G&D:E assignment: Climate change and growth

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1 Introduction

In this assignment we take a closer look on three different papers that deal with climate change and growth, namely *Temperature Shocks and Economic Growth: Evidence from the Last Half Century* by Dell et al. (2012), *Global non-linear effect of temperature on economic production* by Burke et al. (2015) and *GDP and Temperature: Evidence on Cross-Country Response Heterogeneity* by Berg et al. (2021). In the first exercise we discuss the approach of Berg et al. (2021) regarding the decomposition of the data into a global and an idiosyncratic component. We assess the impact this has on the population-weighting done by the authors and the advantage of considering the components separately. In the second exercise we compare all three papers regarding their different approaches, methods and results. In exercise 3, own regressions of GDP growth on temperature were carried out and controlled for selected variables from various sources. In exercise 4 we project the expected temperature effects on India, France, Canada and Brazil for different Shared Socioeconomic Pathway scenarios.

2 Main part

2.1 Exercise 1

1. Berg et al (2021) construct a time series of national temperature from temperature information in small grids, which are aggregated to the national level using population weights. In a second step, they detrend national temperatures and decompose them into a global and an idiosyncratic (i.e., country-specific) components.

a. Does the final decomposition procedure fit to the population-weighted aggregation method in the beginning?

Berg et al. (2021) use monthly temperature data[1] that they then aggregate to annual observations. In a next step they overlay the temperature data with population data[2] and then obtain population-weighted temperatures by country and year. Since temperatures are rising globally, i.e. an upward trend is found in the data, the observations are not stationary. To introduce stationarity, Berg et al. (2021) quadratically detrend the population-weighted annual country temperatures. They then decompose the detrended country temperatures into two components. The common global component is the average of the total population-weighted temperatures. The idiosyncratic component is the residual from regressing detrended country temperature on global temperature. Figure 2 in Berg et al. (2021) shows the global temperature after the quadratic detrend. Overall, the data does not show an upward trend anymore, i.e. the temperature data is now stationary. However, the calculation of the global and hence, also the idiosyncratic, component should be discussed. Berg et al. (2021) compute the global component by taking the average of the sum of population-weighted country temperatures, they do not add another population weight. Therefore, it is possible that the decomposed variables

[1] in a 0.5-degree by 0.5-degree latitude/longitude grid

[2] Population counts in 2.5 minute by 2.5 minute latitude/longitude grid

do not fully account for the countries' sizes which may lead to distorted results. To check whether an additional population-weight is necessary, one could look at where large countries like India and China lie compared to the average and whether this reflects their size and impact. It is also worth pointing out, that the population data used is from the year 2000 only while temperature and GDP data are observed on a yearly basis. This might lead to unwanted effects in the results, though the impact is hard to estimate. Other studies use the same approach, for example, Dell et al. (2012) base the population-weights on data from 1990. They also find largely similar results in an area-weighted temperature approach which suggests that the choice of weighting variable does not have a strong impact and it suffices to link stationary population data to country sizes.

b. Explain why the decomposition into two components is an improvement over the existing literature, which uses national temperatures as right-hand-side variables.

The general approach to estimating the effects of temperature changes on GDP growth in the existing literature was the use of panel regressions with time-fixed effects. These kinds of models estimate "the response of the deviation of a country's growth from the global (cross-sectional) average to variation in the deviation of country temperature from the global average" (Berg et al. 2021). The global component is hereby removed resulting in idiosyncratic variables of temperature variation and GDP per capita growth. In contrast, the authors wanted to study the GDP growth response to actual temperature changes and allow for more heterogeneity. Panel models neutralize a broader variation that may be of interest when looking at a global phenomenon such as climate change. Therefore, they not only look at the idiosyncratic growth response but focus especially on the global component to account for possible spillover effects or influences such as commodity prices that have a global impact.

In line with the previous literature, as the idiosyncratic component is similar to the regressor in panel regressions with fixed effects, the authors find negative growth responses to temperature increases especially in poorer countries. Negative consequences of temperature increases in rich countries, however, seem to be driven by the global component. This effect becomes especially clear when looking at longer horizons (Berg et al. 2021). When analyzing the role of country characteristics, e.g. latitude, average real GDP per capita and long-term growth, the authors come to the conclusion that the growth response to global temperature shocks is more systematically related to the economic structure. The authors assume that variation in global temperature may also have indirect effects on the world economy through interdependent trade and finance. Temperature changes therefore represent a source of global financial risk. Through the use of a global component the authors form an association to climate change as a global phenomenon. By incorporating their findings Berg et al. (2021) support the argument that rich countries should have an economic interest in mitigating global warming.

2.2 Exercise 2

Dell et al. (2012), Burke et al. (2015) and Berg et al. (2021) all estimate the effect of temperature on GDP growth. Compare the results of the three papers, and explain if and how they are consistent with one another.

Dell et al. (2012) examine the relationship between changes in a country's temperature and precipitation and changes in its economic performance, i.e. its GDP per capita income, on the basis of a world sample from 1950 to 2003. They perform a panel regression with fixed effects to control for omitted variable bias. They use country fixed effects, year fixed effects interacted with regional indicators and year fixed effects interacted with an indicator for countries that are poor[3]. Through the use of fluctuations in temperature they aim to isolate the effects from time-invariant characteristics.

[3]Below-median PPP-adjusted per capita GDP in first year of entering data set.

Temperature is entered linearly. For poor countries they find that a one degree Celsius increase reduces per capita income by 1.3 per cent. Changes in precipitation appear to have mild effects. They do not find robust effects of changes in temperature for rich countries. Regarding the influence of temperature variation on economic output, the authors differentiate between the effect on the level of output and the effect on an economy's potential to grow. With the the help of temperature lags, they investigate whether the effects of temperature variation persist and find that growth rates are affected. In the short run, the level effects are robust, but in the medium-run the robustness depends on the specification. Furthermore, Dell et al. (2012) investigate the channels through which temperature influences an economy, agriculture up to then being the main channel identified by the macro-economic literature[4]. Next to agricultural output, they find that higher temperatures negatively influence industrial output and political stability.

Burke et al. (2015) estimate the global non-linear effect of temperature on the change in log gross domestic product (GDP) per capita on the basis of date from 1960 to 2010. One motivation behind their research were the strong output responses to temperature changes observed in the micro analysis in wealthy countries, which were not replicated in the macro studies (Dell et al. 2012). To resolve these contradictory implications between macro and micro observation, they account for non-linearity on the macro-scale. In contrast to Dell et al. (2012) they treat temperature non-linearly, arguing that up to around 20 degrees Celsius economic indicators respond positively to temperature increases, but decline rather abruptly beyond thresholds between 20 and 30 degrees Celsius. Their panel model includes fixed effects, flexible trends and precipitation controls to control for time-invariant regional heterogeneity. They find that economic activity peaks at thirteen degrees Celsius and strongly declines at high temperatures underlining the non-linear effect of temperature variation. Additionally these results are applicable to both rich and poor countries, indicating that rich countries are also vulnerable to increasing temperatures as "their response is statistically indistinguishable from poor countries at all temperatures" (Burke et al. 2015). According to the authors, poor countries tend to suffer more from temperature increases mainly because they record higher average temperatures. Rich countries with high temperatures are projected to experience similar negative consequences as poor countries. Overall the non-linear approach appears to be more flexible. According to their projections unmitigated global temperature increases will reduce average global incomes by 23 per cent by 2100 relative to a scenario with no climate change. Similar to Dell et al. (2012) the authors estimate a distributed lag model to test for growth and level effects. They also find negative growth effects, especially in the short-run, whereas the results become more and more uncertain with an increasing number of included lags.

For poor countries the results of Dell et al. (2012) and Burke et al. (2015) are generally consistent as both find a negative growth response to temperature increases. In the case of rich countries, Dell et al. (2012) do not find a robust effect on growth. One main difference between the two approaches is that Dell et al. (2012) investigate a linear relationship between temperature variation and Burke et al. (2015) examine a non-linear relationship. Burke et al. (2015) also find this non-linear relationship for rich countries implicating that economic activity in all regions are coupled to the global climate. Burke et al. (2015) also use the model of Dell et al. (2012), this time allowing for non-linearity. With the more recent data (up to 2010), the model of Dell et al. (2012) also implies a non-linear structure. Burke et al. (2015) state that the updated data reflects the increase in temperatures since the 1980s more accurately.

Berg et al. (2021) investigate impulse responses of real GDP per capita growth after a temperature shock. Their data set considers 162 countries and includes temperature and GDP per capita data between 1960 and 2017. In contrast to standard panel regressions and the work of Dell et al. (2012) and Burke et al. (2015), they estimate the cross-country response distribution through local projections allowing for more heterogeneity. Additionally, they employ pseudo panel local projections for groupings of countries with similar responses. They perform the pseudo-panel local projection with country, global and idiosyncratic temperature and find both short-term (horizon 0) and medium-term

[4] The micro-economic literature has identified more dimensions often on a local level.

(horizon 7) growth effects. For poorer[5] countries they find mixed results of both positive and negative responses. At horizon 0 the negative growth responses seem to be concentrated in developing economies. Especially in the medium term (horizon 7) rich countries appear to experience negative growth effects, whereas the authors register positive responses in countries like Brazil, China, Nigeria and India. In a counterfactual analysis under the high emissions scenario the authors project that temperature will induce losses of 1.9 per cent by 2100 in the case of the United States[6]. For Brazil and India they project respective gains of 5.3 per cent and 5.7 per cent. To explain the heterogeneous responses across countries the authors employ a cross-sectional regression controlling for latitude, average real GDP per capita in logarithmic form, a country's long-horizon rate, average GDP shares of agriculture, industry and manufacturing (in logarithmic form). Across the different types of temperature shocks, latitude, average real GDP per capita and long-term growth appear to be the most robust variables. In contrast to the findings of Dell et al. (2012), the agricultural share of GDP is not statistically significant. Additionally, for the global temperature shocks the average GDP shares of manufacturing and industry are statistically significant. The authors suspect that the response to variation in the global temperature component is more systematically related to a country's economic structure.

Overall, the three papers support the view that changes in temperature will have uneven effects on economic activity. When comparing the results of Dell et al. (2012), Burke et al. (2015) and the comparable idiosyncratic response discussed by Berg et al. (2021), their findings are relatively consistent with more negative responses of real GDP per capita to temperature variation. Their findings also suggest that temperature increases do only have level effects but also persistent impacts on growth rates. However, Burke et al. (2015) emphasize that rich countries are similarly affected by temperature increases. Berg et al. (2021) find a higher levels of heterogeneity within both groups with richer countries especially being negatively affected over longer horizon and large developing countries actually benefiting.

2.3 Exercise 3

3. Use the attached data for your own regression of GDP growth on temperature. Choose a simple way to allow for a nonlinear effect of temperature on growth. Estimate the following variations of your model:

a. In addition to temperature, control for standard variables in growth regressions (initial GDP, investment, education, population growth)

To understand rebound effects from climate change back to economies, we have investigated the effect of temperature changes on the growth rate of real gross domestic product. In our data set, each data point relates to the aggregate effect of a five-year period for a respective country. The first captured period captures data from 1970-1974, the latest period captures data from 2015-2019.
In the first step, we estimate the linear and quadratic effect of temperature on real GDP growth using data from 73 countries. We differentiate between contemporaneous, previous period average (i.e. five-year lag) and long-term-lag temperature effects with the latter measuring the average temperature from 4 periods earlier. We control for other relevant variables determining real GDP growth: previous period precipitation and population growth as well as initial year values of primary and secondary education levels, log GDP, life expectancy at birth and an estimator for institutional stability [7].

[5]below-median PPP-adjusted real GDP per capita in first year of the sample

[6]For Germany and Japan they project losses of -0.8 per cent and -2.3 percent respectively.

[7]Political rights index according to the Repucci and Slipowitz (2021) report. The school years are taken from Barro and Lee (2013). The temperature and precipitation data is taken from Zermoglio et al. (2021). Gross capital share, population growth and initial log GDP data are taken from Feenstra et al. (2015). Life expectancy at birth data is taken from World Development Indicators 2021.

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.08^{***}	0.18^{**}	0.18^{**}	0.15^{**}
	(0.01)	(0.07)	(0.07)	(0.08)
temp	-0.03^{*}	-0.02		
	(0.02)	(0.02)		
temp.temp	0.00	0.00		
	(0.00)	(0.00)		
lagtemp	0.03^{*}	0.02	-0.00	
	(0.02)	(0.02)	(0.00)	
lag.temp.temp			0.00	
			(0.00)	
longtermlag.temp				0.00
				(0.00)
longtermlag.temp.temp				0.00
				(0.00)
lagprec		-0.00	-0.00	-0.00
		(0.00)	(0.00)	(0.00)
lag.popgrw		-0.71^{***}	-0.71^{***}	-0.66^{***}
		(0.12)	(0.12)	(0.13)
Barro_prim		0.00	0.00	0.00
		(0.00)	(0.00)	(0.00)
Barro_sec		-0.02^{***}	-0.02^{***}	-0.02^{***}
		(0.01)	(0.01)	(0.01)
lngdp_init		-0.02^{***}	-0.02^{***}	-0.01
		(0.01)	(0.01)	(0.01)
PR_init		0.00	0.00	-0.00
		(0.00)	(0.00)	(0.00)
lifeexp_init		0.00	0.00	0.00
		(0.00)	(0.00)	(0.00)
csh_i		0.44^{***}	0.44^{***}	0.44^{***}
		(0.06)	(0.06)	(0.07)
R^2	0.00	0.15	0.15	0.14
Adj. R^2	0.00	0.14	0.14	0.12
Num. obs.	657	657	657	511
RMSE	0.12	0.11	0.11	0.10

Standard errors in brackets. Significance codes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1: Linear regression models on real GDP growth rate. **(lag)temp**: average temperature of contemporaneous or previous period. **(lag/longtermlag).temp.temp**: non-linear squared effect. **longtermlag.temp**: average temperature of the 4 times lagged period. **PR_init**: Political rights index according to Repucci and Slipowitz (2021). **lagprec**: Average previous period precipitation. **lag.popgrw**: Average periodic population growth **Barro_prim, Barro_sec**: years of primary and secondary education at initial year of period. **lngdp_init**: log GDP at initial year of period, in 2017 Mil. US$. **csh_i**: period-average gross capital share of GDP.**lifeexp_init**: Life expectancy at birth from the first year of the period.

Table 1 displays the results. The first model depicts effects of temperature in linear and quadratic terms as well as previous period temperatures regressed on real GDP growth, with opposing signs and significance on the five percent confidence band. Looking at model two, we can see that adding the above mentioned control variables leads to non-significant temperature coefficients. We additionally investigate the effect of long-term effects of temperature. The two coefficients with the prefix 'longtermlag' depict linear and quadratic 4 period, i.e. 20 year-lagged estimators of temperature. Note that the 146 fewer observations in model 4 occur due to the removal of two additional periods for each of the 73 countries. In the standard linear regression, the effects are not significant. It is worth noting that in these regressions, only population growth, secondary education levels and gross capital share as a share of GDP seems to have a significant effect on real GDP growth. To summarize the results, temperature coefficients are of low magnitude with low or no significance at all. A standard linear regression model does not seem to support the hypothesis of temperature changes affecting real GDP growth. Therefore, to follow up on the first exercise, we also investigated the within-transformed versions of the variables which will be discussed in the next section.

b. In addition, remove country and time fixed effects using within-transformations, see section 3.1 in Berg et al (2021) for a short explanation.

Temperature differences across countries or across time might be related to other fixed effects. One hypothetical example for the heterogeneity determined by geography could be the correlation of higher temperature with lower school attendance rates. In a similar fashion, times of boom or bust could correlate with higher temperature which would also distort the isolated temperature effect on real GDP growth. Therefore, we now abstract from time and country-associated fixed effects by performing a within-transformation of the variables. The coefficients are then interpreted as (idiosyncratic) differences from the global mean. Table 2 shows our results. The first three models measure the estimated effect of temperature on the difference between idiosyncratic and global real GDP growth. The control variables are identical to the ones from table 2.3. Note that only the linear effect of long-term temperature has a significant coefficient. One potential explanation could be that countries with above-average temperatures experience lower than average real GDP growth over the long run because temperature affects determinants of economic growth such as productivity. We estimate that a one degree Celsius higher previous average temperature reduces GDP growth by five percent, as a deviation from the global average. To verify this observation, we additionally control for public expenditure share of GDP to see whether another determinant of growth in the long run might be included in the long-term effect of temperature. Model four shows a weaker, non-significant coefficient of 'longtermlag.temp' together with a highly significant negative government spending estimator. This suggests that the potential explanation cannot be verified with the data. Model five shows that including all temperature effects into one regression. The overall impression arises that temperature seems not to be a good indicator of economic growth.

	Model 1	Model 2	Model 3	Model 4	Model 5
(Intercept)	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
temp	0.00				0.01
	(0.02)				(0.03)
temp.temp	0.00				0.00
	(0.00)				(0.00)
lagtemp		0.01			0.03
		(0.03)			(0.03)
lag.temp.temp		-0.00			-0.00
		(0.00)			(0.00)
longtermlag.temp			-0.05^{*}	-0.04	-0.05
			(0.03)	(0.03)	(0.03)
longtermlag.temp.temp			0.00	0.00	0.00
			(0.00)	(0.00)	(0.00)
lagprec	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lag.popgrw	-0.92^{***}	-0.92^{***}	-0.88^{***}	-0.87^{***}	-0.89^{***}
	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
Barro_prim	-0.02	-0.01	-0.02	-0.03^{**}	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Barro_sec	-0.02^{*}	-0.02^{*}	-0.02^{*}	-0.01	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
lngdp_init	-0.25^{***}	-0.25^{***}	-0.25^{***}	-0.25^{***}	-0.25^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
PR_init	-0.01^{***}	-0.01^{***}	-0.01^{**}	-0.01^{***}	-0.01^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lifeexp_init	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
csh_i	0.47^{***}	0.47^{***}	0.47^{***}	0.41^{***}	0.42^{***}
	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)
csh_g				-0.35^{***}	-0.36^{***}
				(0.09)	(0.09)
R^2	0.27	0.27	0.28	0.30	0.30
Adj. R^2	0.26	0.25	0.26	0.28	0.28
Num. obs.	511	511	511	511	511
RMSE	0.08	0.08	0.08	0.08	0.08

Standard errors in brackets. Significance codes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 2: Regressions for real GDP growth rates after removing country and period specific fixed effects. **csh_g**: period-average Government consumption share of GDP. See section 2.3 for other variables' description.

c. Estimate the model with all potential explanatory variables using Bayesian Model Averaging as in the attached code. Refer to the course slides and documentation of the bms-package to explain your results statistically and interpret them economically. How do results change if temperature is added as a fixed regressor?

The selection of control variables in previous regressions is motivated by the attempt to extract any effect on real GDP growth that might otherwise distort the temperature effects. However, one might criticise the selection of variables in the models from table 2.3. Specifically, the weak temperature coefficient could be distorted due to omitting other variables. To account for this, we follow a Bayesian approach and investigate the model fit for randomly drawn regression models with the goal of analyzing the posterior probabilities of including relevant regressors to the model.

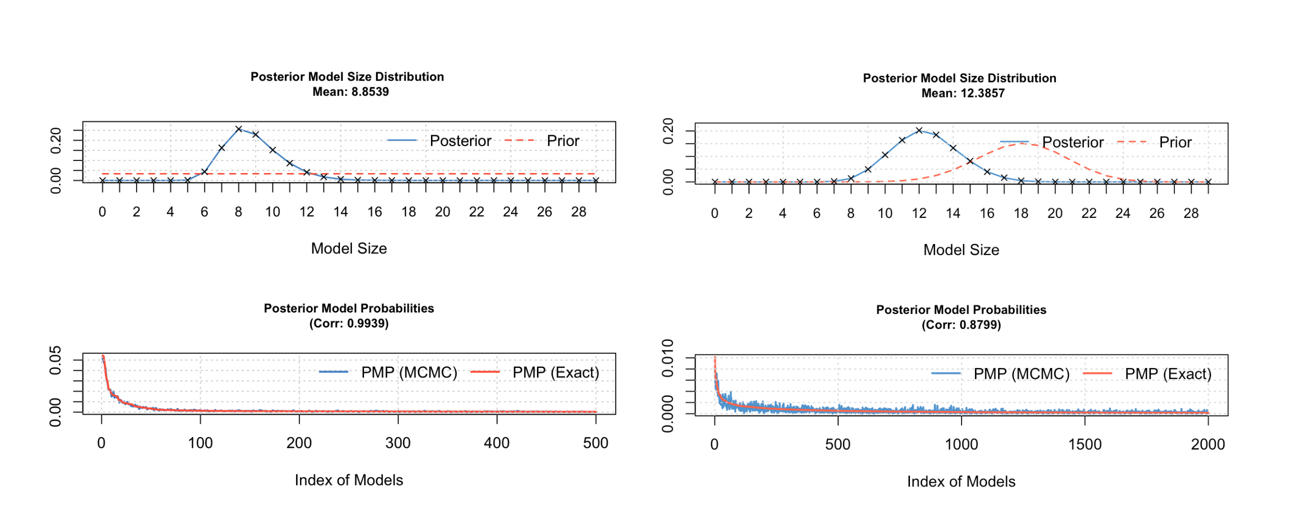

Figure 1: Bayesian Model Sampling results using 100000 draws and burning 50000. Left plots: prior inclusion probabilities set to random, 500 best models considered. Right plots: initial inclusion probabilities set to 18, 2000 best models considered.

For the drawing process, we use the BMS command from the Stargazer package of Hlavac (2018). We let prior estimator weights be randomly assigned according to the function. Initially, we assign an equal model size distribution to see how this changes after the random draws. The top graph of Figure 1 shows that most selected models have between six and ten coefficients. The results suggest that nine estimators are on average the best choice for the considered models (26276 in total which equals 0.49 per cent of all possible models). For reference, the dashed red line depicts the equal distribution for each model size that has been assigned before drawing the models. The bottom graph shows that the likelihood and the Monte Carlo random samples are close to each other for the best models that were chosen. We can see that of the 500 models considered, only for the first 100 models the posterior model probability has values not close to zero. This gives confidence in the amount of coefficients selected previously. A further validation is the low posterior inclusion probability that is below 5 percent for almost all temperature coefficients considered[8]. The only exception is the long-term (4 periods or 20 years) lag which is included in 28.7 percent of models with an average coefficient value of -0.137. The negative sign was present for all considered models. As for robustness checks, we have used the command 'mprior.size' to check whether providing information about the model size ex-ante changes the results. However, the model size distribution mean remains in the range 8-10 as long as 'mprior' (the prior inclusion probability for coefficients) is set to random. Changing the number of best models considered from 500 to 2000 does not change the quality of the results as well. Using the command 'fixed.reg="longtermlag"' to force the long-term lag into all regression models verifies the negative sign for this variable, see table 3 for the inclusion probabilities. Notably, the squared effect of the long-term lag increases to almost 10 percent from previously below five percent. The reason is of statistical rather than economic nature, namely that it is necessary to tell the bms-function which coefficients are constructed manually. The command 'mcmc="bd.int"' takes these interaction effects into consideration and only adds them if the main variable has been included to the model. The results change after this addition and the posterior inclusion probability of squared long-term temperature

[8]See the attached R-output for these results

	PIP	Post Mean	Post SD	Cond.Pos.Sign
longtermlag	1.00000	-4.706667e-02	2.156675e-02	0.00000000
longtermlag#longtermlag	0.09704	1.256419e-04	4.524038e-04	1.00000000
lagtemp#lagtemp	0.03899	-2.273654e-05	1.544375e-04	0.00000000
lagtemp	0.03094	-4.575508e-04	4.158876e-03	0.01131222
temp#temp	0.02091	-2.553804e-06	7.960417e-05	0.26877092

Table 3: Posterior model inclusion probabilities (PIP) when fixing the inclusion probability of 'longtermlag' to 1. Post Mean / SD: posterior expected value / standard deviation of coefficients. Variable description taken from Feldkircher and Zeugner (2013).

drops to 1.2 percent which is in line with previous observations.

To summarize, it has been shown that temperature as an estimator of real GDP growth seems not to have sufficient explanatory power, at least as a contemporaneous effect. This rejects the intuitive economic explanation of high average temperatures negatively affecting economic activities in the short run. Furthermore, a non-linear effect, at least in the way we have examined here in a quadratic form, does not show significant explanatory power. As for longer term effects, at least the negative sign seems to be robust, however more robustness tests are required to validate the impact on real GDP growth that has been found in most of the regressions.

2.4 Exercise 4

Projections of the future effect of temperature increases on GDP growth need to be based on likely local temperature changes, because global temperature increases are "soaked up" by the time-fixed effects. Find a source that provides country-specific projections of temperature growth rates. Select a couple of countries to answer the following question, based on your own estimates in question 3: "What will be the likely effect of temperature increases until year 2050 on average GDP growth in country X?".

We projected the expected effects for India, France, Canada and Brazil. Since we use the coefficient from the 20 year lagged temperature we combine projected scenarios with past temperatures. For projected scenarios we use the Shared Socioeconomic Pathways, which indicate different projections of future carbon outputs. We can see that there is not a lot of variation between the scenarios and the effects on GDP until 2050 are low. The difference between scenarios increases in the second half of the century. In our regression from 3a temperature and temperature squared have a positive effect on GDP growth.

We use different methods to show the effects. First we plot the different effects indicated by the difference in temperature twenty years before the observed year and the base year (see Figure 2). Then we plot a loess, which smooths the effects and therefore makes the difference between scenarios more visible, especially when differences are low (see Figure 3). Furthermore, we plotted the confidence bands. To make the graph visually more appealing, the regular (non-loess) plots depict the confidence band only for the SSP1.0 scenario.

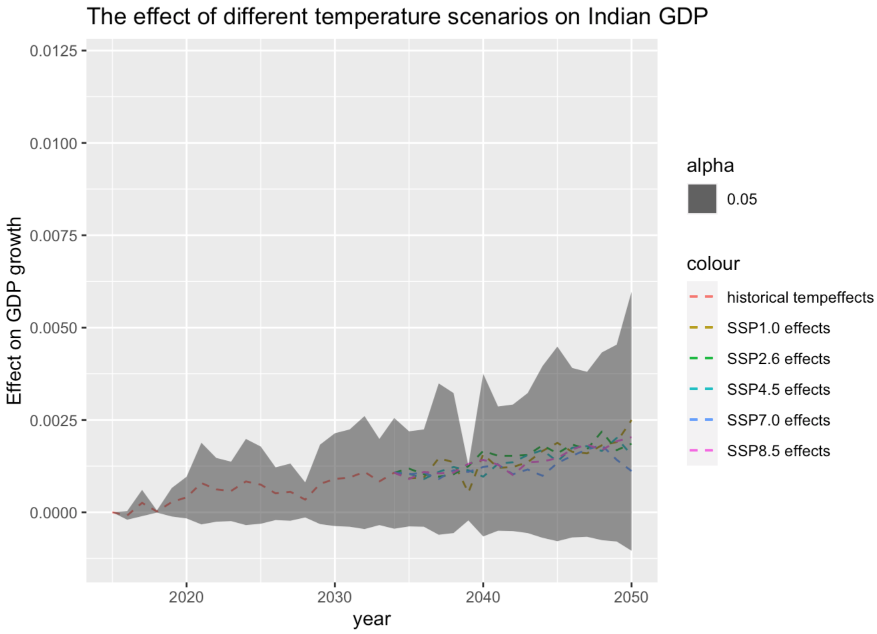

Figure 2: Temperature effects in India

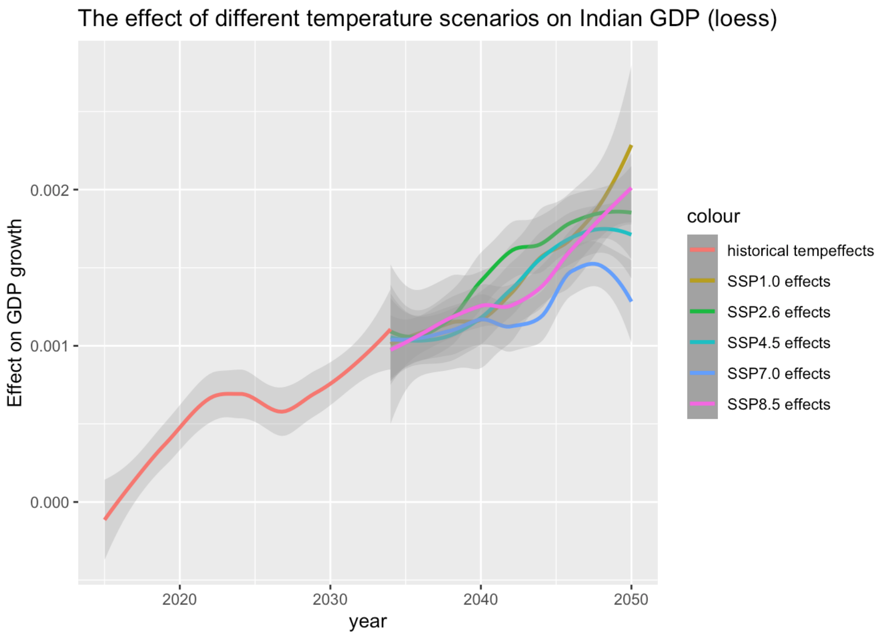

Figure 3: Temperature effects in India (loess)

For India (Figures 2 and 3) the best scenario is the SSP1.0 scenario with a positive effect of 0.225 per cent on GDP growth until 2050. The worst effect is the SSP7.0 scenario with a positive effect of 0.135 per cent. The lower emission scenarios have the most positive effects, because they have higher temperatures in the short run. The past temperature has positive effects on GDP and increases it by 0.11 per cent by 2035.

For French GDP growth the SSP2.6 scenarios is the best achieving higher GDP growth by 0.17 per cent. The low emission scenario achieves higher GDP growth by 0.12 per cent. Past temperature increases GDP by 0.077 per cent.

The effects on Canadian GDP growth are very similar. Canada has a negative average temperature. The best scenario for Canadian GDP is the SSP8.5 scenario, which increases temperature the most until 2035. In this scenario GDP growth is increased by 0.0043 per cent. The worst case scenario is the SSP7.0 scenario. In this scenario GDP is reduced by 0.00075 per cent. Temperature differences between years in the past haven been small, therefore there is a constant negative effect of 0.0027 per cent. The base year stands out with a zero effect simply because the temperature difference here is zero, so there is no additional effect on GDP.

Lastly for Brazilian GDP growth the SSP8.5 scenario, which increases GDP by 0.31 per cent, is the best. The worst scenario is the SSP7.0 scenario, which increases GDP by 0.24 per cent. Past temperatures increase GDP by 0.17 per cent.

All in all the effects on GDP are low. Since temperature increases are positive here Brazil profits the most from climate change, because it has the highest projected temperature increases. Differences become bigger in the long run since temperature difference between scenarios can be as large as six degrees in 2100 in the case of Canada.

3 Conclusion

Overall, the review of the literature and the empirical investigation have shown that the effects of temperature on per capita GDP are quite heterogeneous. In the empirical investigation, we have not found temperature to have sufficient explanatory power, especially in the short term. In the medium and long term we find a negative relationship between temperature and GDP per capita which is in line with the discussed literature by Dell et al. (2012), Burke et al. (2015) and Berg et al. (2021), however the robustness cannot be confirmed by our analysis. Generally, the observed relationships and projections should be treated with caution as the historic relationships do not necessarily correspond with future relationships. The effects of climate change might intensify in the future and at the same time temperature does not capture all the effects of climate change. Extreme weather scenarios such as droughts and floods might also impede economic output. Next to mitigating temperature increases, another important dimension of climate policy is an economy's capability to adapt. Most models base the adaptation process on assumptions. However, unprecedented innovation and investments might improve an economy's adaptability, but social conflict and political restrictions might reduce effects of adaptation.

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