adequately capture the persistence (if any) in second moments.

The sizes of α_i and ξ_i, (i=1,2) determine the short and long run dynamics of the resulting volatility series, respectively. Large ξ_i coefficients indicate that shocks to conditional variance take a long time to die out, implying persistent volatility. On the

[5] More details regarding the logistic function are given in the following paragraphs where this function is used for the case of conditional correlations.

other hand, large α_i coefficients indicate that volatility reacts quite intensively to new information.

To capture temporal changes in the contemporaneous conditional correlation ρ_t we follow Berben and Jansen (2005) and Silvennoinen and Teräsvirta (2005) by letting $G(s_t; \gamma, c)$ be the logistic function (similarly to growth term in equation 2)

$$G(s_t; \gamma, c) = \frac{1}{1 + \exp(-\gamma(s_t - c))}, \qquad \gamma > 0, \tag{9}$$

where s_t is the transition variable, and γ and c determine the smoothness and location, respectively, of the transition between the two correlation regimes.[6] The starting values of γ and c are determined by a grid search (see Berben and Jansen, 2005) and are estimated in one step by maximizing the likelihood function. Regarding the transition variable, while any variable can act like one, given that the purpose of this paper is to examine the effect of humans on climate change, we define it as a function of total anthropogenic forcings (at time t-1). As robustness check we also employ time which is (for a sample size n) described as: $s_t = t/n$ (where n denotes the sample size).[7]

The resulting Smooth Transition Conditional Correlation (STCC) GARCH model is able to capture a wide variety of patterns of change. Differing ρ_0 and ρ_1 imply that the correlations monotonically increase ($\rho_0 < \rho_1$) or decrease ($\rho_0 > \rho_1$), with the pace of change determined by the slope parameter γ. This change is abrupt for large γ, and becomes a step function as $\gamma \rightarrow \infty$, with more gradual change represented by smaller values of this parameter (in the estimation, the maximum value of the γ parameter is set to be 100). Parameter c defines the location of the transition between the two correlation regimes. In other words, c indicates the mid-point of any change in

[6] The transition function $G(s_t; \gamma, c)$ is bounded between zero and one, so that, provided there are valid correlations lying between -1 and +1, the conditional correlation ρ_t will also lie between −1 and +1.
[7] In practice, we scale $(t/n - c)$ by $\sigma_{t/n}$, the standard deviation of the transition variable t/n, to make estimates of γ comparable across different sample sizes.

the correlation due to a change in the transition variable, here anthropogenic forcings. When the transition variable has values less (greater) than c, the correlations are closer to the state defined by ρ_0 (ρ_1).[8]

Prior to employing the STCC specification, a Lagrange Multiplier (LM) test against a constant conditional correlation model (Berben and Jansen, 2005, Silvennoinen and Teräsvirta, 2005) is undertaken. Since the constant correlation null hypothesis is always rejected, a STCC model is estimated. Subsequently we examine whether a second transition (in correlations) exists by performing the LM test for this case developed by Silvennoinen and Teräsvirta (2007).[9] If such evidence is found, then we extend the original STCC-GARCH model by allowing the conditional correlations to vary according to two transition variables. The time-varying correlation structure in the Double Smooth Transition Conditional Correlation (DSTCC) GARCH model is imposed through the following equation:

$$\rho_t = \rho_0(1-G_1(s_t;\gamma_1,c_1))+\rho_1 G_1(s_t;\gamma_1,c_1)(1- G_2(s_t;\gamma_2,c_2))+\rho_2 G_1(s_t;\gamma_1,c_1)G_2(s_t;\gamma_2,c_2), \quad (10)$$

where each transition function has the logistic form of equation (9). The second transition variable is also a function of anthropogenic forcings and as robustness a function of time. Hence, equation (10) allows the possibility of a non-monotonic change in correlation over the sample. The parameters γ_i and c_i (i=1,2) are interpreted in the same manner as for the STCC-GARCH model, but to ensure identification we require $c_1 < c_2$ and hence that the two correlation transitions occur at different levels of anthropogenic forcings or points of time.

[8] The constant conditional correlation model (Bollerslev, 1990) is a special case of the STCC-GARCH model, obtained by setting either $\rho_0 = \rho_1$ or $\gamma = 0$.

[9] For analytical expressions for the test statistics and the required derivatives, we refer to Silvennoinen and Teräsvirta (2007).

The likelihood function at time t (ignoring the constant term and assuming normality) is given by

$$l_t(\theta) = -\frac{1}{2}\ln\left|\Sigma_t\right|^{(-1/2)} - \frac{1}{2}\varepsilon_t^{'}\Sigma_t\varepsilon_t, \tag{13}$$

where θ is the vector of all the parameters to be estimated. The log-likelihood for the whole sample from time 1 to n, $L(\theta)$, is given by

$$L(\theta) = \sum_{t=1}^{n} l_t(\theta). \tag{14}$$

This log-likelihood is maximized with respect to all parameters simultaneously, employing numerical derivatives of the log-likelihood. To allow for potential non-normality of $\varepsilon_t \left| \Psi_{t-1}\right.$, robust "sandwich" standard errors (Bollerslev and Wooldridge, 1992) are used for the estimated coefficients.

Data and Empirical Findings

Data Description

To stimulate the discussion, we first provide an overview of the data underlying our analysis. As usual in the literature, temperature is defined as the temperature anomaly (land and sea temperature combined) with reference to the 1951-1980 base period. Anthropogenic forcings refer to the components of radiative transfer calculation which can be attributed to human actions, and are calculated as the sum of six forcings (well mixed greenhouse gas, ozone, human land use, black carbon snow albedo, the direct effect of tropospheric aerosols and the indirect effect of tropospheric aerosols). All these forcings are the direct or indirect result of human activities.

Similarly, natural forcings refer to factors affecting global temperature which have to be attributed to natural phenomena. These are specified as the sum of stratospheric aerosols, solar irradiance and orbital variations. Data for all forcings were obtained from Miller et al (2014). Economic activity, measured as the World GDP is calculated by summing the domestic production of 21 countries, as produced by Maddison (2009). Details on the data sources and series construction can be found in the appendix.

Figures 2 and 3 provide an overview of the developments in change in anthropogenic and natural forcings, respectively. Changes in anthropogenic forcings depict a volatile behaviour while natural forcings' behaviour is erratic with unstable increases and decreases. Figure 4, presents world GDP growth estimates, in billions of 1990 international Greary-Khamis (GK) dollars.

The change in temperature anomaly, depicted in Figure 5, while overall much noisier than the other estimates, also follows an increasing path, which becomes evident from the late-1970's onwards. Careful observation of Figure 3 though suggests that natural forcings may have played a significant role in hiding the increase in temperature anomaly, as these have mostly contributed to the cooling of the planet from the early 1960's until the mid-1990's. Even though these had a strong effect on temperature, it appears that the impact anthropogenic forcings have had on temperature was much greater, leading to further increases in global warming.

Summary statistics reported in Table 1 (panel a) show positive average values for all variables, with the difference of the global mean temperature anomaly ($tempt_t$) having substantially higher (unconditional) volatility, compared to the rest of the variables. The Ljung-Box (LB) statistics for up to 5 lags, for the levels and their squared values, indicate the presence of linear and partially non-linear dependencies, respectively. Linear dependencies may indicate some dependencies to previous values, while non-linear dependence suggest that an autoregressive conditional heteroskedasticity specification may be useful to model the second moments.

Table 1 (panel b), presents the correlations among the variables. Measured over the whole sample, the (unconditional) correlations indicate a rather low correlation. However, these values may conceal substantial differences over time that are not able to be captured by simple statistics. Therefore, while informative, these unconditional correlations cannot indicate whether the correlations hold for the whole sample period.

For instance, Figure 6 presents the 30-year rolling Pearson correlation between the change in anthropogenic forcings and temperature anomaly. This simple metric highlights the fact that the relationship between the two variables is not only non-linear but fluctuates over time. During the periods where natural forcings fluctuated around zero (i.e. during the period from 1918 to1960 based on Figure 3) correlation reached a value around 0.40. After the 1970's the correlation value drops and increases again by the late 1990's.

The above-documented change in correlation gives indications why several models, using long time-series data may have failed, at times, to find a clear relationship between anthropogenic forcings and temperature anomaly. In addition, this behaviour also warrants the use of alternative methodologies in order to account for the non-linearity of the relationship. To this extent, the (D)STCC methodology is employed in order not only to account for the non-linearity of the relationship but also to examine the threshold after which this change in the relationship between temperature and anthropogenic forcings takes place.

Estimation Results

In this section, we first look at the conditional correlations of the full sample assuming that there is no regime shift within the covered time period. Then, we apply a LM test to investigate whether a structural change has occurred in the correlations between the difference in global mean temperature anomaly and the change in anthropogenic forcings. Next, we estimate the STCC-GARCH model to primarily determine the levels of anthropogenic forcings that change the pattern of this correlation and secondly the timing of this change. Finally, we apply a LM test to investigate whether another transition exists and, where appropriate, we extend the STCC-GARCH model and estimate the DSTCC-GARCH model with more than one transition regimes in correlations.

Table 2, column 1 shows the estimated conditional correlations estimated directly from the constant conditional correlation (CCC) specification under the assumption of no regime shift between the two variables of interest. The results suggest that the conditional correlations are rather low, in line with the descriptive statistics. However, the question whether these correlations change over time remains unanswered.

Evaluation of structural changes

To assess whether the proposed time-varying STCC-GARCH specification improves the model's ability to track the time-series properties of the data over a fixed parameter version, we employ the LM test developed by Silvennoinen and Teräsvirta (2007).[10] This test is designed to discriminate between the constant correlation GARCH model and the STCC-GARCH model and is applied to the residuals of equations (1) and (2).

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[10] Silvennoinen and Teräsvirta (2007) provide an excellent description of the details of this test. Note that the unidentified parameter problem that exists under the null hypothesis is dealt using a Taylor series expansion, following Luukkonen et al. (1988).

Under the null hypothesis, the LM statistic is asymptotically χ^2 distributed with one degree of freedom. The LM test does not discriminate between an increase and a decrease in correlation, but simply tests the null hypothesis H_0: $\gamma = 0$ against the alternative of H_a: $\gamma > 0$, which implies a time-varying conditional correlation. To determine whether the correlation has gone up or down, the STCC-GARCH model has to be estimated. As stated earlier, based on Ljung-box statistics we assume that both variables have time-varying conditional variances that follow a GARCH(1,1) specification.[11]

The last row of Table 2, reports the LM statistics. The test reveals that the null hypothesis of no structural change in the correlation between the difference in global mean temperature anomaly and change in anthropogenic forcings is rejected at any conventional level of significance, supporting the notion of a regime switch in the conditional correlations.

The presence of one structural change in the correlation between the two variables implies a monotonic relationship. We next examine the existence of a second transition that allows for a non-monotonic relationship which can capture more complicated patterns in time-varying correlations using the LM test developed by Silvennoinen and Teräsvirta (2007). The results in the last row of Table 2 suggest that a second break exists.

These findings clearly demonstrate that it is not reasonable to assume that conditional correlations remain constant at all levels of anthropogenic forcings. Therefore, they are characterized by more than two dominant trends. To examine the

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[11] We establish the adequacy of the model specification by performing standardized residual diagnostic tests. The mean and variance of the standardized residuals are found to have values of zero and one respectively for all cases. In addition, the Ljung-Box statistics in the standardized and squared standardized residuals show no evidence of linear dependence, suggesting that the model is well specified. These results are available upon request.

direction and the pattern of change(s), we turn next to the estimation of the STCC-GARCH and the DSTCC-GARCH models.

Time-varying shifts in conditional correlations

Based on the evidence provided by the LM tests, Tables 2 and 3, report the estimated parameters of the (D)STCC-GARCH models described in equations (1)-(9).[12]

Starting with mean equations (Table 2, panels A and B), the change in global mean temperature anomaly ($temp_t$) is negatively correlated to its lag value but the effects of anthropogenic forcings (z_{t-1}) on temperature are insignificant. This finding may be attributed to the low levels of anthropogenic forcings for a long period of the dataset. As for equation (2), anthropogenic forcings are predicted by their lag values with global mean temperature anomaly having insignificant effects. By employing a logistic function with time as a transition variable, the estimates suggest that there is a different behaviour of GDP growth on the change in anthropogenic forcings before and after the threshold point (c_g=0.56) which corresponds to the period around 1960. More specifically, before 1960 the effect of GDP growth on anthropogenic forcings is essentially zero (negative but insignificant), while after it turns positive, suggesting that the increasing human activity regarding greenhouse gases has adverse effects on global temperature.

As far as the coefficients of the conditional covariance matrix of e_t are concerned (Table 2, panels C and D) only the long run persistence coefficients (ξ_1) of the volatility equation of the difference in global mean temperature anomaly are significant, suggesting that changes in temperature have permanent effects. The

[12] The results for the mean and variance equations of the CCC specification (not reported but available upon request) are qualitatively similar to those of the STCC and DSTCC specifications.

insignificance of the rest of the coefficients in equation (6) suggests that the volatility of the difference in anthropogenic forcings is constant over time.

Turning our attention to the examination of the transition functions, Table 3, columns 2 and 3, report the conditional correlations in the original (ρ_0), the interim - where DSTCC is employed - (ρ_1), and the most recent (ρ_1 or ρ_2) regimes, the locations of the transitions (c_1 and/or c_2), and, finally, the shape of the transitions (γ_1 and/or γ_2).

Starting with the case of a single break in conditional correlations (Table 3, column 2), the estimated parameter c_1 suggests that when the level of anthropogenic forcings is above 0.945 the correlation changes from zero (insignificant) to positive 0.544 with the transition being abrupt as γ_1 indicates. The value of this threshold (which coincides with the threshold of the function of growth on anthropogenic forcings) can be traced back in the mid-1960's, during the years of the post-WWII economic boom, when a substantial amount of additional greenhouse gases (compared to the pre-industrial era) had started accumulating in the atmosphere due to the combustion of fossil fuels from human activities (see also Figure 2). In other words, this suggests that after the 1960s a 1% change in anthropogenic forcings coincided with a 0.5% change in temperature anomaly. Nevertheless, the LM test suggests that a second break in correlations should be included; therefore, we proceed with the estimation of the DSTCC specification.

In this case the estimated parameters for c_1 and c_2 are equal to 0.949 and 2.395 respectively, with the conditional correlations varying from -0.074 (ρ_0) when the levels of anthropogenic forcings are below c_1 to 0.521 (ρ_1) when they are between 0.949 and 2.395 and to 0.809 when they are above the upper threshold. Once again the transition from one level to the other is abrupt as γ parameters suggest. As for the timing of the changes, the first one takes place around 1960 (confirming the pattern of the STCC specification) while the second around 1990 - see Figure 7 for graphical illustration.

Robustness Checks

In this section, various robustness checks are employed to examine the validity of our findings.

Firstly, equations (1) – (9) are estimated using time as the transition variable. In this manner, the threshold point identifies the exact point of change of the conditional correlation. The results for conditional correlations are reported in Table 4, column 1 (for STCC specification) and column 2 (for DSTCC specification), respectively.[13] Threshold point for the STCC is given at 0.567 (around the period 1955) confirming the previous findings where anthropogenic forcings were used as transition variable. Previous findings are also confirmed under the DSTCC specification where the first threshold point (c_1) is the same with the STCC model, while the second (c_2) equals 0.964 (around 1990s) which again confirms the findings of previous section. Furthermore, the pattern of conditional correlation is qualitatively similar to previous estimations.

In addition to the above, a different dataset is utilised and the DSTCC specification is re-estimated using both anthropogenic forcings and time as transition variables. The new dataset is employed because the variables previously used are not obtained via direct observation, but are model estimates. To account for any potential loss of information due to this issue, this section provides additional estimations of the short-run effects of changes in anthropogenic forcings on the change of temperature

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[13] The results for mean and variance equations (available upon request) remain qualitatively the same for all robustness checks' estimations.

anomaly using observational data from Stern and Kaufman (2014).[14] The full description of the dataset is given in the Appendix

These findings are presented in Table 4, columns 3 for the DSTCC with anthropogenic forcings as the transition variable and column 4 for the DSTCC with time as the transition variable. Once again structural changes in conditional correlations and their timing confirm the findings of previous section and suggest that the post-WWII economic boom is crucial for the adverse effects on climate change.

Overall, under either single or double smooth transition conditional correlation specification using observational or model-based data with either time or anthropogenic forcings as the transition variable, it is clear that the additional greenhouse gases accumulated in the atmosphere in recent decades have significantly contributed to global warming.

Conclusions

In its latest Synthesis Report, the Intergovernmental Panel on Climate Change emphasized that human influence on the climate system is clear and growing. Many of the observed changes since the 1950s are unprecedented over decades to millennia and it is "extremely likely" (95 percent certain) that more than half of the observed increase in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcings together. In addition, they stressed that the more human activities disrupt the climate, the greater the risks of severe, pervasive and irreversible impacts for people and ecosystems (IPCC, 2014; p. 40 & 48).

[14] We thank Trude Storelvmo and Robert Kaufman for pointing this issue.

Our econometric analysis confirms the above findings of climate science. By employing a Smooth Transition Conditional Correlation model for the first time in climate-related research, we find that the effect of a change in anthropogenic activities on global temperature changes started becoming significant only after WWII. This identifies a non-linear relationship between temperature and anthropogenic forcings, which indicates that the effect of humans on climate is very likely to become more important in the future. Thus, the severity of climate change impacts may worsen in the coming decades. Moreover, the analysis sheds light into the short run effects of human activities on temperature change, a valuable insight for climate scientists which most previous studies have overlooked due to the methodology employed. Our results are robust to alternative specifications and to estimations with a different dataset.

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Appendix I

Table A1 – Data sources and definitions

Variable name	Short name	Unit	Range	Data Source	Link
Well mixed greenhouse gas	$WMGHG_t$	Wm^{-2}	1880-2012	Miller et al (2014)	http://data.giss.nasa.gov/modelforce/
Ozone	$O3_t$	Wm^{-2}	1880-2012	Miller et al (2014)	http://data.giss.nasa.gov/modelforce/
Land Human Use	$LandUse_t$	Wm^{-2}	1880-2012	Miller et al (2014)	http://data.giss.nasa.gov/modelforce/
Black Carbon Snow Albedo	$Snowalb_t$	Wm^{-2}	1880-2012	Miller et al (2014)	http://data.giss.nasa.gov/modelforce/
Tropospheric Aerosols (Direct)	$TropDir_t$	Wm^{-2}	1880-2012	Miller et al (2014)	http://data.giss.nasa.gov/modelforce/
Tropospheric Aerosols (Indirect)	$TropInd_t$	Wm^{-2}	1880-2012	Miller et al (2014)	http://data.giss.nasa.gov/modelforce/
Stratospheric Aerosols	$StratAer_t$	Wm^{-2}	1880-2012	Miller et al (2014)	http://data.giss.nasa.gov/modelforce/
Solar Irradiance	$Solar_t$	Wm^{-2}	1880-2012	Miller et al (2014)	http://data.giss.nasa.gov/modelforce/
Orbital Variations	$Orbital_t$	Wm^{-2}	1880-2012	Miller et al (2014)	http://data.giss.nasa.gov/modelforce/
Temperature Anomaly	$temp_t$	^oC	1880-2015	GISS	http://data.giss.nasa.gov/gistemp/
World GDP	*GDP*	GK Dollars	1884-2006	Maddison (2009)	http://www.ggdc.net/maddison/

From the above, the anthropogenic forcings (z_t) series is defined as:

$$z_t = WMGHG_t + O3_t + LandUse_t + Snowalb_t + TropDir_t + TropInd_t \quad \text{(A1.1)}$$

where $WMGHG_t$, $O3_t$, $LandUse_t$, $Snowalb_t$, $TropDir_t$, and $TropInd_t$ as defined as in Appendix I, Table A1. Similarly, the series for natural (non-anthropogenic) forcings (x_t) is defined as:

$$x_t = StratAer_t + Solar_t + Orbital_t \quad \text{(A1.2)}$$

in which $StratAer_t$, $Solar_t$, and $Orbital_t$ are refer to the definitions in Appendix I, Table A1.

As defined in Table A1, world GDP is compiled as the sum of the national GDP of Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, India, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sri Lanka, Sweden, Switzerland, United Kingdom, United States. Data range from 1884 to 2006 and were obtained from Maddison (2008).

Appendix II

Table A2 – Data sources and definitions

Variable name	Short name	Unit	Range	Data Source	Link
Radiative forcing of carbon dioxide	$RFCO2_t$	Wm^{-2}	1850-2011	Stern and Kaufmann (2014)	http://www.sterndavidi.com/publications_type.html
Radiative forcing of methane	$RFCH4_t$	Wm^{-2}	1850-2011	Stern and Kaufmann (2014)	http://www.sterndavidi.com/publications_type.html
Radiative forcing of dinitrogen oxide	$RFN20_t$	Wm^{-2}	1850-2011	Stern and Kaufmann (2014)	http://www.sterndavidi.com/publications_type.html
Radiative forcing of CFC11	$RFCFC11_t$	Wm^{-2}	1850-2011	Stern and Kaufmann (2014)	http://www.sterndavidi.com/publications_type.html
Radiative forcing of CFC12	$RFCFC12_t$	Wm^{-2}	1850-2011	Stern and Kaufmann (2014)	http://www.sterndavidi.com/publications_type.html
Radiative forcing of anthropogenic sulphur emmisions	$RFSOX_t$	Wm^{-2}	1850-2011	Stern and Kaufmann (2014)	http://www.sterndavidi.com/publications_type.html
Radiative forcing of black carbon	$RFBC_t$	Wm^{-2}	1850-2011	Stern and Kaufmann (2014)	http://www.sterndavidi.com/publications_type.html
Radiative forcing of Solar Irradiance	$RFSOLAR_t$	Wm^{-2}	1850-2011	Stern and Kaufmann (2014)	http://www.sterndavidi.com/publications_type.html
Radiative forcing of stratospheric sulfates	$RFVOL_t$	Wm^{-2}	1850-2011	Stern and Kaufmann (2014)	http://www.sterndavidi.com/publications_type.html
Temperature Anomaly	$temp_t$	^{o}C	1850-2011	HADCRUT4	http://www.sterndavidi.com/publications_type.html
World GDP	GDP	GK Dollars	1884-2006	Maddison (2009)	http://www.ggdc.net/maddison/

From the above, the anthropogenic forcings (z_t) series is defined as:

$$z_t = RFCO2_t + RFCH4_t + RFN20_t + RFCFC11_t + RFCFC12_t + RFSOX_t \quad \text{(A2.1)}$$

where $RFCO2_t$, $RFCH4_t$, $RFN20_t$, $RFCFC11_t$, $RFCFC12_t$ and $RFSOX_t$ are as defined in Appendix II, Table A2 (this definition can also be found as the RFANTH variable in Stern and Kaufman, 2014). Similarly, the series for natural (non-anthropogenic) forcings (x_t) is defined as:

$$x_t = RFSOLAR_t + RFVOL_t \quad \text{(A2.2)}$$

in which $RFSOLAR_t$ and $RFVOL_t$ refer to the definitions in Appendix II Table A1. This definition corresponds to the RFNAT definition of natural forcings in Stern and Kaufman (2014). Real GDP is defined as in Appendix I.

Tables

Table 1. Preliminary statistics

Panel a: Descriptive Statistics				
	$temp_t$	z_t	x_t	$growth_t$
Average	0.659	2.300	-0.267	2.788
Stdev	11.019	1.345	0.576	3.276
Min	-26.000	-0.390	-3.630	-13.888
Max	30.000	7.735	0.227	8.724
LB(Y_t; 5)	21.988***	267.09***	55.599***	30.837***
LB(Y_t^2; 5)	166.98***	2.859	10.356	50.148***
Panel b: Unconditional Correlations				
	$temp_t$	z_t	x_t	$growth_t$
$temp_t$	1	0.003	0.229	0.033
z_t		1	-0.272	0.021
x_t			1	0.035
$growth_t$				1

Notes:

Sample period is 1881 to 2006 (126 years/observations). LB(Y_t; n) is the Ljung-Box statistic for testing autocorrelation up to n lags (distributed as χ^2 with n degrees of freedom), calculated for both the levels and the squares.

** denotes significance at the 5% level.

*** denote significance at the 1% level.

Table 2. Estimated parameters for mean and variance equations

Parameters	STCC	DSTCC
	(1)	(2)
A. Mean Equation 1: $temp_t$		
β_0	3.055*	3.455**
	(1.756)	(1.671)
$temp_{t-1}$	-0.266***	-0.284***
	(0.089)	(0.089)
x_{t-1}	2.854*	3.074**
	(1.584)	(1.477)
z_{t-1}	-0.513	-0.575
	(0.618)	(0.579)
B. Mean Equation 2: z_t		
δ_0	0.188**	0.167**
	(0.085)	(0.084)
$temp_{t-1}$	0.006**	0.007**
	(0.003)	(0.003)
z_{t-1}	0.849***	0.861***
	(0.038)	(0.054)
$growth_{l,t-1}$	-0.032	-0.032
	(0.025)	(0.026)
$growth_{h,t-1}$	0.037**	0.032***
	(0.018)	(0.014)
c_g	0.560***	0.560***
γ_g	25.62	27.44
C. Conditional Variance equation 1: $temp_t$		
ω_1	12.55***	13.37***
	(3.13)	(3.29)
α_1	0.000	0.000
	(0.337)	(0.001)
ξ_1	0.897***	0.892***
	(0.131)	(0.143)
D. Conditional Variance equation 1: z_t		
ω_2	0.038	0.038
	(1.604)	(2.162)
α_2	0.314	0.319
	(0.193)	(0.240)
ξ_2	0.543***	0.536***
	(0.127)	(0.203)
E. Other Information		
$L(\theta)$	-570.0	-559.33

Notes: Transition Variable is z_t. *, **, *** indicate statistical significance at the 10%, 5% and 1% level respectively. Parentheses contain the standard errors, $L(\theta)$ is the log-likelihood value.

Table 3. Estimated parameters for conditional correlation

Parameters		CCC	STCC	DSTCC
		(1)	(2)	(3)
Correlations:	$\rho_{(0)}$	0.061	-0.067	-0.074
		(0.624)	(0.618)	(0.623)
	$\rho_{(1)}$	-	0.544***	0.521***
			(0.254)	(0.244)
	$\rho_{(2)}$	-		0.809***
				(0.073)
Transition parameters:	$c_{(1)}$	-	0.945***	0.949***
			(0.037)	(0.025)
	$c_{(2)}$	-	-	2.395***
				(0.011)
	$\gamma_{(1)}$	-	100	100
			(.)	(.)
	$\gamma_{(2)}$	-	-	100
				(.)
Transition Variable in test:		447.01	51.177	-
		(0.000)	(0.000)	

Notes: Transition Variable is z_t. *, **, *** indicate statistical significance at the 10%, 5% and 1% level respectively. Parentheses contain the standard errors.

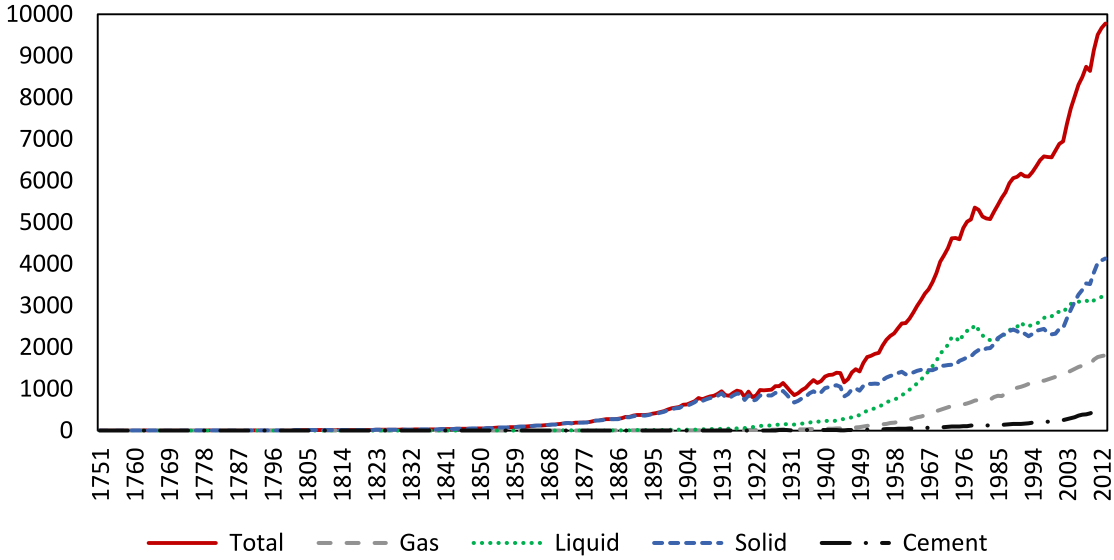
Table 4. Robustness tests results

Parameters		STCC	DSTCC	DSTCC	DSTCC
		(1)	(2)	(3)	(4)
Transition Variable:		Time	Time	z_t	Time
Dataset:		Original	Original	Stern and Kaufmann	Stern and Kaufmann
Correlations:	$\rho_{(0)}$	-0.073	-0.068	0.062	-0.183
		(0.614)	(0.621)	(0.613)	(0.596)
	$\rho_{(1)}$	0.414***	0.378	0.466***	0.192*
		(0.159)	(0.599)	(0.128)	(0.106)
	$\rho_{(2)}$		0.766***	0.849***	0.866***
			(0.098)	(0.099)	(0.011)
Transition parameters:	$c_{(1)}$	0.567***	0.537***	0.537***	0.538***
		(0.169)	(0.005)	(0.001)	(0.027)
	$c_{(2)}$	-	0.964***	0.955***	0.954***
			(0.001)	(0.001)	(0.001)
	$\gamma_{(1)}$	100	100	100	100
		(.)	(.)	(.)	(.)
	$\gamma_{(2)}$	-	100	100	100
			(.)	(.)	(.)
$L(\theta)$		-571.2	-559.33	-1052.21	-1028.8
Transition Variable in test:		52.207	-	-	-
		(0.000)			

Notes:
*, **, *** indicate statistical significance at the 10%, 5% and 1% level respectively. Parentheses contain the standard errors.

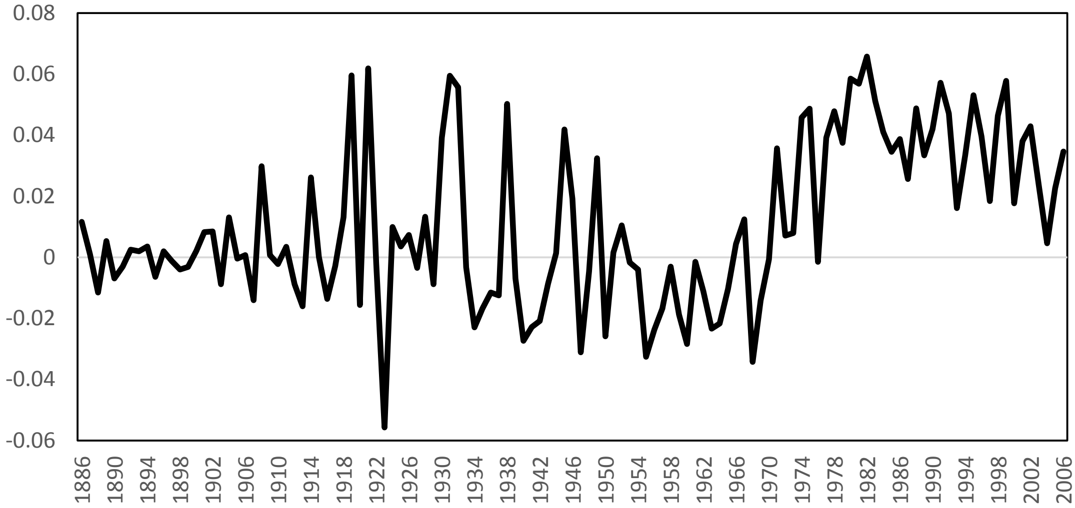
Figures

Figure 1 – Carbon Emissions - million tons carbon (1751-2009)



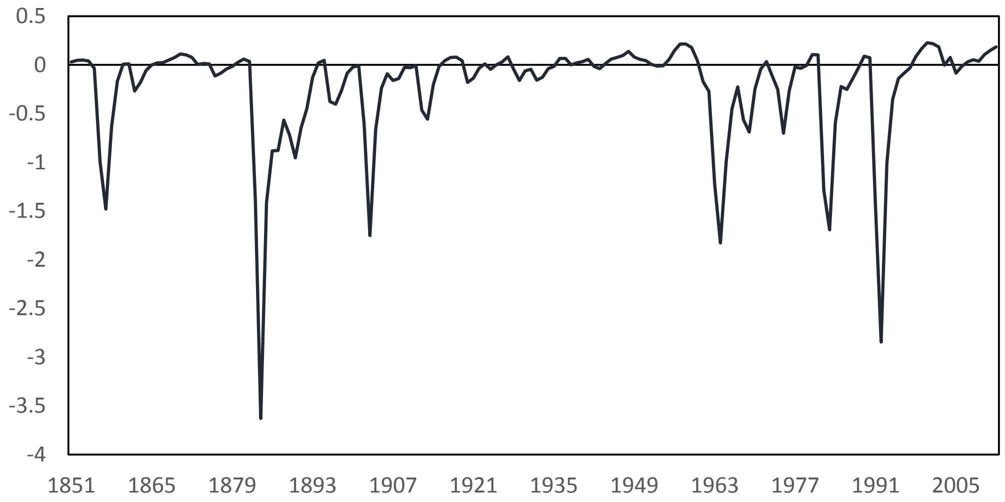
Source: Boden et al (2016)

Figure 2 – Change in Anthropogenic Forcings (1886-2006)



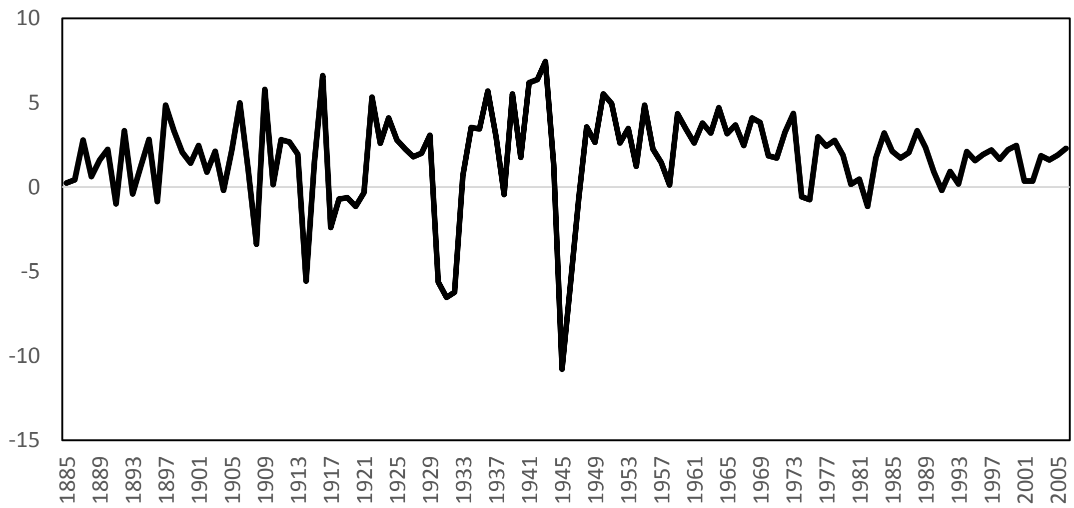
Source: Miller et al (2014).

Figure 3 – Natural Forcings (1851-2012)



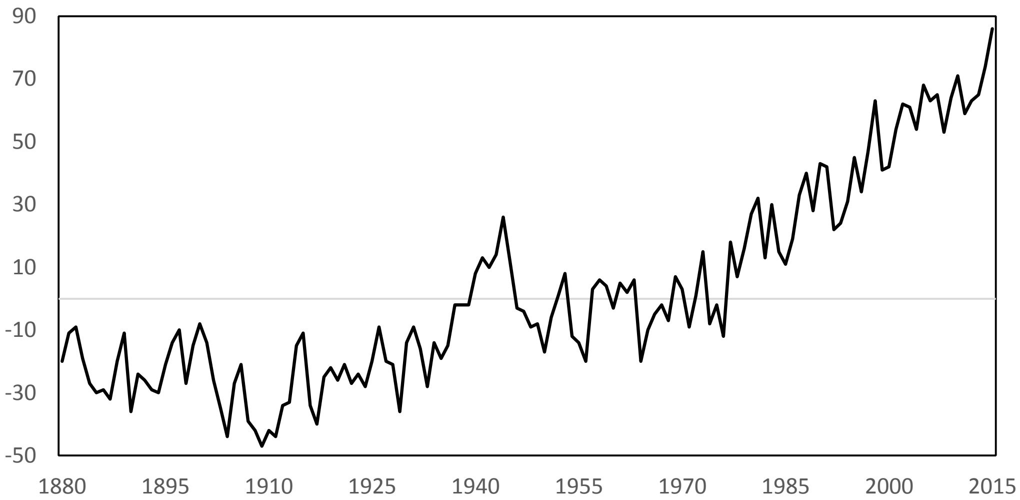
Source: Miller et al (2014).

Figure 4 – World GDP growth (1884-2006)



Source: Maddison (2008)

Figure 5 – Temperature (sea-land-air combined) anomaly in Fahrenheit



Source: GISTEMP Team 2016: GISS Surface Temperature Analysis (GISTEMP) and Hansen et al (2010).

Figure 6 - 30-year rolling correlation of change in Anthropogenic Forcings and Temperature

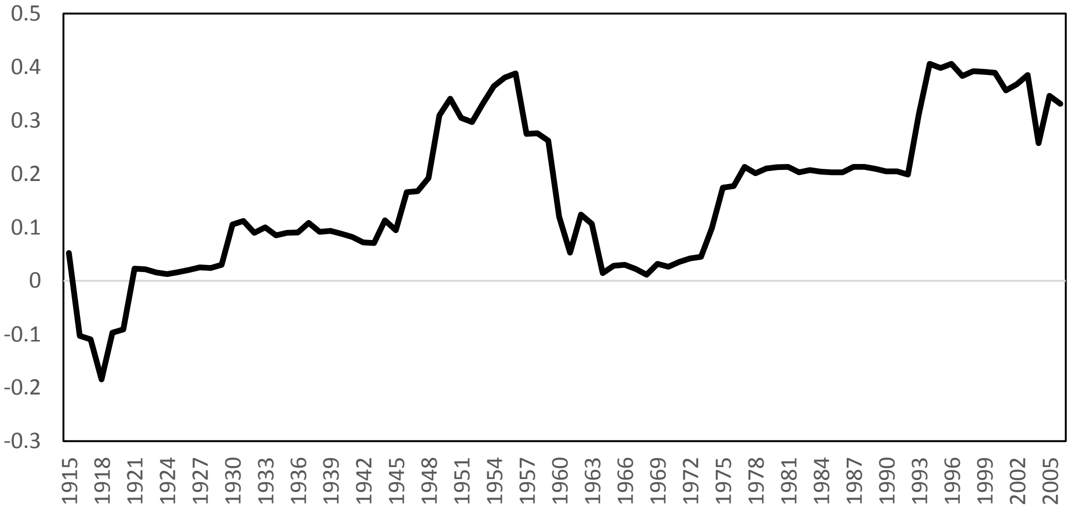


Figure 7 – Double Smooth Transition Conditional Correlation