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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 90 developing countries. In a microsimulation model, climate damages are quantified as losses in consumer surplus and are on average roughly 3 percent of total expenditure. We find evidence that climate damages are regressive, i.e. they disproportionately affect households with lower total 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

Even moderate climate change is expected to have substantial effects on human well-being through various channels such as extreme events or mortality (IPCC, 2022). One channel that has been highlighted in previous research is the adverse effect of climate change on food production and resulting food price increases (Kotz

et al 2024, Hasegawa et al 2018, Wiebe et al 2015). In this study, we assess the distributional impact of food-price increases caused by climate change across heterogeneous households from a wide range of developing countries. Our study adds to the limited literature on how climate change affects households at the subnational scale (Gilli et al 2024, Dasgupta et al 2023, Hallegatte and Rozenberg 2017) by assessing the impact of climate change on final consumption prices and consumer welfare in a microsimulation model.

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 turn will cause an increase in the price of these 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 are likely to adjust through dietary choices, but they will still experience 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.

Based on food price increases caused by climate change, we analyse climate-change-related welfare losses across heterogeneous households in 90 developing countries. Our study adds to the rapidly growing research on the socio-economic impacts of climate change (see e.g. Burke et al 2018, Cattaneo et al 2019, Kalkuhl and Wenz 2020, El-Sayed and Kamal 2020, Vicedo-Cabrera et al 2021, Carleton et al 2022). Within this strand of literature, we are interested in the distribution of monetary climate damages across income groups. Studies on the regional scale 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 sub-national scale, limited evidence exists on how climate damages affect different parts of the population. Some previous studies have focussed on the impact of climate change on poverty (Hertel et al 2010, Hallegatte and Rozenberg 2017). Our study contributes to the recently emerging literature on the distributional implications of climate change across the entire income scale. They find that in most cases, income inequality is adversely affected by climate change using econometric methods that infer association between inequality and climate variables (Sedova et al 2020; Paglialunga et al, 2022; Dasgupta et al, 2023; Gilli et al, 2023). In a single country study, Sedova et al (2020) find that in rural India the income of poor households is more strongly affected by changing seasonal climate variability than that of more affluent households. Paglialunga et al (2022) utilize a global panel dataset to relate national Gini-indices to national climate variables. They find that increases in temperature and precipitation anomalies increase inequality as measured by the Gini-index, especially in countries that rely on agriculture. Dasgupta et al (2023) investigate how the Gini-index is affected by variations in the yearly and long-run average of temperature both in a global panel and in a subnational panel analysis from South-Africa. They find a U-shaped relationship indicating that inequality is higher around an optimal temperature level for decreases and increases in temperature, and project increased inequality in South Africa under future climate change. Gilli et al (2023) use a global panel data set that disaggregates countries into income deciles to derive decile-level damage functions of climate change. They find that climate damages are regressive, i.e. low-income households are disproportionately affected by monetary climate change impacts.

Our article fills a gap in the literature by assessing the impact of food price increases due to climate change across the income distribution using microsimulation based on household expenditure surveys and multi-regional input-output modelling. While this method is standard for economic analysis at the household level, it has so far mainly been used to assess the distributional consequences of policies to mitigate climate change (Grainger and Kolstad 2010, Williams et al 2015, Dorband et al 2019, Cronin et al 2019, Feindt et al 2021).

Concerning climate change damages, a notable exception is the article by Hallegatte and Rozenberg (2017) who use microsimulation tools to assess the effect of climate change on poverty by including multiple impact channels of climate change. Microsimulation approaches complement aforementioned econometric work by enabling a detailed and tractable investigation of how climate change affects heterogeneous parts of the population. In this study, we use the method to calculate welfare losses of different income groups that are caused by climate change, both between and within countries and along the entire income distribution. Additionally, we investigate how changes in the global production of several agricultural commodities diffuse through supply chains to finally increase final consumption prices, thereby enabling a detailed analysis of how different sectors contribute to climate change damages.

For our analysis, we combine a global multi-regional dataset, household data in 90 developing countries and predictions on price increases caused by climate change with economic elasticities. We use projections of price increases due to climate change for selected food categories: ‘rice’, ‘wheat’, ‘cereal grains’, ‘vegetables, fruits and nuts’, ‘oil seeds’, and ‘other agricultural products’. We apply a multi-regional input-output modelling approach to assess the prominence of different agricultural goods for global supply chains. In a second step, we use this information to assess how initial cost pressures due to climate change influence price hikes for final consumption commodities. In this approach, projected price increases approximate the initial cost pressures on agricultural production due to climatic changes. In the multi-regional input-output model, cost pressures are passed upstream the global supply chain to arrive at final consumption prices for households, so that, for example, the initial cost pressure for wheat leads to a final consumption price increase for bread. 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 (Poterba 1989, Poterba 1991, Sterner 2012, Drupp et al 2024). To compare relative damages between and within countries based on welfare losses, we calculate the change in consumer surplus as a share of total consumption for each country and each consumption group.

Our analysis shows that the higher a country’s income level is, the less severe average climate damages from food price increases are. This same trend is also observable within countries: in more than 75% of the countries analysed, the lowest-consumption group is more severely impacted by climate-related food price increases than the highest-consumption groups. We show that climate damages disproportionately affect low-income groups across the entire consumption distribution, and more so in countries with lower per-capita income. In sum, the test of our hypothesis indicates that climate damages due to food price increases are by and large regressive. Economic development will mitigate the adverse distributional effect of climate change. In order to understand what drives regressive effects, we further investigate how different commodities contribute to climate damages by performing a cross-country regression analysis. We find that, *ceteris paribus*, higher dependence on vegetables leads to higher damages *across* countries, while higher dependence on rice leads to more regressive effects *within* countries.

The paper proceeds as follows. In Section 2 we introduce the methods and the data used. Section 3 presents the results. We discuss the limitations of our findings in Section 4 and conclude in Section 5.

2. Methods and Data

2.1. Consumer surplus loss

We measure how price increases due to climate change affect the well-being of individual households via the change in consumer surplus. The change in consumer surplus is a monetary measure of welfare changes when

economic conditions change (Mas-Colell 1995, Willig 1976). According to Willig (1979), the change in consumer surplus when multiple prices change is the line-integral under the uncompensated demand curve. To calculate the integral, we characterize demand via price elasticities. Consider a specific country r and a specific consumption item k . Denote the price of the consumption item in the absence of climate change as $\bar{p}_r^k$ and with the impacts of climate change as p_r^k . An individual h in country r consumes an amount $\bar{x}_{r,h}^k$ of the good in the absence of climate change, has an own price elasticity $\varepsilon_r^{k,k}$ and cross price elasticities $\varepsilon_r^{k,j}$, which measure the change in demand of good k when the price of good j increases. Assuming elasticities are constant, demand for good k as a function of prices is: $\bar{x}_{r,h}^k \prod_j \left(\frac{p_r^j}{\bar{p}_r^j} \right)^{\varepsilon_r^{k,j}}$, where n is the total number of goods.

To calculate the change in consumer surplus, we follow Willig (1979) and assume a rectangular path for the line integral of demand. The final equation for the change in consumer surplus $\Delta CS_{r,h}$ is given in the Appendix 1. Equation (A.1) is the damage to consumers when food prices change due to climate change but assumes that there are no income effects associated with the change in food prices. We justify and relax this assumption in Section 4.

The change in consumer surplus quantifies how climate change affects welfare for an individual household h in country r . As further detailed in Section 2.2.1, individual households in our sample are aggregated in consumption groups by country. Consumption groups order all households according to their total consumption. We thus calculate the total consumer surplus loss by consumption group within each country. To that end, we identify individuals in Equation (A.1) as belonging to consumption group h in country r . To enable comparison between unequal population groups, we either divide each consumption group's change in consumer surplus by their population or expenditure. When dividing by expenditure, the relative loss in consumer surplus is:

$$\Delta CS_{r,h}^{sha} = \frac{-\Delta CS_{r,h}}{\sum_k \bar{x}_{r,h}^k \bar{p}_r^k} \quad (1)$$

We also aggregate the welfare loss at the national level by computing the relative consumer surplus loss as:

$$\Delta CS_r^{sha} = \frac{-\sum_h \Delta CS_{r,h}}{\sum_{h,k} \bar{x}_{r,h}^k \bar{p}_r^k} \quad (2)$$

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 food price increase is 2% of total expenditure in the baseline year.

To compute the change in consumer surplus, Section 2.2 derives the data for (i) household consumption by good ($\bar{p}_r^k \bar{x}_{r,h}^k$), (ii) relative price increases by food item ($\frac{p_r^k}{\bar{p}_r^k}$), (iii) own-price elasticities by good ($\varepsilon_r^{k,k}$) and cross-price elasticities by good ($\varepsilon_r^{k,j}$).

2.2. Data

2.2.1. 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 r , household h 's expenditures $\bar{p}_r^k \bar{x}_{r,h}^k$ are reported by 106 products and services, denoted by $k \in \{1, \dots, 106\}$. The households are categorized into four consumption groups: lowest, low, middle, and higher, denoted by $h \in \{1, \dots, 4\}$. This classification is based on the percentiles of the 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 B1). For seven of the least developed countries, data for higher-consumption groups do not exist due to overall extreme poverty.

2.2.2 Price increases

As a basis for price changes due to climate change, 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). They simulate the impacts of climate change and CO₂ fertilization on global agriculture¹ using GTAP-W, a global Computable General Equilibrium (CGE). GTAP-W divides the world in 16 regions and 22 economic sectors, with 7 sectors belonging to agriculture. Calzadilla et al (2013) further distinguish between irrigated and rainfed agriculture and include water as an explicit factor of production for irrigated agriculture. Their analysis considers changes in temperature, magnitude and distribution of global precipitation, and river flow under the IPCC SRES A1B and A2 scenarios and is conducted for the medium term (2020) and the long term (2050). They identify price increases in the range of 4.78%-5.60% for the selected categories, driven mainly by the decline in crop production. Table 1 shows the price increases in 2020 (along with changes in production) under the A2 climate scenario. We align the timing of climate damages with the GCD inequality data by focusing on the year 2020. We choose the A2 climate scenario because its projected climate change is close to the observed temperature increase, with a slight underestimation (Carvalho et al 2022). Considering the recent SSP-RCP framework by the IPCC (2022), we argue that the SRES A2 scenario closely corresponds to SSP3-8.5. SSP3 envisions a fragmented world characterized by regional disparities in population growth and economic dynamics (O’Neill et al 2017), similar to the A2 scenario. RCP8.5 projects a sharp increase in future greenhouse gas emissions, aligning with the high emission trajectory in SRES A2.

The projections in Table 1 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 below). A detailed matching of the categories in Table 1 and the sectors in the MRIO is given in Appendix B.

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

Crops	Total production (%)	Projected price increase (%)
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

2.2.3 Global MRIO: GTAP 10

For our final welfare analysis of households, we employ a more detailed MRIO analysis to assess how, for example, the price of bread reacts to the wheat price increase in Table 1, differentiated by individual countries. To that end, the projected price increases in Table 1 represent the initial cost pressures due to the climate change that

¹ As for the impacts of CO₂ fertilization, a higher concentration of CO₂ in the atmosphere leads to better plant growth and water-use efficiency.

Calzadilla et al (2013) simulate. This assumption is justified if producers fully pass on their additional farming costs - as their production adjusts to changing climatic conditions - along the global supply chain.²

To estimate how the initial cost pressures in Calzadilla et al (2013) are diffused through supply chains to final consumption good price increases, we apply an input-output analysis to the Global Trade Analysis Project database (GTAP) version 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 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 a Leontief price model where costs are pushed through global supply chains, an approach similar to Feindt et al (2021) for assessing CO₂ taxation impacts, where emissions are virtually traced. We use the analytical approach to trace the content of commodities that see price increases due to climate change, as projected by Calzadilla et al (2013). Standard items of the MRIO analysis are the inter-industry flow matrix Z with $Z \in \mathbb{R}^{r \times s \times r \times s}$, where r is the number of regions, s refers to the number of sectors and the final-demand vector Y , where $Y \in \mathbb{R}^{r \times s \times s}$. 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 . Single elements $z_{r_1 s_1}^{r_2 s_2}$ of Z represent monetary flows entering the industrial sector s_2 of region r_2 arriving from sector s_1 of region r_1 .

Z can be used to derive the technology matrix $A \in \mathbb{R}^{r \times s \times r \times s}$, representing the required input per unit of sectoral output (see Feindt et al 2021). With 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 one unit of final-demand commodities. Hence, single elements $l_{r_1 s_1}^{r_2 s_2}$ of L represent all monetary inputs arriving from sector s_1 of region r_1 (direct and indirect, so all flows that were eventually required) to produce one unit of output of sector s_2 of region r_2 . These entries enable us to directly see how much of relevant commodities (as identified by Calzadilla et al. 2013) are associated with the production of final demand goods. Let $\mu \in \mathbb{R}^{r \times s}$ denote the vector of relative sectoral price increases for each sector according to the projections of Calzadilla et al. (2013) in Table 1, we call these initial cost pressures. We set the initial cost pressures for all sectors not considered in Table 1 to zero. The initial cost pressures for each sector are of equal magnitude for all countries. We use these initial cost pressures as an initial signal, which diffuses through global supply chains. Final consumption price increases (used in section 3.3 to project prices) then come out as $M = \mu \circ L$, which considers how much of the initial cost pressures are contained in final demand goods. Non-technical speaking, we use the Leontief inverse to assesses the ‘virtual content’ of relevant upstream goods, i.e. those that are impacted by initial cost pressures. The matrix M considering the content and the respective initial cost pressures then depicts how price signals would diffuse through supply chains, without adjustments, enabling final consumption price increases due to initial cost pressures. An overview of price-level increases across 90 countries is given in Figure 1.³ 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 $y_{r_1 s_1}^{r_2}$ 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

² Global CGE models often have limited sectoral coverage. The CGE model underlying Table 1 only captures to a limited extent where products enter the supply chain of other products and where these originate from. The MRIO analysis we conduct considers current mutual dependencies in global supply chains. Our approach provides a more disaggregated way to understand the impacts of climate change and, in a way, is complementary to CGE modelling.

³ The price levels increase data is presented for the 90 countries common between the GTAP data and the GCD data.

for producing a specific commodity, the corresponding relative price increase for a commodity k in country r_2 is⁴:

$$\frac{p_{r_2}^k}{\bar{p}_{r_2}^k} = \frac{\sum_r \sum_{r'} \sum_{s'} \mu_{r',s'} L_{r',s'}^{r,k} y_{r,k}^{r_2}}{\sum_r y_{r,k}^{r_2}} \quad (3)$$

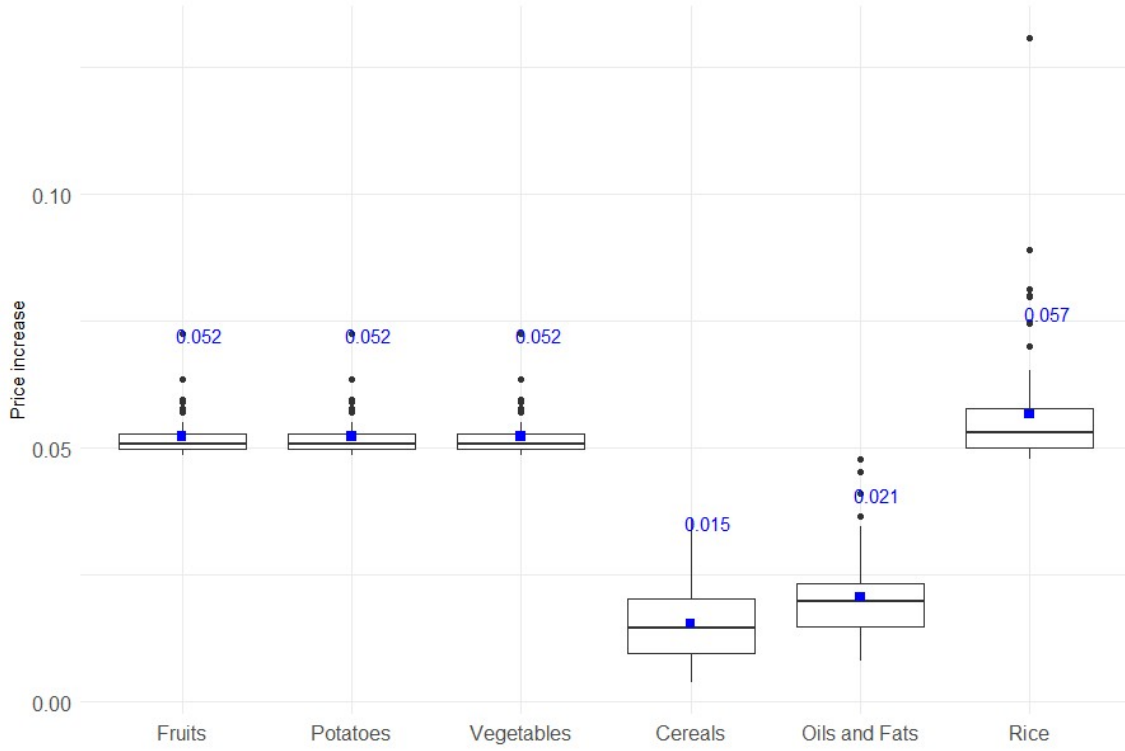


Figure 1: Relative increase in national final consumption prices for each food category as computed by the MRIO across all sample countries. The figure is based on results from formula (3), considering all goods of a category consumed, independent of their origin. Blue markers represent the mean increase in final consumption prices. The lower and upper whiskers correspond to the 25th and 75th percentiles.

2.2.4 Own-price and cross-price elasticities

We use data on own-price and cross-price elasticities from Cornelsen et al (2015). They provide estimates on uncompensated own-price and cross-price elasticities for 7 food groups covering 3 income country groups: low, middle, high. The authors estimate cross-price elasticities by conducting a meta-regression analysis of global cross-price elasticities estimates provided by studies collected through a systematic literature review of 78 studies covering 38 countries. As for the own-price elasticities, the authors use estimates based on Green et al (2013), which use a similar method to derive own-price elasticities based on 136 studies. Given our focus on developing countries, we only use estimates of the low and middle-income countries and match them to our country-level dataset, using World Bank identification of income country groups to match lower income and lower-middle income groups to lower income and upper middle income groups to middle income groups (World Bank, 2025).

The estimates for the uncompensated own-price elasticities range from -0.8 in lower income countries for fish to -0.54 in middle income countries for Oils & Fats with a mean value of -0.68.

⁴ In case of rice, this will consider all rice that is consumed in country r_2 , independent of where it was produced. The weighting is performed according to the previous expenditure shares.

2.2.5 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) where they matched the GCD consumption items to the GTAP 9 version following the detailed descriptions of consumption items provided by the databases. We have updated the matching to GTAP 10, where 103 consumption categories of the GCD household data are linked to 38 GTAP sectors. The matching procedure is given in Table B2.

The food sub-categories of the own-price and cross-price elasticity estimates were matched to the GCD sub-categories (Table B3). After matching the databases, we ended up with data for 90 developing countries.

2.2.6 Consumption elasticity of climate damages

For a more detailed understanding of the distributional impacts of climate-induced food price increase and the resulting loss in consumer surplus, we compute the consumption elasticity of climate damages. 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 the elasticity is constant, the equation for the consumption elasticity of climate damages is:

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

Hence, consumption elasticity α is the proportional change of per-capita climate damages $\left(d\left(\frac{-\Delta CS_{r,h}}{pop_{r,h}}\right) / \frac{-\Delta CS_{r,h}}{pop_{r,h}}\right)$ resulting from a proportional change in per-capita expenditure (α). Here, total population of a consumption group h in country r is $pop_{r,h}$, and total expenditure is $exp_{r,h} = \sum_k \bar{x}_{r,h}^k \bar{p}_r^k$.

If $\alpha = 1$, 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 $\alpha < 1$ shows regressivity in climate damages. 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 (5) yields:

$$\ln\left(\frac{-\Delta CS_{r,h}}{pop_{r,h}}\right) = K + \alpha \ln\left(\frac{exp_{r,h}}{pop_{r,h}}\right) \quad (5)$$

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). We calculate the consumption elasticity across all households in the sample.

2.2.7 Macro-economic variables

In addition to the data on climate damages, we use macro-economic data for variables that may be associated with share of food expenditure, such as income levels, country latitudes (CSGNetwork 2021)⁵ and within-country

⁵ The latitude data for Mauritius, Mongolia, Montenegro, Morocco, Sri Lanka and Yemen was taken from Wikipedia (2021), as they were not listed in CSGNetwork (2021).

inequality. To reflect country-level income levels, we use GDP per capita for the year 2019 measured in current international dollars PPP from the World Development Indicators (WDI) (World Bank 2021). We use the Gini-coefficient from the WDI (World Bank 2022) to reflect within-country income inequality levels, we use the latest available estimate for each country. 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. 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.

3. Results

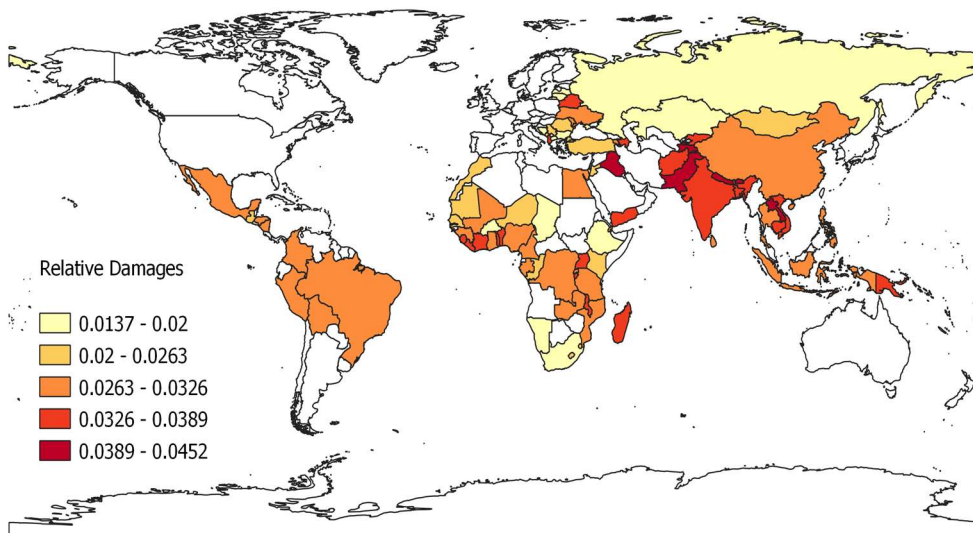
3.1. Comparison of climate damages across countries

Figure 2a shows national aggregates of climate damages due to food price increases relative to national consumption for all countries in our sample. The average relative damage is 2.87% across the 90 developing countries. The largest relative damage is in Lao PDR (4.51 % of total expenditure), followed by Tajikistan (4.47%), Pakistan (4.34%) and Nepal (4.20%). The least affected country is Ethiopia, where relative damage equals 1.36%. Ethiopia is followed by Bulgaria (1.70%), Namibia (1.72%) and El Salvador (1.76 %) (Table B4).

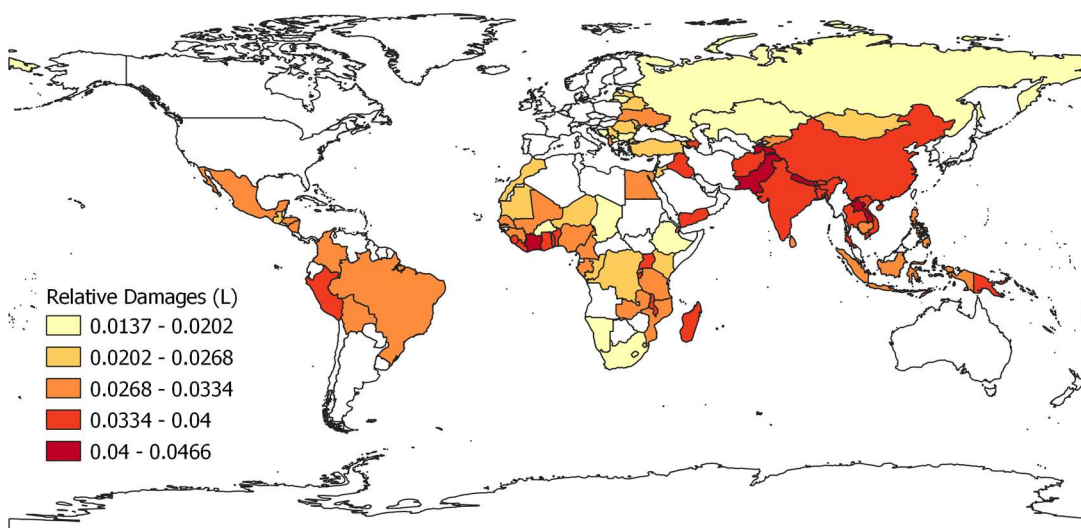
To investigate effects on low-income households, Figure 2b shows the relative damage of the lowest-consumption group in each country. Relative damages for the lowest-consumption group are very similar to the national level with very few exceptions.

We investigate the relationship between relative climate damages arising from an increase in food prices and several macro-economic variables such as income levels and latitude. 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, showing that climate damages are regressive across countries.⁶ We find a similar correlation with latitude: countries located closer to the equator are exposed to severe climate damages (addressed in more detail in Appendix C1).

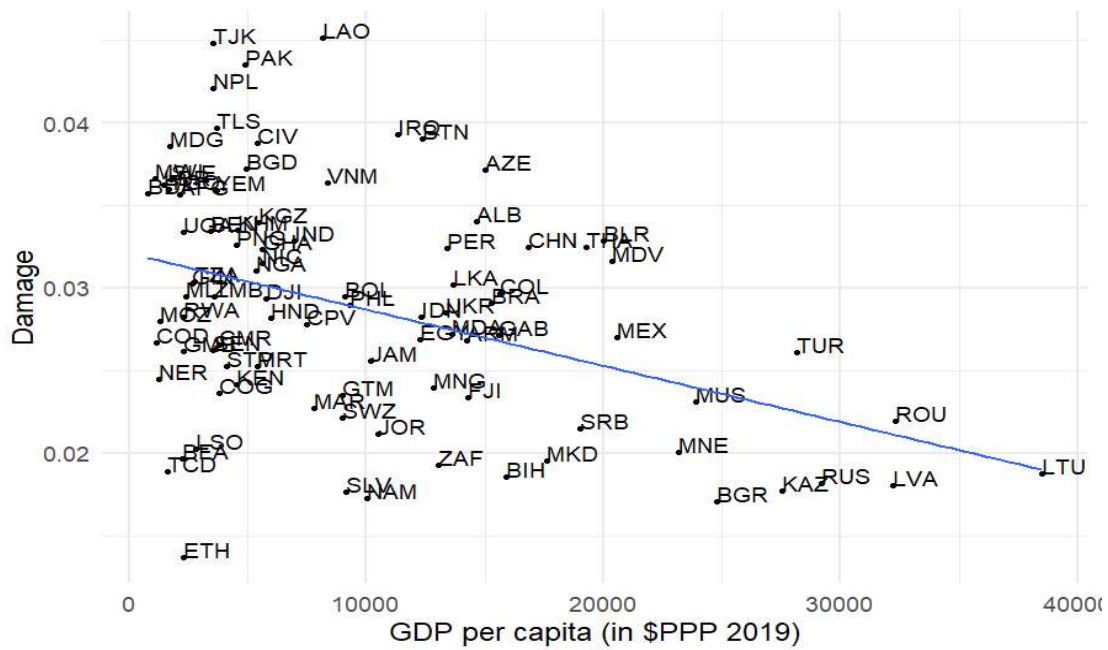
⁶ The relative damage for the lowest-consumption segment caused by climate-induced food-price increases over GDP per capita are very similar to the national level with a slope significant at the 1% level and equal to -0.00000028766.



(a)



(b)



(c)

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 -0.00000034020.

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 4.65% of total expenditure (Table B4). It is followed by Lao PDR (4.63%), Pakistan (4.33%) and Nepal (4.23%). By contrast, the least well-off households in Ethiopia, Kazakhstan, and Bosnia and Herzegovina have relative damages of only 1.36%, 1.47% and 1.74%, respectively.

We take a closer look at the countries with the largest damages due to food price increases, like Lao PDR and Tajikistan. We find that Lao PDR, while having around 5% increase in rice prices, they have the highest share of rice expenditure of around 42% (as a share of total food expenditure), which is around 5 times the sample's average expenditure on rice (9%) and may explain large losses in consumer surplus. We also find that Tajikistan⁷ has by far the largest price increases in both the rice and vegetable sectors manifesting themselves in higher climate damages (Figures A1 and A2). On the other hand, Ethiopia has the least damages and this can be explained by the expenditure patterns on food groups, where they have the largest share of expenditure going to cereals, which has a relatively low price increase of around 0.3%.

3.2. 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 total and relative damages across consumption groups without differentiating by country. In our main analysis we derive the consumption elasticity of climate damages, demonstrating that it largely indicates regressive impacts.

⁷ 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 when aggregating the households in all 90 countries into the four consumption groups (Table 2). The relative damages for the low and lowest consumption groups are higher than for richer households. Overall, the least well-off households incur the highest climate damages. While 32.95% of the consumer surplus loss is borne by the lowest consumption group, only 5.80% of the loss is borne by households in the higher-consumption group (Table 2).

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

Consumption Group	Total consumer surplus change (USD PPP)	% of total	Total Expenditure (USD PPP)	Relative damage (%)
Lowest	-30684.19	32.95	935402.33	3.28
Low	-32986.06	35.42	1091312.76	3.02
Middle	-24055.14	25.83	881613.40	2.72
Higher	-5397.19	5.80	228694.57	2.36

Turning to each country individually, we next compare households in the lowest consumption group with households in the higher consumption group. For 64 of the 83 countries, the lowest-consumption group within the country incurs higher relative damages than the country's highest-consumption group (Table B4).⁸ The lowest-consumption group is often also more seriously affected than the other consumption groups: in 67 out of 90 countries, the lowest-consumption group has higher relative damages than the middle-consumption group. Comparing the lowest to the low consumption group, the poorest bear a larger relative climate damages in 65 out of 90 countries.

Finally, we compute the consumption elasticity of climate damages due to food price increases. To that end, we first plot the per capita consumer surplus change against per capita expenditure (in logged values) for all countries and consumption groups in Figure 3a. As expected, damages increase with expenditure, represented by the upward sloping line. The slope of the line is the consumption elasticity (see Equation 5), with a value of $\alpha=0.96$ in the figure. However, we observe heterogeneity in the data between the different consumption groups and test the relationship further. We run an OLS regression (equation 6), where we regress the log of per-capita damages ($\ln \text{percapita CS}$) against the log of per-capita expenditure ($\ln \text{percapita expenditure}$) and include dummy variables for each consumption group (*lowest*, *low*, *highest*), with the middle consumption group as the reference group.

$$\ln \text{percapita CS} = \beta_0 + \beta_1 \ln \text{percapita expenditure} + \beta_2 \text{lowest} + \beta_3 \text{low} + \beta_4 \text{highest} + \epsilon \quad (6)$$

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 highly significant.⁹ 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 $\alpha=0.838$.¹⁰

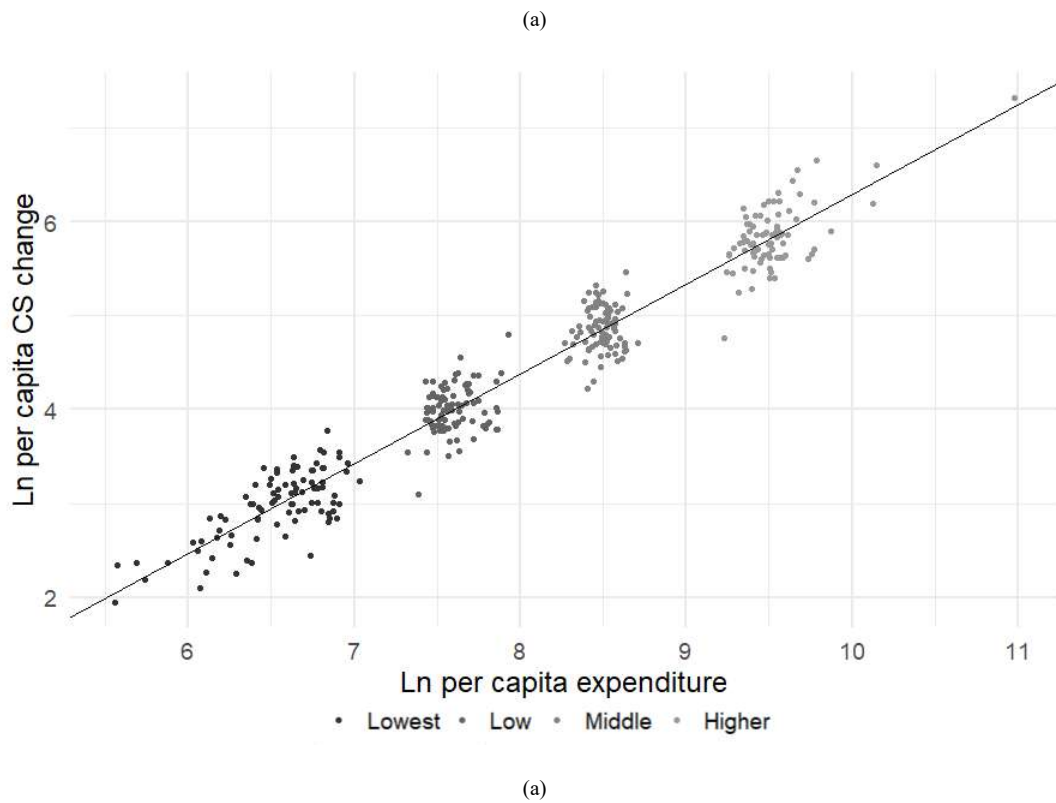
Table 3: Regression results: dependent variable is the logged per-capita damages ($\ln \text{percapita CS}$). Explanatory variables are: logged expenditure ($\ln \text{expenditure}$) and income groups: *lowest*, *low*, *highest*.

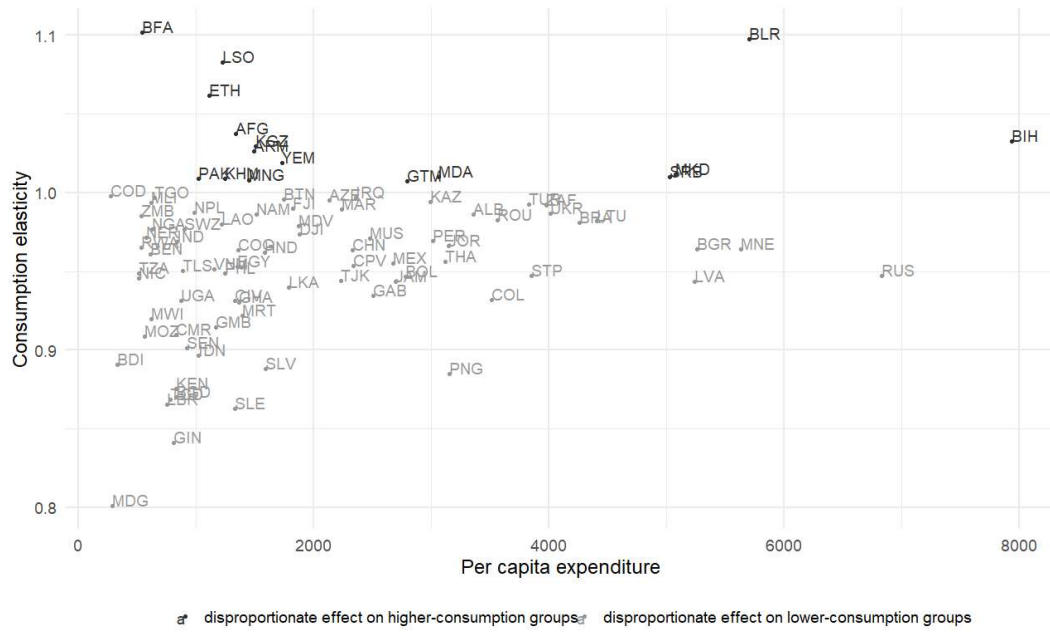
⁸ The 7 countries are: Nicaragua, Guinea, Senegal, Liberia, Burundi, Togo and Benin.

⁹ We run a similar regression with clustered standard errors at the country-level and we find similar results.

¹⁰ We formally test if the coefficient is less than 1 and we find that the coefficient is significantly less than 1 at the 5% level.

<i>Dependent variable:</i>	
	ln_per capita_CS
ln_expenditure	0.838*** (0.063)
lowest	-0.243* (0.129)
low	-0.103 (0.068)
highest	0.131* (0.075)
Constant	-2.256*** (0.537)
Observations	353
R ²	0.948
Adjusted R ²	0.948
Residual Std. Error	0.251 (df = 348)
F Statistic	1,600.138*** (df = 4; 348)
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01	





(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): $Y = -3.27 + 0.96x$ (b) Consumption elasticity within countries against national per-capita expenditure. Countries in black have disproportionately affected higher-consumption groups ($\alpha > 1$). Countries in grey have disproportionately affected lower-consumption groups ($\alpha < 1$).

We next investigate the patterns of regressivity within individual countries. To do this, we calculate the consumption elasticity of climate damages by country using Equation (5). 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 1.1, the country with the most regressive effects being Madagascar and the country with the most progressive effects being Burkina Faso. This means that in Madagascar the impacts of food price increase arising from climate change disproportionately affects lower consumption groups, while in Burkina Faso, the impacts disproportionately affect higher consumption groups. Out of the 90 developing countries analysed, 16 countries show progressive effects where α is larger than 1.¹¹

In Figure 3(b), the 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).

3.3. Sectoral drivers of climate-change damages

To better understand differences in a country's distributional impact, we check whether specific food sectors drive damages. To that end, we analyze each food item's contribution to (i) price increases, (ii) total food expenditure of households and (iii) loss in consumer surplus. 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 the consumption elasticity of damages.

First, we observe a difference between the initial cost pressures shown in Table 1 and the prices for final consumption in Figure 1. Certain countries may be more or less affected by changes in price increases for agricultural products that are input to final consumption goods as their production import and export structure

¹¹ 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 = 0.959) (Figures A3 and A4).

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 projected price of 4.78% and 4.83% shown in Table 1. By contrast, for cereals and for oils and fats, the projected price increase in Table 1 is higher than the final 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 high relative price increases for final consumption goods in the rice sector for Tajikistan, where the rice price increases by 13.07% compared to the baseline, followed by Jordan (8.91%), Yemen (8.12%) and Iraq (7.12%). Further somewhat higher relative price changes of final consumption goods have been observed for Togo and Armenia, which face an increase in the rice sector of around 8% (Figure B1).

Unlike the rice sector, the vegetable sector displays smaller differences between changes in initial cost pressure by Calzadilla et al (2013) and the final consumption prices (Figure B2). For the bulk of countries, the relative final consumption price changes are close to the initial cost pressure change of 4.8%. Higher 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 consumption price increase of 6.3%. Western Africa is also noticeably affected with an increase in the final consumption 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 4, households spend the highest share of total food expenditure on vegetables (roughly 26%) across the entire sample, followed by rice with a share of 23%. However, when differentiating between consumption groups, we find that for the lowest-consumption group, rice constitutes the largest share of total food expenditure (30.74%) followed by cereals and flour (24.1%) and then vegetables (19.56%). On the other hand, for the highest-consumption group, rice plays a moderate role in overall food expenditure (8.18%) and the vegetables sector is the leading sector when it comes to share of food expenditure (36.67%), followed by fruits (31.71%).

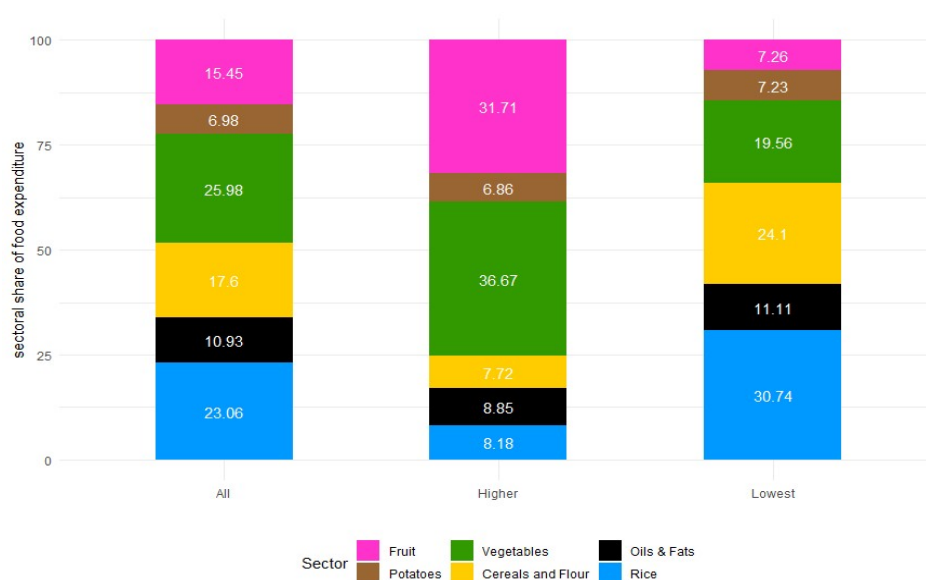


Figure 4: The share of each food sector's contribution to food expenditure in six main food sectors. All: Share of each food sector in food expenditure for all household groups. Higher: Share of each food sector's share in the highest-consumption group's food expenditure. Lowest: Share of each food sector in the lowest-consumption group's food expenditure.

Combining final consumption price increases with household demand, we next show how much each food item contributes to the total consumer surplus loss (i.e., we split the summation that determines total consumer surplus

loss in Equation A.1 by food item and analyze each summand's share in the total). We expect the sectors with the highest expenditure share and/ or final consumption 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 28.47% and 29.08 %, respectively (Figure 5). For the highest-consumption group, we find that the vegetables sector is by far the most significant driver of damages (32.67%) followed by fruits (27.25%) and then rice (19.85%). The differences between the shares of food expenditure and the shares of contribution to damages can be attributed to the difference of the final consumption price increases in each food sector and the respective price elasticity (Figure 1). We find that in the case of potatoes in the lowest-consumption group (Figure 4 and 5) and rice in the highest-consumption group (Figure 4 and 5) 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 4 and 5, is much higher than their share in damages.

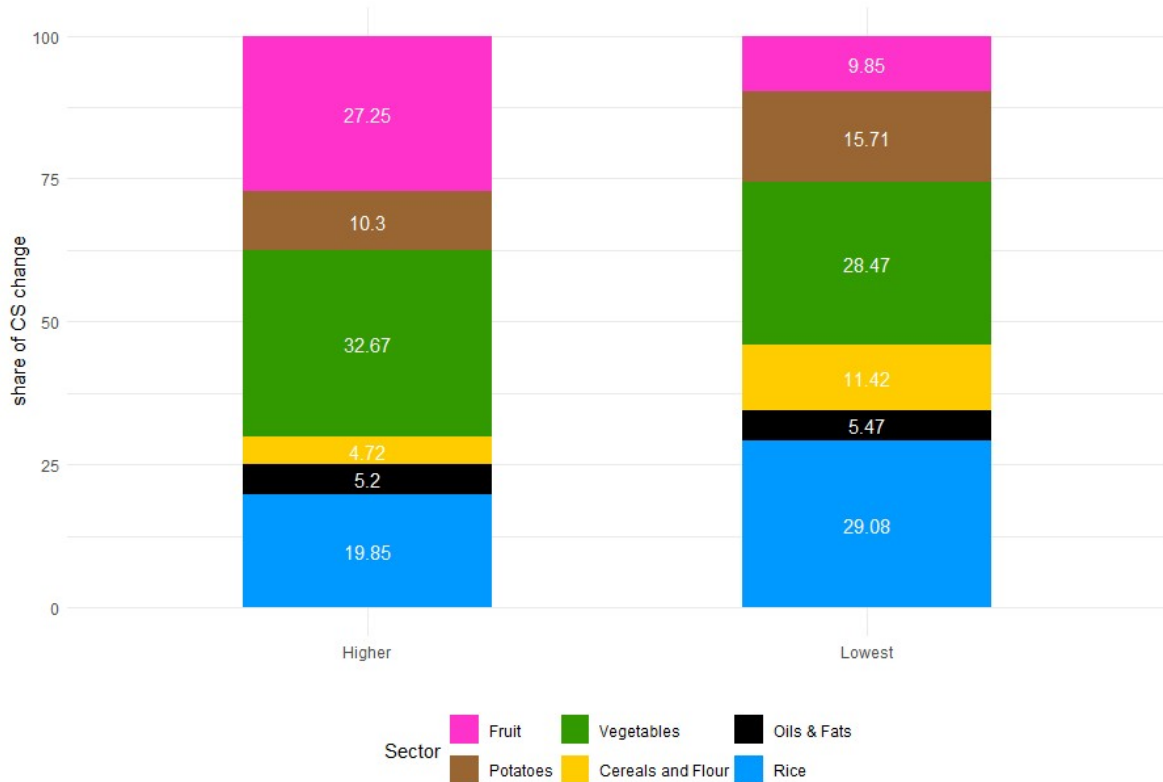


Figure 5: The share of each food sector's contribution to damages in the highest and lowest consumption groups across all countries.

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 (equation 7 and 8). We use two dependant variables to reflect the distributional effects of food-price increase across countries: the relative damages at the national level ($Damages_i$) and consumption elasticity (α_i), presented in Table 4a and 4b, respectively.

We use GDP per capita in PPP ($GDP\ per\ capita$) 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.

We also include the Gini coefficient ($Gini_i$) to reflect the within-country level of income inequality. 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 lower-income households. This means that the lower the income levels of the least well-off households within a country are, the higher the share of food in their expenditure will be, so that they will be disproportionately affected by food price increases.

In addition, we look at the rice ($Rice_i$) and vegetable ($Vegetables_i$) shares in food expenditure. We focus on rice and vegetables as they have the highest final consumption 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 countries' food baskets. Accordingly, we expect households that spend a lot on vegetables to be severely impacted by the climate-induced price increase. We also control for the different regions by including region dummies: sub-Saharan Africa (SSA), east Asia and Pacific (EAP), Europe and central Asia (ECA), Latin America and Caribbean (LAC), Middle East and North Africa (MENA). Our sample covers 87 countries. Some of the observations had to be dropped due to the unavailability of at least one of the control variables.

$$Damages_i = \beta_0 + \beta_1 Rice_i + \beta_2 GDPpercapita_i + \beta_3 Vegetables_i + \beta_4 Gini_i + SSA + EAP + ECA + LAC + MENA + \epsilon \quad (7)$$

$$\alpha_i = \beta_0 + \beta_1 Rice_i + \beta_2 GDPpercapita_i + \beta_3 Vegetables_i + \beta_4 Gini_i + SSA + EAP + ECA + LAC + MENA + \epsilon \quad (8)$$

Table 4: Regression results: a) Dependent variable is relative damages at the 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 its 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.

	a) Damages	b) α
GDP per capita (PPP 2019)	-0.0003*** -0.0001	-0.001 -0.001
Rice	0.030*** -0.007	-0.326*** -0.062
Vegetables	0.055*** -0.014	-0.063 -0.1224
Gini coeff.	-0.0001 -0.0001	-0.001 -0.001
SSA	-0.008***	-0.043*

	-0.002	-0.021
EAP	-0.003	-0.005
	-0.002	-0.022
ECA	-0.002	-0.018
	-0.003	-0.023
LAC	0.003	-0.047*
	-0.003	-0.024
MENA	-0.005	-0.026
	-0.003	-0.026
Constant	0.033***	1.061***
	-0.004	-0.038
Observations	87	87
R ²	0.561	0.370
Adjusted R ²	0.510	0.296
Residual Std. Error	0.005 (df = 77)	0.04 (df = 77)
F Statistic	10.931*** (df = 9; 77)	5.017*** (df = 9; 77)

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 87 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 relatively 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 the consumption elasticity of damages (α). Results from 87 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 the consumption elasticity and sub-Saharan Africa, showing that regressivity is higher in that region, though in relative terms it is not the one most severely affected.

4. Discussion of results and assumptions

By examining 90 developing countries and comparing their consumption groups, 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. One reason is the high final consumption price increase of rice due to climate change in some countries. The high increase can be traced to the specific production technology of this sector. 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. Taking a closer look at 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 sensitivity of the final consumption price that we have observed. Considering all inputs and due to low capital intensity, the ‘Leontief’ production function of rice is more dependent on seeds, direct and indirect and related items, i.e. rice and other rice-intensive inputs.¹² 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 welfare measure (Section 2.1) assumes no income effects of climate change (we address this in Appendix C3). Our model thus only 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 by income group is to the best of our knowledge not available in the necessary detail, this broad regional and sectoral perspective necessarily omits considerations of changes in well-being caused by producers enjoying higher product prices and thus possibly higher income. While our results should thus be interpreted with caution, there are a number of reasons why this shortcoming does little to impair the significance of our results. First, storage, irrigation and other production costs increase in response to climate change, which raises final consumption prices while lowering farmers’ incomes (Mbow et al 2019). This mechanism is consistent with our assumption that projected price changes in Calzadilla et al (2013) represent cost pressures from climate change that arrive at consumers upstream the global value chain. Second, 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). 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.

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 (2013), on which our price increases are based, indeed 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 due to productivity and terms-of-trade effects. Therefore, some income effects are important and we

¹² 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. For a complex global supply chain, there is not only one, but several direct and indirect inputs. Hence, if a farming process is dependent on animal and or human power, these will be fueled by agricultural products. In case of small scale rice farming, these ultimately link back to rice and rice plants in many cases. Additionally, in case of non-capital intensive production function several capital intensive expenditures, such as machinery, fuels, fertilizer or pesticides are less relevant. A second factor that can be of influence is the returns factor. In case of high net gains (selling price minus inputs), the inputs become less relevant.

conduct a sensitivity analysis in Appendix C3, where we measure additional income in the agricultural sector due to food price increases as their total value captured. In the sensitivity analysis, we assume that producers of the agricultural products that experience a price increase in Calzadilla et al (2013) have no additional costs associated with climate change, enjoy higher prices for their products but see their sales diminished as households adjust their demand in response to the price increases. The analysis should be taken with great caution due to a lack of data on additional costs and due to limited comparability of expenditure and income data. We find evidence that the regressive effects we identify on the demand side can be offset by income effects in a subset of countries. On the country level, the additional income outweighs the consumer surplus loss in 26 of our 90 countries, i.e. these countries gain from climate change as a net effect. On the household level within the 26 net-winners, an average of 11% of the additional income is needed to offset the consumer surplus loss of the lowest consumption segment.

The results of our model estimate climate damages around the year 2020. While we recognise that current IPCC scenarios under the SSP-RCP framework are predominately used, we consider the price projections by Calzadilla et al (2013) under A2 to be equally robust and reliable. Aside from the fact that, to our knowledge, more recent scenarios do not provide price projections for 2020, there remains a need for projections that closely align with our 2010 inequality data from the GCD. Comparing the 2050 projections for food price increases of Calzadilla et al (2013) to those shown by Mbow et al (2019) under SSP3-6.0 and Hasegawa et al (2018) under SSP2-6.0, we see similar directional changes in prices. Under SSP3-8.5, which closely corresponds to A2, these price changes can be expected to increase even further. Therefore, we argue that the food price increases per commodities in 2020 are equally trustworthy. 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). 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 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 90 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 are approximately equal to 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 (Barnett and Adger 2007). Our results emphasise that in the short to medium term, policy-makers that are concerned with rising inequality need to especially target poor countries, for example through compensation. 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 a changing climate in the agricultural sector is a crucial factor, especially for vulnerable communities (see, e.g. IPCC 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 slightly 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 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 be combined with our study to obtain a comprehensive picture of how climate change affects human well-being. In addition, our analysis relies on regional estimates about the initial pressure on production costs from climate change by Calzadilla et al (2013), which should be updated with more granular geographic estimates, for example from partial equilibrium models or empirical analysis (see Kotz et al 2024).

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Appendix

A Calculating welfare loss

A.1) Calculation of the change in consumer surplus

To calculate the integral under the demand curve with a rectangular path as in Willig (1979), we fix an order of all consumption items $1, \dots, k, \dots, n$. The change in consumer surplus is:

$$\begin{aligned} \Delta CS_{r,h} = & \bar{p}_r^{-1} \bar{x}_{r,h}^1 \frac{1}{\varepsilon_r^{1,1} + 1} \left(1 - \left(\frac{p_r^1}{\bar{p}_r^1} \right)^{\varepsilon_r^{1,1} + 1} \right) + \\ & \dots + \bar{p}_r^k \bar{x}_{r,h}^k \cdot \left(\frac{p_r^1}{\bar{p}_r^1} \right)^{\varepsilon_r^{k,1}} \cdot \dots \cdot \left(\frac{p_r^{k-1}}{\bar{p}_r^{k-1}} \right)^{\varepsilon_r^{k,k-1}} \frac{1}{\varepsilon_r^{k,k} + 1} \left(1 - \left(\frac{p_r^k}{\bar{p}_r^k} \right)^{\varepsilon_r^{k,k} + 1} \right) + \\ & \dots + \bar{p}_r^n \bar{x}_{r,h}^n \cdot \left(\frac{p_r^1}{\bar{p}_r^1} \right)^{\varepsilon_r^{n,1}} \cdot \dots \cdot \left(\frac{p_r^{n-1}}{\bar{p}_r^{n-1}} \right)^{\varepsilon_r^{n,n-1}} \frac{1}{\varepsilon_r^{n,n} + 1} \left(1 - \left(\frac{p_r^n}{\bar{p}_r^n} \right)^{\varepsilon_r^{n,n} + 1} \right) \quad (A.1) \end{aligned}$$

In case of zero cross-price elasticities, Equation (A.1) is the same as the consumer surplus loss in West and Williams (2004).

B Tables and figures

Table B1: Categorizing households of developing countries into consumption groups based on corresponding percentiles of the global income distribution (World Bank, 2023)

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 B2: Matching databases – GCD consumption sectors and its corresponding GTAP sectors

GCD Consumption Item	GTAP sector
Catering Service	afs
Passenger Transport by Air	atp
Beer	b_t
Coffee, Tea and Cocoa	
Mineral Waters, Soft Drinks, Fruit and Vegetable Juices	
Spirits	
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	ely
Electricity	
Gas	gdt.gas**
Social Protection	hht
Shoes and Other Footwear	lea
Furniture and Furnishings	lum
Cheese	mil
Fresh Milk	
Preserved Milk and Other Milk Products	
Animal Drawn Vehicles	mvh
Bicycles	
Major Durables for Outdoor and Indoor Recreation	
Motor Cars	
Motorcycles	
Eggs and Egg-Based Products	oap
Actual and Imputed Rentals for Housing	obs
Bread	ofd
Confectionery, Chocolate, and Ice Cream	
Food Products n.e.c	
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	ome
Major Household Appliances Whether Electric or Not	
Major Tools and Equipment	
Small Electric Household Appliances	
Therapeutic Appliances and Equipment	
Appliances, Articles and Products for Personal Care	omf
Glassware, Tableware and Household Utensils	
Non-Durable Household Goods	
Other Medical Products	
Other Recreational Items and Equipment	
Small Tools and Miscellaneous Accessories	
Lamb, Mutton and Goat	omt
Other Meats and Meat Preparations	
Pork	

Poultry	
Cultural Services	osg
Postal Services	
Combined Passenger Transport	otp
Other Purchase Transport Services	
Passenger Transport by Railway	
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
Accommodation Services	ros
Dental Services	
Domestic Services	
Hairdressing Salons and Personal Grooming Establishments	
Hospital Services	
Medical Services	
Miscellaneous Services Relating to the Dwelling	
Other Services 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	trd
Maintenance and Repair of Other Major Durables for Recreation and Culture	
Maintenance and Repair of Personal Transport Equipment	
Maintenance and Repair of the Dwelling	
Other Services in Respect of Personal Transport Equipment	
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	v_f
Fresh or Chilled Potatoes	
Fresh or Chilled Vegetables Other than Potatoes	
Butter and Margarine	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	

Water Utility	wtr
Games of Chance	unmatched
Garden and Pets	unmatched
Other Personal Effects	unmatched

Note: 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 B3: Matching of the food sub-categories from the cross-price elasticity data (Cornelsen et al., 2015) with GCD sub-categories.

GCD _category	Elasticity
Fresh or Chilled Fruit	Fruit & Veg.
Fresh or Chilled Potatoes	Fruit & Veg.
Fresh or Chilled Vegetables Other than Potatoes	Fruit & Veg.
Frozen, Preserved or Processed Fruit and Fruit-based Product	Fruit & Veg.
Frozen, Preserved or Processed Vegetables and Vegetable-based Product	Fruit & Veg.
Beef and Veal	Meats
Lamb, Mutton and Goat	Meats
Other Meats and Meat Preparations	Meats
Pork	Meats
Poultry	Meats
Fresh, Chilled or Frozen Fish and Seafood	Fish
Preserved or Processed Fish and Seafood	Fish
Cheese	Dairy
Preserved Milk and Other Milk Products	Dairy
Eggs and Egg-Based Products	Dairy
Fresh Milk	Dairy
Other Cereals, Flour and Other Products	Cereals
Rice	Cereals
Butter and Margarine	Fats & Oils
Other Edible Oil and Fats	Fats & Oils
Beer	Sweets
Bread	Sweets
Coffee, Tea and Cocoa	Sweets
Mineral Waters, Soft Drinks, Fruit and Vegetable Juices	Sweets
Other Bakery Products	Sweets
Spirits	Sweets
Sugar	Sweets
Tobacco	Sweets
Wine	Sweets

Table B4: Climate damages presented by consumer surplus loss per consumption group per country

Country	Lowest	Low	Middle	Higher	National
Lao PDR	0.0463953	0.0438082	0.04224988	0.04374898	0.04515597
Tajikistan	0.04655209	0.04550204	0.04252583	0.04077255	0.0447812

Pakistan	0.04333246	0.04374641	0.04398845	0.04455992	0.04348781
Nepal	0.04230296	0.04176013	0.04051978	0.0408317	0.04207222
Timor Leste	0.04063417	0.0378575	0.03531375	0.03532228	0.0396496
Iraq	0.03954622	0.03926638	0.03914512	0.03918139	0.03926524
Bhutan	0.03841641	0.03939902	0.03906822	0.03801245	0.03904723
Cote d'Ivoire	0.04059871	0.03854275	0.03516211	0.03371541	0.03879952
Madagascar	0.03923741	0.03289926	0.01929378	0.01923652	0.03855288
Bangladesh	0.03932255	0.03111922	0.02814499	0.02736397	0.03718007
Azerbaijan	0.03789437	0.03719769	0.03642391	0.03752906	0.03713515
Malawi	0.03711742	0.03577137	0.03363801	0.02803684	0.03664348
Sierra Leone	0.03928449	0.03561802	0.02916824	0.02693612	0.03653154
Vietnam	0.03798714	0.0346729	0.03235112	0.03344076	0.03639809
Liberia	0.03790702	0.03176775	0.02869781	NA	0.03620918
Togo	0.03598293	0.03614751	0.03567907	NA	0.03600821
Yemen, Rep.	0.03521861	0.03596737	0.03672891	0.03705363	0.03589182
Burundi	0.03610362	0.03142903	0.02665153	NA	0.03569857
Afghanistan	0.03349119	0.03679298	0.03945621	0.0367499	0.03563075
Albania	0.03282547	0.03408626	0.03438173	0.03156077	0.03405458
Kyrgyz Republic	0.0325269	0.03452391	0.03522228	0.03554688	0.03398061
Cambodia	0.03311006	0.03362975	0.03480781	0.03386392	0.03352624
Benin	0.03360438	0.03282981	0.03085592	NA	0.03341386
Uganda	0.03398253	0.03267444	0.03001773	0.02755777	0.03340518
Belarus	0.02680863	0.03036333	0.0330416	0.03398976	0.03287345
India	0.03352205	0.03124794	0.02971725	0.03082779	0.03285549
Papua New Guinea	0.03724247	0.03513115	0.03193757	0.02627233	0.03259927
China	0.03366589	0.03304609	0.03163448	0.0302417	0.03244698
Thailand	0.03461675	0.0332301	0.03073445	0.03127563	0.03244344
Peru	0.03369484	0.03283552	0.03174362	0.03097902	0.03239551
Ghana	0.03379393	0.03203526	0.02955397	0.02754708	0.03231297
Maldives	0.03211188	0.03164224	0.03057195	0.03053715	0.0315951
Nicaragua	0.03191295	0.02885623	0.02837341	NA	0.03146996
Nigeria	0.03086831	0.03143689	0.03118368	0.02842104	0.03100755
Tanzania	0.03070354	0.02887479	0.02541518	0.02692061	0.03042187
Guinea	0.03139685	0.0278329	0.02329751	NA	0.0302455
Sri Lanka	0.03205727	0.02998276	0.02749219	0.02746967	0.0302043
Colombia	0.0325963	0.03097329	0.02903545	0.02653335	0.02967367
Mali	0.02922218	0.03048467	0.02905523	0.02887291	0.02946797
Zambia	0.02971147	0.02886335	0.02870383	0.02816954	0.02946558
Bolivia	0.03100728	0.03009436	0.02868196	0.02654312	0.02945205
Djibouti	0.03070337	0.02915781	0.02861595	0.02849563	0.0293794
Brazil	0.02990641	0.0296343	0.02896397	0.02820232	0.02911475
Philippines	0.03051383	0.02777142	0.02624115	0.02645838	0.02893805
Ukraine	0.02933062	0.02861616	0.02847128	0.02840032	0.02851424
Indonesia	0.03036971	0.02537155	0.02308196	0.02300979	0.02825915
Rwanda	0.02872892	0.02816573	0.02599042	0.02534746	0.02823265
Honduras	0.02994522	0.02756754	0.02702814	0.02650155	0.02819619

Mozambique	0.02841107	0.02582165	0.02348918	0.01960916	0.02797198
Cabo Verde	0.02959509	0.02828668	0.02672018	0.02595926	0.02782034
Moldova	0.02644812	0.02722254	0.02737111	0.02721015	0.02721306
Gabon	0.02945388	0.02732466	0.02631018	0.02437187	0.02714113
Mexico	0.02818974	0.02739687	0.02618823	0.0247896	0.02698205
Egypt, Arab Rep.	0.02744205	0.02666682	0.02552243	0.02407126	0.02689441
Armenia	0.02642804	0.02693849	0.02762144	0.02883548	0.02679948
Congo, Dem. Rep.	0.02680923	0.02290684	0.02354433	0.02575652	0.02669735
Cameroon	0.02754359	0.02543933	0.02315966	0.02059165	0.02654967
Senegal	0.02768176	0.02413623	0.02278216	NA	0.02621113
Gambia, The	0.02758469	0.02594151	0.02328218	0.02178155	0.02619062
Turkey	0.02665612	0.025894	0.02620514	0.02595535	0.02608571
Jamaica	0.02783858	0.02613158	0.02431924	0.02396511	0.02557981
Mauritania	0.02664219	0.02484238	0.02316521	0.02147803	0.02527301
Sao Tome and Principe	0.02780715	0.02612799	0.02485425	0.02427232	0.02526505
Niger	0.02410774	0.02766136	0.0200268	0.02398997	0.02444787
Kenya	0.02494571	0.02355884	0.02044265	0.01650348	0.02416919
Mongolia	0.0236979	0.02414799	0.02440281	0.02419489	0.02398603
Congo, Rep.	0.02466039	0.02314029	0.02306596	0.02201351	0.02363022
Guatemala	0.02311202	0.02347257	0.02384855	0.02355372	0.02352648
Fiji	0.02338887	0.02363109	0.02293702	0.02286009	0.02339583
Mauritius	0.02391658	0.02336852	0.0224124	0.022136	0.02311882
Morocco	0.02296646	0.02275242	0.02261856	0.02227502	0.02272954
Swaziland	0.0213065	0.02313669	0.02313887	0.0192271	0.02211977
Romania	0.02233109	0.02203585	0.02187581	0.02131798	0.02193689
Serbia	0.02101164	0.02157308	0.02148125	0.02162253	0.02151951
Jordan	0.02171619	0.0217004	0.02078234	0.01981167	0.02117819
Lesotho	0.01910159	0.02008643	0.02250113	0.02469528	0.02023572
Montenegro	0.02241559	0.02057736	0.01974078	0.0206608	0.02002922
Burkina Faso	0.0188479	0.02552154	0.02739667	0.0259436	0.01967807
Macedonia, FYR	0.01924444	0.01934713	0.01953734	0.01984089	0.01954169
South Africa	0.01945946	0.01943569	0.01910193	0.0190015	0.01925911
Chad	0.01804607	0.02052903	0.02056034	0.01155563	0.01888212
Lithuania	0.01909566	0.01906952	0.01873436	0.01822353	0.01879185
Bosnia and Herzegovina	0.01747292	0.01725733	0.01826732	0.01896594	0.01855148
Russian Federation	0.02002056	0.01938318	0.01832689	0.01727965	0.01820729
Latvia	0.02051617	0.01843179	0.0180321	0.01749262	0.01805292
Kazakhstan	0.01742832	0.01775417	0.01771773	0.01716147	0.01771693
El Salvador	0.02273769	0.01691662	0.01587954	0.0160207	0.01765186
Namibia	0.01753578	0.01718058	0.01698122	0.0166921	0.01729658
Bulgaria	0.01813601	0.01706157	0.01717081	0.01639309	0.01705673
Ethiopia	0.01366582	0.01364013	0.01515631	0.01616837	0.01367876

Note: 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.

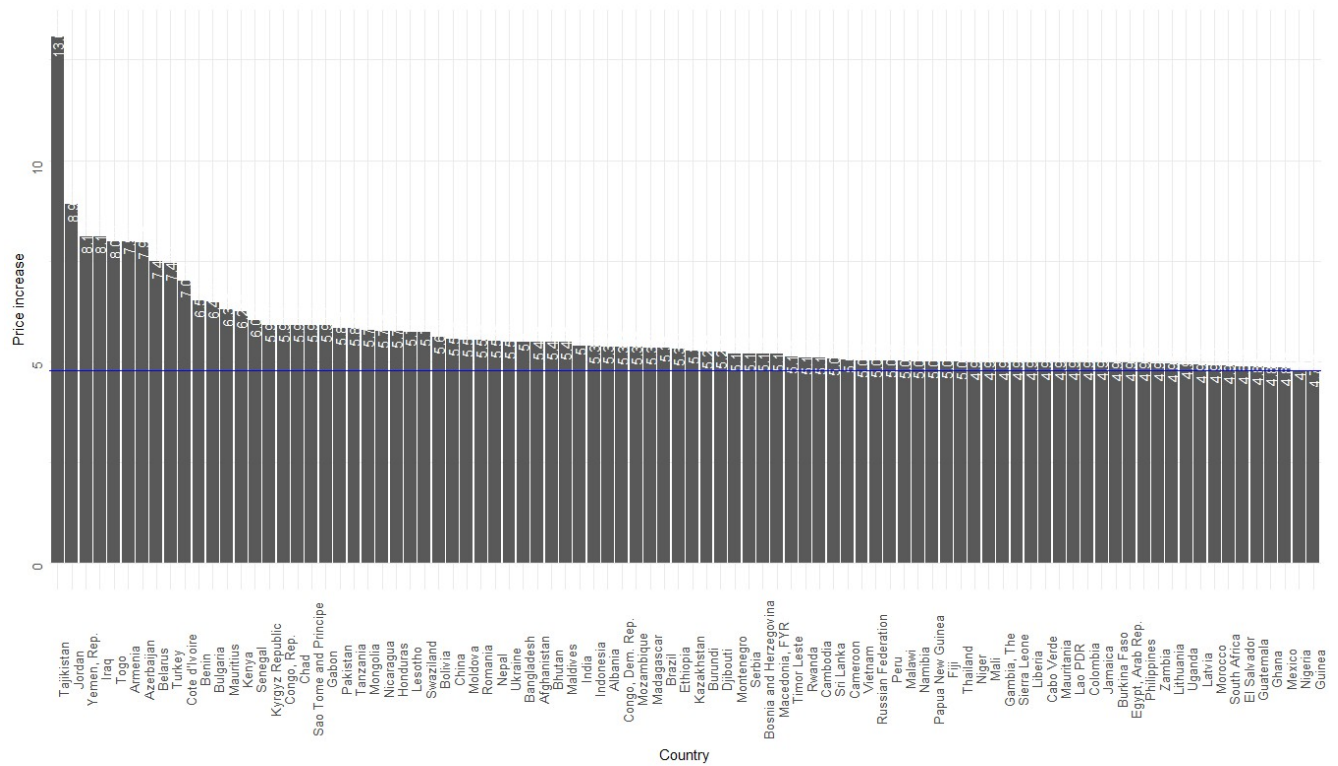


Figure B1: Relative increase in final consumption prices of rice as computed by the MRIO in percent. The projected price of rice as computed by Calzadilla et al. (2013) is depicted with the blue horizontal line.

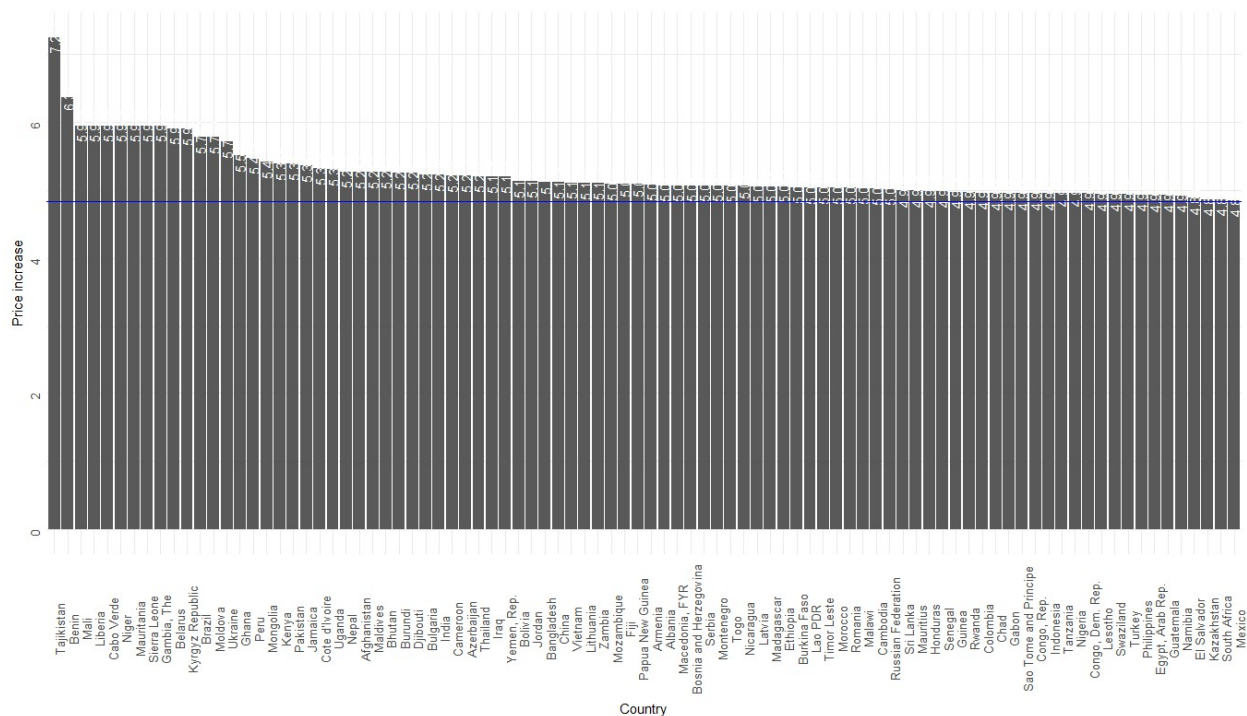


Figure B2: Relative increase in final consumption prices of vegetables as computed by the MRIO in percent. The projected price of vegetables as computed by Calzadilla et al. (2013) is depicted with the blue horizontal line.

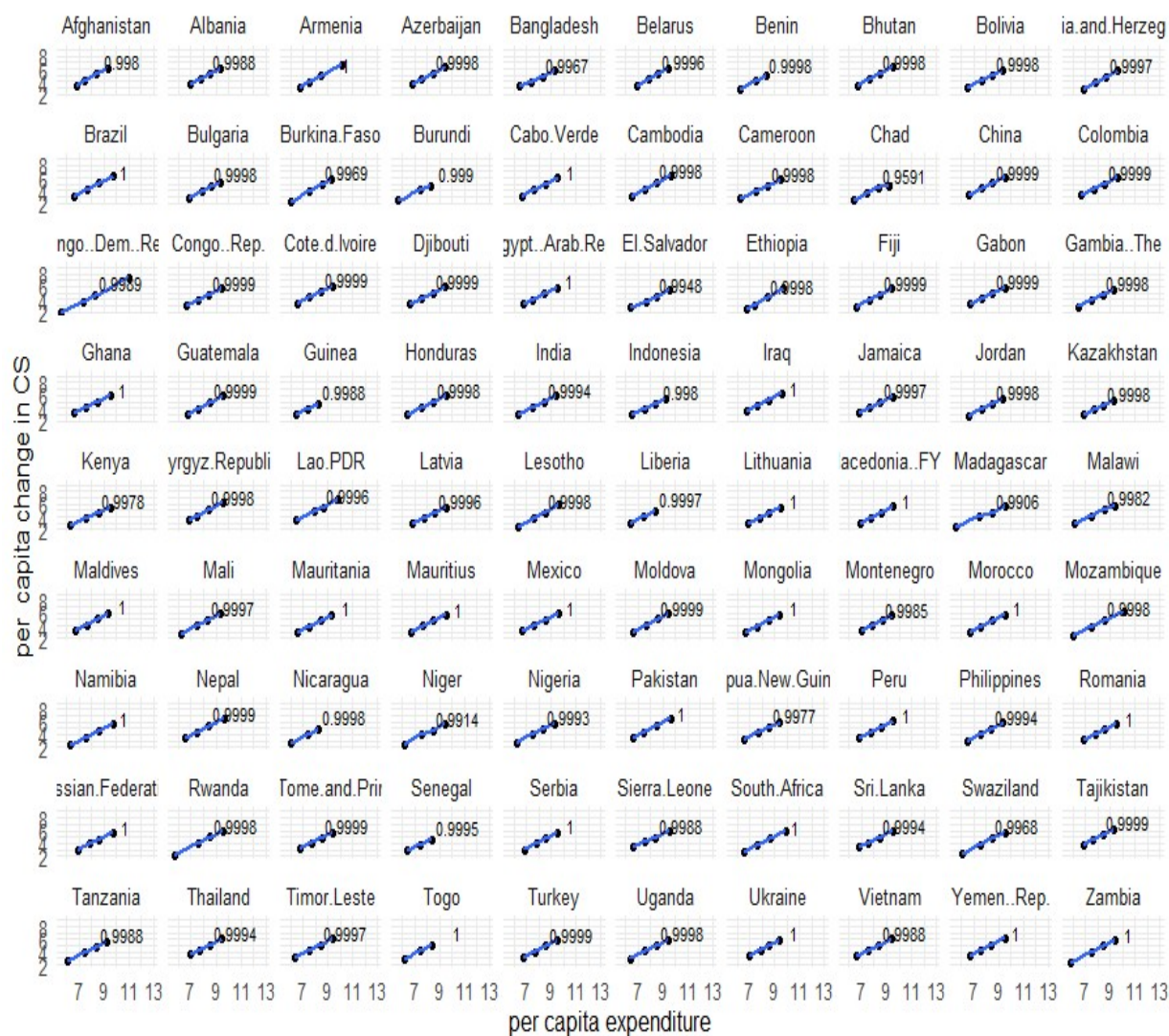


Figure B3: Plotting the consumption elasticity of each country. Per capita expenditure represents the log normal per capita expenditure of each consumption group: Lowest, low, middle, and highest. Per capita change in CS represents the log normal per capita change in consumer surplus for each of the 4 consumption groups.

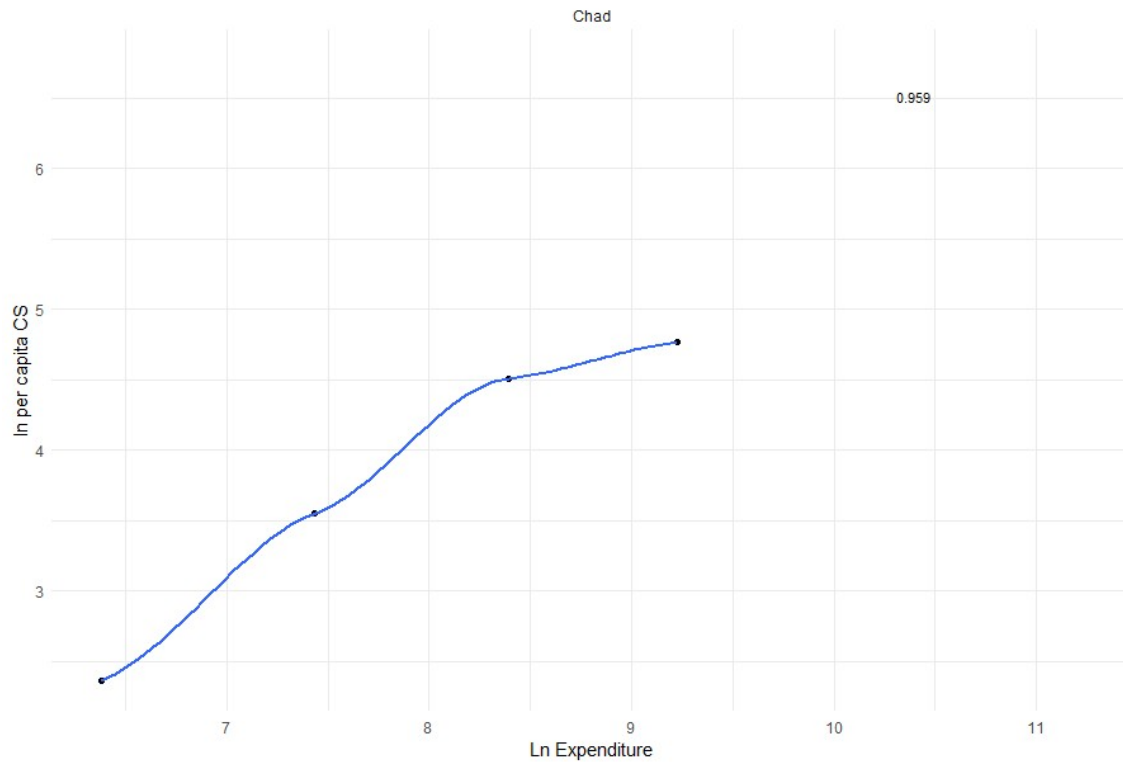


Figure B4: Plotting the consumption elasticity of the country: Chad with R-squared less than 0.99. Per capita expenditure represents the log normal per capita expenditure of each consumption group: Lowest, low, middle, and highest. Per capita change in CS represents the log normal per capita change in consumer surplus for each of the 4 consumption groups. The R-square for each country is on the top-right side of the curve.

C Robustness checks

C1 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 find slightly significant relationship between proximity to equator and the extent of damages, the relationship between damages and latitude, maybe stronger in one side of the hemispheres.

In Table C1, 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 65 countries located in the north of the equator, with latitude ranging from 1°N to 60°N and 22 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 and southern 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.

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.

Table C1: 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.

	alpha (a) North	alpha (b) South	National (c) North	National (d) South
GDP per capita (PPP 2019, in thousands)	-0.001 -0.001	-0.0005 -0.002	-0.0004*** -0.0001	-0.0002 -0.0001
Rice	-0.295*** -0.074	-0.477*** -0.133	0.027*** -0.009	0.037*** -0.010
Vegetables	0.033 -0.1439	-0.222 -0.295	0.061*** -0.018	0.059*** -0.021
Gini coeff.	-0.002 -0.001	-0.002 -0.002	-0.0001 -0.0002	-0.0001 -0.0001
SSA	-0.044* -0.023	-0.020 -0.031	-0.009** -0.003	0.002 -0.002
EAP	0.021 -0.025		0.001 -0.003	
ECA	-0.003 -0.028		-0.001 -0.003	
LAC	-0.036 -0.028	-0.025 -0.039	0.006 -0.003	0.008*** -0.003

MENA	-0.023 -0.026		-0.005 -0.004	
Latitude	-0.0002 -0.001	0.002 -0.001	-0.00001 -0.0001	-0.0002* -0.0001
Constant	1.097*** -0.061	1.088*** -0.103	0.033*** -0.008	0.026*** -0.007
Observations	65	22	65	22
R ²	0.414	0.496	0.573	0.810
Adjusted R ²	0.306	0.243	0.494	0.716
Residual Std. Error	0.043 (df = 54)	0.050 (df = 14)	0.005 (df = 54)	0.003 (df = 14)
F Statistic	3.819*** (df = 10; 54)	1.966 (df = 7; 14)	7.249*** (df = 10; 54)	8547*** (df = 7; 14)

C2 Elasticity sensitivity analysis

To check the sensitivity of our results to the cross-price elasticity estimates we are using, we re-run our analysis, assuming cross-price elasticities between food groups are zero, using own-price elasticities from Cornelsen et al (2015), and we run the analysis using compensated own-price elasticities from Muhammad et al (2011).

Overall, welfare changes do not vary much among the different models as we next show.

C2.1 Estimates without cross-price elasticities from Cornelsen et al (2015)

We compare our main findings with estimates based on own-price elasticities only from Cornelsen et al (2015), assuming cross-price elasticities are zero. Comparing our results for consumer surplus losses across countries, consumption elasticities and sectoral contribution to consumer surplus losses, we find that results are similar on all 3 accounts with very slight differences in some values as shown below.

We find that the largest relative damage is in Lao PDR (4.38% of total expenditure), followed by Tajikistan (4.36%), Pakistan (4.23%) and Nepal (4.09%). The least affected country is Ethiopia, where relative damage equals 1.36%. Ethiopia is followed by Bulgaria (1.70%), Namibia (1.73%) and El Salvador (1.76 %) (Table C2.1).

Table C2.1: Climate damages presented by consumer surplus loss per consumption group per country

Country	Lowest	Low	Middle	Higher	National
Lao PDR	0.04488551	0.04275699	0.04154083	0.04293391	0.0438701
Tajikistan	0.04527893	0.04429572	0.04150968	0.04008915	0.04362227
Pakistan	0.04210456	0.04279295	0.04326967	0.04387173	0.04236498
Nepal	0.04105935	0.04083673	0.03976278	0.0401849	0.04094626
Iraq	0.03964545	0.03939663	0.03928434	0.03934316	0.0393951
Cote d'Ivoire	0.04053405	0.03852365	0.03520861	0.03379911	0.03877341
Timor Leste	0.03957918	0.03722367	0.03491345	0.03494344	0.03873782
Bhutan	0.03744211	0.03859734	0.03838064	0.03740246	0.03821552
Madagascar	0.03809824	0.03218623	0.01908962	0.01851746	0.03745095
Azerbaijan	0.03784166	0.0372292	0.03652646	0.03789802	0.03717494

Bangladesh	0.03837301	0.03058473	0.02777976	0.02704712	0.03633915
Malawi	0.03654083	0.03531176	0.03326468	0.02762665	0.03609999
Sierra Leone	0.03847043	0.03504319	0.02883768	0.02663701	0.03588097
Vietnam	0.03707953	0.03408544	0.03195276	0.03303925	0.03564242
Togo	0.03544689	0.03572001	0.03525917	NA	0.03549909
Liberia	0.03711564	0.03127788	0.02827195	NA	0.03549907
Burundi	0.03589346	0.03111712	0.02642838	NA	0.03548026
Yemen, Rep.	0.03441371	0.03524748	0.03617155	0.03655077	0.0351733
Afghanistan	0.03261711	0.0360767	0.03895294	0.03643404	0.03486278
Albania	0.03286151	0.03415477	0.03448922	0.03174304	0.03414809
Kyrgyz Republic	0.03202407	0.03400705	0.03471132	0.03513673	0.03346877
Belarus	0.02693136	0.0305868	0.03330578	0.03425727	0.03313318
Uganda	0.03369348	0.03231099	0.02972782	0.02729648	0.03309654
Cambodia	0.03262011	0.03319338	0.03439262	0.03349559	0.0330674
Benin	0.03310284	0.03240861	0.03053596	NA	0.03293072
China	0.03380882	0.03319567	0.03179352	0.03039857	0.03259945
Peru	0.03373003	0.03294172	0.03189945	0.03114663	0.03251747
Thailand	0.03457119	0.03321902	0.0307875	0.03135917	0.03245438
Papua New Guinea	0.0369954	0.03479952	0.03149733	0.02589	0.03220849
Ghana	0.0335395	0.03179259	0.0293044	0.02725693	0.0320647
India	0.03266931	0.03060174	0.02921656	0.03034748	0.03206358
Maldives	0.03228083	0.03188715	0.030831	0.03083636	0.0318228
Nicaragua	0.03146352	0.0285973	0.02816133	NA	0.03104834
Nigeria	0.03048725	0.03108256	0.0308755	0.02820241	0.03063379
Tanzania	0.03014329	0.02837705	0.02503593	0.02661065	0.02987128
Guinea	0.03088271	0.02746775	0.02305786	NA	0.02977886
Colombia	0.03258108	0.03100115	0.02908616	0.02659401	0.02971214
Sri Lanka	0.03145938	0.02949731	0.02712633	0.0271724	0.0297054
Zambia	0.02942392	0.02859691	0.02847024	0.02790043	0.02918581
Bolivia	0.03058317	0.0298121	0.02845827	0.02635255	0.02918427
Brazil	0.0299611	0.02969069	0.02902874	0.02827731	0.0291779
Djibouti	0.03025599	0.02882636	0.02835388	0.02820389	0.02903722
Mali	0.02849334	0.02988352	0.02867204	0.02846935	0.02877046
Ukraine	0.02942152	0.02874393	0.02861603	0.02855622	0.02865416
Philippines	0.02984235	0.02734788	0.02593794	0.0261676	0.02840741
Rwanda	0.02854756	0.02784739	0.02569627	0.02503547	0.02800673
Honduras	0.02958505	0.02735274	0.02685408	0.02634649	0.02794408
Indonesia	0.0297798	0.02499043	0.02281575	0.02280889	0.02775815
Mozambique	0.0280468	0.02554343	0.02333275	0.01948537	0.027623
Cabo Verde	0.02897808	0.02789587	0.02646579	0.02576876	0.02745357
Moldova	0.02652209	0.02734067	0.02750728	0.02735248	0.02733532
Gabon	0.02950234	0.02737732	0.02636582	0.02443812	0.02719485
Mexico	0.02829075	0.02751178	0.02630035	0.02488755	0.02709286
Armenia	0.02648552	0.02701327	0.02771016	0.02893068	0.02686919
Egypt, Arab Rep.	0.02717195	0.02643781	0.0253266	0.02385226	0.02665001
Congo, Dem. Rep.	0.02664135	0.02271287	0.0233469	0.02561749	0.02652872
Cameroon	0.02729882	0.02524865	0.02301443	0.02045901	0.02632955

Turkey	0.02669793	0.02593682	0.0262558	0.02601647	0.02613443
Gambia, The	0.02721066	0.02561061	0.02307097	0.02153479	0.02586009
Jamaica	0.02794558	0.02624349	0.02442565	0.0240768	0.02568937
Senegal	0.0270632	0.02374005	0.0225034	NA	0.02568637
Sao Tome and Principe	0.02747934	0.02583995	0.02458542	0.02402315	0.02499112
Mauritania	0.02588869	0.02423584	0.02270128	0.02114436	0.02463198
Mongolia	0.02374508	0.02420268	0.02446327	0.02425042	0.02403814
Kenya	0.02468458	0.02334674	0.0202892	0.01639653	0.02393023
Niger	0.02342194	0.02703369	0.01978066	0.02375233	0.0237794
Guatemala	0.02310573	0.02349028	0.02388825	0.02360701	0.02355022
Congo, Rep.	0.02447706	0.02297232	0.02293039	0.02192505	0.0234616
Fiji	0.02339116	0.02367654	0.02300084	0.02292638	0.02343605
Mauritius	0.02396917	0.02341791	0.02245621	0.0221782	0.02316675
Morocco	0.02266647	0.02251357	0.02243337	0.022117	0.02249965
Romania	0.02237264	0.02208131	0.02192588	0.02136331	0.02198461
Swaziland	0.02108673	0.02291714	0.02294704	0.01906793	0.02190448
Serbia	0.02106367	0.02163634	0.02154696	0.02168638	0.02158436
Jordan	0.02148023	0.02146623	0.0205784	0.01965474	0.02096215
Montenegro	0.02248384	0.02064221	0.01980539	0.02072764	0.02009424
Lesotho	0.01894822	0.01992994	0.02237787	0.0245968	0.02008761
Macedonia, FYR	0.01925105	0.01936917	0.01957048	0.01987974	0.01957291
South Africa	0.01949267	0.01947966	0.01915733	0.0190603	0.01930718
Burkina Faso	0.01845302	0.02513874	0.02720702	0.02572239	0.01928698
Lithuania	0.01917089	0.01914508	0.01880659	0.0182906	0.01886464
Bosnia and Herzegovina	0.01747778	0.0172778	0.0182986	0.01900432	0.0185856
Chad	0.01763232	0.02008761	0.02023891	0.01152086	0.01846228
Russian Federation	0.02005538	0.01942487	0.01837232	0.0173283	0.01825299
Latvia	0.02057314	0.01848992	0.01809076	0.01754805	0.01811092
Kazakhstan	0.01742711	0.01776889	0.0177448	0.01720014	0.01773742
El Salvador	0.02273048	0.01690364	0.01587289	0.0160179	0.0176413
Namibia	0.01755329	0.01721151	0.01701884	0.01673093	0.01732216
Bulgaria	0.01814514	0.01707813	0.01719409	0.0164108	0.01707813
Ethiopia	0.01359346	0.01356764	0.015081	0.01608102	0.01360628

As shown in Figure C2.1, the damage estimates from our main findings are very similar to estimates of damages without including cross-price elasticities.

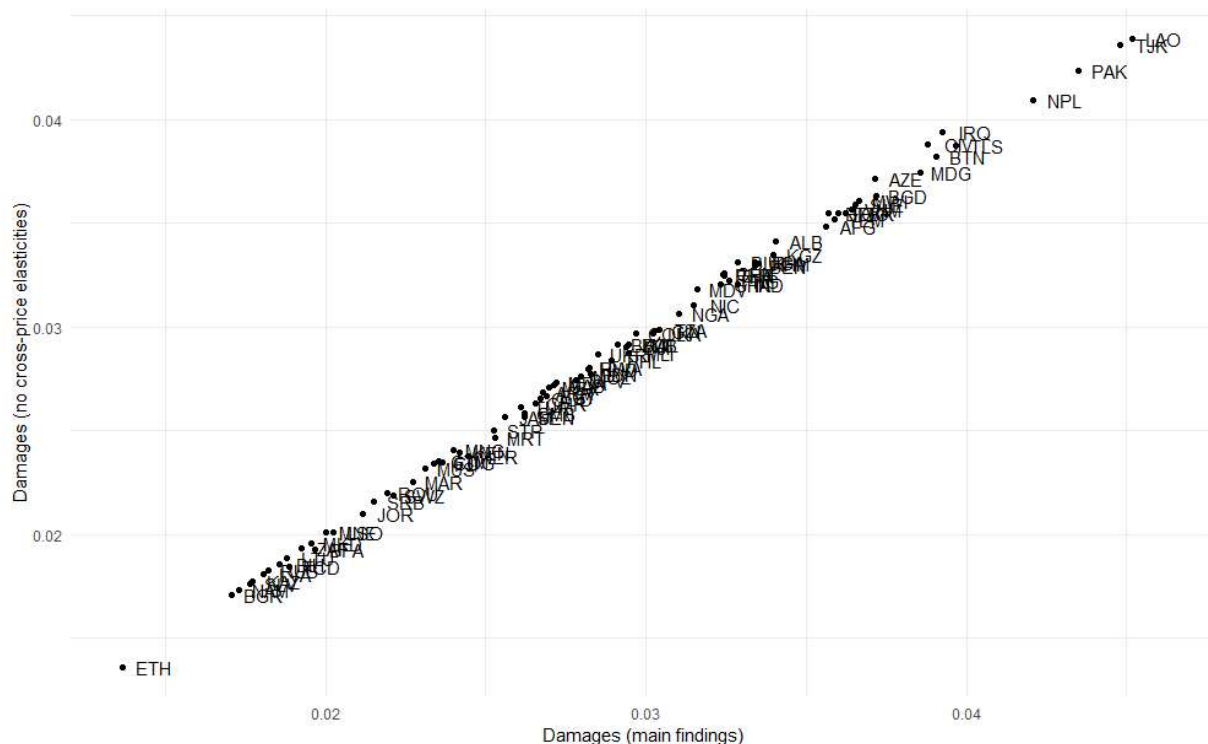


Figure C2.1: Damages estimates from main findings (x-axis) and damages estimates without including cross-price elasticities (y-axis). Results from linear regression show a coefficient of 1.03, statistically significant at <1% level.

Additionally, we compute the consumption elasticity of climate damages. We find that damages increase with expenditure and the slope of the line is the consumption elasticity has value of $\alpha=0.96$. Regressions analysis shows similar results to the main findings, where the logged expenditure is positively and significantly associated with consumption elasticity, with the lowest consumption segment showing a negative and significant coefficient indicating regressive effects. However, the remaining consumption segments do not show a significant coefficients. Plotting the consumption elasticity estimates of the main findings against the estimates without cross-price elasticity, we find that both provide very similar estimates for alpha (Figure C2.2).

Table C2.2: Regression results: dependent variable is the logged per-capita damages ($\ln$ percapita CS). Explanatory variables are: logged expenditure ($\ln$ expenditure) and income groups: lowest, low, highest.

Dependent variable:	
$\ln_percapita_CS$	
$\ln_expenditure$	0.852*** (0.062)
lowest	-0.219* (0.128)
low	-0.092 (0.067)
highest	0.117 (0.074)
Constant	-2.383*** (0.531)
Observations	353
R^2	0.950

Adjusted R ²	0.949
Residual Std. Error	0.248 (df = 348)
F Statistic	1,645.636*** (df = 4; 348)
Note:	*p<0.1; **p<0.05; ***p<0.01

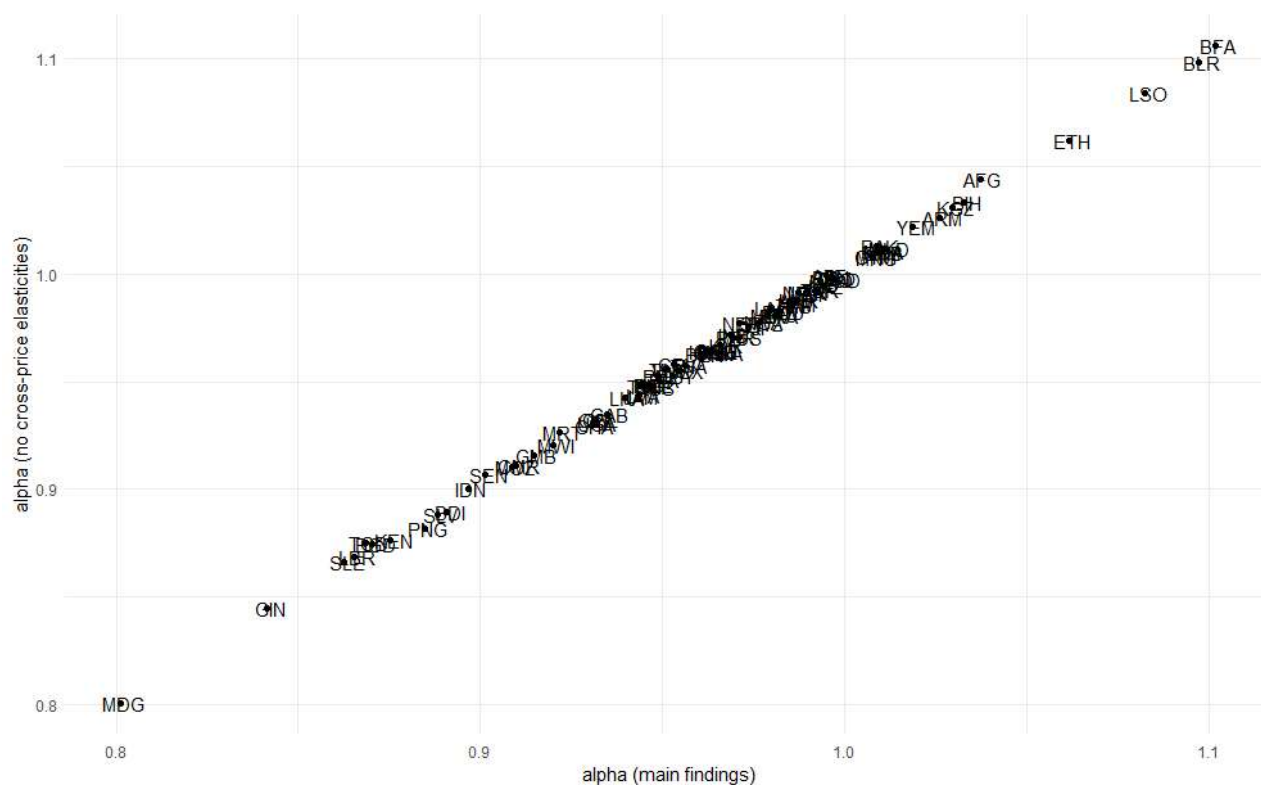


Figure C2.2: Consumption elasticity estimates from main findings (x-axis) and estimates without including cross-price elasticities (y-axis). Results from linear regression show a coefficient of 0.999, statistically significant at <1% level.

Looking at the contribution of the main food groups to the consumer surplus loss, we find similar to our main analysis, for the lowest income group, rice and vegetables contribute the most to the losses in consumer surplus, around 28.6% and 28.8%, respectively. As for the higher income group, we find that vegetables (32.9%), followed by fruits (27.4%) have the highest contribution (Figure C2.3)

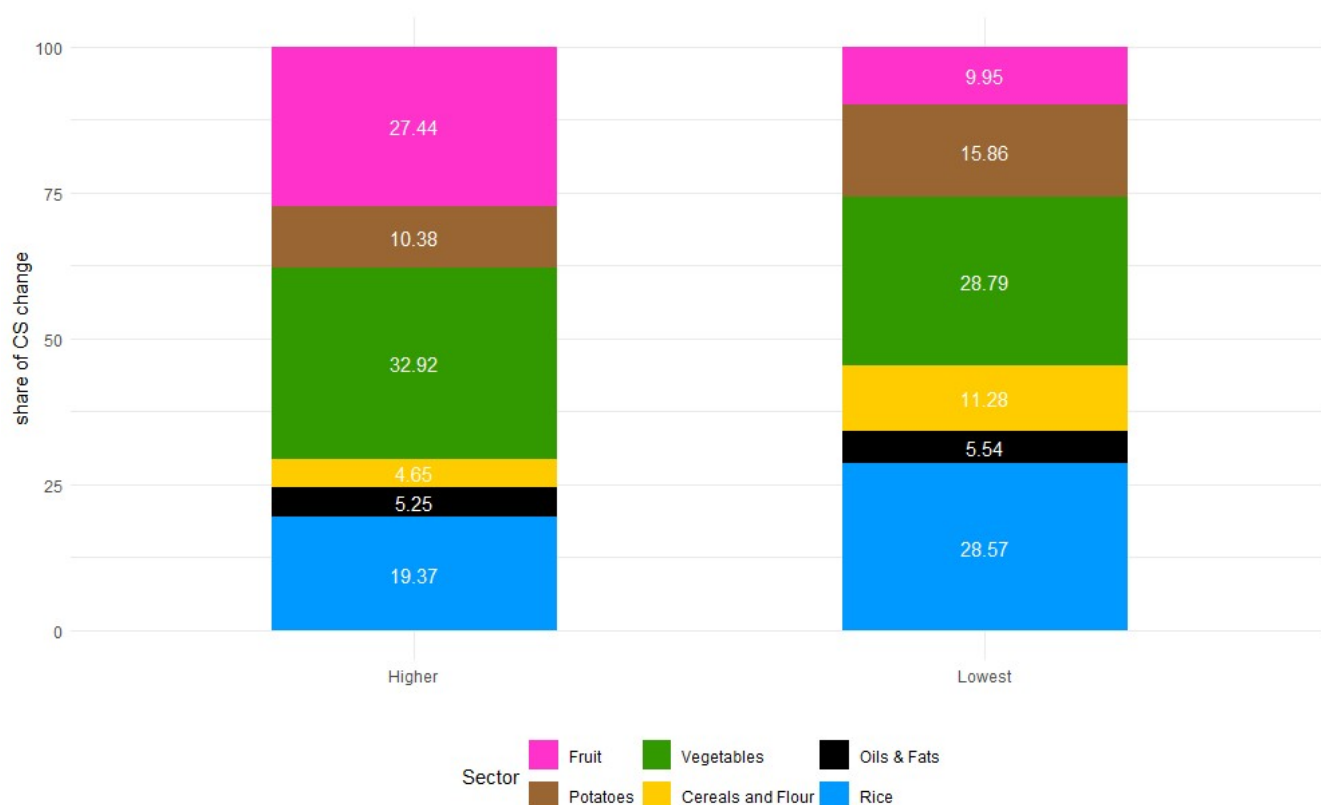


Figure C2.3: The share of each food sector's contribution to damages in the highest and lowest consumption groups across all countries.

C2.2 Estimates using compensated own-price elasticities from Muhammad et al (2011)

The change in consumer surplus is an approximation of monetary measures of welfare losses like the equivalent and the compensating variation (Willig 1979). We resort to the consumer surplus due to a lack of data. As a robustness check, we calculate the compensating variation. According to Willig (1979), the compensating variation when multiple prices change is the line-integral under the compensated demand curve. Thus, the compensating variation is given by Equation (A.1) with two changes. First, elasticities that enter the equation are compensated and not uncompensated. Second, the compensating variation is by definition positive for a price increase. We thus again multiply the value of (A.1) with -1.

We use data on compensated own-price elasticities from Muhammad et al (2011). They provide estimates on price and income elasticities for 114 countries using 2005 International Comparison Program (ICP) data. Three types of own-price elasticity of demand are reported: Slutsky (compensated), Cournot (uncompensated), and Frisch-deflated own-price elasticity. For the purpose of our sensitivity analysis, we use the Slutsky own-price elasticity estimates, as it is the provides compensated estimated for own-price elasticity. The downside of these estimates is that they do not differentiate between food groups and lack some data for 11 countries in our sample as shown below in Table C2.3.

Compensating variation per country are similar to those we find in the main findings. We find that countries with largest damages are Lao PDR (4.44%), followed by Tajikistan (4.41%), Pakistan (4.27%) and Nepal (4.12%). Least impacted countries are Ethiopia (1.37%), Bulgaria (1.71%), Namibia (1.74%) and Kazakhstan (1.65%). Again, results are very similar to our main findings as reflected in Figure C2.4.

Table C2.3: Climate damages presented by compensating variation per consumption group per country based on estimates using compensated own price elasticities.

Country	Lowest	Low	Middle	Higher	National
Lao PDR	0.04525325	0.04313046	0.041923	0.0433297	0.04424094
Tajikistan	0.04577613	0.04478895	0.04196157	0.04052967	0.04410468
Pakistan	0.04243801	0.04314906	0.04364492	0.04425895	0.04270711
Nepal	0.04138887	0.04118269	0.0401042	0.04053405	0.04128139
Iraq	0.03991839	0.03966936	0.03955264	0.03960918	0.03966651
Bhutan	0.03771537	0.03889478	0.03868255	0.03769737	0.03850662
Madagascar	0.03837112	0.03240879	0.0191684	0.01858907	0.03771784
Azerbaijan	0.03805302	0.03744559	0.03674375	0.03813367	0.03739112
Bangladesh	0.03867106	0.03082786	0.02800249	0.02727187	0.03662286
Malawi	0.03684951	0.03562736	0.03355964	0.02785612	0.03640894
Sierra Leone	0.03878086	0.03532792	0.02905593	0.02681956	0.03617012
Vietnam	0.03734665	0.03433817	0.03219187	0.03329222	0.03590249
Burundi	0.03624629	0.03140092	0.02665615	NA	0.03582715
Liberia	0.03744424	0.03154615	0.02850309	NA	0.03581082
Togo	0.03573303	0.03601975	0.03555562	NA	0.03578847
Yemen, Rep.	0.03465598	0.0355059	0.03645081	0.03683936	0.03543067
Albania	0.03305646	0.03436194	0.03470061	0.03192672	0.03435567
Kyrgyz Republic	0.03227236	0.03428094	0.03499417	0.03542169	0.03373569
Uganda	0.03398559	0.03258472	0.02997616	0.02751983	0.03338124
Belarus	0.0270878	0.03078057	0.0335336	0.03449861	0.03335911
Cambodia	0.03286845	0.03345238	0.03466712	0.0337643	0.03332326
Benin	0.0333591	0.03266414	0.03078282	NA	0.03318671
China	0.03402812	0.03341021	0.03199507	0.03058619	0.03280825
Peru	0.0339256	0.03312947	0.03208068	0.03132425	0.03270289
Thailand	0.03474593	0.03339176	0.03095748	0.03154035	0.03262669
Ghana	0.03381042	0.03204722	0.0295333	0.02745915	0.03232146
India	0.03288549	0.03080628	0.02941315	0.03055678	0.03227635
Maldives	0.03246754	0.03207493	0.03100938	0.03101612	0.03200883
Nigeria	0.03069317	0.03129657	0.03108758	0.02838402	0.03084172
Tanzania	0.03034765	0.02857357	0.02521078	0.02680416	0.03007436
Guinea	0.03109498	0.02765923	0.02321632	NA	0.02998435
Sri Lanka	0.03165454	0.02967963	0.02729211	0.02734033	0.02988898
Colombia	0.03275124	0.03116546	0.02923925	0.02673073	0.02986838
Zambia	0.02964891	0.02882142	0.02870109	0.02813452	0.02941104
Bolivia	0.03078633	0.03001501	0.02865121	0.02652813	0.02938198
Brazil	0.0301107	0.02984044	0.02917543	0.02842015	0.02932509
Djibouti	0.03046707	0.02903001	0.02855732	0.02840344	0.02924242
Mali	0.02867956	0.03010824	0.02889933	0.02868993	0.028965
Ukraine	0.02960776	0.02892327	0.02879303	0.02873298	0.02883189
Philippines	0.03002399	0.02751738	0.02609919	0.0263321	0.02858194
Rwanda	0.02878057	0.02806074	0.02588659	0.02521763	0.02822971
Indonesia	0.02997439	0.02515191	0.02295953	0.02295405	0.02793866
Mozambique	0.02824969	0.02572114	0.02349443	0.01960376	0.02782177
Moldova	0.02667329	0.02750454	0.02767646	0.02752173	0.02750065
Gabon	0.0296621	0.02752201	0.02650545	0.02456622	0.02733908
Mexico	0.02845273	0.02766483	0.02644373	0.02502072	0.02724305

Armenia	0.02663585	0.02716993	0.02787435	0.02910161	0.02702409
Egypt, Arab Rep.	0.0273646	0.02663179	0.02551725	0.02403014	0.02684301
Congo, Dem. Rep.	0.0268884	0.0229038	0.0235491	0.02583436	0.02677416
Cameroon	0.02748252	0.02541661	0.02316082	0.02057892	0.02650553
Turkey	0.02683858	0.02607526	0.02640059	0.02616005	0.02627672
Gambia, The	0.02741144	0.02579409	0.02322893	0.02167696	0.02604654
Senegal	0.02723923	0.0238865	0.02264033	NA	0.02585022
Mauritania	0.02603305	0.02436799	0.02282403	0.02125651	0.02476732
Mongolia	0.02385638	0.02432414	0.0245915	0.02437913	0.02415605
Kenya	0.02490135	0.02355266	0.02046563	0.0165355	0.02414045
Niger	0.02354234	0.02722022	0.01990972	0.02392528	0.02390808
Congo, Rep.	0.02465214	0.02312891	0.02308522	0.02207473	0.02362409
Fiji	0.02349341	0.02378691	0.02310948	0.02303707	0.02354415
Mauritius	0.02407931	0.023525	0.02255798	0.02227843	0.02327245
Morocco	0.02278376	0.02263522	0.02255984	0.02224308	0.02262217
Romania	0.02247361	0.02218158	0.02202503	0.02145832	0.02208416
Swaziland	0.02121301	0.02306026	0.02309163	0.01918412	0.02203859
Serbia	0.02117333	0.02174666	0.02165564	0.02179614	0.02169356
Jordan	0.02162984	0.02161415	0.02071658	0.0197851	0.02110476
Lesotho	0.01906978	0.02005767	0.02252297	0.02475551	0.02021671
Montenegro	0.02259826	0.02074427	0.01989902	0.02082837	0.0201904
Macedonia, FYR	0.01934403	0.0194619	0.01966401	0.01997542	0.01966661
South Africa	0.0195815	0.01957051	0.01924848	0.01915251	0.01939804
Burkina Faso	0.01854813	0.02530692	0.02741462	0.02590869	0.01939141
Lithuania	0.01925575	0.01922978	0.01888927	0.01837018	0.01894766
Bosnia and Herzegovina	0.01756096	0.01735637	0.01838385	0.01909377	0.01867253
Chad	0.01772633	0.02020542	0.02035858	0.0115639	0.01856435
Russian Federation	0.02016171	0.01952573	0.01846398	0.01741179	0.01834388
Latvia	0.02067364	0.0185743	0.01817174	0.01762573	0.01819227
Kazakhstan	0.01750064	0.01784712	0.01782537	0.01727794	0.0178166
Namibia	0.01763825	0.01729701	0.01710609	0.01681857	0.01740779
Bulgaria	0.01822867	0.0171528	0.01726906	0.01647958	0.01715228
Ethiopia	0.01369461	0.01366303	0.01518253	0.01619009	0.013705
Afghanistan	0	0	0	0	0
Cabo Verde	0	0	0	0	0
Cote d'Ivoire	0	0	0	0	0
El Salvador	0	0	0	0	0
Guatemala	0	0	0	0	0
Honduras	0	0	0	0	0
Jamaica	0	0	0	0	0
Nicaragua	0	0	0	NA	0
Papua New Guinea	0	0	0	0	0
Sao Tome and Principe	0	0	0	0	0
Timor Leste	0	0	0	0	0

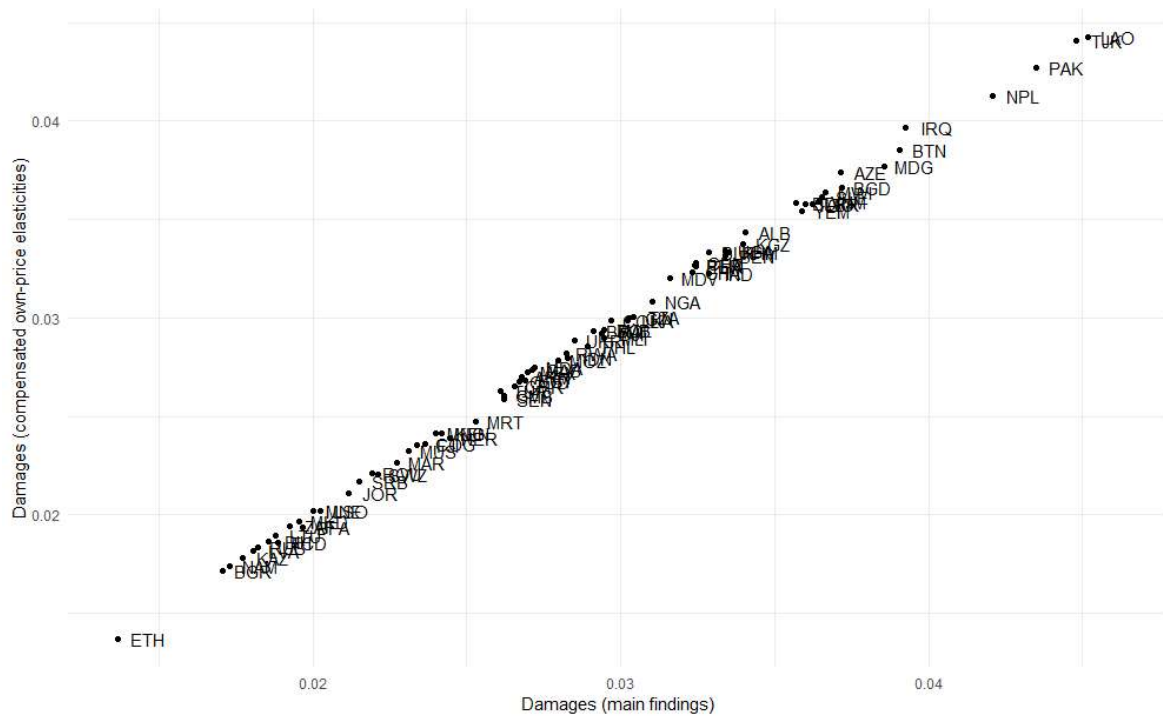


Figure B2.4: Damages estimates from main findings (x-axis) and damages estimates using compensated own-price elasticities (y-axis). Results from linear regression show a coefficient of 1.019, statistically significant at <1% level.

Looking at the differences within countries, we find that damages increase with expenditure and the slope of the line is the consumption elasticity has value of $\alpha=0.96$. Regressions analysis shows results similar to the main findings, where the logged expenditure is positively and significantly associated with consumption elasticity, with none of the consumption groups showing significant coefficients. Figure B2.5 emphasizes the similarity across both results, showing that estimates using compensated own-price elasticities are almost identical to those presented in the main findings.

Table C2.4: Regression results: dependent variable is the logged per-capita damages (Ln percapita CS). Explanatory variables are: logged expenditure (ln expenditure) and income groups: lowest, low, highest.

Dependent variable:	
ln_percapita_CS	
ln_expenditure	0.868*** (0.065)
lowest	-0.193 (0.134)
low	-0.078 (0.071)
highest	0.103 (0.079)
Constant	-2.515*** (0.553)
Observations	310
R ²	0.949
Adjusted R ²	0.948
Residual Std. Error	0.252 (df = 305)

F Statistic	1,416.553*** (df = 4; 305)
Note:	*p<0.1; **p<0.05; ***p<0.01

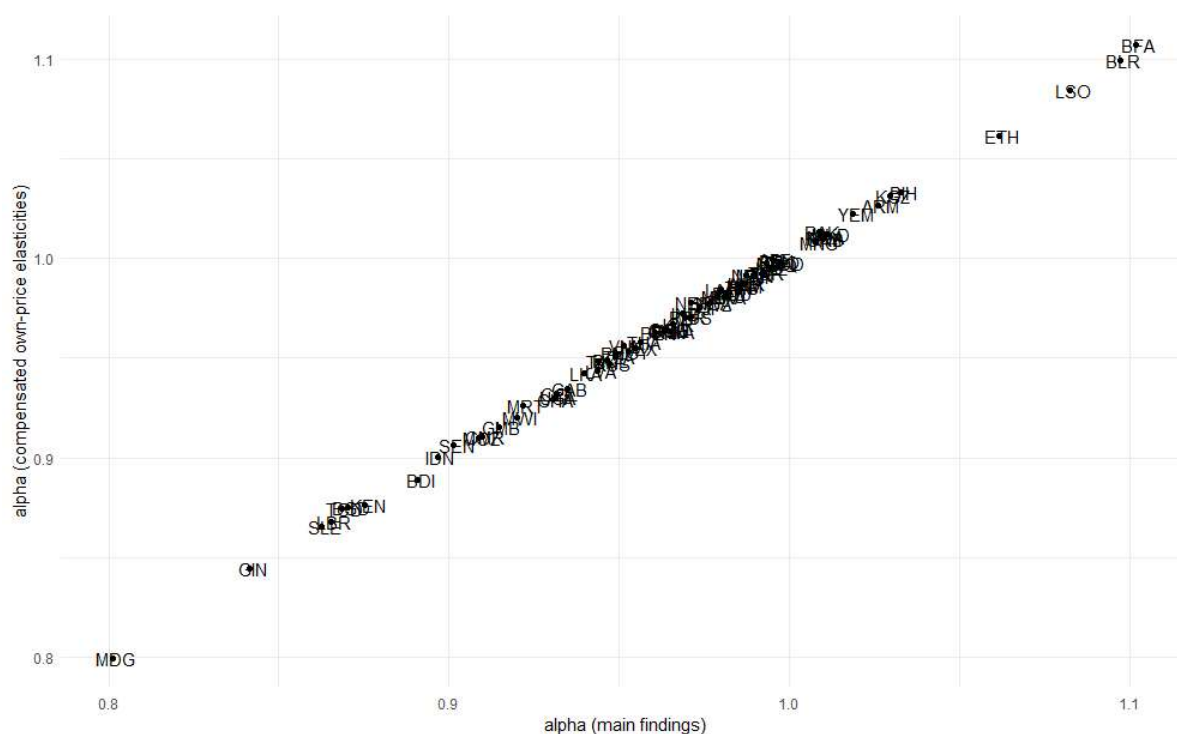


Figure C2.5: Consumption elasticity estimates from main findings (x-axis) and estimates without including cross-price elasticities (y-axis). Results from linear regression show a coefficient of 1.0007, statistically significant at <1% level.

As for the contribution of the main food groups to the compensating variation, again, we find similar to our main analysis, for the lowest income group, rice and vegetables contribute the most to the losses in consumer surplus, around 28.4% and 29.3%, respectively. As for the higher income group, we find that vegetables (33.5%), followed by fruits (27.1%) have the highest contribution (Figure C2.6)

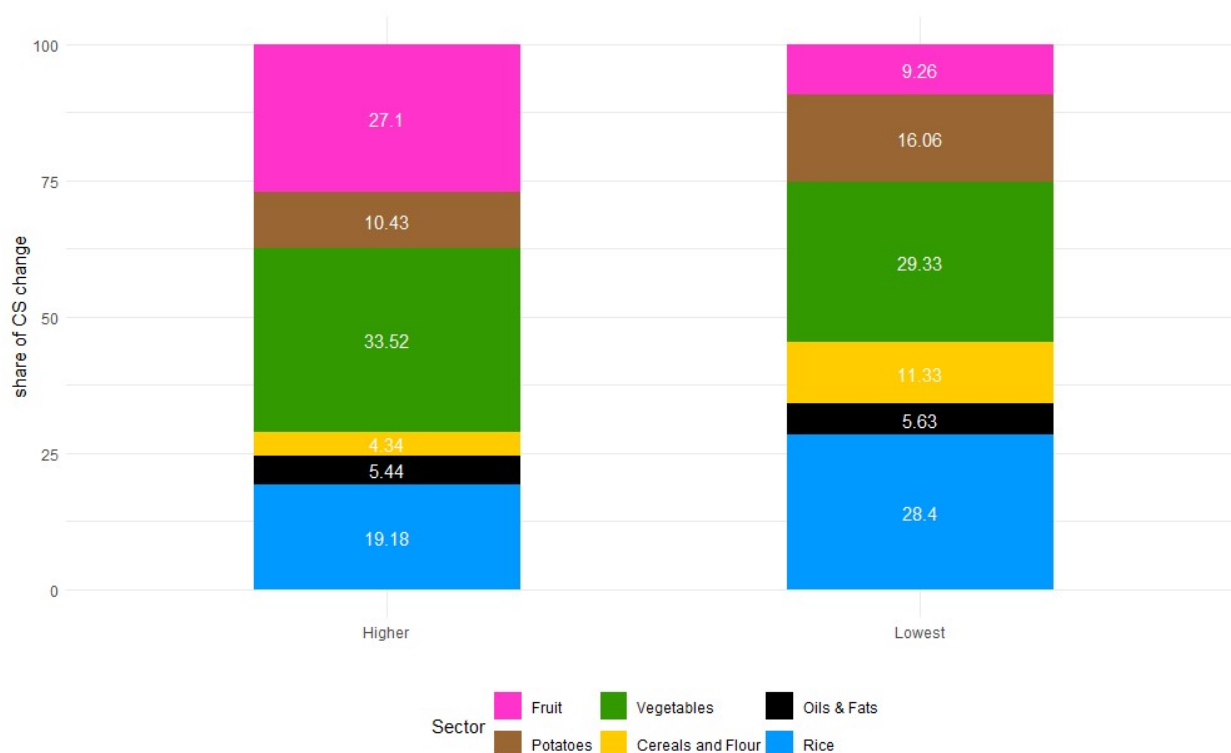


Figure C2.6: The share of each food sector's contribution to damages in the highest and lowest consumption groups across all countries.

C3 Income effects

Price increases arising due to climate change impact final consumers as well as producers. To get a measure of the net impact, we compare the losses in consumer surplus of our main analysis with a potential change in revenues for producers in food sectors as a result of the price increase and the final consumer response in demand to the price increases.

We use data from the GCD on households' consumption for each sector and we use data from GTAP on production value (in millions of dollars) to compute the total value captured by producers in the different sectors. It is important to point out that household consumption data face the challenge of under-reporting, in the sense that the reported households' expenditure is lower than actual expenditure (Dabalen et al 2016). This presents a challenge in our analysis of income effects as household expenditure here is relatively underestimated in comparison to our estimates on producer revenues that rely on national accounts.

Our measure of income change is the change in the total value captured of food sectors. The total value captured changes because (i) prices increase and (ii) demand decreases due to price increases. To compute the change in total value captured, we first assume that the producers of the raw agricultural products in Calzadilla et al (2013) have no additional costs associated with climate change but experience a higher price for their products (the initial cost pressure). Second, we compute the relative change in demand of households due to price increases using our price elasticities by country and by GTAP sector, and assume that governments and industries would adjust their final demand in the same relative way. We then take the previous demand vector y as computed in Section 2.2.3 and adjust it with the relative demand changes of households, government and industry. Hence, final demand is

reduced independent of where goods originated from. The result is a new demand vector y^* , with which we compute the total value captured as in section 3.2 in Ward et al (2019).

We compute the losses in consumer surplus and the change in total value captured by producers for each sector, consumption segment and country in PPP adjusted dollars. We then aggregate all sectors and deduct the consumer surplus loss from the change in total value captured, such that we get a net estimate of the impact of climate induced price increases.

We find that in our sample, 26 countries have a net gain arising from the increase in climate-induced price increases, this means that the total value captured by producers in the food sector exceeds the total losses borne by consumers. The remaining 63 countries in our sample suffer a net loss (Figure C3.1).¹³

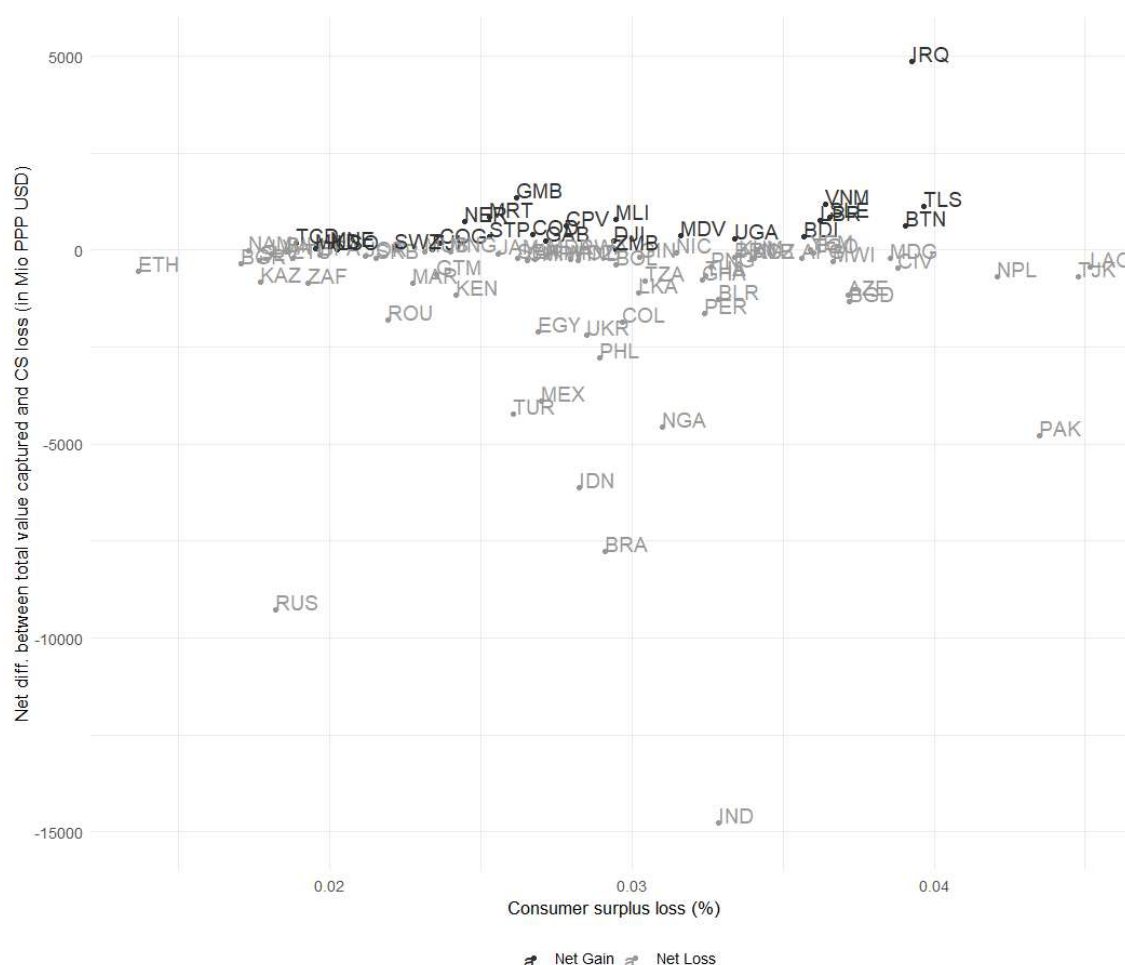


Figure C3.1: Net gains and losses against the relative damage per country. Net gains and losses is the net difference between total value captured in million USD and the consumer surplus loss in million USD. Note: this figure lacks 1 observation to increase readability: China (net loss: 47.8 billion USD).

Given the evidence of regressivity presented in our main findings, we want to quantify how much of the value that is captured by the producers is needed to offset the losses in consumer surplus for the lowest consumption segment. We do that for the 26 countries that have a net gain by dividing the consumer surplus losses for the lowest consumption segment by the change in total revenues. We get a share of revenues that would be sufficient to offset

¹³ Yemen is missing due to missing data on PPP conversion factor from the World Development Indicators.

the losses of the lowest consumption segment. We find on average 11% of the additional income is needed to offset the losses of the lowest consumption segment, which represent an average of 44% of total country-level consumer surplus losses. Overall, the majority of countries need less than 20% of the additional income to offset losses of the lowest consumption segment. However, we observe some higher offsets for Zambia, the Democratic Republic of Congo, Uganda and Vietnam. The country with highest share of needed offset is Zambia, with around 57% of additional income needed to offset the lowest consumption segment’s losses, which represent around 72% of total country-level consumer surplus losses. The Democratic Republic of Congo comes in second with an offset of 40% of total additional income for the consumer surplus losses borne by the lowest consumption segment; this consumption segment represents 97% of total consumer surplus losses in the country.

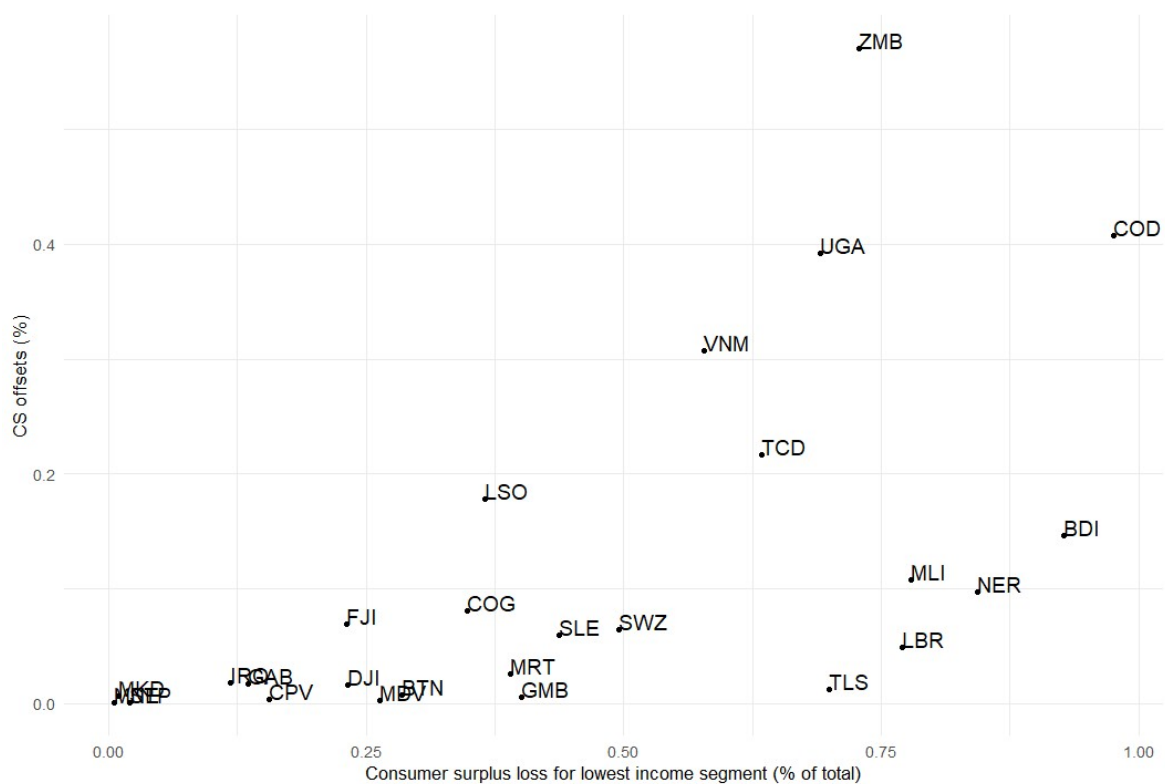


Figure C3.2: Share in additional revenues needed to offset the consumer surplus loss of the lowest consumption segment by country, for which national gains in revenue are positive.

D Data Availability

Data and scripts are available under the following [link](#)