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The impact of climate conditions on economic production. Evidence from a global panel of regions[☆]

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ABSTRACT

We present a novel data set of subnational economic output, Gross Regional Product (GRP), for more than 1500 regions in 77 countries that allows us to empirically estimate historic climate impacts at different time scales. Employing annual panel models, long-difference regressions and cross-sectional regressions, we identify effects on productivity levels and productivity growth. We do not find evidence for permanent growth rate impacts but we find robust evidence that temperature affects productivity levels considerably. An increase in global mean surface temperature by about 3.5°C until the end of the century would reduce global output by 7–14% in 2100, with even higher damages in tropical and poor regions. Updating the DICE damage function with our estimates suggests that the social cost of carbon from temperature-induced productivity losses is on the order of 73–142$/tCO$_2$ in 2020, rising to 92–181$/tCO$_2$ in 2030. These numbers exclude non-market damages and damages from extreme weather events or sea-level rise.

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1. Introduction

Anthropogenic climate change due to greenhouse gas emissions has been the foremost driver of global warming since industrialization (IPCC, 2013, pp. 44–45). Without additional measures to reduce carbon emissions and to decouple economic growth from emissions, global mean surface temperature is likely to increase by 2.6–4.8 °C within this century (IPCC, 2013, p. 60). Extreme weather events are expected to increase in frequency and intensity as global climate change accelerates (Rahmstorf and Coumou, 2011; IPCC-SREX, 2012). Temperature fluctuations and weather extremes have been shown to have major impacts on economic activity (Dell et al., 2014; Burke et al., 2015), human well-being (Patz et al., 2005; Hsiang et al., 2013; Deschenes, 2014) and functioning of ecosystems (Hoegh-Guldberg and Bruno, 2010; IPCC, 2014). For the design of optimal policies to mitigate and cope with climate change, as well as for the design of international agreements to foster cooperation on global emission reductions, a solid understanding of the costs and benefits of climate change mitigation is necessary. Integrated assessment models that aim to calculate optimal climate policies build on the concept of a damage function. A damage function is fit to aggregated sectoral and location-specific damage estimates that are extrapolated to the global scale (Nordhaus and Boyer, 2000). Attempts to quantify the economic impacts of climate change, however, show large variability in damage estimated across regions and sectors. For example, impacts of 5 °C warming have been estimated to reduce global Gross Domestic Product (GDP) by 0–20 percent (Stern, 2008). The poor theoretical and empirical foundation for such damage functions has been widely criticized (Pindyck, 2013; Farmer et al., 2015; Moore and Diaz, 2015; Stern, 2016; National Academies of Sciences E. and Medicine, 2017).

A rapidly growing body of empirical research aims to improve these damage estimates (see e.g. Carleton and Hsiang (2016) or Auffhammer (2018) for recent reviews). Early empirical works on climate and growth (Sachs and Warner, 1997a,b; Nordhaus, 2006) used cross-sectional regression analysis, which is subject to omitted variable bias (Hsiang, 2016). This can be particularly problematic as economic performance is strongly dependent on political and economic institutions (North, 1987; Acemoglu et al., 2005). Climatic conditions, in turn, may have affected the quality of political and economic institutions during and after colonialization (Acemoglu et al., 2001). Thus, cross-sectional regressions can lead to biased estimates of the effect of the current climate on current growth, as the relationship between institutions and historical climate conditions (which are highly correlated to current climate conditions) is omitted.

A more recent strand of literature uses fixed effects panel regression models to explore the relationships between weather shocks, human activity and economic outcomes based on panel data (Dell et al., 2014; Kolstad and Moore, 2019). These models are less prone to omitted variable bias as they control for unobserved time-invariant group heterogeneity, including, for example, differences in institutions. They have been applied to analyze the relationship between temperature and growth (Dell et al., 2009, 2012; Burke et al., 2015; Diffenbaugh and Burke, 2019), labor productivity (Deryugina and Hsiang, 2014), human capital (Graff Zivin and Neidell, 2014; Graff Zivin et al., 2018), energy demand (Auffhammer and Mansur, 2014; Wenz et al., 2017) and crop yields (Schlenker and Roberts, 2009; Chen et al., 2016). These works provide insights on potential impacts of future climate change. In some cases, much higher economic losses are predicted from anthropogenic warming than had been estimated by previous studies using integrated assessment models (Burke et al., 2015).

The strength of fixed effects panel regression techniques lies in their ability to avoid the omitted variable bias. Their weakness lies in their focus on short-term, weather-related shocks rather than variability in long-term climate conditions. The differentiation between short-term impacts, extreme events and long-term impacts is important, as economies and societies may be better equipped to respond to long-term changes than to short-term changes or to extreme events by investing in adaptation. Comparing cross-sectional and panel estimates, Dell et al. (2009) suggest that adaptation reduces half of the negative impacts of temperature shocks.

Over the last few years, new 'hybrid' approaches have been proposed that seek to exploit different sources of variation in panel data with the aim of estimating climate damages while still controlling for unobservable confounding variables (see Kolstad and Moore (2019) or Auffhammer (2018) for a thorough discussion). For instance, Burke and Emerick (2016) use a long difference approach that regresses medium-to long-term changes in yields on medium-to long-term changes in temperature and precipitation to identify adaptation to climate change in US agriculture.

Despite these advances, a rigorous empirical analysis of climate change impacts on economic outcomes at different temporal scales is lacking in the literature. Such an analysis can help to shed light on whether temperature effects on the economy are temporary only or persistent. This so-called 'level-vs.-growth effects' question is heavily discussed in the literature as empirical findings are ambiguous (Dell et al., 2012; Burke et al., 2015; Newell et al., 2018; Diffenbaugh and Burke, 2019; Rosen, 2019). Critically, the implications for optimal climate policies and mitigation pathways are considerable if the effect of weather shocks is persistent with permanently lower levels of GDP or even lower GDP growth rates (Moyer et al., 2014; Moore and Diaz, 2015; Ricke et al., 2018; Ueckerdt et al., 2019). Channels through which weather extremes could affect growth rates of GDP are, for example, damages to capital stocks, labor supply responses or changes in investment behavior (Fankhauser and Tol, 2005; Lecocq and Shalizi, 2007; Moore and Diaz, 2015). Methodologically, existing analyses on the impact of weather shocks on GDP have been criticized for ignoring the effect of average climate conditions on the marginal response to weather and for neglecting trends in climate variables (Mendelsohn, 2016).

This paper aims to fill these research gaps by using a panel of subnational GDP data – Gross Regional Product (GRP) – that allows the depiction of local weather as well as climate conditions on various time scales across the globe (covering more than 1500 regions). We are therefore able to address several of the shortcomings of previous analyses with respect to regional scope, temporal scale and specific technical issues. In particular, our spatially and temporally highly resolved dataset allows us to explicitly differentiate between short-term weather shocks (i.e. deviations from a region's average climate conditions) and long-term climatic changes that might be informative about adaptation.

We find strong and robust evidence that GRP responds to annual temperature shocks as well as long-run temperature levels (climate). With respect to precipitation, the evidence is less robust. We provide further evidence that marginal effects of temperature increase are much higher than assumed in most Integrated Assessment Models (IAMs). In particular, hot regions are more strongly affected by further warming than cooler regions.

Our paper is organized as follows. We first develop a conceptual framework for understanding the differences between weather (short-run) and climate (long-run) impacts on economic growth. The empirical strategy and the data are explained in Sections 3 and 4, respectively. Section 5 provides the key results for panel, long-difference and cross-sectional estimates of economic climate damages. In Section 6, these estimates are applied to projected greenhouse gas concentration trajectories to assess possible GDP losses under a business-as-usual warming scenario. A discussion of results is provided in Section 7; Section 8 concludes.

2. Conceptual framework on climate and growth

To illustrate economic impacts of climate change on different time scales, we consider a stylized Ramsey-type growth model where changes in weather variables affect the productivity level of the entire economy and the growth rate of labor productivity. Let economic output Y (GDP) be defined by $Y = \Theta F(K, AL)$ with F denoting a neoclassical production function (homogeneous of degree one), K the capital stock, A the labor productivity and L the quantity of labor. The latter is used synonymous to total population. Economic damages, Θ, on aggregate productivity levels have been introduced by Nordhaus (1993): $\Theta \equiv \Theta(T)$ decreases in T with T denoting the level of global mean temperature warming above pre-industrial levels (or, more generally, regional mean temperature warming). This specification represents the most widespread form of modeling the impact of global warming on economic output. As a consequence, a permanent shift in mean temperature T reduces long-run consumption by a factor of $1-\Theta$. By design, this specification ignores long-term impacts of global warming levels on the long-run growth rate of the economy. Within the Ramsey model, per-capita GDP and consumption grow in the long-run at the labor productivity growth rate $g_A := \frac{d\ln A}{dt}$. Whereas this rate is a parameter in exogenous growth models, endogenous growth models explain this rate by further structural parameters related to innovation costs, market structure, preferences and technology, among others (Barro and Sala-i Martin, 2003). In endogenous models, global warming could affect g_A through distorted research and innovation incentives (Stern, 2013; Dietz and Stern, 2015; Piontek et al., 2019). As the evaluation of climate policy is highly sensitive to the consideration of productivity level effects, Θ, versus equilibrium growth rate effects, g_A, (Moyer et al., 2014; Moore and Diaz, 2015; Ricke et al., 2018; Ueckerdt et al., 2019), we include climate damages also in the growth rate $g_A \equiv g_A(T)$.

Our framework disregards explicit adaptation choices, damages to capital stocks or labor supply responses as we are not able to explore them in the later empirical analyses. Nevertheless, our chosen approach is already sufficient to analyze short, medium and long-term impacts of climate change by focusing on the most commonly used productivity channel, $\Theta(T)$ and $g_A(T)$.

Since F is linearly homogeneous in K and AL (constant returns to scale)

$$\frac{\partial F}{\partial(AL)} = \frac{F - \frac{\partial F}{\partial K}K}{AL} \tag{1}$$

holds according to Euler's Theorem. Taking the logarithm of GDP, it then follows that:

$$\begin{aligned}\frac{d\ln(Y)}{dt} &= \frac{\Theta'(T)}{\Theta(T)}\dot{T} + \frac{1}{F}\left(\frac{\partial F}{\partial K}\frac{dK}{dt} + \frac{\partial F}{\partial(AL)}\frac{d(AL)}{dt}\right)\\ &= \frac{\Theta'(T)}{\Theta(T)}\dot{T} + \frac{1}{F}\left(\frac{\partial F}{\partial K}\frac{dK}{dt} + \left(F - \frac{\partial F}{\partial K}K\right)\frac{d\ln(AL)}{dt}\right) = \frac{\Theta'(T)}{\Theta(T)}\dot{T} + \Phi\frac{1}{K}\frac{dK}{dt} + (1-\Phi)g_{AL}\end{aligned} \tag{2}$$

with g_x denoting the growth-rate of x, $\dot{T}$ the time-derivative of T and $\Phi = \frac{\partial F}{\partial K}\frac{K}{F}$. Capital stock changes with investment I and depreciation at rate δ according to $\frac{dK}{dt} = I - \delta K = sY - \delta K$ with $0 \leq s \leq 1$ being the saving rate. Hence, per capita-growth can be re-written as

$$g_y = \frac{d\ln(y)}{dt} = \frac{d\ln\left(\frac{Y}{L}\right)}{dt} = \frac{d\ln(Y)}{dt} - g_L = \frac{\Theta'(T)}{\Theta(T)}\dot{T} + \Phi\left(s\frac{Y}{K} - \delta\right) + (1-\Phi)(g_A(T) + g_L) - g_L. \tag{3}$$

This, in turn, can be decomposed into three components:

$$g_y = \underbrace{\frac{\Theta'(T)}{\Theta(T)}\dot{T}}_{\text{(i)immediate climate effect}} + \underbrace{\Phi\left(s\frac{Y}{K} - \delta - g_L - g_A(T)\right)}_{\substack{:=\Psi(T)\\ \text{(ii)transitory effect}}} + \underbrace{g_A(T).}_{\text{(iii)BGP effect}} \tag{4}$$

Hence, growth is affected by (i) the immediate (or short-run) impact of a change in temperature $\dot{T}$ through the impact on the productivity level Θ, (ii) a transitory impact $\Psi(T)$ on the growth rate to converge to the long-run growth rate of the economy

$g_A(T)$, (iii) and the long-run productivity growth rate $g_A(T)$.

To see that $\Psi(T)$ is only a transitory impact, consider that the economy evolves along the balanced growth path (BGP), which is a path where per-capita capital stock and output grow at their long-run growth rate g_A.[1] With $\frac{dK}{dt} = I - \delta K = sY - \delta K$, we obtain that $\Psi(T) = 0$. Thus, there is no transitory growth but only growth at the long-run growth rate (i.e. along the BGP). If productivity is reduced due to a change in temperature, Y decreases unexpectedly (whereas K was determined by previous investment decisions). Hence, $\Psi(T)$ becomes negative with lower Y. This is intuitive as the economy now has to converge to a lower steady state level of effective capital $K/(AL)$. The economy has to reduce its excessive capital stock that was built in expectation of a higher productivity level. This temporary disinvestment reduces GDP as well. However, the long-run growth rate of the economy is again determined by $g_A(T)$ and will only change via the BGP-effect channel, i.e. if $g_A(T)$ changes in temperature.

This stylized model provides a clear framework for specifying a growth regression equation, reflecting the key terms of Eq. (4) in a time-discrete notion (where $\Delta T = \dot{T}$ denotes temperature changes between two periods):

$$g_y = G(T)\Delta T + F(T) \tag{5}$$

with $G(T) := \frac{\Theta'(T)}{\Theta(T)}$, $\Delta T = \dot{T}$ and $F(T) := \Psi(T) + g_A(T)$. An empirical model should therefore test for the following hypotheses: (1) a sudden change in climate conditions, ΔT, affects contemporaneous growth rates; (2) the impact is conditional on the prevailing (historic) climate conditions T (via $G(T)$); (3) additionally, prevailing climate conditions T affect transitory and long-run growth (via $F(T)$). A clear testing of these hypothesis is, however, difficult for two reasons: First, including region-fixed effects in panel regressions absorbs long-term climate conditions contained in T. Hence, only fluctuations in T can be used for identifying growth-effects. Second, fluctuations in T are highly correlated to changes in T, ΔT. Collinearity problems arise, when several lags are added – but lags should be added because Eq. (4) shows that growth rates depend also on the capital stock K, which is affected by past climate events. Considering region fixed-effects as well as various lags in temperature hampers therefore an unequivocal testing of the different impact channels. Nevertheless, our approach emphasizes that differentiating between temperature effects and temperature change effects can be crucial for understanding growth dynamics. We will make use of this in the later regression analyses where we aim to test for these different channels. Analogously to changes in temperature, we investigate changes in annual total precipitation.

3. Empirical strategy

3.1. Annual panel model

We take on the previous notation but define $\mathbf{T_{i,t}} = (T_{i,t}, P_{i,t})$ as a vector of annual mean temperature levels (in °C) and annual total precipitation values (in m) within year t at region i (referred to as annual weather hereafter). To specify functional forms for the parametric regression model, we consider a linearization of $G(T) = \alpha + \beta T$ and a quadratic function $F(T) = \gamma_1 T + \gamma_2 T^2$ as preferred model that is parsimonious but still allows for non-linear dynamics. Hence, the regression model, based on Eq. (5), reads:

$$g_{i,t} = \alpha\Delta\mathbf{T_{i,t}} + \beta\mathbf{T_{i,t}}\Delta\mathbf{T_{i,t}} + \gamma_1\mathbf{T_{i,t}} + \gamma_2\mathbf{T^2_{i,t}} + p_i(t) + \delta_i + \mu_t + \varepsilon_{i,t}; \tag{6}$$

where $g_{i,t}$ denotes the per-capita growth rate (logarithmic change) of gross regional product in region i, compared to GRP in the previous year, and $\Delta\mathbf{T_{i,t}} = \mathbf{T_{i,t}} - \mathbf{T_{i,t-1}}$ describes the respective change in weather. Region-specific polynomial time trends which control for various possible slow-moving regional changes that affect growth (e.g. technological change, institutional change, demographic change, etc.) are given by $p_i(t)$. δ_i is a region dummy to consider region fixed effects in the regression.[2] Year fixed effects that account for global covariate shocks like economic crises or climate phenomena like El Niño are given by μ_t. Referring to term (i) in Eq. (4), coefficients α and β capture the immediate effect of weather shocks. This effect depends on the change in weather conditional on the current or past weather. Contrary, γ_1 and γ_2 capture transitory and long-run growth effects, which cannot be separately identified as they both depend on temperature and precipitation levels.

To compare our approach with other specifications that have been used in the literature, we consider several variants of Eq. (6) that differ in the set of covariates:

(1) a linear model in weather change only, with contemporaneous and one-year lagged changes in weather $\Delta\mathbf{T_{i,t}}$, excluding the β and γ terms (this follows the approach in Dell et al. (2012)). This model can only detect linear impacts on production through weather changes, disregarding transitory or balanced-growth rates effects (channel (ii) and (iii) in Eq. (4));
(2) a model in linear and quadratic contemporaneous weather $\mathbf{T_{i,t}}$ variables, excluding α and β terms (this follows the approach in Burke et al. (2015)). This model disregards the immediate climate effect channel (i) in Eq. (4); significant

[1] A balanced growth path is characterized by constant growth rates of key macroeconomic variables such as GDP or capital stock (Barro and Sala-i Martin, 2003, Ch. 2). It represents the 'steady state' of an exponentially growing economy (i.e. exponentially de-trended state variables do not change over time). In neoclassical growth models, the economy converges in the long-run to the balanced growth path. The speed of convergence depends on the initial state (capital stock). If the economy starts with the capital stock of the balanced growth path, it exhibits constant growth rates.

[2] Region-specific polynomial time trends include already such a region dummy. In case of country-specific polynomial time trends (used in the robustness analyses), δ_i implies a region fixed effect panel regression.

coefficients suggest the existence of transitory or long-run growth effects (channel (ii) and (iii) in Eq. (4));
(3) a model with interaction term and linear weather term (i.e. only γ_2 excluded in Eq. (6)) where all impact channels of Eq. (4) are considered;
(4) as in (3) but with quadratic weather terms as stated by Eq. (6);
(5) as model (3) but using lagged temperature and precipitation for the $\mathbf{T_{i,t}}$ variable in Eq. (6); hence, the impact of weather change is calculated conditional on the previous year's temperature and growth rate effects are calculated based on the previous year's temperature;
(6) as model (4) but using lagged temperature and precipitation for the $\mathbf{T_{i,t}}$ variable in Eq. (6).

We consider various lags for $\mathbf{T_{i,t}}$ and $\Delta\mathbf{T_{i,t}}$.

3.2. Long-difference model

In the annual panel model, the transitory growth impact and the balanced growth path impact in Eq. (4) are estimated jointly. It is therefore not possible to disentangle transitory from permanent growth effects. Additionally, the annual panel model exploits only annual weather variability (within regions); region fixed effects and region time-trends absorb long-run climate conditions and long-run climate change which are more relevant for understanding impacts of gradual global warming. In particular, the annual panel model may underestimate adaptation investments as a response to gradual long-term climate change. One way to overcome these limitations is to use cross-sectional regressions in growth rates over longer time intervals (long-difference model):

$$g_i = \alpha\Delta\mathbf{T_i} + \beta\mathbf{T_i}\Delta\mathbf{T_i} + \gamma_1\mathbf{T_i} + \gamma_2\mathbf{T_i^2} + \lambda X_i + \delta_c + \varepsilon_i; \tag{7}$$

where $\Delta\mathbf{T_i}$ denotes changes in average temperature and precipitation levels and g_i logarithmic changes in average economic output over a longer period. We first determine average temperature and precipitation levels for the decades 2005–2014, 1995–2004 and 1985–1994 (referred to hereafter as climate conditions) and average economic productivity for the same periods. We then analyze the differences between 2005-2014 and 1995–2004 and between 2005-2014 and 1985–1994, respectively. Similar to the annual panel regression, we include prevailing climate conditions, $\mathbf{T_i}$ referring to temperature and precipitation levels in the earlier period. The coefficients α and β estimate again how total productivity changes with climate conditions. Contrary to the annual panel model, transitory growth effects in the long-difference model can be expected to be rather small because of the longer time-periods considered. We therefore interpret γ_1 and γ_2 as coefficients that capture how long-run growth rates of the economy (i.e. balanced growth paths) are affected by climate conditions. Regional covariates with respect to geography and resource endowments that might influence growth are considered in X_i. We further include country fixed effects, δ_c, to account for unobserved country-heterogeneity (e.g. institutions) that affect GDP growth. Essentially, this regression is a generalization of the long-difference approach proposed by Burke and Emerick (2016) where we have added β, γ_1 and γ_2.

3.3. Cross-sectional model

Eq. (7) allows to detect how climate conditions ($\mathbf{T_i}$) and their change ($\Delta\mathbf{T_i}$) affect growth rates. The latter relationship, however, requires sufficient variation in the data. As within-country temperature and precipitation *changes* are much stronger correlated than their respective *levels*, statistical power for estimating α_1 and α_2 can potentially be very low. A final regression will therefore explain how (log) levels of GRP per capita, y_i, depend on climate conditions over a longer time period:

$$y_i = \alpha_1\mathbf{T_i} + \lambda X_i + \delta_c + \varepsilon_i, \tag{8}$$

with $\mathbf{T_i}$ describing the average climate conditions and y_i average log GRP per capita over a longer period (i.e. a decade). This regression exploits cross-sectional heterogeneity in climate conditions to estimate the impact on economic output. It does not allow to differentiate between long-run growth rate effects (g_A) and productivity level effects of climate conditions as both are captured in y_i. As in the long-difference model, we include regional covariates with respect to geography and resource endowments, X_i, and country fixed effects, δ_c. A major strength of our sub-national data set is that we can include country fixed effects in the cross-sectional approach to avoid omitted variable bias which was one of the main shortcomings of previous cross-sectional estimates on the impact of climate on economic output.

Since we do not have interaction coefficients in the cross-sectional model on GRP levels, we disregard quadratic effects but use instead a more general non-linear estimation approach with temperature and precipitation bins. To this end, we sort the weather variable into N_B discrete bins (of 4°C-width in case of temperature and of 0.4m-width in case of precipitation). Average log GRP, y_i, is then regressed on dummy variables B_k representing the bins:

$$y_i = \sum_{k=1}^{N_B} \alpha_{k,i} B_k(\mathbf{T_i}) + \lambda X_i + \delta_c + \varepsilon_i; \tag{9}$$

$$\text{with} B_k(\mathbf{T_i}) = \begin{cases} 1 & \text{if } \mathbf{T_i} \in \text{k} - \text{th Bin} \\ 0 & \text{else.} \end{cases}$$

4. Data

We use climate and economic data at the subnational level for the years 1900–2014.[3] For the climate variables, we use gridded climate data at 0.5° resolution from the Climate Research Unit of the University of East Anglia (CRU TS v3.23; Harris et al., 2014). We aggregate these gridded data to the region level by computing area-weighted averages (see Fig. S1 in the Supplementary Materials for an overview of how many grid cells fall into a region). By region we denote the highest administrative unit of a country as indicated in the GADM database.[4] In the case of the United States, for example, this administrative category corresponds to States. In Canada, it is Provinces, in Germany Bundesländer, etc. Henceforth, we refer to these administrative units as *regions*. In order to ensure a precise assignment of CRU climate information to regions – in particular if a region is smaller than a 0.5° grid cell or lies only partly within it – we apply a two-step algorithm. In a first step, the gridded climate information at 0.5° resolution is translated into information on a 0.25° grid, assuming that each 0.5° grid cell consists of four even 0.25° grid cells and that the climate data is the same for all four cells. In a second step, the algorithm considers 100 equally distributed points in each 0.25° grid cell and then counts how many of those points lie within the region. The respective percentage is then used as a weighting for the region-specific aggregation of climate data. Temporally, the monthly observations of the CRU database are aggregated to annual mean temperature and annual total precipitation values per region.

The CRU database, which has been used widely throughout the related literature (Dell et al., 2014; Burke et al., 2015), is chosen because of its high spatial resolution, its global coverage and extensive temporal time scale. Furthermore, since only countries that have economic output data at the subnational level are part of our database, country selection is likely to be biased to countries with higher weather station coverage. As a consequence, we are confident that the CRU data, which were statistically interpolated across weather stations, are well suited for our analysis (Auffhammer et al., 2013). We provide a robustness check using re-analysis data from the recently released ERA5 data set, which relies on information from weather stations, satellites, and sondes.[5] The reanalysis data is therefore less prone to station weather bias but might be biased via the climate models that are used to generate a gridded product (Auffhammer et al., 2013). From the ERA5 data set, we use monthly means of average temperature 2 m above surface and monthly sums of total precipitation, which are provided from 1979 onward at a grid of approximately 0.25 longitude by 0.25 latitude degree resolution.

We include further geographical variables in our analysis that stem from various sources. Distance to navigable rivers and distance to coasts are taken from CIA World DataBank II. Altitude is obtained from the Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010). Data on cumulative oil and gas reserves is based on USGS World Petroleum Assessment Data and taken from the data appendix of Gennaioli et al. (2014).

Temperature projections for 2015–2099 in accordance with the Representative Concentration Pathway 8.5 (business-as-usual scenario (Van Vuuren et al., 2011)) are derived from the climate data set of the Intersectoral Impact Model Intercomparison Project (ISIMIP (Warszawski et al., 2014)). These projections, at 0.5° resolution, originate from different climate models and were bias-corrected (Hempel et al., 2013) to ensure long-term statistical agreement with observational data from the WATCH database (Weedon et al., 2011). We here use bias-corrected grid cell-level projections from the Princeton Earth System Model, GFDL-ESM2M, and aggregate them to the region level by means of the algorithm described above.

We use annual Gross Regional Product (or related data) as a measure of economic activity on the regional level. To this end, we have assembled a unique data set spanning more than 1500 regions in 77 countries worldwide and dating as far back as the early 1900s (Fig. S3 in the Supplementary Materials Appendix). The data stem from various statistical agencies of central or federal governments as well as from yearbooks (see Tab. S1). We converted values in country-specific currencies to USD using exchange rates from the FRED database of the Federal Reserve Bank of St. Louis. This conversion avoids diverging national inflationary tendencies.

Tables 1–3 show the summary statistics for the panel, the long-difference and the cross-sectional analysis, respectively. Average annual per-capita growth in USD is 7%. The high variability of growth is mainly driven by the large volatility of economic growth over time as the within-region standard deviation, SD_w, is 3 times larger than the between-region standard deviation, SD_b. There are some very high GRP growth rates in the data that are linked to structural breaks in the underlying data sources (e.g. change of data source or deflator). We included structural break dummy variables for each of these changes in data sources.

Temperature and precipitation are more stable over time, but show large spatial variability. Comparing Table 1 with Table 3 indicates that inter-annual temperature variation within a region over the observed time period is rather low (standard deviation of 0.67) compared to spatial variability of long-term temperature (standard deviation of 8.204). The discrepancy is less pronounced for rainfall. Similarly, the change in annual mean temperature from 1985 to 1994 to 2005–2014 and especially from 1995 to 2004 to 2005–2014 is small compared to the spatial variability (Table 2). The respective change in log GRP is small

[3] In some specifications, we restrict the sample to the years 1980–2014 as data coverage is best for these more recent years.

[4] The GADM Database of Global Administrative Areas is a high-resolution database of country administrative areas that provides maps and spatial data for all countries and their sub-divisions. We use information on administrative borders at the highest level below the nation state (level 1) to map grid cell-level climate data to administrative units. https://gadm.org/.

[5] The ERA5 climate data set uses information from radiosondes e.g. for temperature, wind, humidity profiles. Radiosondes are battery-powered telemetry instruments. They are carried into the atmosphere usually by a weather balloon that measures various atmospheric parameters and transmits them by radio to a ground receiver.

Table 1
Summary statistics - annual panel data. Summary statistics for data used in annual panel model. Standard deviation is abbreviated by SD with SD_b denoting the between-region and SD_w the within-region standard deviation.

	Variable	Mean	SD	Min	Max	SD_b	SD_w
Per-capita growth rate	$g_{i,t}$	0.070	0.158	−2.442	2.303	0.058	0.154
Annual mean temperature (°C)	$T_{i,t}$	14.614	7.713	−15.490	29.625	8.011	0.567
Change in annual mean temperature (°C)	$\Delta T_{i,t}$	0.026	0.671	−3.655	3.573	0.074	0.670
Annual total precipitation (m)	$P_{i,t}$	1.100	0.714	0.000	5.843	0.721	0.196
Change in annual total precipitation (m)	$\Delta P_{i,t}$	0.002	0.276	−2.039	1.920	0.063	0.275
Number of observations		35,283					
Number of regions i		1545					
No. time periods		22.837					

Table 2
Summary statistics - long-difference data. Summary statistics for data used in long-difference model.

	Variable	Obs	Mean	SD	Min	Max
Change in log GRP (1995–2004 vs 2005–2014)	g_i	1309	.774	.406	-.763	2.197
Change in log GRP (1985–1994 vs 2005–2014)	g_i	619	1.111	.552	−1.101	3.067
Average annual temperature (°C; 1995–2004)	T_i	1306	14.594	8.254	−13.731	29.028
Average annual precipitation (m; 1995–2004)	P_i	1306	1.067	.726	.003	5
Change in temperature (°C; 1995–2004 vs 2005–2014)	ΔT_i	1306	.157	.285	-.989	1.162
Change in precipitation (m; 1995–2004 vs 2005–2014)	ΔP_i	1306	.023	.095	-.43	.544
Change in temperature (°C; 1985–1994 vs 2005–2014)	ΔT_i	617	.46	.432	-.669	1.834
Change in precipitation (m; 1985–1994 vs 2005–2014)	ΔP_i	617	.052	.151	-.524	.9
Log GDP (USD; 1995–2004)		1309	8.035	1.459	4.714	11.595
Cum Oil Gas (log mln bbl OE)		1479	.001	.006	0	.122
Distance to coast (log km)		1478	11.603	1.423	7.157	14.647
Distance to river (log km)		1477	10.135	.838	7.571	14.172
Altitude (km)		1478	.571	.652	-.012	4.882

Table 3
Summary statistics - cross-sectional data. Summary statistics for data used in cross-sectional model. Data refer to period 2005–2014.

	Variable	Obs	Mean	SD	Min	Max
Regional GDP (log USD)	y_i	1479	8.727	1.396	5.193	12.026
Average annual temperature (°C)	T_i	1470	14.652	7.975	−13.398	29.007
Average annual precipitation (m)	P_i	1470	1.101	.744	.004	5.18
Cum Oil Gas		1479	.001	.006	0	.122
Distance coast		1478	11.603	1.423	7.157	14.647
Distance river		1477	10.135	.838	7.571	14.172
Altitude		1478	.571	.652	-.012	4.882
No. of CRU pixels in region		1479	27.561	108.372	0	2434.1

as well as there is not a big time gap between the periods.

Differences in mean temperature levels between Table 1 and Tables 2 and 3 are related to differences in spatial and temporal coverage. In Tables 2 and 3, temperature values for all regions over the periods 1995–2004 and 2005–2014, respectively, are considered, independent of whether GRP data are missing or not whereas in Table 1 all temperature observations for a given year and region were excluded where the respective GRP information was missing.

5. Results

5.1. Annual panel model

We first run regression model (6), exploiting the annual panel structure of our data. Results for variants (1)–(6) of Eq. (6) are shown in Table 4, with column (j) referring to variant (j) as explained in Sec. 3.1. Across all model variants, the effect of precipitation changes on GRP is largely insignificant. We find, however, a significant negative effect of a temperature increase on GRP. This can be seen by determining the marginal effect of a change in temperature (change).[6] In all specifications, the

[6] Note that depending on the model specification, marginal effects are determined differently. In case of the linear model, marginal effects simply correspond to the regression coefficients, i.e. $\alpha_1 + \alpha_2$, which amount to 0.9% but are not significant at the 10% level. For specification (2), marginal effects are analytically given by $\gamma_1 + 2\gamma_2 T$. Here, marginal effects are relative to a change in temperature levels (i.e. marginal effect of an increase in T; as in Burke et al. (2015)). In all other variants, marginal effects refer to a change in temperature changes (i.e. marginal effect of an increase in ΔT). In panel variants (3)–(6), marginal effects are given by $\alpha_1 + \alpha_2 + (\beta_1 + \beta_2)T$ because of the interaction term. In all models with lags, marginal effects are calculated as cumulative effects over lags.

Table 4

Panel regression results. Panel model results for the effect of annual weather (changes) on annual changes of log Gross Regional Product. Columns refer to different variants of the panel model as described in Section 3.1. Differences across model variants are further indicated in the lower rows. Annual mean temperature and annual total precipitation are denoted by T and P, respectively. ΔT and ΔP refer to annual changes in weather and $L.$ indicates lagged effects. T_{opt} denotes temperature levels at which losses are smallest in non-linear models. ME stands for marginal effects (computed as detailed in footnote 6) and SE for standard error.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔT	−0.00243		0.0155*	0.0165	0.00641	0.00780
	(−0.96)		(1.85)	(1.59)	(1.04)	(1.14)
$L.\Delta T$	−0.00652*		0.00612	0.00671	0.00345	0.00200
	(−1.68)		(1.26)	(1.15)	(0.67)	(0.32)
$T \times \Delta T$			−0.00130**	−0.00140*	−0.00109**	−0.00117*
			(−2.37)	(−1.80)	(−2.04)	(−1.82)
$T \times L.\Delta T$			−0.000960**	−0.00102**	−0.000718*	−0.000660
			(−2.34)	(−2.17)	(−1.69)	(−1.29)
T		0.00947	−0.00679	−0.00846	−0.00675	−0.00254
		(1.34)	(−0.74)	(−0.64)	(−0.74)	(−0.20)
T^2		−0.000709**		0.0000762		−0.000107
		(−2.10)		(0.17)		(−0.23)
ΔP	0.00175		0.0120	0.0287	−0.00171	−0.00842
	(0.15)		(0.38)	(0.76)	(−0.07)	(−0.33)
$L.\Delta P$	0.0195**		0.0305	0.0395	0.0230	0.0282
	(2.51)		(1.45)	(1.66)	(1.10)	(1.22)
$P \times \Delta P$			−0.00553	−0.0150	−0.000491	0.00303
			(−0.53)	(−0.92)	(−0.06)	(0.31)
$P \times L.\Delta P$			−0.00680	−0.0120	−0.00220	−0.00477
			(−0.79)	(−1.10)	(−0.24)	(−0.46)
P		0.000651	−0.00504	−0.0326	−0.00517	−0.0223
		(0.02)	(−0.27)	(−0.86)	(−0.28)	(−0.59)
P^2		−0.000800		0.00785		0.00436
		(−0.14)		(0.87)		(0.57)
Observations	35,257	35,257	35,257	35,257	35,257	35,257
No. regions	1545	1545	1545	1545	1545	1545
No. countries	77	77	77	77	77	77
R^2-adj	0.214	0.214	0.216	0.216	0.215	0.221
BIC	−43304.5	−43273.3	−43327.8	−43317.8	−43296.7	−43533.3
Weather (T,P)	NA	Contemporaneous	Contemporaneous	Contemporaneous	Lagged	Lagged
Data	CRU	CRU	CRU	CRU	CRU	CRU
Years	1900–2014	1980–2014	1900–2014	1900–2014	1900–2014	1900–2014
Fixed effects	Region, Year	Region, Year	Region, Year	Region, Year	Region, Year	Region, Year
Reg. Trend	Squared	Squared	Squared	Squared	Squared	Squared
Cluster (SE)	Country	Country	Country	Country	Country	Country
T_{opt}		6.684	9.553	9.587	5.443	5.344
ME at 10 °C		-.0047	-.001	-.001	-.0083	-.0085
.. SE		.0047	.0076	.0077	.0053	.0053
ME at 25 °C		-.026**	-.0349**	-.0374**	-.0354**	-.036**
.. SE		.0123	.0142	.0176	.0141	.0141

t statistics in parentheses. Standard errors clustered at country level.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

marginal effect of an increase in temperature (change), conditional on the average temperature in that year (or the previous year), is negative for high average temperatures. At 10 °C the marginal effect is insignificant but at 25 °C it is mostly significant (at 10% or higher) and amounts to 2.6%–3.7%. Hence, a temperature increase of 1 °C in a hot region decreases GRP by about 3%. For the nonlinear panel model variants (2)–(6), we can compute an optimal annual average temperature level which ranges between 5 °C and 10 °C.

With respect to the question of whether temperature reduces economic growth permanently, the comparison of the different model variants suggests the following. Panel variant (2), which follows Burke et al. (2015), shows effects that are comparable in magnitude to those found in models (3)–(4). The significant impact of T^2 indicates that temperature changes affect transitory or long-run growth (i.e. via $\psi(T)$ or $g_A(T)$ in Eq. (4)). However, in the model specifications with interaction term (models (3)–(6)) the coefficient for transitory or long-run growth effects, γ, is insignificant, implying no clear effect of temperature levels on the growth rate. We find, however, strong evidence for direct productivity effects of temperature shocks as the respective coefficient β is significant. When quadratic temperature and precipitation levels are considered in the model with interaction terms (variants (4) and (6)), the respective coefficients for T and T^2 are not significant. Hence, in these regressions, there are no long-run growth effects visible.

In variants (3)–(6) we consider contemporaneous and one-year lagged ΔT. We run regressions (2) and (5) with different cumulative lag structures, as shown in Tab. S2 and Tab. S3 in the Supplementary Materials Appendix.[7] Compered to regressions with zero lags, adding one-year lagged weather changes increases R^2-adjusted and BIC considerably but adding more lags has only minor impacts on the two performance indicators. In most of our regressions with multiple lags, the contemporaneous and the first-lag temperature coefficient are significant whereas higher lags are rarely significant. This suggests that transitory effects comprise up to two years and that they become weaker (and statistically insignificant) over time. Another indication for catch-up effects is that cumulative lags reverse sign when more lags are added, although cumulative lags are also largely insignificant. However, having more lags generally increases the estimated standard errors (see Figs. S4 and S5), implying a less precise estimation of the climate impact. We therefore chose a parsimonious lag structure with lagged annual temperature for $\mathbf{T}$ and consider contemporaneous and lagged temperature changes for $\Delta\mathbf{T}$.

Overall, models (5)–(6) have the highest explanatory power when comparing the adjusted R^2 and BIC values of all models. The difference between model (5) and model (6) is very small. As quadratic temperature effects are insignificant, we consider (5) as our preferred specification and use it for the later impact modeling.

Even though we do not find evidence for persistent growth effects, our preferred model specification reports higher marginal effects of temperature increases on GRP than Burke et al. (2015) (Fig. 1). This implies that hot years might harm local economies even more than previously thought. Model specification (2) which follows Burke et al. (2015) gives comparable but slightly higher marginal effects than the original study (see also Tab. S2 and Fig. S5 for a comparison over various lags). Differences could be due to the higher geographic resolution in our sample or due to different geographical coverage.

We perform a number of further robustness checks (see Tab. S4 and Fig. S6). Including country-year fixed effects gives insignificant results for all coefficients as they absorb a substantial amount of the annual climate variability (column 2). Restricting the panel to years from 1981 on (where it becomes most balanced), hardly changes the results (column 3). Using re-analysis climate data (ERA5) instead of the statistically interpolated data set CRU leads to similar estimates but increases standard errors (column 4). Replacing the quadratic regional time trends with linear ones reduces standard errors slightly while coefficients remain very similar (column 5). Excluding small regions from the panel (with less than three grid cells from the CRU data set) does not change results either (column 6).

5.2. Long-difference model

Second, we use long-difference models (7) to investigate whether the results from the annual panel model translate to longer time scales. We choose a period length of 10 years and compare different periods to each other. Results are summarized in Table 5. Columns (1)–(3) refer to models that look at changes from 1995 to 2004 to 2005–2014 whereas columns (4)–(6) show estimates for changes between 1985-1994 and 2005–2014. Model specifications summarized by columns (2) and (5) include a term for the first period's GRP value to account for convergence growth effects.[8] The respective coefficients are highly significant. Columns (3) and (6) display results for model variants that look at changes in temperature and precipitation only (α in Eq. (7)) without inclusion of an interaction term or a term for previous climate conditions (β and γ in Eq. (7)).

We find no evidence that a change in 10-year average temperature affects growth since the respective coefficients as well as the marginal effects are insignificant across all model specifications. Considering our results for the annual panel model, we would have expected that the interaction term $\Delta T_i \cdot T_{i,t-1}$ was significant in the long-difference model as well. An explanation for this insignificance could be that adaptation took place from one period to the next. More likely, however, is that the temperature change between the two periods considered was too small: Comparing the periods 2005–2014 and 1985–1994, temperature increased by only 0.46 °C on average (see Table 2). The standard deviation of the within-country temperature change was only 0.39 whereas the standard deviation of within-country temperature levels for the period 2005–2014 was 3.83 (see also Fig. S2).

With regards to precipitation, model specifications (1) and (2) show significant effects for the interaction term $\Delta P_i \cdot P_{i,t-1}$. An increase in precipitation decreases growth. Yet, the effect is not robust over time (columns (4)+(5)). We conduct a number of robustness checks using ERA5 data or different time periods that do not show a significant relationship for precipitation or temperature either (Supplementary Materials S3.2).

The coefficients for temperature, squared-temperature, precipitation and squared-precipitation are also insignificant even though the within-country variability of temperature and precipitation levels is high (Fig. S2). Summing up, the long-difference regressions do not provide evidence for long-run growth effects of climate conditions.

5.3. Cross-sectional model

Third, we investigate how prevailing climate conditions affect GRP using the cross-sectional model (8). We include country fixed effects, distance to coast, distance to navigable rivers, altitude and cumulative oil and gas extraction (million bbl oil equiv-

[7] We also run model variant (3) and a variant where we use long-term average climate conditions as interaction term with different cumulative lag structures. Since we later choose model variant (5) as preferred specification, the - structurally similar - results of these lagged regressions are not shown but are available upon request.

[8] Cross-sectional growth-regressions robustly show that growth is negatively linked to initial GDP levels due to convergence growth effects, i.e. poorer countries tend to grow at faster rates than richer economies (see Mankiw et al. (1992)).

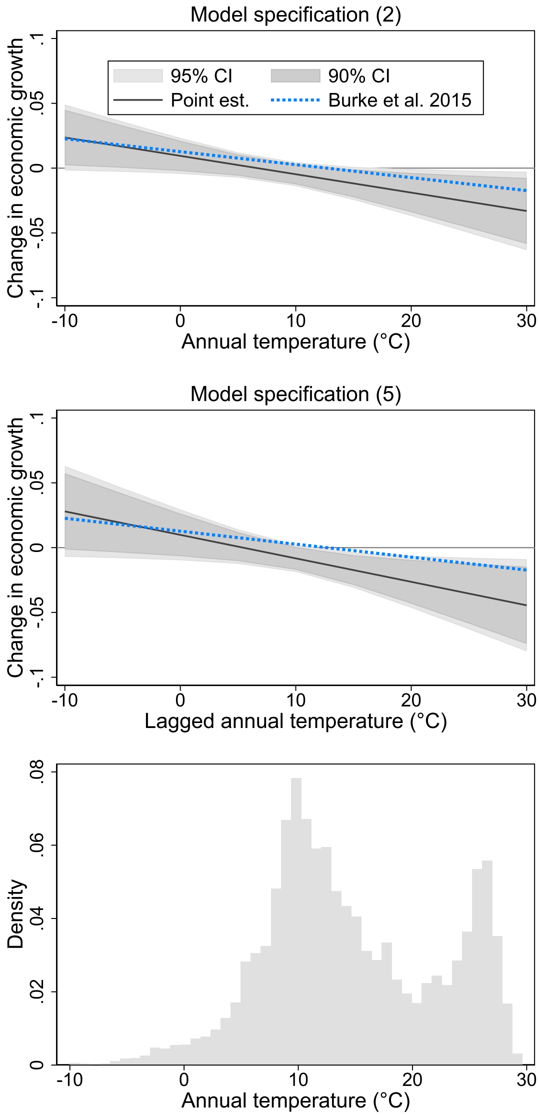

Fig. 1. Marginal effect of temperature (change) on economic growth. Top panel: Marginal effect of a 1 °C change in annual average temperature on regional economic growth (y-axis) conditional on annual average temperature in that region (x-axis). Based on specification (2) in Table 4. The dashed line shows the marginal effect as reported by Burke et al. (2015) using a zero-lag specification. Middle panel: Marginal effect of an annual temperature increase on regional economic growth (y-axis) conditional on lagged annual average temperature in that region (x-axis). Based on specification (5) in Table 4. Marginal effect is calculated as cumulative effects over lags. Bottom: Histogram of annual average temperature.

alents) for the region. Climate and GRP data are aggregated to 10-year intervals with 2005–2014 as reference period because data coverage is largest for that period. Table 6 shows the results for different 10-year time periods, with varying geographical data coverage.

Over all decades, the temperature coefficient is remarkably stable and, except for the earliest period (1955–1964), significant at the 10%-level. One degree of temperature increase reduces GRP by 2–4%. Precipitation is not significant. As expected, fossil resource extraction increases GRP whereas higher values for distance to coast, distance to navigable rivers and altitude reduce GRP. The last three covariates can be understood as proxies for trade costs and trade integration (Gallup et al., 1999).

We provide a number of robustness checks in the Supplementary Materials (see Tab. S8). The temperature results are robust against the inclusion of geographical covariates (columns 2–4), except for altitude (geography). Altitude is negatively correlated with temperature. As mountainous regions are colder and more difficult to access, omitting altitude from the regression biases the temperature coefficient downward. Running the regression without country fixed effects leads to much higher temperature coefficients of about 0.1 (column 5). Reducing the sample such that smaller regions, i.e. regions that contain less than three 0.5°

Table 5

Long-difference regression. Long-difference model results on the effect of a change in 10-year average weather on economic growth (changes in log GRP between the two periods). Columns (1)–(3) give coefficients for model variants that compare 1995–2004 to 2005–2014, columns (4)–(6) refer to changes from 1985 to 1994 to 2005–2014. Columns (2) and (4) show estimates for model variants that include a term for the earlier period's GRP value. Model specifications summarized by columns (3) and (4) look at changes in temperature and precipitation only. ME stands for marginal effect and SE for standard error.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔT	0.0284	0.0414	−0.00772	0.0241	−0.0222	−0.0484
	(0.0387)	(0.0352)	(0.0487)	(0.0762)	(0.0690)	(0.0392)
$T \times \Delta T$	−0.00385	−0.00398		−0.00662	−0.000295	
	(0.00323)	(0.00302)		(0.00601)	(0.00502)	
T	0.00551	0.00198		−0.00538	−0.00948	
	(0.00400)	(0.00397)		(0.0131)	(0.0105)	
T^2	−0.0000380	0.0000402		0.000110	−0.0000240	
	(0.000156)	(0.000156)		(0.000500)	(0.000373)	
ΔP	−0.428*	−0.381**	−0.0580	−0.0604	0.0949	−0.166
	(0.215)	(0.163)	(0.0718)	(0.215)	(0.253)	(0.104)
$P \times \Delta P$	0.196*	0.199**		−0.0742	−0.102	
	(0.112)	(0.0833)		(0.143)	(0.170)	
P	0.00546	−0.0154		0.0279	−0.0419	
	(0.0433)	(0.0389)		(0.0699)	(0.0726)	
P^2	−0.00187	0.00422		0.00765	0.0201	
	(0.0108)	(0.0101)		(0.0191)	(0.0219)	
Log initial GRP		−0.0862***			−0.308***	
		(0.0253)			(0.0789)	
Cum Oil Gas	1.455***	1.945***	1.212**	−1.460	−0.0477	−1.072
	(0.545)	(0.453)	(0.473)	(1.103)	(1.004)	(0.884)
Distance coast	0.0116	0.00133	0.00905	−0.0322	−0.0460**	−0.0342*
	(0.0136)	(0.0101)	(0.0132)	(0.0198)	(0.0183)	(0.0185)
Distance river	−0.00326	−0.00978	−0.00181	−0.00709	−0.0147	−0.0124
	(0.0111)	(0.00911)	(0.0111)	(0.0151)	(0.0177)	(0.0170)
Altitude	0.0365*	0.0240	0.0237	0.0856*	0.0192	0.0976**
	(0.0214)	(0.0197)	(0.0198)	(0.0486)	(0.0473)	(0.0406)
Observations	1304	1304	1304	616	616	616
No. countries	61	61	61	31	31	31
R^2-adj	0.837	0.844	0.836	0.760	0.813	0.759
BIC	−998.7	−1051.2	−1027.8	176.0	28.39	145.1
Periods	95-04 vs.	95-04 vs.	95-04 vs.	85-94 vs.	85-94 vs.	85-94 vs.
	05-14	05-14	05-14	05-14	05-14	05-14
Interval (years)	10	10	10	10	10	10
Lag (periods)	1	1	1	2	2	2
Data	CRU	CRU	CRU	CRU	CRU	CRU
ME at 10 °C	-.0101	.0016		-.0422	-.0251	
.. SE	.049	.0417		.0371	.0342	
ME at 25 °C	-.0679	-.0581		-.1415	-.0295	
.. SE	.0876	.077		.091	.0723	

Standard errors in parentheses.
Country fixed effects included. Standard errors clustered at country level.
$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

grid cells according to the CRU data, are excluded, decreases standard errors and increases the precision of estimates (column 6). The sample with larger areas has higher within-country climate variability. Using ERA5 instead of CRU climate data leads to temperature coefficients of similar magnitude.

To test for a possibly non-linear relationship between GRP and climate, we replace temperature and precipitation with bins that encode whether a specific temperature or precipitation level (average over 2005–2014 period) holds for a region. Fig. 2 shows non-linear estimates using 8–12 °C as reference temperature bin and 400–800 mm/year as reference precipitation bin. Regions with hot climate tend to have lower GRP. For example, in regions with an average temperature of 20–24 °C, GRP is approximately 28% lower than in the reference temperature bin. In regions with 24°-28 °C, the difference amounts to 35% lower gross regional product. A strong non-linear relationship is not observed except for extreme temperature bins where only few observations are available. With respect to precipitation, we find a u-shaped pattern implying high GRP in very dry and in very wet regions. Standard errors of the different bins are large, however, making it difficult to draw robust conclusions on the impact of precipitation on GRP.[9]

[9] Using ERA5 data instead of CRU data in the binned regression gives very similar results for the temperature effects. Estimated precipitation effects differ to a larger extent but still show a similar pattern for ERA5. Restricting the analysis to large regions shows only minor differences as well (results are available from the authors upon request).

Table 6
Cross-sectional regression results. Cross-sectional regression results on the effect of changes in long-term climate conditions on the log of Gross Regional Product. Climate and GRP data are aggregated to 10-year intervals and different columns refer to different 10-year periods.

	(1)	(2)	(3)	(4)	(5)	(6)
T	−0.0230*	−0.0289**	−0.0201**	−0.0259**	−0.0427*	−0.0244
	(0.0132)	(0.0131)	(0.00886)	(0.0108)	(0.0219)	(0.0169)
P	0.00189	0.0214	−0.0683	−0.0544	0.0116	−0.197
	(0.0604)	(0.0600)	(0.0540)	(0.0584)	(0.103)	(0.205)
Cum Oil Gas	7.075**	5.588	3.914***	4.055*	−0.525	0.973
	(3.082)	(3.414)	(1.207)	(2.096)	(1.925)	(1.612)
Distance coast	−0.113***	−0.125***	−0.0542*	−0.0769*	−0.0972	−0.0517
	(0.0327)	(0.0425)	(0.0296)	(0.0435)	(0.0716)	(0.0598)
Distance river	−0.0664*	−0.0791*	−0.0488	−0.0960	−0.0325	0.0453
	(0.0354)	(0.0451)	(0.0483)	(0.0568)	(0.0834)	(0.0524)
Altitude	−0.183**	−0.189**	−0.190***	−0.167*	−0.104	−0.117
	(0.0807)	(0.0877)	(0.0650)	(0.0844)	(0.131)	(0.0956)
Observations	1467	1379	672	507	315	210
No. countries	74	65	34	23	14	7
R^2-adj	0.914	0.928	0.946	0.924	0.909	0.933
BIC	1481.1	1525.3	796.4	653.3	532.2	203.0
Period	2005–2014	1995–2004	1985–1994	1975–1984	1965–1974	1955–1964
Data	CRU	CRU	CRU	CRU	CRU	CRU

Standard errors in parentheses.
Country FE included. Standard errors clustered at country level.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

6. Future climate damages

In this section, we use the empirical estimates from the historic GRP-climate relationship to (i) project future economic losses, (ii) derive an approximate reduced-form global GDP damage function and (iii) calculate the social cost of carbon.

6.1. Projected economic losses

Based on our panel and cross-sectional regression results of the historic climate-GRP relationship, we project GRP losses under past and future warming. For future warming, we consider a business-as-usual scenario, i.e. a scenario in line with the highest greenhouse gas concentration trajectory considered by the Intergovernmental Panel on Climate Change (IPCC) in its latest report (see Data section for detail).

In case of the panel regression estimate, we calculate region-specific output losses based on projected changes in temperature from one year to the next in the respective region. We also include the coefficient for the interaction term with previous-year temperature. This corresponds to our preferred specification (5) in Table 4. As to the cross-sectional regression estimate, we multiply the coefficient reported in column (1) in Table 6 with the projected warming from 2015 to 2019 to 2095–2099 in that region. As the precipitation coefficients from our empirical models are mostly insignificant, we disregard the effect of precipitation[10].

In order to generate globally aggregated impacts, we use region-specific baseline population growth and economic growth in line with the 'middle-of-the-road' socio-economic development pathway adopted in the latest IPCC report (i.e. Shared Socio-economic Pathway 2 (O'Neill et al., 2014)). The respective data, on a 0.5°-grid, are again taken from the ISIMIP data set and aggregated to the region level by means of the algorithm described in the Data section. Specifically, we apply four different weighting methods to derive a global number from regional estimates: (i) unweighted, (ii) land-surface area weighted, (iii) output (GRP) weighted and (iv) population weighted. The unweighted average warming from 2015 to 2019 to 2095–2099 over all regions is 2.9 °C, whereas the area weighted average warming is 3.5 °C and the population-as well as baseline GRP-weighted average warming is 3.2 °C.

Contrary to the historic economic data, population and GDP projections are available at a global grid. We can therefore include regions in our computation of future climate damages for which we did not have data in the econometric analysis. Table 7 summarizes the global aggregate of region-specific impacts of end-of-the-century warming in line with the business-as-usual climate change mitigation scenario on GRP. According to the panel estimate, regions' annual GRP is on average reduced by around 11–14% in 2099 compared to a scenario with no additional warming from 2015 to 2019 onward. Losses are highest if regional impacts are weighted by population projections (14.2%) and lowest when the surface weighting scheme is applied (11.2%). Using the cross-sectional estimates gives GRP losses of about 6–8% at the end of the century compared to a no warming scenario.

[10] Moreover, projections of warming-induced changes in regional precipitation are subject to high uncertainties IPCC (2013).

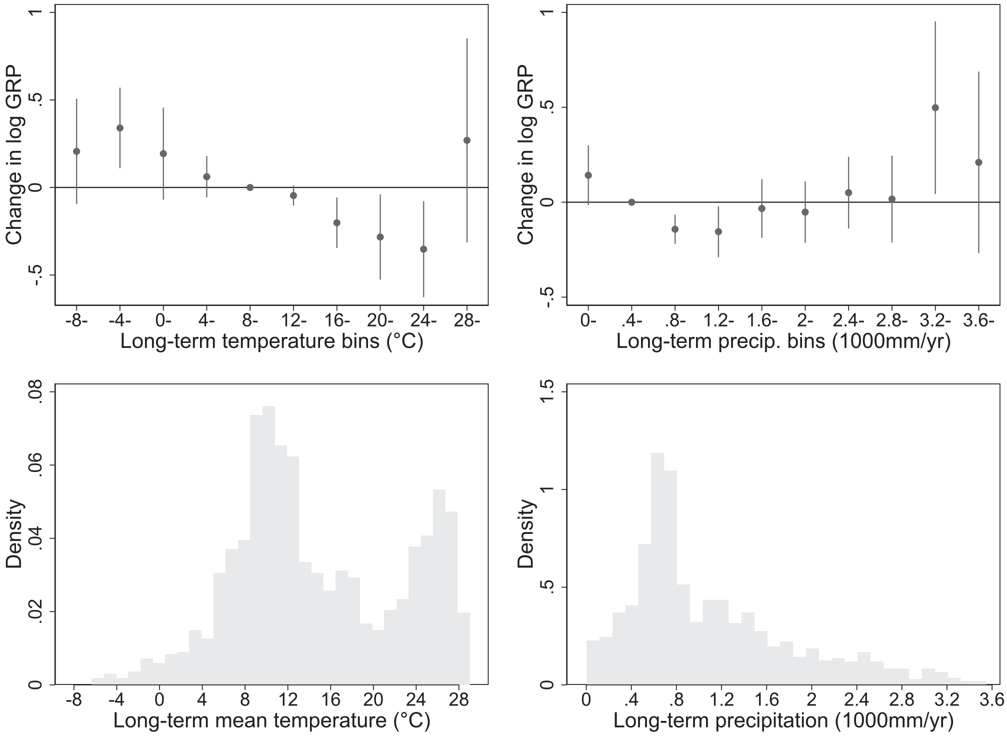

Fig. 2. Binning of climate variables to capture non-linearities. Upper panels show results of cross-sectional regression when average temperature and precipitation levels in 2005–2014 are binned. For temperature, bins of 4 °C step-width are considered. As to precipitation, bins refer to steps of 400 mm/year. Geographical covariates and country fixed effects are included. Bars indicate 90% confidence intervals. The bottom shows histograms of temperature and precipitation levels.

Table 7
Global warming and global GRP reductions (in %) in 2099 for the RCP 8.5 warming scenario. Different columns refer to different weighting schemes that were applied to aggregate region-specific warming and GRP losses to the global level.

	unweighted	surface area	weighted by output (GRP)	population
Global mean temperature in 2015–2019 (°C)	19.15	14.82	20.06	21.48
Temperature increase from 2015 to 2019 to 2099 (°C)	2.88	3.51	3.20	3.23
Reduction in global GRP based on cross-sectional estimate (%)	6.6	8.1	7.4	7.4
Reduction in global GRP based on panel estimate (%)	11.4	11.2	13.4	14.2

On a globally aggregated level, damages inferred from the annual panel model are hence larger than those from the cross-sectional model on long-term climate conditions. On a regional level, damages can vary substantially depending on whether the projections are based on the cross-sectional or the panel results (Fig. 3). The interaction term in the panel approach leads to a strong diversification of impacts: cold regions benefit from warming whereas hot regions lose disproportionately. In the cross-sectional approach, on the contrary, variability in GRP losses is driven by heterogeneous warming across regions only. As warming is stronger in polar regions, these regions experience higher GRP losses.

It is worth mentioning that this heterogeneity of climate damages is in both cases correlated to baseline GRP, with a pronounced correlation for the panel estimate (Fig. 4). Hence, poorer regions tend to suffer stronger from global warming. This is intuitive as the marginal effect of warming is stronger in hot regions that tend also to be poor regions in the baseline SSP2 scenario.

6.2. Global damage function

Next, we derive a reduced-form damage function that maps global warming to global GDP losses. This is useful as such a reduced-form damage function can be directly implemented in state-of-the art integrated assessment models of global warming, such as the DICE model (Nordhaus, 2018), thereby producing updated estimates of the social cost of carbon in accordance with

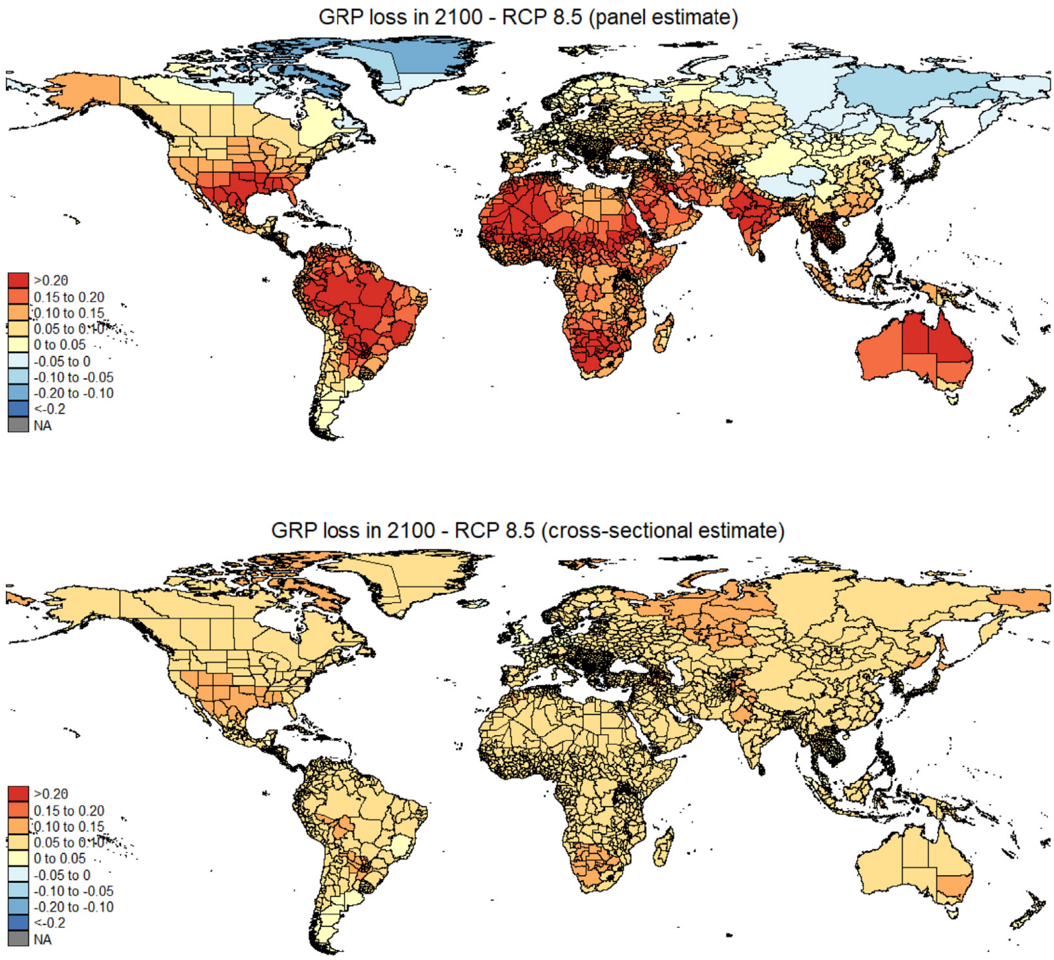

Fig. 3. Losses in Gross Regional Product (GRP) in 2099 under a business-as-usual warming scenario (RCP-8.5). Countries are colored according to the percentage change by which GRP would be reduced in 2099 if average warming from now until then was in the order of 3.5 °C compared to a scenario with no additional warming from 2015 to 2019 on. Red denotes highest losses (more than 20% reduction in GRP) whereas blue indicates that regions benefit. Losses were computed based on panel regression estimate (upper panel) and cross-sectional estimate (lower panel).

our empirical results.

The cross-sectional regression model implies a log-linear damage function, giving a change in GRP by

$$\Theta(\tau_i) - 1 = \ln(y_i(\tau_i)) - \ln \widetilde{y}_i = \gamma \tau_i. \tag{10}$$

with $\widetilde{y}_i$ the baseline GRP level in i assuming no further warming, τ_i the total warming in region i, and γ the estimated coefficient from the cross-sectional model (e.g. $\gamma = 0.023$ according to model (1) in Table 6).

Deriving a global GDP-damage function from the panel-based estimate is less straight-forward. As shown in Supplementary Materials S4.1, a constant warming trend with a total warming of τ_i in region i over a period of t years implies regional GDP changes

$$\Theta(\tau_i) - 1 = \ln(y_{i,t}(\tau_i)) - \ln \widetilde{y}_{i,t} = (\alpha + \beta T_{i,0})\tau_i + \frac{\beta}{2}\frac{t-1}{t}\tau_i^2; \tag{11}$$

with α the sum of the estimated coefficients of annual temperature change over all lags and β the sum of the estimated coefficients of the interaction term between temperature change and temperature level over all lags. Importantly, damages here are a quadratic function of the warming level and they depend on the initial temperature level $T_{i,0}$ in region i because marginal damages differ among hot and cold regions in the panel regression. Another subtle difference is that damages depend on the length of the considered time period: If the damage of a one-year warming $t = 1$ is considered, the quadratic term vanishes and we can infer the GRP effect directly from the panel regression. For large time horizons, $(t - 1)/t$ approaches one and GDP changes therefore converge to

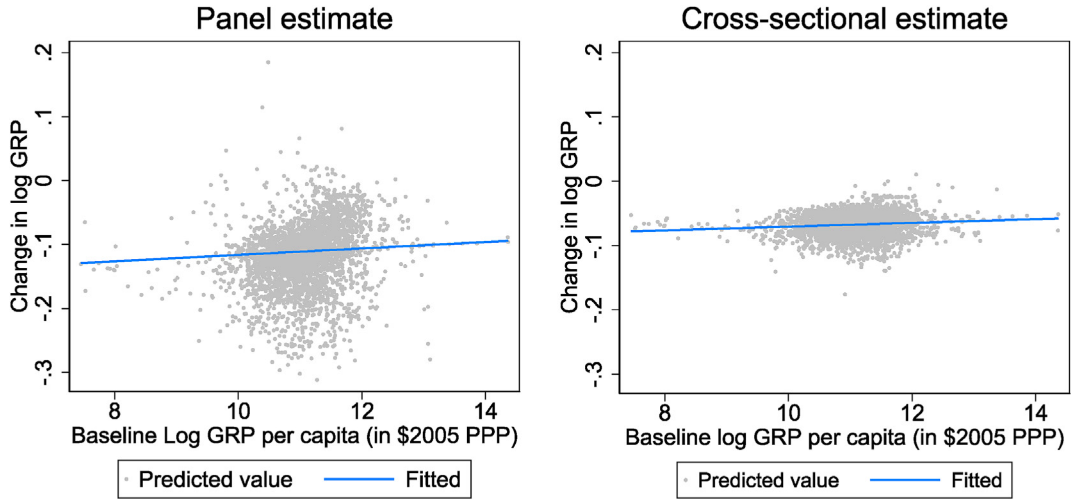

Fig. 4. GRP losses in 2099 under business-as-usual warming scenario are highest in poor countries. Scatter plots show that projected losses at the end of the century are on average highest in those regions that have the lowest baseline GRP levels. Changes in log GRP in 2099 under the RCP8-5 warming scenario (y-axis) were computed based on panel (right panel) and cross-sectional (left panel) estimates. Baseline GRP per capita in 2099 (x-axis) correspond to SSP2 scenario.

$$\Theta(\tau_i) - 1 = \ln(y_{i,t}(\tau_i)) - \ln \widetilde{y}_{i,t} = (\alpha + \beta T_{i,0})\tau_i + \frac{\beta}{2}\tau_i^2; \tag{12}$$

If we employed an econometric specification that is quadratic in temperature levels (as in Burke et al. (2015)), damages would increase exponentially with the length of the considered time horizon (see Supplementary Materials S4.2). Hence, a warming by 2 °C that occurs over 10 years would cause much smaller GDP losses than the same warming occurring over 100 years.

Because of the non-linear form and the heterogeneity in initial temperature levels $T_{i,0}$ over regions, it is not possible to aggregate Eq. (11) or Eq. (12) into a quadratic function which depends on the level of global mean warming τ only, even if warming would be homogeneous among all regions. Such a dependence is however required if the damage function was to be used in IAMs that typically describe global warming by an average global mean temperature increase only. As a consequence, a parsimonious damage function suitable for use in integrated assessment models such as the DICE model cannot be derived from our panel approach.

Instead, we estimate an approximate reduced-form global damage function that takes the functional form of Eq. (12). That is, we use the quadratic coefficient, β, as the cumulative coefficient of the interaction terms in the panel model and determine the linear coefficient $\widetilde{\alpha} = (\alpha + \beta T_{i,0})$ such that the surface area-weighted global warming creates the same damages as in Table 7.[11] We use again specification (5) in Table 4 as our preferred specification, i.e. $\beta = -0.0018$. With that, $\widetilde{\alpha} = -0.035$ replicates the output-weighted global damages and $\widetilde{\alpha} = -0.0373$ the population-weighted global damages in Table 7.

Fig. 5 illustrates the different damage functions obtained based on our estimates and compares them to the damage function used in the DICE 2016R model (Nordhaus, 2018). Note that the DICE damage function expresses damages relative to the pre-industrial temperature level. Correcting for this modification in the temperature base gives $\widetilde{\alpha}_{PI} = -0.0335$ for the output-based damages and $\widetilde{\alpha}_{PI} = -0.0357$ for the population-based damage.[12]

Although (log) damages are linear in the cross-sectional regression, they are considerably higher than the DICE damage function for warming levels up to 9 °C. The panel based damages do not differ substantially for an output-weighted or population-weighted calibration of the reduced-form damage function. They exceed the DICE damages by a factor of two or more.

6.3. The social cost of carbon

Finally, we integrate the damage functions derived in the previous section into the recent DICE-2016 model, calculate the social cost of carbon (SCC) and compare these updated SCC numbers to the original estimates provided by Nordhaus (2018) (Table 8). Our panel based damage functions imply that the optimal carbon price in 2020 is almost four times higher as assessed by Nordhaus in the 2018 study. In relative terms, this discrepancy decreases over time: In 2100, carbon prices according to our damage estimate would be roughly 2.7 times (output-weighted) or 2.9 times (population-weighted) higher than Nordhaus'

[11] We calibrate our damage function on surface area-weighted global warming because IAMs use this single indicator as a measure for global warming.

[12] For deriving a damage function relative to pre-industrial temperature changes, we need to adjust the estimation of $\widetilde{\alpha}_{PI}$ slightly: Temperature increase since industrialization is about 0.9 °C in DICE in period 2015–2019. Thus, we need to determine $\widetilde{\alpha}_{PI}$ such that a 0.9 °C+3.5 °C = 4.4 °C of warming matches the predicted global GDP losses in Table 7 plus the damages from a 0.9 °C or warming. Because of the weak curvature of the damage function, the resulting differences in the social cost of carbon are only 5% compared to the unadjusted choice of $\widetilde{\alpha}$.

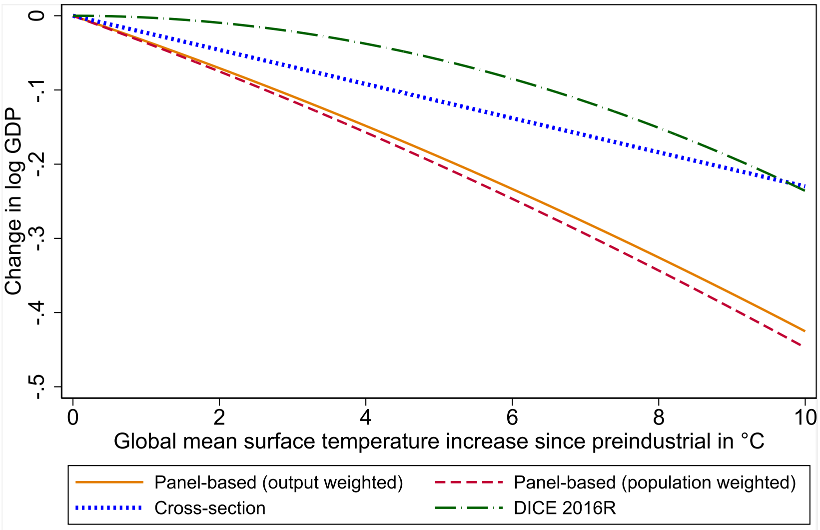

Fig. 5. Global damage function. Reduced-form damage functions map increases in global mean surface temperature to changes in global GDP (compared to zero temperature increase). DICE-2016R refers to damage function as used in the DICE2016R model, all other damage functions are based on our panel and cross-sectional regression results. Panel-based damage functions were calibrated to replicate output- and population-weighted global damages as given in Table 7, respectively.

Table 8
Social cost of carbon. Estimates for the social cost of carbon (in $/tCO$_2$, in 2010-US$) based on different damage functions. Damage functions are the same as those shown in Fig. 5.

Damage function	Year			
	2020	2030	2050	2100
DICE-2016R (Nordhaus)	37	51	91	271
Based on cross-sectional estimate	73	92	144	377
Based on panel estimate (output-weighted)	132	170	270	731
Based on panel estimate (population-weighted)	142	181	288	780

numbers. The damage function derived from the cross-sectional results in SCC that are twice as high in 2020 as those computed in Nordhaus (2018). As detailed in the Discussion section, it is important to keep in mind here that our SCC estimates only include direct total factor productivity (TFP) impacts of changes in temperature and abstract from other important climate impacts such as sea-level rise or non-market effects of temperature.

7. Discussion

In this section, we compare our estimates to results of related studies and discuss the implications for modeling climate damages in macroeconomic and integrated assessment models.

Table 9 provides an overview of damage estimates from our and other panel and cross-sectional regressions. With respect to the cross-sectional analysis, our results are of similar magnitude, but slightly higher than those reported by related studies (Dell et al., 2009; García-León, 2015) that were based on data with lower geographical coverage. Dell et al. (2012) were the first to use panel models to identify temperature impacts on national GDP growth. Contrary to our approach, they regress growth rates on temperature levels (not changes in temperature levels). Burke et al. (2015) extended this approach by including quadratic temperature levels; García-León (2015) provide estimates using a similar methodology for EU-NUTS regions and Burke and Tanutama (2019) use district-level data for several countries. All these studies report similar marginal effects of a 1 °C temperature increase. As these studies regress growth on temperature levels, they imply permanent growth rate impacts after a onetime 1 °C temperature increase. Marginal effects in our study tend to be slightly larger, in particular at higher temperature levels, even if we use a comparable econometric specification that is based on temperature levels rather than temperature changes.

We find strong evidence that output levels are affected after a onetime temperature increase. If such a shift in temperature is permanent, production levels are affected permanently as well – but we do not find evidence that the (long-run) balanced growth rate of the economy is affected. Our conclusion is therefore different than Burke et al. (2015) who conclude that also long-run growth rates could be affected by temperature changes. The reason for this discrepancy is partly due to the choice of the regression model in Burke et al. (2015) which suggests long-run growth rate effects when (cumulative) coefficients in temperature levels are significant. The small historic within-country variability in long-term climate trends might further explain the

Table 9

GRP losses of a 1°C temperature increase – overview of findings from the literature. Table shows different estimates from the literature for the effect of a 1 °C temperature increase on reductions of economic output and compares them to our results. Upper rows refer to findings from annual panel models, lower rows to those from cross-sectional models. For non-linear annual panel specifications, marginal effects at 25 °C are given. Studies differ in regional scope and modeling choice, as detailed in the main text.

Study	Finding
	Annual panel models
Dell et al. (2012)	1–1.3% for poor countries, no significant effect for full sample
Burke et al. (2015) (0 lag)	−0.3% at 10 °C and 1.2% at 25 °C temperature
Burke et al. (2015) (5 lags)	0.6% at 10 °C and 0.9% at 25 °C temperature
García-León (2015)	0.03–0.06% for EU NUTS regions
Burke and Tanutama (2019) (0 lag)	0.1% at 10 °C and 1.7% at 25 °C temperature
Burke and Tanutama (2019) (5 lags)	0.8% at 10 °C and 2.9% at 25 °C temperature
Our study: temperature change (preferred; 1 lag)	0.8% at 10 °C and 3.5% at 25 °C temperature
Our study: temperature level (0 lag)	0.5% at 10 °C and 2.6% at 25 °C temperature
Our study: temperature level (5 lags)	2.4% at 10 °C and 2.6% at 25 °C temperature
	Cross-sectional models
Dell et al. (2009)	1.2–1.9% for Latin American municipalities
García-León (2015)	1.6–2.2% for EU NUTS regions
Our study	2.0–4.3%

non-significant findings on growth effects in our long-difference model. Hence, existing research does not give an unambiguous answer to the growth-vs.-level question.

Our projected total losses by the end of the century are lower than those reported by Burke et al. (2015). The main reason for this is the compound effect of permanently lower growth rates in Burke et al. (2015). As argued in Sec. 6.2 and shown in Supplementary Materials S4.1, damages of the same amount of warming grow exponentially in the considered time frame where this warming occurs according to the Burke et al. (2015) approach. Hence, a fundamental difference between our study and related approaches concerns the interpretation of the economic impacts as growth vs. level effects. As shown in Sec. 5.1, when including temperature differences and (quadratic) temperature levels into one regression, the latter becomes insignificant, suggesting that growth rates are not permanently affected. Moreover, the long-difference regression does not find evidence that temperature levels affect growth rates.

As the cross-sectional regressions suggest a negative relationship between temperature and GRP that is stable over different decades, we conclude that technological change has not reduced the temperature sensitivity of our economies. The long-difference regressions confirm this interpretation: If technological change had weakened this temperature sensitivity in recent times, there would have been a significant positive effect of temperature (level) on decadal growth.

Both, the cross-sectional as well as the panel estimate, imply damages that are high compared to that reported by damage functions used in integrated assessment models (e.g. Nordhaus and Boyer, 2000). Contrary to damage functions in IAMs, our estimates only refer to the effect of (historic) temperature and precipitation variability on GDP. That is, they primarily cover impacts on labor productivity, land productivity (agricultural yields) and depreciation of capital. Non-market damages such as loss of life, conflicts and violence, biodiversity and ecosystem damages are not captured (confer to Howard and Sterner (2017) for a comprehensive overview of climate damage estimates based on various approaches). In particular, years of life lost are not considered in our analysis. This climate impact has been found to constitute the major share of the costs of global warming in the United States (Hsiang et al., 2017). Damages due to sea level rise are also excluded from our regression model. As a consequence, it is important to keep in mind that our cost estimates do not cover the full spectrum of potential climate damages but contribute to a better understanding and quantification of several specific impact channels, i.e. labor productivity, land productivity and capital depreciation.

When looking at globally aggregated GRP losses, we find that projected losses are about twice as large when computed based on the panel regression estimates instead of on their cross-sectional equivalent. This suggests that short-term weather shocks have a larger effect on economic output than long-term climate changes, possibly due to adaptation.

One important aspect to consider when comparing panel and cross-sectional results are dynamic equilibrium effects that take place over the long-run. Fankhauser and Tol (2005) emphasize that changes in productivity also affect savings dynamics. This, in turn, determines capital stocks and production levels in the long-run and adds to the original productivity shock due to climate change. Kalkuhl and Edenhofer (2016) derive a multiplier effect due to savings dynamics that increases GDP losses compared to the original total factor productivity (TFP) shock. In a one-sector Ramsey growth model with a Cobb-Douglas production function, this multiplier is $1/(1-\alpha)$ with α denoting the capital income share. For a typical value of $\alpha = 1/3$, long-run GDP reductions due to endogenous decreases in capital stocks are about 50% higher than the immediate short-run reductions due to lower productivity. The multiplier effect can, however, change substantially in both directions if sectoral reallocations are also possible (Kalkuhl and Edenhofer, 2016). Against this background, our panel estimates can be considered as actual TFP impacts that occur without any adjustments in saving dynamics. In the long-run, GRP impacts of weather shocks are likely to be larger because reduced productivity decreases savings and, thus, output further. Hence, GRP impacts in the panel-based approach would even be larger than displayed in Table 7 and in Fig. 3. Contrary, the SCC estimates in DICE consider already adjusted savings because savings are an endogenous variable.

Our cross-sectional results could be interpreted as estimates that implicitly include the endogenous saving response because they rely on long-run output. The actual TFP impacts of climate would then be lower - by how much exactly depends, inter alia, on how integrated capital markets are *within* countries. If capital markets within countries are perfectly integrated, changes in saving rates are homogeneous in all regions and, thus, captured by our country fixed effect. In this case, our estimates would indicate TFP impacts, as the panel estimate. Similar to the panel estimate, long-run impacts would then be higher than suggested by our estimates due to endogenous saving dynamics. Contrary, if regions within countries are closed economies with no exchange of capital across regions of the same country, our cross-sectional estimates would include the autonomous adjustments in savings. Actual TFP impacts of climate would then be lower than suggested by our cross-sectional estimate.

8. Conclusions and outlook

An increasing number of analyses aims at improving estimates of damage functions, which play a central role in the evaluation of climate policies. For example, econometric studies have analyzed how temperature fluctuations influence various socio-economic outcomes to assess the effect of future warming on the economy or on specific economic sectors (e.g. reviewed by Carleton and Hsiang (2016)).

Our analysis adds to this research as follows: Using a stylized growth model, we illustrate how weather shocks and changes in climate conditions affect economic output and growth rates. This provides a theoretical underpinning for the choice of the regression models. By using a comprehensive data set of economic activity at the subnational level with almost global coverage, we empirically analyze the climate–growth nexus at various time scales.

Consistent with existing evidence on labor productivity and agricultural yields, we find strong evidence that changes in annual mean temperatures affect economic output in a non-linear way. Increases in temperature tend to increase gross regional product (GRP) in cold regions (where annual mean temperature is below 5 °C) and reduce GRP in hot regions. We find no evidence that a unique temperature increase changes the long-run growth rate of the economy. However, our panel specification suggests that a permanent increase in temperature will lead to a permanent loss in economic output in hot regions. This loss is considerable: a 1 °C temperature increase in a region with an annual mean temperature of 25 °C, reduces GRP by about 3.5% in that region.

By means of a long-difference regression model, we test whether the results from the annual panel model translate to longer time scales. We do not find that temperature (or precipitation) levels affect growth rates of regions over long periods. Using a cross-sectional model on per-capita GRP shows, however, significant negative temperature effects that are stable over time. Both findings suggest that technological change has not weakened the temperature-sensitivity of our economies. As we are using sub-national data, we can include country fixed effects in the cross-sectional approach, hence avoiding omitted variable bias which is one of the major limitations of cross-sectional regressions on the climate-economy relationship.

Applying the panel and cross-sectional results to projected warming levels for a high-warming scenario, we project considerable production losses, around 7–14% in the year 2099 compared to a scenario of no further warming. In tropical regions, output losses of up to 20% are possible. Note that non-market impacts and costs due to sea-level rise are excluded from our damage estimates.

Our findings can help to improve the formal representation of climate change impacts within existing integrated assessment models (IAMs) by: (i) better quantifying damage functions; and (ii) differentiating climate change impacts among productivity and growth-rate impacts. Most IAMs include only the impacts of long-term climate conditions on economic production but neglect annual weather shocks, extreme events or uncertainty about weather realizations. By incorporating our damage function from the panel regression model in the DICE-2016 model, we find that the social cost of carbon more than triple compared to what the original DICE-2016 damage function suggests.

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Declaration of competing interest

We – the authors – declare no conflict of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeem.2020.102360.

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