5 Estimating the global impacts of climate variability and change during the 20th century

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 fluctuated between negative and positive. 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 percent 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 estimated economic impacts at the end of the 20th century, producing larger impacts than those of low-frequency 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.

5.1 Introduction

This paper is based on Estrada F., Tol R.S.J. Estimating the global impacts of climate variability and change during the 20th century. Submitted for publication.

Integrated assessment models (IAMs) 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. Recently, Tol (2013) applied the FUND model in its national version for projecting the impacts of climate change during the 20th century using observed global temperatures averaged over 5-year periods. 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.

However, even when filtering out part of the high-frequency variability in observed global temperatures (e.g., by averaging over periods, running means or filters), the underlying climate change signal is still distorted by the intrinsic low-frequency variability of the climate system and the different contributions of natural and anthropogenic forcing factors to this signal cannot be identified (e.g., Wu et al., 2011; Swanson et al., 2009; Estrada et al., 2013b). A better understanding of the economic impacts of the observed climate during the 20th century and of the relative importance of their anthropogenic and natural drivers can provide relevant information for policy-making, socioeconomic research and the society at large. 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 estimated impacts of climate change into their anthropogenic and natural components.

IAMs are widely used for advising climate policy and are one of the few available tools for analyzing the economics of climate change at the global level in an internally consistent manner (e.g., Nordhaus, 2011; Parson and Fisher-Vanden, 1997). However, given the large complexity of the systems and interactions these models are designed to represent, IAMs are inevitably fraught with epistemic uncertainty, large simplifications and omissions as well as some ad-hoc and subjective constructs (Schneider, 1997; Tol and Fankhauser, 1998; Pindyck, 2013; Stern, 2013; Ackerman et al., 2009). At best, these models can only crudely represent the current fragmented and incomplete knowledge regarding climate change science and economics. Therefore, caution should be exerted when interpreting their numerical results, as they can give an illusory impression of precision when they are only gross approximations that are conditional on a large set of factors, limitations and incomplete knowledge.

A large part of the recent discussion about IAMs has focused on the behavior of their impact functions for large increases in warming and the possible occurrence of catastrophic events (e.g., Weitzman, 2009; Pindyck, 2013). Much less attention has been devoted to the uncertainty of these impact functions for small increases in global temperatures such as that observed in the 20th century or those that are commonly projected to occur during the next few decades. The analyses presented here contribute to the IAMs literature by exploring the multi-model uncertainty for such small increases in warming.

The structure of this paper is as follows: Section 5.2 describes the data, scenarios and methods that are used in this paper. The results are presented in Section 5.3 and the influence of anthropogenic and natural factors over the estimated economic impacts is discussed. Section 5.4 presents a decomposition of the anthropogenic and natural contributions to the estimated impacts at the sector level. Section 5.5 concludes.

5.2 Data and methods

5.2.1 Climate and radiative forcing databases

We use the HadCRUT3 global surface temperature anomalies time series (Brohan et al., 2006)[8]. Commonly considered to be the most important natural sources of inter-annual global and hemispheric climate variability (Trenberth, 1984; Enfield et al., 2001; Hurrell,

[8] http://hadobs.metoffice.com/hadcrut3/diagnostics/index.html. These are temperature anomalies with respect to the 1961-1990 period. For projecting the economic impacts this reference period is changed to match that of the impact functions.

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)[9] as a proxy for El Niño/Southern Oscillation; the North Atlantic Oscillation (NAO) from Climatic Research Unit[10]; the Atlantic Multidecadal Oscillation (AMO)[11] from the National Oceanic and Atmospheric Administration (NOAA); and the Pacific Decadal Oscillation (PDO)[12] 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. (2013a) the total radiative forcing (TRF) is defined as the sum of all the radiative forcing variables mentioned above.

5.2.2 Statistical methods for the attribution of climate change and temperature scenarios generation

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, 2013a). 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

[9] http://www.cgd.ucar.edu/cas/catalog/climind/soi.html
[10] http://www.cru.uea.ac.uk/cru/data/nao/
[11] http://www.esrl.noaa.gov/psd/data/timeseries/AMO/
[12] http://jisao.washington.edu/pdo/

modeling methodologies to tackle this task (e.g., IPCC, 2013a; Hasselmann, 1993; Tol and Vos, 1993; Tol and Vos, 1998; Kaufmann and Stern, 1997; Kaufmann et al., 2006a,b; Estrada et al., 2013a,b). 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:

$$T_t = \alpha + \beta TRF_t + u_t \tag{5.1}$$

$$T_t - \beta TRF_t = \alpha + u_t = \tilde{t}_t \tag{5.2}$$

$$\tilde{t}_t + \beta\left(TRF_t - RFGHG - RAER\right) = \tilde{t}_t^{\,*} \tag{5.3}$$

where T_t is the observed global temperature series and u_t are the regression residuals. Equations (5.2) and (5.3) are used to detrend and partially detrend observed global temperatures, respectively. These time series, depicted in Figure 5.1, provide alternative climate scenarios for running the selected IAMs. The first scenario, $\tilde{t}_t$ from equation (5.2), 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 (5.3), 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 (5.1), corresponds to the observed temperature records.

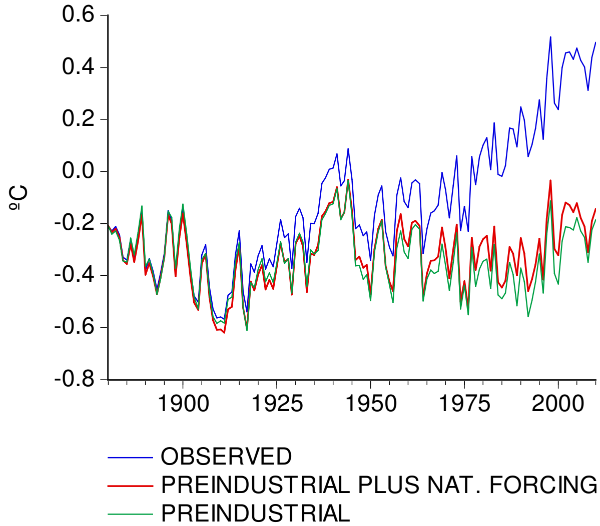

Figure 5.1. Observed global temperatures, $\tilde{t}_t$ (preindustrial forcing) and $\tilde{t}_t^*$ (preindustrial anthropogenic forcing) for the period 1880-2010.

5.2.3 Damage functions from IAMs

5.2.3.1 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) and the reference temperature value is the average of the 1961-1990 period. 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.

5.2.3.2 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:

$$D_t = \theta_1 T_t + \theta_2 T_t^2 \tag{5.4}$$

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 1900 value. For this paper we consider the DICE99 (Nordhaus and Boyer, 2000) and the DICE2007 (Nordhaus, 2008; Nordhaus, 2010). Parameterizations are shown in Table C1. 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.

5.2.3.3 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:

$$I_{t,d,r} = \alpha_{d,r} \left(\frac{\Delta T_{t,r}}{2.5} \right)^{\beta} Y_{t,r} \qquad (5.5)$$

$$D_{t,r} = \gamma_{t,r} \pi_t Y_{t,r} \qquad (5.6)$$

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 (in this case, its value in 1880); 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 (5.6) 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 (5.5) and (5.6).

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 (5.5) only. The regional weights for scaling the impact functions are those from the PAGE2002 model (reproduced in Table C2; 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/)[13]. 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

[13] 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.

climate damages during the 20th century presented here are simple averages of the regional damage functions. The updated version PAGE2009 includes significant changes in its climate, impacts, emissions and adaptation modules (Hope, 2011a,b). However, in this study we focus on the PAGE2002 since it has been used in influential studies (e.g., Stern, 2006) and has been widely discussed in the literature. Besides, PAGE2009 cannot be used without permission.

5.2.3.4 Damage function from recent literature review

Based on a literature review of all published estimates of the global costs of climate change, Tol (2009; 2014) estimates a damage function that synthesizes all findings. The damage function takes the same functional form of equation (4), but the parameters values are $\theta_1 = \text{-}0.25$ and $\theta_2 = \text{-}0.16$. This damage function is calibrated with respect to the preindustrial climate (in this case, global temperature in 1880). We will refer to this impact function as MA (for meta-analysis).

5.3 Results and discussion

In this section we present estimates of the contributions of natural and anthropogenic factors to the projected costs of observed global temperature during a period comprising the 20th century. Based on the three temperature scenarios in section 2.2, five economic impact 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 $\tilde{\tau}_t^*$. 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.

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).

5.3.1 Estimates of costs obtained from observed global temperatures

Panel a) of Figure 5.2 shows the estimated impacts 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 estimated welfare impacts. Nevertheless, as in the case of global temperature series, the 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, MA and DICE2007, by the end of the century the observed global temperature had a negative effect on welfare. For DICE99 and FUNDn3.6 the effect was positive. While DICE99, DICE2007, MA and PAGE2002 suggest that the economic impacts during the last decade are small (about -0.26% to 0.14% of global GDP), FUNDn3.6 shows considerably larger (positive) impacts reaching about 1% of GDP in 2000. FUNDn3.6 equity weighting results show the highest benefits[14]: 1.19% in 2000 and a maximum of 1.61% in the mid-1970s. Note that the magnitude of the impacts over the last three decades is unprecedented over the last century. Only in the case of DICE99 the impacts before the anthropogenic intervention became significant are larger than those estimated for the end of the 20th century.

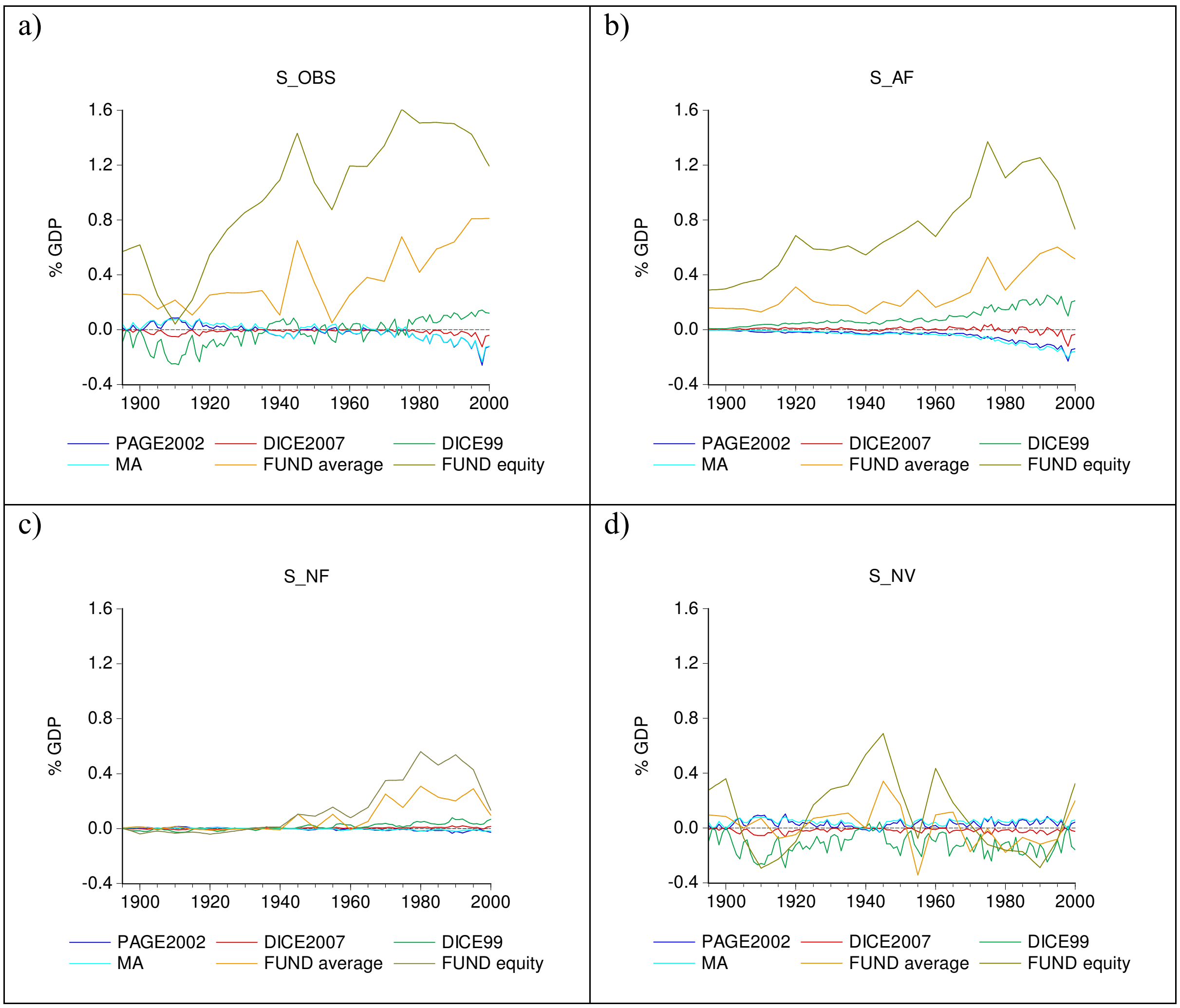

Figure 5.2. Estimated economic effects over the 20th century obtained from S_OBS (panel a), S_AF (panel b), S_NF (panel c) and S_NV (panel d).

Figure 5.3 panel a) shows the multimodel mean of S_OBS and the corresponding two standard deviation intervals representing the uncertainty in this estimate. For the

[14] According to the FUND model during the 20th century the poorer countries experienced greater benefits, primarily from CO_2 fertilization, than the richer countries and therefore the equity weighted impacts are more positive than the non-weighted average (see Tol, 2009).

estimates in Figure 5.3 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 5.3 panel a) shows a steady positive trend that leads to net benefits of about 0.30% 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 0.56%).

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

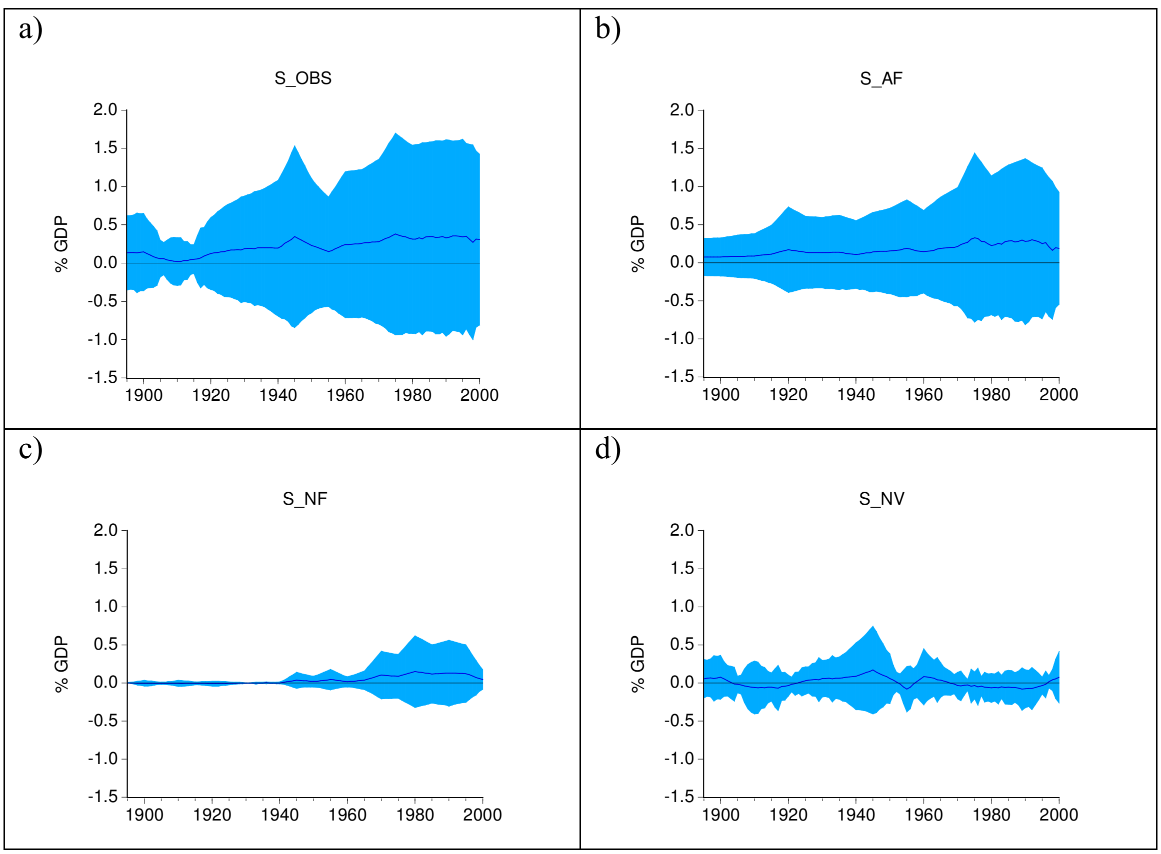

Figure 5.3. Multimodel mean of the estimated economic effects over the 20th century. S_OBS (panel a), S_AF (panel b), S_NF (panel c) and S_NV (panel d).

5.3.2 Contributions of the natural and anthropogenic radiative forcing to the estimated impacts from the observed global temperatures

Panels a), b) and c) of Figure 5.2 show that the trending behavior of the estimated 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 5.3.3 for an analysis of the natural variability impacts).

S_AF (Figure 5.2b) describes quite closely the general nonlinear trend in S_OBS. Although estimates of the different IAMs 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 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 at the end of the century are, for most models, about one order of magnitude lower than those associated to anthropogenic forcing (see Figure C1 for a comparison of natural and anthropogenic contributions per model). Moreover, its impacts where practically zero until the late 1940s.

According to PAGE2002, MA, DICE99 and DICE2007, the welfare 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 -0.23% in PAGE2002 to 0.24% in DICE99). This figure is considerably larger for FUNDn3.6 which indicates benefits in the range of about 0.60% to 1.37%. 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 0.19% of GDP in 2000 after reaching about 0.33% in the 1990's (Figure 5.3 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 5.2. 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 0.91, 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 estimated 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, increases in radiative forcing from natural and anthropogenic origin should not produce opposite effects (trends), but reinforce the impacts in the same direction instead.

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 (mainly solar) produced small but increasing benefits reaching around 0.04% of GDP in 2000. 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 estimated economic impacts, producing similar or larger impacts than those of low-frequency natural variability.

5.3.3 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 until the last three decades of the 20th century and are much larger than those that can be associated to the observed natural forcing (Figure 5.2d). The main difference is that the natural variability impacts follow low-frequency oscillations instead of sustained trends. Only in the case of DICE2007 the impacts of natural variability are strictly negative, while for DICE99 are mostly negative and for PAGE2002 and MA they are mainly positive. These non-monotonic impacts are dominated 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 C3, S_NV is highly and 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 (AMO and SOI) were found to significantly contribute to explain the variability of the estimated costs. The following specification was found to be statistically adequate for most of the IAMs projections[15] (see Tables C4 and C5 for parameter estimates and misspecification tests):

$$S\_NV_{it} = c + \alpha S\_NV_{it-1} + \delta_1 AMO_t + \delta_2 AMO_{t-1} + \gamma SOI_t + \varepsilon_t \tag{5.7}$$

where S_NV_{it} are the estimated costs for model $i = 1,...,5$. This regression model has a similar specification to those in Estrada et al. (2013b) and Estrada and Perron (2012) for global temperature series. In all cases AMO and SOI are highly significant, except for the estimates obtained with FUNDn3.6 where only AMO is significant. This result probably has to do with the limited number of observations (and time-step) in the projections 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 impact functions of PAGE2002, DICE99, DICE2007 are simple power functions of temperature, and results 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 S_NV_{it}: a one standard deviation shock to AMO produces a cumulative long-run response of about 0.60 times the standard deviation of S_NV_{it} (positive for DICE99 and DICE2007, negative for PAGE2002 and MA) while a shock of one standard deviation to SOI generates a long-term response 0.45 times the standard deviation of S_NV_{it} (negative for DICE99 and DICE2007, the opposite occurs with PAGE2002. See Table C6). 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 S_NV_{it}.

[15] 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. In the case of MA, SOI was omitted due to functional form problems.

The multimodel mean of S_NV is mainly negative and shows a low-frequency oscillatory pattern similar to AMO (correlation coefficient of 0.60) varying in a range of -0.08% to 0.17% 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 impacts. 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.

5.4 The anthropogenic and natural components of the estimated impacts per sector.

As mentioned above, FUNDn3.6 allows us to investigate the projected impacts separately for each sector. Figure 5.4 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 5.4 panel a). This sector is 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 one 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.

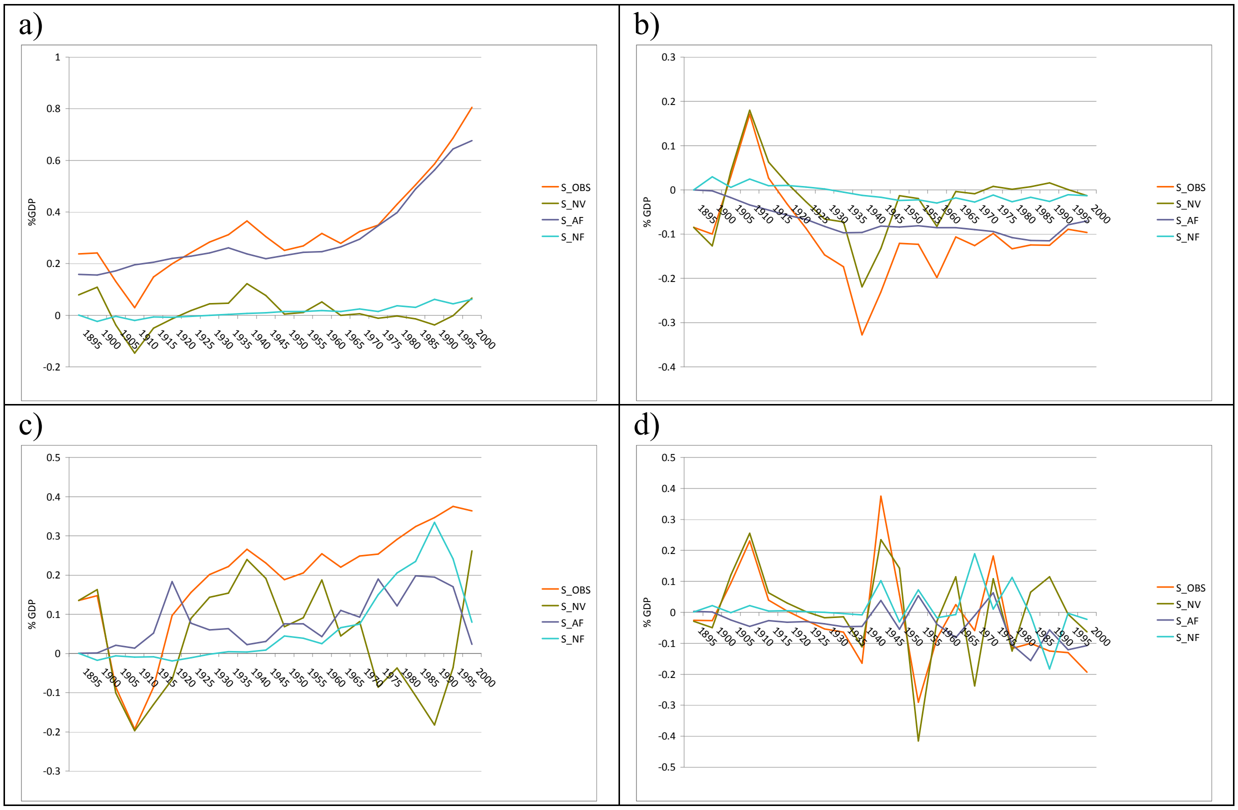

Figure 5.4. Estimated economic effects over the 20th century per sector: panel a) agriculture, panel b) water resources, panel c) energy and panel d) health.

In the water resources sector, both anthropogenic and natural forcing imparted a trend on losses (Figure 5.4 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 low-frequency natural variability is considerably larger compared to the individual or joint contributions of natural and anthropogenic factors.

Low-frequency natural variability plays a dominant role on the costs of the two remaining sectors (Figure 5.4 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 5.4 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 5.4 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 5.5, the anthropogenic contribution to the estimated number of deaths per million people related to climate is dominant (panel b). As shown in panels a) and b) of Figure 5.5, the trend in the estimated 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.

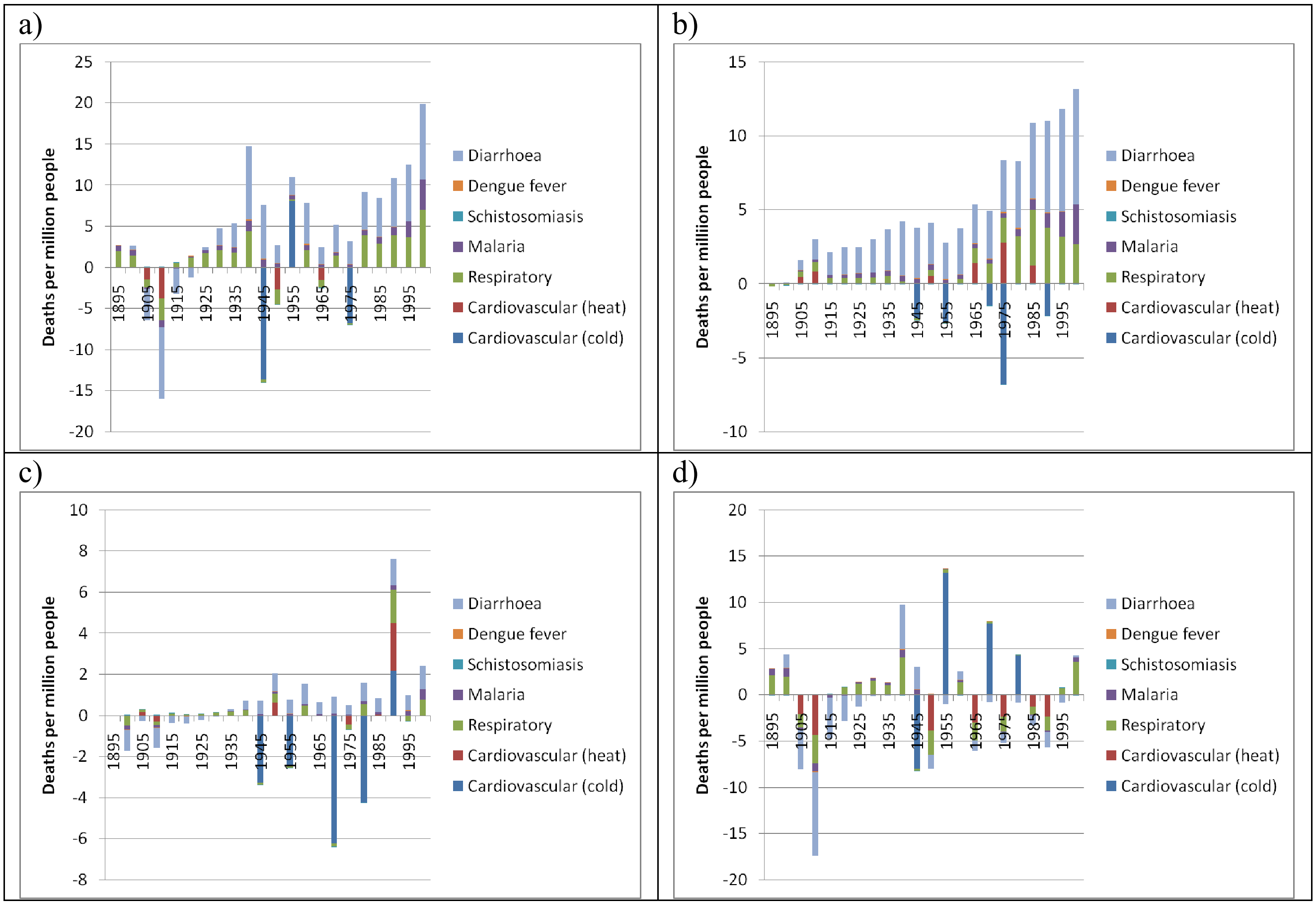

Figure 5.5. Estimated deaths per million people during the 20th century per disease obtained from S_OBS (panel a), S_AF (panel b), S_NF (panel c) and S_NV (panel d).

5.5 Discussion and conclusion

The decomposition of the estimated impacts of observed global temperature reveals a clear anthropogenic influence that at the end of the century becomes even larger in magnitude than the 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 intra- and inter-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. These non monotonic impacts are mostly determined by the low-frequency variability modes and persistence of the climate system.

IAMs do not agree in the sign nor the magnitude of the impacts for small changes in temperature. In the case of FUNDn3.6 and DICE99 the observed warming has brought benefits to the global GDP, while according to DICE2007, MA and PAGE2002 the opposite is true. With the exception of FUNDn3.6, which estimates the magnitude of the impacts in about 1% of GDP at the end of the 20th century, the rest of the IAMs considered value the impacts in only a few tenths of percent.

According to the sectoral decomposition of the estimated impacts obtained by FUNDn3.6, the effects of anthropogenic forcing in agriculture account 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 to economic losses in human health and water resources. The model strongly suggests that the contribution of anthropogenic forcing to the estimated number of deaths per thousand people is dominant in the case of diarrhoea, respiratory diseases and malaria.

This chapter adds to the recent discussion regarding IAMs by illustrating the large differences in the projections obtained from model to model for small increases in temperatures. This is related to the problem of model validation which could help to improve the specification and calibration of the impact functions in IAMs, to reduce the large uncertainty characterizing these models, and to increase their credibility. However, while the assessment of the performance of other types of models (e.g., general circulation models) is straightforward 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. Until now the performance of the different IAMs has not been assessed and the validity of their projections thus remains unknown. The current lack of proper validation methods and of research efforts devoted to develop them constitutes a significant challenge for the advancement of integrated assessment models.

Appendix C

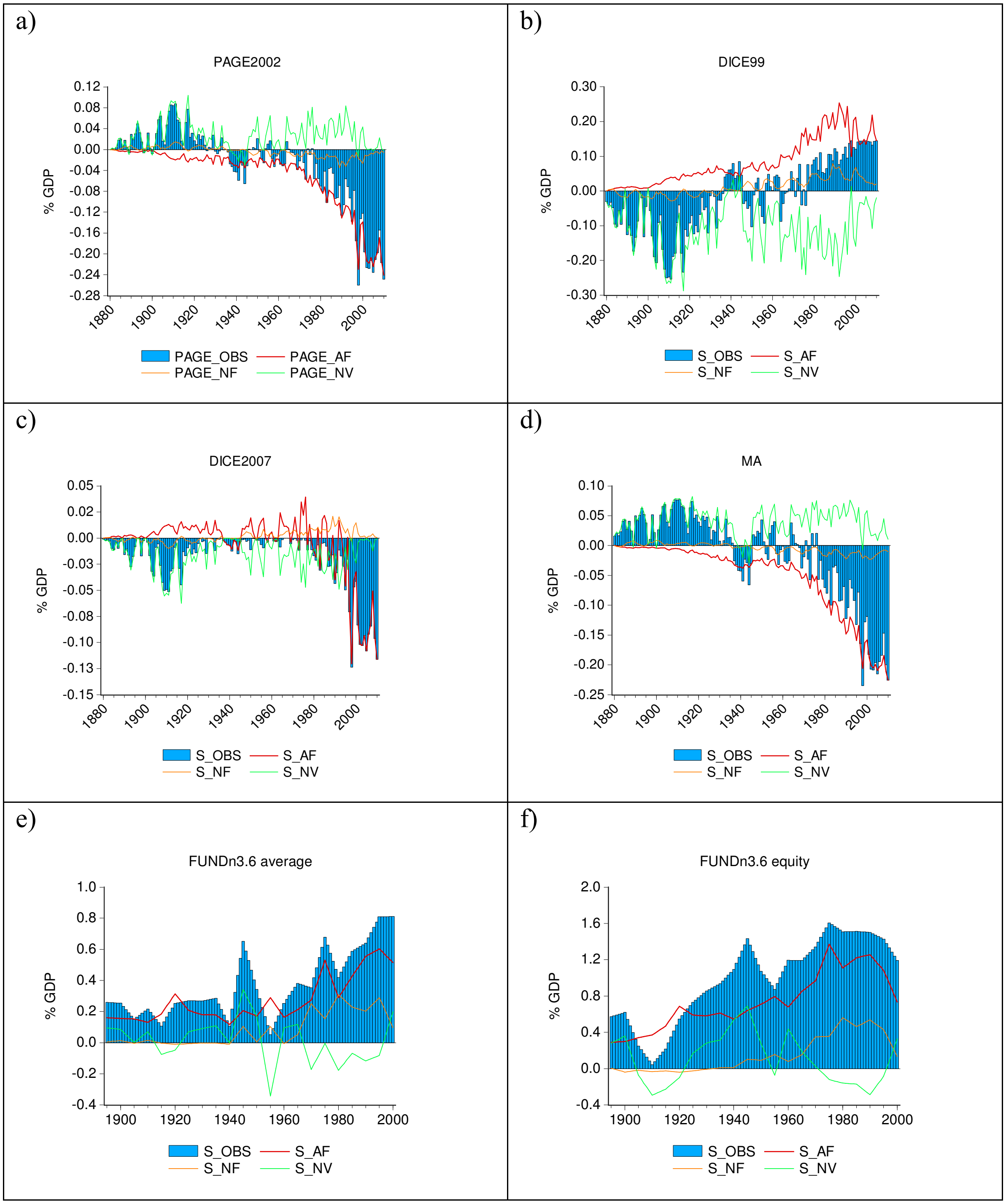

Figure C1. Estimated economic effects for the 20th century per IAM. Panel a) PAGE2002, panel b) DICE99, panel c) DICE2007, panel d) MA, panel e) FUNDn3.6 average and panel f) FUNDn3.6 equity.

Table C1. 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 C2. 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

Table C3. 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)	0.28 (0.004)	0.31 (0.001)	0.18 (0.452)	0.10 (0.673)
PDO	0.21 (0.025)	-0.18 (0.061)	-0.23 (0.015)	-0.20 (0.032)	-0.05 (0.829)	-0.06 (0.817)

P-values in parenthesis.

Table C4. 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)**	0.3632 **(4.66)**	0.0463 **(6.87)**	-0.0169 **(-2.24)**	-0.0374 **(-4.61)**	0.58
MA	0.0211 **(-6.34)**	0.4721 **(6.04)**	-0.0915 **(-9.34)**	0.0518 **(4.46)**	**--**	0.62
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 C5. 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)	1.498 (0.137)	0.545 (0.469)	1.028 (0.317)
2	0.218 (0.805)	2.355 (0.099)	0.077 (0.926)	1.114 (0.332)	0.311 (0.737)	1.096 (0.355)
3	0.245 (0.865)	2.123 (0.101)	0.078 (0.972)	1.041 (0.377)	0.241 (0.866)	0.692 (0.569)
4	0.590 (0.670)	2.117 (0.083)	0.911 (0.460)	1.003 (0.409)	0.401 (0.805)	0.602 (0.667)
Jarque-Bera						
	1.064 (0.588)	6.654 **(0.036)**	2.904 (0.234)	1.483 (0.476)	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)	0.123 (0.726)	0.523 (0.470)	2.564 (0.109)
2	1.813 (0.404)	3.877 (0.144)	3.122 (0.210)	0.504 (0.777)	2.809 (0.246)	4.595 (0.101)
3	1.825 (0.609)	3.928 (0.269)	3.140 (0.371)	0.829 (0.843)	5.270 (0.153)	6.151 (0.104)
4	7.631 (0.106)	8.099 (0.088)	8.539 (0.074)	3.876 (0.423)	5.324 (0.256)	6.152 (0.188)
White (F-statistic)						
	1.252 (0.249)	1.620 (0.084)	1.580 (0.095)	1.230 (0.283)	0.724 (0.498)	0.442 (0.649)
McLeod-Li						
1	0.064 (0.800)	2.857 (0.091)	1.080 (0.299)	1.404 (0.236)	0.359 (0.549)	0.889 (0.346)
2	0.193 (0.908)	4.408 (0.110)	1.334 (0.513)	1.520 (0.468)	2.530 (0.282)	2.180 (0.336)
3	0.224 (0.974)	7.485 (0.058)	2.430 (0.488)	1.698 (0.637)	2.610 (0.456)	2.569 (0.463)
4	0.708 (0.950)	7.743 (0.101)	2.664 (0.616)	1.741 (0.783)	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)	0.525 (0.470)	0.417 (0.526)	2.184 (0.156)
2	2.161 (0.120)	2.564 (0.081)	2.730 (0.069)	0.281 (0.756)	1.299 (0.297)	3.288 (0.061)
3	1.481 (0.223)	1.700 (0.171)	1.834 (0.145)	0.299 (0.826)	1.230 (0.330)	2.071 (0.142)
4	2.363 (0.057)	1.901 (0.115)	2.328 (0.060)	1.041 (0.389)	0.880 (0.498)	1.492 (0.251)
ARCH (F-statistic)						
1	0.062 (0.804)	2.803 (0.097)	1.046 (0.309)	1.360 (0.246)	0.278 (0.605)	0.713 (0.409)
2	0.091 (0.913)	1.861 (0.160)	0.582 (0.560)	0.800 (0.451)	0.864 (0.439)	0.679 (0.520)
3	0.082 (0.970)	1.907 (0.132)	0.668 (0.574)	0.590 (0.623)	0.502 (0.686)	0.433 (0.732)
4	0.174 (0.951)	1.637 (0.169)	0.569 (0.686)	0.434 (0.784)	0.536 (0.712)	0.581 (0.682)
CUSUM	Stability	Stability	Stability	Stability	Stability	Stability
CUSUMQ	Stability	Stability	Stability	Stability	**Instability**	Stability

Bold figures indicate statistical significance at the 5% level. P-values are given in parenthesis.

Table C6. 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]	-0.014 [-0.598]	-0.017 [-0.602]	0.058 [0.390]	0.216 [0.767]
SOI	-0.033 [-0.451]	0.007 [0.444]	--	0.014 [0.470]	--	--

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