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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 estimate the impacts of climate on economic growth using Gross Regional Product (GRP) for more than 1,500 regions in 77 countries. In temperate and tropical climates, annual temperature shocks reduce GRP whereas they increase GRP in cold climates. With respect to long-term climate conditions, one degree of temperature increase reduces output by 2-3%. The effect of annual or long-term precipitation is found to be less important and less robust among specifications. For projected global warming of 4°C until 2100, we find that regions lose 9% of economic output on average and more than 20% of output in tropical regions.

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1 Introduction

Anthropogenic climate change due to greenhouse gas emissions is 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; Carleton and Hsiang, 2016), 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. The 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 GDP by 0 to 20 percent (Stern, 2008). The poor theoretical and empirical foundation for such damage functions has widely been criticized (Pindyck, 2013; Farmer et al., 2015; Moore and Diaz, 2015; Stern, 2016; National Academies of Sciences and Medicine, 2017).

There is a growing body of empirical research that aims to improve these damage estimates. 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 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 rather new strand of literature uses panel regression models to explore the relationships between climate, weather, human activity and economic outcomes based on panel data (Dell et al., 2014). 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), labor productivity (Deryugina and Hsiang, 2014) human capi-

tal (Zivin and Neidell, 2014), energy demand (Auffhammer and Mansur, 2014) and crop yields (Schlenker and Roberts, 2009). These works provide insights on potential impacts of future climate change, partially with much higher economic losses from anthropogenic warming than previous estimates used in integrated assessment models (Burke et al., 2015).

While the strength of panel regression techniques is to avoid omitted variable bias, their weakness is 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. Yet, a rigorous empirical analysis of climate change impacts on economic outcomes on different temporal scales is lacking. One analysis in this direction is a recently published paper by Burke and Emerick (2016). However, this work has a limited geographical and sectoral focus as it only considered agricultural yields in the US. Existing analyses on the impact of weather shocks on GDP have further been criticized to ignore those climate conditions that affect the marginal response to weather (Mendelsohn, 2016) or to neglect trends in climate variables.

This paper aims to fill this gap by using a panel on subnational GDP data – Gross Regional Product (GRP) – that allows for depicting local weather as well as climate conditions on various time scales. We are therefore able to address some of the shortcomings of previous analyses with respect to regional scope, temporal scale and specific technical issues. We further extend these works by including human heat-stress related climate variables, the Simplified Wet Bulb Globe Temperature-index (Budd, 2008; Willett and Sherwood, 2012). As humidity and vapor pressure is expected to increase further under climate change (IPCC, 2013), the increase in *sensed temperature* will be larger than the increase in actual air temperature. Some regions, e.g. in the Arabian peninsula, might become even inhabitable due to excessive wet-bulb temperature under future climate change (Pal and Eltahir, 2015).

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, only annual shocks matter. The estimated marginal effects of temperature increase are slightly higher than previous estimates. In particular, hot regions are more strongly affected by further warming than cooler regions. Furthermore, the impact of short-run shocks and long-run climate conditions on GRP is of similar magnitude which suggests little macroeconomic adaptation.

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 GDP. We next explain the data and the empirical strategy (Section 3). Section 4 provides the key results for panel and cross-sectional estimates of climate impacts. We apply these estimates to projected greenhouse gas concentration trajectories to assess possible GDP losses under a

business-as-usual scenario in Section 5. The last section concludes with implications for future research.

2 Weather vs. climate impacts in the neoclassical growth model

To frame our empirical analysis, we consider a simple neoclassical growth model with unanticipated, temporary annual weather shocks ω and anticipated, permanent changes in climate Ω on labor productivity or capital stocks. Output per capita y is produced using a neoclassical production function $y(t) = F[K(t), A(t)L(t)]/L(t)$ with labor-augmenting technological change $A(t)$, capital $K(t)$ and labor $L(t)$. As $F(\cdot)$ is assumed to be homothetic of degree one, $y(t) = f[k(t), A(t)]$ with $k(t)$ per-capita capital. Following the standard approach in climate-economy models (Nordhaus, 1993), we assume that technological progress $A(t)$ is exogenous and technology grows at the constant rate g_A .

A basic consequence from the neoclassical growth model is that per-capita output grows at the constant rate g_A , augmented by a convergence term $\psi(\cdot)$ (Barro and Sala-i Martin, 2003):

$$g := \frac{d \ln[y(t)]}{dt} \approx g_A + \psi[y(t)/y^*(t)] \quad (1)$$

with $\psi'(\cdot) > 0$ and $y^*(t)$ the per-capita GDP along the balanced growth path (BGP). Thus, the lower the per-capita GDP is with respect to the BGP GDP of the economy, the higher is the growth rate. For $t \rightarrow \infty$, the per capita GDP growth rate approaches the growth rate of the technology g_A .

Previous works emphasized that the level of labor productivity levels and agricultural yield depends on weather, ω , and climate, Ω , (Mendelsohn et al., 1994; Schlenker and Roberts, 2009; Deryugina and Hsiang, 2014) implying $A(t) = \phi(\omega, \Omega)e^{g_A t}$. If weather shocks, e.g. storms or floods, destroy assets, they also affect depreciation of capital (Hsiang and Jina, 2015). In the growth model, capital stocks would therefore evolve according to $dK/dt = I - \delta(\omega, \Omega)K$.

A weather shock ω at time t' is temporary and unanticipated (and assumed to be not serially correlated). It reduces per-capita GDP instantaneously by $\frac{\partial f(k, A)}{\partial A} \frac{\phi(\omega, \Omega)}{\omega}$. Because of lower GDP per capita during a negative shock, growth for $t > t'$ will be higher than without the shock due to (1). Long-run per-capita GDP levels will not be affected and follow a balanced growth path. A shock on capital has qualitatively the same dynamics: output is reduced by $\frac{\partial f(k, A)}{\partial k} \frac{\partial \delta(\omega, \Omega)}{\partial \omega}$ and growth for $t > t'$ increased to catch up with GDP levels along the balanced growth path. Hence, within the neoclassical production framework, weather shocks affect GDP instantaneously but the GDP loss fades out over time and diminishes to zero. Damages to labor productivity or capital stocks do not have permanent implications on living standards.

Permanent anticipated changes in climate, Ω , however, do affect the long-run wealth *level* of the economy but not the long-run growth rates. A permanent reduction in A due to Ω implies a lower technology level and, thus, a downward shift of the balanced growth path for per-capita GDP $y^*(t)$. A permanent increase in capital depreciation δ implies a similar reduction in the balanced growth path through the Euler equation which is, along the balanced growth path, given by $\tilde{f}'(\tilde{k}) = \rho + \delta(\omega, \Omega) + \eta(c)g_A$ with ρ the pure time preference rate of households and $\eta(c) \geq 0$ the inverse of the intertemporal elasticity of substitution of the utility function. The tilde denotes functions and variables in intensive form, i.e. divided by $A(t)$. As $\tilde{f}''(\tilde{k}) < 0$ holds, a higher depreciation implies a lower capital stock \tilde{k} .

The neoclassical framework therefore provides two testable hypotheses: unanticipated temporary shocks affect GDP instantaneously and are followed by a growth reversal effect while anticipated and permanent changes in climate lead to permanently different income per capita.

3 Data and empirical strategy

For the climate data, gridded data at 0.5 degree resolution from the Climate Research Unit of the University of East Anglia (CRU TS v3.23 [Harris et al., 2014](#)) are used. The climate data are aggregated to the regional level where the highest administrative unit of a country from the GADM database is used. Hence, states in the US and provinces in Canada are considered as *regions* in our dataset. The CRU TS 3.23 contains monthly observations from 1901 to 2014. It is chosen because of its high spatial resolution which allows for a mapping of climate conditions to subnational administrative units. The CRU data are statistically interpolated across weather stations. As we include only countries in our database which have GDP data at the subnational level, country selection will be biased to countries with higher statistical capacity. Hence, statistically interpolated data may be more accurate than re-analysis data which are more advantageous for data-poor regions ([Auffhammer et al., 2013](#)). The data are processed using GNU R. In order to ensure a precise assignment of climate information to administrative units – in particular if an administrative unit is smaller than a 0.5° grid cell or lies only partly in it – we apply a two-step algorithm. In a first step, the gridded climate information at 0.5 degree resolution is translated into information on a 0.25° grid assuming that each 0.5° grid cell consists of four 0.25° grid cells and that the climate data is the same for all four cells.¹ In a second step, the algorithm considers 100 equally distributed points in each 0.25° grid cell and then counts how many of those lie within the administrative unit. The respective percentage is then used as a basis for the region-specific aggregation of the climate

¹For Europe, higher-resolution climate data at 0.25 degree provided by the E-OBS gridded dataset ([Haylock et al., 2008](#)) for the years 1950-2016 are used for robustness checks. For further robustness checks of the cross-sectional analysis, the WORLDCLIM 2 database ([Fick and Hijmans, 2017](#)) on climate variables for 1970-2000 are considered.

data. Robustness checks with alternative climate data are conducted.

Further geographical variables are obtained from various sources: Distance to navigable rivers and distance to coast 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 2013-2099 in accordance with the Representative Concentration Pathway 8.5 (business-as-usual scenario, ([Van Vuuren et al., 2011](#))) are derived from the climate dataset of the Intersectoral Impact Model Intercomparison Project (ISIMIP, ([Warszawski et al., 2014](#))). Precisely, we use data, also at 0.5 degree resolution, that originate from the Princeton Earth System Model of the Geophysical Fluid Dynamics Laboratory (GFDL-ESM2M, ([Dunne et al., 2012](#))) and include a bias-correction technique ([Hempel et al., 2013](#)) to ensure long-term statistical agreement of the projections with observational data from the WATCH database ([Weedon et al., 2011](#)).

We use annual Gross Regional Product (or related data) as a measure of economic activity on the regional level. These data are retrieved from various statistical agencies of central or federal governments (see Tab. 8 in the Appendix). We restrict the regression on economic data from 1980 onward as for earlier years the panel would become extremely unbalanced due to data scarcity (Fig. 6). We convert 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.

In the empirical analysis, we use mean temperature ET and mean precipitation EP over longer periods (30 years) as major climate variables, $\Omega = (ET, EP)$. We use two different approaches to calculate weather shocks $\omega = (T, P)$ in temperature T and precipitation P : Consistent with the time-series literature, we use first-differences of annual climate data and obtain a stationary series on changes in annual climate. Alternatively, we follow the approach of [Mendelsohn \(2016\)](#) and calculate climate shocks as deviations from the long-term mean. Hence, in a ‘normal’ year, we would observe $(T, P) = (0, 0)$. As temperature and precipitation follow trends, we de-trend both variables for each region assuming linear trends with respect to their 1980 values.² Based on the conceptual growth model in Section 2, we are interested in two basic relationships: (i) the role of weather, conditional on climate and (ii) the role of climate on growth, and estimate the following two basic models:

$$g_{i,t} = \sum_{s=0}^S \alpha_1 T_{i,t-s} + \sum_{s=0}^S \alpha_2 T_{i,t-s} \tau_{i,t-s} + p_i(t) + \mu_t + \varepsilon_{i,t}, \quad (2)$$

$$y_i = \beta_1 \tau_i + \gamma X_i + \delta_c + \eta_i, \quad (3)$$

²In our sample, average temperature increases by 0.24°C per decade. Without de-trending, these gradual changes would be reflected in the temperature shock variable T after some time.

with S denoting the number of time lags. In particular, we include an interaction term between weather and climate in the panel regression as these two might not be additively separable (Mendelsohn, 2016). Thus, we can capture the weather effect on GDP conditional on the prevailing climate.

While the panel model (2) captures the short-term dynamics of weather on growth, the cross-sectional regression (3) is relevant for long-term dynamics which account for adaptation (change in technology) in particular. The per-capita growth rate of region i , compared to GRP in the previous year, is denoted by g_{it} ; α_1 measures the climate-independent weather impact while α_2 measures the marginal impact of weather conditional on climate. Region or country-specific time trends (including fixed-effects) are captured by $p_i(t)$; μ_t includes year-fixed effects. Because of the regional fixed effects and because climate is almost time invariant for the considered period, we cannot include climate directly in the panel regression.

For analyzing the impact of climate on GRP, we estimate in (3) log per capita GRP y_i in region i with linear temperature and precipitation (β_1). Equation (3) is a cross-sectional regression for a specific time period; in our base specification, we use the 2005-2014 decade as it provides the highest data coverage. We further include regional covariates with respect to geography and resource endowments, X_i , and country fixed-effects, δ_c , to account for unobserved country-heterogeneity, e.g. institutions, that affect GDP.

Recent research has emphasized the role of other weather and climate variables than temperature and precipitation (e.g. Zhang et al., 2017). We tested for including cloud cover, water vapor pressure and climatological potential evapotranspiration from the CRU database in the regressions. Data quality is, however, highest for temperature and precipitation in the CRU database (Harris et al., 2014): Vapor pressure has less dense observations than temperature and precipitation; it relies therefore on many synthetic observations to fill data gaps. Evapotranspiration is derived from other climatological variables like temperature, precipitation and vapor pressure, and therefore not independent. Also, there exists a high correlation between these additional climate variables and temperature and precipitation causing multicollinearity problems in the regression. We therefore exclude them in our analysis and do not report them.

Besides high temperature, high temperature combined with high humidity causes heat stress for humans as it reduces the natural cooling mechanism through transpiration. Various papers have therefore used (Simplified) Wet Bulb Globe Temperature (SWBGT) as an indicator for sensed temperature and heat stress (Somanathan et al., 2015; Pal and Eltahir, 2015; Matthews et al., 2017) which affects labor productivity (Hsiang, 2010) and mortality (Barreca et al., 2016). With the data available from the CRU data, we calculate SWBGT according to the approximation given in Willett and Sherwood (2012):

$$\text{SWBGT} = 0.567\tilde{T} + 0.393V + 3.94,$$

with $\tilde{T} = ET + T$ the actual air temperature and V the vapor pressure. Because of the large

diurnal temperature variation, we do not use the mean temperature, but the (averaged) daily maximum temperature provided in the CRU data for calculating SWBGT. Critical thresholds for SWBGT range from 25 (heavy activities) to 30 (light activities). Values larger than 35 are considered to be dangerous (Willett and Sherwood, 2012; Pal and Eltahir, 2015; Matthews et al., 2017).

Table 1: Summary statistics - annual panel data

Variable	Obs	Mean	Std. Dev.	Min	Max
Annual GRP growth in region	29863	.062	.157	-2.442	2.303
Change in annual mean temperature (°C)	29752	.031	.688	-3.655	3.573
Change in annual precipitation (1000mm)	29752	.002	.279	-2.039	1.92
Temperature shocks (de-trended)	29752	-.065	.555	-3.314	2.744
Precipitation shocks (de-trended)	29752	.005	.21	-1.509	1.681
Temperature mean (de-trended, 1980)	29752	13.974	8.29	-14.178	28.697
Precipitation mean (de-trended, 1980)	29752	1.096	.73	0	4.823
SWBGT mx = 31,32	29863	.114	.318	0	1
SWBGT mx = 33,34	29863	.121	.326	0	1
SWBGT mx = 35,36	29863	.049	.215	0	1
SWBGT mx = 37,38	29863	.012	.107	0	1
SWBGT mx = 39,40	29863	.001	.034	0	1
Coast (dummy)	29863	.444	.497	0	1
Port (dummy)	29863	.318	.466	0	1
Distance to coast (log km)	29849	4.716	1.45	.118	7.739

Table 2: Summary statistics - cross-sectional data

Variable	Obs	Mean	Std. Dev.	Min	Max
Regional GRP (log USD)	1515	8.723	1.4	5.193	12.026
Annual mean temperature (°C)	3039	18.17	8.204	-20.623	30.395
Annual precipitation (1000mm)	3039	1.148	.795	0	5.18
Cum Oil Gas (log mln bbl OE)	3522	0	.004	0	.122
Distance to coast (log km)	3501	11.098	2.039	4.962	14.647
Distance to river (log km)	3473	10.498	1.316	6.215	15.592
Altitude (km)	3516	.542	.628	-.012	4.882
Surface area (log km2)	3521	8.231	2.689	-1.204	15.039

Tab. 1 and Tab. 2 show the summary statistics for the panel and cross-sectional analysis, respectively. Average annual per-capita growth in USD is 6.2%. The high variability of growth is mainly driven by the large volatility of economic growth over time (as the within standard deviation is larger than the between standard deviation). 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 include 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. Weather variables have been de-trended and de-meanead before they are included in the unbalanced GRP data. The temperature and precipitation shocks in Tab. 1 have non-zero means as only those year-region observations with non-missing GRP data are included in the panel. The SWBGT dummies contain the maximum Simplified Wet Bub Globe Temperature within one year. In about 11% of the years, the SWBGT reached maximum values of 31 or 32°C while it

reached only in 1% of the year values of 37°C or larger. Almost 45% of the observations are in regions with a coast and 32% in regions with port.

Comparing Tab. 1 with Tab. 2 indicates that inter-annual temperature variation is rather low (standard deviation of 0.688 (change) and 0.555 (deviation)) while spatial variability of long-term temperature is large (standard deviation of 8.204). The discrepancy is less pronounced for rainfall.

4 Results

4.1 Annual temperature and precipitation shocks

We first run regression model (2) with first-differenced weather data, exploiting the annual panel structure of our data. Hence, we exclude the direct impact of the time-invariant local climate τ_i because of its perfect collinearity with region fixed-effects but include interaction terms with weather shocks. Year fixed-effects and region fixed-effects are included to account for various drivers of regional growth besides local climate (such as global covariate climate shocks like El Niño, economic shocks as well as time-invariant local geographic or institutional conditions). Additionally, we include quadratic country-specific time trends which address changes in institutions and political or economic conditions over time that affect growth rates. Standard errors are clustered at region level.

Tab. 3 shows the main results, using annual changes in temperature and precipitation as weather shock variables. Column (1) is a linear regression with one lag. The cumulative effects (at the bottom of the table) indicate that an increase of annual mean temperature by 1°C in a specific region reduces GRP by 0.6% in that region, with most of the reduction occurring in the year after the temperature increase. An additional amount of rainfall of 100mm in one year increases GRP by 0.4%. Both estimates are highly statistically significant. In column (2), intertemporal interaction effects are included. If temperature increases by 1°C for two years in a row, GRP decreases by 2% while the impact of precipitation is close to the estimate in (1). This indicates that the impact of weather events is not independent of past weather events. Finally, column (3) displays the results where annual temperature and precipitation changes are interacted with the prevailing long-term climate conditions. While the interaction term is irrelevant for precipitation, it is highly statistically significant for temperature. The resulting marginal effects of a temperature change conditional on climate are shown in Fig. 1. We find stronger negative impacts for most regions compared to [Burke et al. \(2015\)](#) (see Fig. 7 in the appendix for a comparison). While a 1°C temperature increase reduces GRP by 0.8% in a region with long-term mean temperature of 10°C (a typical temperate climate region), it reduces GRP by 4.6% in a region with long-term temperature of 26°C (a typical tropical climate region).

Table 3: Panel Regression: Main Results (Using Weather 1st-Diff)

	(1)	(2)	(3)
T	-0.00218* (0.00123)	-0.00115 (0.00120)	0.0102*** (0.00195)
L.T	-0.00414*** (0.00125)	-0.00328*** (0.00120)	0.00588*** (0.00209)
T \times L.T		-0.0160*** (0.00129)	
T \times ET			-0.00135*** (0.000187)
L.T \times ET			-0.00104*** (0.000193)
P	0.0109*** (0.00399)	0.0107*** (0.00393)	0.00631 (0.0109)
L.P	0.0304*** (0.00360)	0.0311*** (0.00358)	0.0321*** (0.00944)
P \times L.P		-0.00325 (0.00673)	
P \times EP			0.000618 (0.00466)
L.P \times EP			-0.00275 (0.00437)
Observations	29307	29307	29307
N regions	1545	1545	1545
bic	-38109.1	-38269.2	-38120.5
T (cum)	-.0063	-.0204	.0161
T (cum) [SE]	.0022	.0027	.0037
T \times ET (cum)			-.0024
T \times ET (cum) [SE]			.0003
P (cum)	.0413	.0386	.0384
P (cum) [SE]	.0059	.0097	.0148
P \times EP (cum)			-.0021
P \times EP (cum) [SE]			.0066

Standard errors in parentheses

(cum) - cumulative effect over lags. [SE] - standard error. All standard errors clustered at region level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

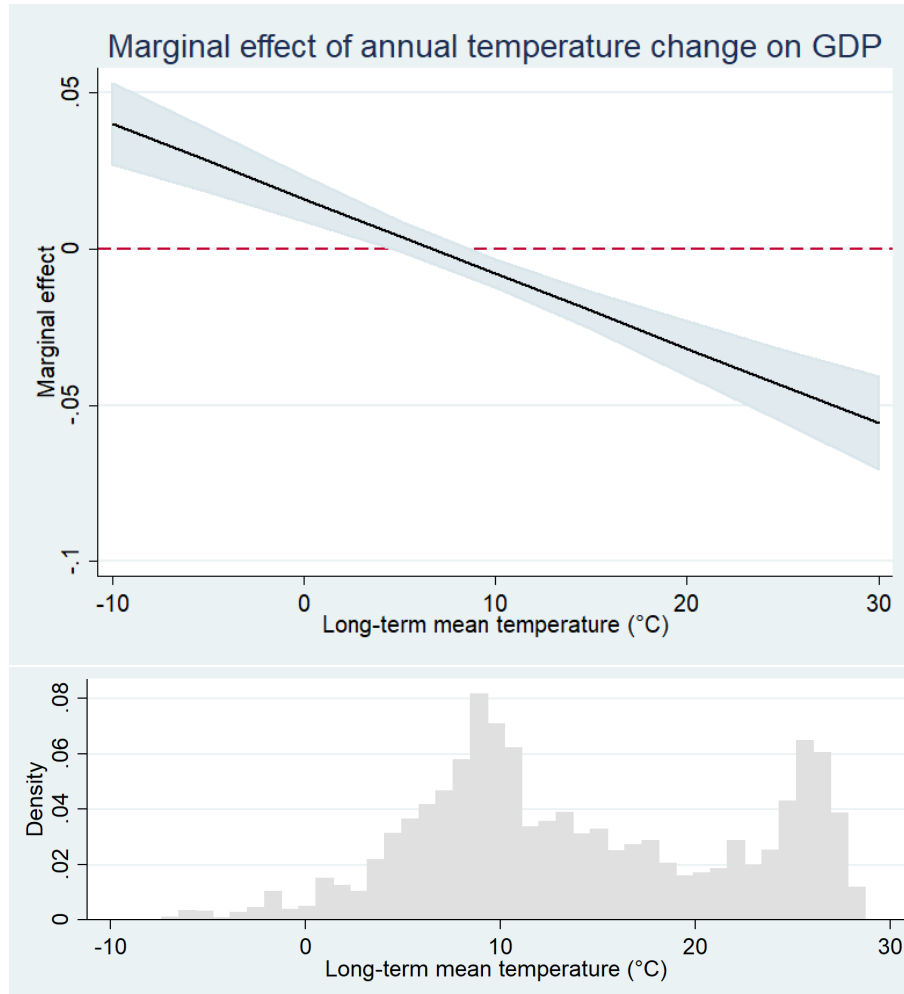


Figure 1: Top: Marginal effect of annual temperature change according to column (3) in Tab. 3. The shaded area indicates the 95% confidence interval. Bottom: density of temperature observations in our panel.

There are various reasons for the discrepancy between our estimates and those of [Burke et al. \(2015\)](#). First, one strength of our approach is that our estimates are based on spatially highly resolved data. Thus, our estimates can account for potentially large regional variations in the data which is averaged out at the national level. Second, [Burke et al. \(2015\)](#) use a different specification with temperature and temperature squared while we rely on first differences of temperature and an interaction term with long-term temperature. In addition to using first differences, we use the deviation of annual temperature from the long-term de-trended temperature mean and its interaction with the long-term de-trended temperature mean (see Tab. 11 in the appendix and the respective marginal effect for the zero lag model in Fig. 7). Specification (4) in Tab. 11 is close to [Burke et al. \(2015\)](#) except for the (small) quadratic temperature deviation term that is implicitly included in their quadratic specification.³

As Tab. 11 shows, the coefficients are highly sensitive to the number of lags considered as the level of significance strongly changes. Moreover, even the sign of the interaction term may reverse. The opposing sign of the two-year lagged weather variable compared to the non-lagged and one-year lagged variable is consistent with the predicted catch-up growth after negative weather shocks discussed in Section 2. The loss of significance of cumulative effects over time indicates that weather deviations do not have permanent impacts on GRP levels. In contrast, the specification with first differences shows a stable interaction term for various choices of lags (see Tab. 10 in the appendix).

Tab. 4 considers in addition to the covariates of the main regression also dummy variables that indicate whether a specific heat event occurred. For consistency, we consider again first-differences in weather variables but also in heat event dummies. Hence, the 31-32°C dummy equals one if the current year has at least one month with a SWBGT of 31 or 32°C and if the previous year did not experience such an event. We always include the same number of lags for heat events as for weather variables. Adding heat events hardly changes the estimates of temperature and precipitation variables though their magnitude decreases marginally. Heat events, however, additionally reduce GRP. The impact of a 37-38°C event is particularly strong as it reduces GRP by 6% to 8%.

Further robustness checks are provided in Tab. 9 in the appendix. We modify the base specification of the linear regression and the regression with interaction term by considering different time trends (country specific and region specific) and by including the lagged endogenous variable. Compared to the base specification, including the lagged endogenous variable does hardly change the results.⁴ The negative coefficient of the endogenous variable indicates that there is convergence growth after a shock has reduced GRP. This again emphasizes that

³The quadratic regression in [Burke et al. \(2015\)](#) is basically $y = \alpha x + \beta x^2 + \varepsilon$. Using temperature shocks T from the time-invariant mean temperature \bar{x} , we can substitute $x = \bar{x} + T$ and obtain (after leaving out time-invariant terms) $y = \alpha T + 2\beta T\bar{x} + \beta T^2 + \varepsilon$.

⁴The inclusion of the lagged dependent variable will, however, bias the estimated coefficients to a certain extent ([Nickell, 1981](#)). However, as the coefficient of the lagged dependent variable is small (around -0.1) and as we have a rather large number of observations over time, the Nickel bias should be small.

Table 4: Panel Regression: Heat Events

	(1)	(2)	(3)	(4)	(5)	(6)
T	-0.000664 (0.000985)	0.000490 (0.000988)	-0.00218* (0.00123)	-0.000934 (0.00124)	0.0102*** (0.00195)	0.00863*** (0.00196)
L.T			-0.00414*** (0.00125)	-0.00378*** (0.00126)	0.00588*** (0.00209)	0.00549*** (0.00213)
T × ET					-0.00135*** (0.000187)	-0.00108*** (0.000189)
L.T × ET					-0.00104*** (0.000193)	-0.00101*** (0.000205)
P	-0.00352 (0.00389)	-0.00555 (0.00391)	0.0109*** (0.00399)	0.00848** (0.00402)	0.00631 (0.0109)	0.00349 (0.0110)
L.P			0.0304*** (0.00360)	0.0288*** (0.00360)	0.0321*** (0.00944)	0.0309*** (0.00945)
P × EP					0.000618 (0.00466)	0.00157 (0.00469)
L.P × EP					-0.00275 (0.00437)	-0.00246 (0.00438)
Observations	29752	29752	29307	29307	29307	29307
N regions	1545	1545	1545	1545	1545	1545
bic	-38342.5	-38327.1	-38109.1	-38071.2	-38120.5	-38059.2
T (cum)			-.0063	-.0047	.0161	.0141
T (cum) [SE]			.0022	.0022	.0037	.0037
T × ET (cum)					-.0024	-.0021
T × ET (cum) [SE]					.0003	.0003
31-32°C		-.0023		.0012		-.0021
31-32°C [SE]		.0038		.006		.0003
33-34°C		-.01		-.0181		-.0069
33-34°C [SE]		.006		.0099		.0101
35-36°C		-.0406		-.049		-.0267
35-36°C [SE]		.0071		.0126		.0131
37-38°C		-.0701		-.0943		-.061
37-38°C [SE]		.009		.0153		.0158
39°C		-.0396		-.0576		-.021
39°C [SE]		.017		.0577		.0582

Standard errors in parentheses

(cum) - cumulative effect over lags. [SE] - standard error. All standard errors clustered at region level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

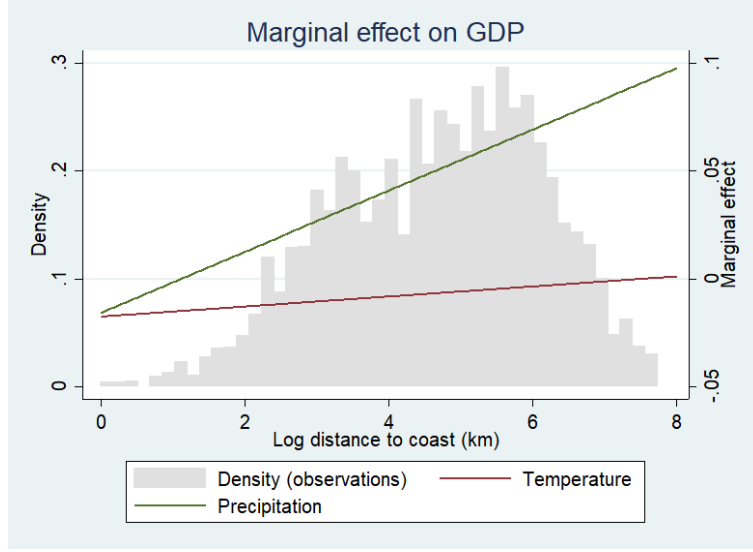


Figure 2: Marginal effect of annual temperature change, conditional on distance to coast (according to column (2) in Tab. 12)

negative impacts of climate shocks on GRP diminish over time.

With respect to the consideration of time trends, we observe no major differences between including country-specific or region-specific linear time trends (Tab. 9). The linear temperature effect, however, becomes larger if we use only linear time trends compared to quadratic time trends in our base specification.

It would be interesting to analyze further interaction terms, e.g. with respect to poverty, national income, sectorial composition of GRP, population density or trade. All of these variables suffer from potential endogeneity problems as they might be affected by long-term climate conditions as well as by temperature shocks. A clearly exogenous variable in our dataset is, however, distance to coast. We expect regions with smaller distance to coast to be richer and more open to trade. Thus, weather shocks might affect these regions differently than land-locked regions. We therefore test three major specifications: we interact weather with (i) a dummy for whether the region has a port; (ii) a dummy for whether the region has a coast; (iii) and the average distance to coast of the region.⁵ The results are shown in Tab. 12. The main findings are that the interaction terms with dummy variables on port or coast are always insignificant. Hence, regions with a port or a coast do not respond differently to weather shocks than other regions. With respect to the continuous variable distance to coast, however, we find a statistically significant impact of the interaction term.

Fig. (2) shows the marginal effect of annual temperature change with respect to distance to coast. First, the sign of the marginal effect is for the vast majority of regions equal to the sign of our base regression. Only in the extreme lower tale of regions close to the coast the marginal effect of precipitation is negative. These findings suggest that regions which

⁵This is calculated from all points within the region and therefore always nonzero.

are far away from the coast respond more strongly to precipitation but are less sensitive to temperature changes. One explanation for this could be that the size of the agricultural sector is larger in remote areas.⁶ While agriculture, in particular in developing countries, is strongly dependent on rainfall, service and manufacturing sectors might be more strongly affected by temperature shocks which reduce labor productivity. Another explanation could be related to trade openness which should be higher for regions closer to the coast. Trade allows for smoothing local agricultural supply shocks which tends to stabilize prices and food security. In regions with little trade, rainfall shocks affect food supply strongly and, thus, might have stronger impacts on the entire economy. As we cannot control directly for trade or sectoral composition due to endogeneity problems, these considerations remain tentative and might be subject to future research.

Overall, these robustness checks confirm the findings of the main specification: temperature shocks are positive (negative) for cold (hot) climates while the impact of precipitation is positive and independent of climate conditions. Weather shocks affect GRP instantaneously (up to the following year) but dissipate over time due to stronger convergence growth and, hence, do not have permanent impacts on GRP level.

4.2 Long-term climate conditions

For investigating the impacts of the prevailing climate conditions, we use the cross-sectional model (3). We include country fixed effects, distance to coast, distance to navigable rivers, altitude and cumulative oil and gas extraction (million bbl oil equivalents) for the region. Climate and GRP data are aggregated to 10 year intervals with 2005-2014 as the reference period because data coverage is largest for that period.⁷ Tab. 5 shows the results for three decades, with varying geographical coverage.

First, over all three decades, the coefficient on temperature and GRP is statistically significant and remarkably stable. One degree of temperature increase reduces GRP by 2-3%. Precipitation is not significant. As expected, fossil resource extraction increases GRP while 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.

We provide a number of robustness checks in the appendix. First, if we reduce the sample such that smaller regions are excluded, standard errors decrease and we get more precise estimates for the climate impacts (see Tab. 13). Larger areas show higher variability of climate compared to other regions in the same country. The results also remain stable with respect to the choice of covariates, except for altitude. Altitude is negatively correlated with temperature (mountainous regions are colder and more difficult to access). Omitting altitude from the

⁶We can confirm this relationship also in our data. If distance to coast doubles, the share of the agricultural sector increases by almost 1 percentage point.

⁷As GRP is volatile, we only consider regions for temporal aggregation with at least two observations in a decade.

Table 5: Crosssectional Regression

	(1)	(2)	(3)
Temperature	-0.0231* (0.0135)	-0.0290** (0.0135)	-0.0204** (0.00902)
Prec	-0.00364 (0.0612)	0.0193 (0.0597)	-0.0655 (0.0561)
Cum Oil Gas	7.080** (3.160)	5.588 (3.495)	3.819*** (1.210)
Distance to Coast	-0.113*** (0.0336)	-0.125*** (0.0435)	-0.0541* (0.0303)
Distance to River	-0.0660* (0.0361)	-0.0783* (0.0460)	-0.0484 (0.0495)
Altitude	-0.184** (0.0824)	-0.190** (0.0898)	-0.191*** (0.0668)
Observations	1482	1398	673
N countries	75	67	34
Period	2005-2014	1995-2004	1985-1994

Standard errors in parentheses

Country FE included. Standard errors clustered at country level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

regression biases the temperature coefficient downwards which is also visible in Tab.13. Running the regression without country fixed-effects leads to much higher temperature coefficients of about 10%. The magnitude of the temperature coefficient is similar among different climate data sources, although significance levels slightly differ (Tab. 15).

In order to test for possible non-linear relationships between GRP and climate we replace temperature and precipitation with bins that encode whether a specific temperature or precipitation level hold for a region. Fig. 3 shows the estimated coefficients for the temperature bins, using the 10-15°C bin as reference point. Regions with hot climate tend to have lower GRP. For example, regions with on average 20-24°C per decade have approximately 30% lower GRP. We do not observe strong non-linearities.

With respect to precipitation we find a u-shaped pattern (Fig. 4) implying high GRP in very dry and in very wet regions. Standard errors of the different bins are, however, large so that it is difficult to draw robust conclusions on the impact of precipitation on GRP.

4.3 Discussion

In Tab. 6, we contrast our estimates of climate impacts on GDP to panel and cross-sectional analyses that are comparable to our analysis but use data at a lower level of regional resolution and/or different methodological specifications (i.e. log levels of weather variables rather than deviations or first differences). For the panel as well for the cross-sectional results, our estimates are, in general, slightly above previous ones. Particularly, the panel estimates for tropical countries are three times higher than previous numbers. Since our estimates are based on a large sample of countries and regions from all continents of the world, they improve these

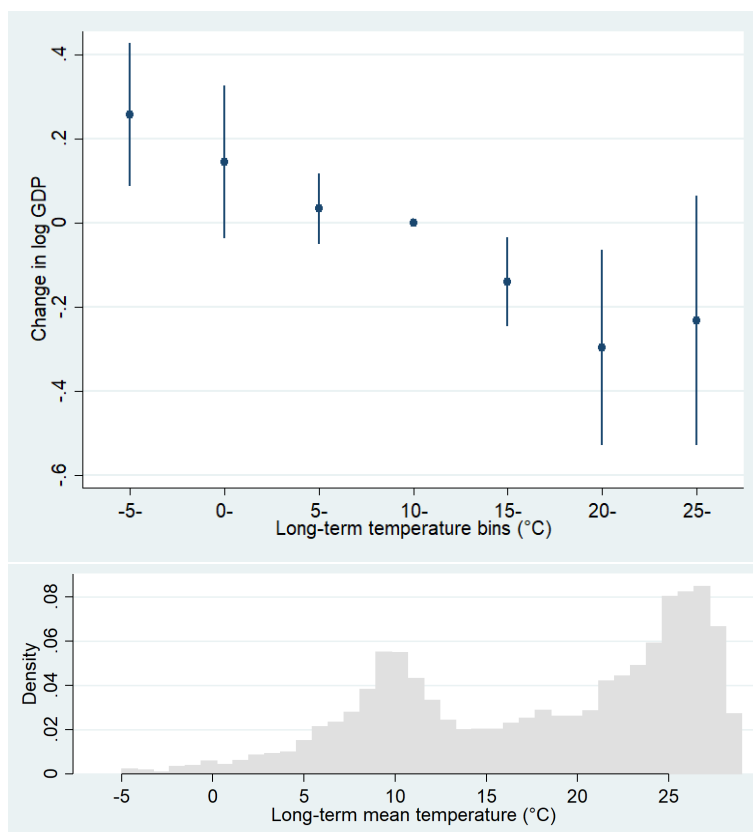


Figure 3: Cross-sectional regression with temperature bins. Geographical covariates and country fixed effects included. Considered period: 2005-2014. Bars indicate 90% confidence intervals. The bottom shows a histogram over temperature levels.

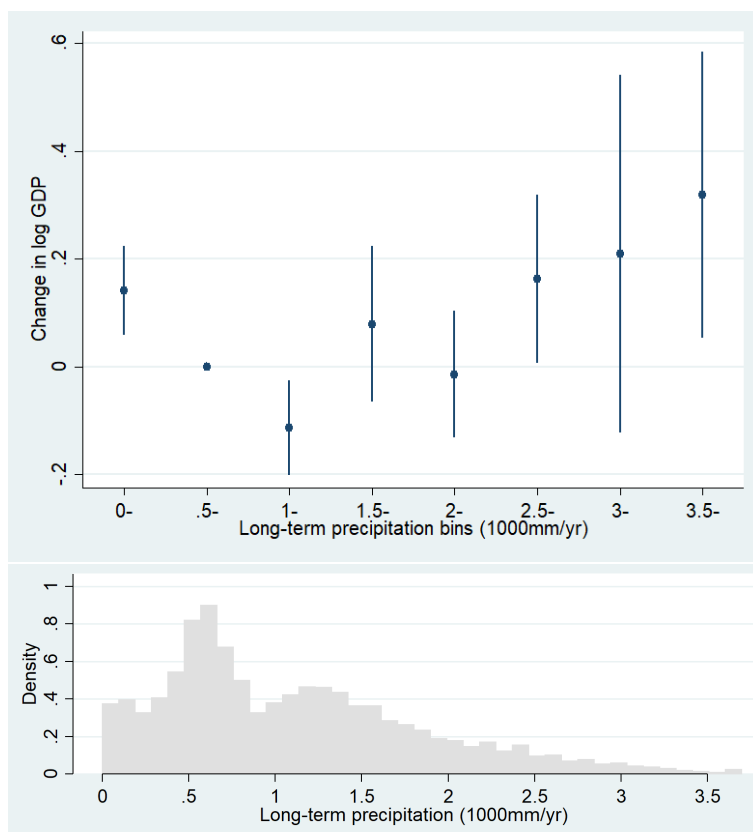


Figure 4: Cross-sectional regression with precipitation bins. Geographical covariates and country fixed effects included. Considered period: 2005-2014. Bars indicate 90% confidence intervals. The bottom shows a histogram over precipitation.

Study	Finding
<i>Annual panel models</i>	
Dell et al. (2012)	1-1.3% for poor countries, no effect for full sample
García-León (2015)	0.03-0.06% for EU NUTS regions
Burke et al. (2015)	-0.3% at 10°C and 1.3% at 26°C mean temperature
Our study	0.8% at 10°C and 4.6% at 26°C mean temperature
<i>Cross-sectional models</i>	
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	2.0-2.9%

Table 6: Impact of 1°C temperature increase on GDP - overview on findings from the literature

previous estimates and contribute to a more comprehensive understanding of climate impacts.

One particularly striking implication of our estimates as well as the overview provided in Tab. 6 is that there tend to be small differences between panel and cross-sectional estimates when looking at globally aggregated GDP losses. This suggests that short-term weather shocks and long-term climate changes tend to have similar impacts on GDP and that adaptation is hence limited. Regionally, however, short-run temperature shocks have quite different impacts on GDP than long-run temperature changes as the former are conditional on climate while the latter are linear in climate.

The results with respect to precipitation are less clear. While we find strong evidence of positive impacts on GDP in our panel, precipitation is insignificant in the cross-sectional regression. In related analyses (cited above), precipitation is also mostly insignificant.

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 affect also 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 also sectoral re-allocations are possible. Against this background, the long-term GDP impacts from the panel estimation are likely to increase and become larger than the estimates from the cross-sectional regression. Interpreting the cross-sectional results as estimates that include the endogenous saving response, the underlying productivity impact of climate is lower than the impact of short-term (annual) climate in the panel. This perspective would indicate that similar estimates of GDP losses from panel and cross-sectional regression are consistent with substantial adaptation as the panel measures only productivity impacts while the latter approach measures GDP impacts with saving and adaptation response.

Table 7: Annual GDP Losses at RCP 8.5 in 2100

Variable	Obs	Mean	Std. Dev.	Min	Max	P1	P10	P50	P90	P99
<i>Estimate from panel regression</i>										
Point estimate	3035	.102	.086	-.46	.321	-.105	-.007	.12	.204	.278
Lower estimate - 90% CI	3035	.073	.077	-.582	.25	-.139	-.024	.093	.159	.217
Upper estimate - 90% CI	3035	.131	.095	-.339	.392	-.072	.007	.147	.249	.34
<i>Estimate from cross-sectional regression</i>										
Point estimate	3035	.092	.024	0	.221	.02	.067	.091	.121	.149
Lower estimate - 90% CI	3035	.004	.001	0	.009	.001	.003	.004	.005	.006
Upper estimate - 90% CI	3035	.181	.047	0	.433	.04	.131	.179	.238	.293

5 Projected economic output losses

We use our regression results on historic climate-GRP impacts to project GRP losses under future warming. Projections on globally aggregated impacts rely not only on scenarios of future warming but also on forecasts of region-specific economic and population growth. As these are highly uncertain, we provide a basic region-specific estimation of the GRP loss in the year 2100 with warming forecasts based on the RCP8.5 scenario.⁸ We further neglect potential impacts on saving dynamics that may exacerbate GRP losses from productivity changes (see discussion above).

For the estimate based on the panel regression, we calculate the region-specific damage with the region-specific projected warming from 1980 to 2100, including the interaction term with the de-trended temperature in 1980. This follows precisely the specification (3) in Tab. 3. For the cross-sectional regression, we multiply the projected region-specific warming with the estimated coefficient from (1) in Tab. 5. We provide additional estimates at the lower and upper bound of the 90% confidence interval of the temperature-GRP coefficient. The (unweighted) mean warming over all regions is 4°C.

Tab. 7 summarizes the region-specific impacts. We first see that regions' annual GRP (unweighted mean) decreases by more than 9% for both approaches (panel as well as the cross-sectional) in 2100 compared to the no-warming scenario. On an aggregate level, differences between short-run climate shocks and long-run climate changes tend to be small. Regionally, damages can vary substantially under cross-sectional and panel-based projections (Fig. 5). Both approaches agree in the rather large losses in tropical areas but lead to diverging predictions for temperate and (sub-)polar regions. Because of the climate interaction term, impacts are much more diverse for the panel approach, as cold regions even benefit from warming while hot regions lose disproportionately. At the first percentile, gains from warming are about 7.4% while at the 99th percentile, losses from warming are about 23.3%.

Contrary, the variability of GRP losses in the cross-sectional approach is purely driven by heterogeneous warming of regions. Warming is stronger in polar and tropical regions – these regions experience high GRP losses up to 15% of GRP (99th percentile). For the cross-sectional regression, these estimates double if the upper estimate from the 90% confidence

⁸Hence, we assume homogeneous population and economic growth among regions.

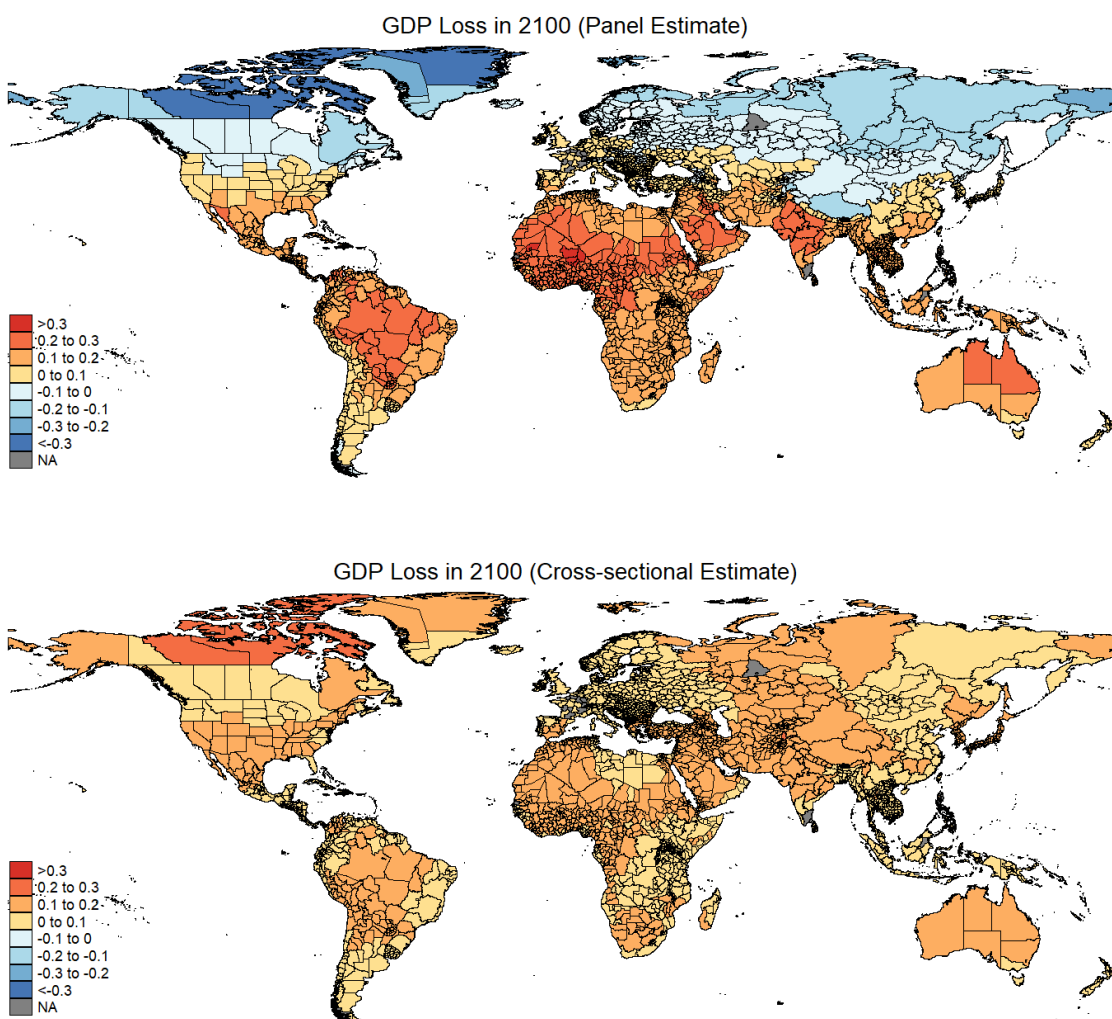


Figure 5: Regional GDP losses in 2100 in the RCP8.5 scenario with an average warming of 4.3°C using panel estimates (above) and cross-sectional estimates (below).

interval is used.

Compared to [Burke et al. \(2015\)](#) we find larger marginal effects because our regression builds on spatially highly resolved data and can hence capture regional heterogeneity more effectively (see Figure 1). Nonetheless, the projected total losses are lower than those found by [Burke et al. \(2015\)](#). The main reason for this is that we use the first-difference specification in estimating the damages while [Burke et al. \(2015\)](#) effectively use deviations in temperature levels. The latter implies that in their projection, a permanent shift in temperature by, say, 1°C causes every year the marginal damage again, although the temperature does not change. In our first-difference approach, the economic damage only occurs in the year of the temperature change (and the following year(s), depending on the lags considered). Thus, in our model, an unanticipated but persisting temperature change in one year has a once-and-for-all effect on GDP level compared to a once-and-for-all effect on GDP growth in [Burke et al. \(2015\)](#). As discussed above, the main reason to choose the first-difference specification as the preferred model is due to non-robustness of the specification of temperature levels with respect to the lags considered. Using the level specification as in [Burke et al. \(2015\)](#) would lead to higher damages than their projections because of the larger marginal effects.

Our estimated damages are high compared to existing damage functions in integrated assessment models (e.g. [Nordhaus and Boyer, 2000](#)). However, the GDP-temperature relationship from the regression models are essentially linear and scale with the level of warming. Compared to widely adopted quadratic damage functions, this implies relatively large damages for small temperature changes but lower damages for high levels of warming.

[Howard and Sterner \(2017\)](#) provide a comprehensive overview on climate damage estimates which includes various approaches. Contrary to damage functions in IAMs, our estimates focus only on GDP shocks due to (historic) variability in temperature and precipitation. We can understand these impacts primarily as impacts on labor productivity, land productivity (agricultural yields) and depreciation of capital. Non-market damages like loss of life, conflicts and violence, biodiversity and ecosystem damages are not captured. In particular, years of life lost are not considered in our analysis which have 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 further not included in our regression model. As a consequence, one should understand our damage estimates as estimates on labor productivity, land productivity and capital only. They contribute to the broader set of overall climate damages and provide only a partial number to the total damages.

6 Conclusions and outlook

An increasing amount of analyses has been carried out to improve estimates of damage functions which play a central role in the evaluation of climate policies. For example, economet-

ric 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 (recently reviewed by [Carleton and Hsiang \(2016\)](#)).

Our analysis adds to this research as follows: by using a comprehensive dataset on regional economic activity with almost global coverage, we identify the impact of (annual) weather and (permanent) climate on economic activity. Consistent with existing evidence on labor productivity and agricultural yields, production is non-linearly influenced by temperature. Our panel and cross-sectional estimates are also in line with the predicted impacts of a standard neoclassical growth model where weather is represented by unanticipated, temporary productivity and capital shocks while climate is represented by anticipated, permanent changes in productivity and capital depreciation. While annual temperature shocks tend to have only temporary GDP impacts that dissipate over the long-run due to convergence growth, changes in long-term temperature conditions affect output levels permanently. This indicates that adaptation is limited. Moreover, the impact of extreme temperature events emphasizes further limits to adaptation.

Our estimates of climate-GDP impacts are slightly higher than previous ones that were obtained using data with less spatial detail. Using regional temperature projections from the RCP8.5 scenario, we find that temperature increases of 4°C (unweighted mean) reduce GDP, on average, by 9%. In tropical regions, however, output losses exceeding 20% are possible. Note that non-market impacts and costs due to sea-level rise are not included in our damage estimates. Further, changes in saving dynamics as a response to productivity changes may effectively increase GDP losses from the panel estimate, but not from the cross-sectional estimate as the latter establishes the long-run relationship between climate and GDP.

Our findings can help improve the formal representation of climate change impacts within existing integrated assessment models by (i) better quantifying damage functions and (ii) differentiating climate change impacts among short-term weather and long-term climate impacts. So far, most integrated assessment models (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.

Finally, the discussion on endogenous saving dynamics and adaptation emphasizes that a careful interpretation of the results of panel and cross-sectional regressions is necessary. This, in turn, underlines the importance of incorporating empirical estimates correctly in aggregate damage functions in IAM growth models.

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A Data sources for GRP

Country	# of Admin. Units	Data Source	Years available	Income measurement
Albania	12 counties	Albania Institute of Statistics	2008-2014	Nominal GDP per capita (ALL)
Argentina	24 provinces	Ministry of Economics - Buenos Aires	1993-2014	GDP (ARS, available in both current and 1993 prices)
Argentina	24 provinces	Chubut Department of Statistics and Censuses	2003-2013	GDP (ARS, current prices)
Argentina	24 provinces	Cordoba Department of Statistics and Censuses	1993-2014	GDP (ARS, available in both current and 1993 prices)
Argentina	24 provinces	Corrientes Department of Statistics and Censuses	1993-2013	GDP (ARS, available in both current and 1993 prices)
Argentina	24 provinces	Entre Rios Department of Statistics and Censuses	2004-2014	GDP (ARS, available in both current and 2004 prices)
Argentina	24 provinces	La Pampa Directorate General of Statistics	2000-2008	GDP (ARS, current prices)
Argentina	24 provinces	Ministry of Economics - Mendoza	1971-2014	GDP (ARS, current prices)
Argentina	24 provinces	Neuquen Department of Statistics and Censuses	1960-2013	GDP (ARS, various base years)
Argentina	24 provinces	Rio Negro Department of Statistics and Censuses	2004-2013	GDP (ARS, current prices)
Argentina	24 provinces	Ministry of Economics - Salta	1993-2012	GDP (ARS, available in both current and 1993 prices)
Argentina	24 provinces	San Luis Department of Statistics and Censuses	1993-2007	GDP (ARS, available in both current and 1993 prices)
Argentina	24 provinces	Santa Fe Department of Statistics and Censuses	1993-2013	GDP (ARS, available in both current and 1993 prices)
Argentina	24 provinces	Tierra del Fuego Department of Statistics and Censuses	"1980-1984 2003-2014"	GDP (ARS, constant 1993 prices)
Argentina	24 provinces	Tucuman Department of Statistics and Censuses	1995-2013	GDP (ARS, constant 1993 prices)
Australia	6 states, 2 territories	Australian Bureau of Statistics - Australian State Accounts 1995-96	1985-1996	Real GDP (AUD, average 1989/1990 prices)
Australia	6 states, 2 territories	Australian Bureau of Statistics - Australian State Accounts 2014-15	1991-2014	Real GDP (AUD, chain volume measures and current prices)
Australia	6 states, 2 territories	Neri (1998)	1861-1992	Real GDP per capita (AUD, 1910/11 prices)
Austria	9 Regions	Statistik Austria	2000-2014	GVA in basic prices (Eur)
Azerbaijan	10 regions	The State Statistical Committee of the Republic of Azerbaijan	2006-2016	Output production (AZN)
Belarus	6 Regions	National Statistical Office of the Republic of Belarus	2009-2014	GVA (BYR)
Belgium	3 Regions	Eurostat	2003-2013	GDP in current prices (EUR)
Belgium	3 Regions	Eurostat: Regional Yearbooks	1970-1985, 1989-1990, 1992-1994	Gross value added in market prices (ECU)
Bolivia	9 departments	Bolivia National Institute of Statistics	1989-2014	GDP (BOB, available in both current and 1990 prices)
Bosnia and Herzegovina	3 Regions	Agency for Statistics of Bosnia and Herzegovina	2003-2015	GDP in current prices (KM)
Brazil	27 federative units	Brasilian Institute for Applied Economic Research	1939-2009	Real GDP, 2000 prices
Brazil	27 federative units	Brasilian Institute for Applied Economic Research	2010-2013	GVA (%)
Bulgaria	28 Provinces	National Statistical Institute of the Republic of Bulgaria	2000-2014	GVA in current prices
Canada	10 provinces, 3 territories	Statistics Canada	1984-1999	Real GDP (CAD, constant 1992 prices, also available in current prices)
Canada	10 provinces, 3 territories	Statistics Canada	1998-2008	GDP (CAD, current prices)
Canada	10 provinces, 3 territories	Statistics Canada	2009-2012	Real GDP (CAD, chained 2007 prices, also available in current prices)
Chile	13 regions	Vernon (2004)	1960-2001	RGDP per capita (CLP, 1996 prices)

Chile	13 regions	Central Bank of Chile	1985-2009	Real GDP (CLP, various base years)
Chile	16 regions	Central Bank of Chile	2010-2015	Real GDP (CLP, base year 2008)
China	31 provinces	National Bureau of Statistics: China Compendium of Statistics 1949-2008	1949-2008	Real per capita GDP (CNY)
China	31 provinces	National Bureau of Statistics: China Statistical Yearbooks	1995-2014	GDP (CNY, current prices)
Colombia	32 departments	Colombia National Administrative Department of Statistics	1990-2012	GDP (COP, available in both current and constant prices (various base years))
Colombia	32 departments	Colombia National Administrative Department of Statistics	2000-2015	GVA (COP, current prices and constant price based on 2005 level)
Colombia	32 departments	Lira (2003)	1980-1996	RGDP (COP, 1976 prices)
Croatia	20 counties	Croatian Bureau of Statistics	2000-2014	GVA in current prices (Kuna)
Czech Republic	13 regions	Czech Statistical Office	1995-2015	GVA (CZK, current prices)
Denmark	5 Regions	Statistics Denmark	1993-2015	Production and generation of income (current prices)
Ecuador	24 provinces	Central Bank of Ecuador	2007-2014	GVA, current prices (USD)
Ecuador	24 provinces	Central Bank of Ecuador	1993-1996	GVA, 2000 prices (USD)
Ecuador	24 provinces	Central Bank of Ecuador	2001-2006	GVA, 2000 prices (USD)
Egypt	27 Governorates	UN Human Development Reports	1998-2001, 2003, 2005, 2007	GDP (LE)
El Salvador	14 Departments	UN Human Development Reports	1996, 1999, 2002, 2004, 2006, 2009, 2012	GDP per capita PPP (USD)
Estonia	15 counties	Statistics Estonia	1995-2015	GDP in current prices (EUR)
Ethiopia (Amhara)	9 regional states	Amhara Bureau of Finance and Economic Development	1998-2003	GDP (ETB, current prices)
Ethiopia (Oromiya)	9 regional states	Oromia Bureau of Finance and Economic Development	1992-2001	GDP (ETB, current prices)
Ethiopia (Tigray)	9 regional states	Tigray Bureau of Planning and Finance	2005-2009	GDP per capita (ETB, current prices)
Finland	5 provinces	Statistics Finland	1975-2008, 1990-2013	GDP in current prices (EUR)
France	21 regions (excluding overseas)	INSEE	1990-2013	GVA (EUR, 2010 prices)
France	21 regions (excluding overseas)	Eurostat: Regional Yearbooks	1970-1985, 1989-1990, 1992-1994	Gross value added in market prices (ECU)
Georgia	12 regions	National Statistics Office of Georgia	2006-2014	GVA (GEL, current prices)
Greece	13 regions	Hellenic Statistical Authority	2000-2013	GVA (current prices, EUR)
Greece	13 regions	Eurostat: Regional Yearbooks	1985, 1989-1990, 1992-1994	Gross value added in market prices (ECU)
Guatemala	22 departments	Secretariat of Planning and Programming of the Presidency	2004-2008	GDP per capita (GTQ)
Honduras	18 Departments	UN Human Development Reports	1990-2004	Estimated GDP per capita PPP
Hungary	19 counties + Budapest	Hungarian Central Statistical Office	2000-2015	GDP per capita (HUF, current prices)
Hungary	19 counties + Budapest	Nagy (2005)	1975; 1994-2002	GDP index values (country=100)
India	29 states	Indian Ministry of Statistics	1980-1985	GDP (INR, current prices)
India	29 states	Indian Ministry of Statistics	1993-2005	GDP (INR, current prices)
India	29 states	Indian Ministry of Statistics	2004-2014	GDP (INR, current prices)
Indonesia	34 provinces	Statistics Indonesia: Gross Regional Domestic Product of Provinces in Indonesia by Industrial Origin	2004-2014	GDP (IDR, available in both current and constant prices)
Indonesia	34 provinces	Resosudarmo and Vidyattama (2009)	1971, 1983, 1996, 2002	Per capita GDP (current prices)
Iran	31 provinces	Statistical Centre of Iran	2000-2013	GVA (current prices, IRR)
Ireland	32 counties	Central Statistics Office	2000-2014	Income per person (EUR)
Ireland	32 counties	Central Statistics Office	1995-2003	Income per person
Italy	20 regions	Italian National Institute of Statistics	1995-2013	Gross value added (EUR, available in both nominal and real (chain-linked 2010 prices))

Italy	20 regions	Eurostat: Regional Yearbooks	1970-1985 1989-1990 1992-1994"	Gross value added in market prices (ECU)
Italy	20 regions	Felice and Vecchi (2015)	1871-2009	RGDP per capita (EUR, 2011 prices)
Japan	47 prefectures	Cabinet Office, government of Japan	1975-2012	GDP (JPY, available in both nominal and real)
Japan	47 prefectures	Cabinet Office, government of Japan	1955-1974	RGDP (JPY, 1980 prices)
Kazakhstan	14 regions	National Accounts of the Republic of Kazakhstan	1998-2014	GVA (KZT, current prices)
Kenya	8 provinces	Kenya National Bureau of Statistics: Statistical abstracts	1969-2012	Labour earnings (KES), 2000 prices
Kyrgyzstan	9 regions	National Statistical Committee of the Kyrgyz Republic	2006-2015	Gross regional product (current price, KGS)
Laos	18 regions	Yale Gecon	1995	GDP per capita (LKP)
Laos	18 regions	JICA (2012)	2010	GDP(LKP, current prices)
Laos (Savanvan)	18 regions	Poverty-Environment Initiative (2011)	2006-2010	GDP (LKP, current prices)
Laos (Savan-nakhet)	18 regions	Nolintha (2011)	2006-2010	GDP per capita (USD)
Latvia	5 regions	Central Statistical Bureau of Latvia	2000-2011	GDP, current prices (EUR)
Lithuania	10 Regions	Eurostat	2000-2014	GVA, current prices (EUR)
Malaysia	15 States	Cheng (2011)	1970, 1971, 1980, 1985, 1990, 1995, 2000	GDP per capita (constant price)
Malaysia	15 states	Department of Statistics Malaysia	2005-2013	GDP (RM, constant 2005 prices)
Malaysia	16 states	Department of Statistics Malaysia (e-statistik service)	2010-2015	GDP (RM, constant 2010 prices)
Mexico	31 states	National Institute of Statistics	2005-2014	GDP (MXN, current prices)
Mexico	31 states	National Institute of Statistics	1993-2007	GDP (MXN, current prices)
Mexico	31 states	German-Soto (2005)	1940-2001	RDGP per capita (MXN, 1993 prices)
Mongolia	22 provinces	Mongolia Statistical Information Services	2000-2015	GDP per capita (MNT, current prices)
Morocco	12 regions	Moroccan High Planning Commission	2007, 2009-2013	Per capita GDP (constant 2007 prices, MAD)
Mozambique	11 regions	African Development Bank	2000-2009	GDP per capita (current prices MT)
Nepal	5 Regions	UN Human Development Reports	1996, 1999, 2001, 2006, 2011	GDP at market prices (RS), GVA, GDP per capita (USD PPP), per capita income
Netherlands	12 regions	Statistics Netherlands	1995-2014	GVA (EUR)
New Zealand	15 regions	Statistics New Zealand	2000-2014	GDP (NZD, current prices)
Norway	21 Counties	Statistics Norway	1973, 1976, 1980, 1983	GVA current prices (NOK)
Norway	22 Counties	Statistics Norway	1986.1992	Gross Production current prices (NOK)
Norway	21 Counties	Statistics Norway	1997-2014	GVA current prices (NOK)
Pakistan	4 provinces	Arby (2008)	1970-2005	Real GDP (PKR, 1999-2000 prices)
Pakistan	4 provinces	Pakistan Bureau of Statistics - Household Integrated Economic Survey	2005-2013	Household income
Panama	10 provinces	Panama National Institute of Statistics	1996-2010	Real GDP (PAB, 1996 prices)
Paraguay	17 departments	General Directorate of Statistics Paraguay - Permanent household survey (EPH)	2006-2015	Average monthly income
Peru	25 regions	Peru National Institute of Statistics	2007-2014	GDP (PEN, available in both current and 2007 prices)
Peru	25 regions	Peru National Institute of Statistics	2001-2011	Real GDP (PEN, 1994 prices)
Peru	25 regions	Lira (2003)	1970-1995	RGDP (PEN, 1979 prices)
Philippines	18 regions	Philippines Institutue for Development Studies	2002-2009	GDP(PHP, current prices)
Philippines	18 regions	Philippines Institutue for Development Studies	2009-2015	GDP(PHP, current prices)
Philippines	19 regions	Philippines Statistics Authority	1975-2001	GDP(PHP, current prices)
Poland	16 provinces	Central Statistical Office of Poland	1995-2014	GVA, current prices (PLN)
Romania	42 counties	National institute of Statistics Romania	1995-1999	GDP basic prices (RON)
Romania	42 counties	Eurostat	2000-2014	GVA basic prices (RON)
Russia	83 federal subjects	Federal State Statistics Service of the Russian Federation	2004-2014	GVA (RUB, current prices)

Russia	83 federal sub-jects	Federal State Statistics Service of the Russian Federation	1998-2014	GVA (RUB, current prices)
Russia	83 federal sub-jects	Ponomarenko (2000)	1994-1996	GDP per capita (RUB, current prices)
Serbia	25 districts	Statistical office of the Republic of Serbia	1999-2015	GDP, GDP per capita
Slovakia	8 regions	Statistical Office of the Slovak Republic	2010-2015	GVA in current prices (EUR)
Slovenia	12 regions	Statistics Office of the Republic of Slovenia	2000-2015	GVA, current prices (EUR)
South Africa	9 provinces	Statistics South Africa	1995-2004	GDP (ZAR, current prices)
South Africa	9 provinces	Statistics South Africa	2004-2013	GDP (ZAR, current prices)
South Korea	16 provinces	Korean Statistical Information Service	1985-2014	GDP (KRW, current prices)
Spain	19 autonomous communities	Eurostat	2000-2014	Gross value added in basic prices (EUR)
Spain	17 autonomous communities	Eurostat: Regional Yearbooks	”1985 1989-1990 1992-1994”	Gross value added in market prices (ECU)
Spain	19 autonomous communities	Instituto Nacional de Estadística	1995-2003, 1986-1996	Gross Value Added at market prices
Sweden	21 counties	Enflo et al. (2015)	1855-2000	GDP (SEK, current prices)
Sweden	21 counties	Statistics Sweden	1993-2000	GDRP (SEK, current prices)
Sweden	21 counties	Eurostat	2000-2014	GVA (EUR, current prices)
Switzerland	26 cantons	Swiss Federal Statistics Office	2008-2013	GVA (CHF, current prices)
Tanzania	30 regions	Tanzania National Bureau of Statistics	2000-2013	Per capita GDP (TZS, current prices)
Tanzania	30 regions	The Planning Commission Dar Es Salaam	1980, 1985, 1990, 1994	Per capita GDP (TZS, current prices)
Thailand	76 provinces	Office of the National Economic and Social Development Board	1981-2013	GDP (THB, available in both current and 2002 prices)
Turkey	81 provinces	Turkish Statistical Institute	1987-2014	RGDP per capita (TRY)
Turkey	81 provinces	Karaca (2004)	1975-1986	RGDP per capita (TRY)
UAE	7 emirates	UAE Statistics Institute	2001-2009	GDP per capita (AED, current prices)
UK	4 regions	Office for National Statistics	1997-2011	GVA (GBP, current prices)
UK	4 regions	Office for National Statistics	1968-1970	GDP per capita (GBP, current prices)
UK	4 regions	Eurostat: Regional Yearbooks	”1970-1985 1989-1990 1992-1994”	Gross value added in market prices (ECU)
UK	4 regions	Crafts (2005)	1871-1911	GDP (GBP, current prices)
Ukraine	27 regions	State Statistics Service of Ukraine	2004-2014	GDP per capita, current prices (UAH)
Ukraine	27 regions	Mykhnenko and Swain (2009)	1990-2007	GDP per capita (index values, country=100)
Uruguay	19 departments	García et al. (2014)	1908, 1936, 1955, 1961	GVA current prices (UYU)
Uruguay	19 departments	Observatorio Territorio Uruguay	2008-2011	GDP current prices (UYU)
USA	50 states	Bureau of Economic Analysis	1963-2014	Real per capita GDP (USD)
Uzbekistan	14 Regions	UN Human Development Reports	1995-2005	Real GDP per capita (PPP USD)
Venezuela	23 states	Valecillos (1998)	1950-1990	Real GDP (VEF)
Vietnam	64 provinces	Data received from Thang	1995-2008	Real GDP, 1994=100 (VND)
West Germany	10 states	Statistische Ämter des Bundes und der Länder	2000-2012	Gross value added (EUR, current prices)

Table 8: Data sources for regional economic output.

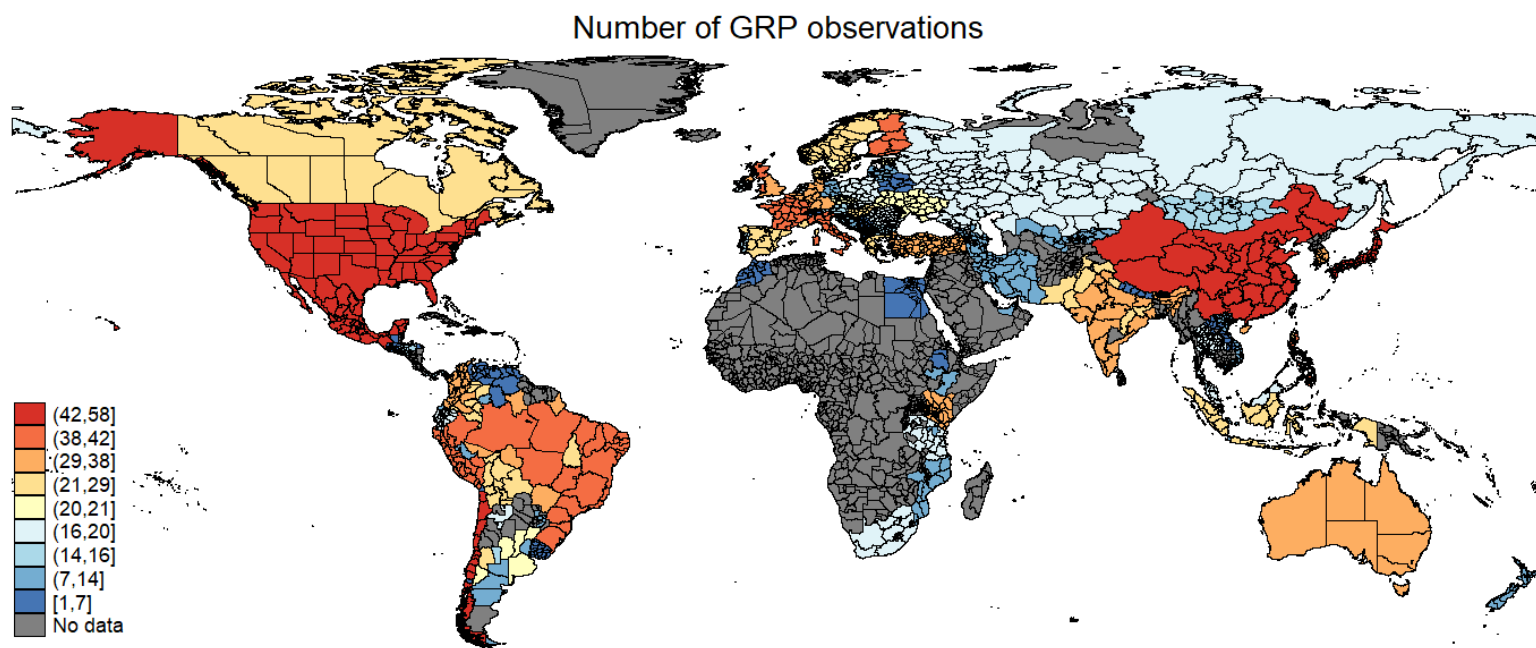


Figure 6: Data coverage: Availability of Gross Regional Product (GRP) data per region

B Robustness Checks

B.1 Annual Panel Model

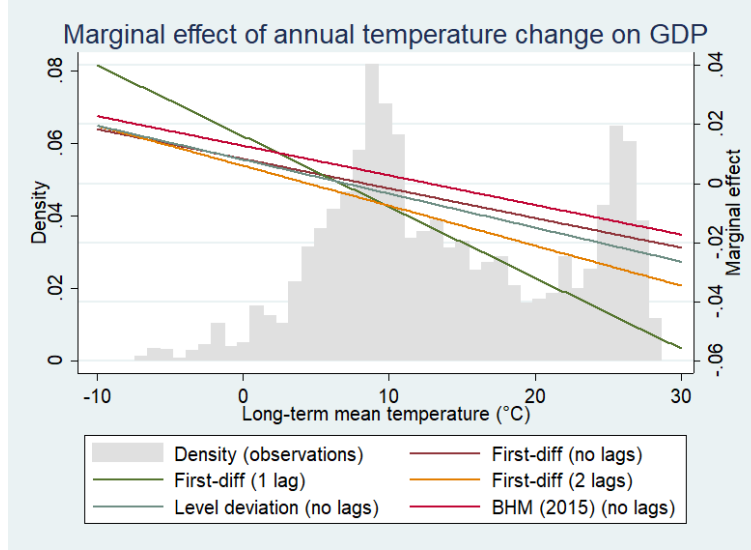


Figure 7: Marginal effect (right y-axis) of annual temperature change according to column (4)–(6) in Tab. 10 (first-difference with 0,1 and 2 lags), column (4) in Tab. 11 (deviation from trend) and Burke et al. (BHM 2015). Grey bars indicate frequency of temperature observations in our panel.

Table 9: Panel Regression: Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T	-0.00218* (0.00123)	-0.00430*** (0.00118)	-0.00445*** (0.00122)	-0.000954 (0.00119)	0.0102*** (0.00195)	0.00696*** (0.00184)	0.00669*** (0.00189)	0.00921*** (0.00178)
L.T	-0.00414*** (0.00125)	-0.00631*** (0.00117)	-0.00648*** (0.00121)	-0.00585*** (0.00111)	0.00588*** (0.00209)	0.00229 (0.00197)	0.00200 (0.00204)	0.00281* (0.00170)
T × ET					-0.00135*** (0.000187)	-0.00123*** (0.000180)	-0.00121*** (0.000186)	-0.00108*** (0.000177)
L.T × ET					-0.00104*** (0.000193)	-0.000896*** (0.000187)	-0.000884*** (0.000193)	-0.000896*** (0.000176)
P	0.0109*** (0.00399)	0.0107*** (0.00394)	0.0110*** (0.00406)	0.00592 (0.00414)	0.00631 (0.0109)	0.00721 (0.0108)	0.00757 (0.0111)	0.00265 (0.0111)
L.P	0.0304*** (0.00360)	0.0280*** (0.00359)	0.0283*** (0.00369)	0.0270*** (0.00342)	0.0321*** (0.00944)	0.0298*** (0.00938)	0.0298*** (0.00970)	0.0270*** (0.00921)
P × EP					0.000618 (0.00466)	0.000142 (0.00463)	0.000121 (0.00478)	0.000319 (0.00473)
L.P × EP					-0.00275 (0.00437)	-0.00256 (0.00437)	-0.00245 (0.00454)	-0.00154 (0.00430)
L. Annual GDP growth in region				-0.0929*** (0.0166)				-0.0930*** (0.0165)
Observations	29307	29307	29307	27833	29307	29307	29307	27833
N regions	1545	1545	1545	1519	1545	1545	1545	1519
bic	-38109.1	-35437.1	-36739.9	-37489.5	-38130.8	-35452.9	-36744.3	-37506.2
Note	Base	Cn trend	Reg trend	Dynamic	Base	Cn trend	Reg trend	Dynamic
T (cum)	-.0063	-.0106	-.0109	-.0068	.0161	.0092	.0087	.012
T (cum) [SE]	.0022	.0021	.0021	.002	.0037	.0034	.0035	.003
T × ET (cum)					-.0024	-.0021	-.0021	-.002
T × ET (cum) [SE]					.0003	.0003	.0003	.0003
P (cum)	.0413	.0387	.0393	.0329	.0384	.037	.0374	.0297
P (cum) [SE]	.0059	.0059	.006	.006	.0148	.0146	.0151	.0151
P × EP (cum)					-.0021	-.0024	-.0023	-.0012
P × EP (cum) [SE]					.0066	.0066	.0068	.0068

Standard errors in parentheses

(cum) - cumulative effect over lags. [SE] - standard error. All standard errors clustered at region level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Panel Regression: Various Lags (Using Weather 1st-Diff)

	(1)	(2)	(3)	(4)	(5)	(6)
T	-0.000664 (0.000985)	-0.00218* (0.00123)	-0.00209 (0.00133)	0.00828*** (0.00154)	0.0102*** (0.00195)	0.00852*** (0.00230)
L.T		-0.00414*** (0.00125)	-0.00451*** (0.00155)		0.00588*** (0.00209)	0.00294 (0.00312)
L2.T			-0.000930 (0.00143)			-0.00548* (0.00295)
T × ET				-0.001000*** (0.000156)	-0.00135*** (0.000187)	-0.00114*** (0.000217)
L.T × ET					-0.00104*** (0.000193)	-0.000743*** (0.000270)
L2.T × ET						0.000534** (0.000243)
P	-0.00352 (0.00389)	0.0109*** (0.00399)	0.0139*** (0.00408)	-0.00891 (0.0113)	0.00631 (0.0109)	0.00415 (0.0114)
L.P		0.0304*** (0.00360)	0.0314*** (0.00406)		0.0321*** (0.00944)	0.0346*** (0.0103)
L2.P			0.00258 (0.00341)			0.00000429 (0.00884)
P × EP				0.00150 (0.00474)	0.000618 (0.00466)	0.00342 (0.00485)
L.P × EP					-0.00275 (0.00437)	-0.00350 (0.00448)
L2.P × EP						0.00187 (0.00440)
Observations	29752	29307	28855	29752	29307	28855
N regions	1545	1545	1545	1545	1545	1545
F
bic	-38321.9	-38109.1	-36037.2	-38529.7	-38120.5	-36035.2
T (cum)	-.0007	-.0063	-.0075	.0083	.0161	.006
T (cum) [SE]	.001	.0022	.0036	.0015	.0037	.0075
T × ET (cum)				-.001	-.0024	-.0013
T × ET (cum) [SE]				.0002	.0003	.0006

Standard errors in parentheses

(cum) - cumulative effect over lags. [SE] - standard error. All standard errors clustered at region level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Panel Regression: Various Lags (Using Weather Deviation)

	(1)	(2)	(3)	(4)	(5)	(6)
T	-0.00261* (0.00146)	-0.00247* (0.00150)	-0.00196 (0.00151)	0.00802*** (0.00243)	0.00742*** (0.00249)	0.00665*** (0.00247)
L.T		-0.00216 (0.00143)	-0.00232 (0.00147)		-0.00877*** (0.00254)	-0.00751*** (0.00256)
L2.T			0.00380*** (0.00146)			-0.00980*** (0.00237)
T × ET				-0.00115*** (0.000218)	-0.00109*** (0.000223)	-0.000954*** (0.000220)
L.T × ET					0.000768*** (0.000221)	0.000604*** (0.000222)
L2.T × ET						0.00142*** (0.000223)
P	0.0120*** (0.00429)	0.0121*** (0.00441)	0.0147*** (0.00455)	0.00708 (0.0115)	0.00863 (0.0120)	0.00253 (0.0124)
L.P		0.0205*** (0.00533)	0.0183*** (0.00525)		0.0270* (0.0145)	0.0287* (0.0147)
L2.P			-0.0279*** (0.00449)			-0.0350*** (0.0114)
P × EP				0.00125 (0.00490)	0.000174 (0.00517)	0.00468 (0.00542)
L.P × EP					-0.00266 (0.00632)	-0.00571 (0.00641)
L2.P × EP						0.00575 (0.00543)
Observations	29752	29307	28855	29752	29307	28855
N regions	1545	1545	1545	1545	1545	1545
F
bic	-38312.8	-38101.7	-35872.4	-38271.6	-38099.1	-35820.5
T (cum)	-.0026	-.0046	-.0005	.008	-.0014	-.0107
T (cum) [SE]	.0015	.0021	.0026	.0024	.004	.0046
T × ET (cum)				-.0011	-.0003	.0011
T × ET (cum) [SE]				.0002	.0003	.0004

Standard errors in parentheses

(cum) - cumulative effect over lags. [SE] - standard error. All standard errors clustered at region level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Panel Regression: Interaction with Coastal Distance

	(1)	(2)	(3)	(4)
T	-0.00218* (0.00123)	-0.0166*** (0.00406)	-0.000546 (0.00157)	-0.00216 (0.00149)
L.T	-0.00414*** (0.00125)	-0.000915 (0.00377)	-0.00575*** (0.00156)	-0.00543*** (0.00149)
T × Dist Coast		0.00297*** (0.000768)		
L.T × Dist Coast		-0.000646 (0.000742)		
T × Coast			-0.00357 (0.00232)	
L.T × Coast			0.00417* (0.00242)	
T × Port				0.000498 (0.00234)
L.T × Port				0.00424* (0.00248)
P	0.0109*** (0.00399)	-0.0361*** (0.0118)	0.0212*** (0.00720)	0.0166*** (0.00527)
L.P	0.0304*** (0.00360)	0.0204* (0.0106)	0.0296*** (0.00662)	0.0304*** (0.00491)
P × Dist Coast		0.0117*** (0.00315)		
L.P × Dist Coast		0.00246 (0.00285)		
P × Coast			-0.0171** (0.00766)	
L.P × Coast			0.00134 (0.00759)	
P × Port				-0.0149** (0.00678)
L.P × Port				-0.000724 (0.00691)
Observations	29307	29293	29307	29307
N regions	1545	1544	1545	1545
bic	-38109.1	-38167.3	-38085.2	-38077.4
Note	Base	Dist to Coast	Coast Dummy	Port Dummy
T (cum)	-.0063	-.0176	-.0063	-.0076
T (cum) [SE]	.0022	.0066	.0027	.0026
T Interact Eff (cum)		.0023	.0006	.0047
T Interact Eff (cum) [SE]		.0013	.0041	.0042
P (cum)	.0413	-.0157	.0508	.047
P (cum) [SE]	.0059	.0163	.0102	.0075
P Interact Eff (cum)		.0142	-.0157	-.0156
P Interact Eff (cum) [SE]		.0043	.0116	.0108

Standard errors in parentheses

(cum) - cumulative effect over lags. [SE] - standard error. All standard errors clustered at region level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.2 Cross-sectional model

Table 13: Cross-sectional Regression – Robustness against Area Size of Regions

	(1)	(2)	(3)	(4)	(5)
Temperature	-0.0231* (0.0135)	-0.0228* (0.0135)	-0.0253* (0.0135)	-0.0261** (0.0127)	-0.0259** (0.0128)
Prec	-0.00364 (0.0612)	0.0113 (0.0651)	0.0304 (0.0702)	0.0180 (0.0818)	-0.00481 (0.0736)
Cum Oil Gas	7.080** (3.160)	7.267** (3.119)	7.023** (3.210)	7.009** (3.179)	7.008** (3.087)
Distance to Coast	-0.113*** (0.0336)	-0.100*** (0.0335)	-0.0922** (0.0351)	-0.0781** (0.0300)	-0.0577** (0.0276)
Distance to River	-0.0660* (0.0361)	-0.0452 (0.0348)	-0.0223 (0.0334)	-0.00939 (0.0349)	-0.00158 (0.0416)
Altitude	-0.184** (0.0824)	-0.172** (0.0833)	-0.171** (0.0854)	-0.168** (0.0795)	-0.172** (0.0774)
Observations	1482	1412	1273	1051	877
N countries	75	75	74	71	67
Minimum area (km2)	All	1000	2500	5000	7500

Standard errors in parentheses

Country FE included. Standard errors clustered at country level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Cross-sectional Regression – Robustness Against Geographical Covariates

	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	-0.0231* (0.0135)	-0.0979*** (0.0188)	-0.0248* (0.0147)	-0.0252* (0.0141)	-0.0249* (0.0131)	0.00112 (0.00996)
Prec	-0.00364 (0.0612)	0.0891 (0.170)	0.00409 (0.0631)	0.00303 (0.0622)	0.0391 (0.0647)	0.0687 (0.0636)
Cum Oil Gas	7.080** (3.160)	9.793** (3.923)	7.474** (2.949)			
Distance to Coast	-0.113*** (0.0336)	-0.303*** (0.0790)	-0.0919** (0.0372)	-0.111*** (0.0338)		
Distance to River	-0.0660* (0.0361)	-0.0428 (0.141)	-0.0481 (0.0385)	-0.0597 (0.0361)		
Altitude	-0.184** (0.0824)	-0.309*** (0.114)	-0.193** (0.0869)	-0.197** (0.0842)	-0.256*** (0.0764)	
Area			-0.0389* (0.0208)			
Observations	1482	1482	1482	1482	1483	1484
N countries	75	75	75	75	75	75
Country FE	yes	no	yes	yes	yes	yes

Standard errors in parentheses

Country FE included. Standard errors clustered at country level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ **Table 15:** Crosssectional Regression – Robustness against Climate Data Sources

	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	-0.0231* (0.0135)	-0.0149 (0.0124)	-0.0217 (0.0143)	-0.0290** (0.0135)	-0.0255* (0.0129)	-0.0280* (0.0145)
Precipitation	-0.00364 (0.0612)	-0.00101 (0.00116)	-0.0000602 (0.0000579)	0.0193 (0.0597)	-0.000810 (0.00153)	-0.0000116 (0.0000632)
Cum Oil Gas	7.080** (3.160)	7.703** (3.241)	6.923** (3.136)	5.588 (3.495)	5.955 (3.650)	5.215 (3.505)
Distance to Coast	-0.113*** (0.0336)	-0.113*** (0.0345)	-0.119*** (0.0331)	-0.125*** (0.0435)	-0.124*** (0.0448)	-0.131*** (0.0419)
Distance to River	-0.0660* (0.0361)	-0.0720* (0.0365)	-0.0727** (0.0334)	-0.0783* (0.0460)	-0.0874* (0.0456)	-0.0789* (0.0434)
Altitude	-0.184** (0.0824)	-0.145* (0.0757)	-0.191** (0.0858)	-0.190** (0.0898)	-0.176** (0.0878)	-0.195** (0.0960)
Observations	1482	1482	1490	1398	1398	1400
N countries	75	75	75	67	67	67
Data source	CRU	CRU/E-OBS	WorldClim	CRU	CRU/E-OBS	WorldClim
Period	2005-2014	2005-2014	2005-2014	1995-2004	1995-2004	1995-2004

Standard errors in parentheses

Country FE included. Standard errors clustered at country level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.3 Damage projections

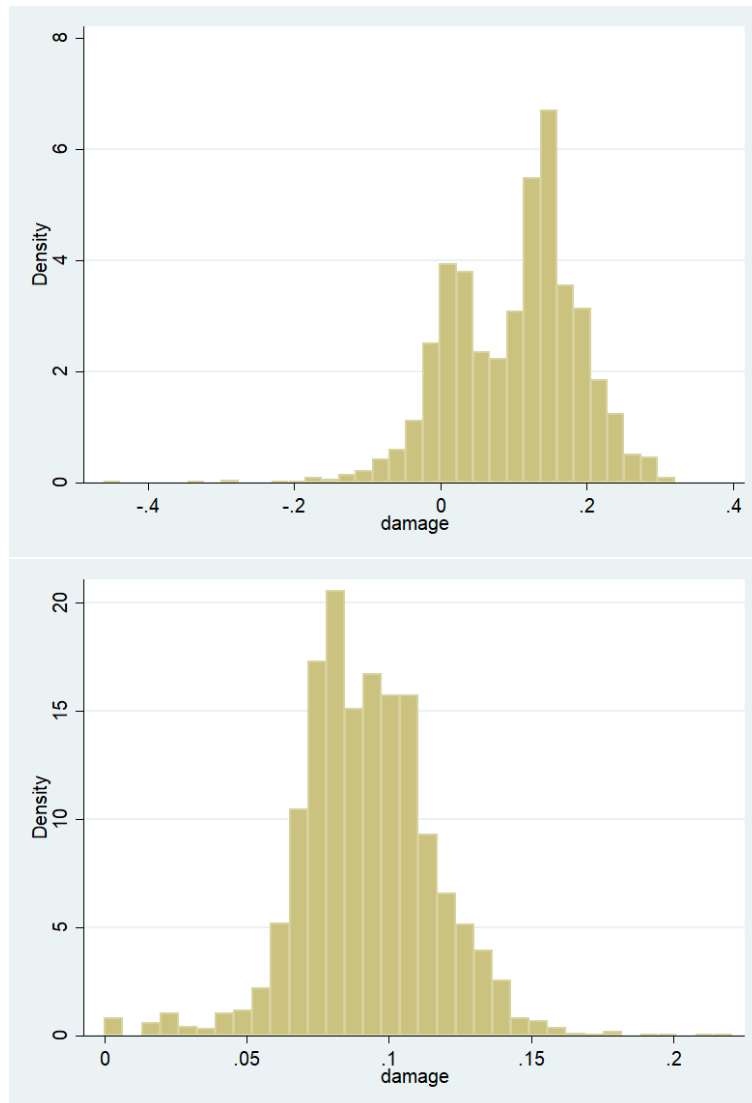


Figure 8: Frequency of damage magnitude over all regions. Top: Damages based on panel estimate. Bottom: Damages based on cross-sectional estimate.