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A Seat at the Table: Distributional impacts of food-price increases due to climate change

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Abstract: Although climate change is expected to have a significant impact on the global population, little is known about how it will affect individual households in their daily lives. Based on food price increases caused by climate change, we analyse how climate-change-related damages distribute across households in over 75 developing countries. In a microsimulation model, climate damages are quantified as losses in consumer surplus, on average roughly 3 percent of total expenditure. We find evidence that climate damages are regressive, i.e. they disproportionately affect households with lower consumption. Damages display regressivity when we compare (a) national averages across countries, (b) all households in our sample, and (c) households within countries. However, there are some - often more developed - countries, where damages are progressive, i.e. damages disproportionately affect more affluent households in those countries. At a sectoral level, damages tend to be more regressive in countries where in relative terms rice consumption contributes more to the welfare of households.

Keywords: Climate damages, Distributional impacts, Food prices, Regressivity

1. Introduction

Recent and current crises like the Covid19 pandemic and the Russian invasion in Ukraine have starkly demonstrated how extreme events significantly impact the well-being of households on an international plane as a result of market-price increases. Along with other effects of global

warming, climate change is expected to increase the frequency and intensity of extreme events. Researchers predict that even moderate climate change will have substantial effects on human well-being (IPCC, 2022). Here, climate change displays its impact through subtle channels, including changes in eating habits induced by the increase in food prices. We assess the distributional impact of food-price increases caused by climate change across households from a wide range of developing countries and indicate possible ways of dealing with the adverse impacts of climate change on low-income households.

Climate change has manifold interactions with human well-being, which makes it increasingly significant for public policy. Agricultural productivity will be seriously affected by changes in precipitation, temperature, carbon dioxide fertilization, climate variability and surface water runoff (Rosenzweig et al, 2014; Hasegawa et al, 2021). Accordingly, one of the most notable effects of climate change will be its detrimental effect on food provisioning and security. Rising population and climate-related losses in agricultural food production will lead to shortages of food, which in their turn will cause an increase in the price of goods. Given our interconnected global economic system, even regional climate-induced impacts affect the rest of the world (Bren d'Amour et al., 2016). Conceivable adaptation strategies at the national level would include switching to more suitable crops and advanced water and soil management. At the household level, people can be expected to adjust by way of dietary changes, but they will still feel the impact of monetary pressure because of increased prices and higher variability. Therefore, commodity-price increases will usher in the arrival of climate change as a quiet and unexpected guest in each individual household. Its hunger will also potentially increase with further growing levels of global warming, as indicated in (IPCC, 2022).

Our article fills a gap in the literature by assessing the impact of this unwelcome guest across income distribution. Although specific price increases and a general change in consumer and producer surplus have been assessed and predicted (see Calzadilla et al., 2014), little is known about the potential distributional impacts across all households. We use a microsimulation model to analyse climate damages in over 75 developing countries. For our analysis, we combine a global multi-regional dataset, household data and predictions on price increases caused by climate change with economic elasticities. We use projections of world market price increases due to climate change for selected food categories: 'rice', 'wheat', 'cereal grains', 'vegetables, fruits and nuts', 'oil seeds', 'sugar cane, sugar beet' and 'other agricultural products'. We apply an approach using a Leontief inverse to assess the prominence of different agricultural goods for global supply chains. In a second step, we use this information to assess how world market-price increases due

to climate change influence price hikes for final consumption commodities. The methodology used is similar to approaches implemented in economic studies on climate policy (Feindt et al., 2021).

Our aim is to test the hypothesis that climate-induced price increases will have a regressive distributional impact, i.e. they will impose a disproportionate burden on the lowest-income groups in comparison to higher-income groups (see e.g. Leichenko and Silva 2014, Letta et al 2018). Our indicator for economic inequality is household consumption, which is a proxy for lifetime income and relatively more suitable for measuring well-being than current income (Poterba 1989, Poterba 1991, Sterner 2012). To compare relative damages between and within countries, we calculate the change in consumer surplus as a share of total consumption for each country and each consumption group. Furthermore, we investigate the distribution of climate damages in relation to the income levels across countries. Our analysis shows that the higher a country's income level is, the less severe average climate damages are. This same trend is also observable within countries. In more than 70% of the countries analysed, the lowest-consumption groups tend to be more severely impacted than the highest-consumption groups.

For an in-depth discussion of distributional impacts, consumption elasticities are computed using a sample of all corresponding households. Consumption elasticity measures the percentage change in climate damages when the consumption of a household increases by one percent. Thus, higher elasticity indicates more progressive impact on the part of climate damages. Most of the countries in our sample show consumption elasticity close to, but below, one, i.e. within these countries climate damages are regressive. Another of our findings is that consumption elasticity is positively correlated with per-capita income. This shows that countries with lower per-capita income are susceptible to more disproportionate impacts of climate change on the poorest individuals in their societies. In sum, the test of our hypothesis indicates that climate damages due to food-price increases are by and large regressive, even though they are close to being proportional to consumption. Economic development will mitigate the adverse distributional effect of climate change.

In order to understand what drives regressive effects, we investigate how different commodities contribute to climate damages. The sectoral analysis reveals that the shares of the rice and vegetables sectors in overall expenditure are the most relevant factors for climate damages. Additionally, the contribution of rice is severe in certain areas within Asia. To better understand the sectoral contribution to damages, we perform a cross-country regression analysis of food expenditure shares against damages and against consumption elasticity, while controlling for inequality, income and regional fixed effects. We find that, *ceteris paribus*, higher vegetable

consumption leads to higher damages *across* countries, while higher rice consumption leads to more regressive effects *within* countries.

Our results are an addition to the rapidly growing research on the socio-economic impacts of climate change (see e.g. Cattaneo et al 2019, El-Sayed and Kamal 2020, Vicedo-Cabrera et al 2021). Within this strand of literature, we are interested in the distribution of monetary climate damages across income groups. Our findings are in line with previous studies on the regional scale, which have shown that less developed regions experience a disproportionate loss in economic growth due to climate change (Burke et al 2015, Hsiang et al 2017, Kalkuhl and Wenz 2020). At the subnational scale, most studies focus on the impact of climate change on poverty (Hertel et al 2010, Hallegatte and Rozenberg 2017). Our article is one of the few studies that analyse the distributional implications of climate change across the entire income scale. Recent advances have shown that welfare impacts from additional heat stress may be regressive within countries (Park et al 2018) and that in rural India, the income of poor households is more strongly affected by changing seasonal climate variability than that of more affluent households (Sedova et al 2020).

The paper proceeds as follows: In section 2 we introduce the methods and the data used. Section 3 presents the results. We discuss our findings in section 4 and conclude thereafter.

2. Methods

a. The microsimulation model

We measure how price increases due to climate change affect individuals via the equivalent variation. We cover the consumption effects of the equivalent variation through changes in consumer surplus. The subsequent derivation closely follows (Mas-Colell, p. 82ff).

Denote all variables in the absence of climate change with a bar. The equivalent variation of individual i is the change in the expenditure function:

$$EV_i = e(\bar{p}, u_i) - e(\bar{p}, \bar{u}_i).$$

With \bar{p} , p (\bar{u}_i, u_i) pre- and post-impact prices (utilities). If only the price of good 1 changes, the equivalent variation is equal to the area under the Hicksian demand curve plus income changes:

$$EV_i = \int_{p^1}^{\bar{p}^1} h^1([t^1, p^{-1}], u_i) dt^1 + y_i - \bar{y}_i.$$
 (1)

where $h^1([p^1, p^{-1}], u_i)$ is the Hicksian demand for good 1, p^{-1} the prices of all other goods except good 1, and the change in individual i's income is $y_i - \bar{y}_i$. To derive a formula for the consumer surplus that can be estimated with the available data, we make four assumptions: (i) the area under the Hicksian demand curve is equal to the area under the Marshallian demand curve (this is

true if utility is quasilinear in a different good than good 1 (Mas-Colell, p. 82)); (ii) when the prices of multiple goods change due to climate change, the total equivalent variation is the sum of (1) across all goods when substituting good 1 for each affected good (so there are no interactions between price changes of different goods); (iii) Marshallian demand has constant own-price elasticity for each good, with elasticity denoted as ε^k ; (iv) there are no income effects. We return to the implications of our assumptions in the discussion section.

With our assumptions, the equivalent variation becomes (see also West and Williams 2004):

$$EV_i = \Delta CS_i = \sum_k \frac{1}{\varepsilon^k + 1} \bar{p}^k \bar{x}_i^k \left(1 - \left(\frac{p^k}{\bar{p}^k} \right)^{\varepsilon^k + 1} \right). \tag{2}$$

By approximating the Hicksian demand with the Marshallian demand and abstracting from interaction effects, the equivalent variation is the sum of changes in consumer surplus from price changes for each good.

To compute the change in consumer surplus, Section 2b derives the data for (i) relative price increases by commodity $\left(\frac{p^k}{\bar{p}^k}\right)$, (ii) household consumption by commodity $(\bar{p}^k\bar{x}_i^k)$, and (iii) own-price elasticities by commodity (ε^k) .

b. Data

i. Price increases

As a baseline for future price developments we use the price increase projections for the seven categories 'rice', 'wheat', 'cereal grains', 'vegetables, fruits and nuts', 'oil seeds', 'sugar cane, sugar beet' and 'other agricultural products' in Calzadilla et al. (2013). The authors simulate the impacts of climate change and CO_2 fertilization on global agriculture, identifying world market-price increases in the range of 4.78%-5.60% for the selected categories. These projections are then fed into a Multi-Regional Input-Output (MRIO) framework to assess supply-chain effects that have an influence on final consumption commodities (see next section). A detailed matching of the categories in Table 1 and the sectors in the MRIO is given in the Appendix.

Table 1: Estimated changes in production and production-based world price changes for 2020. Price changes are simulated under an A2 climate scenario compared to the baseline (source: Calzadilla et al., 2013).

Crops	Total production (%)	World market price (%)
Rice	-1.28	4.78
Wheat	-0.60	5.21
Cereal grains	0.64	5.33

Vegetables, fruits and nuts	-0.36	4.83
Oil seeds	-1.29	4.80
Sugar cane, sugar beet	-0.55	5.60
Other agricultural products	-0.36	4.97

ii. Global MRIO: GTAP 10

To estimate how the market-price increases are diffused through supply chains, we apply input-output analysis to the Global Trade Analysis Project database (GTAP) 10 (Aguiar et al. 2019). GTAP covers 65 sectors and sector aggregates in 141 different regions and region aggregates (see the Appendix for an overview). GTAP 10 provides basic data for four different years (2004, 2007, 2011, 2014). We use only the most recent one, which is 2014. The raw version of GTAP as released is not a MRIO dataset but can be transferred into such a dataset by proceeding in the way proposed by Peters et al. (2011). We use their endogenous international transportation pool approach. The analysis utilizes basic MRIO analysis (see Miller and Blair (2009) for an overview). A technically similar approach has been adopted by Feindt et al. (2021) for assessing CO₂ taxation impacts. Standard items of the MRIO analysis are the interindustry flow matrix Z with $Z \in \mathbb{R}^{m \cdot n \times m \cdot n}$, where r is the number of regions, s refers to the number of sectors and the final-demand vector Y, where $Y \in \mathbb{R}^{m \cdot n \times n}$. Single elements $y_{r_1 s_1}^{r_2}$ of Y represent monetary consumption expenditures in region r_2 on goods from sector s_1 of region r_1 . Z can be used to derive the technology matrix $A \in \mathbb{R}^{m \cdot n \times m \cdot n}$, representing the required input per unit of sectoral output (see Feindt et al. 2021). With L-A, the Leontief inverse can be calculated, resulting in L = $(I-A)^{-1}$, where I denotes the identity matrix. L accounts for all pre-products that may have been used in upstream supply chains for the production of final-demand commodities. Let $\mu \in \mathbb{R}^{m \cdot n}$ denote the vector of relative sectoral price increases for each sector according to the projections of Calzadilla et al. (2014), see Table 1. We set the price increases for all sectors not considered in Table 1 to zero. The forecasted direct price increases for each sector are of equal magnitude for all countries. Price increases for final demand goods then come out as $M = \mu \circ L$, as the Leontief inverse assesses the 'virtual content' of upstream goods. The matrix M describes how price signals become diffuse through supply chains. An overview of price-level increases across countries is given in Figure 1. For assessing the vulnerability of households, we are further interested in the underlying consumption patterns, i.e. where does the average good actually being consumed originate from? Let $y_{r_1s_1}^{r_2}$ be the expenditures of region r_2 on commodities of sector s_1 from region r_1 . Induced by price increases of different origins and intermediate inputs for producing a specific commodity, the corresponding price increase for a commodity k in country r_2 is:

$$\frac{p^k}{\bar{p}^k} = 1 + \frac{\sum_r \sum_{r'} \sum_{s'} \mu_{r',s'} L_{r',s'}^{r,k} y_{r,k}^{r_2}}{\sum_r y_{r,k}^{r_2}}$$

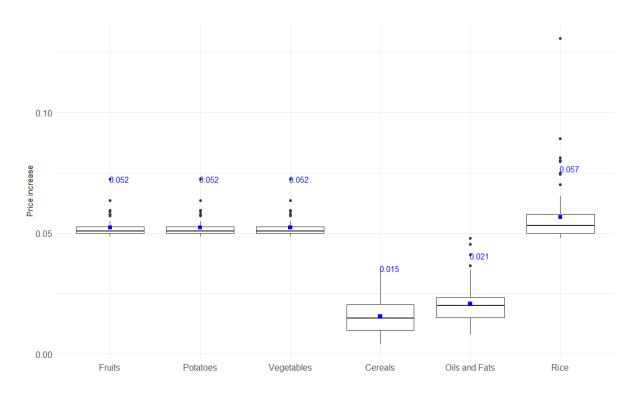


Figure 1: Relative increase in national consumer prices for each food category as computed by the MRIO. Blue markers represent the mean increase in consumer prices. The lower and upper whiskers correspond to the 25th and 75th percentiles.

iii. Global consumption database

The Global Consumption Database (GCD) provides data on household consumption patterns in 92 developing countries based on representative national household surveys conducted between 2000 and 2010. In each country, the household expenditures on consumption items are divided into 106 products and services. The households are categorized into four consumption groups: lowest, low, middle, and higher. This classification is based on the percentiles of global income distribution according to the definition of the World Bank. The poorest consumption group is defined by a daily per-capita consumption of less than 2.97 US\$ in purchasing power parity (PPP). Ranking the global population by per-capita income, the lowest-consumption group is equivalent to the 50th percentile and less, i.e., the lower half of global income distribution. In comparison, the fixed thresholds indicate that the higher-consumption groups in most countries are relatively smaller than other consumption groups, accounting for the 91st percentile and higher. In this

group, daily consumption per capita is defined as above 23.03 US\$ in PPP (see Appendix A3). For seven of the least developed countries, data for higher-consumption groups do not exist due to overall extreme poverty.

iv. Own-price elasticities

We use data on own-price elasticities from the report entitled "International Evidence on Food Consumption Patterns: an Update using 2005 International Comparison Program Data" (Muhammad et al 2011). The report provides estimates on price and income elasticities for 114 countries using 2005 International Comparison Program (ICP) data. It covers three types of estimation for the own-price elasticity of demand: Slutsky (compensated), Cournot (uncompensated), and Frisch-deflated own-price elasticity. For the purpose of our analysis, we use the unconditional Frisch own-price elasticity estimates, as it is the only estimate that provides differentiated own-price elasticity for the different food groups, covering 8 sub-groups (Table A1). The estimation of the Frisch own-price elasticity is the elasticity computed from price changes and income is compensated such that the marginal utility is constant. Muhammad et al (2011) show that the estimates for the unconditional Frisch own-price elasticities are between those of the Slutsky own-price elasticities and the Cournot own-price elasticities and can reasonably be regarded as plausible estimates of average own-price elasticity for the different food sub-groups.

The own-price elasticity estimates range from -5.2 to zero. They are also in line with economic theory, as estimates for consumers in lower-income countries are more sensitive to price changes than those for consumers in wealthier countries.¹

v. Matching databases

In order to link the MRIO output to the household data from the GCD, we refer to the matching procedure set out in Dorband et al. (2019). According to conversion tables and detailed descriptions of consumption items provided by the databases, the authors matched the GCD consumption items to the GTAP 9 version. We have updated the matching to GTAP 10, where 103 consumption categories of the GCD household data are linked to 38 GTAP sectors. The holistic matching procedure is given in Table A2.

The food sub-categories of the own-price elasticity estimates were matched to the GTAP sub-categories and the more specific GCD sub-categories (Table A1). For some food sub-categories in the elasticity data, the GTAP sub-categories were too broad. In cases where the GTAP category

¹ In the rare cases (inferior food sub-groups) where the estimated Frisch own-price elasticity was positive (e.g. oils and cereals in a small number of rich countries), the own-price elasticity values were replaced by zero (Muhammad et al 2011).

entailed a broader definition than the one reflected by the elasticity data, we used the GCD sectors, as these are more specific. Table A1 shows the matching of the food sub-categories.

After matching the databases, we ended up with data for 79 developing countries.

3. Results

The change in consumer surplus of households demonstrates how climate change affects welfare within countries. We calculate the overall change in consumer surplus for each country (nation-wide) and also for each consumption group, so that we can compare effects both between and within countries. To enable comparison between unequal populations, we divide each consumption group's (national) change in consumer surplus by their (national) expenditure. The relative loss in consumer surplus is:

$$\Delta CS_{r,h}^{share} = \frac{-\Delta CS_{r,h}}{\sum_{k} \overline{x_{r,h}^{k}} \overline{p_{r,h}^{k}}} \left(\Delta CS_{r}^{share} = \frac{-\sum_{h} \Delta CS_{r,h}}{\sum_{h,k} \overline{x_{r,h}^{k}} \overline{p_{r,h}^{k}}} \right),$$

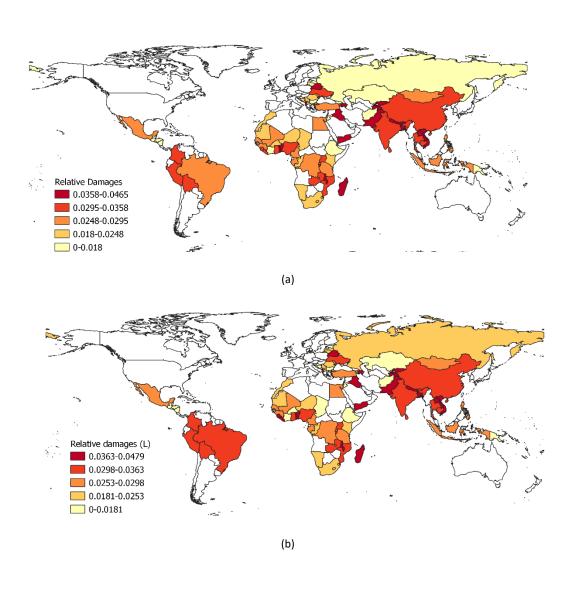
with r indicating the country and h the consumption group. The change in consumer surplus is negative for all countries and consumption groups and is thus referred to as a damage. We multiply with minus 1 to indicate climate damages as a loss in consumer surplus. This means that if the relative damage is 2%, the loss in consumer surplus resulting from the climate-induced price increase and accounting for the good's own-price elasticity is 2% of total expenditure in the baseline year.

a) Comparison of climate damages across countries

Across 79 countries the relative damage averages out at 2.5%. The largest relative damage is in Lao PDR (4.38% of total expenditure), followed by Tajikistan (4.35%), Pakistan (4.25%) and Nepal (4.08%). The least affected country is Ethiopia, where relative damage equals 1.36%. Ethiopia is followed by Bulgaria (1.71%), Namibia (1.73%) and Kazakhstan (1.77%) (Table A4). Figures 2a and 2b illustrate relative damages at the national level and for the lowest-consumption group, respectively. Relative damages for the lowest-consumption group are very similar to the national level. Exceptions are few.

We investigate the relationship between several macro-economic variables such as income levels and latitude and climate-change damages. Our assumption is that an increase in income levels will be associated with fewer relative damages, as we expect higher-income households to spend less on food and related items relative to their total expenditure. Also, countries closer to the equator may be more severely affected than countries located further away. Comparing between countries, we find that relative damages fall with GDP per capita (in \$ PPP). As illustrated in Figure

2c, the higher a country's GDP per capita is, the less relative damage it displays. The negative correlation indicates that lower-income countries are more severely affected by climate damages than higher-income countries.² We find a similar correlation- though not statistically significant-with latitude: countries located further away from the equator are exposed to less severe climate damages (addressed in more detail in Appendix B).



 $^{^2}$ The relative damage for the lowest-consumption segment caused by climate-induced food-price increases over GDP per capita are very similar to the national level with a slope significant at the 1% level and equal to -0.00000028766.

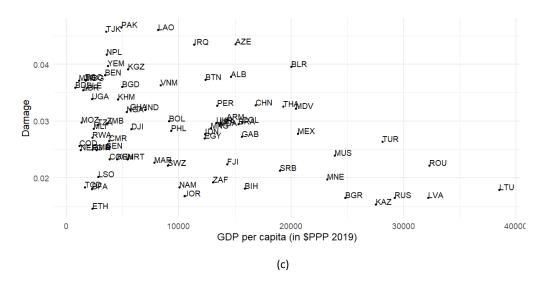


Figure 2: Relative climate-change damages measured by the loss in consumer surplus as a share of total expenditure. (a) Map illustrating the national relative damage: red indicates larger relative damages and yellow indicates smaller relative damages. (b) Map illustrating relative damages of the lowest-consumption group in each country: red indicates larger relative damages and yellow indicates smaller relative damages. (c) National relative damages against GDP per capita. The slope is significant at the 1% level and is equal to -0.00000028766. GDP data from the World Bank, 2021.

Comparing the lowest-consumption groups in all countries, we find that the households in Tajikistan are the most severely impacted, with relative damages equivalent to 4.52% of total expenditure (Table A4). Then come Lao PDR (4.47%), Pakistan (4.22 %) and Nepal (4.09%). By contrast, the least well-off households in Ethiopia, Kazakhstan, and Bosnia and Herzegovina have relative damages of only 1.36%, 1.74% and 1.75%, respectively.

Taking a closer look at the countries with the largest damages, we find that Tajikistan³ has by far the largest price increases in both the rice and vegetable sectors manifesting themselves in higher climate damages (Figures A3 and A4).

b) Comparison of climate damages within countries

We next present evidence for the assumption that climate damages are regressive within most countries, i.e. that households with lower total expenditure are disproportionately affected by food-price increases. For this purpose, we first briefly compare relative damages across consumption groups. In our main analysis we derive the consumption elasticity of climate damages, demonstrate that it largely indicates regressive impacts and compare its value across countries.

³ Tajikistan faced severe food process hikes in 2011 before the GTAP database was compiled, see https://www.dw.com/de/tadschikistan-%C3%B6ffnet-lebensmittel-notreserve/a-6441071 (German only). GTAP 10 uses Tajikistan 2011 data as its basis, see https://www.gtap.agecon.purdue.edu/databases/IO/table_display.asp?IO_ID=505. Hence, our findings are likely to have been influenced by this unusually prominent year.

Relative damages vary across the different consumption groups. The lowest and the low consumption group are on average more heavily affected than the higher-consumption group. The relative damages for the low and lowest consumption groups are higher than for richer households (Table 2). Overall, the least well-off households incur the highest climate damages. While 32.67% of the consumer surplus loss is borne by the lowest consumption group, only 5.93% of the loss is borne by households in the higher-consumption group (Table 2).

Consumption Group	Total consumer surplus change (USD PPP)	% of total	Total Expenditure (USD PPP)	Relative damage (%)
Lowest	-29483.1	32.67	935402.331	3.15
Low	-31714.5	35.14	1091312.76	2.90
Middle	-23699.0	26.26	881613.407	2.68
Higher	-5350.8	5.93	228694.572	2.33

Table 2: For each consumption group: total consumer-surplus change across countries, share of global consumer-surplus change in percent, total expenditure, and relative damage.

The sample covers 79 developing countries, 7 of which lack data for higher-consumption groups as these do not exist. ⁴ For 55 of the 72 countries analysed, the lowest-consumption group within the country incurs higher relative damages than the country's highest-consumption group (Table A4). The lowest-consumption group is also more seriously affected than other consumption groups: in 58 out of 79 countries, the lowest-consumption group is more seriously affected than the middle-consumption group, and in 57 out of 79 countries, the lowest-consumption group is more seriously affected than the low-consumption group.

For a more detailed understanding of the distributional impacts of climate-induced price increase and the resulting loss in consumer surplus, we compute consumption elasticity. A consumption elasticity of α means that the climate damages of an individual country increase by α percent when its total consumption increases by 1 percent.

To compute consumption elasticity, we use the general formula for elasticities, e.g. income elasticity, which defines elasticity as the proportional change in quantity of the variable in question as a result of proportional change in income. Assuming that elasticity is constant, the equation for the consumption elasticity of climate damages is:

⁴ The 7 countries are: Nicaragua, Guinea, Senegal, Liberia, Burundi, Togo and Benin.

$$\alpha = \frac{d\left(\frac{\Delta CS_{r,h}}{pop_{r,h}}\right) \frac{exp_{r,h}}{pop_{r,h}}}{d\left(\frac{exp_{r,h}}{pop_{r,h}}\right) \frac{\Delta CS_{r,h}}{pop_{r,h}}}$$
(4)

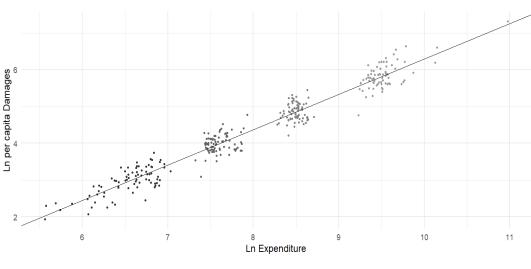
Hence, consumption elasticity α is the proportional change of per-capita climate damages $(\mathrm{d} \left(\frac{\Delta CS_{r,h}}{pop_{r,h}}\right) / \frac{\Delta CS_{r,h}}{pop_{r,h}}) \text{ resulting from a proportional change in per-capita expenditure} (\mathrm{d} \left(\frac{exp_{r,h}}{pop_{r,h}}\right) / \frac{exp_{r,h}}{pop_{r,h}}) .$

If α = 1, the damage due to climate-induced price increases is proportional to expenditure, i.e. all consumption groups would have the same relative damage. By contrast, the case of α < 1 shows regressivity in climate damages. Elasticity α < 1 reflects an increasing disparity between consumption groups. If α is zero, absolute consumer-surplus change is independent of income, i.e. in absolute terms, households in the lowest-consumption group will have the same climate damage as households in the higher-consumption group. In other words, the smaller the consumption elasticity α , the more regressive is the effect on households.

For the computation of consumption elasticity (α), Equation (4) yields:

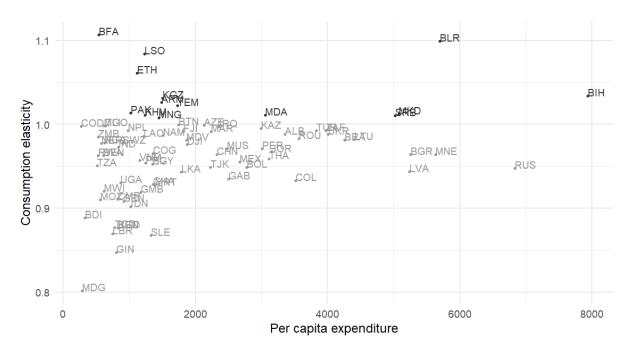
$$\ln\left(\frac{\Delta CS_{r,h}}{pop_{r,h}}\right) = K + \alpha \ln\left(\frac{exp_{r,h}}{pop_{r,h}}\right)$$

with some constant K. Thus, we regress the logged per-capita expenditure against the logged per-capita damages (absolute loss in consumer surplus) to obtain consumption elasticity as the slope (α) .



Consumption group * Lowest * Low * Middle * Highe

(a)



a disproportionate effect on higher-consumption groups a disproportionate effect on lower-consumption groups

(b)

Figure 3: (a) Regressing the logged per-capita expenditure against the logged per-capita damages, the consumption groups are represented by different colours ranging from black (lowest group) to light grey (highest group). The slope of the line is the consumption elasticity (α): Y=-3.32+0.96x (b) Consumption elasticity within countries against national per-capita expenditure. Countries in black have disproportionately affected higher-consumption groups (α >1). Countries in grey have disproportionately affected lower-consumption groups (α <1).

We start by calculating consumption elasticity across all households in the sample. Figure 3(a) shows the result. The per-capita damages increase with expenditure, represented by the upward sloping line. The slope of the line is the consumption elasticity, with a value of α =0.96 in the figure. However, we observe heterogeneity in the data between the different consumption groups and test the relationship further. We regress the log of per-capita damages against the log of per-capita expenditure and include dummy variables for each consumption group. In Table 3, we observe a positive and highly significant correlation between per-capita expenditure and per-capita damages. The coefficients for the consumption groups are not significant but they show that lower-consumption groups tend to have a smaller coefficient than the middle-consumption group. In addition, the higher-consumption group has a larger coefficient than the middle-consumption group. This shows that the lower-consumption groups tend to suffer more (more regressive impacts) than the higher-consumption groups. Overall, the consumption elasticity in Table 3 is α =0.885.

We next investigate the patterns of regressivity within individual countries. To do this, we calculate consumption elasticity by country. As illustrated in Figure 3(b), the consumption elasticity (α) for most

countries is less than 1, showing a disproportionate effect on lower-consumption groups. It ranges between 0.80 and 1.07, the country with the most regressive effects being Madgascar and the country with the most progressive effects being Burkina Faso. Out of the 79 developing countries analysed, 14 countries show progressive effects where α is larger than 1.5

In Figure 3(b), consumption elasticity is positively correlated with per-capita income. This shows that the higher the income level of a country, the less regressive are the climate damages (significant at the 1% level).

Dependent variable:

	Dependent variable:
	Ln percapita CS
ln_expenditure	0.885***
	-0.086
_	- 1
lowest	-0.155
	-0.175
low	-0.058
10	-0.09
highest	0.083
	-0.099
constant	-2.657***
	-0.728
Observations	286
\mathbb{R}^2	0.934
Adjusted R ²	0.933
Residual Std. Error	0.286 (df = 281)
F Statistic	992.282*** (df = 4; 281)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 3: Regression results: dependent variable is the logged per-capita damages

⁵ Checking the goodness of fit of our estimates for country-level consumption elasticity, we find that all countries have a squared value of R of at least 0.99, with one exception: Chad (r-squared= 0.958) (Figures A1 and A2).

c. Sectoral drivers of climate-change damages

To better understand differences in a country's distributional impact, we check whether specific food sectors drive damages. Please note that these values are different from the overall impacts presented in section a. We assess how dependence on certain food categories correlates with relative damages and consumption elasticity. We first discuss differences in price increases across food items and countries. Food items with higher price increases will, *ceteris paribus*, contribute more to damages. Additionally, the share of expenditure on each food category is expected to play a role in the resulting damages, as a price increase in food categories contributing substantially to food expenditure would have a larger effect on damages and –possibly- on consumption elasticity.

First, we observe a difference between the production-based world market prices shown in Table 1 and the prices for final consumption in Figure 1. Certain countries may be more or less affected by changes in food price increases on the world market as their production import and export structure differs (Aguiar et al., 2019). As shown in Figure 1, the relative price change for final rice demand is 5.7% on average. For fruits, potatoes and vegetables, the relative price increase is 5.2%. This does not differ greatly from the relative change in the production price of 4.78% and 4.83% shown in Table 1. By contrast, for cereals and for oils and fats, the production price increase is higher than the price that consumers face. Thus, rice, fruits, potatoes and vegetables can be expected to contribute more to climate damages both across and within countries.

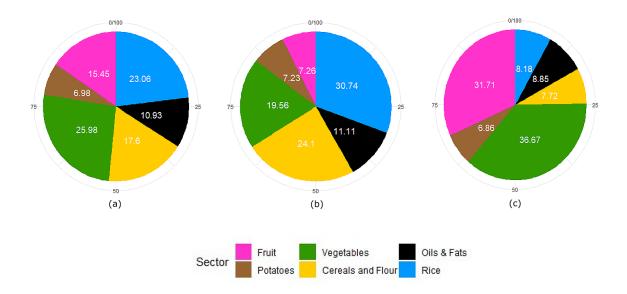
Second, we observe extreme relative price increases for final-demand goods in the rice sector for Tajikistan, where the rice price increases by 13.07% compared to the baseline, followed by Iraq (8.12%), Yemen (8.12%) and Armenia 7.99%). Further striking relative consumer-price changes have been observed for Belarus and Benin, which face an increase in the rice sector of 6.5% over and against the base year (Figure A4).

Unlike the rice sector, the vegetable sector displays smaller differences between changes in production and the final-demand price (Figure A4). For the bulk of countries, the relative consumer price changes are close to the producer-price change of 4.8%. Extreme price increases are found again for Tajikistan, where the final demand for vegetables faces a price increase of 7.2%. The second-highest price increase materializes in Benin, with a final-demand price increase of 6.3% compared to the baseline. Western Africa is also noticeably affected with an increase in the final-demand price of vegetables of 5.9%.

In general, price increases in the rice sector are highest compared to other sectors. To assess the impact of stronger price increases for rice (and to a lesser extent for fruits, potatoes and vegetables) on the welfare of a household, the household's demand for rice is important. As shown in Figure (4a),

the share of expenditure on vegetables is the largest at around 26%, followed by rice with a share of 23% of expenditure on the main food sectors. When differentiating between consumption groups, we find that for the lowest-consumption group, rice constitutes the largest share of expenditure (30.74%) followed by cereals and flour (24.1%) and then vegetables (19.56%). On the other hand, for the highest-consumption group, we observe that the vegetables sector is the leading sector when it comes to share of expenditure (36.67%), followed by fruits (31.71%) and then rice (8.18%).

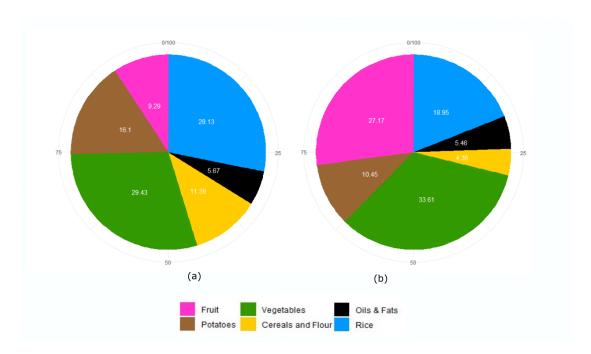
Figure 4: The share of each food sector's contribution to food expenditure in six main food sectors. (a) Share of each food sector in national expenditure. (b) Share of each food sector in the lowest-consumption group's expenditure. (c) Share of each food sector's share in the highest-consumption group's expenditure.



Combining price increases with household demand, we next show the share in consumer-surplus loss for each sector. We expect the sectors with the highest expenditure share and/ or price increase to be the highest contributors to the damages (given that their own-price elasticity is not very different). More specifically, we focus on the rice and vegetables sectors for the lowest-consumption and higher-consumption groups, given the observed difference in the shares of expenditures across the consumption groups. For the lowest-consumption group, the sectors contributing most to the damages are vegetables and rice with a share of 29.43% and 28.13%, respectively (Figure 5a). For the highest-consumption group, we find that the vegetables sector is by far the most significant driver of damages (33.61%) followed by fruits (27.17%) and then rice (18.95%). The differences between the shares of food expenditure and the shares of contribution to damages can be attributed to the difference of the price increases in each food sector (Figure 1). We find that in the case of potatoes in the lowest-consumption group (Figure 4b and 5a) and rice in the highest-consumption group (Figure 4c and 5b) their contribution to damages is much higher than their share of expenditure, this being due to the relatively higher price increases of 5.2% and 5.8%, respectively. On the other hand, the

price increase in cereals is much lower (1.5%). Accordingly, the share of cereals in food expenditure, as depicted in Figures 4b and 5a, is much higher than their share in damages.

Figure 5: The share of each food sector's contribution to damages in the lowest (a) and highest (b) consumption groups across all countries.



Drawing upon these insights, we now investigate the macroeconomic and sectoral factors that drive distributional impacts of climate change across countries in an OLS regression. We use three variables to reflect the distributional effects of food-price increase across countries: the relative damages at the national level (Table 4a), the relative damages for the lowest-consumption group (Table 4b) and consumption elasticity α (Table 4c).

We use GDP per capita in PPP as one of the explanatory variables. Countries with higher income levels are expected to be less severely impacted by climate-induced price increases than lower-income countries and to have a higher α . The reasoning behind this is that higher-income countries – arguably, even their lowest-consumption groups- can more easily afford food products than lower-income countries. Thus, an increase in food prices can be expected to lead to more severe relative damages in lower-income than in higher-income countries.

Another measure we use is that of income inequality, viz. the Gini coefficient from the World Bank data (World Bank, 2022). We draw upon the most recently available estimate for each country. In countries where there is high inequality in income distribution, we expect α to be lower so that there will be a disproportionate impact of climate damages on the poor. If the least well-off households within a country are poorer, we expect the share of food in their expenditure to be disproportionately higher so that they will be disproportionately affected.

In addition, we look at the rice and vegetable shares in food expenditure. We focus on rice and vegetables as they have the highest price increases and the highest share of expenditure and we use the national shares in food expenditure. The rice sector has the highest relative price increase compared to other food categories, and given that its share in the food basket is one of the highest, especially for the lowest-consumption group, we expect households that are largely dependent on rice to be more severely impacted by climate-induced price increases. The larger the share of rice in the food basket, the more severe the relative damage will be. Also, given the dependence of the lowest-consumption group on rice compared to other food sectors and compared to other consumption groups, a larger share of rice in food expenditure will tend to make damages more regressive, i.e. be correlated with a lower α .

We also include the vegetables sector since it has the largest share of expenditure in most regions' food baskets. Accordingly, we expect households that spend a lot on vegetables to be severely impacted by the climate-induce priced increase. We also control for the different regions by including region dummies. Our sample covers 68 countries. Some of the observations had to be dropped due to the unavailability of at least one of the control variables.

	a) Damages	h) a
		b) α
Rice	0.022***	-0.393***
	-0.008	-0.069
GDP per capita (PPP		
2019)	-0.0003***	-0.001
,	-0.0001	-0.001
Vegetables	0.059***	-0.137
	-0.016	-0.136
Gini coeff.	-0.0002	-0.001
	-0.0001	-0.001
SSA	-0.007***	-0.052**
	-0.002	-0.021
EAP	-0.003	-0.017
	-0.003	-0.024
ECA	-0.002	-0.037
	-0.003	-0.025
T + G	0.004	0.044
LAC	0.001	-0.046
	-0.003	-0.029
MENIA	0.006*	0.04
MENA	-0.006*	-0.04
	-0.003	-0.03

Constant	0.035***	1.114***
	-0.005	-0.043
Observations	68	68
\mathbb{R}^2	0.524	0.45
Adjusted R ²	0.45	0.365
Residual Std. Error	0.005 (df = 58)	0.044 (df = 58)
F Statistic	7.098*** (df = 9; 58)	5.278*** (df = 9; 58)

Table 4: Regression results: (a) Dependent variable is relative damages at a national level; the larger the value, the more severe the loss as a share of expenditure. (b) Dependent variable is consumption elasticity α . *Rice* indicates the share of rice in food expenditure. *Vegetables* indicates the share in food expenditure. The region dummies: *SSA* sub-Saharan Africa, *EAP* east Asia and Pacific, *ECA*, Europe and central Asia, *LAC* Latin America and Caribbean, *MENA* Middle East and North Africa.

In Table 4 (a), the dependent variable reflects the absolute losses in national consumer surplus as a share of base expenditure. The larger the value, the more severe the damages are. Results from 68 countries show that the per-capita GDP in 2019 (in thousands) is negatively and significantly associated with the national relative damages, i.e. countries with higher income levels are less impacted than those with lower income levels. On the other hand, we find a positive and statistically significant association between the share of rice/vegetables in food expenditure and the relative damages, showing that countries that are more dependent on rice and vegetables tend to face more severe losses in consumer surplus. We also find that the dummy for sub-Saharan Africa is negative and significant, indicating that sub-Saharan Africa as a region tends to be less affected than other regions. This is in line with Figures 2a and 2b, where we see more severe losses in consumer surplus, for example in East Asia and Pacific or Latin America.

To understand what drives the regressive impacts of climate-induced price increase within countries, we regress the sectoral shares in food expenditure, national income, income inequality and the regional dummies against consumption elasticity (α). Results from 68 countries show that the rice share in food expenditure is negative and statistically significant. This indicates that regressive impacts are more prominent within countries that are more dependent on rice consumption. Neither the share of vegetables nor the income levels are significantly associated with more regressive impacts. One main reason for the strong impact of rice is that it is essential in the food basket of low-income households but is less important for more affluent households. Thus the strong increase in the price of rice affects low-income households disproportionately, adding to the regressivity of climate damages within countries. Additionally, increases in the rice price have a significant influence on processed rice/rice products as well as an influence (depending on the country) on dairy products, cattle, cattle meat, other meat, wool, beverages, other food, especially in Asia and African countries. Accordingly, an increase in rice prices will also affect other food sectors. We also see a negative and significant correlation between consumption elasticity and sub-Saharan Africa, showing that regressivity is higher in that region, though in general terms it is not the one most severely affected.

4. Discussion

Examining 79 developing countries and comparing their consumption groups, we find several variables that play an important role in how big the seat at the table is that climate change will get. Income plays an important role both across countries and within countries; households with higher incomes overall tend to be relatively less affected than households with lower incomes. We also find that the dependence of households on specific food sectors may play a role in determining the severity of damages borne by the households. In national terms, rice and vegetables seem to be responsible for the largest damages. This can be attributed (a) to the relatively high price increases in those two sectors and (b) to the fact that those two food sectors consume a large share of household expenditure. We find that rice, in particular, plays a special role in the impact on resulting changes in consumer surpluses and the regressive effects across and within countries. What makes rice so special? Rice is the main source of calories in Asia and tends to be produced in less developed countries. The main rice producers are China, India and Indonesia. Zooming in on the way rice is produced, one observes that the average farm size for rice production is smaller than for comparable other crops (IRRI, 2023; Our World In Data, 2023). Hence, the production is less capital-intensive, which has a bearing on the consumer-surplus sensitivity that we have observed. Considering all inputs and due to low capital intensity, the 'Leontief' production function of rice is more dependent on seeds and related items, i.e. rice and other rice-intensive inputs.⁶ Hence, these production functions react more sensitively to a rice-price increase caused by the changing climate. Especially China and India have high shares of small farms (<1ha). Also, both in India and in some Asian and African countries near the equator, average farm sizes have decreased since the 1960s (Our World In Data, 2023; Statista, 2023).

To verify the influence of rice on other commodities, we performed an additional robustness check (not shown). Assessing the influence of rice on downstream supply chains, we find that (paddy) rice has a significant influence on processed rice/rice products and serves in some countries, especially in Asia and Africa, as an important input to the sectors dairy products, cattle, cattle meat, other meat, wool, beverages and other food. Its influence on the supply chain is thus stronger than is the case with similar items, such as wheat, corn or other cereals.

Our model assesses climate damages occurring when households adjust their demand to price increases for a large variety of goods and in a wide range of countries. Because micro-level data combining consumption with income sources is scarce, this broad regional and sectoral perspective necessarily omits consideration of changes in well-being caused by income effects. While our results should thus be interpreted with caution, there are a number of reasons why this shortcoming does

⁶ Technically speaking, this is related to a geometrical series. Imagine an infinitely long iterative production function, where the seeds of the last year and the year before are considered. If one item of output requires 0.1 of input, the total inputs sum up to 0.11111.... In the case of 0.2, this amount increases to 0.25.

little to impair their significance. First, there is evidence in the literature that in developing countries food-price increases affect low-income populations more strongly through the demand channel than through the income channel (Ivanic and Martin 2008, De Janvry and Sadoulet 2009, Ferreira et al 2013, Avalos 2016). However, the income channel can be important and may even outweigh the demand channel for poor net-food-producing households living in rural areas (Vu and Glewwe 2011, Dimova and Gbakou 2013). The study by Calzadilla et al (2014), on which our price increases are based, shows that on average a subset of regions - Central America, South America, China and Sub-Saharan Africa - experience a gain in well-being from climate change. Second, storage and irrigation costs may increase in response to climate change, which raises consumer prices while lowering farmers' incomes (Mbow et al 2019). Third, the income channel is not as important for urban populations that make up a large share of households in many countries (Ferreira et al 2013). Lastly, our results show the significance of the demand channel and can be directly compared to results that focus on the income channel.

We also make specific assumptions about the shape of household utility. Our model neglects interactions between changes in income and food prices across different commodities, i.e. there is no consideration of the fact that households may consume more of certain goods in response to a price increase for other goods. Wood et al (2012) and Avalos (2016) report that while such substitution effects attenuate adverse welfare impacts, first-order effects remain important.

The results of our model estimate climate damages around the year 2020. The A2 climate change scenario drawn upon here is close to the observed temperature increase but slightly underestimates it (Carvalho et al 2022), so that our results tend to estimate how food-price increases due to climate change affected the distribution of well-being in 2020. However, there are many other factors that significantly affect food prices (such as the COVID-19 pandemic, see Laborde et al, 2020) and science has so far only presented limited evidence that climate change has affected food prices (Verschuur et al 2021, O'Neill et al 2022). Accordingly, our results cannot be directly linked to the observed distributional impacts of food-price changes in recent years. Instead, they present an underlying trend in the responses to food prices realized in the market, a trend that will also tend to play a role in the near future.

5. Conclusion

The impacts of climate change make themselves felt not only in more readily apparent physical effects, but also in their indirect influence on the daily lives of households. Distributional impacts are not only dependent on more ambitious climate-policy measures, they are also operative where such measures are absent. We examine the impact of climate change-induced food-price increases on household welfare in over 75 developing countries. Our results show that, by and large, climate change has a

disproportionate impact on less affluent households through the food-price channel, both between and within countries. Quantifying the regressive nature of climate change damages, we find that impacts deviate only moderately from being proportional to household consumption: consumption elasticities of climate damages approximate 0.9 for most countries and also globally. It also appears that economic development may alleviate the adverse distributional consequences of climate change as in countries with higher per-capita GDP, we find damages to be more or less proportional to household consumption. In addition, our results highlight the fact that rice consumption is a major driver of regressive climate damages within countries.

Our findings have important implications for policy design and future research. Monitoring redistribution between and within countries is an important way of regarding the adverse impacts of climate change. Ignoring the heterogeneous impacts that are most prominent for low-income groups might increase inequality both globally and in countries, fuelling tension. Our results emphasise that in the short to medium term, compensation is especially needed when global poverty is prevalent and climate change already has a significant impact on human lives. To avert adverse impacts on the poor, compensation could be linked to the inflation rate or directly to food-price increases. The attribution of price increases to climate change is an important area for future research. It would enhance the likelihood of systematic compensatory measures, which are also important for the loss and damage mechanism under the Paris Agreement.

Adaptation to changing climate in the agricultural sector is a crucial factor, especially for vulnerable communities (see, e.g. O'Neill et al 2022). Our results demonstrate that there should be a specific focus on rice. Rice is fundamental to calorie intake in many countries, and less affluent households display a disproportionate reliance on rice in their food basket. In addition, rice is especially prone to locally sensitive price increases due to its specific production properties. We show that price increases for rice on the world market significantly drive regressive climate-change damages. Thus, political measures would do well to focus on improving the resilience of rice production and setting up early warning systems monitoring deviations in harvest potential and thus helping the poor cope with climate change.

Further research needs to engage in a comprehensive assessment of the way in which climate damages affect different social groups. Most importantly, all channels through which climate change affects human well-being need to be understood, including extreme weather events, the rise in sea-levels and impacts on health. Such assessments could use our analysis and results as a starting point for obtaining a comprehensive picture of how climate change affects human well-being.

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Appendix

A Tables and figures

Table A1: Matching databases – own-price elasticity with GCD consumption sectors and its corresponding GTAP sectors

Elasticity category	GTAP	GCD	NOTES
Meats	omt,		All categories are relevant
Dairy	mil		All categories are relevant
Fish	ofd (partial)	Fresh, Chilled or Frozen Fish and Seafood; Preserved or Processed Fish and Seafood	Not all categories of the GTAP category "ofd" were relevant so we match based on the GCD more specific categories.
Fruits & Vegetables	v_f, b_t (partial),	Frozen, Preserved or Processed Fruit and Fruit-based Product; Frozen, Preserved or Processed Vegetables and Vegetable-based Product	Not all categories in the GTAP categories "b_t" and "ofd" are relevant, so they were matched based on the GCD more specific categories
Oils and Fats	vol		All categories are relevant
Beverages and Tobacco	b_t		All categories are relevant
Food Other	oap, pdr, sgr, ofd	Bread; Other Bakery Products	All other food categories that weren't matched are matched to this category.
Cereals	ofd	Other Cereals,	Not all categories of the GTAP category "ofd" were relevant so we match based on the GCD more specific categories

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Table A1: Matching of the food sub-categories from the Own-price elasticity data (Muhammad et al., 2011) with the GTAP and GCD sub-categories.

Table A2: Matching databases – GCD consumption sectors and its corresponding GTAP sectors

GCD Consumption Item	GTAP sector
Catering Service	afs
Passenger Transport by Air	atp
Beer	
Coffee, Tea and Cocoa	
Mineral Waters, Soft Drinks, Fruit and Vegetable Juices	b_t
Spirits	b_t
Tobacco	
Wine	
Narcotics	bph
Pharmaceuticals Products	
Telephone and Telefax Services	cmn
Beef and Veal	cmt
Education	edu
Audio-Visual, Photographic and Information Processing Equipment	ele
Telephone and Telefax Equipment	
Electricity	ely
Gas	gdt.gas**
Social Protection	hht
Shoes and Other Footwear	lea
Furniture and Furnishings	lum
Cheese	
Fresh Milk	mil
Preserved Milk and Other Milk Products	
Animal Drawn Vehicles	
Bicycles	
Major Durables for Outdoor and Indoor Recreation	mvh
Motor Cars	
Motorcycles	
Eggs and Egg-Based Proucts	oap
Actual and Imputed Rentals for Housing	obs
Bread	
Confectionery, Chocolate, and Ice Cream	
Food Products n.e.c	ofd
Fresh, Chilled or Frozen Fish and Seafood	
Frozen, Preserved or Processed Fruit and Fruit-Based Product	

Frozen, Preserved or Processed Vegetables and Vegetable-Based Product	
Jams, Marmelades and Honey	
Other Bakery Products	
Other Cereals, Flour and Other Products	
Pasta Products	
Preserved or Processed Fish and Seafood	
Insurance	ofi
Other Financial Services n.e.c.	ofi
Jewellery, Clocks and Watches	
Major Household Appliances Whether Electric or Not	
Major Tools and Equipment	ome
Small Electric Household Appliances	
Therapeutic Appliances and Equipment	
Appliances, Articles and Products for Personal Care	
Glassware, Tableware and Household Utensils	
Non-Durable Household Goods	omf
Other Medical Products	omf
Other Recreational Items and Equipment	
Small Tools and Miscellaneous Accessories	
Lamb, Mutton and Goat	
Other Meats and Meat Preparations	omt
Pork	omt
Poultry	
Cultural Services	0.00
Postal Services	osg
Combined Passenger Transport	
Other Purchase Transport Services	0440
Passenger Transport by Railway	otp
Passenger Transport by Road	
Fuels and Lubricants for Personal Transport Equipment	p_c
Other Fuels	p_c.coa**
Rice	pdr
Newspapers, Books and Stationery	ppp
Recording Media	ppp
Accomodation Services	
Dental Services	
Domestic Services	
Hairdressing Salons and Personal Grooming Establishments	
Hospital Services	
Medical Services	ros
Miscellaneous Services Relating to the Dwelling	ros
Other Sercives n.e.c.	
Package Holidays	
Paramedical Services	
Recreational and Sporting Services	
Veterinary and Other Services for Pets	

Sugar	sgr
Carpets and Other Floor Coverings	tex
Household Textiles	tex
Cleaning, Repair and Hire of Clothing	
Maintanance and Repair of Other Major Durables for Recreation and Culture	
Maintanance and Repair of Personal Transport Equipment	
Maintenance and Repair of the Dwelling	
Other Services in Respect of Personal Transport Equipment	trd
Repair and Hire of Footwear	
Repair of Audio-Visual, Photographic and Information Process Equipment	
Repair of Furniture, Furnishings and Floor Coverings	
Repair of Household Appliances	
Fresh or Chilled Fruit	
Fresh or Chilled Potatoes	v_f
Fresh or Chilled Vegetables Other than Potatoes	
Butter and Magarine	vol
Other Edible Oil and Fats	vol
Clothing Material, Other Articles of Clothing and Clothing Accessories	wap
Garments	
Passenger Transport by Sea and Inland Waterway	wtp
Water Utility	wtr
Games of Chance	unmatched
Garden and Pets	unmatched
Other Personal Effects	unmatched

Table A2: Matching the GCD consumption sectors with its corresponding GTAP sectors. The GCD consumption item "gas" matches with two GTAP sectors, namely, "gdt" and "gas". Furthermore, the GCD consumption item "other fuels" is attributed to the following to GTAP sectors: "fuels and lubricants for personal transport equipment" and "other fuels". In both cases, the respective GTAP sectors are attributed with equal shares to GCD consumption good.

Table A3: Categorizing households of developing countries into consumption groups

Consumption groups	Lowest	Low	Middle	Higher
Daily per capita consumption (in US\$ PPP)	< 2.97	2.97-8.44	8.44-23.03	> 23.03
Global income distribution (percentile)	< 50th	51st-75th	76th-90th	> 91st

Table A3: Consumption groups and corresponding percentiles of the global income distribution (World Bank, 2023)

Table A4: Damages per consumption group per country

Country		Lowest	Low	Middle	Higher	National
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Lac DDD	0.0449	0.0427	0.0416	0.0420	0.0429
Lao PDR	-0.0448	-0.0427	-0.0416	-0.0430	-0.0438
Tajikistan	-0.0453	-0.0442	-0.0415	-0.0401	-0.0436
Pakistan	-0.0422	-0.0429	-0.0434	-0.0441	-0.0425
Nepal	-0.0410	-0.0408	-0.0398	-0.0402	-0.0409
Iraq	-0.0397	-0.0395	-0.0393	-0.0394	-0.0394
Bhutan	-0.0375	-0.0387	-0.0385	-0.0375	-0.0383
Azerbaijan	-0.0380	-0.0374	-0.0367	-0.0380	-0.0373
Madagascar	-0.0378	-0.0320	-0.0191	-0.0185	-0.0372
Malawi	-0.0367	-0.0354	-0.0334	-0.0277	-0.0362
Bangladesh	-0.0382	-0.0305	-0.0278	-0.0270	-0.0362
Sierra Leone	-0.0382	-0.0349	-0.0288	-0.0265	-0.0357
Burundi	-0.0360	-0.0311	-0.0264	NA	-0.0356
Vietnam	-0.0370	-0.0341	-0.0320	-0.0331	-0.0356
Togo	-0.0355	-0.0357	-0.0353	NA	-0.0355
Yemen, Rep.	-0.0345	-0.0353	-0.0362	-0.0366	-0.0352
Liberia	-0.0368	-0.0311	-0.0281	NA	-0.0352
Albania	-0.0330	-0.0343	-0.0346	-0.0319	-0.0343
Kyrgyz Republic	-0.0321	-0.0341	-0.0348	-0.0353	-0.0336
Belarus	-0.0270	-0.0307	-0.0335	-0.0344	-0.0333
Uganda	-0.0338	-0.0324	-0.0298	-0.0273	-0.0332
Cambodia	-0.0326	-0.0332	-0.0345	-0.0336	-0.0331
Benin	-0.0332	-0.0325	-0.0306	NA	-0.0330
China	-0.0338	-0.0332	-0.0318	-0.0305	-0.0326
Peru	-0.0339	-0.0332	-0.0320	-0.0313	-0.0326
Thailand	-0.0346	-0.0332	-0.0308	-0.0313	-0.0325
Ghana	-0.0346	-0.0332	-0.0293	-0.0273	-0.0323
India	-0.0330	-0.0316	-0.0293	-0.0304	-0.0321
Maldives	-0.0327	-0.0300	-0.0309	-0.0304	-0.0321
Nigeria	-0.0323	-0.0319	-0.0309	-0.0309	-0.0318
Tanzania	-0.0303	-0.0311	-0.0309	-0.0265	-0.0307
Colombia	-0.0326	-0.0311	-0.0292	-0.0267	-0.0298
Sri Lanka	-0.0315	-0.0295	-0.0272	-0.0272	-0.0297
Guinea	-0.0306	-0.0273	-0.0229	NA	-0.0295
Bolivia	-0.0307	-0.0299	-0.0286	-0.0264	-0.0293
Brazil	-0.0300	-0.0298	-0.0291	-0.0284	-0.0293
Zambia	-0.0295	-0.0286	-0.0285	-0.0279	-0.0292
Djibouti	-0.0303	-0.0289	-0.0284	-0.0283	-0.0291
Ukraine	-0.0295	-0.0289	-0.0287	-0.0287	-0.0288
Mali	-0.0284	-0.0298	-0.0287	-0.0284	-0.0287
Philippines	-0.0298	-0.0274	-0.0260	-0.0262	-0.0284
Rwanda	-0.0286	-0.0278	-0.0257	-0.0250	-0.0281
Indonesia	-0.0298	-0.0250	-0.0229	-0.0229	-0.0278
Mozambique	-0.0281	-0.0255	-0.0233	-0.0195	-0.0276
Moldova	-0.0266	-0.0274	-0.0276	-0.0274	-0.0274
Gabon	-0.0296	-0.0274	-0.0264	-0.0245	-0.0272
Mexico	-0.0284	-0.0276	-0.0264	-0.0250	-0.0272
Armenia	-0.0266	-0.0271	-0.0278	-0.0290	-0.0270

Egypt, Arab Rep.	-0.0273	-0.0266	-0.0254	-0.0239	-0.0268
Congo, Dem. Rep.	-0.0267	-0.0227	-0.0233	-0.0257	-0.0266
Cameroon	-0.0274	-0.0253	-0.0231	-0.0205	-0.0264
Turkey	-0.0268	-0.0260	-0.0264	-0.0261	-0.0262
Senegal	-0.0270	-0.0237	-0.0225	NA	-0.0256
Gambia, The	-0.0266	-0.0251	-0.0228	-0.0212	-0.0253
Mauritania	-0.0258	-0.0242	-0.0227	-0.0211	-0.0246
Mongolia	-0.0238	-0.0242	-0.0245	-0.0243	-0.0241
Kenya	-0.0247	-0.0234	-0.0203	-0.0164	-0.0240
Niger	-0.0233	-0.0268	-0.0197	-0.0236	-0.0236
Congo, Rep.	-0.0245	-0.0230	-0.0230	-0.0220	-0.0235
Fiji	-0.0234	-0.0237	-0.0231	-0.0230	-0.0235
Mauritius	-0.0240	-0.0235	-0.0225	-0.0222	-0.0232
Morocco	-0.0227	-0.0226	-0.0225	-0.0222	-0.0226
Romania	-0.0224	-0.0222	-0.0220	-0.0214	-0.0221
Swaziland	-0.0211	-0.0230	-0.0230	-0.0191	-0.0220
Serbia	-0.0211	-0.0217	-0.0216	-0.0218	-0.0217
Jordan	-0.0215	-0.0215	-0.0206	-0.0197	-0.0210
Montenegro	-0.0226	-0.0207	-0.0199	-0.0208	-0.0202
Lesotho	-0.0190	-0.0200	-0.0224	-0.0247	-0.0201
Macedonia, FYR	-0.0193	-0.0194	-0.0196	-0.0200	-0.0196
South Africa	-0.0195	-0.0195	-0.0192	-0.0191	-0.0194
Burkina Faso	-0.0184	-0.0251	-0.0273	-0.0258	-0.0193
Lithuania	-0.0193	-0.0192	-0.0189	-0.0184	-0.0189
Bosnia and					
Herzegovina	-0.0175	-0.0173	-0.0184	-0.0191	-0.0187
Chad	-0.0176	-0.0200	-0.0202	-0.0115	-0.0184
Russian Federation	-0.0201	-0.0195	-0.0185	-0.0174	-0.0183
Latvia	-0.0207	-0.0186	-0.0182	-0.0176	-0.0182
Kazakhstan	-0.0175	-0.0178	-0.0178	-0.0173	-0.0178
Namibia	-0.0176	-0.0173	-0.0171	-0.0168	-0.0174
Bulgaria	-0.0182	-0.0171	-0.0173	-0.0165	-0.0171
Ethiopia	-0.0136	-0.0136	-0.0151	-0.0161	-0.0136

Table A4: The change in consumer surplus as a share of total expenditure. Lowest: represents the consumer surplus share of total expenditure for the lowest consumption group. Low: represents the consumer surplus share of total expenditure for the low consumption group. Middle: represents the consumer surplus share of total expenditure for the middle consumption group. Higher: represents the consumer surplus share of total expenditure for the highest consumption group. National: represents the consumer surplus share of total expenditure for all consumption groups.

Figure A1: Plotting the consumption elasticity of each country. Per capita expenditure represents the log normal per capita expenditure of each consumption group: Lowest, low, middle, and highest. Per capita change in CS represents the log normal per capita change in consumer surplus for each of the 4 consumption groups.

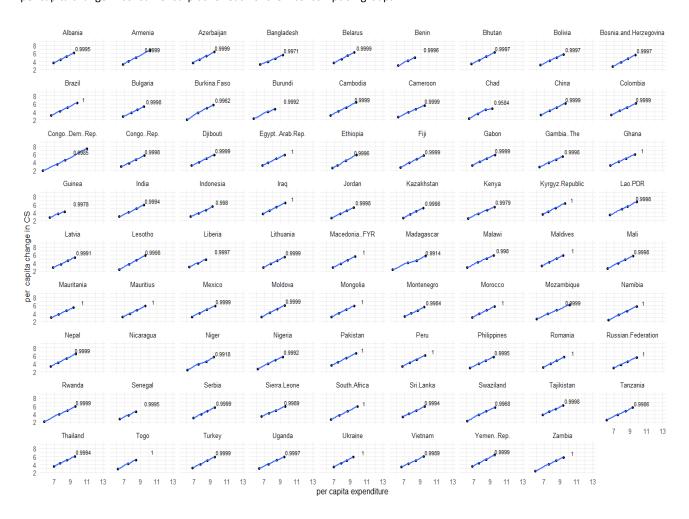


Figure A2: Plotting the consumption elasticity of the country: Chad with R-squared less than 0.99. Per capita expenditure represents the log normal per capita expenditure of each consumption group: Lowest, low, middle, and highest. Per capita change in CS represents the log normal per capita change in consumer surplus for each of the 4 consumption groups. The R-square for each country is on the top-right side of the curve.

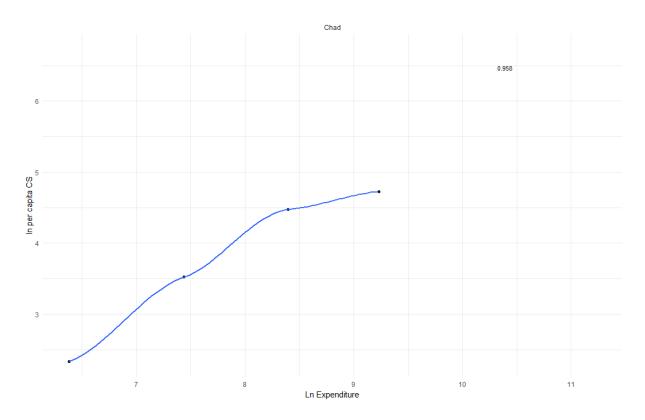


Figure A3: Relative increase in consumer prices of rice as computed by the MRIO in percent. The production price of rice as computed by Calzadilla et al. (2014) is depicted with the blue horizontal line.

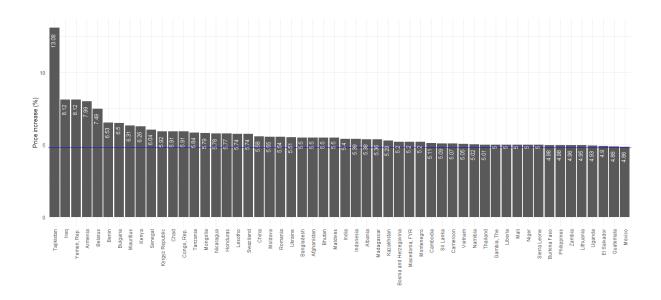
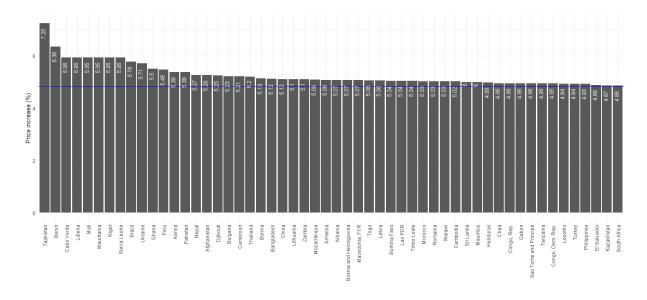


Figure A4: Relative increase in consumer prices of vegetables as computed by the MRIO in percent. The production price of vegetables as computed by Calzadilla et al. (2014) is depicted with the blue horizontal line.



B Robustness checks

B1 Latitude effects across the two hemispheres

The association between latitudes and potential damages arising from climate-induced increase in food prices is expected to be negative; in the sense that the further away a country is from the equator the lower the potential climate damages. While we did not find a statistically significant relationship between proximity to equator and the extent of and regressivity of climate damages in our full sample, it might be the case that this association exists only in one side of the hemispheres.

In Table B1, we replicate the main results but with the hemispheres split, we use the absolute latitude to reflect the proximity to the equator. Our sample includes 51 countries located in the north of the equator, with latitude ranging from 1°N to 60°N and 17 countries located south of the equator with latitudes ranging from 1°S to 29.5°S. Columns (a) and (b) present the regressions against regressivity of climate damages for the northern and the southern hemispheres, respectively. Results show that for the southern hemisphere (b), latitude has positive and significant correlation with regressivity, indicating that countries located closer to the equator (lower latitudes), face more regressive impacts from price increases. We don't observe any significant association between latitude and regressivity for the northern hemisphere.

In columns (c) and (d), we present the regressions against damages, expressed as the absolute loss in national consumer surplus, for the northern and southern hemispheres, respectively. For the southern hemisphere, we find that there exists a negative and statistically significant between latitudes and national losses in consumer surplus. This means that countries located at higher latitudes are subject to less severe damages compared to countries located closer to the equator. Similar to the results on regressivity, no significant association between latitude and climate damages can be found here.

One way to explain those results could be due to colonization patterns as discussed by Acemoglu et al (2001). In their paper they discuss that European colonizers shaped the institutions according to the conditions they found. If a country had a good climate, then Europeans themselves could settle in the country and those settlers set up quality institutions. If this was not the case, due to extreme climates that the settlers were not used to, or due to viruses, malaria or similar conditions, they set up extractive institutions. The quality of institutions set up by the colonizers influenced by the mortality rate still persists today. Acemoglu et al (2001) first find lower income levels in countries located closer to the equator, but once they control for quality of institutions the effect vanishes. It could be that the results presented here observe a similar pattern but on a different dimension, where countries more severely affected are countries that may have weaker institutions.

	alpha	alpha	National	National
	(a) North	(b) South	(c) North	(d) South
Rice	-0.354***	-0.570***	0.008	0.038***
	-0.081	-0.123	-0.013	-0.009
GDP per capita (PPP 2019, in thousands)	-0.001 -0.001	-0.001 -0.002	-0.001*** -0.0002	-0.0001 -0.0001
Vegetables	0.003	-0.588*	0.074***	0.087***
	-0.157	-0.301	-0.025	-0.022

-	-0.002			
		-0.001	-0.0002	-0.0001
CCA	0.04	0.02	0.010**	0.005*
	-0.04	-0.03	-0.010**	0.005*
-	-0.025	-0.033	-0.004	-0.002
EAP	0.004		0.001	
-	-0.026		-0.004	
	-0.03		-0.001	
-	-0.03		-0.005	
LAC -	-0.013	-0.037	0.002	0.011***
	-0.04	-0.038	-0.006	-0.003
	0.01	0.030	0.000	0.002
MENA -	-0.035		-0.010**	
-	-0.03		-0.005	
	-0.00004	0.003*	0	-0.0003**
-	-0.001	-0.001	-0.0001	-0.0001
Constant 1	1.177***	1.091***	0.044***	0.020***
	-0.071	-0.085	-0.011	-0.006
	51	17	51	17
\mathbb{R}^2	0.494	0.771	0.487	0.879
Adjusted R ²	0.368	0.594	0.359	0.786
Residual Std. Error	0.043 (df = 40)	0.038 (df = 9)	0.007 (df = 40)	0.003 (df = 9)
H Statistic	3.907*** (df = 10; 40)	4.339** (df = 7; 9)	3.803*** (df = 10; 40)	9.374*** (df = 7; 9)

Table B1: Regression results: (a) Northern Hemisphere, dependent variable is the consumption elasticity, the smaller the value, the more regressive the impacts. (b) Southern Hemisphere, dependent variable is the consumption elasticity, the smaller the value, the more regressive the impacts. (c) Northern Hemisphere, dependent variable is the absolute national loss in consumer surplus as a share of base expenditure, the larger the value, the more severe the losses. (d) Southern Hemisphere, Dependent variable is the absolute loss in consumer surplus for as a share of base expenditure, the larger the value, the more severe the losses.