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Global Economic Impacts of Physical Climate Risks

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Abstract

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Keywords

Climate change, Climate risks, Extreme events, Macroeconomic modelling

JEL Classification

C51, C53, C54, C55, C68, F41, Q51, Q54

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GLOBAL ECONOMIC IMPACTS OF PHYSICAL CLIMATE RISKS

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ABSTRACT

This paper evaluates the global economic consequences of physical climate risks under two Shared Socioeconomic Pathways (SSP 1-2.6 and SSP 2-4.5) using firm-level evidence. Firstly, we estimate the historical sectoral productivity changes from chronic climate risks (gradual changes in temperature and precipitation) and extreme climate risks (representative of heatwaves, coldwaves, droughts, and floods). Secondly, we produce forward-looking sectoral productivity changes for a global multisectoral sample of firms. For floods, these estimates account for the productivity changes from the damage to firms' physical capital. Thirdly, we assess the macroeconomic impact of these shocks within the global, multisectoral, intertemporal general equilibrium model: G-Cubed. The results indicate that, in the absence of additional adaptation relative to that already achieved by 2020, all the economies would experience substantial losses under the two climate scenarios, and the losses would increase with global warming. The results can be useful for policymakers and practitioners interested in conducting climate risk analysis.

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1.0 INTRODUCTION

The Intergovernmental Panel on Climate Change (IPCC), in one of its latest reports (IPCC 2021), notes that many changes in the climate system are becoming larger, including increases in the frequency and intensity of natural hazards, as a result of *physical climate risks* emerging from global warming. These include both *extreme risks* (also called acute risks) from extreme weather events[2], such as heat and cold waves, droughts, and floods, and *chronic risks,* reflecting the potential impacts of long-term changes in climate patterns, such as those in temperature, precipitation, and sea level.

An extensive and fast-growing body of literature has attempted to estimate the potential economic impact of physical risks. However, most of the literature focuses on chronic risks, while studies to estimate the economic impact of extreme risks are lagging. Analyses of the combined effect of both chronic and extreme risks within a single framework are even rarer. Furthermore, studies on disaggregated sectoral heterogeneous impacts and their transmission across countries are also scarce. Filling these gaps is important for climate risk analysis and has been the focus of the Network for Greening the Financial System (NGFS) for their latest vintage of scenarios (2022a, b)[3].

This paper addresses these gaps in the literature in two main ways. Firstly, we estimate sectoral changes in Total Factor Productivity (TFP)[4] due to physical climate risks. This is to capture both the immediate and long-lasting decline in productivity from both extreme and chronic risks. To achieve this, we use two types of damage functions.

The first type of damage functions, empirically derived within this paper, accounts for the sectoral productivity impact of physical climate risks at the firm level. We consider a global multisectoral sample of 20,215 firms from 48 countries, for which we have historical TFP estimates, and derive the damage functions separately for four broad sectors: agriculture, mining, manufacturing, and services. The damage functions account for both chronic (changes in average temperature and precipitation from a historical

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[2] The IPCC defines an extreme weather event as: "an event that is rare at a particular place and time of year. Definitions of rare vary, but an extreme weather event would normally be as rare as or rarer than the 10th or 90th percentile of a probability density function estimated from observations. By definition, the characteristics of what is called extreme weather may vary from place to place in an absolute sense. When a pattern of extreme weather persists for some time, such as a season, it may be classed as an extreme climate event, especially if it yields an average or total that is itself extreme (e.g., drought or heavy rainfall over a season)."

[3] NGFS Phase III Scenarios (NGFS 2022b) includes the impacts of acute physical risks (floods and tropical cyclones) for different scenarios. However, the impacts are only computed for GDP and no other macro-financial variable. The impacts of chronic and extreme risks are also only evaluated separately. For the NGFS Phase II Scenarios, the NGFS investigated how to increase the granularity of sectoral breakdown using the G-Cubed model (NGFS 2022a). The NGFS concluded that: "*While divergences in the results generated by the G-Cubed model and the existing NGFS models mean that we cannot incorporate the sectoral breakdown into our NGFS scenarios at this stage, the G-Cubed model undoubtedly provides a rich set of insights.*"

[4] Following the climate economic literature, we study the evolution of physical risk over time due to changes in the climate indicators but do not consider changes in exposures and vulnerabilities. In this respect, we deviate from the IPCC definition of physical risk (Reisinger et al. 2020).

baseline) and some extreme risks (extreme conditions related to temperature and precipitation)[5]. We then use these damage functions to project forward up to 2100 the productivity impact of physical risks for a broader sample covering the largest 1,000 firms by asset size in each member nation of the International Monetary Fund (IMF)[6]. The projections are for two climate scenarios, defined by Shared Socioeconomic Pathways (SSPs) and the approximate global effective radiative forcing achieved from the emission concentration resulting from the Representative Concentration Pathways related to the SSPs. Specifically, we consider SSP 1-2.6 and SSP 2-4.5, representing a low and an intermediate greenhouse gas emission scenario, respectively[7].

The second type of damage functions, which is from an existing global study (Huizinga et al. 2017), allows us to assess the impact of floods (coastal and river) on firms' physical capital for different sectors[8]. Depending on the reliance of the firms on capital as an input for production, we project forward the persistent effects on firms' productivity due to floods under the two SSPs.

Secondly, we feed these sectoral productivity shocks to the global, multisectoral, intertemporal general equilibrium model, G-Cubed, and illustrate the global economic consequences of the two SSPs.

Our results indicate that all sectors will experience losses from the projected sectoral productivity changes due to physical climate risks. However, the magnitude of the losses is heterogeneous across sectors and regions. Agriculture is the most vulnerable sector, with its productivity reducing by 10 – 20 percent in most regions under the two SSPs. The mining sector also experiences notable losses, which exceed five percent in certain regions under the two SSPs. The manufacturing and service sectors are the least affected, potentially due to the higher degree of flexibility in locating their operations, thereby reducing their exposure to physical climate risks.

When examining the macroeconomic impacts of these shocks, the results indicate substantial losses to all the economies under the two SSPs, and the losses increase with global warming. Climate shocks under SSP 1-2.6 could cost the world 1.2 percent of GDP per annum on average from 2021 to 2100 (2.4 percent of GDP in 2100). Under SSP 2-4.5, the losses could more than double, amounting to 3.2 percent of GDP per annum on average from 2021 to 2100 (6.4 percent of GDP in 2100).

We illustrate the substantial change in consumption and investment patterns across the world. Given the physical adjustment costs in G-Cubed, we illustrate how the investment contractions could be much larger when exposed to climate shocks. Given the supply-side shocks, adjustments to consumption, and relative

[5] These extreme climate indicators are relatable to heatwaves, coldwaves, droughts, and extreme precipitation.

[6] Specifically, the sample consists of 59,554 firms. The largest 1,000 firms by asset size in each member nation of the International Monetary Fund have been selected according to the aggregate asset value reported in the Orbis database by the firms for the latest financial year after 2018.

[7] See Section 2.3 for more details on the scenarios.

[8] We note that other extreme events, such as tropical cyclones and wildfires, are not explicitly accounted for in our model. We leave this extension for future studies.

price changes, we illustrate how imports and exports change amidst climate change. We also demonstrate the changes in other macro-financial variables (real interest rates, current account balance, real exchange rate, trade balance, and inflation) from the readjustments to the global economy amidst the physical climate risks under the two SSPs.

We further utilize the sectoral disaggregation in the G-Cubed to illustrate how different sectors would be affected when exposed to climate shocks. The general equilibrium effects in the model allow us to illustrate how two sectors in the same region would be affected differently when faced with the same shock. We also demonstrate how the same shock to the same sector in two different regions could lead to different consequences. We emphasize the importance of general equilibrium effects when analyzing climate shocks and how those effects provide richer insights compared to models without such effects.

Our study contributes primarily to two streams of literature: studies on firms and the sectoral impact of physical risks and studies adopting various approaches (Integrated Assessment Models (IAMs), econometrics, and economic modeling) to evaluate how climate change could affect economies[9].

The former stream of literature has primarily focused on the agriculture sector, with only a few studies focusing on the other sectors. Further, papers are mostly limited to a single region, if not to a country, and focus primarily on temperature and precipitation and rarely on extreme conditions. We contribute to this literature by looking at different sectors using a global sample of firms and considering both chronic and extreme physical risks.

The latter stream of literature tends to consider the entire economy as a whole, ignoring sectoral heterogeneity in their estimates and lacking firm-level effects. The closer papers for this paper, accounting for sectoral changes, are Fernando (2023) and Fernando et al. (2021). They also adopt the G-Cubed to estimate the global economic consequences of climate shocks. Fernando et al. (2021) investigate the economic impacts of both physical and transition risks[10] on different sectors[11] in different economies. We extend their framework by estimating the sectoral productivity impacts of physical risks using firm-level data. Further, we incorporate persistent productivity impacts from flood damage to firms' physical capital.

We note the existing debate on whether certain sectors (such as agriculture and services) in certain regions (such as Canada and Russia) could benefit from warmer climates. This paper does not observe these positive effects due to at least two main differences from those studies supporting the claim. Firstly, those studies supporting the claim assume adaptation (such as via mass migration), whereas this paper does not assume any additional adaptation other than those undertaken by 2020. Assessing the likelihood and impact of such assumptions regarding adaptation is beyond the scope of this paper. Secondly, most of the quantitative

[9] We refer to Sections 2.7 and 3.2 for additional discussions on these two streams of literature, respectively.

[10] That is the macroeconomic effects of climate policies designed to transition to low-carbon economies.

[11] A granular sectoral representation is one of the key advantages of the G-Cubed model for assessing climate risks. We refer to NGFS (2022a) for a review of Integrated Assessment Models and a comparison with G-Cubed.

studies supporting the claim only assume the chronic effects of climate change on crops. In contrast, this paper incorporates both chronic and extreme effects of climate change and the entire agriculture sector, including livestock and crops.

The results produced in this paper can be used as scenarios for policymakers and practitioners interested in conducting climate risk analysis. As noted by the NGFS (2022a, b), these types of scenarios help central banks and supervisors explore the possible impacts of the physical risks on the economy and the financial system. Relative to the NGFS scenarios, we assess the impact of both chronic and extreme climate risks on a broad set of macro-financial and sectoral variables. Our macro-financial results can be used to assess the risks and impact on bank capital via standard stress testing approaches for credit and market risks. We refer to Adrian et al. (2022) for more details and a discussion on different approaches to climate risk analysis for the banking sector in the context of the IMF Financial Sector Assessment Programs (FSAP).

The rest of the paper is organized as follows. Section 2 discusses the estimation of the sectoral impacts of physical climate risks, detailing the firm data, climate scenarios, climate data, climate indicators, empirical estimation of sectoral productivity changes due to physical climate risks, and the projected sectoral impacts from physical climate risks. Section 3 outlines the global, multisectoral, intertemporal hybrid DSGE-CGE model: the G-Cubed, used to project the economic consequences under the two SSPs, and how the economic shocks are derived from the empirical estimates. Section 4 illustrates the results from the G-Cubed simulations. Section 5 discusses the policy implications of the study, and Section 6 concludes with a summary of the study.

2.0 SECTORAL IMPACTS OF PHYSICAL CLIMATE RISK

2.1 Overview

This section outlines the data and methodology used to estimate the sectoral impacts of physical climate risks. Sections 2.2, 2.3, and 2.4 describe the firms' data, climate scenarios, and climate data used in this paper, respectively. Section 2.5 introduces the climate indicators that are constructed using the climate data. Section 2.6 describes the empirical estimation strategy, combining firm-level data with climate indicators to derive the productivity impacts of physical climate risks. Section 2.7 discusses the results from empirical estimations and the projected productivity impacts of physical climate risks under the two SSPs. Section 2.8 outlines the data used to calculate the persistent productivity changes from flood damage to firms' physical capital and introduces the projected impacts under the two SSPs. Section 2.9 summarizes Section 2.

2.2 Firm Data

In order to estimate sectoral productivity changes from physical climate risks, we use a multi-county and multisectoral sample of 59,554 firms (Sample 1). The firms have been selected as the top 1,000 non-financial firms from each IMF member nation, for which data are available according to the aggregate asset value reported by the firms for the latest financial year after 2018. We incorporate all the available firms into our sample for countries with less than 1,000 firms in the Bureau van Dijk Orbis database (hereafter Orbis database). The final sample of firms is spread across 147 countries, and they can be broadly aggregated into four sectors: agriculture, mining, manufacturing, and services, following the Standard Classification of Economic Activities in the European Community (NACE).

We obtain the firms' financial data from the Orbis database from 2000 to 2018. We also extract the addresses of the firms from the database to identify their locations. The addresses of the firms available from the Orbis database are consistently available only for the head offices of the firms. Therefore, in this paper, the firms' locations are represented only via head office locations. Future studies could attempt to incorporate the locations of all the establishments for a given firm[12].

The financial data has been cleaned following the procedure outlined in Kalemli-Ozcan et al. (2015), and TFP for firms has been computed following the approach by Ackerberg et al. (2015). However, due to the lack of additional information (such as industry-specific deflators) which is required to clean the data, the cleaned dataset is available only for 20,215 firms (Sample 2) spread across 48 countries (out of the 59,554 firms spread across 147 countries). Figures 1 and 2 present the distribution of the 59,554 and 20,215 firms across the four broad sectors and the United Nations (UN) regions, respectively. Table 1 summarizes the number of firms and countries covered within the two samples from each sector. Supplementary Annexure 1 outlines the distribution of the 59,554 firms and 20,215 firms across the UN countries and regions.

As reflected in Figures 1 and 2, Table 1, and Supplementary Annexure 1, both samples consist of a higher number of firms from the manufacturing and services sectors compared to the agriculture and mining sectors. Data for a higher number of firms is available from Europe, in general. It is also evident that although the number of firms for which financial data is available is lower, the distribution of the firms in the two samples, both across the regions and sectors, remains roughly constant. Thus, the firms from the second sample (Sample 2), which are used to estimate the climate damage functions for TFP, are assumed to be representative of the larger first sample of firms (Sample 1), which is used to project the sectoral productivity impacts under the two SSPs.

Supplementary Annexure 2 summarizes the historical average annual growth in operating revenue, operating profit, fixed assets, capital, labor costs, material costs, and TFP across the firms from Sample 2 from 2001 to 2018. The financials of the firms have been aggregated across the four broad sectors and the UN regions.

[12] For example, Pelli et al. (2020) use the Google Places algorithm to identify the locations of all establishments for a given firm for a study on the vulnerability of the capital stock of Indian manufacturing firms to storms.

Table 1: Distribution of Firms across Sectors and Countries

Sectors	Sample 1 (59,554)		Sample 2 (20,215)	
	No. of Firms	No. of Countries	No. of Firms	No. of Countries
Agriculture	1,401	91	519	45
Mining	1,605	101	464	46
Manufacturing	15,849	125	6,945	48
Services	40,699	143	12,287	47

Source: Constructed by Authors.

2.3 Climate Scenarios

The IPCC has developed emission scenarios for climate modelers to adopt since 1990. The initiative aims to provide a range of alternative futures representing different carbon emission pathways built on various socioeconomic and technological growth assumptions. Using these common scenarios helps to harmonize the modeling outputs from impact models to be better compared[13].

This paper focuses on two of the five scenarios introduced in the IPCC Sixth Assessment Report as Shared Socioeconomic Pathways (SSPs). The SSPs are denoted with two numbers. The first number refers to the SSP, and the second number refers to the Representative Concentration Pathway (RCP) related to the SSP. Thus, the numbers indicate the approximate global radiative forcing achieved by a particular SSP by 2100. The complete narratives underlying SSPs are provided in Supplementary Annexure 3. Table 2 summarizes the warming outcomes under the SSPs. The two SSPs focused on in this paper, namely SSP 1-2.6 and SSP 2-4.5, represent low and intermediate greenhouse gas emission concentration pathways. This paper excludes very low, high, and very high greenhouse gas emission concentration pathways mainly due to data availability[14].

It is also worth noting that these scenarios are used to obtain a range of estimates for the economic consequences of physical climate risks. We do not attribute any likelihood to any of the scenarios and do not assume any scenario to be "business as usual". Hausfather and Peters (2020) provide a detailed discussion on how best to interpret RCPs, which provide the warming pathways for SSPs, in line with the most recent developments in climate science.

[13] See O'Neill et al. (2016) for more details.

[14] Specifically, the projected data for floods described in Section 2.4 is only available for SSP 1-2.6, SSP 2-4.5, and SSP5-8.5. We exclude SSP 5-8.5 as it is an extreme scenario, and its viability is heavily debated in the literature.

Figure 1: Distribution of the Sample 1 Firms across Broad Sectors and United Nations Regions

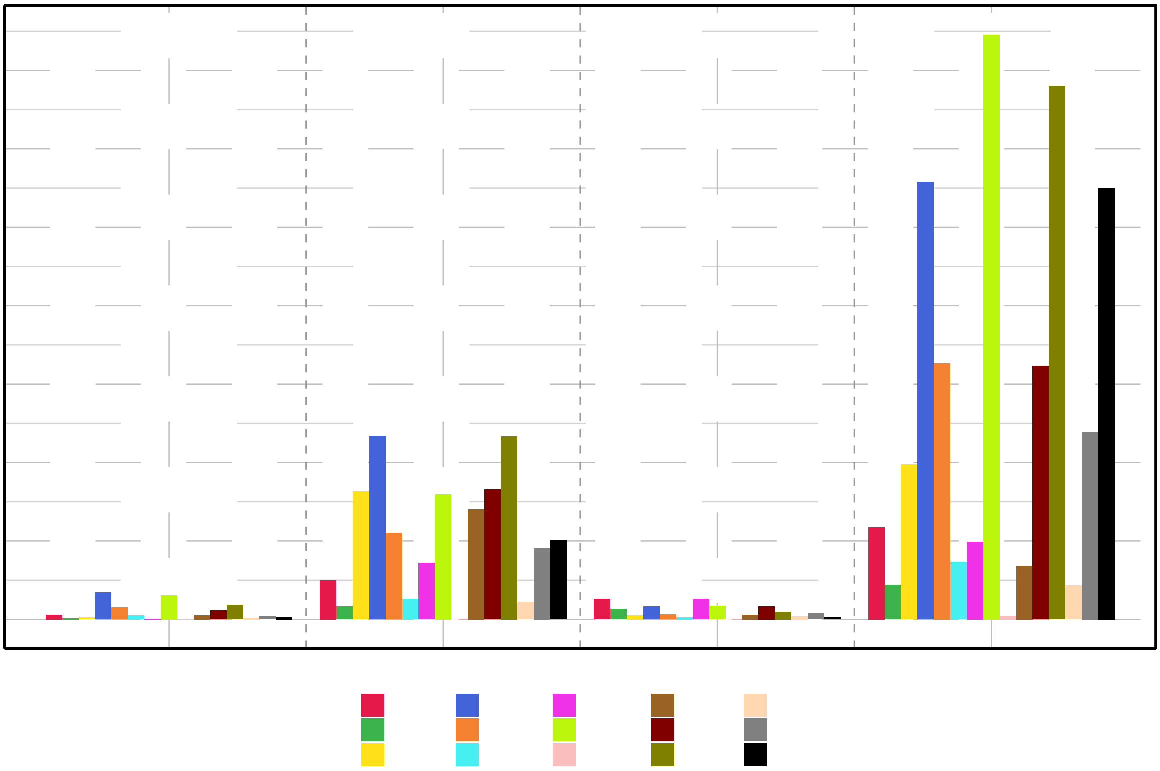


Figure 2: Distribution of the Sample 2 Firms across Broad Sectors and United Nations Regions

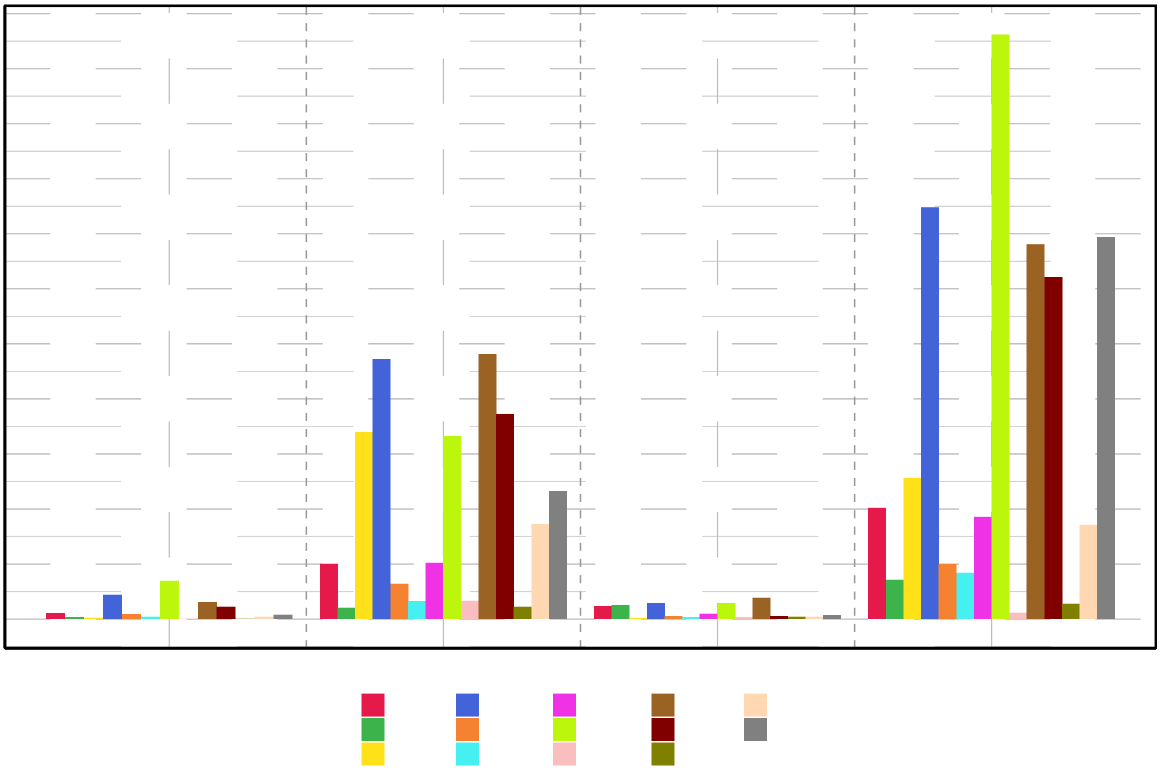


Table 2: Temperature Outcomes under SSPs

SSP	Scenario	Estimated Global Warming		
		2041-2060 (^0C)	2081-2100 (^0C)	2081-2100 (Range in ^0C)
SSP1-1.9	Very low GHG emissions: CO_2 emissions reduced to net zero around 2050	1.6	1.4	1.0 – 1.8
SSP1-2.6	Low GHG emissions: CO_2 emissions reduced to net zero around 2075	1.7	1.8	1.3 – 2.4
SSP2-4.5	Intermediate GHG emissions: CO_2 emissions around current levels until 2050, then falling but not reaching net zero by 2100	2.0	2.7	2.1 – 3.5
SSP3-7.0	High GHG emissions: CO_2 emissions double by 2100	2.1	3.6	2.8 – 4.6
SSP5-8.5	Very high GHG emissions: CO_2 emissions triple by 2075	2.4	4.4	3.3 – 5.7

Source: IPCC (2021).

2.4 Climate Data

Historical Climate Data

We use the historical data on climate variables from the Climate Research Unit of the University of East Anglia (2022) for the empirical estimation of the sectoral productivity impact of climate risks. The data is available at monthly frequencies from 1901 to 2020 at 3 arcsec (0.5^0 x 0.5^0) resolution for different climate variables[15]. We use the data on Mean, Maximum, and Minimum Temperature and Precipitation from 1961 to 2020 to obtain indicators of chronic and extreme climate risks as described in Section 2.5. We process the data for both monthly and annual frequencies for the 59,554 firms and 147 countries[16] in Sample 1.

We compute these climate indicators for both the firm location, represented by the address of the head office as explained in Section 2.2, and the country the firm belongs to in order to evaluate how productivity changes are affected both by firm-specific (which we also call unsystematic) and country-level (which we also call systematic) changes in climate risks. Accounting for both systematic and unsystematic risks acknowledges that the firm-level TFP could be affected not only by the changes in firm-specific climate

[15] Specifically: Cloud cover, Diurnal Temperature Range, Frost Day Frequency, Mean Temperature, Maximum Temperature, Minimum Temperature, Potential Evapotranspiration, Precipitation, Vapor Pressure, and Wet Day Frequency.

[16] When associating a firm's geolocation with climate data, the firm's latitude and longitude coordinates are rounded to the nearest 0.5^0, and the value of the climate observation at the particular grid is attributed to the firm.

risks but also by the changes in climate risks the country (in which a given firm is situated) faces as a whole. This is because the home country houses other domestic establishments of the firm, the domestic production network of the firm, and the domestic infrastructure on which the firm relies. Furthermore, since only the location of the main address of the firm is available from the Orbis database, this approach also allows us to partially account for the climate impacts on the rest of the firm establishments spread across the country and their implications on the firm-level TFP[17].

Projected Climate Data for SSPs

We use the data on climate variables under SSPs from the Geophysical Fluid Dynamics Library Earth System Model as reported by the Intersectoral Impact Model Intercomparison Project (ISIMIP) (Potsdam-Institute for Climate Impact Research 2022). The daily data is available from 2016 to 2100 at 3 arcsec (0.5^0 x 0.5^0) resolution for Mean Temperature, Maximum Temperature, Minimum Temperature, and Precipitation. We use the data from 2020 to 2100 to obtain chronic and extreme climate risk indicators, described in Section 2.5, under the two SSPs. We process the data for both monthly and annual frequencies for 59,554 firms and 147 countries in Sample 1.

In addition, we obtain riverine and coastal flood severity projections for the same sample of firms under the SSPs from a private data provider, Jupiter Intelligence[18]. Specifically, Jupiter Intelligence provides the projected flood depths and the fraction of land flooded at the firm locations under 10, 20, 50,100, 200, or 500-year return periods. The measures are provided from 2020 to 2100 with 5-year increments at 3 arcsec (0.5^0 x 0.5^0) grid resolution.

2.5 Chronic and Extreme Climate Indicators

As indicators of chronic climate risks, we construct the annual changes in temperature and precipitation from the 1961-1990 historical climate baseline. The indicators are constructed for each firm location and country using historical temperature and precipitation data. Table 3 summarizes the two chronic climate indicators constructed.

As indicators of extreme climate risks, we construct several indicators following the approaches in Lai and Dzombak (2019)[19] for extreme temperatures and McKee et al. (1993) for extreme precipitation using the Standardized Precipitation Index (SPI). The extreme climate indicators use the monthly values of Maximum

[17] This approach, however, cannot control for the exposure a multinational firm would have with its establishments across multiple countries in addition to the domestic country.

[18] For coastal floods, Jupiter Intelligence uses multiple climate projection datasets to estimate the effects of sea-level rise, storm surge, and tides on coastal inundation and storm surge and lake levels on lake shoreline inundation. For riverine floods, their inland river flooding model uses projected regional changes in extreme streamflow to estimate how flood depth and extent may change under a future climate. We also note that Jupiter accounts for adaptation measures in some countries. Specifically, for Germany, the Netherlands, the UK, and the USA, Jupiter assumes that locations currently protected by levees will be protected up to and including a 100-year flood in the future.

[19] Their indices were selected based on those defined and used in the IPCC Assessment Reports [i.e., the World Meteorological Organization's Expert Team on Climate Change Detection and Indices (ETCCDI)].

Temperature, Minimum Temperature, and Precipitation to identify short and long-term extreme conditions associated with temperature and precipitation.

The extreme climate indicators of temperature evaluate how the monthly maximum (or minimum) temperature has deviated from the 90th and 10th percentiles of the historical (1961-1990) climate baseline distribution of monthly maximum (or minimum) temperatures. Assuming the maximum temperature of a day is experienced during the daytime, a maximum temperature exceeding the 90th percentile of the baseline maximum temperature distribution indicates a month with warmer days on average, and a maximum temperature experienced below the 10th percentile of the baseline maximum temperature distribution indicates a month with colder days on average. Similarly, assuming the minimum temperature of a day is experienced during the night, a minimum temperature exceeding the 90th percentile of the baseline minimum temperature distribution indicates a month with warmer nights on average, and a minimum temperature experienced below the 10th percentile of the baseline minimum temperature distribution indicates a month with colder nights on average. We construct these short-term extreme temperature indicators for each month at each firm location and country for both the historical period (1991-2020) and the projected period (2021-2100) under the two SSPs and obtain the annual average percentage deviation of the maximum (or minimum) temperatures from the 90th and 10th percentiles of the historical climate baseline distribution.

The extreme climate indicators of precipitation evaluate how monthly precipitation patterns for a given firm location or a country have changed compared to the historical (1961-1990) climate baseline distribution. SPI is one such indicator widely used in meteorology to identify dry and wet conditions. SPI is a statistical indicator comparing the total precipitation received at a particular location during a period of n months with the long-term rainfall distribution for the same period at that location. It is calculated monthly for a moving window of n months, where n indicates the rainfall accumulation period, typically 1, 3, 6, 9, 12, 24, or 48 months (European Commission 2013). Following the procedure in McKee et al. (1993), we calculate the monthly SPI across all firms' locations and countries for both the historical period (1991-2020) and the projected period (2021-2100) under the two SSPs. We then obtain the percentage deviation of those values from extremely dry and wet conditions, defined as SPI values lower than -2 and higher than 2, respectively[20]. We use the annual average of the monthly values to obtain the indicators.

Table 3 summarizes the six extreme climate indicators constructed: (1) MaxTemp90P as an indicator of short-term extremely warm conditions during the day; (2) MaxTemp10P as an indicator of short-term extremely cold conditions during the day; (3) MinTemp90P as an indicator of short-term extremely warm conditions during the night; (4) MinTemp10P as an indicator of short-term extremely cold conditions during the night; (5) SPIDry as an indicator of long-term extremely dry conditions, and (6) SPIWet as an

[20] Following McKee et al. (1993), World Meteorological Organization (2012) defines SPI ranges as below: Extremely wet: SPI > 2; Very wet: 1.5 < SPI < 1.99; Moderately wet: 1.0 < SPI < 1.49; Near Normal: -0.99 < SPI 0.99; Moderately Dry: -1.0 < SPI < -1.49; Severely Dry: -1.5 < SPI < -1.99; Extremely Dry: SPI < -2.

indicator of long-term extremely wet conditions. Following the insights in the literature[21] using indicators of extreme conditions, our indicators relate to heatwaves, coldwaves, droughts, and extreme precipitation events.

The indicators of extreme conditions should not, however, be interpreted as indicators of extreme events, as the occurrence of extreme events[22] would depend on a complex set of other factors, including local weather conditions and land-use management practices, which we do not explicitly account for when constructing the indicators of extreme conditions. Only for floods, we estimate the damage to firms' physical capital separately, using a different methodology, as explained in Section 2.8.

We also note that, as discussed in Akyapi et al. (2022), extreme weather events lack an unambiguous definition, and a vast number of possible measures exist for extreme climate indicators. Our approach is to draw from the existing literature to select some of the most commonly used extreme climate indicators for temperature and precipitation. However, evaluating the most relevant climate indicators to explain sectoral productivity changes among all possible indicators is beyond the scope of this paper and is left for future studies[23].

Annexure 1 shows the average historical (1991-2020) deviation of the climate indicators relative to 1961-1990 across the UN regions. Annexure 2 summarizes the average forward-looking projected (2021-2100) deviation of the climate indicators relative to 1961-1990 across the UN regions under the two SSPs. We also present the average historical and projected deviation of climate indicators relative to 1961-1990 at firm locations by the broad sectors and the UN regions. Supplementary Annexures 4-6 summarize the historical and projected exposure of the Agriculture, Mining, Manufacturing, and Services sectors to chronic climate risks, extreme temperature-related conditions, and extreme precipitation-related conditions, respectively.

[21] Russo et al. (2014) use short-term indicators of extreme conditions to project heat and coldwaves. A few recent studies using SPI to predict droughts and/or extreme precipitation events include Ekwezuo et al. (2020) for West Africa, Ali et al. (2020) for Pakistan, Bhunia et al. (2020) for India, Golian et al. (2015) for Iran, Wang and Cao (2011) for China, and Manasta et al. (2010) for Zimbabwe.

[22] An alternative approach to constructing extreme climate risk indicators would be to use historical data on extreme events. To the best of our knowledge, the EM-DAT (Centre for Research on the Epidemiology of Disasters 2022) database provides the most comprehensive open-source collation of historical extreme events and their details, including the location, duration, magnitude (where applicable), lives affected, lives lost, insured losses, and total damages. However, we observe that the details reported, especially pertaining to the location, magnitude, and duration of the events, are not complete and consistent. Furthermore, the database only reports events that meet certain criteria specific to the event category, which could lead to underreporting. Given these limitations, we do not use historical data on extreme events but rather construct indicators of extreme conditions using climate variables. The approaches followed when constructing the indicators are common and applicable to the entire world alike.

[23] We refer to Akyapi et al. (2022) for a comprehensive discussion of weather variables and a methodology to select the weather variables that contribute the most to explaining macroeconomic outcomes.

Table 3: Indicators of Chronic and Extreme Climate Conditions

	Indicator	Description	Unit
Chronic Climate Indicators			
1	Mean Temperature	Change in the mean annual temperature compared to the mean annual temperature within the baseline period of 1961 – 1990.	^{0}C
2	Precipitation	Percentage change in annual total precipitation compared to the mean annual total precipitation within the baseline period of 1961 – 1990.	%
Extreme Climate Indicators			
4	MaxTemp90P	In a given year, the average percentage change of the monthly maximum temperature from the 90th percentile of the 1961 – 1990 monthly maximum temperature distribution.	%
5	MaxTemp10P	In a given year, the average percentage change of the monthly maximum temperature from the 10th percentile of the 1961 – 1990 monthly maximum temperature distribution.	%
6	MinTemp90P	In a given year, the average percentage change of the monthly minimum temperature from the 90th percentile of the 1961 – 1990 monthly minimum temperature distribution.	%
7	MinTemp10P	In a given year, the average percentage change of the monthly minimum temperature from the 10th percentile of the 1961 – 1990 monthly minimum temperature distribution.	%
8	SPIDry	In a given year, the average percentage deviation of the monthly SPI index from -2 (SPI Index < -2 indicates Extreme Dry conditions).	%
9	SPIWet	In a given year, the average percentage deviation of the monthly SPI index from 2 (SPI Index > 2 indicates Extreme Wet conditions).	%

Source: Constructed by the Authors based on Lai and Dzombak (2019) and McKee et al. (1993).

2.6 Estimation of the Sectoral Productivity Impact of Physical Climate Risks

Following the standard definition of productivity in economics[24], we refer to productivity as a measure of a firm's efficiency in transforming factor endowments (such as labor, capital, land, and natural resources) and intermediate inputs from other firms to produce an output useful either for consumption or production of another good or service. Accordingly, productivity abstracts from the availability of inputs and refers to the ability to transform the available inputs into useful output. Physical climate risks could affect the ability of firms to transform their inputs into useful outputs via different channels, which could be best understood through the sectors in which the firms operate.

We use a variant of the Ordinary Least Square (OLS) regression to estimate how the chronic and extreme climate indicators have historically affected firm productivity. OLS and its variants have been widely used in estimating the empirical relationships between variables, including deriving climate damage functions on

[24] See Rogers & Rogers (1998) for a detailed discussion on the definition and measurement of productivity.

productivity[25]. OLS regression, in general, attempts to find the magnitudes of the coefficients that minimize the residual error between the actual observations and their predicted counterparts.

However, when using linear regression models for predictions, two significant problems could occur: overfitting and underfitting. Overfitting happens when the regression model performs well on the training data but poorly on the testing data. Underfitting occurs when the regression model does not perform well on either data. Regularization prevents overfitting in regression models without changing the number of features or predictor variables. LASSO (Least Absolute Shrinkage and Selection Operator) and Ridge are two widely used regularization algorithms. The objective functions of LASSO and Ridge are presented in Equations 1 and 2[26].

Equation 1: Objective Function of a LASSO Regression Problem

$$\operatorname{argmin}\left(\sum_{i=1}^{N}\left[Y_i - \beta_0 - \sum_{j=1}^{n}\beta_j X_{ij}\right]^2 + \alpha\sum_{j=1}^{n}|\beta_j|\right)$$

Equation 2: Objective Function of a Ridge Regression Problem

$$\operatorname{argmin}\left(\sum_{i=1}^{N}\left[Y_i - \beta_0 - \sum_{j=1}^{n}\beta_j X_{ij}\right]^2 + \alpha\sum_{j=1}^{n}{\beta_j}^2\right)$$

As illustrated in Equations 1 and 2, both LASSO and Ridge regressions start with the conventional objective function of linear regression and impose a non-negative penalty on the coefficients of the predictors. The penalty prevents the coefficients from being too large when optimizing the conventional objective function. The penalty in LASSO regression works with the linear summation of coefficients and, thus, could shrink some coefficients to zero. However, Ridge regression works with the squared summation of the coefficients and does not necessarily reduce the coefficients to zero.

The changes in the objective functions qualify LASSO to be used as a feature selection algorithm when there is a large group of predictors, out of which the optimum set of predictors has to be identified. However, the risk remains that LASSO may suggest some less critical predictors at the expense of the more important ones, depending on the ordering of predictors. This risk, nevertheless, does not exist with Ridge regressions as it treats all the correlated variables the same[27].

[25] See Roson and Sartori (2016) for a synthesis of their development of chronic climate damage functions for various economic sectors using linear regression models.

[26] The notation in the equations follows the standard interpretation of an OLS regression problem, where Y_i is the dependent variable and X_{ij} is an independent variable with β_j as its coefficient. β_0 is the intercept of the regression equation, and α is the regularization parameter.

[27] See Hastie et al. (2017) for a detailed discussion on linear, LASSO, and Ridge regression models.

In this paper, we encounter two challenges when we assess how the chronic and extreme climate indicators introduced in Section 2.5 have historically affected sectoral productivity. Firstly, some chronic and extreme climate indicators are linked to the same distributions, although their methods of construction are independent[28]. Secondly, we have a considerably higher number of climate indicators as predictors (especially compared to existing studies that mostly use temperature and (rarely) precipitation). Accordingly, both accounting for collinearity and retaining the predictors are central to our estimations. Therefore, in this paper, we utilize a Ridge regression approach to estimate the impacts of physical climate risks on firm TFP.

We control for the GDP growth in the regression model to control for the impact of the national economic growth on the productivity growth of firms in the same country. This term also enables us to control for the country and year-specific fixed effects that could have affected the firm TFP growth. We acknowledge that some climate indicators could also affect this term, even though it is still debated in the literature[29].

We also include additional region-specific and year-specific fixed effects to control for unobserved time-invariant regional heterogeneities, such as those in climate indicators, and any other unobserved time-variant effects. These fixed effects also account for any time-variant and/or time-invariant historical climate adaptation measures[30, 31].

As mentioned in Section 2.4, due to practical difficulties in finding all the establishments of a given firm, we use the single address available for a firm, which corresponds to the head office location of the firm, to represent its location. As the firms in the manufacturing and service sectors have the flexibility to choose locations to reduce the vulnerability to climate risks when establishing their operations, we assume the climate risks faced by the available firm location to be representative of those climate risks faced by the whole domestic production network of the firm. However, this flexibility does not exist for the agriculture

[28] For example, while a chronic indicator could measure the deviation in mean temperature in a given year from baseline, an extreme indicator could measure the average deviations of the monthly maximum temperature from a percentile of the distribution. Accordingly, both indicators could be related to the same distribution, but the method of construction enables identifying mean vs. extreme values.

[29] Kalkuhl and Wenz (2020) do not find evidence for permanent growth rate impacts from changes in temperature and precipitation. In contrast, Kahn et al. (2021) find that per-capita real output growth is adversely affected by persistent changes in the temperature above or below its historical norm. However, they do not obtain any statistically significant effects for changes in precipitation.

[30] We note that adaptation is not explicitly controlled for in our framework. This is common in the literature due to the lack of global adaptation measures and datasets. However, in addition to regional fixed effects, all our climate indicators use thresholds that implicitly account for adaptation by incorporating local climate distributions.

[31] The objective of the empirical estimates in this paper is not to comprehensively explain the productivity or production patterns of the agriculture and energy/electricity sectors but to obtain the implications of physical climate risks on those sectors. Therefore, the omitted variables contributing to explaining productivity/production patterns could affect the estimates only to the extent they correlate with the climate indicators. As climate risks are mainly exogenous, we assume the omitted variables do not significantly affect the current estimates. In this paper, following the existing literature, we also assume the relationship between physical climate risks and TFP to be linear. Future studies could relax this assumption.

and mining establishments, as the primary operations of those firms are usually conducted in areas more vulnerable to climate risks than the head office location[32].

Therefore, incorporating the firm-specific and country-specific climate indicators, GDP growth, and region and year-specific fixed effects, we estimate the panel regression model presented in Equation 3 in the Ridge regression form for manufacturing and services sectors. We estimate Equation 4 for the agriculture and mining sectors, which excludes the firm-specific climate indicators in Equation 3.

Equation 3: Estimated Model for Manufacturing and Service Sectors in Country *i, Region j,* and Year *k*

$$\begin{aligned} Growth\ in\ Firm\ TFP_{i,j} &= \beta_0 + \beta_{GDP} * GDP\ Growth_{i,k} \\ &+ \sum_{n=1}^{8} \gamma_n * Country - level\ Climate\ Indicator_{i,k} \\ &+ \sum_{m=1}^{8} \delta_m * Firm - level\ Climate\ Indicator_{i,k} + \theta_j + \vartheta_k + \varepsilon_{i,j,k} \end{aligned}$$

Equation 4: Estimated Model for Agriculture and Mining Sectors in Country *i, Region j,* and Year *k*

$$\begin{aligned} &Growth\ in\ Firm\ TFP_{i,j} \\ &= \beta_0 + \beta_{GDP} * GDP\ Growthi_{,k} + \sum_{n=1}^{8} \gamma_n * Country - level\ Climate\ Indicator_{i,k} + \theta_j + \vartheta_k + \varepsilon_{i,j,k} \end{aligned}$$

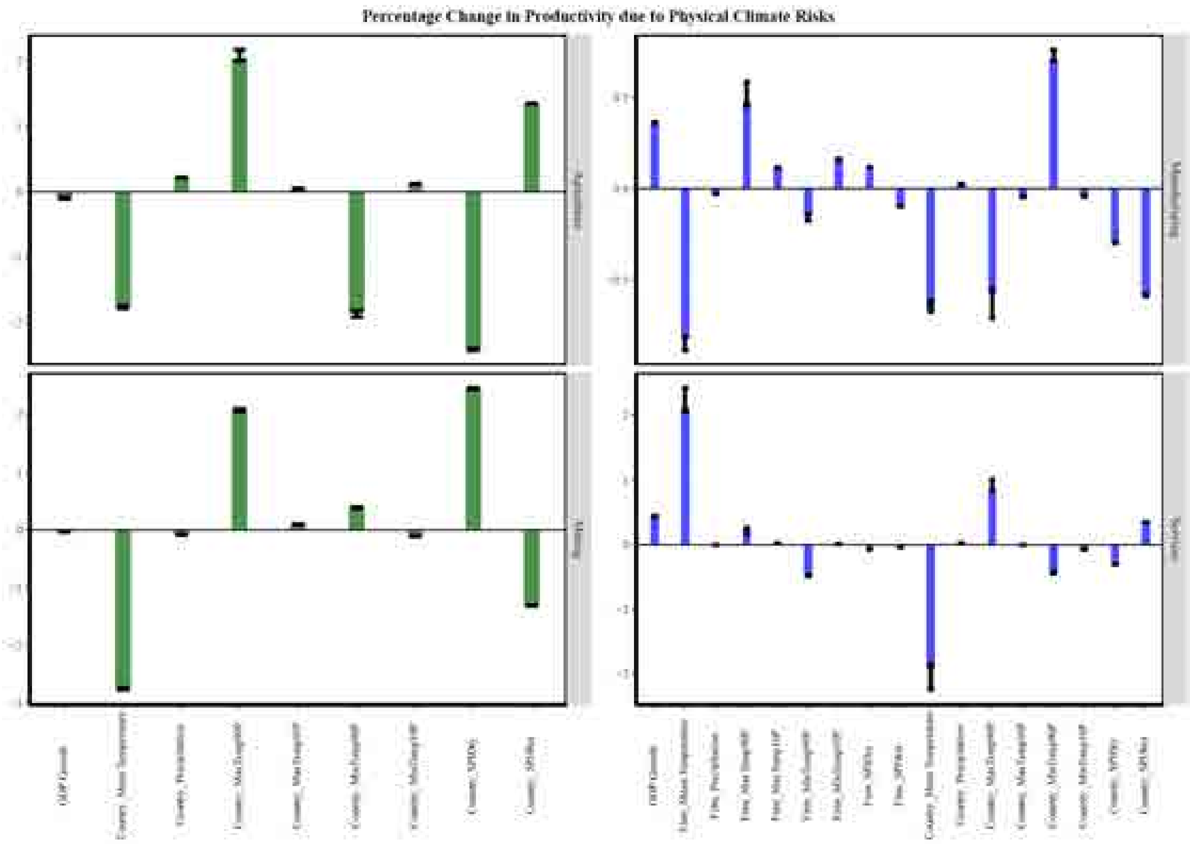
2.7 Physical Climate Risk Impacts on Sectoral TFP

In this section, we discuss the empirical estimates from the above panel regressions for the sectoral productivity impact of physical climate risks and the projected sectoral productivity changes from applying those estimates to the variation in climate indicators (by firm location and country) under the two SSPs. Figure 3 summarizes the empirical impacts of physical climate risks on TFP for different sectors. Annexure 3 illustrates the projected sectoral productivity changes from 2021 to 2100 due to the variations in physical climate risks under two SSPs aggregated for the UN region for ease of representation. The variations have been normalized for each region relative to their 2020 levels to illustrate the relative changes in TFP across time[33].

[32] We also confirm this statement by checking a few selected firms in the mining sector. We cannot, however, extend this exercise to the whole sample of agriculture and mining firms, as the firms are only identified by an ID in the Orbis database.

[33] For example, a two percent reduction under a given scenario in a given sector in a given region in a given year should be interpreted as a two-percentage-point reduction in productivity on top of its productivity change in 2020. That means if the productivity reduction experienced under the same scenario in 2020 in the given sector in the given region was one percent, the absolute productivity reduction experienced in the given year is three percent.

Figure 3: Percentage Change in Productivity in Sectors Attributable to Physical Climate Risks



We discuss our results within the context of other existing studies covering climate impacts on agriculture, mining and energy, manufacturing, and service sectors. However, we note that not all the sectors and climate indicators considered in this paper have been comprehensively covered in the existing studies. We observe that many existing empirical studies focus on the climate impacts on agriculture, and very few focus on the other sectors[34].

Agriculture

Agriculture mainly consists of crops, livestock, fishery, and forestry. As outlined in Hulme (1996), climate risks affect crops at least in three main ways: (1) changes in the soil moisture content due to evaporation, crop respiration rate, and the length and timing of the growing seasons due to temperature and precipitation variations affecting the crop growth; (2) changes in the water-use efficiency and photosynthesis due to carbon dioxide concentration variation, and (3) changes in quality of water and soil, shifts in weed growth, and vulnerability to diseases due to extreme events, such as droughts and floods. In forestry, climate change

[34] We also observe that some studies focus on labor productivity instead of TFP if the firm sample is more biased toward labor-intensive firms. There also are independent studies focusing solely on labor productivity amidst global warming. For example, Dasgupta et al. (2021) conduct a comprehensive global study illustrating the non-linear changes in labor productivity amidst global warming, and Levi et al. (2018) provide a comprehensive framework for understanding climate impacts on labor productivity.

could alter the growth cycle of trees and change their resilience to diseases, even though increased carbon dioxide concentration could promote the growth of trees (US Climate Change Science Program 2008a).

The livestock and fishery could also be vulnerable to diseases because climate variability and extreme conditions affect the physiology, behavior and movements, growth and development, and fertility of animals, birds, and fish. Even though higher carbon dioxide concentrations could increase the quantity of feed available for livestock, the quality of the feed could deteriorate and reduce livestock productivity. In the fishery, the lifecycle of aquatic species and their migration patterns are also affected by climate change, thus affecting sectoral productivity (US Climate Change Science Program 2008a).

The existing studies use both empirical estimations and process-based integrated assessment models to evaluate the impacts of climate risks on agriculture. Given their strong reliance on agriculture, most studies have focused on developing countries. Using a Ricardian model of the agriculture sector, Mendelsohn (2014) estimates 13.3 and 28.1 percent reductions in annual revenue from Asian agriculture under 1.5^{0}C and 3^{0}C warming scenarios, respectively. In Africa, Dinesh et al. (2015) estimate that livestock productivity could shrink by almost 50 percent in most regions, and the productivity of maize cultivation could shrink up to 25 percent under the RCP 8.5 scenario by 2050. Seo and Mendelsohn (2008) estimate that the agriculture sector could lose 14, 20, and 53 percent of its revenue under a severe climate scenario by 2020, 2060, and 2100, respectively. Due to climate change, developed countries could also experience substantial negative impacts on agriculture. Sheng and Xu (2019) evaluate the effect of the Millennium drought on the Australian agriculture sector and observe an 18 percent reduction in TFP from 2002 to 2010. In Europe, a set of questionaries to agro-climatic and agronomy experts reveal that climate change is expected to affect agriculture negatively, mainly via droughts, heatwaves, pest diseases, weeds, and soil erosion (Olsen et al. 2011).

In this paper, we assess the physical climate impacts on agriculture using 519 firms spread across 45 countries from Sample 2 (as specified in Table 1). However, most of the firms are located in Europe and North America, as illustrated in Figure 2. Therefore, despite controlling for region-specific fixed effects, we expect the estimates to be somewhat biased towards those regions. This bias is particularly observable in the impact of extremely warm conditions during the day on agriculture productivity. As demonstrated in Figure 3, extremely dry conditions and extremely warm conditions during the night have the most substantial negative impact on agriculture, where a one percent increase in those conditions could reduce agriculture productivity by more than two percent. An increase in mean temperature by a degree also reduces productivity by more than one percent. While increased precipitation increases agriculture productivity, a one percent increase in extremely wet conditions could boost productivity by almost 1.5 percent. This effect is attributable to the potential improvements in the country-wide ecosystems, such as rivers and soil, on which agriculture relies.

Based on the results from the empirical estimations, we derive the agriculture productivity changes for 1,401 firms spread across 91 countries from Sample 1 (as specified in Table 1). Annexure 3 summarizes the average impact across 15 UN regions under the two SSPs from 2021 to 2100. Under SSP 1-2.6, almost all the regions experience a reduction in agriculture productivity compared to their respective productivity changes in 2020. The negative impact increases across the century for all regions except for Eastern Europe, where it remains closer to 2020 productivity change. Central Asia, North America, and Western Europe experience the highest reductions, exceeding six percentage points compared to 2020 by 2100. Under SSP 2-4.5, all the regions experience declining productivity. South Asia also experiences substantial productivity reductions along with North America and Western Europe, which experienced the highest contractions under SSP 1-2.6. Their reductions by 2100 exceed 15 percentage points relative to their respective productivity change in 2020. Australia and New Zealand experience the least reduction, roughly above two percentage points compared to its productivity change in 2020.

Mining and Energy

In the mining sector, both chronic and extreme climate risks could disrupt and primarily increase the cost of exploration, extraction, production, transportation, and decommission, even though newer opportunities could also arise for exploration and access to natural resources that were previously inaccessible. While the existing studies covering the physical climate impacts on the mining sector are minimal[35], Pearce et al. (2011) have shown that rising water scarcity is the primary driver of increasing costs in the mining sector with climate change. Rising temperatures could further deteriorate the environmentally challenging conditions in mining regions and operational sites, reducing the labor efficiency in the mining sector (Sun et al. 2020).

The energy sectors, especially the fossil fuel sectors, which involve significant mining operations, could also be expected to experience similar productivity challenges. Furthermore, the productivity of energy and electricity generation, transmission, and distribution could deteriorate with the demand for more inputs to produce the same output. The higher cooling water requirement in thermal power plants, disruptions to hydroelectric power plants from changes in water availability, and more frequent maintenance of transmission and distribution lines due to disruptions from extreme climate risks are exemplary of the impacts of climate risks on the energy sector (US Climate Change Science Program 2008b).

This paper assesses the physical climate impacts on mining using 464 firms spread across 46 countries from Sample 2 (as specified in Table 1). However, similar to agriculture, most firms are located in Europe and North America, as illustrated in Figure 2. Therefore, despite controlling for region-specific fixed effects, we expect the estimates to be somewhat biased towards those regions. As demonstrated in Figure 3, the increase in mean temperature by one degree reduces mining productivity by almost three percent. The extremely wet conditions also disrupt operations and reduce mining productivity by almost 1.5 percent.

However, we observe that the extremely warm conditions during the day and night and prolonged extremely dry conditions tend to affect mining productivity positively. This observation potentially reflects an

[35] See Odell et al. (2018) for a review of the literature on the impacts of climate change on the mining sector.

improved efficiency in managing the water available under extreme conditions, as the mining operations frequently require water and are often faced with water scarcity. It could also be due to fewer disruptions from colder climate conditions, which are usually prevalent in the countries where most of the firms in the sample are based. It is also noteworthy that, as explained in Section 2.2, the sample of firms considered in this paper consists of the leading firms in the industry in the respective countries covered. Hence, they could be efficient in facing certain extreme conditions. However, those may not represent the response of an average mining firm.

Based on the results from the empirical estimations, we derive the mining productivity reductions for 1,605 firms spread across 101 countries from Sample 1 (as specified in Table 1). Annexure 3 summarizes the average impact across 15 UN regions under the two SSPs from 2021 to 2100. Under SSP 1-2.6, eight regions experience a notable reduction in mining productivity compared to their respective productivity changes in 2020. Among these, North America experiences the most substantial reduction, where its productivity would reduce almost by five percentage points compared to its productivity change in 2020. A few regions, such as Southern Europe, Western Europe, and Latin America, experience minimal productivity changes. Under SSP 2-4.5, almost all regions experience notable productivity reductions relative to 2020, Northern Europe being the only exception with a less than one percentage point reduction.

Manufacturing

The manufacturing sector generally includes the production of food and beverages, textiles and apparel, wood and paper, chemicals and pharmaceuticals, rubber, plastics, and metals, electrical and electronic equipment, and transport equipment (GTAP 2022). The impacts of climate risks on these sectors could both be direct and indirect. The direct channels include the implications of warming and extreme events on labor efficiency. Another impact pathway is via the increased production costs stemming from temperature increases. These include substituting or reallocating raw materials, altering processes, retrofitting production equipment, failures in production equipment, especially in industries involving high temperature and moisture-sensitive equipment and raw materials, and investment adjustment costs (e.g., Zhang et al. 2017). Hayakawa et al. (2015) also illustrate how firms change their procurement patterns using a flood in Thailand as a case study. The indirect channels include the increased production costs due to the climate impacts on the upstream (agriculture, mining, energy, and utilities) and downstream activities (such as transportation) of the supply chain.

The existing studies covering the physical climate impacts on manufacturing focus on both labor productivity and TFP channels. In a study focusing on a half-million manufacturing firms in China, Zhang et al. (2018) observe an inverted-U relationship between chronic climate risks (temperature, precipitation, humidity, and wind speed) and TFP, with substantial adverse effects at high temperatures. They observe a wide heterogeneity in the effects among manufacturing firms. Manufacturing processes linked to mining illustrate the positive effects of changes in climate risks, while durable manufacturing processes mainly experience more significant adverse impacts. Furthermore, they extend their empirical analysis to project the effects of future climate change and show that Chinese manufacturing output could reduce by 12 percent annually during 2040-2059 due to climate change without adaptation.

Somanathan et al. (2021) evaluate the implications of global warming on labor productivity among manufacturing firms in India and observe a non-linear relationship between temperature and labor productivity. They estimate a four to nine percent productivity reduction on warm days. They approximate that between 1971 and 2009, India could have lost at least three percent of its manufacturing output compared to a counterfactual without warming. Kumar and Yalew (2012) also illustrate the indirect impacts of climate change on manufacturing productivity due to the reliance on primary sectors exposed to climate risks (e.g., effects on the production of food, beverages, wood, and paper due to dependence on agriculture).

This paper assesses the physical climate impacts on manufacturing using 6,945 firms spread across 48 countries from Sample 2 (as specified in Table 1). As illustrated in Figure 3, most climate indicators have lower impacts on manufacturing productivity than on other sectors. However, a unit increase in the mean temperature both at the firm location and in the country decreases manufacturing productivity. In contrast, the average temperature increase at the firm location has a more substantial effect. The country-wide extremely warm conditions are also detrimental to manufacturing productivity. Country-wide, extremely wet and dry conditions reduce manufacturing productivity, potentially due to their impact on raw materials. The remaining indicators, mainly those of short-term extreme temperature conditions, have mixed impacts on manufacturing productivity, potentially via their impact on working conditions.

Based on the empirical estimations, we derive the manufacturing productivity reductions for 15,849 firms spread across 125 countries from Sample 1 (as specified in Table 1). Annexure 3 summarizes the average impact across 15 UN regions under the two SSPs from 2021 to 2100. Under SSP 1-2.6, most regions experience manufacturing productivity contractions compared to their respective changes in productivity in 2020. North America and East Asia experience the highest contractions, between one and two percentage points towards 2100. Some regions, such as Western and Southern Europe, experience minimal productivity changes. Under SSP 2-4.5, more regions experience productivity reductions. North and Latin America are the most vulnerable regions, with their productivity reductions exceeding 1.75 percentage points by 2100 relative to their respective changes in 2020.

Services

The service sector encompasses utilities (which is strongly linked to the energy sector), trade, accommodation and food services, transportation and warehousing, communication, financial and business services, construction and real estate activities, recreation, education and health, and public administration and defense (GTAP 2022). Similar to manufacturing, physical climate risks could both directly and indirectly affect services. As Kumar and Yalew (2012) point out, climate change directly affects construction. The disruptions to ongoing construction projects increase the operational costs of the firms. However, they could also benefit from reconstruction projects after extreme climate risks, such as floods and storms. The food services are exemplary of the indirect climate impacts due to the reliance on agriculture, which is disproportionately vulnerable to climate risks.

This paper assesses the physical climate impacts on services using 12,287 firms spread across 47 countries from Sample 2 (as specified in Table 1). As illustrated in Figure 3, an increase in the average mean temperature across the country has the most substantial adverse effect on service sector productivity. However, the firm-specific increase in mean temperature can boost productivity. The extreme short-term temperature conditions also have mixed impacts on service sector productivity, with the country-level indicators having more pronounced effects than those at the firm level. The extremely dry and wet conditions in the country reduce productivity, potentially indicating indirect effects on the service sector due to reliance on other sectors, such as agriculture in food services and wholesale and retail trade.

Based on the results from the empirical estimations, we derive the service-sector productivity reductions for 40,699 firms spread across 143 countries from Sample 1 (as specified in Table 1). Annexure 3 summarizes the average impact across 15 UN regions under the two SSPs from 2021 to 2100. Under SSP 1-2.6, all the regions experience service sector productivity reductions. Western Europe experiences the least change from its change in 2020. The service sector in Central Asia is the most vulnerable, reaching almost a one percentage point reduction by 2100 compared to its 2020 productivity change. Under SSP 2-4.5, all regions experience declining productivity compared to their changes in 2020, and most of the regions observe reductions within one to two percentage points towards 2100. Notably, Sub-Saharan Africa and Western Europe experience almost three percentage point reductions towards 2100 compared to their 2020 productivity changes.

Summary of Sectoral TFP Impacts

The projected results indicate that all sectors experience losses from changes in physical climate risks, although the magnitude of the losses is heterogeneous across time and regions. Agriculture is the most vulnerable sector, and its productivity reduces by 10 to 20 percentage points in most regions under the two SSPs. Mining also experiences losses exceeding five percentage points in certain regions under SSPs. Manufacturing and services are the least affected potentially due to the higher degree of flexibility in locating and arranging their operations to reduce exposure to physical climate risks.

This paper considers the top 1,000 (or fewer) firms in each IMF member nation by asset value, leading to a sample of 59,554 firms from 147 countries. Being the leading firms in the respective countries and potentially globally, we expect these firms to have already taken some steps towards reducing their exposure to physical climate risks. The estimation sample of 20,215 firms is also biased toward the developed countries due to the lack of additional data required to calculate TFP measures, as explained in Section 2.2. Therefore, the empirical estimates and projections derived from them should only be interpreted as an optimistic upper bound of climate impacts on productivity. Normalizing the changes relative to 2020 helps us eliminate region-specific biases (such as historical adaptation measures) that could prevail in the derived projections.

Notwithstanding the limitations arising from data, we present a comprehensive assessment of the responses of sectoral productivity to physical climate risks. The strength of the exercise lies in incorporating both chronic and extreme climate indicators, derived both at the firm and country levels, within a single framework to assess their impacts on sectoral productivity covering a global sample of multisectoral firms. The exercise also utilizes improvements to conventional estimation approaches to overcome some of their limitations.

2.8 Impact of Floods on Sectoral Capital

Extreme events, such as storms and floods, could result in devastating instantaneous damage to firms by destroying their physical capital stocks. These effects could have non-linear disruptive effects (such as the sudden unavailability of business premises). These effects may be overlooked in our sectoral TFP elasticities discussed in Section 2.7 due to the lack of additional information (such as land-use patterns) to incorporate those effects into the empirical estimation methodology. Those additional effects induced by extreme events on firm physical capital can be assessed using damage functions linking hazards' intensity to damage rates (that is, the percentage of asset value lost). Such damage functions for both riverine and coastal floods have been made available with global coverage by Huizinga et al. (2017). Therefore, we use those damage functions in this paper to estimate the damage to firms' physical capital from floods.

Different from existing regional, national, or sub-national studies providing damage estimates for floods, global studies estimating the damage within a common framework are rare[36]. Huizinga et al. (2017) present a global dataset of damages caused by river floods obtained from an extensive review and collection of quantitative data on global flood damages from floods worldwide[37]. The study provides global and regional damage functions depicting fractional damage as a function of water depth. They also distinguish the damage caused by the depth of the floods across agriculture, infrastructure, transport, residential buildings, commercial buildings, and industrial buildings. Figure 4 illustrates the sectoral damage functions by continent, where 0 represents no damage, and 1 represents complete destruction. We map the damage functions from Huizinga et al. (2017) for different sectors to the 21 NACE sectors to which the 59,554 firms in Sample 1 belong (see Supplementary Annexure 7 for the mapping of sectors).

As described in Section 2.4, we obtain projected data on flood severity from Jupiter Intelligence in terms of flood depth and the fraction of land flooded under five different return periods (1/10, 1/20, 1/50, 1/100, 1/200, 1/500) for the two SSPs from 2020 to 2100. We apply the continent- and sector-specific

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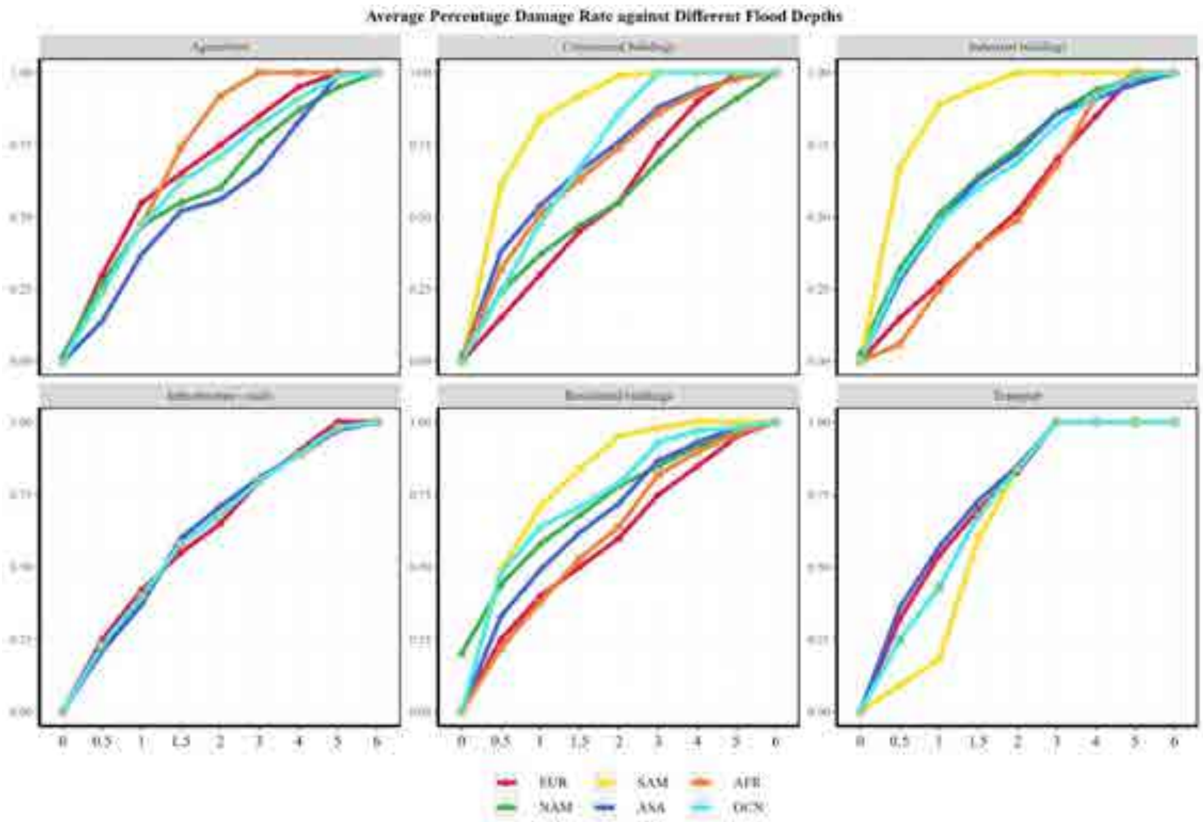
[36] We focus on floods as the availability of global damage functions for other extreme events, such as droughts, storms, and wildfires, is still limited.

[37] The NGFS has also used these damage functions to estimate damages from floods. We refer to NGFS (2022c) for more details.

damage functions to the flood depth and fraction of land flooded at the firm locations to derive the average annual damage to firms' physical capital stock (see Annexure 4 for more details) under the two SSPs from 2020 to 2100. We then average the damage estimates for firms within the four broad sectors (Agriculture, Mining, Manufacturing, and Services) and the 15 UN regions and obtain the loss of physical capital stock for each sector in each region under the two SSPs.

Annexure 5 shows the average annual damage to the firms' physical capital stock in agriculture, mining, manufacturing, and services across the 15 UN regions under the two SSPs. Our estimates show that the flood impacts are unevenly distributed across different regions, in line with other global studies (Dottori et al. 2018). Specifically, under SSP 1-2.6, firms in Asia and Africa are exposed to significant increases in flood damage over time across all sectors. In contrast, firms in the other regions experience moderately increasing, constant, or slightly declining damages. Under SSP 2-4.5, the patterns remain similar to the ones under SSP 1-2.6. However, over time, damages further increase relative to SSP 1-2.6 in Asia and Africa and further decrease in some regions, such as North America (for mining in particular). Under both scenarios, the most significant damages occur in Asia for all sectors except mining, for which the most considerable damages occur in North America.

Figure 4: Percentage Damage Rates from Floods by Continent and Sector



Source: Huizinga et al. (2017)

3.0 MODELING PHYSICAL CLIMATE RISKS IN THE G-CUBED

3.1 Overview

In this section, we simulate the physical climate impacts on sectoral productivity, estimated in Section 2 for the two SSPs within the G-Cubed. Section 3.2 provides a brief background on the existing studies modeling the economic consequences of climate scenarios. Section 3.3 introduces the G-Cubed and outlines its features relevant to this paper, and explains the model baseline. Section 3.4 describes how the physical climate impacts derived in Sections 2.7 and 2.8 are transformed into economic shocks to be assessed within the G-Cubed.

3.2 Modeling Physical Climate Risks in Economic Models

Economists have quantified the economic impacts of physical risks using a variety of approaches. Integrated Assessment Models (IAMs) account for most of the earliest efforts to evaluate the economic consequences of climate change within a single framework. Since the 1970s, when the earliest IAMs were constructed, they have been widely used to assess physical climate risks and climate policies.

There is a vast number of IAMs (e.g., benefit-cost integrated models, process-based IAMs, etc.), which vary in many different aspects, primarily depending on the questions the model tries to answer and the approach the model conceptualizes to answer those questions[38]. Goodess et al. (2003) identify three classes of IAMs: cost-benefit analysis models, biophysical models, and policy guidance models.

The cost-benefit analysis models focus on assessing the costs and benefits of climate change against the cost of adaptation and mitigation policies. The Dynamic Integrated Model of the Climate and the Economy (DICE) by Nordhaus, the Climate Framework for Uncertainty, Negotiation, and Distribution (FUND) model, and the Policy Analysis of the Greenhouse Effect (PAGE) model are famous examples. The cost-benefit analysis models tend to follow vertical integration with the simple causal chain and are widely used to optimize policies.

Biophysical impact models emphasize climate impacts on ecosystems and illustrate feedback across systems in vertical integration. However, due to the absence of explicit focus on policies, their economic modules are less developed. Therefore, they are better suited for policy evaluation rather than optimization.

Policy guidance IAMs combine the policy optimization and evaluation approaches within tolerable windows defined by the policymakers. Yet, the extreme complexities involved in both natural and social

[38] Specifically, the resolution of the human and natural systems and their interactions, the elements of the systems, and how the human and natural systems are thought to evolve are some of the important aspects in which IAMs vary. For example, in the natural systems, the differences could be in the climate forcings the global circulation modules focus on. The differences in economic systems could be in the assumptions of how economies grow or how economic agents interact.

systems in IAMs make it challenging to untangle the dynamic adjustments to the systems in response to shocks, among others.

Different from the IAMs' approach of endogenizing the natural and social systems and their interactions, economists have also harnessed advances in econometrics and economic modeling to evaluate how climate change affects the economies and what economic policies could contribute to mitigating climate change and facilitating adaptation. An array of economic studies focusing on different climate risks, using different approaches, and focusing on different regions is available. The approaches currently span across cross-sectional and panel regressions (e.g., Kalkuhl and Wenz 2020; Kahn et al. 2021), Structural Vector Auto-Regressive (SVAR) models (e.g., Gallic and Vermandel 2020), Dynamic Stochastic General Equilibrium (DSGE) models (e.g., Xu 2021), Computable General Equilibrium (CGE) models (e.g., Kompass et al. 2018; Roson & van der Mensbrugghe 2010), Agent-based models (ABM) (e.g., Niamir et al. 2020). Fernando et al. (2021) use the hybrid DSGE-CGE economic model G-Cubed to evaluate the chronic, extreme, financial, and transition risks under RCPs.

However, most economic studies consider the economy as a whole (e.g., cross-sectional and panel regressions, SVAR, and DSGE models). Studies using CGE models (e.g., Kompass et al. 2018; Roson & van der Mensbrugghe 2010) and hybrid DSGE-CGE models (e.g., Fernando 2023; Fernando et al. 2021) develop the shocks using damage functions for the primary sectors and derive shocks for secondary and tertiary sectors mainly through their reliance on the primary sectors. Those studies have not accounted for firm-level estimations due to the lack of access to firm-level data on productivity. Furthermore, empirical estimates of the implications of both chronic and extreme physical risks at the firm level are scarce. Most existing studies (except for those using CGE and DSGE models), as indicated in Section 2.7, are also limited to a single region, if not to a country, and they tend to focus primarily on temperature and precipitation and rarely on extreme conditions.

In terms of the economic channels of propagation of physical climate risks, existing studies have broadly focused on the following:

1. **Immediate physical capital destruction**: Destruction of physical capital stock by extreme events can be modeled as a one-time immediate increase in capital depreciation calibrated using damage rates (Hallegatte et al. 2022a). The impacts can also vary across different capital types, e.g., infrastructure and non-infrastructure (Hallegatte et al. 2022b).
2. **Decline in TFP**: Chronic physical risks can affect the ability of firms to transform their inputs into useful outputs via different channels (see Section 2.7 for a review), thus reducing their productivity. Further, the damage from extreme events can misallocate the remaining capital,

leading to a decline in TFP. Persistent effects can also emerge from the changes in the cost of capital[39].

3. **Reconstruction after extreme events**: Households adjust their consumption, and firms adjust their investment patterns following an extreme event. This channel can be accounted for in models incorporating consumption preferences and investment adjustment costs (Hallegatte et al. 2022a). Furthermore, reconstruction investment choices vary depending on the use of private or public capital (Hallegatte et al. 2022b). Favorable impacts on firm performance can also arise, and countries can gain economic benefits after disasters due to financial aid and international cashflows[40].
4. **Impact on unemployment**: Since capital and labor are complementary, there could be concurrent shocks to employment in the event of immense/immediate destruction of capital stock. IMF (2022) uses the elasticity of unemployment to changes in capital stock to evaluate the concurrent impacts of extreme events on employment in Mexico.
5. **Effects from financial markets**: Although not extensively studied as capital destruction or reconstruction, capital reallocation via financial markets amidst exposure to extreme events is also an emerging area of interest in the existing literature[41]. Physical climate shocks could reduce investor attraction to countries and sectors more vulnerable to physical risks. If physical risks are priced in financial markets, the extreme events could be reflected in equity or corporate bond markets[42]. This channel has been captured via changes in equity risk premia by Fernando et al. (2021), estimated by regressing country-level equity risk premia changes against the incidence of extreme climate shocks, and in IMF (2022), using a shock based on the elasticity of changes in overall equity market returns to changes in capital stock in Mexico. The extreme events could also weaken the sovereign credit rating, increasing the real interest rate on external debt (Marto et al. 2017).

In this paper, we focus on the TFP channel. Firstly, we account for the TFP shock from both chronic and extreme climate risks (excluding floods), as estimated and projected in Section 2.7. Secondly, we compute the persistent TFP effect due to floods' damage to firms' physical capital. However, we recognize that other channels might also be important and are left to future studies.

[39] Fernandez-Villaverde and Levintal (2018) uses shocks on capital and TFP to replicate extreme risks in DSGE models. Hallegatte et al. (2022b) use shocks on capital depreciation rate and TFP from typhoons, calibrated using Catastrophe (CAT) models, in a DSGE model to develop macro-scenarios for stress testing banks in the Philippines.

[40] Leiter et al. (2009) illustrate the positive impacts of disasters on firms in Europe, Coelli and Manasse (2014) in Italy and Noth and Rehbein (2017) in Germany; Okubo and Strobl (2020) present evidence of mixed impacts in Japan aftermath of a typhoon, and Gunathilaka (2018) illustrates negative impacts on micro, small and medium enterprises after a flood in Sri Lanka.

[41] Albert et al. (2021) illustrate how prolonged dry periods could move capital away from vulnerable areas and how extremely dry conditions could even lead to structural changes in vulnerable areas.

[42] See Giglio et al. (2021) for a literature review.

3.3 The G-Cubed Model

Overview

The G-Cubed is a global, multisectoral, intertemporal general equilibrium model developed by McKibbin and Wilcoxen (2013; 1999). The model is designed to bridge the gaps between econometric general-equilibrium modeling, international trade theory, and modern macroeconomics. The model is particularly well suited to capture climate risks due to its regional and sectoral representation. The model has already been used to study the economic consequences of climate change (Fernando 2023; Fernando et al. 2021) and transition pathways (Jaumotte et al. 2021; Liu et al. 2020), as well as to explore increasing the sectoral coverage of the existing NGFS scenarios (NGFS 2022a)[43].

In the version of the model (version GGG20C_v169) used in this paper, there are eleven regions and twenty sectors. The model regions are presented in Table 4. Supplementary Annexure 8 shows the countries aggregated under the regions and their concordance with the UN regions. The model sectors are presented in Table 5. The first twelve sectors are aggregated from the 65 sectors in the GTAP 10 database as indicated in Supplementary Annexure 9. The electricity sector is then disaggregated into the electricity delivery sector (Sector 1 in Table 5) and eight electricity generation sectors (Sectors 13-20 in Table 5).

Table 4: Regions in the G-Cubed Model

Region Code	Region Description
AUS	Australia
CAN	Canada
CHI	China
EUW	Europe
IND	India
JPN	Japan
OEC	Rest of the OECD
OPC	Oil-Exporting developing countries
ROW	Rest of the World
RUS	Russian Federation
USA	United States

Source: G-Cubed Model (version GGG20C_v169).

Table 5 also presents the mapping of the four broad sectors (for which we calibrated TFP shocks due to climate risks in Section 2) to G-Cubed sectors. From the energy production and electricity generation sectors, we only map the mining or manufacturing sector shocks to the non-renewable energy sectors. We exclude the renewable electricity generation sectors from the shocks as the firms covered in this paper do

[43] As the NGFS (2022a) noted, a sectoral model similar to G-Cubed is critical for understanding how physical and transition-related climate risks could materialize within different sectors. The report details the findings of a pilot project to investigate integrating the G-Cubed into the NGFS model suite.

not include firms engaged in renewable electricity generation. We also do not expect the current broad sectors to reflect the climate risk exposures to renewable electricity generation sectors[44].

Table 5: Sectors in the G-Cubed Model

Number	Sector Name	Notes	Broad Sector for Mapping Shocks
1	Electricity delivery	Energy Sectors excluding Electricity Generation	Manufacturing
2	Gas extraction and utilities		Manufacturing
3	Petroleum refining		Manufacturing
4	Coal mining		Mining
5	Crude oil extraction		Mining
6	Construction	Goods and Services	Manufacturing
7	Other mining		Mining
8	Agriculture and forestry		Agriculture
9	Durable goods		Manufacturing
10	Non-durable goods		Manufacturing
11	Transportation		Services
12	Services		Services
13	Coal generation	Electricity Generation Sectors	Mining
14	Natural gas generation		Mining
15	Petroleum generation		Mining
16	Nuclear generation		No Shocks were Applied.
17	Wind generation		No Shocks were Applied.
18	Solar generation		No Shocks were Applied.
19	Hydroelectric generation		No Shocks were Applied.
20	Other generation		No Shocks were Applied.

Source: G-Cubed Model (version GGG20C_v169).

Model Structure and Features

The structure of the model is set out in McKibbin and Wilcoxen (2013). The production structure of the G-Cubed is presented in Supplementary Annexure 10. Several key features of the G-Cubed relevant to this paper are briefly described below.

Firstly, the model features heterogeneous households and firms, a government, and a central bank in each region. The representative households and firms in each sector could either possess forward-looking expectations or follow more straightforward rules of thumb, which are optimal in the long run but not

[44] See Fernando (2023) for a detailed global analysis of the impacts on energy sectors distinguishing renewables and non-renewables.

necessarily in the short run. In the presence of continuing economic shocks, the forward-looking agents would thus smoothen their consumption and investment patterns over the horizon.

Secondly, the model illustrates the domestic and international linkages between sectors via trade. As a result, the economic shocks experienced in one sector could spill over to other domestic and foreign sectors relying on that sector. Furthermore, the ultimate impact on a given sector in a given region, even when faced with adverse economic shocks, would depend on the influence that sector has on world prices.

Thirdly, the model also illustrates global linkages via capital flows and distinguishes physical capital from financial capital. Therefore, financial capital could immediately move across industries and regions in response to an economic shock. Subject to sector-specific quadratic adjustment costs, the physical capital would sluggishly adjust, giving rise to stranded assets.

Baseline Construction

The G-Cubed baseline assumes how the economies would grow given the historical experiences but in the absence of additional future climate risks, as explained below in more detail. The climate scenarios are assessed against this baseline. The baseline starts in 2018 and is projected up to 2100. 2018 corresponds to the latest year for which a comprehensive data collection is available to calibrate the model. The region-specific sectoral productivity growth rates, a function of labor force growth and labor productivity growth in the respective countries, drive the baseline economic growth.

The labor force growth rates are derived from the working-age population projections from the United Nations Population Prospects (2019) data. The sectoral labor productivity growth rates (labor-augmenting technological progress) are determined using a Barro-style catch-up model, which assumes that the average annual catch-up rate of an individual economy to the global frontier would be two percent. The initial sectoral productivity data are obtained from the Groningen Growth and Development database (2022), and the corresponding sectors in the US are assumed to form the frontier, which the sectors in individual economies would try to reach. The G-Cubed also varies the catch-up rates of different economies, given the most recent growth experiences.

Given the above approach to constructing the baseline, the baseline would inherently include the various climate policies and adaptation measures those different economies had already implemented by 2018. As the climate shocks imposed under the two SSPs have been normalized relative to 2020, the model simulations effectively assess the economic outcomes relative to a baseline simulation that includes climate shocks up to the 2020 levels. In summary, there are effectively two layers to the baseline. Firstly, there is a model baseline that assumes historical climate policies and adaptation measures and no future climate shocks. Secondly, there is an effective baseline simulation from 2020 to 2100, which has climate shocks equivalent to 2020 levels and assumes adaptation for those shocks.

The normalized shocks under the two SSPs from 2020 to 2100 are then introduced as unanticipated shocks to the G-Cubed baseline described above. The simulation results indicate how the economies attempt to return to the baseline given the shocks imposed.

3.4 Economic Shocks from Physical Climate Risks

In this paper, we utilize two main types of TFP shocks to replicate the effects of physical climate risks under the two SSPs[45]. Firstly, we introduce the sectoral TFP changes due to changes in chronic and extreme climate risks (excluding floods), as estimated and projected in Section 2.7. Secondly, we compute the persistent TFP effect due to floods' damage to firms' physical capital. When converting the impacts of floods on physical capital (discussed in Section 2.8) to TFP effects, we consider the reliance of a given sector on capital as a proportion of its total inputs. We use the Input-Output tables from the GTAP 10 database (Aguiar et al. 2019) to derive the reliance of the G-Cubed sectors on capital.

Accordingly, the ultimate TFP shock imposed on a given sector (e.g., Coal Mining) would be the summation of two components: (1) the contemporaneous TFP shock on the corresponding broad sector (i.e., Mining for Coal Mining) due to the exposure to chronic and extreme climate risks, and (2) the persistent TFP shocks on the corresponding broad sector[46] arising from the flood damage to firms' physical capital adjusted for the reliance on capital in each sector. Due to the changes in reliance on capital across all sectors in the G-Cubed (from the underlying GTAP Input-Output linkages), two sectors that would be mapped onto the same broad sector (e.g., Mining mapped onto both Coal Mining and Crude Oil Extraction) could still have different final TFP shocks.

Annexure 6 presents the cumulative TFP shocks introduced to eight selected sectors under the two SSPs. The sectors include Coal Mining, Crude Oil Extraction, Construction, Other Mining, Agriculture, Durable Manufacturing, Non-durable Manufacturing, and Services. Following the discussion in Section 2.6, both series of shocks have been normalized relative to 2020 before aggregation. Supplementary Annexure 11 presents the descriptive statistics for the shocks grouped by region and sector under the two SSPs.

[45] We note that physical risk can have macro-financial effects through other channels not currently included in this paper. We have discussed some of these channels in Section 3.2.

[46] See Table 5 for mapping G-Cubed sectors to the four broad sectors (Agriculture, Mining, Manufacturing, and Services) discussed in this paper.

4.0 ECONOMIC IMPACTS OF PHYSICAL CLIMATE RISKS

4.1 Overview

We now discuss the simulation results under the two SSPs compared to the baseline. The results are discussed for changes in Real GDP, Consumption, Investment, Imports, Exports, Real Interest Rates, Current Account Balance, Real Exchange Rates, Trade Balance, Inflation, and Sectoral Output. Even though the G-Cubed version used for this paper consists of 20 sectors, we focus only on the first 15 sectors and exclude the renewable electricity generation sectors, as no shocks have been imposed on those[47].

All the results for the main variables discussed in Section 4 are presented in Annexures 7, 8, and 9. Several factors drive the results observed. Firstly, we impose different shocks across countries and sectors (the sectoral productivity changes imposed directly by the chronic and extreme climate risks detailed in Section 2.7 and by the persistent TFP effects imposed by the flood damage to firms' physical capital detailed in Section 2.8). Secondly, these shocks create ripple effects in the economies due to changes in relative prices (mainly due to the changes in sectoral productivity of countries that are dominating the global market, thereby affecting both domestic and foreign demand and supply equilibria via trade linkages), and the decisions of agents (particularly those that are forward-looking) as they adjust their consumption and investment decisions to respond to income and employment changes, among others. Thirdly, the effects could also be moderated by the policy responses of the monetary and fiscal authorities. Accordingly, given the sophistication of the G-Cubed and close reflection of the realistic reactions of economic agents to global economic shocks, the ultimate results observed can be very different from what could be linearly predicted from the economic shocks.

The results are discussed relative to a baseline. As mentioned in Section 3.3, the G-Cubed baseline does not assume any climate shocks. However, as the shocks have been normalized for each sector in each G-Cubed region for their 2020 levels, the current baseline assumes climate shocks equivalent to their respective 2020 levels. Therefore, the results should be interpreted as the economic consequences of additional climate shocks under SSPs relative to 2020 levels.

4.2 Changes in Real GDP

Introduction

When assessing the global economic consequences of physical climate risks, given the sectoral disaggregation in the G-Cubed (as explained in Section 3.4), the TFP shocks have been introduced at the sectoral level. This approach distinguishes our study from most existing studies, which use either econometric or DSGE models without sector disaggregation. There, a cumulative TFP shock is introduced

[47] Transition risks are beyond the scope of this paper and are left for future studies. See Fernando (2023) for a survey of the economic consequences arising from the exposure of both renewable and non-renewable energy sectors to physical climate risks.

to the entire economy. Given the ability to introduce the shocks at the sectoral level, from the supply side of the economy, the ultimate Real GDP changes are the cumulative effect of the changes in sectoral production. From the demand side of the economy, the ultimate Real GDP changes are the cumulative effect of the changes in consumption, investment, government expenditure, and expenditure on net exports.

This section presents an overview of the changes in Real GDP under the two SSPs. We also compare our estimates for Real GDP losses with the existing studies. Sections 4.3 and 4.4 discuss the results for Consumption, Investment, Imports, and Exports to understand the demand-side decomposition of the Real GDP changes. Section 4.5 discusses the changes in sectoral production that drive the changes in Real GDP from the supply side of the economy.

Real GDP Changes under the SSPs

Overall, all the regions experience losses under both SSPs (see Annexure 7). Under both SSP 1-2.6 and 2-4.5, all regions permanently experience increasing losses throughout the century. Under SSP 1-2.6, Japan, Russia, and Canada experience the strongest deviation in Real GDP, which exceeds four percent below the baseline towards 2100. Europe experiences the lowest deviation in Real GDP, less than one percent below the baseline. Under SSP 2-4.5, the losses experienced by all the regions increase. Different from SSP 1-2.6, Oil Producing Countries and the Rest of the World also experience large deviations from the baseline, which exceed eight percent below the baseline towards 2100. Other OECD countries and India experience the lowest deviations from the baseline.

Table 6 presents the average annual percentage deviation in Real GDP across the regions under the two SSPs. Accordingly, all regions except Japan, which observes a marginal reduction in the average annual losses, experience increasing average annual losses with warming. Oil Producing Countries, Canada, Russia, and the Rest of the World, experience substantial average annual losses compared to other regions.

Results Comparison with Existing Estimates

To benchmark the GDP results from this paper, we looked at the other existing estimates (Table 7). Kahn et al. (2019) assess both chronic and some extreme risks and illustrate that the GDP losses per capita could vary between 0.58 to 9.96 percent across different RCPs by 2100. Kompass et al. (2018) expect the annual global losses to be between $US 5.55 and 23.15 trillion under three warming scenarios. Roson and van der Mensbrugghe (2010) illustrate that the average percentage of GDP change could vary between 3.5 to -12 percent under an extreme warming scenario. Fernando et al. (2021), which evaluates the global economic consequences of both chronic and extreme physical risks of RCPs, illustrate global annual losses to be between $US 4 and 15 trillion[48].

[48] Fernando et al. (2021) also evaluate two sources of transition risks (financial risks and carbon prices) besides physical risks. The estimates compared and presented in this paper only relate to the physical risks.

Table 6: Average Annual Percentage Deviation in Real GDP

Region	Average Percentage Deviation in Real GDP (2021 – 2100): SSP 1-2.6	Average Percentage Deviation in Real GDP (2021 – 2100): SSP 2-4.5
AUS	-1.03	-3.10
CAN	-2.81	-5.90
CHN	-1.79	-2.02
EUW	-0.21	-3.65
IND	-0.93	-1.71
JPN	-2.07	-1.88
OEC	-0.63	-0.88
OPC	-1.66	-5.47
ROW	-1.07	-5.10
RUS	-2.47	-10.15
USA	-1.34	-2.36

Source: Constructed by the Authors using G-Cubed Simulation Results (2023).

As observed from Table 7, the estimates from this paper are within the existing range of estimates, which is, however, wide. A comprehensive comparison of the estimates directly with each other is difficult due to at least three reasons: (1) the differences in various approaches undertaken among the studies, (2) the differences in scenarios assessed, and (3) the differences in climate variables, indicators, and datasets used. The closest studies this paper could be compared with are Fernando et al. (2021) and Fernando (2023).

Fernando et al. (2021) incorporate both chronic and extreme risks similar to this paper. The paper considers the following chronic risk channels: labor productivity impacts due to changes in heat stress in agriculture, manufacturing, and services, disease incidence changes, the impact on agriculture productivity from temperature and precipitation changes, and land availability changes due to sea level rise. The impacts on the other sectors are derived based on their reliance on agriculture, labor, and land. The impacts of extreme risks due to droughts, floods, heatwaves, coldwaves, wildfires, and storms on agriculture and energy sectors are estimated and mapped onto the other sectors based on their reliance on agriculture and energy. The paper also adopts an earlier version of the G-Cubed with similar regional and sectoral disaggregation.

However, there are four main differences between this paper and Fernando et al. (2021). Firstly, this paper directly assesses the productivity changes in agriculture, mining, manufacturing, and services using firm-level data. In contrast, Fernando et al. (2021) first assess most of the effects for the agriculture and energy sectors and then derive the impact on the other sectors based on historical input-output linkages. Secondly, this paper also incorporates both chronic and extreme risks within the same empirical estimation framework, accounting for any potential collinearities among the chronic and extreme climate indicators. In contrast, Fernando et al. (2021) assess the chronic and extreme risks separately. Thirdly, this paper focuses only on a global multisectoral sample of 59,554 firms, whereas the approach followed by Fernando et al. (2021) identifies the sector-wide average impact on productivity. Fourthly, Fernando et al. (2021) do not normalize the shocks for 2020 compared to this paper and, hence, do not allow for the additional adaptation channel in this paper.

Compared to Fernando et al. (2021), Fernando (2023) shares additional similarities to this paper. There, the impacts of a series of climate indicators on the agriculture and energy sectors are estimated, and the effects on the other sectors are derived based on their reliance on agriculture and energy. Fernando (2023) also normalizes the shocks for 2020 and allows for the initial adaptation channel in this paper. Furthermore, Fernando (2023) uses the same version of the G-Cubed model used in this paper.

Different from this paper, Fernando (2023) distinguishes impacts on crops and livestock within agriculture and incorporates impacts on renewable energy sources in addition to non-renewable sources. Fernando (2023) also uses two additional climate indicators to account for relative humidity and extreme wind speeds compared to this paper. The approach followed by Fernando (2023), however, captures only the effects on an average firm in a given sector. In contrast, this paper accounts for a selected sample of firms at the production frontier in a given sector.

Despite the differences in approaches, the estimates from this paper are close to those of Fernando (2023) and Fernando et al. (2021). Compared to Fernando et al. (2021), the estimates from this paper are marginally smaller for SSP 1-2.6 and marginally more significant for SSP 2-4.5. However, the estimates from this paper are consistently larger than those of Fernando (2023). These differences in estimates illustrate the importance of more granular estimates when assessing the physical climate impacts and how granular estimates could reveal certain effects that may not be captured via input-output linkages. The three studies also illustrate the robustness of the estimates and their range despite the subtle methodological differences.

4.3 Changes in Consumption and Investment

As observed in Annexure 7, changes in consumption closely follow the changes in Real GDP due to the income effects on consumption. Under SSP 1-2.6, European consumers observe the lowest consumption adjustment as they experience the lowest Real GDP contraction. Russia experiences the highest consumption contraction, seven percent below the baseline towards 2100. Canada closely follows Russia from 2050 onwards. China, the Oil Producing Countries, and Japan also experience higher contractions, although they are lower than Canada and Russia. Under SSP 2-4.5, all the regions experience higher consumption contractions compared to SSP 1-2.6. However, the consumption reduction patterns remain similar across the scenarios. Canada and Russia experience the strongest consumption reductions under SSP 2-4.5. Under both scenarios, all regions experience stronger consumption declines after 2050, reflecting the substantial changes in physical risks in the medium to long term.

Table 7: Summary of Current Estimates of the Global Economic Consequences of Physical Climate Risks

Study	Risks	Scenario	Focus	Horizon	Unit	Estimates
Fernando & Lepore (2023)	Chronic and extreme risks	SSP 1-2.6	World	2021 - 2100	$US Trillion in GDP per annum	-2.38 (-1.2% of GDP per annum)
		SSP 2-4.5				-7.10 (-3.2% of GDP per annum)
Fernando (2023)	Chronic and extreme risks	SSP 1-2.6	World	2021 - 2100	$US Trillion in GDP per annum	-2.00 (-0.9% of GDP per annum)
		SSP 2-4.5				-6.70 (-2.9% of GDP per annum)
		SSP 5-8.5				-15.45 (-6.4% of GDP per annum)
Fernando et al. (2021)	Chronic and extreme risks	RCP 2.6	World	2021 - 2100	$US Trillion in GDP per annum	-3.82
		RCP 4.5				-6.91
		RCP 6.0				-7.85
		RCP 8.5				-13.83
Kahn et al. (2019)	Chronic and (some) extreme risks	RCP 2.6	World	2100	% GDP per capita Loss	0.58% to 1.57%
		RCP 8.5	World	2100		4.44% to 9.96%
Kompas et al. (2018)	Chronic risks	2^0C	World	2020 - 2100	$US Trillion in GDP per annum	-5.55
		3^0C				-9.59
		4^0C				-23.15
Roson & van der Mensbrugghe (2010)	Chronic risks	5.2^0C	World	2100	% GDP Change	+3.5% to -12%
Hsiang et al. (2017)	Extreme risks	2^0C	USA	2080 - 2099	% GDP Change	0.5%
		4^0C				2.0%
Narita et al. (2010)	Storms		World	2100	% GDP Change	0.006%

Source: Constructed by the Authors.

Changes in investment across the scenarios follow a similar pattern to Real GDP and consumption. However, the investment changes can be much more significant than Real GDP and consumption. Notably, the investment reductions in the G-Cubed are more significant than in similar CGE/DSGE models and especially IAMs. This is mainly due to the explicit distinction of capital as physical and financial capital. In response to an economic shock or a series of economic shocks expected in the future for a given sector, the financial markets in the G-Cubed could respond swiftly. As a result, the financial capital in the given sector could immediately get relocated to sectors and regions experiencing lower risks. Furthermore, the physical investment adjustment costs discourage investors from reinvesting in the sectors and regions more vulnerable to physical climate risks. Due to the vulnerability to climate risks, the stranded assets or the idling stock of capital without productive use in a given sector also have feedback effects on the Real GDP[49]. Investment readjustment is also affected by the structural features of the economies, such as capital controls. Economies with capital controls, therefore, experience much more significant investment reductions when investors respond to physical climate risks.

Accordingly, the results presented in Annexure 7 for investment under the two SSPs are due to a combination of climate shocks, characteristics of agents, and structural features of the economies. Under SSP 1-2.6, all the regions experience substantial investment reductions. Canada experiences the highest contraction, almost 11 percent below the baseline by 2100. Investment in Russia is more than eight percent below the baseline by 2100. Under SSP 2-4.5, both the initial and subsequent investment reductions are more significant than SSP 1-2.6. Russia also experiences notably larger investment reductions under SSP 2-4.5 compared to SSP 1-2.6.

4.4 Changes in Exports and Imports

In the G-Cubed, the changes in exports and imports are affected by three main channels. Firstly, the physical climate impacts on sectoral productivity and reduce export production and export competitiveness. Secondly, due to the reduction in productivity and export competitiveness, income decreases, and the affordability of imports among consumers reduces. Thirdly, exports and imports are also affected by exchange rate changes triggered by capital flows due to changes in returns to capital. This could further affect import affordability and export competitiveness. The ultimate effects observed in exports and imports are the cumulative effects of these channels.

As observed in Annexure 7, Japan experiences the most substantial export reduction, almost 13.5 percent below the baseline towards 2100. The rest of the OECD Countries experience the lowest contraction, and the rest of the regions experience a contraction between two to six percent from the baseline. Under SSP 2-4.5, the contractions increase, although the patterns of reductions remain somewhat similar to SSP 1-2.6.

[49] See NGFS (2022a) for a discussion of the implications of investment adjustment costs on determining carbon prices as an instrument to incentivize transitions to low-carbon economies in G-Cubed vs. IAMs.

As observed in Annexure 7, the imports also significantly change across all the regions even though their lower bound is not as low as for exports. Under SSP 1-2.6, Canada and Russia experience the most substantial import reductions, about five percent below the baseline in 2100. India minimally adjusts its imports compared to the other regions. Similar to exports, the import adjustments under SSP 2-4.5 are much higher, with all the regions experiencing contractions between 3 to 19 percent by 2100.

4.5 Changes in Other Macro-financial Variables

4.5.1 Changes in Real Interest Rates

Amidst the TFP changes induced by climate risks, the marginal productivity of capital falls. This leads to a reduction in the long-term interest rate, which, combined with the loosening monetary policy by central banks to raise growth to target rates, leads to a decline in the short-term nominal interest rate. Annexure 8 illustrates the changes in both short and long-term real interest rates.

Given the continued exposure of economies to climate risks, the long-term real interest rates reduce. Under all scenarios, China experiences the highest reduction. The variations in short-term real interest rates remain similar to those of long-term real interest rates. Under SSP 1-2.6, China experiences the highest short-term real interest rate reduction while Europe experiences the lowest by 2100. Under SSP 2-4.5, both China and the Rest of the World experience similar and the highest reduction in the short-term real interest rates, while Japan and the rest of the OECD countries experience the lowest reduction from the baseline.

4.5.2 Changes in Current Account Balance

The changes in real interest rates trigger investment flows. The countries experiencing relatively lower productivity reductions experience capital inflows, and those experiencing relatively higher productivity reductions experience capital outflows. As observed in Annexure 8, under SSP 1-2.6, China and the US experience capital inflows, whereas Oil Producing Countries and Russia experience substantial capital outflows throughout the century. Under SSP 2-4.5, China, Europe, and the Rest of the World experience capital inflows, while Russia, Canada, and Japan experience capital outflows.

4.5.2 Changes in Real Exchange Rate

The changes in capital flows trigger exchange rate changes. As observed in Annexure 8, China, India, and the US experience a real exchange rate appreciation under SSP 1-2.6, while most other regions experience a depreciation. Under SSP 2-4.5, India and the Rest of the World experience a sharp real exchange rate appreciation. Similar to SSP 1-2.6, under SSP 2-4.5, the US experiences a real exchange rate appreciation in the first half of the century. However, the real exchange rate depreciates towards the second half of the century.

4.5.3 Changes in Trade Balance

The change in trade flows is consistent with the movement of the current and capital accounts. This is achieved through real exchange rate changes, which affect the prices of exports and imports. Those countries experiencing capital inflows observe appreciating real exchange rates and, hence, higher imports due to income effects and lower exports due to reduced competitiveness, and vice versa. As observed in Annexure 8, Oil Producing Countries experience trade balance improvements amidst the deterioration of the current balance due to capital outflows. China, Canada, India, and Australia, although experiencing an improvement at the beginning, experience a reduced trade balance from the mid-century. In contrast, some other regions, such as Russia, observe an improved trade balance towards the mid-century. Under SSP 2-4.5, the trade balance changes become less dynamic for most regions. However, Japan experiences a sharp trade balance improvement starting from the mid-century.

4.5.4 Changes in Inflation

Two main factors drive the changes in inflation in the G-Cubed. Firstly, the changes in production patterns, income, and prices triggered by the productivity impacts of climate risks affect inflation. Secondly, the effects are moderated by the central banks in the respective regions depending on their objectives. As observed in Annexure 8, inflation will be permanently higher under both climate scenarios as we assume that central banks have not adjusted their baseline projections of real economic growth. Thus, an inflation bias emerges from the central bank reaction functions. Under SSP 2-4.5, they will settle at higher levels compared to SSP 1-2.6. China and Russia mainly observe significant inflation variations.

4.6 Changes in Sectoral Output

Annexure 9 summarizes the G-Cubed simulation results for changes in output for eight selected sectors: coal mining, crude oil extraction, construction, other mining, agriculture, durable manufacturing, non-durable manufacturing, and services. The results for these sectors are discussed under each of the broad sectors they belong to, i.e., agriculture, mining, manufacturing, and services. Similar to the macroeconomic results discussed under Sections 4.2, 4.3, and 4.4, the sectoral results are affected primarily by the shocks imposed on them and the other general equilibrium effects.

Agriculture

As observed in Annexure 9, Canada experiences the highest decline in agriculture output under SSP 1-2.6, almost 20 percent lower than the baseline towards 2100. From the rest of the regions, the US experiences the highest contraction. India, Australia, Europe, and the Rest of the OECD countries experience the lowest adjustments. Under SSP 2-4.5, the deviations increase further from the baseline.

When looking at the decomposition of the shocks, the decline in agriculture productivity is primarily driven by the increasing mean temperature and warmer nights. As illustrated by Muthuraj (2021), warmer nights increase plant respiration rates and reduce the amount of carbon available for grains, reducing overall crop production. Paschal (2022) also indicates that a 1^{0}C increase in night-time temperature could reduce rice yields by six percent. Sadok and Jagadish (2020) identify the limited carbon availability for yields due to increased night-time respiration and increased vulnerability to droughts resulting from declining water use efficiency as the main impact pathways of warmer nights on crops. Tesfaye (2022) reports on the implications of warmer nights on cattle reproduction and, thereby, consequences on livestock in the US.

Sectoral results for agriculture also provide an opportunity to illustrate how the shocks of the same magnitude on the same sector in two regions could lead to different results in the G-Cubed due to the general equilibrium effects, explained in Section 4.1. Canada and the US experience the same shocks on agriculture in the same UN region, i.e., North America. However, the ultimate sectoral impact is quite different. Given the higher dominance of the US in global agriculture, it always experiences much weaker reductions compared to Canada.

Mining

In this paper, we impose the shocks computed for the mining sector on Coal Mining, Crude Oil Extraction, and Other Mining in the G-Cubed. As observed in Annexure 9, Other Mining in Canada experiences the highest contraction under SSP 1-2.6, which is almost 9.5 percent below the baseline by 2100. Europe experiences the lowest contraction. Under SSP 2-4.5, the effects further deviate from the baseline. While Russia experiences higher contractions than Canada, Japan experiences the lowest adjustments.

Sectoral results for mining also provide an opportunity to illustrate how the shocks of the same magnitude on different sectors in the same region could lead to different results in the G-Cubed due to the general equilibrium effects, explained in Section 4.1. As observed in Annexure 9, Coal Mining, Crude Oil Extraction, and Other Mining experience similar shocks as they are mapped onto the same broad sector, i.e., mining. However, while the Coal Mining sector in Japan experiences moderate contractions compared to the other regions, the contractions in Japan are much stronger in Other Mining and Crude Oil Extraction.

Manufacturing

The G-Cubed distinguishes manufacturing durable (or capital) goods from non-durable (or consumption) goods. Even though we map the same shock from the manufacturing broad sector to these two sectors, they vary slightly due to their reliance on different capital inputs and the impact of investment in durable goods. As observed in Annexure 9, under SSP 1-2.6, the non-durable manufacturing in Europe and Canada, respectively, experience the lowest and highest deviations from the baseline. The contraction in Canada is as high as eleven percent towards 2100. Under SSP 2-4.5, along with Canada, Russia also experiences significant contractions in non-durable manufacturing, which exceed 18 percent below the baseline.

Despite experiencing comparable shocks, durable manufacturing experiences weaker contractions compared to non-durable manufacturing. The demand reduction for capital goods arises from the investment contractions, as discussed in Section 4.2. Under SSP 1-2.6, Canada experiences the highest durable manufacturing contraction, which reaches almost seven percent by 2100. Europe experiences the lowest contraction, close to 1.5 percent, in 2100. The contractions for other regions are two to five percent below the baseline by 2100. Under SSP 2-4.5, the initial contractions are similar, although the regions deviate from the baseline much stronger compared to SSP 1-2.6. Under SSP 2-4.5, India experiences the lowest adjustment for durable manufacturing while Russia experiences the highest contraction, reaching 19 percent by 2100.

Services

As observed in Annexure 9, Russia experiences the strongest reduction in service sector output under SSP 1-2.6, almost three percent below the baseline in 2100. The impacts on regions are much more divergent compared to other sectors. Under SSP 2-4.5, the effects on all the regions increase compared to SSP 1-2.6 and further diverge from the baseline towards 2100. The rest of the OECD countries and India generally experience lower adjustments across both scenarios.

5.0 POLICY IMPLICATIONS

Since the 1970s, which observed the genesis of the IAMs of climate change, policymakers have used various approaches and tools to understand the environmental and socioeconomic consequences of climate change and to devise policies to mitigate and adapt to them. With physical climate risks increasing, it is even more important for policymakers to evaluate the potential impact of climate change on the economy and financial system. Establishing the Network for Greening the Financial System (NGFS) and its increased participation from central banks and supervisors exemplify this importance. This section highlights some of the critical policy implications arising from our paper.

Firstly, this paper illustrates the cost of not responding to climate change. The results indicate that, in the absence of additional adaptation relative to that already achieved by 2020, all the economies would experience substantial losses under the two climate scenarios, and the losses would increase with global warming. We also discuss how physical climate risks under warming scenarios affect economic productivity and reduce the ability of exposed sectors in different regions to contribute to the global economy. We demonstrate how the changes in production affect income and prices and lead to consumption and investment changes worldwide. Within a globally connected world via investment and trade, we also illustrate how these risks could magnify and spill over into the rest of the world.

Secondly, the results produced in this paper can be used by policymakers and practitioners interested in assessing the impact of climate risks on the economy and financial sector. For example, our macro-financial variables projections can be used as scenarios to assess the risks and impact on banks' capital via standard stress testing approaches for credit and market risks (Adrian et al. (2022)). Relative to the NGFS scenarios, we assess the impact of both chronic and extreme climate risks on a broad set of macro-financial and sectoral variables.

Moreover, this paper demonstrates the importance of general equilibrium effects when assessing the economic consequences of climate risks. We observe how the same shock to the same sector in two different regions and to two different sectors in the same region could lead to different consequences depending on the relative changes among the regions and sectors. Therefore, the economic consequences observed from general equilibrium models can differ greatly from what could be linearly projected from the shocks. Policymakers should be alert to the impact of these modeling choices.

Yet, we acknowledge that assessing the economic consequences of climate risks within economic models involves multiple sources of uncertainty, such as those related to climate data, statistical estimation procedures, economic modeling, and climate scenarios. In this paper, we also face these uncertainties and allude to them when comparing our estimates to those from other studies. Hence, estimates from different models following different philosophies are vital to better understanding the economic consequences of climate risks. We believe encouraging diversity in modeling assessments (despite their limitations) and relying on various assessments will empower policymaking under uncertainty.

6.0 CONCLUSIONS

In this paper, we evaluate the global economic consequences of both chronic and extreme physical climate risks. We empirically estimate the physical climate impacts on sectoral productivity using a global sample of firms representing agriculture, mining, manufacturing, and service sectors. We also evaluate the flood damage to firms' physical capital and the persistent TFP impact arising from that for the same sample of firms. We then project the sectoral productivity changes under two SSPs: SSP 1-2.6 and 2-4.5. We illustrate the economic consequences of physical climate risks using the productivity shocks for the two SSPs in the global multisectoral intertemporal general equilibrium model G-Cubed.

The results indicate substantial losses to all the economies under the two SSPs, and the losses increase with global warming. Climate shocks under SSP 1-2.6 cost the world 1.2 percent of GDP per annum on average from 2021 to 2100. Under SSP 2-4.5, the losses amount to 3.2 percent of GDP per annum on average from 2021 to 2100 (6.4 percent of GDP in 2100). The distribution of the losses under the two SSPs is heterogeneous.

We also investigate the consumption, investment, exports, and imports changes. We observe substantial adjustments to consumption and investment patterns across the world. Given the physical adjustment costs in the G-Cubed, the results show that investment contractions could be much larger when exposed to climate shocks. The G-Cubed also links the supply-side shocks and adjustments to consumption, illustrating how imports and exports change amidst climate change.

Given the rich sectoral disaggregation in the G-Cubed, we also identify how different sectors are affected when exposed to climate shocks. As we are mapping shocks for four broad sectors onto 15 G-Cubed sectors, we illustrate how two sectors in the same region could be affected differently when faced with the same shock. We also demonstrate how the same shock to the same sector in two different regions could lead to different results. Thereby, we emphasize the importance of general equilibrium effects when analyzing climate shocks and how those effects could provide richer insights compared to models without such effects.

From a research perspective, this paper addresses several gaps in the existing literature evaluating the economic consequences of physical climate risks. Firstly, we empirically estimate the responsiveness of sectoral productivity to both chronic and extreme climate risks using a global multisectoral sample of firms. This extends the existing estimates, focusing mainly on a single sector and country or region. Secondly, at a granular firm level, we project forward the physical climate impacts on productivity. Comparing the quantitative estimates from existing studies, we illustrate how firm-level estimations capture additional impact pathways of climate risks compared to sector-level estimates and Input-Output linkages. Thirdly, we use a global, multisectoral, intertemporal general equilibrium model to simulate the economic consequences of physical climate risks under two SSPs. We provide a comprehensive set of results for various economic variables, including Real GDP, Consumption, Investment, Exports and Imports, Real Interest Rates, Current Account Balance, Real Exchange Rates, Trade Balance, Inflation, and Sectoral Output changes.

Future studies, extending this paper could attempt to relax some of the constraints we faced during our study. Firstly, we focus only on the largest firms in each country. Expanding this sample globally to include smaller, potentially less efficient firms could improve the results. Secondly, moving beyond firms' head office locations, future studies could aim to identify the locations of the other establishments and assets of the firms. Thirdly, future studies could incorporate additional indicators of extreme climate risks to account for storms and wildfires. Lastly, given the significant uncertainties around climate modeling and scenarios, expanding the scenario coverage and including measures of modeling uncertainty would be valuable for future studies.

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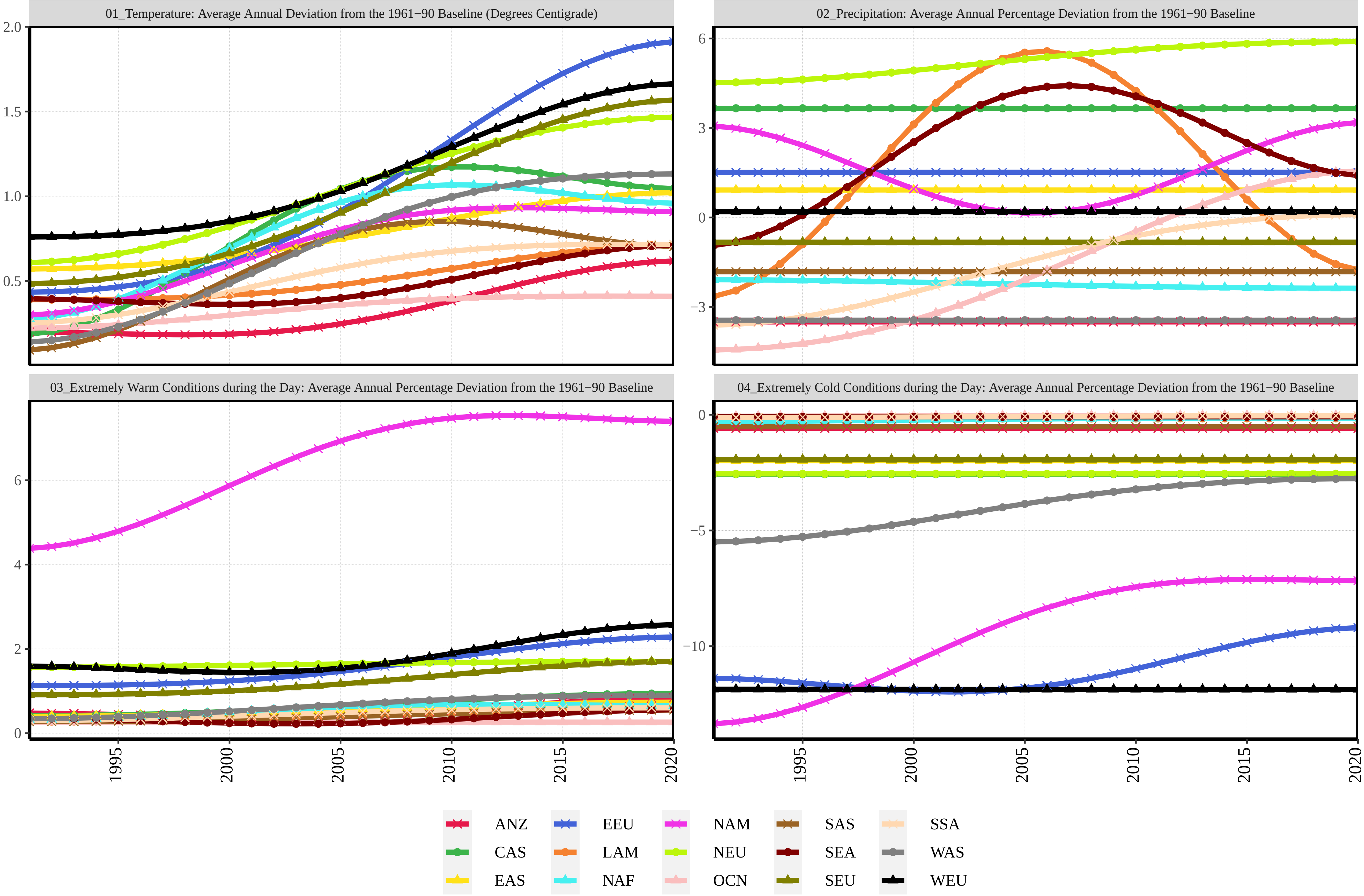
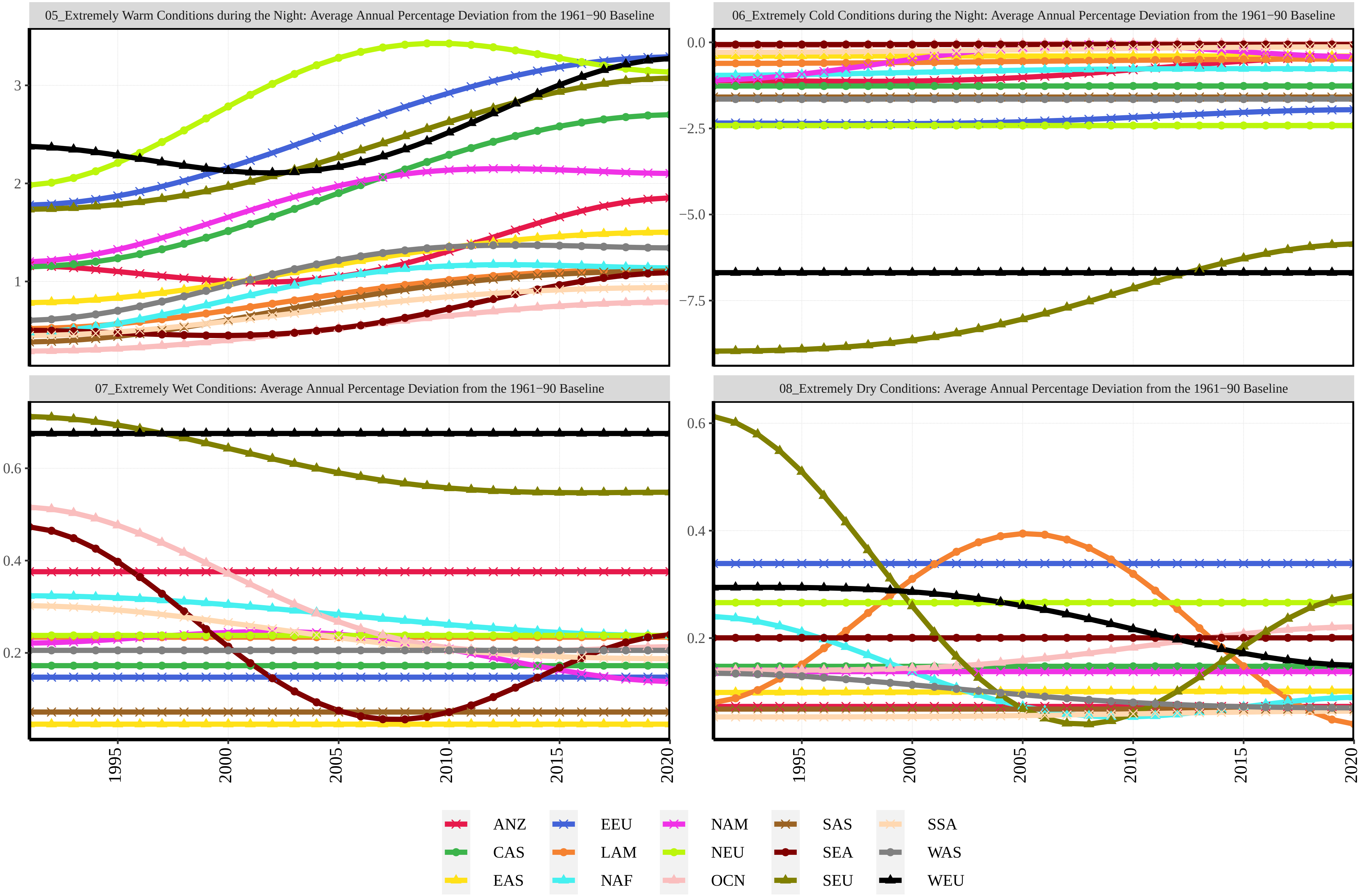
Annexure 01: Historical Variation in Climate Indicators



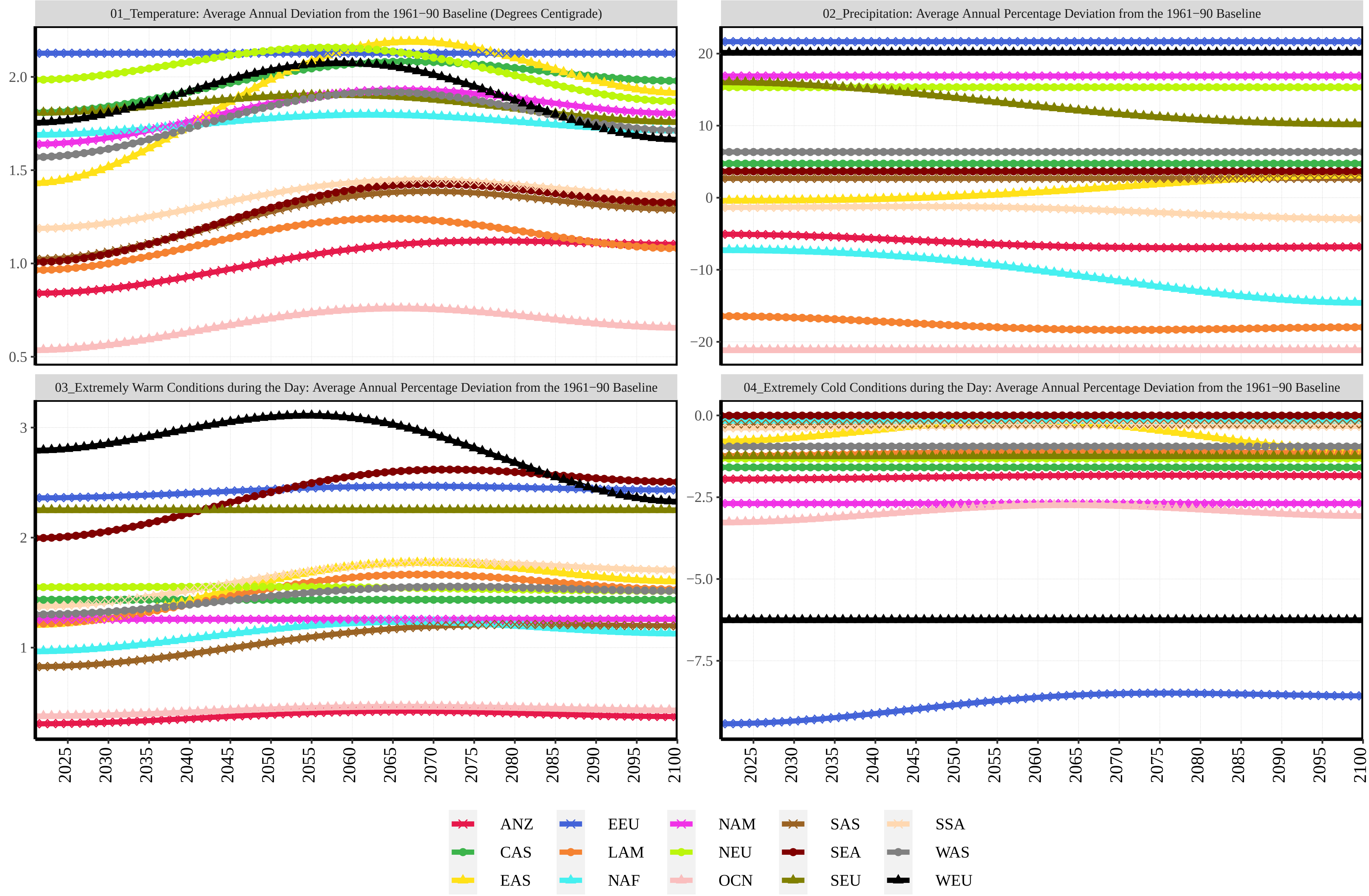
Source: Constructed by the Authors using Data from CRU (2022).

Annexure 01: Historical Variation in Climate Indicators (Contd.)



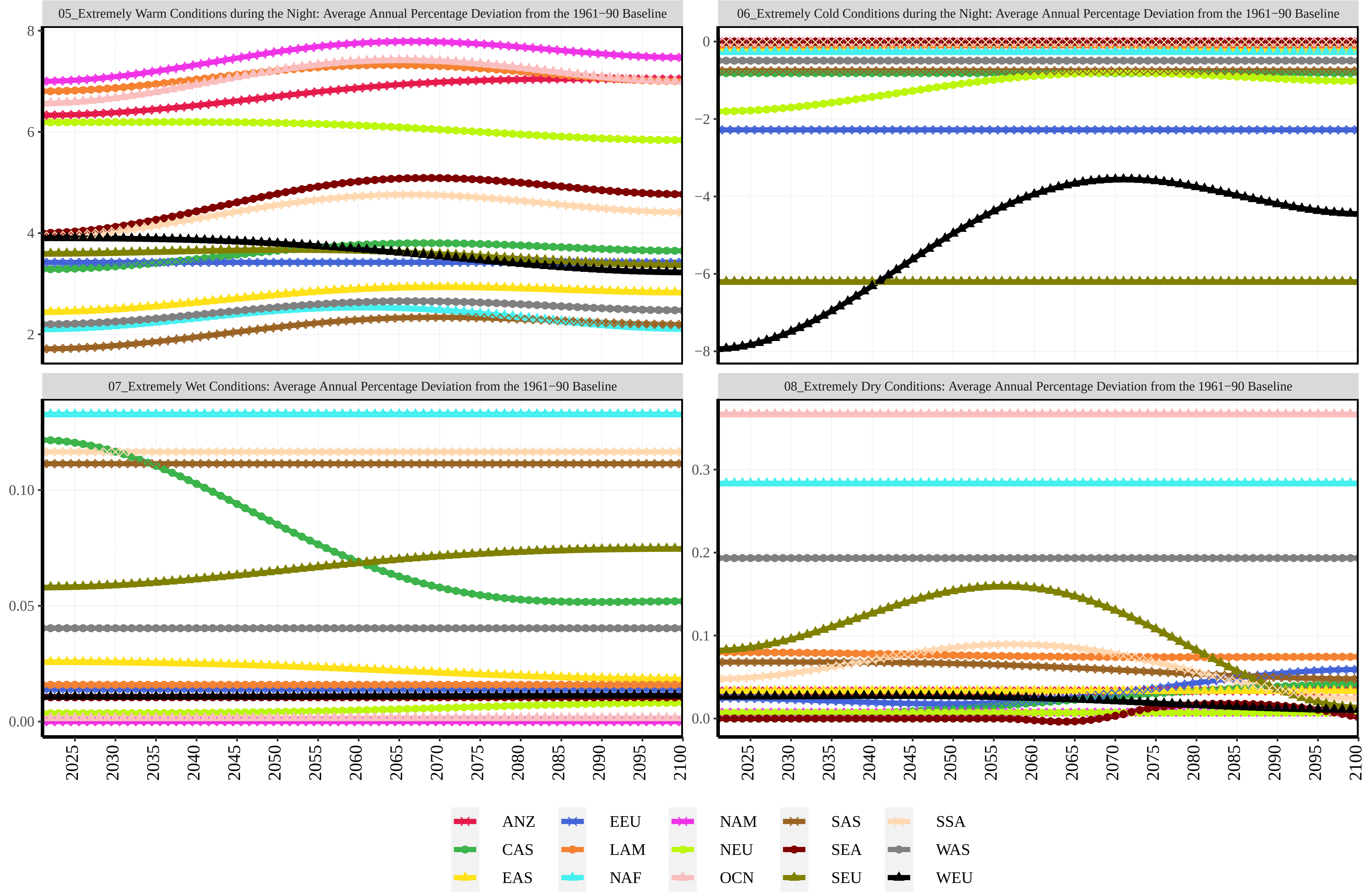
Source: Constructed by the Authors using Data from CRU (2022).

Annexure 02: Projected Variation in Climate Indicators under SSP 1−2.6



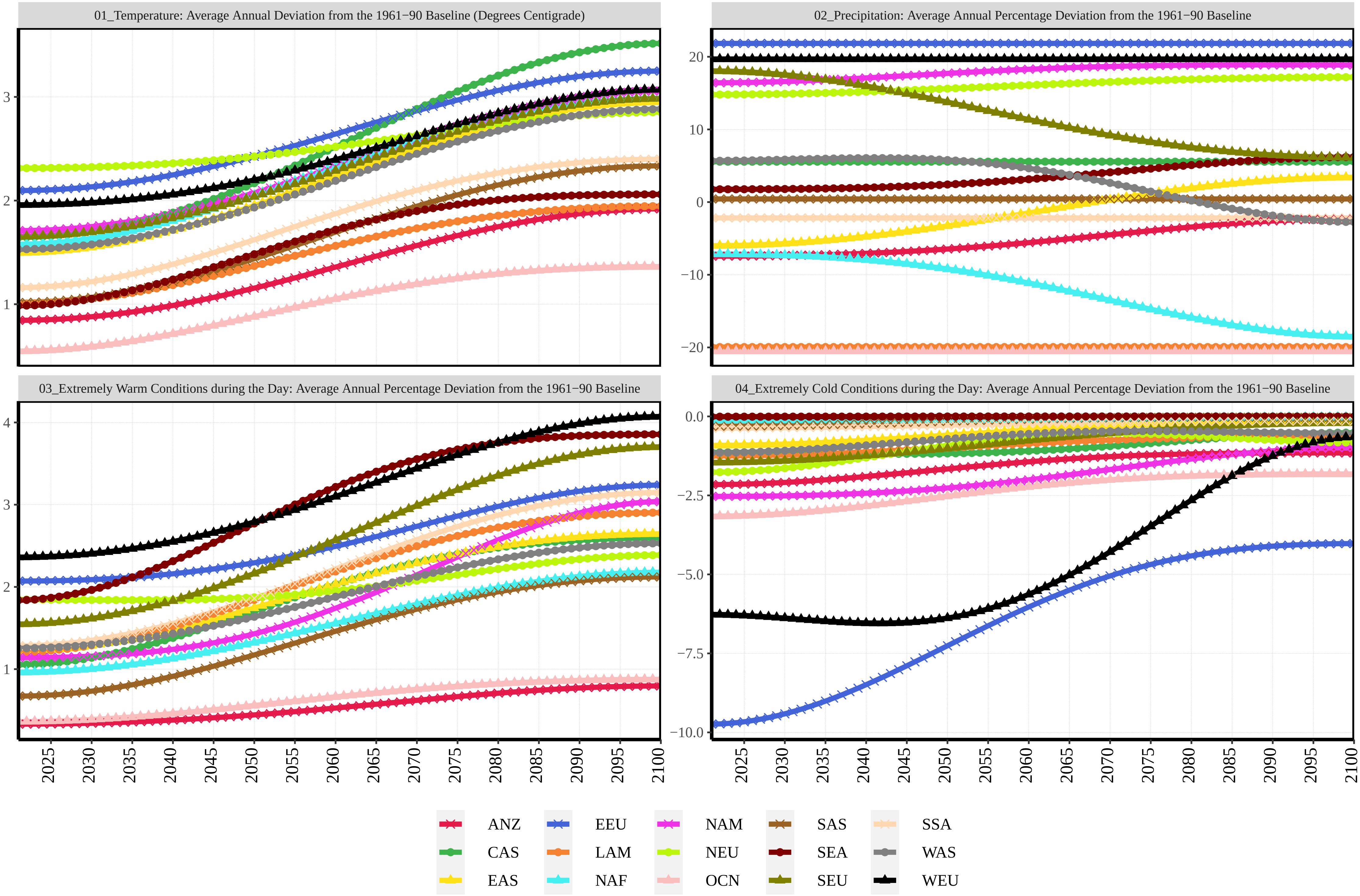
Source: Constructed by the Authors using Data from ISIMIP (2022).

Annexure 02: Projected Variation in Climate Indicators under SSP 1−2.6 (Contd.)



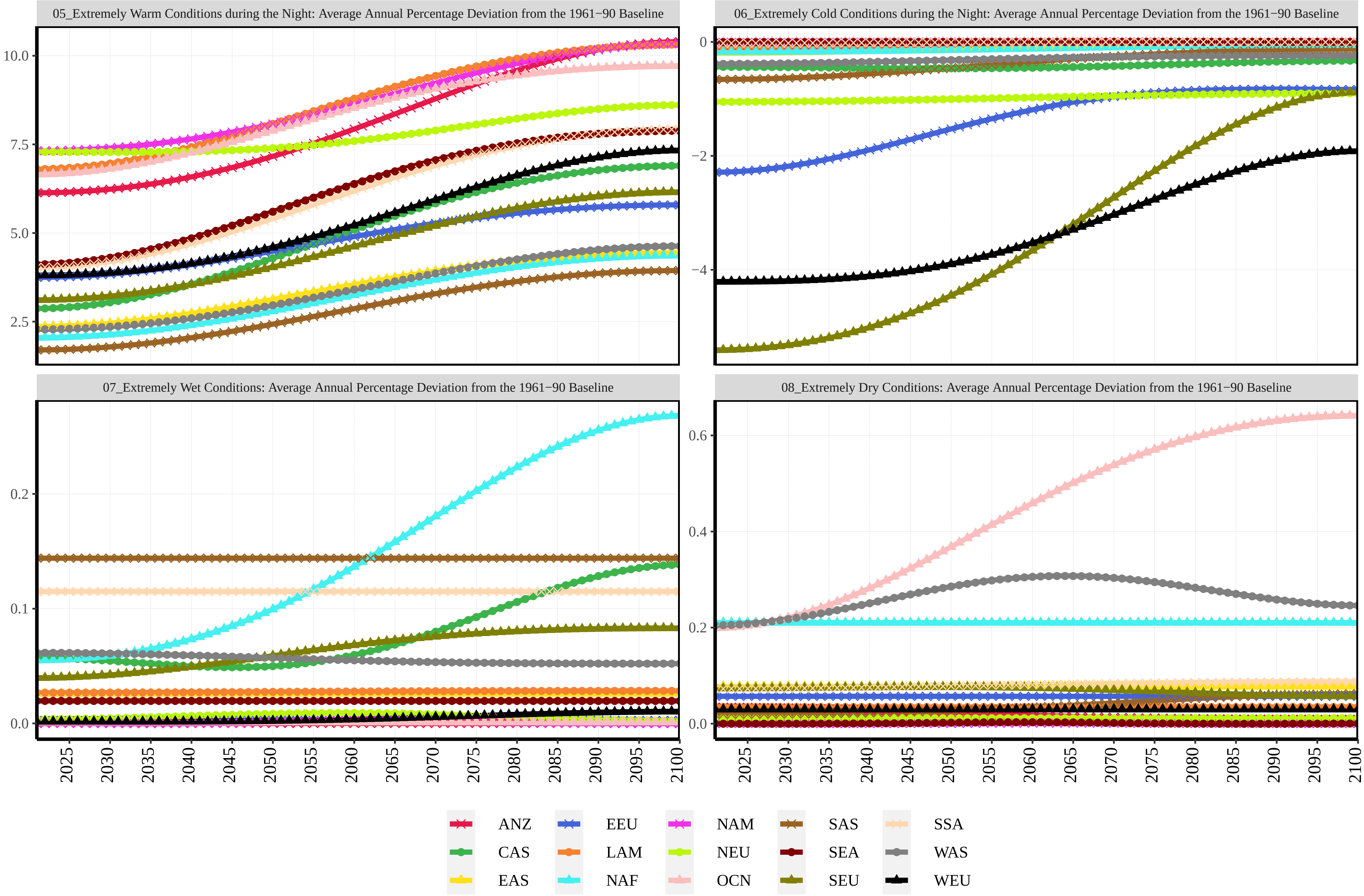
Source: Constructed by the Authors using Data from ISIMIP (2022).

Annexure 02: Projected Variation in Climate Indicators under SSP 2−4.5



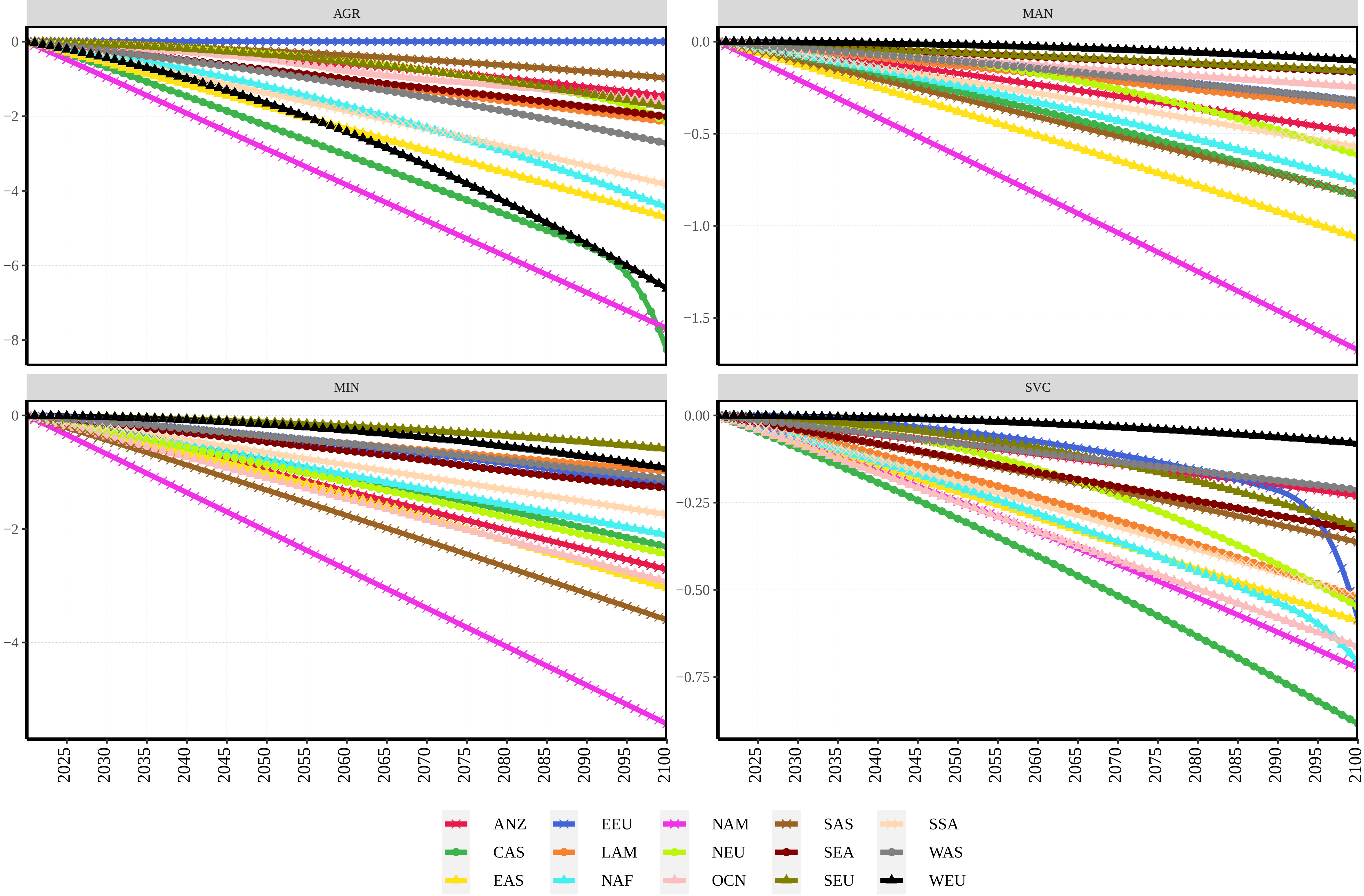
Source: Constructed by the Authors using Data from ISIMIP (2022).

Annexure 02: Projected Variation in Climate Indicators under SSP 2−4.5 (Contd.)



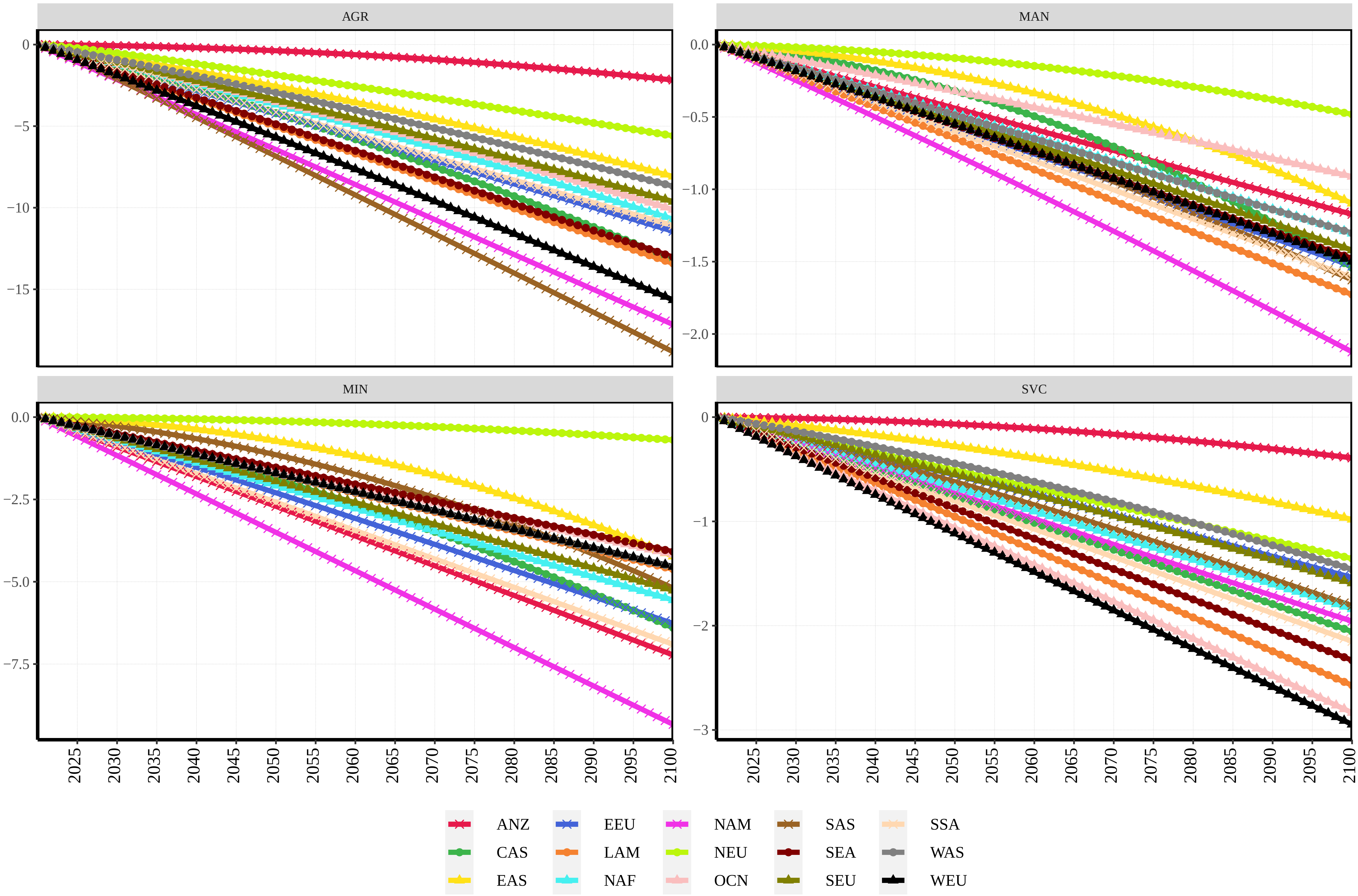
Source: Constructed by the Authors using Data from ISIMIP (2022).

Annexure 03: Projected Variation in Productivity under SSP 1−2.6



Source: Estimated by the Authors.

Annexure 03: Projected Variation in Productivity under SSP 2−4.5



Source: Estimated by the Authors.

ANNEXURE 04:
IMPACTS OF FLOOD RISKS ON THE PHYSICAL CAPITAL STOCK OF FIRMS

This Annexure describes how we compute damage rates from floods under one SSP scenario at a given time for a firm in a given sector. We follow the methodology developed by Fornino et al. (2023). To ease notation, we do not report the scenario, time, or sector subfix. Denote for each firm i (identified by the latitude and longitude of its head office address) in country c and a specific return period RP, the flood depth (in meters) and the fraction of land flooded respectively by $\delta_{c,i,RP}$ and $\varphi_{c,i,RP}$. Jupiter provides these variables for the following return periods: 1-in-10 years (RP_{10}), 1-in-20 years (RP_{20}), 1-in-50 years (RP_{50}), 1-in-100 years (RP_{100}), 1-in-200 years (RP_{200}), 1-in-500 years (RP_{500}). For example, in the figures below we plot the flood depth for each firm in our sample in 2100 under SSP 1-2.6 and 2-4.5 for a 1-in-100 years event.

Figure A: Flood depth projections under SSP 1-2.6. Source: Jupiter Intelligence.

Figure B: Flood depth projections under SSP 1-2.6. Source: Jupiter Intelligence.

For a given return period RP, we define:

$$pd_{c,i,RP} = \varphi_{c,i,RP} * f(\delta_{c,i,RP}),$$

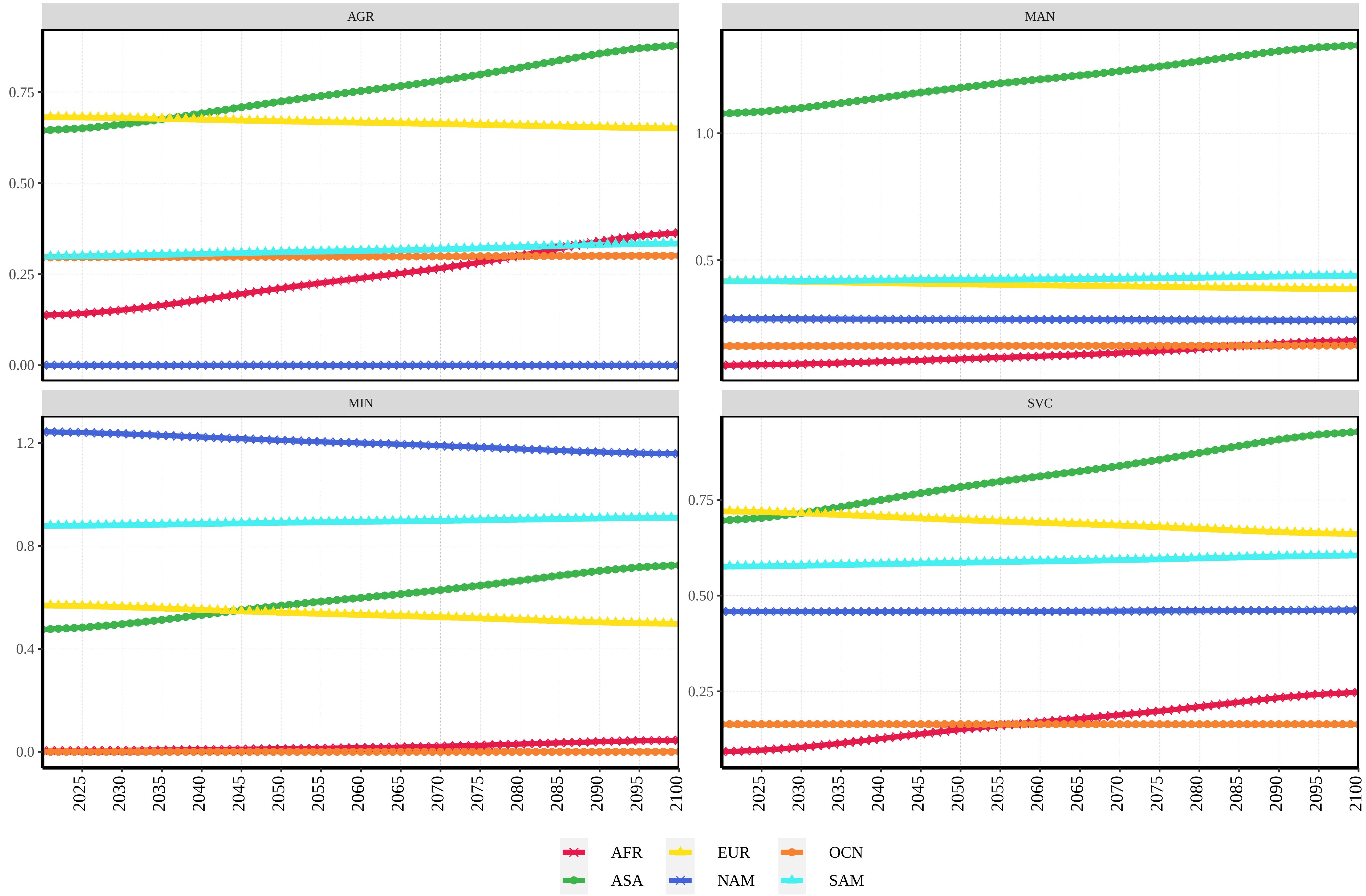
where $f(\cdot)$ is the damage function from Huizinga et al (2017) for the firms' sector and continent. Accounting for the different return periods, we can define the percentage of damage for a firm i in country c is given by:

$$D_{c,i} = \begin{cases} 0, if\ \delta_{c,i,RP} < \delta_{c,i,RP_{10}} \\ \dfrac{pd_{c,i,RP_{10}} + pd_{c,i,RP_{20}}}{2}, if\ \delta_{c,i,RP_{10}} < \delta_{c,i,RP} < \delta_{c,i,RP_{20}} \\ \dfrac{pd_{c,i,RP_{20}} + pd_{c,i,RP_{50}}}{2}, if\ \delta_{c,i,RP_{20}} < \delta_{c,i,RP} < \delta_{c,i,RP_{50}} \\ \dfrac{pd_{c,i,RP_{50}} + pd_{c,i,RP_{100}}}{2}, if\ \delta_{c,i,RP_{50}} < \delta_{c,i,RP} < \delta_{c,i,RP_{100}} \\ \dfrac{pd_{c,i,RP_{100}} + pd_{c,i,RP_{200}}}{2}, if\ \delta_{c,i,RP_{100}} < \delta_{c,i,RP} < \delta_{c,i,RP_{200}} \\ pd_{c,i,RP_{500}}, \quad if\ \delta_{c,i,RP} \geq \delta_{c,i,RP_{500}} \end{cases}$$

It follows that the expected percentage of annual damage for firm i in country c is given by:

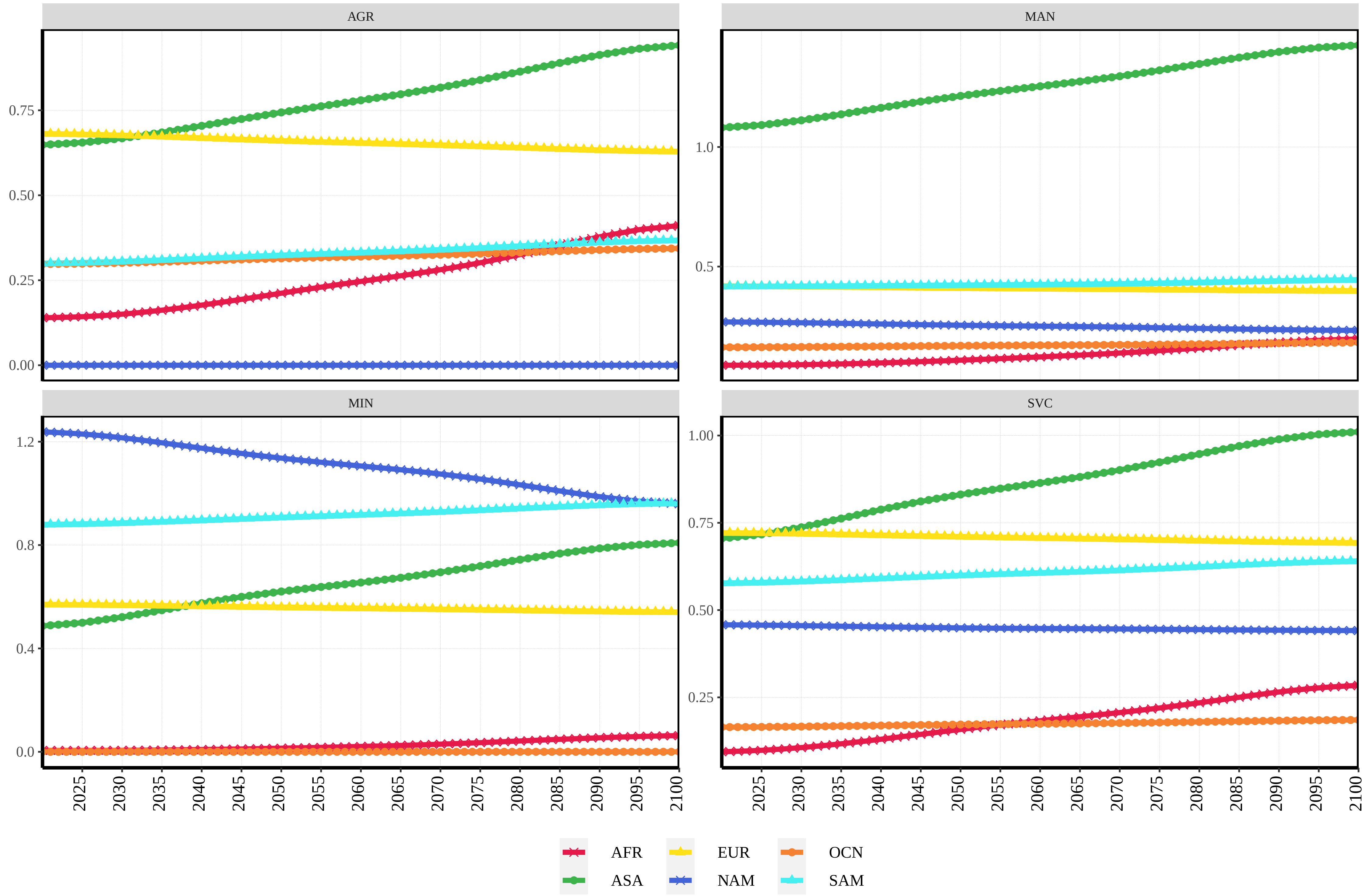
$$\begin{aligned} E[D_{c,i}] = {} & 0 * \frac{1}{10} + \frac{pd_{c,i,RP_{10}} + pd_{c,i,RP_{20}}}{2} * \left(\frac{1}{10} - \frac{1}{20}\right) + \frac{pd_{c,i,RP_{20}} + pd_{c,i,RP_{50}}}{2} * \left(\frac{1}{20} - \frac{1}{50}\right) \\ & + \frac{pd_{c,i,RP_{50}} + pd_{c,i,RP_{100}}}{2} * \left(\frac{1}{50} - \frac{1}{100}\right) + \frac{pd_{c,i,RP_{100}} + pd_{c,i,RP_{200}}}{2} * \left(\frac{1}{100} - \frac{1}{200}\right) \\ & + pd_{c,i,RP_{500}} * \frac{1}{500}. \end{aligned}$$

Annexure 05: Mean Flood Damage under SSP 1−2.6



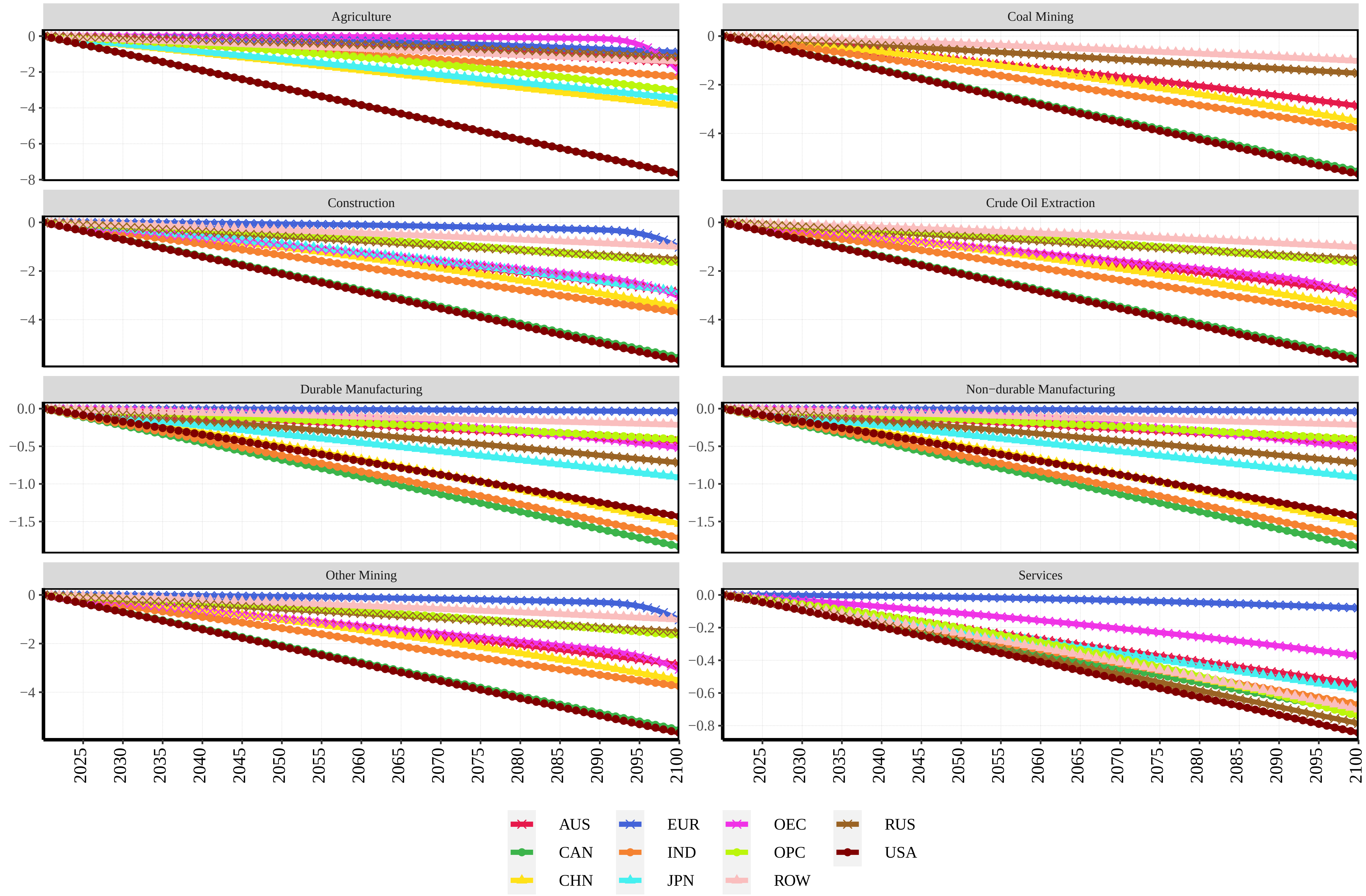
Source: Constructed by the Authors using Data from Huizinga et al. (2017).

Annexure 05: Mean Flood Damage under SSP 2−4.5



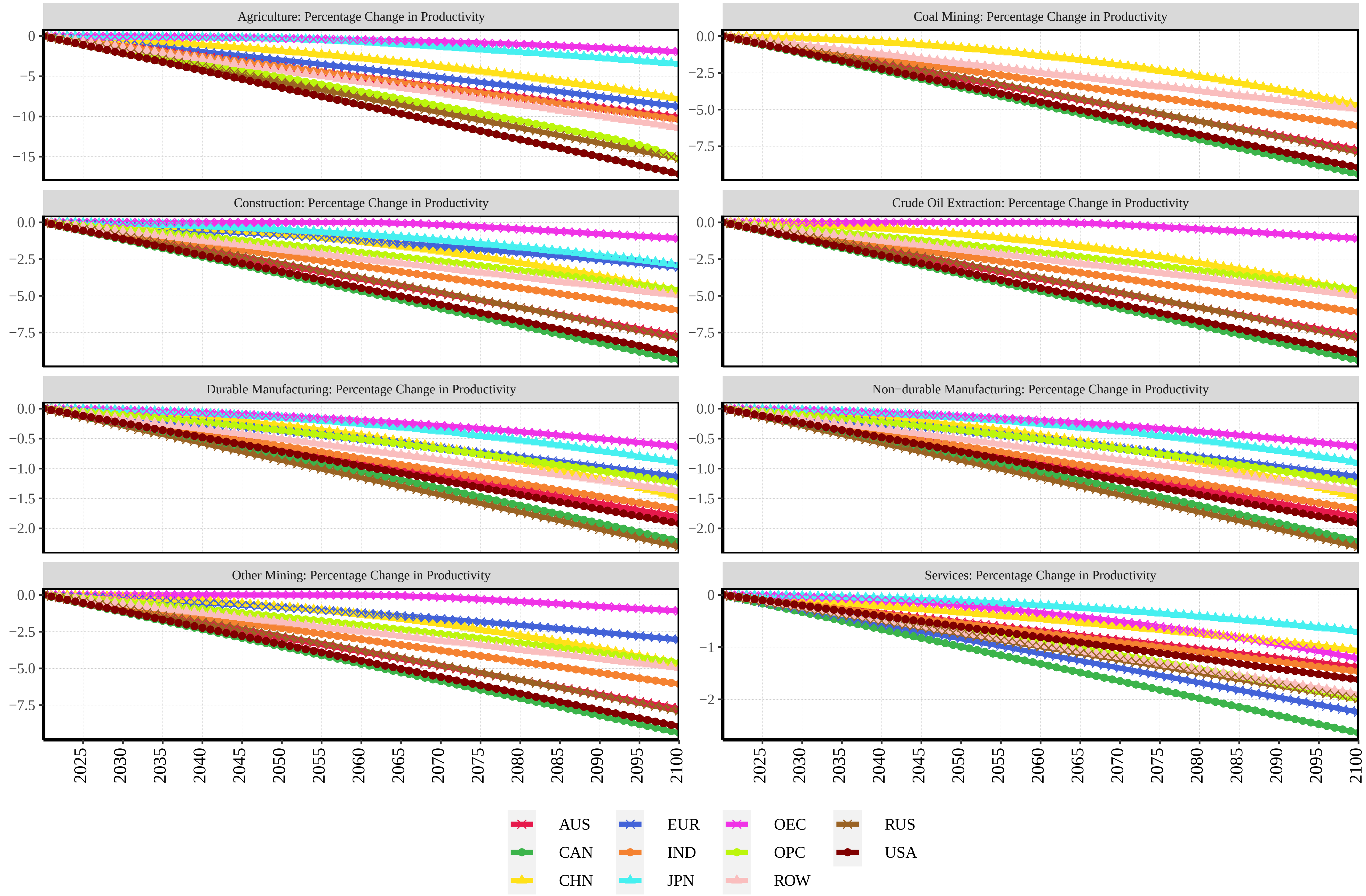
Source: Constructed by the Authors using Data from Huizinga et al. (2017).

Annexure 06: TFP Shocks under SSP 1−2.6



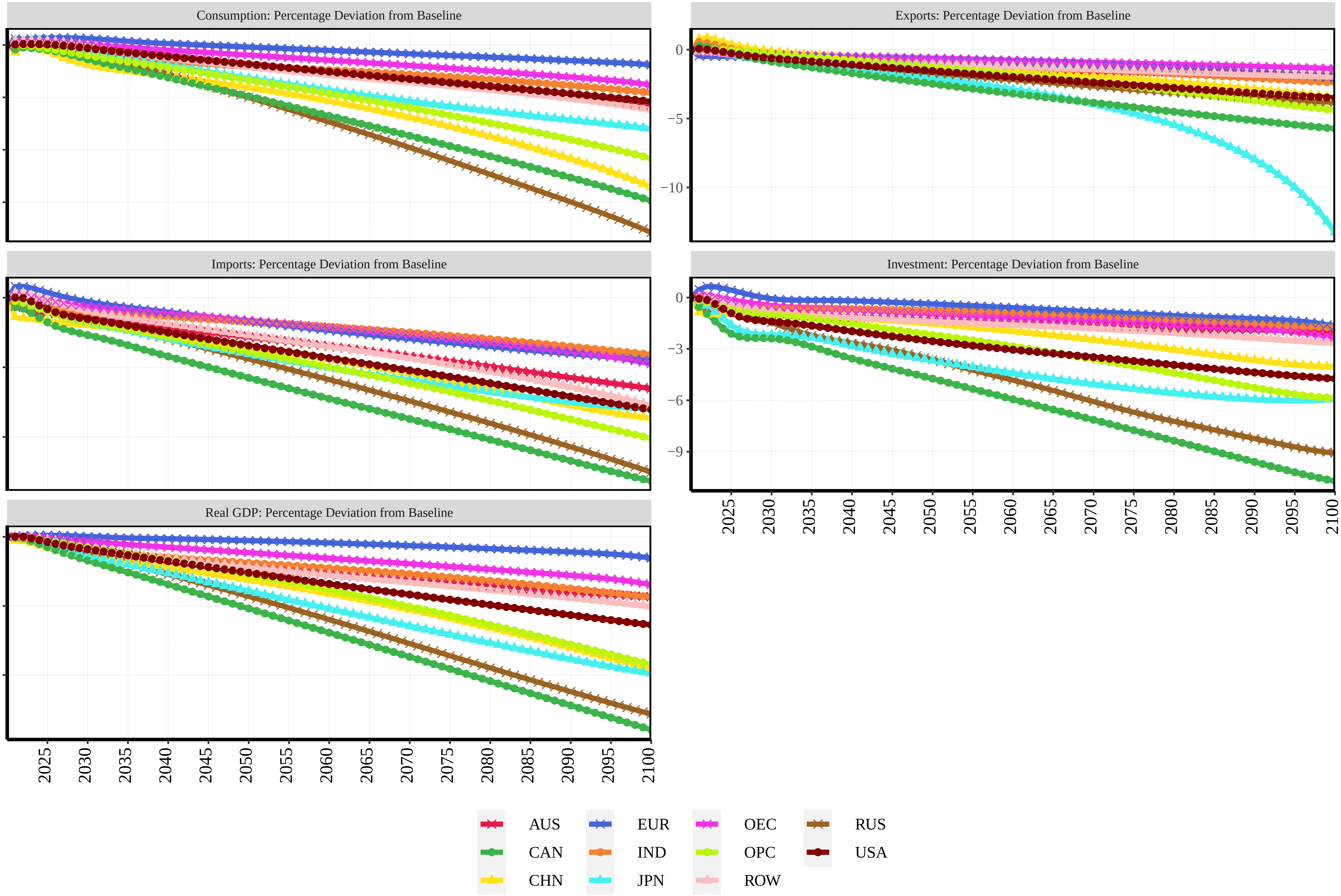
Source: Constructed by the Authors.

Annexure 06: TFP Shocks under SSP 2−4.5



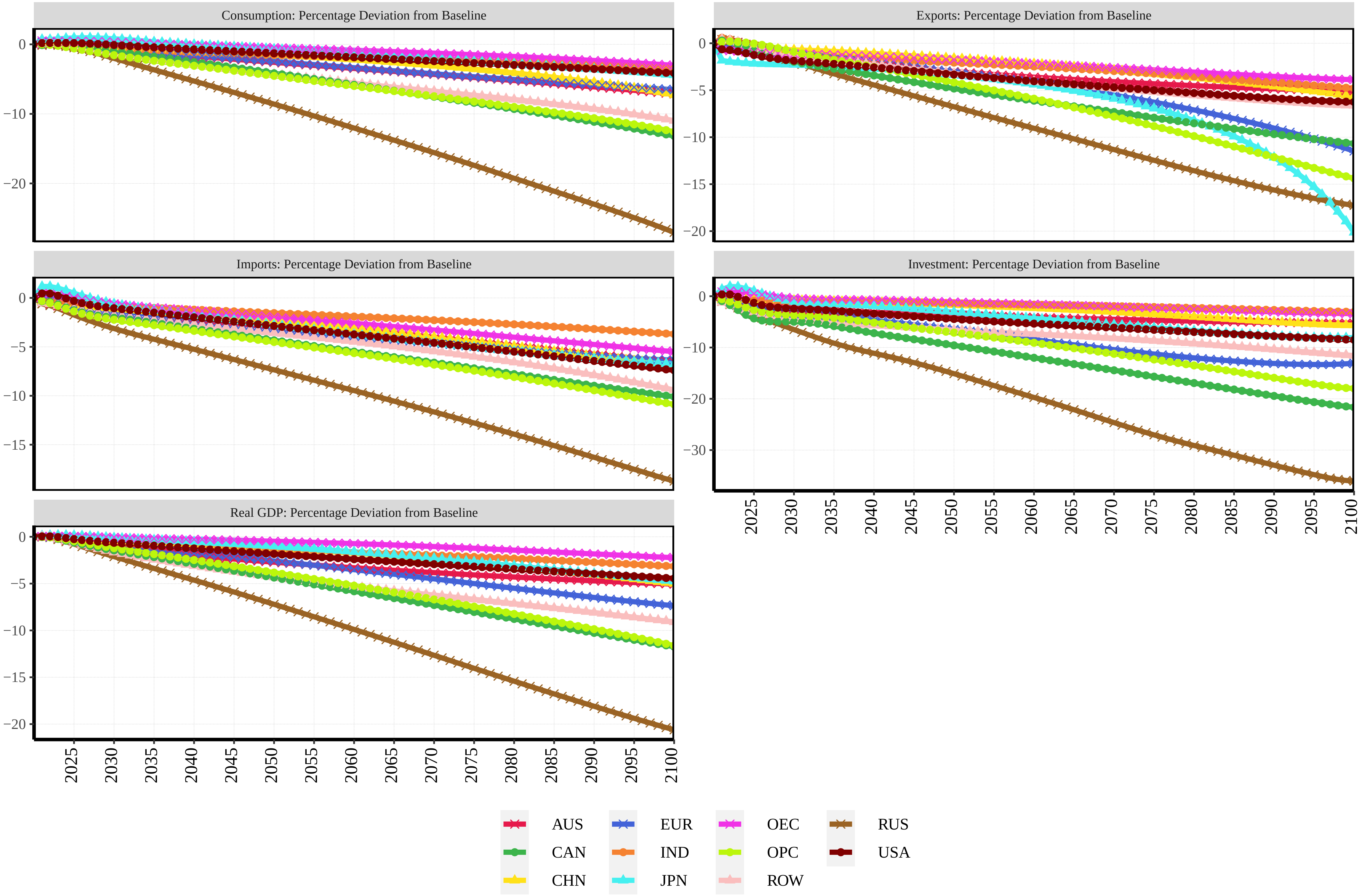
Source: Constructed by the Authors.

Annexure 07: Macroeconomic Results under SSP 1−2.6



Source: Constructed by the Authors using G−Cubed Simulation Results (GGG20C_v169).

Annexure 07: Macroeconomic Results under SSP 2−4.5



Source: Constructed by the Authors using G−Cubed Simulation Results (GGG20C_v169).

SUPPLEMENTARY ANNEXURE 01

DISTRIBUTION OF THE 20,215 FIRMS (THOSE USED FOR THE EMPIRICAL ANALYSIS) ACROSS UNITED NATIONS REGIONS

Region	Count_AGR	Count_MAN	Count_MIN	Count_SVC	Proportion_AGR	Proportion_MAN	Proportion_MIN	Proportion_SVC
ANZ	25	251	57	506	4.82	3.61	12.28	4.12
CAS	8	52	62	179	1.54	0.75	13.36	1.46
EAS	6	849	4	641	1.16	12.22	0.86	5.22
EEU	111	1,181	71	1,870	21.39	17.01	15.30	15.22
LAM	21	161	12	249	4.05	2.32	2.59	2.03
NAF	10	81	7	210	1.93	1.17	1.51	1.71
NAM	-	256	24	465	-	3.69	5.17	3.78
NEU	174	831	72	2,654	33.53	11.97	15.52	21.60
SAS	1	82	8	29	0.19	1.18	1.72	0.24
SEA	76	1,205	97	1,700	14.64	17.35	20.91	13.84
SEU	55	931	13	1,554	10.60	13.41	2.80	12.65
SSA	2	56	11	69	0.39	0.81	2.37	0.56
WAS	11	430	10	427	2.12	6.19	2.16	3.48
WEU	19	579	16	1,734	3.66	8.34	3.45	14.11
Total	**519**	**6,945**	**464**	**12,287**	**100.00**	**100.00**	**100.00**	**100.00**

DISTRIBUTION OF THE 20,215 FIRMS (THOSE USED FOR THE EMPIRICAL ANALYSIS) ACROSS UNITED NATIONS COUNTRIES

ISO	Count_ AGR	Count_ MAN	Count_ MIN	Count_ SVC	Proportio n_AGR	Proportio n_MAN	Proportio n_MIN	Proportio n_SVC
AT	0	67	1	284	-	0.96	0.22	2.31
AU	7	118	50	186	1.35	1.70	10.78	1.51
BE	4	92	3	225	0.77	1.32	0.65	1.83
BG	11	175	7	300	2.12	2.52	1.51	2.44
CH	3	98	1	385	0.58	1.41	0.22	3.13
CL	13	51	7	132	2.50	0.73	1.51	1.07
CN	0	1	0	0	-	0.01	-	-
CO	5	17	3	31	0.96	0.24	0.65	0.25
CZ	46	186	3	308	8.86	2.68	0.65	2.51
DE	3	137	2	321	0.58	1.97	0.43	2.61
DK	2	88	1	331	0.39	1.27	0.22	2.69
EE	58	68	6	222	11.18	0.98	1.29	1.81
ES	4	80	2	231	0.77	1.15	0.43	1.88
FI	4	147	2	383	0.77	2.12	0.43	3.12
FR	5	140	6	327	0.96	2.02	1.29	2.66
GB	6	126	29	298	1.16	1.81	6.25	2.43
GR	14	188	4	415	2.70	2.71	0.86	3.38
HU	11	91	1	211	2.12	1.31	0.22	1.72
ID	11	150	26	183	2.12	2.16	5.60	1.49
IE	4	52	6	223	0.77	0.75	1.29	1.81
IL	1	114	4	145	0.19	1.64	0.86	1.18
IR	1	82	8	29	0.19	1.18	1.72	0.24
IT	11	256	1	290	2.12	3.69	0.22	2.36
JP	2	260	2	432	0.39	3.74	0.43	3.52
KR	4	588	2	209	0.77	8.47	0.43	1.70
KZ	8	52	62	179	1.54	0.75	13.36	1.46
LT	19	127	5	369	3.66	1.83	1.08	3.00
LU	2	2	0	39	0.39	0.03	-	0.32
LV	66	86	9	445	12.72	1.24	1.94	3.62
MA	10	81	7	210	1.93	1.17	1.51	1.71
MX	3	93	2	86	0.58	1.34	0.43	0.70
MY	37	281	11	243	7.13	4.05	2.37	1.98
NL	2	43	3	153	0.39	0.62	0.65	1.25
NO	13	75	12	313	2.50	1.08	2.59	2.55
NZ	18	133	7	320	3.47	1.92	1.51	2.60
PH	5	251	18	451	0.96	3.61	3.88	3.67
PL	3	80	3	233	0.58	1.15	0.65	1.90
PT	15	113	1	217	2.89	1.63	0.22	1.77
RO	16	253	11	321	3.08	3.64	2.37	2.61
RU	8	245	42	198	1.54	3.53	9.05	1.61
SE	2	62	2	70	0.39	0.89	0.43	0.57
SI	11	294	5	401	2.12	4.23	1.08	3.26
SK	16	151	4	299	3.08	2.17	0.86	2.43
TH	4	259	10	343	0.77	3.73	2.16	2.79
TR	10	316	6	282	1.93	4.55	1.29	2.30
US	0	256	24	465	-	3.69	5.17	3.78
VN	19	264	32	480	3.66	3.80	6.90	3.91
ZA	2	56	11	69	0.39	0.81	2.37	0.56
Total	**519**	**6945**	**464**	**12287**	**100.00**	**100.00**	**100.00**	**100.00**

DISTRIBUTION OF THE 59,554 FIRMS (THOSE USED FOR THE PROJECTIONS) ACROSS UNITED NATIONS REGIONS

Region	Count_AGR	Count_MAN	Count_MIN	Count_SVC	Proportion_AGR	Proportion_MAN	Proportion_MIN	Proportion_SVC
ANZ	58	498	260	1174	4.14	3.14	16.20	2.88
CAS	14	165	131	438	1.00	1.04	8.16	1.08
EAS	24	1632	53	1975	1.71	10.30	3.30	4.85
EEU	341	2339	165	5578	24.34	14.76	10.28	13.71
LAM	153	1103	61	3267	10.92	6.96	3.80	8.03
NAF	49	259	26	731	3.50	1.63	1.62	1.80
NAM	7	718	260	991	0.50	4.53	16.20	2.43
NEU	308	1596	171	7456	21.98	10.07	10.65	18.32
OCN	2	3	3	46	0.14	0.02	0.19	0.11
SAS	54	1405	59	684	3.85	8.86	3.68	1.68
SEA	113	1655	166	3231	8.07	10.44	10.34	7.94
SEU	183	2336	98	6801	13.06	14.74	6.11	16.71
SSA	20	220	41	431	1.43	1.39	2.55	1.06
WAS	42	908	80	2393	3.00	5.73	4.98	5.88
WEU	33	1012	31	5503	2.36	6.39	1.93	13.52
Total	**1401**	**15849**	**1605**	**40699**	**100.00**	**100.00**	**100.00**	**100.00**

DISTRIBUTION OF THE 59,554 FIRMS (THOSE USED FOR THE PROJECTIONS) ACROSS UNITED NATIONS COUNTRIES

ISO	Count_AGR	Count_MAN	Count_MIN	Count_SVC	Proportion_AGR	Proportion_MAN	Proportion_MIN	Proportion_SVC
AE	1	17	0	49	0.07	0.11	-	0.12
AG	0	1	0	0	-	0.01	-	-
AI	0	0	0	1	-	-	-	0.00
AL	1	5	0	70	0.07	0.03	-	0.17
AM	0	13	3	71	-	0.08	0.19	0.17
AO	0	0	1	0	-	-	0.06	-
AR	12	61	7	104	0.86	0.38	0.44	0.26
AT	0	122	3	860	-	0.77	0.19	2.11
AU	16	313	242	428	1.14	1.97	15.08	1.05
AZ	0	0	2	2	-	-	0.12	0.00
BA	28	250	25	552	2.00	1.58	1.56	1.36
BB	0	3	1	2	-	0.02	0.06	0.00
BD	3	141	1	46	0.21	0.89	0.06	0.11
BE	8	152	4	820	0.57	0.96	0.25	2.01
BF	0	0	0	3	-	-	-	0.01
BG	14	222	14	696	1.00	1.40	0.87	1.71
BH	0	3	0	10	-	0.02	-	0.02
BJ	0	1	0	1	-	0.01	-	0.00
BO	6	11	2	17	0.43	0.07	0.12	0.04
BR	15	211	16	731	1.07	1.33	1.00	1.80
BS	0	2	0	6	-	0.01	-	0.01
BT	0	5	1	2	-	0.03	0.06	0.00
BW	1	2	2	14	0.07	0.01	0.12	0.03
CA	7	420	228	322	0.50	2.65	14.21	0.79
CD	0	1	0	1	-	0.01	-	0.00
CG	0	0	0	1	-	-	-	0.00
CH	3	128	3	527	0.21	0.81	0.19	1.29
CI	1	11	1	15	0.07	0.07	0.06	0.04
CL	21	63	13	237	1.50	0.40	0.81	0.58
CM	0	1	0	2	-	0.01	-	0.00
CN	4	483	32	329	0.29	3.05	1.99	0.81
CO	20	131	4	822	1.43	0.83	0.25	2.02
CR	0	2	0	8	-	0.01	-	0.02
CV	0	2	0	1	-	0.01	-	0.00
CW	0	1	1	0	-	0.01	0.06	-
CY	8	76	17	805	0.57	0.48	1.06	1.98
CZ	58	257	5	669	4.14	1.62	0.31	1.64
DE	3	253	4	734	0.21	1.60	0.25	1.80
DK	8	121	2	851	0.57	0.76	0.12	2.09
DM	0	0	0	1	-	-	-	0.00
DO	0	0	0	2	-	-	-	0.00
DZ	28	47	10	163	2.00	0.30	0.62	0.40
EC	24	52	1	78	1.71	0.33	0.06	0.19
EE	87	124	6	750	6.21	0.78	0.37	1.84
EG	7	74	5	75	0.50	0.47	0.31	0.18
ES	4	118	3	700	0.29	0.74	0.19	1.72
FI	4	211	4	775	0.29	1.33	0.25	1.90
FJ	1	2	0	7	0.07	0.01	-	0.02
FR	10	247	8	702	0.71	1.56	0.50	1.72
GA	0	0	2	1	-	-	0.12	0.00

GB	7	189	71	672	0.50	1.19	4.42	1.65
GD	0	0	0	1	-	-	-	0.00
GE	7	68	4	338	0.50	0.43	0.25	0.83
GH	0	6	0	2	-	0.04	-	0.00
GN	0	0	0	4	-	-	-	0.01
GR	17	225	7	645	1.21	1.42	0.44	1.58
GT	0	0	0	2	-	-	-	0.00
HK	0	158	8	738	-	1.00	0.50	1.81
HR	26	225	5	724	1.86	1.42	0.31	1.78
HU	31	176	2	759	2.21	1.11	0.12	1.86
ID	21	215	44	331	1.50	1.36	2.74	0.81
IE	13	114	16	810	0.93	0.72	1.00	1.99
IL	2	167	23	366	0.14	1.05	1.43	0.90
IN	15	601	25	324	1.07	3.79	1.56	0.80
IQ	2	8	0	14	0.14	0.05	-	0.03
IR	4	145	19	79	0.29	0.91	1.18	0.19
IS	39	89	3	700	2.78	0.56	0.19	1.72
IT	15	329	2	620	1.07	2.08	0.12	1.52
JM	0	20	0	23	-	0.13	-	0.06
JO	1	29	6	38	0.07	0.18	0.37	0.09
JP	2	282	2	572	0.14	1.78	0.12	1.41
KE	1	9	0	7	0.07	0.06	-	0.02
KG	0	3	1	11	-	0.02	0.06	0.03
KH	0	1	0	4	-	0.01	-	0.01
KN	0	0	0	1	-	-	-	0.00
KR	4	666	3	271	0.29	4.20	0.19	0.67
KW	1	15	2	69	0.07	0.09	0.12	0.17
KZ	11	67	122	322	0.79	0.42	7.60	0.79
LA	0	1	0	1	-	0.01	-	0.00
LB	0	3	0	5	-	0.02	-	0.01
LC	0	0	0	1	-	-	-	0.00
LK	23	85	1	113	1.64	0.54	0.06	0.28
LR	0	0	1	4	-	-	0.06	0.01
LT	29	171	5	774	2.07	1.08	0.31	1.90
LU	5	14	3	972	0.36	0.09	0.19	2.39
LV	78	113	11	782	5.57	0.71	0.69	1.92
MA	14	121	10	469	1.00	0.76	0.62	1.15
MD	93	239	9	612	6.64	1.51	0.56	1.50
ME	7	99	16	744	0.50	0.62	1.00	1.83
MH	0	1	1	36	-	0.01	0.06	0.09
MK	25	183	19	544	1.78	1.15	1.18	1.34
ML	0	1	0	4	-	0.01	-	0.01
MM	0	0	0	2	-	-	-	0.00
MN	14	43	8	65	1.00	0.27	0.50	0.16
MT	1	30	5	310	0.07	0.19	0.31	0.76
MU	8	39	2	166	0.57	0.25	0.12	0.41
MW	0	2	0	5	-	0.01	-	0.01
MX	21	385	5	383	1.50	2.43	0.31	0.94
MY	50	337	16	507	3.57	2.13	1.00	1.25
MZ	0	1	1	0	-	0.01	0.06	-
NA	0	2	2	7	-	0.01	0.12	0.02
NG	1	44	6	40	0.07	0.28	0.37	0.10
NL	4	96	6	888	0.29	0.61	0.37	2.18
NO	37	142	36	754	2.64	0.90	2.24	1.85

NP	0	1	0	3	-	0.01	-	0.01
NZ	42	185	18	746	3.00	1.17	1.12	1.83
OM	2	28	6	34	0.14	0.18	0.37	0.08
PA	1	7	0	48	0.07	0.04	-	0.12
PE	7	25	6	48	0.50	0.16	0.37	0.12
PG	1	0	2	2	0.07	-	0.12	0.00
PH	9	291	42	586	0.64	1.84	2.62	1.44
PK	9	427	12	117	0.64	2.69	0.75	0.29
PL	8	328	11	652	0.57	2.07	0.69	1.60
PT	22	128	1	742	1.57	0.81	0.06	1.82
PY	1	10	0	17	0.07	0.06	-	0.04
QA	0	4	0	19	-	0.03	-	0.05
RO	24	339	22	570	1.71	2.14	1.37	1.40
RS	24	409	9	508	1.71	2.58	0.56	1.25
RU	10	294	61	318	0.71	1.86	3.80	0.78
RW	0	1	0	4	-	0.01	-	0.01
SA	7	56	4	58	0.50	0.35	0.25	0.14
SD	0	0	0	1	-	-	-	0.00
SE	6	322	17	588	0.43	2.03	1.06	1.44
SG	8	231	18	741	0.57	1.46	1.12	1.82
SI	13	335	6	642	0.93	2.11	0.37	1.58
SK	21	231	4	737	1.50	1.46	0.25	1.81
SN	0	0	1	1	-	-	0.06	0.00
SV	0	0	0	5	-	-	-	0.01
SY	0	2	0	3	-	0.01	-	0.01
SZ	1	0	0	1	0.07	-	-	0.00
TG	0	0	0	1	-	-	-	0.00
TH	5	290	10	508	0.36	1.83	0.62	1.25
TN	0	17	1	23	-	0.11	0.06	0.06
TR	11	419	13	512	0.79	2.64	0.81	1.26
TT	0	11	0	7	-	0.07	-	0.02
TZ	0	5	2	4	-	0.03	0.12	0.01
UA	82	253	37	565	5.85	1.60	2.31	1.39
UG	0	2	0	1	-	0.01	-	0.00
US	0	298	32	669	-	1.88	1.99	1.64
UY	25	104	5	720	1.78	0.66	0.31	1.77
UZ	3	95	8	105	0.21	0.60	0.50	0.26
VE	0	3	0	2	-	0.02	-	0.00
VN	20	289	36	551	1.43	1.82	2.24	1.35
WS	0	0	0	1	-	-	-	0.00
ZA	2	65	16	120	0.14	0.41	1.00	0.29
ZM	0	7	0	4	-	0.04	-	0.01
ZW	5	18	4	17	0.36	0.11	0.25	0.04
Total	**1401**	**15849**	**1605**	**40699**	**100.00**	**100.00**	**100.00**	**100.00**