University of Sussex
Economics

Working Paper Series

No. 62-2013

Estimating the Global Impacts of Climate Variability and Change During the 20th Century

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Abstract: Estimates of the impacts of observed climate change during the 20th century obtained by different integrated assessment models (IAMs) are separated into their main natural and anthropogenic components. The estimates of the costs that can be attributed to natural variability factors and to the anthropogenic intervention with the climate system in general tend to show that: 1) during the first half of the century, the amplitude of the impacts associated to natural variability is considerably larger than that produced by anthropogenic factors and according to most models the effects of natural variability were mainly negative. These non-monotonic impacts are mostly determined by the low-frequency variability and the persistence of the climate system; 2) IAMs do not agree on the sign (nor on the magnitude) of the impacts of anthropogenic forcing but indicate that they steadily grew over the first part of the century, rapidly accelerated since the mid 1970's, and decelerated during the first decade of the 21st century. The economic impacts of anthropogenic forcing range in the tenths of percentage of the world GDP by the end of the 20th century; 3) the impacts of natural forcing are about one order of magnitude lower than those associated to anthropogenic forcing and are dominated by the solar forcing. Human activities became dominant drivers of the infrapolated economic impacts at the end of the 20th century, rivaling in magnitude with those of natural variability. FUNDn3.6 allows to further decompose the natural and anthropogenic contributions into different sectors. The benefits of anthropogenic contribution in agriculture and energy are shown to outweigh the losses in health and water resources.

JEL classification: Q54

Key words: climate change; impacts; 20th century

1. Introduction

Integrated assessment models (IAM) have been widely used for estimating the potential costs of climate change over the 21st and later centuries and for advising policy regarding the desirability of alternative mitigation and adaptation portfolios. However, these models have seldom been applied to the 20th century. Estimation of past impacts is the first step towards model validation.

Model validation is difficult because IAMs estimate welfare losses, which are not observed. Recently, Tol (2013) applied the FUND model in its national version for infrapolating the impacts of climate change during the 20th century. His main findings are that while global average impact over the century was positive, regional and temporal differences are important: most countries benefited from climate change until 1980, but since then the impacts for poor countries have been negative and positive for the rich. The largest negative impacts occur in water and human health. In the present paper, we extend the analysis in Tol (2013) in two directions. First, we use five IAMs, rather than one. Second, we separate the infrapolated impacts of climate change into their anthropogenic and natural components.

The structure of this paper is as follows: Section 2 describes the data, scenarios and methods that are used in this paper. The results are presented in Section 3 and the influence of anthropogenic and natural factors over the estimated economic impacts is discussed. Section 4 presents a decomposition of the anthropogenic and natural contributions to the infrapolated costs at the sector level. Section 5 concludes.

2. Data and methods

2.1 Climate and radiative forcing databases

We use the HadCRUT3 global temperature time series (Brohan et al., 2006)[1]. Commonly considered to be the most important natural sources of inter-annual global and hemispheric climate variability (Trenberth, 1984; Enfield et al., 2001; Hurrell, 1995; Wolter and Timlin, 1998), we take into account the following indices: the Southern Oscillation Index (SOI) from the National Center for Atmospheric Research (NCAR; Trenberth, 1984)[2] as a proxy for El Niño/Southern Oscillation; the North Atlantic Oscillation (NAO) from Climatic Research Unit[3]; the Atlantic Multidecadal Oscillation (AMO)[4] from the National Oceanic and Atmospheric Administration (NOAA); and the Pacific Decadal Oscillation (PDO)[5] from the Joint Institute for the Study of the Atmosphere and Ocean.

The radiative forcing series used in this paper are those in Hansen et al. (2011); available at http://data.giss.nasa.gov/modelforce/RadF.txt). We use the following variables (in W/m^2): well mixed greenhouse gases (RFGHG; carbon dioxide (CO2), methane (NH4), nitrous oxide (N2O); chlorofluorocarbons (CFCs)); ozone (O3); stratospheric water vapor; solar irradiance (SOLAR); land use change; snow albedo; black carbon; reflective tropospheric aerosols (RAER) and; the indirect effect of aerosols. As in Estrada et al. (2013) the total radiative forcing (TRF) is defined as the sum of all the radiative forcing variables mentioned above.

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1 http://hadobs.metoffice.com/hadcrut3/diagnostics/index.html.
2 http://www.cgd.ucar.edu/cas/catalog/climind/soi.html
3 http://www.cru.uea.ac.uk/cru/data/nao/
4 http://www.esrl.noaa.gov/psd/data/timeseries/AMO/
5 http://jisao.washington.edu/pdo/

2.2 Statistical methods for the attribution of climate change and temperature scenarios

The detection and attribution of climate change has been an area of intense research that has proven to be of interest for a wide range of applications including climate modeling, risk and impact assessment, mitigation and adaptation studies, economics and policy making (IPCC, 2007). The separation of the anthropogenic warming signal from the natural variability in global temperatures has received significant attention during the last decades, leading to the development and adaptation of a variety of statistical and physical modeling methodologies to tackle this task (e.g., Hasselmann, 1993; Tol and Vos, 1993; Tol and Vos, 1998; Kaufmann and Stern, 1997; Kaufmann et al., 2006; Estrada et al., 2013a; Estrada et al., 2013b). Although these studies are characterized by strong methodological differences (e.g., Estrada et al., 2010), most of them have conclude that global temperature and the total radiative forcing series share a common secular trend, being anthropogenic forcing a major contributor to the observed warming and natural variability is characterized as a stationary process.

The existence of this common secular trend allows separating this warming signal from observed global temperature series. For constructing the scenarios used in this paper we apply a simple regression model to detrend observed global temperatures as follows:

$$T_t = \alpha + \beta TRF_t + u_t \qquad (1)$$

$$T_t - \beta TRF_t = \alpha + u_t = \tilde{t}_t \qquad (2)$$

$$\tilde{t}_t + \beta\left(TRF_t - GHG - RAER\right) = \tilde{t}_t^{*} \qquad (3)$$

where T_t is the observed global temperature series and u_t are the regression residuals. Equations (2) and (3) are used to detrend and partially detrend observed global temperatures, respectively. These time series, depicted in Figure 1, provide alternative climate scenarios for running the selected IAMs. The first scenario, $\tilde{t}_t$ from Equation (2), represents natural variability under a stationary climate where all external radiative forcings are held constant at their preindustrial values (preindustrial scenario). The second scenario, $\tilde{t}_t^{*}$ from Equation (3), represents the evolution of global temperatures holding the main anthropogenic forcing factors (GHG and RAER) constant at their preindustrial values, but allowing all other forcing factors to vary according to the observed records (natural forcing scenario). The third scenario, represented by Equation (1), corresponds to the observed temperature records.

2.3 Damage functions from IAMs

2.3.1 FUND model description

In this paper we apply the national version of the Climate Framework for Uncertainty, Negotiation and Distribution (FUNDn3.6). In contrast to other versions of the model, which endogenously generate scenarios for population, economy, energy use and emissions and include a simple carbon cycle and climate model, this version of FUND is limited to the impacts of climate change. The impact module includes the following categories: agriculture, forestry, sea level rise, cardiovascular and respiratory disorders related to cold and heat stress, malaria, dengue fever, schistosomiasis, diarrhoea, energy consumption, water resources, unmanaged ecosystems, and tropical and extra tropical storms (Tol, 2002a; Tol, 2002b). The model estimates the climate related damages attributed to either the rate of change or to the level of change with damages slowly fading due to autonomous adaptation. This version of the model runs in 5-year time steps (Tol, 2002b; Tol, 2013). For a more detailed description of the model, the reader is referred to the original papers and technical documentation available at http://www.fund-model.org/; the model code for this version is at http://dvn.iq.harvard.edu/dvn/dv/rtol.

2.3.2 The DICE damage function

The damage function of DICE was developed from estimates from 12 world regions and includes damages to major sectors such as agriculture, the cost of sea-level rise, adverse impacts on health, and nonmarket damages, as well as estimates of the potential costs of catastrophic damages (Nordhaus, 2008). The aggregated impact function can be described as follows:

$$D_t = \theta_1 T_t + \theta_2 T_t^2 \qquad (2)$$

where D_t represents the climate damage as fraction of output, θ_1 and θ_2 are the parameters of the damage function calibrated for the world, T_t is global temperature increase over its preindustrial value. For this paper we consider the DICE99 (Nordhaus and Boyer, 2000) and the DICE2007 (Nordhaus, 2008; Nordhaus, 2010). Parameterizations are shown in Table 1. The main difference in the parameterization of DICE99 and DICE2007 consists in that in the former the climate impacts for small temperature increases were estimated to produce net positive benefits, while in the latter all temperature increases lead to net negative impacts (Nordhaus, 2008). A one-year time step was chosen for all estimates presented here.

2.3.3 The PAGE2002 damage function

The PAGE2002 model damage functions include the uncertainty in the functions' coefficients by means of triangular distributions parameterized to cover the range of possible impacts that have been reported in the literature. The main aim is to offer a probabilistic representation of the potential climate change damages to inform decision-making (Hope, 2006).

The impact functions of PAGE2002 can be expressed as follows:

$$I_{t,d,r} = \alpha_{d,r} \left(\frac{\Delta T_{t,r}}{2.5} \right)^{\beta} Y_{t,r} \qquad (3)$$

$$D_{t,r} = \gamma_{t,r} \pi_t Y_{t,r} \qquad (4)$$

where $I_{t,d,r}$ represents the economic impacts in time *t*, in the sector *d* (*d=1,2*; representing the economic and the noneconomic sectors, respectively) and in region *r*; $\Delta T_{t,r}$ is the increment in regional temperature with respect to its preindustrial value; β is the exponent that determines the functional form of the impact function; and $\alpha_{d,r}$ are regional parameters to express the percentage of GDP ($Y_{t,r}$) lost for a benchmark warming of 2.5°C in each impact sector and region. Equation (4) represents the impacts associated to the occurrence of a large-scale discontinuity in the climate system. $D_{t,r}$ represents the economic impacts of a discontinuity at time *t* and region *r*; $\gamma_{t,r}$ is the economic impact of a discontinuity at time *t* in region *r*; and π is the probability of occurrence of the discontinuity. The total economic impacts are the sum of equations (3) and (4).

Given that the observed warming during the 20th century was below the lower limit for the occurrence of large-scale discontinuities, the economic damages presented here come from equation (3) only. The regional weights for scaling the impact functions are those from the PAGE2002 model (reproduced here in Table 2; see Hope, 2006) and the regional estimates of temperature where produced using the scaling factors obtained from the emulation of the UKMOHADCM3 General Circulation Model of the Magicc/Scengen software (http://www.cgd.ucar.edu/cas/wigley/magicc/) [6]. The outcomes of the damage functions described above were estimated using simulation experiments of 1,000 realizations and the time-step was chosen to be one year. The global estimates of the climate damages during the 20th century presented here are simple averages of the regional damage functions.

2.3.4 Damage function from recent literature review

Based on a literature review of all published estimates of the global costs of climate change, Tol (2013) estimates a damage function that synthesizes all findings. The damage function takes the same functional form of equation (2), but the parameters values are $\theta_1 = 2.46$ and $\theta_2 = -1.11$. This damage function is calibrated with respect to the 1961-1990 global temperature average. We will refer to this impact function as MA (for meta-analysis).

3. Results and discussion

In this section we present estimates of the contributions of natural and anthropogenic factors to the infrapolated costs of observed global temperature during a period comprising the 20th century. Based on the three temperature scenarios in section 2.2, five infrapolated costs scenarios are defined:

1. S_OBS: The expected economic costs given the observed global temperature evolution, obtained using T_t.
2. S_NV: The expected costs associated to natural variability under a stationary climate holding all external forcing factors constant at their preindustrial levels, obtained using $\tilde{t}_t$.
3. S_NVF: The expected costs associated to the observed natural external forcing and internal variability, obtained using $\tilde{t}_t^*$. This scenario is used only for estimating S_AF and S_NF described below.
4. S_AF: The expected costs associated to the anthropogenic radiative forcing, obtained as the difference of S_OBS and S_NVF.
5. S_NF: The expected costs associated to the natural radiative forcing, obtained as the difference of S_NVF and S_NV.

[6] The regional scaling factors are: 1.56 for Europe; 1.39 for Latin America; 1.49 for North America/OECD; 1.30 for Africa; 2.04 for North Asia; 1.33 for South Asia and; 1.45 for China.

Note that this approach for separating the contributions of internal variability and anthropogenic and natural forcing preserves their interaction effects (e.g., the effects of natural variability under a stationary climate are not the same that under an externally forced climate due to the nonlinearities in the damage functions).

3.1. Estimates of costs obtained from observed global temperatures

Panel a) of Figure 2 shows the results of infrapolating the costs of the observed climate during the 20th century according to the 5 different IAMs. These models do not agree on the sign or the magnitude of the infrapolated economic impacts. Nevertheless, as in the case of global temperature series, the infrapolated costs obtained from the different IAMs show, in general, a slight trend from the beginning of the sample until the mid-1970's when a large increase in their rates of growth occurred. A slight deceleration since the mid-1990s is also noticeable, which is in line with the recent slowdown in the rate of warming that has been reported (Estrada et al., 2013b; Kaufmann et al., 2011). According to PAGE2002 and DICE2007, by the end of the century the observed global temperature had a negative effect on GDP while for DICE99, FUNDn3.6 and MA the effect was positive. While DICE99, DICE2007 and PAGE2002 suggest that the economic impacts during the last decade are small (about -0.20% to 0.14% of global GDP), FUNDn3.6 and MA show considerably larger (positive) impacts reaching about 1% of GDP in 2000. FUNDn3.6 equity weighting results show the highest benefits: 1.19% in 2000 and a maximum of 1.61% in the mid-1970s. Note, however, that the magnitude of these impacts is not unprecedented over the last century. Large impacts also occurred before the anthropogenic intervention became significant and, according to some IAMs, these impacts are comparable or even larger than those estimated for the end of the 20th century. For example, DICE2007, DICE99 and MA infrapolate large losses at the beginning of the first decade of the century in the range of -0.05% to -1.66% of GDP.

Figure 3 panel a) shows the multimodel mean of S_OBS and the corresponding two standard deviation intervals representing the uncertainty in this estimate. For the estimates in Figure 3 all IAMs are weighted equally, implying that all of them produce equally credible estimates. Although this is probably not the case, until now IAMs' projections have not been validated and their performance is unknown. The multimodel mean in Figure 3 panel a) shows a steady positive trend that leads to net benefits of about 0.42% of GDP in 2000. Note however that throughout the 20th century, the multimodel mean value is always smaller than the standard deviation of the models' outcomes, underlying the very large uncertainty in these estimates (e.g., the standard deviation in 2000 was 0.52%).

In the following subsections, the infrapolated costs associated to observed climate variability and change are decomposed into their natural and anthropogenic components.

3.2. Contributions of the natural and anthropogenic radiative forcing to the infrapolated impacts from the observed global temperatures

Panels a), b) and c) of Figure 2 show that the trending behavior of the infrapolated global economic impacts S_OBS can only be explained by S_AF and S_NF. As clearly shown in panel d), the costs associated to natural variability describe oscillatory patterns around a fixed mean that cannot account for the trend in global impacts (see Section 3.3 for an analysis of the natural variability impacts).

S_AF (Figure 2b) describes quite closely the general nonlinear trend in S_OBS. Although estimates of the different IAM do not agree on the sign (nor on the magnitude) of the effects of anthropogenic forcing, all of them describe the anthropogenic contribution steadily increased over the first part of the century and rapidly accelerated since the mid 1970's. They also show a deceleration during the first decade of the 21st century, which is consistent with the reported slowdown in the warming during the last two of decades (e.g., Estrada et al., 2013b). Note that S_NF also shows a similar nonlinear trend, but as described below, the effects of natural forcing are, for most models, about one order of magnitude lower than those associated to anthropogenic forcing (see Figure A1 for a comparison of natural and anthropogenic contributions per model). Moreover, with the exception of MA, its impacts where practically zero until the late 1940s.

According to PAGE2002, DICE99 and DICE2007, the economic impacts of anthropogenic forcing lie in the range of a few tenths of percent of the world GDP by the end of the 20th century (from -0.24% in PAGE2002 to 0.22% in DICE99). This figure is considerably larger for FUNDn3.6 and MA which indicate benefits in the range of about 0.50% to 1.50%. It is also worth noting that DICE2007 provides the smallest estimates of impacts, reaching only about -0.1% at the end of the century.

The multimodel mean of S_AF indicates that the human contribution to the observed warming during the 20th century produced net benefits in the world average. The benefits increased from about 0.08% at the beginning of the century to about 0.45% of GDP in 2000 (Figure 3 panel b). As before, the uncertainty is quite large: the multimodel mean is always smaller than the standard deviation of the models' outcomes.

The contribution of S_NF to the overall impacts is depicted in panel c) of Figure 2. The effects of natural forcing are dominated by the eleven-year cycle in solar forcing. The correlation between the impacts attributed to natural forcing factors with solar forcing is very large and positive for DICE99, DICE2007, MA and FUNDn3.6 ranging from 0.62 to 0.90, while for PAGE2002 is -0.84. Note that in all cases except DICE2007, the increases in natural forcing observed since the mid-20th century make S_NF contribute in the same direction as S_AF to the infrapolated total costs. This is expected from climate physics: irrespective of their origin, increases in radiative forcing simply add up, leading to larger climate transient response and equilibrium temperatures (Schwartz, 2012). Thus, the effect of increases in radiative forcing from natural and anthropogenic origin should not produce opposite effects (trends), but add up instead. These results likely point to a poor specification of the impact function in DICE2007.

The multimodel mean shows that the impacts of S_NF where practically zero until the 1940s. In the second half of the century natural forcing produced small but increasing benefits reaching 0.11% of GDP in 2000. Figure A2 depicts the multimodel mean of the anthropogenic and natural forcing contributions and natural variability (discussed in section 3.3). When the magnitude of the anthropogenic contribution is compared to the other sources of impacts, it can be argued that at the end of the 20th century human activities became dominant drivers of the infrapolated economic impacts, rivaling in magnitude with those attributed to natural variability.

3.3. Estimates of costs obtained from the preindustrial radiative forcing scenario

All of the impact functions indicate that the natural variability alone can lead to impacts that are comparable in magnitude to those that can be attributed to anthropogenic factors at the end of the 20th century and are much larger than those that can be associated to the observed natural forcing (Figure 2d). The main difference is that the natural variability impacts are not sustained nor show any trend. Only for DICE2007 the impacts of natural variability are strictly negative, while for DICE99 and MA are mostly negative and for PAGE2002 they are mainly positive. These non-monotonic impacts are mostly determined by the low-frequency variability and large persistence of the climate system.

The impacts under the preindustrial scenario can be associated with some of the main modes of interannual climate variability. As shown in Table A1, S_NV is significantly correlated with AMO and to a lesser extent with SOI, PDO and NAO. The magnitude of these correlations is broadly similar for the estimates obtained using the PAGE2002, MA, DICE99 and DICE2007 impact functions (about 0.70, 0.30, 0.20 and 0.24 in absolute value for AMO, SOI, PDO and NAO, respectively) although the signs are different depending on the specification of the impact functions. In the case of FUNDn3.6, the correlation coefficients between these climate modes and S_NV are generally lower in magnitude and not statistically significant (with the exception of AMO and FUNDn3.6 equity), probably due to the 5 year time-step of this model, the limited number of observations available for estimating these quantities (22 data points) and possibly to the model structure, as discussed below.

Linear regression models using AMO, SOI, PDO and NAO as explanatory variables were estimated but only the first two were found to contribute explaining the variability of the infrapolated costs. The following specification was found to be statistically adequate for most of the IAM infrapolations[7] (see Tables A2 and A3 in Appendix for parameter estimates and misspecification tests):

$$S\_NV_{it} = c + \alpha S\_NV_{it-1} + \delta_1 AMO_t + \delta_2 AMO_{t-1} + \gamma SOI_t + \varepsilon_t \qquad (6)$$

where S_NV_{it} are the infrapolated costs for model $i = 1,...,5$. This regression model has a similar specification to those in Estrada et al. (2013b) for global temperature series. In all cases AMO and SOI are highly significant, except for the infrapolations obtained with FUNDn3.6 where only AMO is significant. This result has to do probably with the limited number of observations (and time-step) in the infrapolations obtained with FUNDn3.6 and more importantly, with the large differences in the structure and complexity of FUNDn3.6 compared to the other IAMs. The results of PAGE2002, DICE99, DICE2007 and MA are simple power functions of temperature, and thus preserve strong similarities with the characteristics of global temperatures. However, this is not the case of FUNDn3.6 as its impact functions significantly modify the characteristics of the input temperature series.

For most IAMs, the estimated regressions explain about 60% of the variance of the impacts associated to natural variability. Furthermore, AMO and SOI generate important fluctuations from the mean of WI_{it}: a one standard deviation shock to AMO produces a cumulative long-run response of about 0.60 times the standard deviation of WI_{it} (positive for DICE99, MA

[7] Most of the regression models are statistically adequate according to the misspecification tests that were applied. Only in the case of DICE2007 and FUNDn3.6 average deviations from the normality assumption were found. In addition, the CUSUMQ test suggests some evidence of parameter instability for FUNDn3.6.

and DICE2007, negative for PAGE2002) while a shock of one standard deviation to SOI generates a long-term response 0.45 times the standard deviation of WI_{it} (negative for DICE99, DICE2007 and MA, i.e., an El Niño episode causes benefits while a La Niña produces damages; the opposite occurs with PAGE2002. See Table A4). For FUNDn3.6 a one standard deviation shock in AMO produces a response of 0.39 (average) and 0.77 (equity) times the standard deviation of WI_{it}.

The multimodel mean of S_NV is mainly negative and shows an oscillatory pattern similar to AMO (correlation coefficient of 0.71) varying in a range of -0.39% to 0.15% of GDP during the 20th century. The multimodel mean of S_NV suggest that until the last three decades of the 20th century, natural variability was the main source of economic impact. Since then, the main driver of impacts is anthropogenic forcing. It is worth noticing that the standard deviation of the models' outcome is in average almost 3 times larger than the multimodel mean, indicating the large uncertainty in this estimate.

4. The anthropogenic and natural components of the infrapolated impacts per sector.

As mentioned above, FUNDn3.6 allows us to investigate the projected impacts separately for each sector. Figure 4 shows the anthropogenic and natural contributions to the economic costs of observed 20th century climate for agriculture, health, water resources, and energy.

Agriculture is the sector for which the observed climate had the largest effect, leading to benefits of about 0.8% of GDP in 2000 (Figure 4 panel a). This sector is also by far where the anthropogenic influence is more evident, leading at the end of the 20th century to gains of 0.68% of GDP. This is the only sector for which the anthropogenic contribution is considerably larger than the effects of natural variability. Carbon dioxide fertilization contributes most to these gains. The effects of natural forcing became positive around the 1930's and reached 0.06% in 2000, about an order of magnitude lower than the estimates of the anthropogenic contribution. For this sector, natural variability produced fluctuations in the range of about -0.15% to 0.06% of GDP, substantially larger than the contribution of natural forcing.

In the water resources sector, both anthropogenic and natural forcing imparted a trend on losses (Figure 4 panel b). The anthropogenic contribution led to losses of up to -0.12% of GDP and, in the last decades of the past century, it became about five times larger than the effects of natural forcing. However, the amplitude of the costs produced by natural variability is considerably larger compared to the individual or joint contributions of natural and anthropogenic factors.

Natural variability plays a dominant role on the costs of the two remaining sectors (Figure 4 panels c and d). The interaction effects between natural variability and forcing factors are large and add significant noise to the anthropogenic and natural forcings signals. In the energy sector benefits from the observed global temperature of about 0.36% were attained in 2000 (Figure 4 panel c). The anthropogenic forcing contributed to these gains during the whole 20th century reaching up to 0.20% in the 1990s. In comparison, the positive effects of natural forcing started around the 1930s and due to the interaction effects, the benefits from natural forcing reached 0.34% in 1990. In 1995, the anthropogenic and natural contributions generated gains of about 0.17% and 24%, respectively, and then dropped considerably.

Although in all sectors the effects of the slowdown in the warming can be detected, in the energy sector this is more evident due to the large interaction effects of forcing factors and natural variability. In 2000 the benefits of anthropogenic and natural forcing amounted to only 0.02% and 0.08%, respectively.

In the health sector, the negative impacts of the 20th century climate reached about 0.2% of GDP in 2000 (Figure 4 panel d). Although the contribution of anthropogenic forcing was negative during most of the century it was not until the 1970s that a negative trend became noticeable. For this sector, both anthropogenic and natural contributions to the costs of the 20th century climate are well within the amplitude of the effects of natural variability.

Nevertheless, as shown in Figure 5, the anthropogenic contribution to the infrapolated number of deaths per million people related to climate is dominant (panel b). As shown in panels a) and b) of Figure 4, the trend in the infrapolated number of deaths of these of climate related diseases is mainly imparted by the anthropogenic forcing. The largest contribution of anthropogenic forcing to these numbers occurs in diarrhoea, respiratory diseases and malaria. Natural forcing (panel c) and internal variability (panel d) mainly provided the low-frequency oscillatory pattern shown by the proportion of deaths.

5. Discussion and conclusion

The decomposition of the infrapolated impacts of observed global temperature reveals a clear anthropogenic influence that at the end of the century rivals in magnitude with the largest impacts of natural variability. Anthropogenic impacts increased over the period of analysis in a non monotonic way, slowly for the first part of the 20th century, accelerating significantly after the 1970s and reducing their rate of increase after the 1990s when a slowdown in global warming started (Gay-Garcia et al., 2009; Estrada et al., 2013b). As expected, natural forcing is shown to reinforce the impacts attributed to anthropogenic forcing. The contribution of natural forcing to the total estimated impacts is about one order of magnitude lower than that of the anthropogenic forcing or that of the internal interannual variability. The main driver of the impacts associated to natural factors is solar forcing, which imprinted its 11-year cycle and a slight positive trend.

In the annual and decadal scales the amplitude of the impacts associated to natural variability is considerably larger than that produced by anthropogenic factors during the first half of the century and their effects were mainly negative according to most models. These non monotonic impacts are mostly determined by the low-frequency variability modes and persistence of the climate system.

As has been discussed previously in the literature (see Tol, 2009), IAMs do not agree in the sign of the impacts for small changes in temperature. In the case of FUNDn3.6, DICE99 and MA the observed warming has brought benefits to the global GDP, while according to DICE2007 and PAGE2002 the opposite is true. With the exception of FUNDn3.6 and MA, which estimate the magnitude of the impacts in about 1% to 1.5% of GDP at the end of the 20th century, the rest of the IAM considered value the impacts in only a few tenths of percent.

According to the sectoral decomposition of infrapolated impacts from FUNDn3.6, anthropogenic forcing in agriculture accounts for most of the economic benefit in the past century. Benefits attributable to the anthropogenic forcing are also found for the energy sector, while this forcing imparted a trend in the economic losses in human health and water resources. The model strongly suggests that the contribution of anthropogenic forcing to the infrapolated number of deaths per thousand people is dominant in the case of diarrhoea, respiratory diseases and malaria.

Model validation could help to reduce the large uncertainty characterizing IAMs projections, to improve the specification of their impact functions and to increase their credibility. Until now the performance of the different IAMs has not been assessed and the validity of their projections is thus unknown. While the assessment of the performance of other types of models (e.g., general circulation models) is possible due to the existence of readily available observed datasets covering long periods of time and with high spatial resolution (e.g., temperature and precipitation), this is not the case of the welfare impacts of observed climate. As discussed in Tol (2013), the infrapolation of past expected climate impacts is the first step for testing models' performance. However, data availability is a fundamental issue: while in some sectors (e.g., energy demand, agriculture and water) datasets may be available with adequate coverage and length, for many sectors only case studies for selected parts of the world may be possible (Tol, 2013). This is further complicated in the case of models that summarize all impacts in one or two equations (e.g., DICE, PAGE2002) as it becomes harder to gather all the required information and to compare like with like.

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Table 1. Parameter values of the damage functions in the DICE99 and DICE2007 models.

Model	θ_1	θ_2
DICE99	-0.00450	0.00350
DICE2007	0.00000	0.00284

Table 2. Parameter values for the economic and non-economic sectors for EU and regional weights from PAGE2002.

	Mean	Min	Mode	Max
Economic impact in EU (%GDP for 2.5°C)	0.5	-0.1	0.6	1
Non-economic impact EU (%GDP for 2.5°C)	0.73	0	0.7	1.5
Impact function exponent	1.76	1	1.3	3
Eastern Europe & FSU weights factor	-0.35	-1	-0.25	0.2
USA weights factor	0.25	0	0.25	0.5
China weights factor	0.2	0	0.1	0.5
India weights factor	2.5	1.5	2	4
Africa weights factor	1.83	1	1.5	3
Latin America weights factor	1.83	1	1.5	3
Other OECD weights factor	0.25	0	0.25	0.5

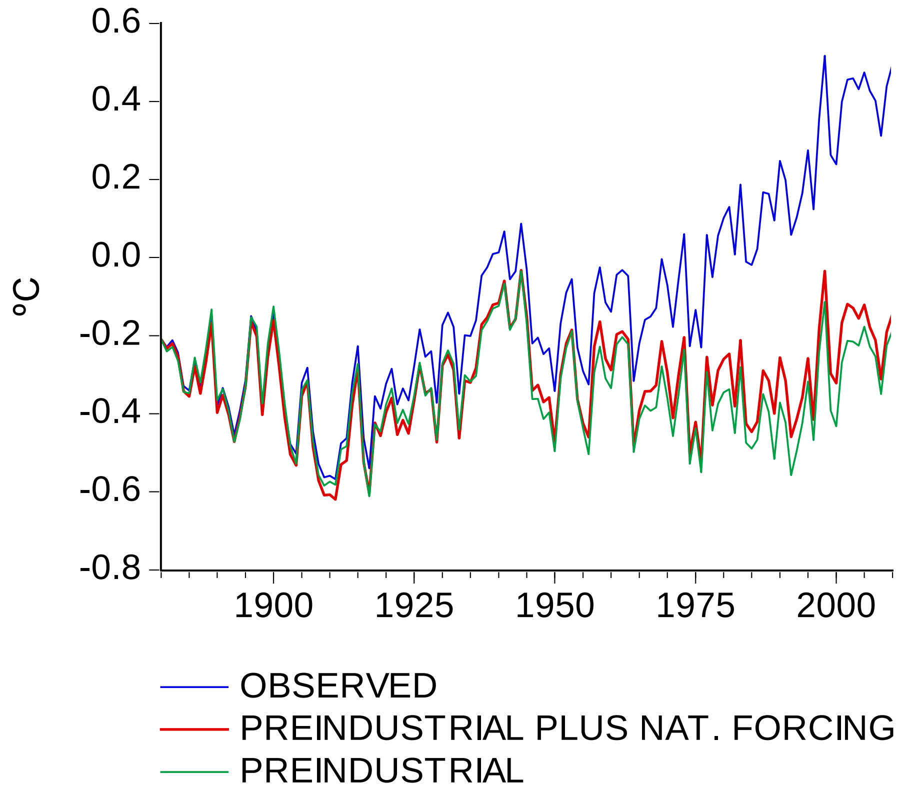

Figure 1. Observed global temperatures, $\tilde{t}_t$ (preindustrial forcing) and $\tilde{t}_t^*$ (preindustrial anthropogenic forcing) for the period 1880-2010.

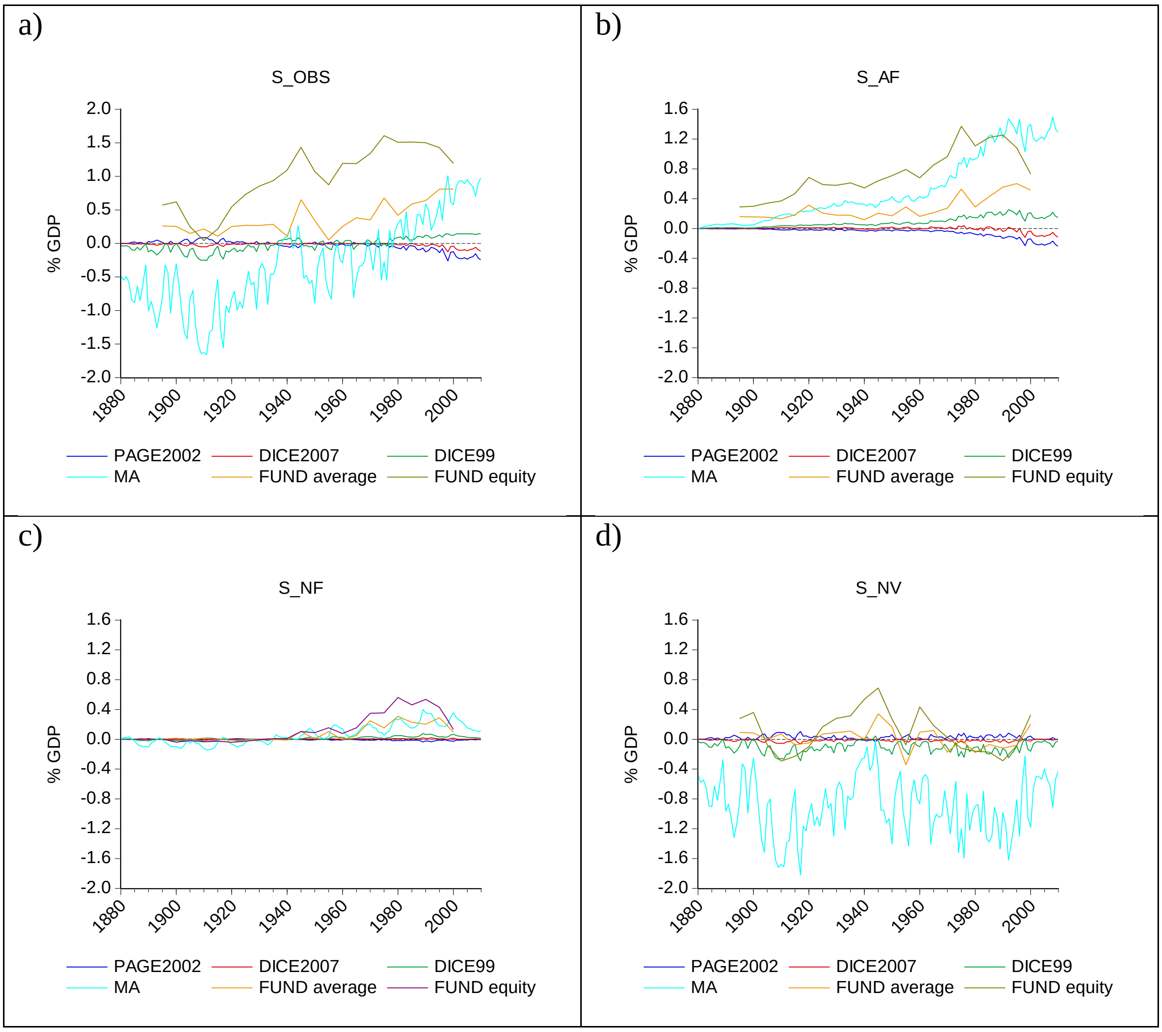

Figure 2. Infrapolated economic costs for the 20th century obtained from S_OBS (panel a), S_AF (panel b), S_NF (panel c) and S_NV (panel d).

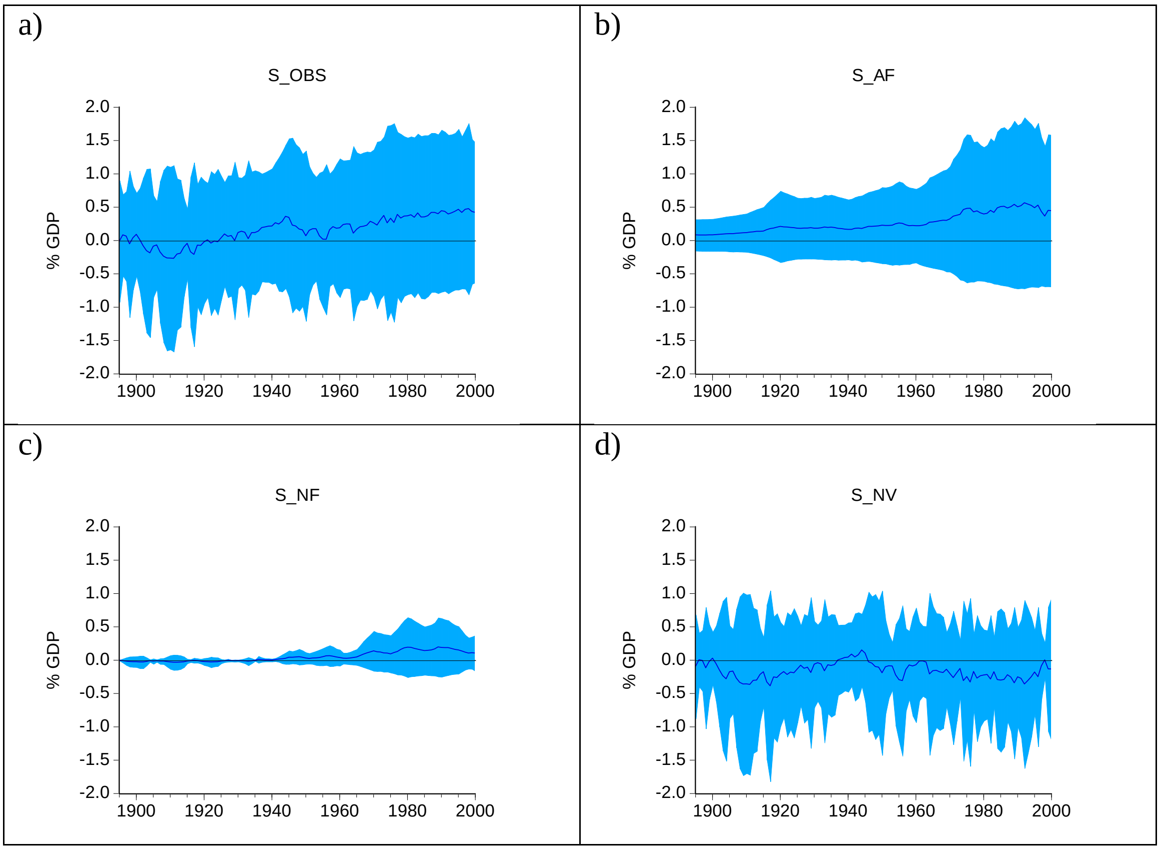

Figure 3. Multimodel mean of the infrapolated economic costs for the 20th century. S_OBS (panel a), S_AF (panel b), S_NF (panel c) and S_NV (panel d).

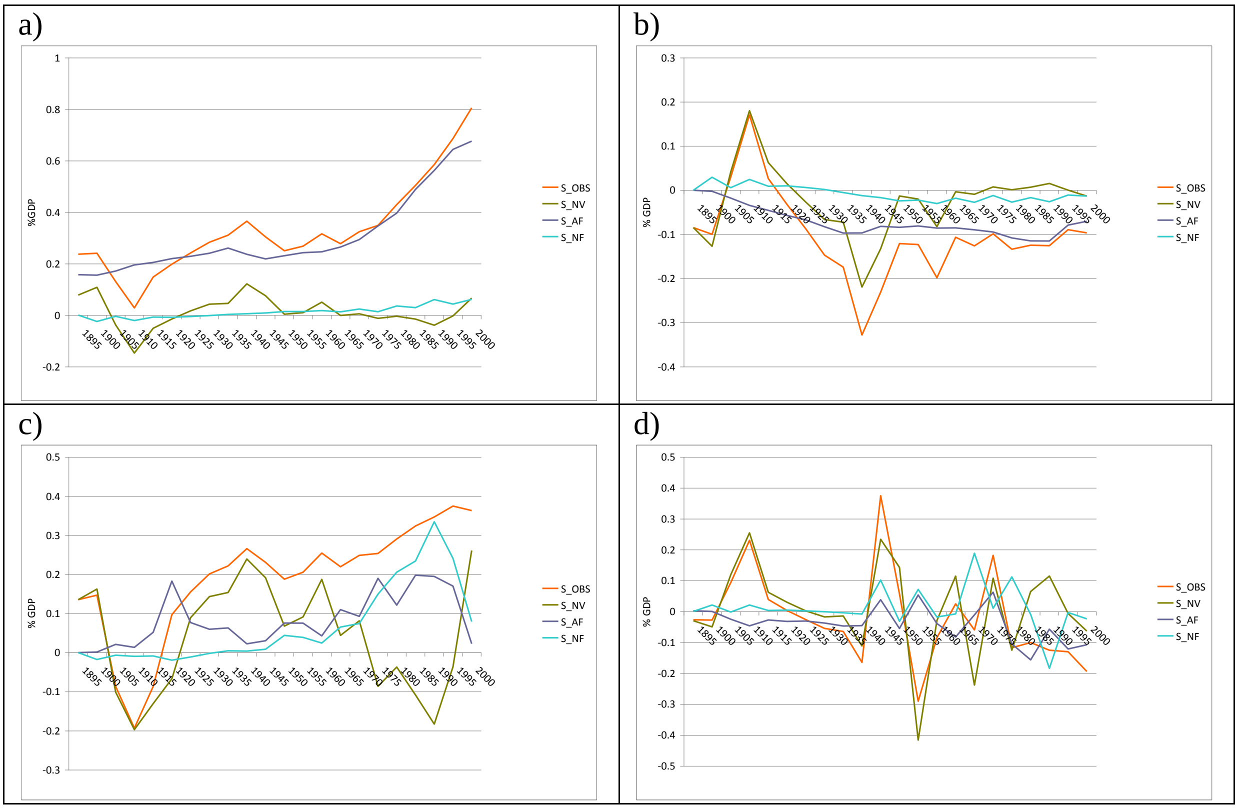

Figure 4. Infrapolated economic costs for the 20th century per sector: panel a) agriculture, panel b) water resources, panel c) energy and panel d) health.

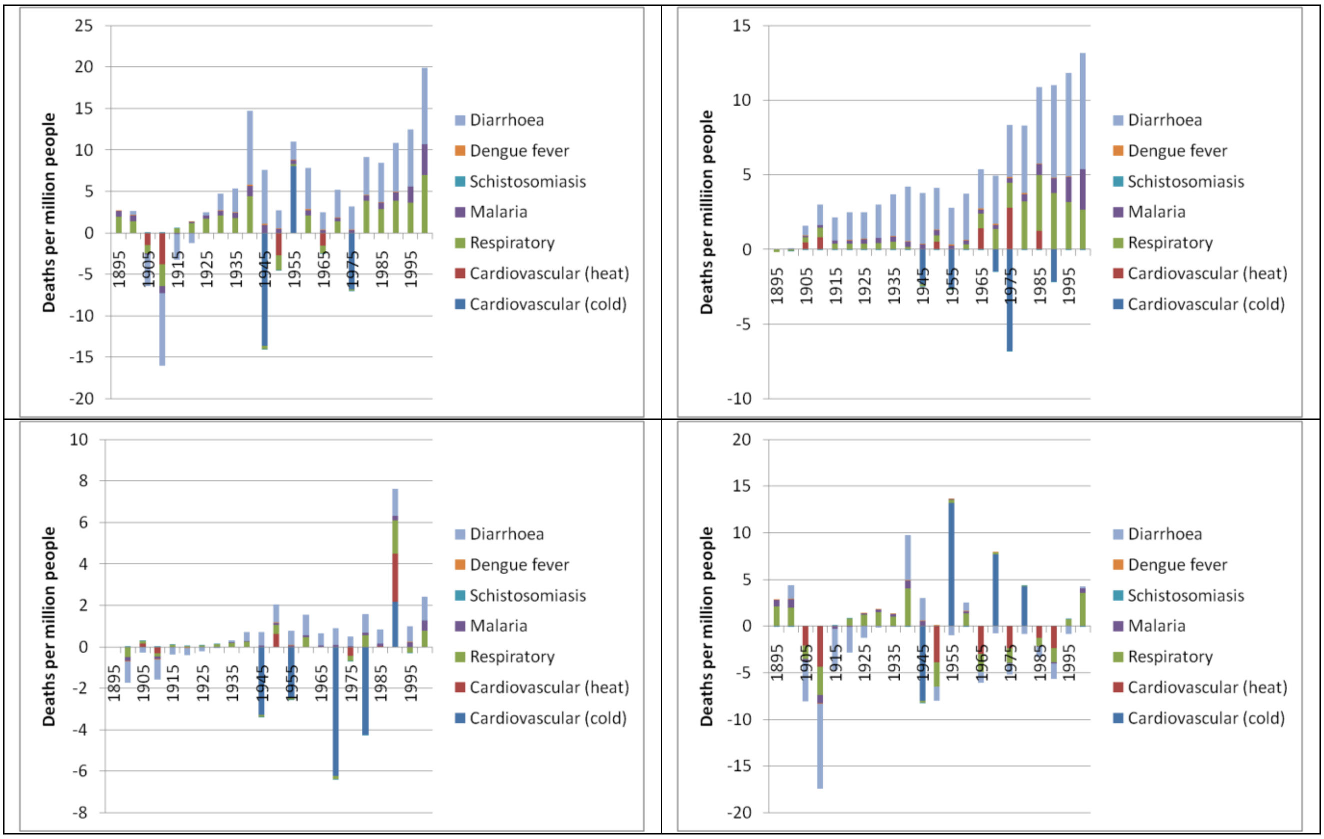

Figure 5. Infrapolated deaths per million people during the 20th century per disease obtained from S_OBS (panel a), S_AF (panel b), S_NF (panel c) and S_NV (panel d).

Supplementary material

Supplementary Figures

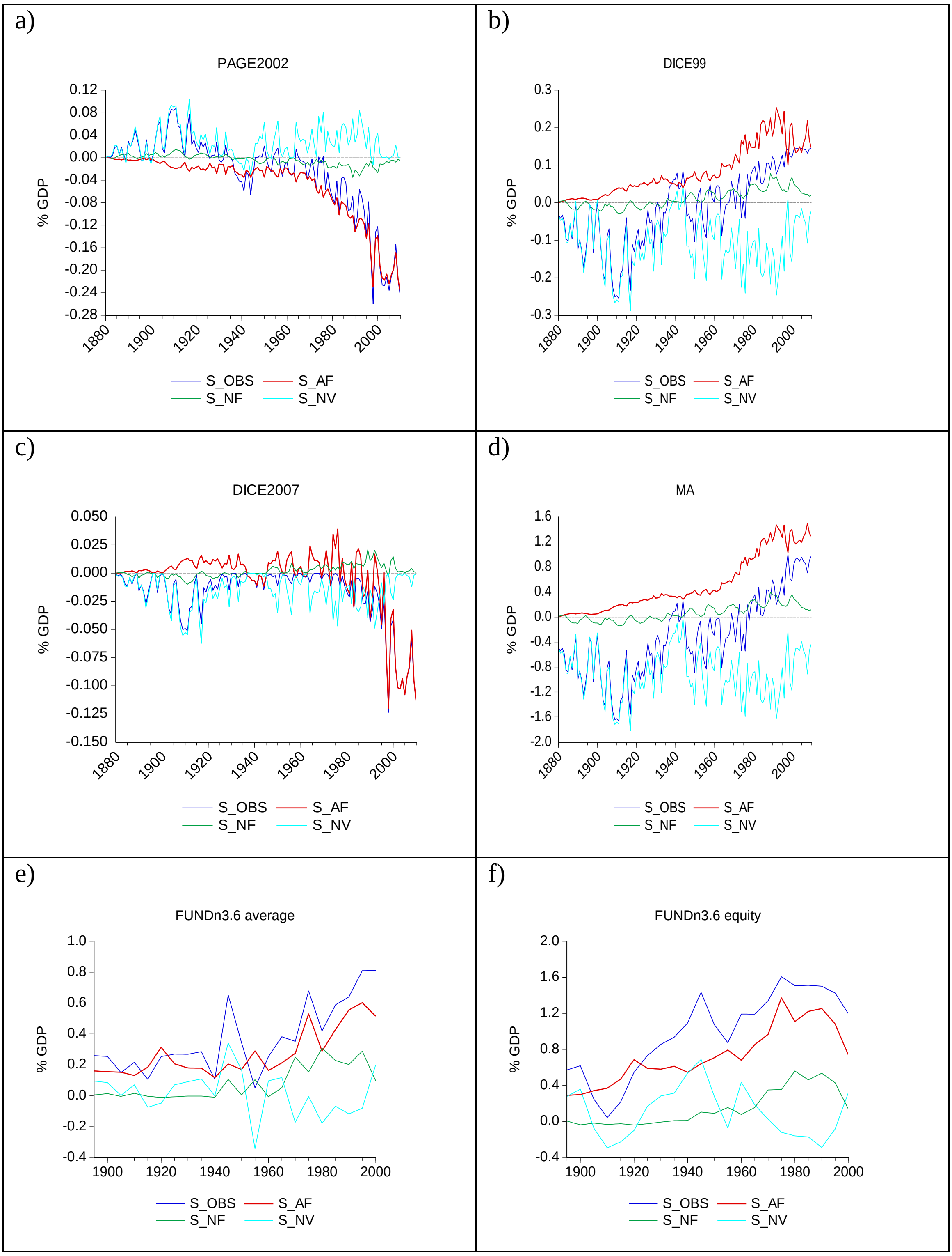

Figure A1. Infrapolated economic costs for the 20th century per IAM. Panel a) PAGE2002, panel b) DICE99, panel c) DICE2007, panel d) MA, panel e) FUNDn3.6 average and panel f) FUNDn3.6 equity.

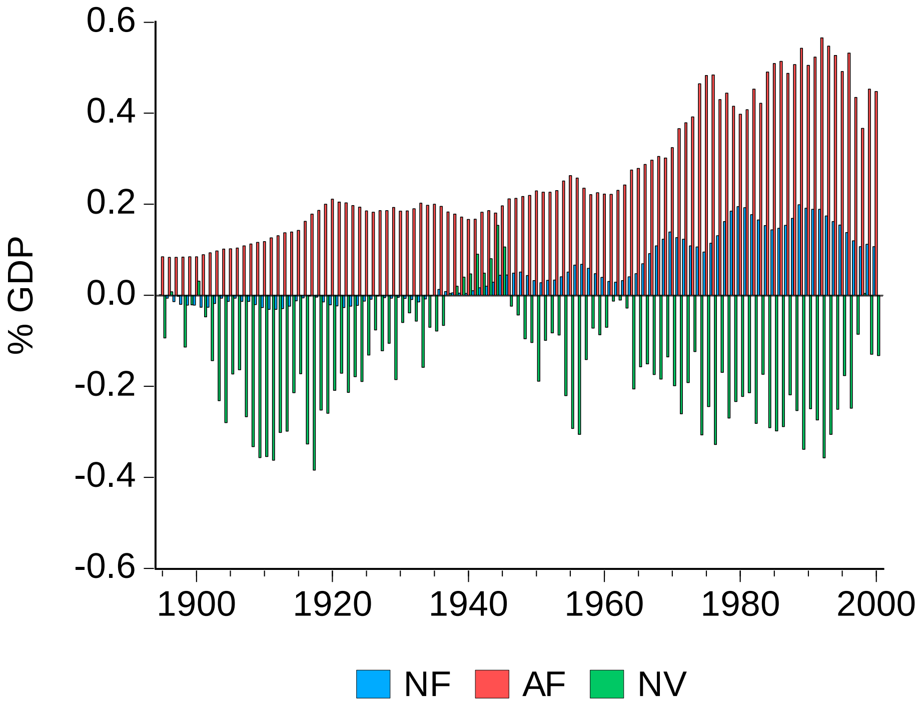

Figure A2. Multimodel means of the infrapolated economic costs attributed to natural forcing (NF), anthropogenic forcing (AF) and natural variability (NV).

Supplementary Tables

Table A1. Correlation coefficients between the estimated impacts from the preindustrial scenario and AMO, SOI, NAO and PDO.

	DICE99	DICE2007	MA	PAGE2002	FUND average	FUND equity
AMO	0.70 (0.000)	-0.65 (0.000)	0.70 (0.000)	-0.68 (0.000)	0.38 (0.097)	0.77 (0.000)
NAO	-0.24 (0.012)	0.23 (0.017)	-0.24 (0.012)	0.24 (0.011)	0.16 (0.506)	-0.19 (0.428)
SOI	-0.30 (0.002)	0.31 (0.001)	-0.29 (0.002)	0.31 (0.001)	0.18 (0.452)	0.10 (0.673)
PDO	0.21 (0.025)	-0.18 (0.061)	0.22 (0.023)	-0.20 (0.032)	-0.05 (0.829)	-0.06 (0.817)

P-values in parentheses.

Table A2. Regression models for S_NV_{it} based on key variability modes and the persistence of impacts.

S_NV_{it}	c	α	δ_1	δ_2	γ	R^2
DICE99	-0.0638 **(-7.41)**	0.4147 **(5.55)**	0.2500 **(8.27)**	-0.1041 **(-2.92)**	-0.0174 **(-4.75)**	0.65
DICE2007	-0.0099 **(-7.06)**	0.4220 **(5.68)**	0.0463 **(6.87)**	-0.0169 **(-2.24)**	-0.0917 **(-4.71)**	0.66
MA	-0.5240 **(-7.68)**	0.4220 **(5.68)**	1.3471 **(8.38)**	-0.5711 **(-3.00)**	-0.0917 **(-4.71)**	0.66
PAGE2002	0.0160 **(6.79)**	0.3941 **(5.21)**	-0.0925 **(-7.83)**	0.0387 **(2.85)**	0.0070 **(4.88)**	0.63
FUND average	0.0311 (1.01)	--	0.3917 *(1.89)*	--	--	0.15
FUND equity	0.1595 **(3.91)**	--	1.4678 **(5.35)**	--	--	0.59

Bold and italic figures indicate statistical significance at the 5% and 10 levels. t-statistics are given in parenthesis.

Table A3. Misspecification testing for the models for S_NV_{it} based on key variability modes and the persistence of impacts.

Misspecification test	DICE99	DICE2007	PAGE2002	MA	FUND average	FUND equity
RESET (F-statistic)						
1	0.399 (0.529)	1.887 (0.062)	0.149 (0.700)	0.961 (0.329)	0.545 (0.469)	1.028 (0.317)
2	0.218 (0.805)	2.355 (0.099)	0.077 (0.926)	0.481 (0.619)	0.311 (0.737)	1.096 (0.355)
3	0.245 (0.865)	2.123 (0.101)	0.078 (0.972)	0.380 (0.768)	0.241 (0.866)	0.692 (0.569)
4	0.590 (0.670)	2.117 (0.083)	0.911 (0.460)	0.673 (0.612)	0.401 (0.805)	0.602 (0.667)
Jarque-Bera						
	1.064 (0.588)	6.654 **(0.036)**	2.904 (0.234)	1.055 (0.590)	9.54 **(0.009)**	0.509 (0.775)
Ljung-Box (Q-statistic)						
1	0.094 (0.759)	0.023 (0.879)	0.016 (0.900)	0.148 (0.700)	0.523 (0.470)	2.564 (0.109)
2	1.813 (0.404)	3.877 (0.144)	3.122 (0.210)	1.431 (0.489)	2.809 (0.246)	4.595 (0.101)
3	1.825 (0.609)	3.928 (0.269)	3.140 (0.371)	1.433 (0.698)	5.270 (0.153)	6.151 (0.104)
4	7.631 (0.106)	8.099 (0.088)	8.539 (0.074)	7.361 (0.118)	5.324 (0.256)	6.152 (0.188)
White (F-statistic)						
	1.252 (0.249)	1.620 (0.084)	1.580 (0.095)	1.143 (0.329)	0.724 (0.498)	0.442 (0.649)
McLeod-Li						
1	0.064 (0.800)	2.857 (0.091)	1.080 (0.299)	0.021 (0.885)	0.359 (0.549)	0.889 (0.346)
2	0.193 (0.908)	4.408 (0.110)	1.334 (0.513)	0.376 (0.829)	2.530 (0.282)	2.180 (0.336)
3	0.224 (0.974)	7.485 (0.058)	2.430 (0.488)	0.377 (0.945)	2.610 (0.456)	2.569 (0.463)
4	0.708 (0.950)	7.743 (0.101)	2.664 (0.616)	0.853 (0.931)	3.099 (0.541)	3.238 (0.519)
Breusch-Godfrey (F-statistic)						
1	0.277 (0.599)	0.081 (0.777)	0.048 (0.827)	0.432 (0.512)	0.417 (0.526)	2.184 (0.156)
2	2.161 (0.120)	2.564 (0.081)	2.730 (0.069)	1.980 (0.143)	1.299 (0.297)	3.288 (0.061)
3	1.481 (0.223)	1.700 (0.171)	1.834 (0.145)	1.388 (0.250)	1.230 (0.330)	2.071 (0.142)
4	2.363 (0.057)	1.901 (0.115)	2.328 (0.060)	2.397 (0.054)	0.880 (0.498)	1.492 (0.251)

ARCH (F-statistic)						
1	0.062 (0.804)	2.803 (0.097)	1.046 (0.309)	0.020 (0.888)	0.278 (0.605)	0.713 (0.409)
2	0.091 (0.913)	1.861 (0.160)	0.582 (0.560)	0.180 (0.836)	0.864 (0.439)	0.679 (0.520)
3	0.082 (0.970)	1.907 (0.132)	0.668 (0.574)	0.137 (0.938)	0.502 (0.686)	0.433 (0.732)
4	0.174 (0.951)	1.637 (0.169)	0.569 (0.686)	0.226 (0.924)	0.536 (0.712)	0.581 (0.682)
CUSUM	Stability	Stability	Stability	Stability	Stability	Stability
CUSUMQ	Stability	Stability	Stability	Stability	**Instability**	Stability

Table A4. Long-run response of estimated impacts to one standard deviation shocks to AMO and SOI as a percentage of GDP.

	DICE99	DICE2007	MA	PAGE2002	FUND average	FUND equity
AMO	0.046 [0.635]	-0.009 [-0.587]	0.248 [0.638]	-0.017 [-0.602]	0.058 [0.390]	0.216 [0.767]
SOI	-0.033 [-0.451]	0.007 [0.444]	-0.174 [-0.449]	0.014 [0.470]	--	--

Numbers in brackets represent the response of the estimated impacts as a fraction of their standard deviation.