

Climate change and within-country inequality: new evidence from a global perspective

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ABSTRACT

This paper investigates the impact of climate change on within-country income inequality for more than 150 nations over the period 2003-2017. Specifically, we control for a large number of determinants of income disparities detected by extant literature and focus on agriculture as one of the most crucial channels in the climate change-inequality nexus. We find that temperature increases and precipitation anomalies have significant adverse effects on within-country inequality, especially in the presence of larger shares of population in rural areas and of workers in agriculture. We also provide evidence on the lower distributional impact of climate change in economies that are more diversified across value chain activities.

JEL classification:

D63; Q54; F21.

Keywords:

Inequality; Climate change; Agriculture; FDI; Global value chains.

1. INTRODUCTION

Climate change represents a major threat to our societies. According to the IPCC (2018), catastrophic consequences will be triggered if average global temperatures are allowed to exceed 1.5°C above pre-industrial levels, and even worse for increases above 2°C. Nonetheless, the dramatic effects of climate stress have already manifested in diverse forms, such as heat extremes, heavy precipitation, droughts, rising sea levels, floods, mudslides, water scarcity and biodiversity losses, resulting in impacts on health, livelihoods, food security, water supply, and human security (Antimiani et al., 2017; DARA, 2012; Markandya et al., 2017).

Scholars have begun to investigate the distributional impacts of climate change and relatively extensive research has been carried out on the role played by climatic hazards in explaining between-country inequality (Ahmed et al., 2009; Diffenbaugh & Burke, 2019; Hallegatte & Rozenberg, 2017; King & Harrington, 2018; Rao et al., 2017). However, the impact of climate-related events on within-country inequality is far less investigated. Aim of this paper is to contribute to this strand of research by exploring how different measures of climate variability affect within-country inequality. In addition, we will stress the relevance of some key structural factors conditioning the ability of countries to deal with the distributional effects of climate change.

To the best of our knowledge, this work provides the first large-scale econometric analysis on the climate change-inequality nexus, including more than 150 countries over the period 2003-2017. More precisely, we explore if and to which extent temperature and precipitation variations affect income disparities and identify agriculture as one of the most important channels in this relation. Nonetheless, our analysis also accounts for other key drivers of within-country inequality that are related to the development path of the

economies, their technological, structural and institutional features, as well as to the impact of globalization (Alvaredo et al., 2018; Atkinson et al., 2011; Piketty & Saez, 2003).

Our results show that warmer temperature and precipitation anomalies represent strong drivers of income inequality. Temperature increases are particularly associated with inequality in the presence of high shares of population and workers in rural areas, hence confirming the importance of the agricultural channel. Our findings also highlight that different types of climate events exert non-linear impacts on income disparities according to the population distribution in urban and rural areas and the productive structure of countries. Regarding the latter, we provide novel albeit largely exploratory evidence on the distributional impact of climate change in economies that are exposed to different patterns of inward FDIs. More precisely, we find that opening economies to foreign capital flows exacerbates inequality in some circumstances, especially when cross-border investment inflows are accompanied by hyper-specialization in selected GVC activities. Conversely, a greater diversification of incoming FDIs across value-adding functions – enabling economies to expand their domestic capabilities by leveraging complementarities along value chains – emerges as a resilience-enhancing factor which mitigates within-country inequality.

The remainder of the paper is organized as follows. Section 2 reviews the literature on the linkages between climate change and income disparities and highlights the mediating factors that can influence the climate change-inequality nexus. Section 3 describes data and methods used for our econometric exercise and Section 4 illustrates the main results of the empirical analysis. Section 5 offers a discussion on the distributive impact of climate change in the light of our findings and draws some policy implications.

2. LITERATURE REVIEW

2.1 The climate change-inequality nexus and the agricultural channel

The Earth's warming affects societies very unequally. Besides the inter-generational inequity due to the trade-off between the costs of implementing climate policies today and the benefits that will accrue to future generations (or the costs of inaction today and the climate damages in the future), also the intra-generational inequality is nowadays widely recognized (Hallegatte et al., 2016; Mendelsohn et al., 2006; Tol et al., 2004).

The uneven distribution of climate change impacts across countries reflects the exposure of economic systems to climate-related risks and their capacity to adapt (Hallegatte, 2009). In particular, Least Developed Countries (LDCs) risk bearing the brunt of the adverse consequences of climate change. On the one side, they are among the warmest regions on the Earth, where additional climate variability would be particularly harmful (Burke et al., 2015; Dell et al., 2014; Diffenbaugh & Burke, 2019). On the other side, these countries are less equipped with resources to implement adaptation measures and feature a fragile economic structure as well as limited institutional capacity (Moore & Diaz, 2015; Otto et al., 2017).

Most importantly, the cost of climate change unevenly affects different regions and population groups within countries. Previous research documents that temperature increases, extreme precipitation anomalies (as flood and drought) and the occurrence of natural disasters result in losses of both physical and human capital (e.g., damage to agricultural grassland, reduction in industrial output, children pull out of school, increasing mortality), potentially fueling migration pressures and conflicts. In this context, the most harmful consequences of the long-lasting decline in income are often mainly borne by less affluent groups (Asfaw et al., 2020; Cappelli et al., 2021; Carter et

al., 2007; Dell et al., 2014; Hallegatte & Rozenberg, 2017; Hallegatte et al., 2018; Hsiang et al., 2017; Rao et al., 2017), with the result of increasing within-country inequality. For instance, Hsiang et al. (2017) analyse the county-level impact of projected global temperature increases in market and non-market sectors (agriculture, human mortality, energy expenditure, labour, coastal damages, and crime) in the United States and find a stronger adverse effect of higher temperature in poorer counties, thus increasing inequality.

Nonetheless, the impact of climate change on income inequality largely depends on the structural conditions of the economies affected by it. Among these structural factors, extant literature has paid special attention to agricultural production as the most likely affected by climate variability (Hertel et al., 2010). In particular, Hallegatte and Rozenberg (2017) and Rao et al. (2017) suggest that agriculture is one of the main channels through which climate change affects poverty and income inequality. To this regard, several mechanisms are simultaneously involved. First, higher temperatures, low rainfall and heat waves tend to reduce yields and agricultural output, resulting in negative effects on the income of farmers, with more pronounced effects on rural income in developing countries (De Laubier et al., 2019; Dell et al., 2014; Mideksa, 2010). Second, people employed in agricultural activities are further at risk because climate change may reduce labour productivity and lead to output losses even more than in other sectors, given the higher share of outdoors jobs (Day et al., 2019; Graff Zivin & Neidell, 2014). Third, more disadvantaged households often live in rural areas, with less-favoured agricultural lands and poor market access (Barbier & Hochard, 2018; Castaneda et al., 2018; Wunder et al., 2018). As a consequence, they are more exposed to natural hazards because their assets and occupation are often more affected by environmental constraints, scarcity, or

1 volatility (Ahmed et al., 2011; Narloch & Bangalore, 2018; Yamamura, 2015);
2 nonetheless, they are also more vulnerable because of their higher dependence on natural
3 resources and lower adaptive capacity (Angelsen & Dokken, 2018). Finally, climate
4 change can lead to increases in food prices, with adverse consequences on real wages and
5 consumption patterns of workers also outside the agricultural sector. Demand side effects
6 induced by changes in food prices may significantly vary according to the share of
7 households' income dedicated to food consumption and their reliance on international
8 markets, namely food and agricultural imports (Bandara & Cai, 2014; Janssens et al.,
9 2020).

10 Overall, the theoretical and empirical literature reviewed shows that the impact of climate
11 change on income disparities occurs through specific sectoral channels, with agriculture
12 being among the most relevant. We will therefore empirically address this outcome in
13 Section 3 and 4. Nonetheless, a proper assessment of the climate change-inequality nexus
14 cannot fail to consider the other multiple aspects which can affect the distributional
15 patterns of the economies and may alter the impact of climatic events on income
16 inequality. These factors will be discussed in the remainder of this section.

18 **2.2 Broader perspectives on inequality and the role of economic** 19 **diversification**

20 The identification of the distributional consequences of climate change must be framed
21 in a broader analysis which considers the overall level of economic, technological and
22 institutional development of countries, as well as their international exposure and
23 structural characteristics (Rosenstein-Rodan, 1943; Todaro & Smith 2011).

1 Regarding the role of economic development, a seminal contribution is provided by
2 Kuznets (1955), who suggested that income inequality patterns are related to the level of
3 per-capita income by an inverted U-shaped relationship.

4 Technological change has also been detected by the literature as one of the main drivers
5 of increasing inequality, especially through its positive impact on wage income dispersion
6 in advanced countries (Acemoglu & Autor, 2011; Autor et al., 1999; Card & Di Nardo,
7 2002). This is substantially due to the skill- and task-biased character of technological
8 progress, which may induce a greater demand for higher-skilled, non-routine tasks while
9 being substitute for lower skilled, routine tasks, hence boosting wage polarization and
10 income disparities (Goos et al., 2014).

11 In addition, the quality of institutions and domestic policies play a major role in defining
12 the welfare regime, which greatly affects the allocation of resources and opportunities
13 among domestic social groups with the result of shaping the distributive patterns of
14 countries (Chong & Gradstein, 2007; Levy & Temin, 2007; Ostry et al., 2018).

15 The international exposure of countries is also widely acknowledged to affect inequality
16 through various channels. According to the standard theory, the liberalization of trade and
17 capital flows rises the remuneration of the relatively abundant production factor,
18 favouring an increase in the capital share as well as wages of skilled workers in advanced
19 economies. However, low-skilled labour-intensive productions offshored by capital
20 abundant economies can be relatively skilled labour-intensive for less developed recipient
21 countries. It follows that globalization will entail an increasing demand for high-skilled
22 labour in both advanced and less developed economies, increasing wage inequality
23 (Feenstra & Hanson, 1997; Jaumotte et al., 2013). In addition, as suggested by Rodrik
24 (1997), globalization would favour the most mobile production factor, i.e., capital, by

1 decreasing the bargaining power of workers, thus reducing the wage share and increasing
2 inequality in both advanced and less developed economies. Among the structural
3 characteristics affecting inequality, the literature has emphasised the diversification of
4 sources of income. On the one hand, Hartmann et al. (2017) suggest that the array and
5 complexity of goods produced by an economy largely reflects the competencies, know-
6 how, social capital and regulatory framework available in the country. Their findings
7 especially show that the economic complexity of regions is a strong predictor of their
8 distributional dynamics, i.e., income dispersion is higher in countries exporting simpler
9 products than those that produce more diversified and sophisticated ones (see also
10 Hartmann et al., 2020). On the other hand, a growing literature shows that countries with
11 a highly diversified economic structure are usually better equipped in terms of adaptation
12 and recovery after a shock (Dissart, 2003; Martin, 2012; Martin & Sunley, 2015;
13 Ormerod, 2010; Pike et al., 2010). In fact, in the context of international climate
14 negotiations the need for economic diversification (especially for LDCs) has been
15 highlighted as a way to reduce countries' exposure to external shocks and, ultimately,
16 their vulnerability to climate change (Cosbey, 2017; Zhang, 2003).

17 The diversification of sources of income can also be considered from a Global Value
18 Chain (GVC) perspective. In this regard, the growing literature on the international
19 fragmentation of production has shown that the “slicing up” of GVCs has prompted
20 countries to increasingly specialize in specific value-adding activities – also called
21 “functions” – necessary to bring a product to market, rather than in particular industry
22 products (Feenstra, 1998; Grossman & Rossi-Hansberg, 2006; Sturgeon, 2008; Sturgeon
23 & Gereffi, 2009; Sturgeon et al., 2013; Timmer et al., 2014). Consistently, Stöllinger
24 (2021) and Grieveson et al. (2021) have shown that the “functional specialization” of the

1 economies largely occurs *across industries*.¹ Greater attention should be paid to this
2 often-neglected perspective. In fact, the specialization in highly sophisticated products
3 can hardly represent an indicator of the growing domestic capabilities of a country if the
4 simplest and least skilled intensive activities (e.g., assembly operations) are the only ones
5 performed in the economy. Conversely, the ability of countries to carry out diverse and
6 more complex tasks could be a proxy for a more balanced productive structure and
7 inclusive development. Greater functional diversification would sustain a larger and
8 increasingly diverse set of skills, leveraging complementarities across activities that share
9 a different knowledge base. This could favour the enrichment of the technological and
10 production matrix of countries and enlarge the human capital an economy is equipped
11 with. As a consequence, the resilience of the economies to promptly react to external
12 shocks, including climatic hazards, might be enhanced by their capability to perform a
13 more diverse set of GVC functions.

14 Our work moves a first step in this direction by looking at inward FDIs distinguished
15 according to the value chain functions they are aimed to perform. On the one hand, by
16 considering the functional composition of inward FDIs, we go beyond the standard
17 control for the overall inflow of foreign investment received and account for the
18 heterogeneity of international exposure of countries. On the other hand, we use FDIs to
19 provide novel though exploratory evidence on the relationship between economies'
20 productive diversification in terms of value chains functions and income distribution, as
21 well as on the distributional impact of climate change in countries marked by different

¹ For example, China's specialization in the export of electronic products is actually due to its specialization in performing the fabrication stages of the value chain of these goods, mainly manufacturing and assembly (Timmer et al., 2019).

level of the former. We suggest that a greater variety of FDI inflows across GVC functions, fostering both backward and forward linkages with domestic firms and the accumulation of new domestic capabilities, can support a greater range of skills and thus promote more inclusive development (Amendolagine et al., 2019; Crescenzi & Iammarino, 2017; Fu et al., 2011; Lectard & Rougier, 2018).² In fact, inward FDIs represent a key manifestation of a country's ability to mobilize foreign sources of assets (e.g., capital goods, skills and knowledge) which contribute to the generation, diversification and distribution of income, thereby affecting the capacity of the productive systems to tackle internal and external shocks (Coveri et al., 2020; Hartmann et al., 2017, 2020).

3. METHODOLOGY AND DATA

3.1 The empirical model

Our empirical approach is based on panel methodologies allowing to account for different climate-related drivers of inequality and to fully consider the main economic, technological and institutional determinants of within-country income disparities. Our identification strategy relies on observing how income distribution is impacted by country variation in climate after controlling for key country-level factors which are known to affect inequality.

² The potential benefits for host countries are mainly associated to the transfer of capital, know-how and expertise which might occur through FDIs and interactions with multinational enterprises involved in GVCs (Rojec & Knell, 2018; Saliola & Zanfei, 2009). This would also result in promoting new job and learning opportunities, better living conditions and possibly a more inclusive economic development (Antonietti & Franco, 2021; Javorcik et al., 2018; Tadesse & Shukralla, 2013).

More precisely, we exploit monthly weather data on temperature and precipitation to build different (country-year) climate indicators and compare how income distribution varies across time in a country when a climate variation is registered, all else being equal. Building on the literature reviewed in the previous section, we consider potential sources of heterogeneity in responding to climate changes by including measures related to countries' vulnerability and resilience conditions, which may modify how economies cope with such changes. In particular, we focus on the agricultural sector as one of the most crucial channels in the climate change-inequality nexus. Furthermore, by using value chain-based data, we account for the level of diversification of inward FDIs across GVCs activities. Finally, we include country and time fixed effects to control for time-invariant characteristics of countries and common time trends, and perform all estimates using standard errors robust to heteroskedasticity and autocorrelation of residuals and clustered at the country-level.

Formally, we estimate the following regression equation:

$$Gini_{i,y} = \beta_0 + \beta_1 Climate_{i,y} + \beta_2 X_{i,y} + \gamma_i + \delta_y + \varepsilon_{i,y} \quad (1)$$

where $Gini_{i,y}$ is our measure of income inequality in country i and year y and $Climate_{i,y}$ includes different specifications of the climate indicators (see below for further details). The term $X_{i,y}$ includes key determinants of income distribution detected by the literature, distinguished between socio-economic, technological, institutional and global drivers of inequality (see below for further details). Finally, γ_i and δ_y are respectively country and time fixed effects, $\varepsilon_{i,y}$ is the error term, and β_0 the intercept.

Our analysis is conducted on a global unbalanced panel database including more than 150 countries over the period from 2003 to 2017. Building the dataset, we aimed at achieving

the widest possible countries' coverage (including as many LDCs as possible). The data sources and metrics used to construct the dependent and explanatory variables are described below. The definition of the variables and their sources as well as the descriptive statistics are reported in Table A.1 and A.2 of the Appendix.

3.2 Data and definition of variables

Measure of income inequality

As for the dependent variable, the Gini index for household disposable income is the metric we use to assess income inequality distribution within a country. The Gini index is computed on the income available to households after government taxes and transfers, excluding indirect and value-added taxes, public services, and indirect government transfers. It ranges between 0% and 100% signalling, respectively, perfect equality and inequality in the distribution of income.

Data are pooled from the Standardized World Income Inequality Database (SWIID) that aggregates a wide array of official data sources which provide clear welfare definition and a scale of equivalence for household income (Solt, 2020). Compared to other data sources, SWIID data maintain the widest possible coverage across countries and over time, and it is well suited for broad cross-national analysis (Solt, 2009, 2020). In addition, SWIID data are highly reliable since they are harmonized with the Luxembourg Income Study (LIS), the latter being the most trusted database providing Gini data at the country

level (the LIS has however the disadvantage of covering fewer countries for fewer years compared to SWIID data).³

Definition of climate indicators

Since climate indicators are our main variables of interest, we follow Baarsch et al. (2020) and consider both temperature and precipitation in the analysis. The metrics used have been elaborated aggregating the national-level data recorded for each month in a given year by the Climatic Research Unit (CRU) at the University of East Anglia, thus resulting in the yearly averages for each country.⁴

In particular, for each year and country included in the dataset we used CRU monthly data to build the following temperature indicators, aimed at capturing both the existence of a warming trend and the cases in which a country has been hit by a more extreme event. The first indicator is *temperature*, that is expressed as the average of monthly temperature recorded in a given year. Since temperatures are not strictly positive, we apply the inverse hyperbolic sine transformation, which approximates the natural logarithm and allows keeping zero and negative observations (Burbidge et al., 1988). Second, we computed the *temperature increase* as the ratio between the temperature recorded in country i in year y

³ Solt (2020) estimates the relationships between LIS data and the Gini indices available for the same country-years from other sources, and then uses these relationships to estimate what the LIS Gini would be in country-years not included in the LIS. When it is not possible to compare LIS data with other data sources, the author uses a Bayesian inferential framework to infer the missing data, assuming that changes in the Gini index over time can be modelled with a Monte Carlo Markov Chain (MCMC).

⁴ Note that CRU provides country-level data in terms of area-weighted means from gridded (0.5x0.5 degree) time-series dataset (Harris et al., 2014, 2020). In a robustness check, we test a different method of aggregation to compute climate indicators and, using gridded climate data from CRU (0.5x0.5 degree) and gridded population data from HYDE (5 arc minutes, Klein Goldewijk et al., 2017), we build *population-weighted* temperature and precipitation variables for the six largest countries in the world, which are those with a total area larger than 5,000,000 km² (i.e., Australia, Brazil, Canada, China, Russia, USA). Given that gridded population data are available for 1990 and from 2000 onwards, we have performed the comparison for the time period of our main dataset (2003-2017). Reassuringly, by comparing yearly and monthly data, the correlation between the two sets of climate variables (area and population weighted) is on average around 80%.

and the same variable recorded at time $y-1$, signalling whether year y has been warmer than the previous one. The third indicator is a dummy variable taking the value of one if a heat wave is registered in country i in year y , and zero otherwise. A heat wave is roughly defined as an extreme average increase of the temperature recorded in a country at time t with respect to the average temperature recorded in that country between 1900 and 1950. Formally, a heat wave is equal to $tmv_{i,y} = \frac{1}{12} \cdot \sum_{m=1}^{12} temperature_{i,y,m} - base_temperature_{i,m}$, where $temperature_{i,y,m}$ is the temperature recorded in country i , year y and month m , and $base_temperature_{i,m} = \frac{1}{50} \cdot \sum_{y=1901}^{1950} temperature_{i,y,m}$ (i.e., the average monthly temperature in the base period). In the existing literature (see for example Carril et al. 2008; Della-Marta et al. 2007; Fischer and Schär 2010; Hoy et al. 2017), the temperature is considered extreme if it is above a specific threshold determined from the empirical distribution of the observed temperature data across years, with the threshold ranging between the 75th and the 99th percentiles: it is extreme if above the threshold level. Two elements need to be considered when setting the threshold. On the one hand, the choice of a particular high threshold (e.g., the 99th percentile) increases the probability of identifying climate events with extremely strong consequences. On the other hand, a lower threshold allows selecting a sufficiently large sample for analysing the climate variations. To account for both elements in our analysis, we considered an appropriate threshold the 85th percentile, which corresponds to an increase in temperature larger than 1.5 degree Celsius.⁵

⁵ As a robustness check, we have also used a higher threshold level (the 99th percentile of the observed empirical distribution of the temperature data) corresponding to an increase in temperature larger than 2.4 degree Celsius. Results (available upon request from the authors) remain qualitatively unchanged and the estimated coefficient associated to the variable ‘Heat wave’ is larger, which is consistent with our expectations.

Consistently, the variable *heat wave* is formalized as:

$$\mathbb{I}_{(x=tmv_{i,y})} \begin{cases} 1; & x > 1.5 \\ 0, & x \leq 1.5 \end{cases}$$

where $\mathbb{I}$ is an indicator function.

With regard to precipitation variables, we use CRU precipitation data to construct indicators of extreme precipitation and the existence of a drying/flooding trend. More specifically, precipitation data can be used to draw information about: i) meteorological droughts, ii) agricultural droughts, and iii) hydrogeological droughts (WMO, 2012). These data are obtained by using different aggregations of the Standardized Precipitation Index (SPI), which is an index that registers drought (or flood) on different timescales. The SPI index can be interpreted as the number of standard deviations by which a precipitation anomaly recorded in a specific time period deviates from the long-term mean. When taking positive (negative) values, SPI signals the presence of wet (dry) conditions (McKee et al., 1993).⁶ In both cases, larger absolute values signal the presence of extreme conditions.

Accordingly, we use the monthly precipitation data from the CRU dataset to calculate the SPI index by using the R package SPEI by Beguería and Vicente-Serrano.⁷ It is worth noting that, on a long-term scale, SPI approximates the groundwater and reservoir storage, while on a short-term scale it is closely related to the value of soil moisture. In particular, the value of the SPI index can be interpreted as follows: 1- or 2-month SPI to record meteorological droughts (or floods); from 1- to 6-month SPI for agricultural

⁶ Table A.3 in Appendix provides the range of values that the index can take.

⁷ <https://cran.r-project.org/web/packages/SPEI/SPEI.pdf>

droughts; from 6- to 24-month SPI to register the presence of hydrogeological droughts (WMO, 2012). Given our focus on the agricultural channel, we primarily rely on the SPI-3 index and create two additional variables from this metric. Specifically, referring to country i in year y , we compute:

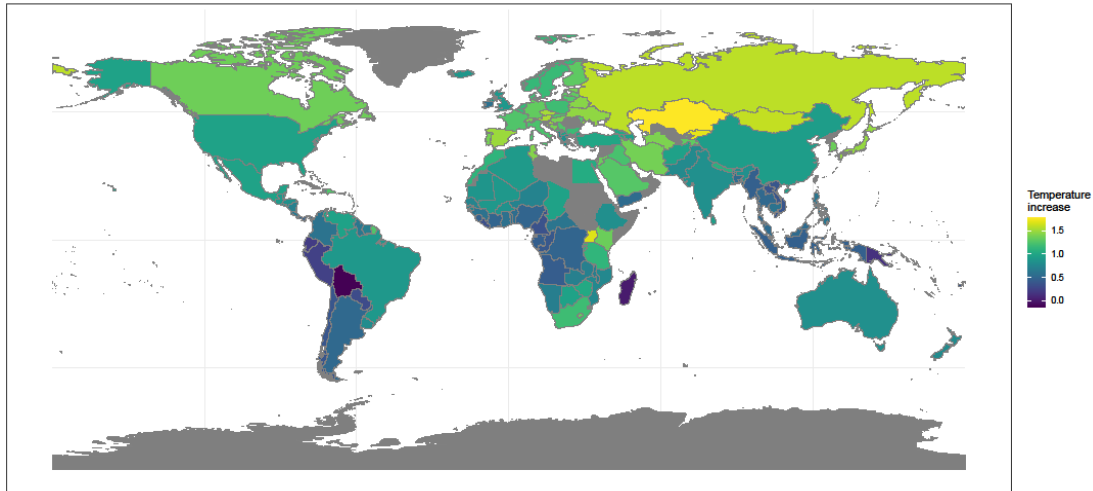
1. the average absolute value of SPI from year y to year $y-4$. For this variable, referred to as *precipitation anomalies* (5-years average), larger values represent more severe drying/flooding conditions;
2. a dummy variable taking the value of one if the ratio of the SPI index registered in year y and the average in the 10 previous years is higher than one, and zero otherwise. This variable, referred to as *increasing precipitation anomalies* (10-years), indicates if country i has experienced an extremization of precipitation anomalies (either drying or flooding) over the past 10 years.

Figure 1 provides some descriptive evidence based on our indicators. In particular, the figure shows the country-average (2003-2017) of the temperature increase with respect to 1900-1950 (*panel a*) and the SPI-3 index (*panel b*), revealing an increase in heat and precipitation anomalies across the world, although with considerable heterogeneity between countries.⁸

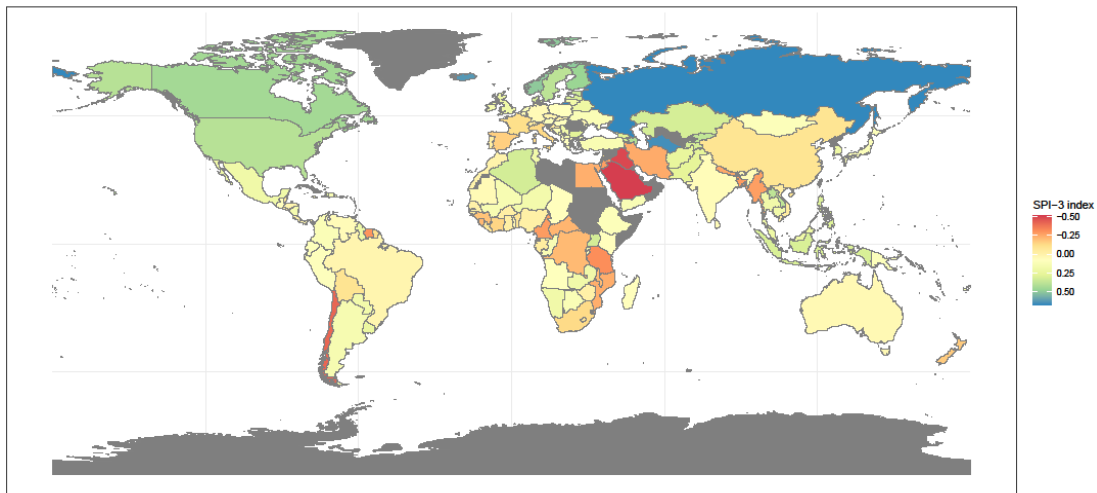
⁸ Descriptive evidence on the negative relationship between a broader indicator of climate resilience – i.e., the Notre Dame Global Adaptation Initiative (ND-GAIN) index – and income inequality at global level is provided by Figure A.1 in Appendix. See Appendix A for further details on the ND-GAIN index.

1 **Figure 1. Temperature increase and the SPI-3 index**

Panel a. Temperature increase



Panel b. The SPI-3 index



2 Source: authors' elaboration on CRU data.

3

4 ***Socio-economic, technological and institutional drivers of inequality***

5 With regard to socio-economic indicators, we include in all our model specifications the

6 GDP per capita (at PPP in constant 2011 international dollar), both in linear and squared

7 terms. Moreover, we account for the level of development and structural dynamics related

8 to industrialization and urbanization processes of countries, as well as for the relevance

9 of the primary sector in affecting the link between climate and inequality. To this aim, we

10 include indicators for the rural population (as percentage share of total population),

employment in agriculture (as percentage share of total employment), as well as the share of industry value added (as percentage of GDP).

In this regard, Table 1 provides evidence on the strong correlation between the main socio-economic, climatic, and geographical characteristics obtained by grouping countries on the basis of the population distribution between rural and urban areas over the whole period. A high share of rural population is associated to latitudes closer to the equator (e.g., within the tropical belt), warmer mean temperature, lower precipitation level, lower GDP per capita, as well as a strong dependence on the agricultural sector (employment in agriculture being almost 60% of total employment). Conversely, a low share of rural population is associated to higher latitude, colder mean temperature, lower precipitation level, but the largest flooding anomalies, i.e., the greatest magnitude of *precipitation anomalies* in absolute terms and the largest value of the SPI-3 index. At the same time, countries that fall into this category feature a higher GDP per capita, a lower Gini index and a very low percentage share of employment in agriculture over total employment.

Table 1. Socio-economic and geographical indicators by rural population share

Rural population share	Latitude	Temp.	Precip.	Precip. anomalies	SPI-3 (av. 5)	Gini	GDP pc (log)	Agric. empl.
<i>Low</i>	41.600	13.828	2.668	0.264	0.117	34.531	10.081	8.763
<i>Mid</i>	24.882	19.443	3.427	0.193	0.045	41.054	8.813	32.778
<i>High</i>	15.272	23.164	3.713	0.194	0.025	42.334	7.819	57.348
<i>Total</i>	27.661	17.973	3.186	0.221	0.069	38.754	9.115	28.190

Source: authors' elaboration.

Note: latitude is computed by considering the absolute value of the latitude of the Capital.

As for the impact of technological development on inequality, we include in our model the following three variables. First, since adaptation strategies and access to basic services for rural population (e.g., access to electricity, irrigation systems and resilient crops) have a potentially strong scope for alleviate agricultural losses and income disparities

(Castaneda et al., 2018; Sarkodie & Adams, 2020; Wunder et al., 2018), we account for the percentage share of rural population with access to electricity. Second, we include the number of mobile-cellular subscriptions per 100 inhabitants, which is an ICT indicator available for a wide range of countries at global level (data are drawn from the World Bank and sourced from the World Telecommunication/ICT indicators Database of the International Telecommunication Union). Lastly, we also control for the percentage share of the Gross Fixed Capital Formation (GFCF) over GDP as an additional, albeit rough, proxy of technology.

Finally, regarding the institutional factors which shape the social readiness of countries, key indicators are represented by the affordability of healthcare services (Berg et al., 2018; IMF, 2015) and the level of education (Bergh & Fink, 2008; De Gregorio & Lee, 2002).⁹ Accordingly, we include variables on the years of schooling (as in Hartmann et al., 2017) and the percentage share of domestic general government health expenditure (over general government expenditure).

All data described so far are taken from the World Bank's World Development Indicators (WDI) database.

Global drivers of inequality

Firstly, we acknowledge the role of financial globalization as a likely determinant of inequality within countries in the last decades (Claessens & Perotti, 2007; de Haan & Sturm, 2017). We take this factor into account by including in our model the *de facto*

⁹ It is worth noting that climate change can accelerate the diffusion of diseases (e.g., child stunting and malaria) and increasing mortality, and since some individuals more at risk than other for biological (e.g., elderly and infants) or socio-economic reasons (e.g., access to medical facilities, health insurance, being able to afford medical expenses), impacts are likely to be unequally distributed (Deschênes & Greenstone, 2011; Hallegatte & Rozenberg, 2017).

Financial Globalization Index provided by the KOF Swiss Economic Institute database of ETH Zurich. This is a comprehensive indicator which is measured by capital flows and stocks of foreign assets and liabilities, hence capturing actual short- and long-term international financial flows.¹⁰

Secondly, we exploit the wealth of information provided by the fDi Markets database and include in our dataset a set of variables capturing both the overall amount and the composition of inward FDIs for each country.¹¹ We classify inward FDIs according to value chain activities by adopting the canonical classification in three GVC stages: upstream (e.g., headquarter activities, knowledge-intensive tasks as R&D, design and training), production (e.g., manufacturing and assembly) and downstream (e.g., logistics, marketing and post-sales services) segments (Mudambi, 2008; Baldwin & Evenett, 2015; Stöllinger, 2021). These indicators are computed as the share of inward FDIs related to each GVC stage over the total number of FDIs received by each country.

Finally, we adopt a GVC-oriented approach to the analysis of the productive diversification of economies. Accordingly, we use the above classification of cross-border investment flows to calculate an index of *functional diversification in FDI* based on the normalized Herfindahl–Hirschman index (HHI). Formally, for each country i and year y , the index is computed as follows:

¹⁰ Further details on the construction of the index are provided in Appendix A.

¹¹ fDi Markets is an online database provided by fDi Intelligence – a specialist division of Financial Times Ltd – which collects detailed information on announced cross-border greenfield investments (i.e., new wholly-owned subsidiaries, including joint ventures whether they lead to a new physical operation) from several publicly available information sources, covering all sectors and countries worldwide from 2003 onwards. See Appendix A for additional details.

$$Functional\ diversification\ in\ FDI_{i,y} = 1 - HHI_{i,y} = 1 - \left[\left(\sum_{k=1}^3 \left(\frac{FDI_{i,y}^k}{FDI_{i,y}} \right)^2 - \frac{1}{k} \right) / \left(1 - \frac{1}{k} \right) \right]$$

where the ratio in parenthesis represents the share of FDIs related to the k -th of the three GVC stages over the total inward FDIs for country i in year y .¹² As discussed in Section 2.2, we expect a greater functional diversification to be associated with lower within-country inequality.

4. RESULTS

We begin by estimating a model where the Gini index is regressed against the linear and squared GDP per capita and in which we include one by one each of the climate indicators described in the previous section: *temperature*, *temperature increase*, *heat wave*, the absolute magnitude of precipitation anomalies over the last 5 years – i.e. *precipitation anomalies* – and the dummy registering if a (medium-long term) process of drying or flooding is in place, namely *increasing precipitation anomalies*. The estimation results are shown in Table 2.

First of all, the signs of the linear and squared GDP per capita suggest an inverted-U shape relationship between economic development and inequality, providing a confirmation of the Kuznets curve. The first term is positive while the second is negative, and both are statistically significant, meaning that increasing per capita income is associated first with an increase and then a reduction in inequality.

¹² This modified version of HHI is also known as Berry-Herfindahl index (Berry, 1971). By virtue of the normalization process, both the inverse HHI and the dependent variable range between 0 and 100, making the interpretation of the estimated coefficient associated to the inverse HHI easier. In a robustness check, we replace the normalized inverse HHI with the standard inverse HHI, and results (available upon request from the authors) remain qualitatively unchanged.

Moreover, the estimated coefficient of each climate indicator bears positive sign and all but one have a statistically significant impact on inequality when entered individually in the regression model (columns 1 to 5). Specifically, the temperature and the two indicators recording respectively the entity of the temperature variation (with respect to the previous year) and an extreme temperature increase report positive and statistically significant coefficients. As for precipitation, the variable recording the magnitude of the *precipitation anomalies* in the country in the previous 5 years does not seem to have a statistically significant effect. At the same time, the second precipitation index – i.e., *increasing precipitation anomalies*, which indicates whether there was an increase in precipitation anomalies in the country at time y compared to the previous 10 years – shows a positive and significant coefficient.

Overall, we find that almost all variables – capturing different nuances of climate change – contribute to rising inequality. Notably, two of these climate indicators record the magnitude of temperature and precipitation (drying/flooding) anomalies, while the remaining ones proxy more extreme variations. We test the separate effect of these two groups of variables respectively in column 6 (changes in climate conditions) and 7 (extreme changes in climate conditions). The estimates obtained show that our results are left qualitatively unchanged when using more refined model specifications which account for both these kinds of climate-related event.

If we look at the size of the coefficients, we observe that a 1% temperature increase is associated to an increase of about 0.5 Gini percentage points, while the occurrence in a specific year of an extreme climate variation (heat wave and increasing precipitation anomalies) raises inequality by 0.2 and 0.1 Gini percentage points. We need to stress that these are average effects resulting from the overall panel of more than 150 countries.

However, as extant literature suggests, some are expected to lose more than others, thus we need to account for potential heterogeneity and test whether these average effects are larger (or lower) depending on some structural factors mediating the distributional effects of climate change.

Table 2. Climate change indicators and their impact on income inequality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(GDP pc)	7.102** (3.530)	6.917* (3.526)	7.677** (3.535)	7.057** (3.496)	6.882* (3.488)	7.246** (3.502)	7.644** (3.497)
ln(GDP pc) ²	-0.489** (0.209)	-0.479** (0.208)	-0.519** (0.209)	-0.488** (0.206)	-0.474** (0.206)	-0.499** (0.206)	-0.517** (0.206)
Temperature	0.519** (0.238)					0.501** (0.249)	
Temperature increase		0.070*** (0.023)					0.063* (0.032)
Heat wave			0.243*** (0.088)				0.236*** (0.087)
Precipitation anomalies				0.512 (0.310)		0.507 (0.309)	
Increasing precip. anomalies					0.123** (0.050)		0.123** (0.050)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1918	1918	1918	1918	1918	1918	1918
R ²	0.136	0.135	0.140	0.140	0.138	0.142	0.145
R ² _adjusted	0.129	0.127	0.132	0.132	0.131	0.134	0.136
F	2.200	2.446	2.630	2.519	2.195	2.258	2.251

Note: the dependent variable is the Gini index for disposable income. Robust standard errors clustered at the country-level in parentheses. Results are robust also when controlling for: Industry share (%); Mobile subscription; GFCF over GDP (%); Rural electricity access (%); Rural pop. (%); Schooling; Gov. health expenditure (%); Financial globalization; Incoming FDI (see Table B.1 in Appendix). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We conduct a battery of robustness checks of the described findings. The first exercise we implement is aimed to test whether our results suffer from the presence of unobservables. For this reason, we first augment our model specification to include variables proxying socio-economic, technological and institutional factors, incoming FDI and financial globalization (Table B.1 in Appendix). Second, we include a set of controls for the quality of institutions, as measured by the Worldwide Governance Indicators from World Bank, to account for the potential role of domestic policies on

1 inequality.¹³ All our results are qualitatively unchanged. Incidentally, we also note that
2 an increase in the indicators of technological change, education and health expenditure
3 has a negative and statistically significant effect on inequality, which is consistent with
4 our expectations.

5 As a second exercise, we lag all control variables by one year in the model specification
6 to exclude problems of reverse causality in the estimates (Table C.1 in Appendix).¹⁴ Also
7 in this case, all our findings are confirmed. In our third exercise, we cluster the standard
8 errors from our main estimates, with each cluster including countries sharing a similar
9 income (following the World Bank country classification), as the variation in the level of
10 inequality in a country may be correlated with that of other countries sharing similar
11 characteristics. The potential correlation in the error term within clusters does not seem
12 to represent a threat to our estimates, since all our results are again confirmed (results are
13 available upon request).

14 Finally, a potential bias in our estimates may be present if the strict exogeneity assumption
15 does not hold in our analysis, i.e., if a shock affecting the level of inequality in a year in
16 one country is correlated with future values of inequality in the same country. From a
17 formal standpoint, this would be the case if the error terms obtained from our model are
18 correlated across time. To sort out this potential source of endogeneity in our estimates,
19 and account for the potential persistency in the value of the Gini index, we employ the

¹³ These indicators include corruption control, government effectiveness, political stability, regulatory quality, rule of law, and voice and accountability. The results of the estimates in which we control also for these indicators are available upon request.

¹⁴ The lag structure was also tested by taking the two-year lagged values of all explanatory variables. Our results remain stable in sign and statistical significance and are available upon request.

dynamic panel estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998), namely the System Generalized Method of Moments (GMM) (Table B.2 in Appendix). We find that all our findings on the effect of climate variation on inequality are confirmed. It is worth stressing however, that the use of GMM in our analysis is not necessarily appropriate, and there are pros and cons in adopting this estimation strategy. As noted by Dell et al. (2014), estimating the impact of climate variation on an economic variable by excluding the lagged dependent variable is indeed appropriate; yet, including lags in short panel ($T < 15$), as in our case, also risks biasing the coefficient estimates. For this reason, and since GMM and OLS estimations return consistent results in relation to the effect of climate variation, we prefer to use a OLS estimator in our main analysis.

We now focus on the role played by the agricultural channel by testing whether our climate indicators exert heterogenous effects on income distribution according to specific characteristics of the economic structure of countries.¹⁵ To this aim, in Table 3 we empirically assess if the effect of climate variations is *heterogenous* with respect to the share of population living in rural areas (e.g., the effect is present only in countries with a specific share of population). This is done by modelling this effect using a variable which registers the value of climate variations in countries with a specific characteristic (e.g., those with a low share of population), and it is zero otherwise. Specifically, in Table 3 (Columns 1-3) we investigate the heterogenous impact of the temperature level and/or of the entity of drying/flooding anomalies on inequality.

¹⁵ Since in Table 2 *precipitation anomalies* is not significant while the results of the sys-GMM estimation show that its coefficient is positive and statistically significant (see Table B.2 in Appendix), it may be the case that model specifications in Table 2 do not properly account for the effect of this variable, as the heterogeneity of its effects is hindering the correct identification.

1 More precisely, we control for two dummy variables which respectively assume value
2 equal to 1 if the country is largely urbanized (*Low rural pop.*) or largely rural (*High rural*
3 *pop.*), and 0 otherwise. The coefficient of these dummy variables – when statistically
4 significant – is negative, suggesting that a more balanced population distribution between
5 rural and urban areas is associated with a higher level of inequality.¹⁶

6 Two major results emerge from this empirical strategy. First, *higher average*
7 *temperatures* exhibit a statistically significant association with greater inequality in the
8 presence of medium and high shares of population living in rural areas. If we look at the
9 magnitude of the coefficients, we observe that in the case of a high share of rural
10 population the effect is larger if compared to the medium rural population case. Overall,
11 our results suggest that in cases of low rural population share the effect of 1% temperature
12 increase on inequality is negligible; in cases of medium rural population share the same
13 1% temperature increase is associated to an increase in the Gini index of 0.664 percentage
14 points, while in cases of high rural population share it is associated to an increase in the
15 Gini index of more than 2 points. This means that warmer temperatures have a stronger
16 adverse impact on income distribution in largely rural countries, where the social and
17 economic position of the most disadvantaged individuals strongly inhibits their capability
18 to cope with higher average temperatures. In other words, our results suggest that poorer
19 population segments in largely rural countries are the most exposed to the detrimental
20 consequences of temperature increases. This confirms our hypothesis that the climate
21 effects on within-country inequality are *heterogeneous* with respect to the category into

¹⁶ This is consistent with the hypothesis formulated by Kuznets (1955) on the relationship between economic development and urbanization, and further expanded by Rauch (1991, p. 20), according to whom “when all inequality is between sector it tends to be maximized when the two sectors are of equal size”.

1 which a country falls (i.e., Low, Medium or High rural population share), and that the
2 agricultural channel is therefore an important mechanism through which climate change
3 impacts on inequality.

4 In addition, we also test whether the effect of warmer temperatures on within-country
5 inequality is greater the larger the number of people living in rural areas (namely it is
6 incremental) on the basis of the category into which a country falls. Results confirm that
7 a 1% temperature increase has a stronger adverse effect on income disparities the larger
8 the number of people living in rural areas, but only in those countries in which the share
9 of rural population is Mid or High, while the same effect is not statistically significant if
10 the share of rural population is Low.¹⁷

11 This finding is also consistent with the estimate results reported in column 4, which shows
12 that warmer temperatures are significantly associated with higher inequality in the
13 presence of higher shares of employees in the agricultural sector. In terms of standardized
14 value (i.e., beta coefficient), an increase of one standard deviation in “*Agric. empl.**
15 *Temperature*” (26.62), would increase the Gini index by 0.877 of its standard deviation
16 (8.20). This effect is clearly sizable in magnitude. To understand why, consider that the
17 average value of “*Agric. empl.*” is 30%, which implies that the effect of a 1% temperature
18 increase corresponds to an increase in the Gini index equal to 0.31 for the average country.

19 Second, a larger magnitude of *precipitation anomalies* shows a statistically significant
20 association with higher inequality in largely urbanised countries, recording an increase
21 larger than 1 Gini percentage point. We also note that in our sample, more urbanized

¹⁷ Results are available upon request from the authors.

1 countries are the most affected by these phenomena (see Table 1). In urban areas,
2 characterized by high density of people and buildings, the capacity of soils to retain water
3 is indeed limited and intense precipitations might result in flood risks (e.g., inundation of
4 buildings, damage to infrastructure, overloading of drainage systems); in this context, the
5 less affluent groups living in marginal and vulnerable areas likely bear the highest
6 damage. Furthermore, by decreasing the availability of food and potentially increasing
7 prices, precipitation anomalies are likely to mostly impact those who spend a larger share
8 of income in the market for their nourishment, namely the poorer segments of urban
9 population. Therefore, it is plausible to expect that *precipitation anomalies* may further
10 exacerbate the level of income inequality in these countries.

11 We consider these findings as revealing of the complexities of the climate change-
12 inequality nexus. Different climate-related events are associated with a distinctive role of
13 the agricultural channel in vehiculating inequality. In fact, while we find that rising
14 temperatures are associated with greater inequality in largely rural countries (or with
15 larger shares of agricultural workers), extreme precipitations anomalies appear to rather
16 increase income disparities in predominantly urban regions, whose poorer population can
17 result even more vulnerable to such events.

18 Once again, our results are robust to: i) the inclusion of variables capturing the economic,
19 technological and institutional determinants of inequality, as well as indicators
20 controlling for the (adverse) impact of incoming FDIs and financial globalization (Table
21 B.3 in Appendix); ii) the inclusion of the lagged values (in years $y-1$) of the explanatory
22 variables (Table C.2 in Appendix).

23

Table 3. How agriculture affects the climate change-inequality nexus

	(1)	(2)	(3)	(4)
ln(GDP pc)	8.532** (3.686)	8.537** (3.677)	8.782** (3.689)	9.496** (3.653)
ln(GDP pc)^2	-0.544** (0.214)	-0.531** (0.214)	-0.556*** (0.213)	-0.593*** (0.212)
Rural electricity access	-0.047*** (0.016)	-0.046*** (0.015)	-0.047*** (0.015)	-0.046*** (0.017)
Low rural pop.	0.593 (0.379)	-1.095* (0.591)	0.303 (0.414)	
High rural pop.	-5.006*** (1.753)	-0.615* (0.370)	-4.693*** (1.672)	
Temperature		0.231 (0.262)		0.360* (0.206)
Precipitation anomalies	0.500* (0.272)			0.419 (0.272)
Temperature in Low rural pop.	0.127 (0.232)		0.156 (0.233)	
Temperature in Mid rural pop.	0.664** (0.322)		0.675** (0.325)	
Temperature in High rural pop.	2.109*** (0.644)		2.021*** (0.618)	
Precipitation anomalies in Low rural pop.		1.168** (0.476)	1.161** (0.468)	
Precipitation anomalies in Mid rural pop.		-0.155 (0.326)	-0.072 (0.321)	
Precipitation anomalies in High rural pop.		-0.181 (0.386)	-0.133 (0.385)	
Agric. empl.				-0.003 (0.022)
Agric. empl.* Temperature				0.001*** (0.000)
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1888	1888	1888	1866
R ²	0.228	0.226	0.237	0.200
R ² _adjusted	0.218	0.216	0.227	0.191
F	1.992	1.762	1.999	2.053

Note: the dependent variable is the Gini index for disposable income. Robust standard errors clustered at the country-level in parentheses. Results are robust also when controlling for: Industry share (%); Mobile subscription; GFCF over GDP (%); Schooling; Gov. health expenditure (%); Financial globalization; Incoming FDIs (see Table B.3 in Appendix). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

As a last step of our investigation, in Table 4 we assess the association between the functional diversification of FDI inflows and the distributional dynamics of receiving countries. To this purpose, we estimate an augmented version of Eq. (1) by including the variable $FDI_{i,y}$, which represents alternative measures related to the amount and composition of inward FDIs.

First, the estimates reported in all columns show that our previous findings are largely

confirmed. The indicators signalling the presence of extreme climatic variability continue to show their relevance in adversely (and uniformly) shaping income distribution. Similarly, all other relevant control variables maintain the sign and significance emerged in early estimations. All results are also confirmed when considering the lagged values (in years $y-1$) of the explanatory variables (see Table C.3 in Appendix).

Table 4. FDIs and the functional diversification in FDI as mediating factor in the climate change-inequality nexus

	(1)	(2)	(3)	(4)	(5)
ln(GDP pc)	9.720** (4.111)	9.657** (4.137)	9.510** (4.138)	9.364** (4.130)	9.366** (4.113)
ln(GDP pc) ²	-0.565** (0.233)	-0.559** (0.234)	-0.552** (0.234)	-0.542** (0.234)	-0.542** (0.233)
Temperature increase	0.065* (0.039)	0.065* (0.038)	0.062 (0.039)	0.060 (0.038)	0.060 (0.037)
Heat wave	0.145* (0.081)	0.148* (0.080)	0.150* (0.080)	0.148* (0.081)	0.147* (0.081)
Increasing precip. anomalies	0.099** (0.049)	0.104** (0.050)	0.103** (0.050)	0.111** (0.050)	0.327*** (0.107)
Incoming FDIs	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
FDI sh. in Upstream activities	-0.647** (0.314)				
FDI sh. in Production activities		0.290** (0.136)			
FDI sh. in Downstream activities			0.071 (0.118)		
Functional diversification in FDI				-0.003*** (0.001)	-0.002** (0.001)
Func. diversification in FDI *					-0.003**
Increasing precipitation anomalies					(0.001)
Country FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	1721	1721	1721	1721	1721
R ²	0.300	0.299	0.296	0.302	0.304
R ² _adjusted	0.288	0.287	0.284	0.290	0.291
F	2.396	2.286	2.405	2.419	2.381

Note: the dependent variable is the Gini index for disposable income. Robust standard errors clustered at the country-level in parentheses. Results are robust to the inclusion of: Industry share (%); Mobile subscription; GFCF over GDP (%); Rural electricity access (%); Rural pop. (%); Schooling; Gov. health expenditure (%); Financial globalization (see Table B.4 in Appendix). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Second, the coefficient of total incoming FDIs is always significant and positive. Although the size is rather small, it is important to include such control to rule out a potential issue due to the presence of this omitted variable, given that the number of

incoming FDIs greatly vary across countries.¹⁸

Third, column 1 shows that the coefficient associated to the share of FDIs in upstream GVC activities is negative and statistically significant. Conversely, when accounting for the share FDIs in production activities (column 2) the sign of the coefficient is positive and statistically significant. Looking at column 3, we do not find any significant association between the share of FDIs in downstream GVC stages and income inequality. This implies that a larger share of inward FDIs in upstream and knowledge-intensive activities is associated with economies characterized by a less polarized income distribution, while the opposite is true for countries receiving a larger share of FDIs in production activities.

The last two columns in Table 4 allow us to dig into the relationship between the functional diversification in FDI and inequality. Interestingly, estimation results reported by column 4 suggest that a greater functional diversification in FDI (i.e., a higher dispersion of inward FDIs across GVC stages) is significantly associated with lower within-country inequality. Finally, in column 5 we interact the climate indicator which resulted the most significant in previous columns, namely *increasing precipitation anomalies*, with the variable capturing the level of functional diversification. The negative and statistically significant coefficient of the interaction term suggests that, whereby an increase in precipitation anomalies occurs, economies featured by greater functional diversification in FDI suffer from smaller adverse consequences on income

¹⁸ If we omit this variable from the model specification, our results are qualitatively unchanged, but the goodness of fit of our model to the data, measured in terms of R^2 , decreases by almost 5% (results are available upon request). This means that while the effect of this variable on inequality is negligible, it is sizable its contribution to the extent to which our model is able to explain inequality.

distribution. When looking at the marginal effects of the functional diversification in FDI in the event or absence of precipitation anomalies, we find that the average difference between the two effects is approximately -0.19 (p-value equal to 0.04). However, relevant heterogeneities emerge between the two effects when focusing on the case in which the functional diversification in FDI is either low or high. Notably, a higher level of the functional diversification in FDI is associated to: i) lower expected values of inequality within countries; ii) similar values of inequality among countries, regardless of whether they experienced increasing precipitation anomalies or not. This second condition highlights that greater functional diversification in FDI is associated to stronger resilience of countries to extreme climatic events and lower within-country income disparities.¹⁹

5. DISCUSSION AND CONCLUSIONS

A relatively large literature has focused on the role exerted by climate change in increasing poverty and between-country inequality. However, few studies have explicitly addressed the impact of climate-related events on within-country inequality. This work contributes to fill this gap by empirically investigating the adverse consequences of climate change on income inequality within more than 150 countries. Accounting for different climate indicators and controlling for a large number of determinants of inequality detected by the extant literature, we find that climate change has worsened the distribution of income, playing a relevant role in increasing within-country income disparities.

¹⁹ Results are available upon request.

Moreover, the evidence provided highlights that the share of population living in rural areas and the share of employment in agriculture represent key structural factors underlying the vulnerability of countries to temperature increases and precipitation anomalies. More precisely, we show that higher average temperatures have a stronger adverse impact on income distribution in largely rural countries. A confirmation of this comes from the further observation that the larger the share of employment in agriculture, the greater the impact of higher temperatures on inequality.

Building on previous literature, our interpretation is that the larger the share of people relying on agriculture, the larger the adverse impact on inequality as many will be exposed, but not all at the same rate – in other words, some will suffer more than others. Higher temperatures tend to reduce yields, agricultural output, and rural income; however, these effects are more pronounced in the case of crops that are more sensitive to temperature change (Dell et al., 2014; Jackson et al., Jägermeyr et al., 2021; Zhao et al., 2017). Hence, while all farmers and agricultural employees are at risk, the larger the number of people relying on these activities, the more likely it is that someone will be affected by climate damages larger than other. This unequal impact therefore leads to greater income disparities.

The results associated to the precipitation anomalies (i.e., their adverse effect on inequality is statistically significant only if the share of rural population is low) also deserve further discussion. Low rural population areas are – by definition – characterised by a high urbanisation. In urban areas exposed to flood risks, disadvantage groups are more endangered because they usually live in more vulnerable areas and their houses are generally made of more fragile materials, hence exposed to more serious damages. While affluent people can afford to buy insurance and get compensation for the costs of disasters

1 associated to anomalous precipitations, disadvantaged segments of the population may
2 not be able to buy coverage (insurance premiums may also increase due to climate
3 hazards) and bear the entire loss on their own, which can be particularly high with respect
4 to their wealth. Furthermore, while precipitation anomalies may destroy crops and
5 directly affect rural income, they will also have an indirect effect on the income of
6 disadvantaged people, especially in urban areas, via a generalised increase in food prices.
7 Overall, agricultural activities thus emerge as crucial channel through which, directly and
8 indirectly, climate change can exacerbate inequality.

9 At the same time, the lack of a statistically significant impact of precipitations anomalies
10 on income disparities in mostly rural and agricultural countries calls for further analysis
11 considering the following aspects. First, agricultural activities are particularly sensitive
12 to the precipitation anomalies during the growing season (see for example Harari and La
13 Ferrara, 2018; Cappelli et al., 2022), hence the time of the year these climate shocks occur
14 may result in highly heterogeneous impacts. Unusually low (high) precipitation level may
15 have a negative (positive) impact on economic growth and rural income in developing
16 countries, although the effects are less clear elsewhere (Dell et al., 2014). In addition,
17 these effects are crop-specific and depend on the type of the agricultural practice (e.g.,
18 irrigated, rain-fed, industrialized, subsistence). Farmers with an irrigation system in place
19 will suffer less from dry precipitation anomalies if compared to those relying on rain-fed
20 agriculture. Further, some of these effects may be enhanced or mediated by the soil
21 conditions, which can be spatially heterogeneous, and other location-specific aspects.
22 Examples in this regard includes the presence of (or the distance from) water bodies, deep
23 soil moisture, which is a highly important source of water for vegetation (Gou & Zhu,
24 2021), or the land slope, which is an important factor influencing the flood risk through

1 surface runoff velocity and vertical percolation (Youssef, et al., 2011). Hence, further
2 research should investigate the within-year (e.g., monthly or seasonal) climate variation
3 at a lower spatial aggregation (e.g., regional or gridded analysis) combined with the
4 analysis of crop-specific features and the role of irrigation systems in order to identify
5 these specific channels.

6 Nonetheless, several policy considerations can already be gathered from our results on
7 the role played by agriculture as a mediating factor in the climate-inequality nexus. First,
8 the ability of people relying on agriculture to cope with climate change need to be
9 strengthened with (more efficient) water and crops management techniques (e.g., efficient
10 irrigation system and rainwater harvesting, precision farming, crop diversification and
11 climate-resilient adaptive crops). Second, it is also necessary to implement risk reduction
12 measures (e.g., early warning systems), immediate assistance in case of extreme events
13 and funds for adverse climatic events. Most importantly, adaptation policies to climate
14 change need to be designed to strengthen the linkages between development and
15 redistributive policies and foster resilience of economic systems. In this regard, income
16 diversification can be encouraged by calibrating corporate taxes and investment
17 incentives, e.g., related to access to credit, while establishing requirements to ensure safer
18 labour conditions for workers.

19 In addition to the role of agriculture as a mediating factor, we have paid attention to the
20 role played by the composition of FDIs attracted by countries as a further structural factor.
21 First, we find that countries attracting a larger share of FDIs in the most upstream value
22 chain functions report lower income inequality, while the opposite emerges in the case of
23 those drawing mainly foreign investments aimed to perform production activities. This
24 finding is consistent with previous evidence showing that a greater involvement in

1 knowledge-intensive GVC stages fosters the technological upgrading of the economies,
2 supporting the creation of better-paid jobs and lowering income inequality (Morris &
3 Staritz, 2017; Pöschl et al., 2016). We suggest that the negative association between the
4 share of production (mainly fabrication) incoming FDI and inequality might instead be
5 due to the footloose character of production offshoring and the consequent deterioration
6 of workers' bargaining position vis-à-vis firms (Rodrik, 1997; Stansbury & Summers,
7 2020; Stockhammer, 2017). Accordingly, domestic policies aimed to dampen the
8 possibility to quickly relocate production by multinational corporations – with
9 detrimental consequences on salaries and working conditions – should be considered by
10 policymakers concerned with growing income inequalities. Second, we find that countries
11 characterised by a greater functional diversification in FDI – defined as the capability to
12 attract foreign investments related to different value chain activities – exhibit a more equal
13 distribution of income. This appears consistent with the hypothesis that a larger mix of
14 value-adding activities an economy carries out allows to expand the learning
15 opportunities and occupational choices for its workers and is conducive to a more
16 inclusive development. Third, we find that the adverse distributional impact of climate
17 change in countries marked by greater functional diversification in FDI is lower. In other
18 terms, countries attracting a wider range of FDI inflows across GVC stages appears to be
19 better able to diversify their productive structure, thus expanding the available set of skills
20 and making conversion of domestic production more feasible in case of artificial disasters
21 or climate-induced extreme events.

22 Nonetheless, our findings in this regard have yet to be conceived as exploratory. On the
23 one side, including the composition of inward FDI in our empirical analysis allowed us
24 to provide novel and insightful evidence on the potential role played by an often-neglected

mediating factor in the climate change-inequality nexus, namely the functional diversification of economies. On the other side, FDI inflows can hardly be assumed as a strictly exogenous factor in our model. In fact, $FDI_{i,y}$ might suffer from problems of endogeneity with respect to the dynamics of income distribution. Although suggestive, our estimation results can therefore only provide preliminary empirical support to the analysis of functional diversification of economies as a key moderating factor in the climate change-inequality nexus, as suggested in Section 2.2. This calls for future research in this direction, with the aim to deepen and better identify how the international fragmentation of production and the resulting change in specialization patterns contribute to shape the resilience of countries in face of climate-related events.

Finally, if FDI inflows represent a potential source of external finance – especially for developing countries – as well as a potential flywheel for the absorption by local actors of foreign knowledge and technological capabilities, domestic policies aimed at reducing inequality while favouring the resilience of economies to climate-related events are crucial. For example, our findings suggest that fiscal policies can reduce income disparities by empowering the public health system, widening the inclusiveness of the education system, enlarging access to electricity for rural populations, and expanding the employment subsidies to avoid a lasting impact on employees and increase their possibility to access public services. Nonetheless, domestic industrial policies can foster the adaptation of economic systems by promoting public investments in strategic infrastructures (e.g., public transports, logistics); and they can provide support to firms most damaged by extreme climatic events by conditioning aid to their commitment to adopt production techniques less vulnerable to climate change.

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7

APPENDIX A

Table A.1: Description of variables

Variable name	Description	Original source
Gini index	Gini index, post-tax, post-transfer (computed on the income available to household after government taxes and transfers)	SWIID
Temperature	Average yearly temperature (inverse hyperbolic sine transformation)	CRU
Temperature increase	Ratio between temperature _{i,t} and temperature _{i,t-1}	CRU
Heat wave	Heat wave (dummy=1 if difference of the average temperature w.r.t. historical mean 1900-1950 is larger than 1.5°C)	CRU
Precipitation anomalies	3-month Standardized Precipitation Index (SPI-3) (absolute value, 5-years average from t to t-4)	CRU
Increasing precipitation anomalies	Extremization of drying/flooding anomalies (dummy=1 if the ratio between SPI-3 _t and the average SPI-3 in the 10 previous years > 1)	CRU
ln(GDP pc)	GDP per capita at PPP, constant 2011 international dollar (log)	WDI
ln(GDP pc) ²	GDP per capita at PPP, constant 2011 international dollar (log) squared	WDI
Rural electricity access	Rural population with access to electricity (percentage share of total population)	WDI
Industry share	Share of industry value added including construction (% of GDP)	WDI
Agric. empl.	Employment in agriculture as % share of total employment (ILO estimate)	WDI
Rural pop.	Rural population as percentage share of total population	WDI
Low rural pop.	Highly urban population (dummy=1 if rural pop. share < 1/3)	WDI
High rural pop.	Highly rural population (dummy=1 if rural pop. share > 2/3)	WDI
Mobile subscription	Mobile-cellular subscriptions per 100 inhabitants	WDI
GFCF over GDP	Gross Fixed Capital Formation (% of GDP)	WDI
Schooling	Years of schooling	WDI
Gov. health expenditure	Domestic general government health expenditure (% share of general government expenditure)	WDI
Financial globalization index	Financial Globalization Index (<i>de facto</i>)	KOF-ETH ^[1]
Incoming FDI	Number of incoming FDI	fDi Markets ^[2]
FDI sh. in Upstream activities	Share of incoming FDI in Upstream activities	fDi Markets ^[2]
FDI sh. in Production activities	Share of incoming FDI in Production activities	fDi Markets ^[2]
FDI sh. in Downstream activities	Share of incoming FDI in Downstream activities	fDi Markets ^[2]
Functional diversification in FDI	Inward FDI diversification across GVC stages	fDi Markets ^[2]

Source: authors' elaboration.

Notes: **[1] KOF-ETH:** The *de facto* measure of financial globalization is computed as the weighted average of the following components: (a) sum of stocks of assets and liabilities of FDI (% of GDP); (b) sum of stocks of assets and liabilities of international equity portfolio investments (% of GDP); (c) sum of inward and outward stocks of international portfolio debt securities and international bank loans and deposits (% of GDP); (d) international reserves, including foreign exchange (excluding gold), SDR holdings and reserve position in the IMF (% of GDP); (e) sum of capital and labour income to foreign nationals and from abroad (% of GDP). Data are drawn from the KOF Swiss Economic Institute (ETH Zurich) database (Gygli et al., 2019). See <https://kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-globalisation-index.html>. **[2] fDi Markets:** The fDi Markets database represents one of the main data sources in

UNCTAD's World Investment Report (notably, fDi Markets is the only source on greenfield FDI's used by UNCTAD) and has been exploited in publications by the Economist Intelligence Unit. Notably, since fDi Markets includes planned future investment projects, some of the latter might not be carried out or may be realized in a form which differs from the one reported by the database. Although the database is daily updated, this data-collection method may cast some doubts on the reliability of information on the most recent FDI's. We thus chose not to consider the FDI projects recorded during the last available year, namely 2018, limiting our analysis to the time span 2003-2017. Over this period, fDi Markets includes almost 190,000 investment projects worldwide. On the reliability of the distribution of the investment projects included in fDi Markets see Castellani & Pieri (2013, 2015), Crescenzi et al. (2014) and Ascani et al. (2016).

Table A.2: Descriptive statistics

<i>Variable name</i>	N	Mean	St.Dev	min	max
Gini index	1918	38.77	8.20	22.90	66.00
Temperature	1918	3.37	0.93	-2.38	4.07
Temperature increase	1918	1.00	0.34	-11.82	4.56
Heat wave	1918	0.16	0.37	0.00	1.00
Precipitation anomalies	1918	0.22	0.17	0.00	0.92
Increasing precipitation anomalies	1918	0.44	0.50	0.00	1.00
ln(GDP pc)	1918	9.11	1.15	6.36	11.10
ln(GDP pc) ²	1918	84.26	20.54	40.43	123.20
Rural electricity access	1888	71.97	36.85	0.00	100.00
Industry share	1885	26.58	10.23	5.00	77.41
Agric. empl.	1896	28.38	23.76	0.06	92.55
Rural pop.	1918	43.30	22.27	2.04	91.09
Low rural pop.	1918	0.39	0.49	0.00	1.00
High rural pop.	1918	0.19	0.40	0.00	1.00
Mobile subscription	1910	76.94	45.61	0.07	207.75
GFCF over GDP	1802	23.16	7.17	2.00	69.67
Schooling	1770	9.53	2.22	4.00	16.00
Gov. health expenditure	1890	50.13	21.07	4.18	87.60
Financial globalization index	1918	61.43	19.13	15.90	98.64
Incoming FDI's	1918	82.73	194.06	0.00	1733.00
FDI sh. in Upstream activities	1918	0.09	0.12	0.00	1.00
FDI sh. in Production activities	1918	0.29	0.26	0.00	1.00
FDI sh. in Downstream activities	1918	0.46	0.27	0.00	1.00
Functional diversification in FDI	1918	54.34	24.79	0.00	100.00

Source: authors' elaboration.

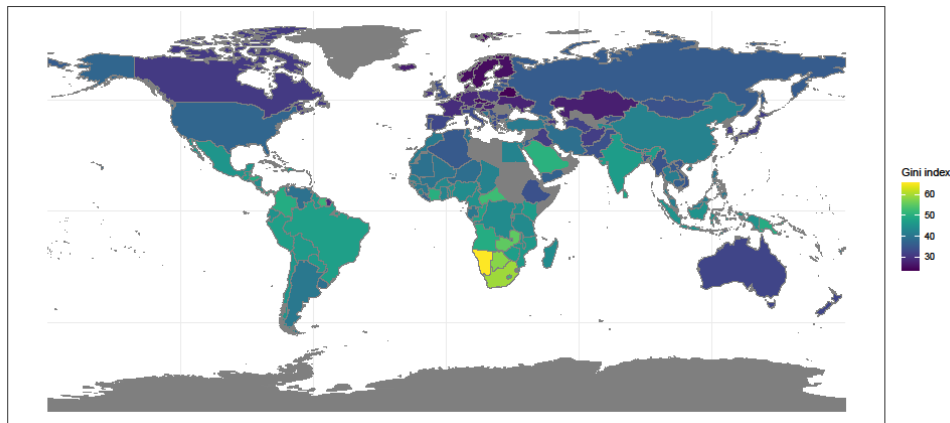
Table A.3 SPI index

<i>SPI values</i>	<i>Drought and flood condition</i>
2.0+	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
-2.0 and less	Extremely dry

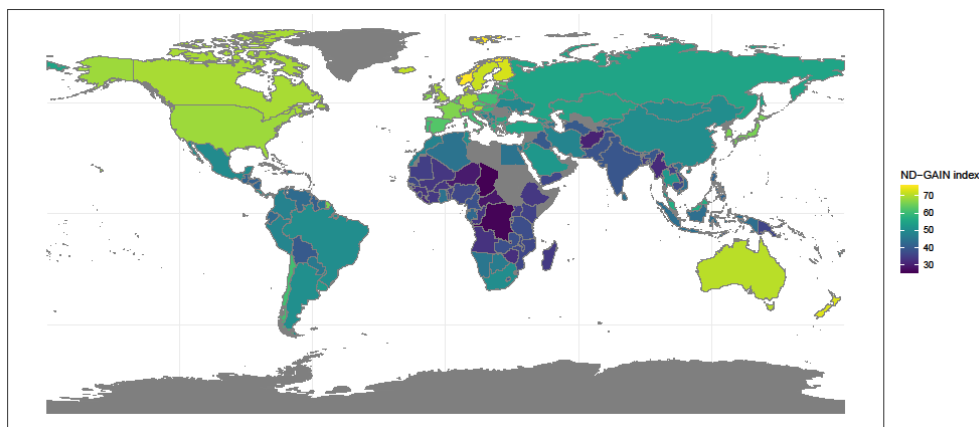
Source: WMO (2012).

1 Figure A.1 The Gini index and the ND-GAIN index

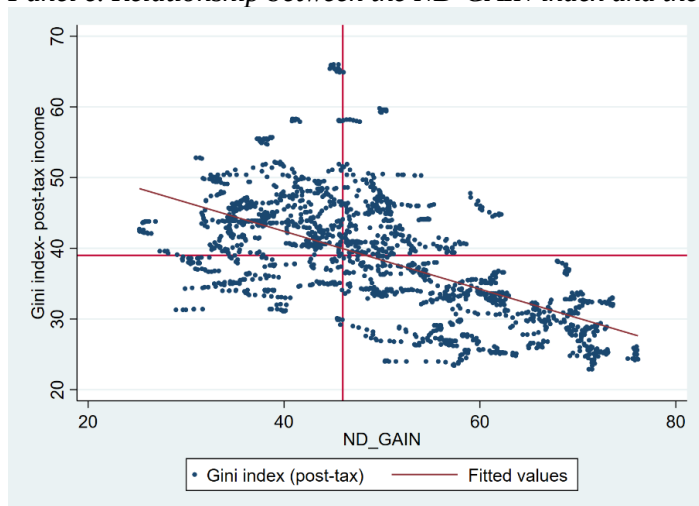
Panel a. Gini index



Panel b. ND-GAIN index



Panel c. Relationship between the ND-GAIN index and the Gini index



2 Source: authors' elaboration on SWIID and ND-GAIN data.

3 Note: the figure offers a graphical representation comparing the country-average (2003-2017) of Gini index (*panel a*) to
 4 the Notre Dame Global Adaptation Initiative (ND-GAIN) index (*panel b*). The ND-GAIN is an indicator of country level
 5 climate vulnerability constructed such that a high value indicates that a country is less vulnerable to climate change with
 6 respect to another country featuring lower values (i.e., the higher the value, the more resilient the country). As summarized

by *panel c*, countries reporting a higher value of the ND-GAIN index (i.e., higher resilience to climate change) are mostly characterized by a lower value of the Gini index (e.g., lower level of income inequality).

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APPENDIX B

Table B.1 Climate change indicators

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(GDP pc)	9.312** (4.122)	9.180** (4.109)	9.660** (4.120)	9.235** (4.117)	9.171** (4.096)	9.354** (4.131)	9.618** (4.110)
ln(GDP pc) ²	-0.542** (0.234)	-0.535** (0.233)	-0.561** (0.234)	-0.538** (0.233)	-0.532** (0.232)	-0.546** (0.234)	-0.558** (0.233)
Rural electricity access	-0.048*** (0.018)	-0.048*** (0.018)	-0.047** (0.018)	-0.047*** (0.018)	-0.048*** (0.018)	-0.047*** (0.018)	-0.047** (0.018)
Industry share (%)	-0.007 (0.018)	-0.007 (0.018)	-0.007 (0.018)	-0.008 (0.018)	-0.008 (0.018)	-0.008 (0.018)	-0.007 (0.018)
Mobile subscription	-0.346** (0.151)	-0.349** (0.150)	-0.347** (0.150)	-0.345** (0.150)	-0.348** (0.150)	-0.342** (0.150)	-0.344** (0.149)
GFCF over GDP (%)	-0.005 (0.011)	-0.005 (0.011)	-0.005 (0.011)	-0.005 (0.011)	-0.005 (0.011)	-0.005 (0.011)	-0.005 (0.011)
Rural pop. (%)	-0.053 (0.054)	-0.052 (0.054)	-0.054 (0.055)	-0.052 (0.054)	-0.052 (0.054)	-0.053 (0.054)	-0.052 (0.055)
Schooling	-0.454*** (0.162)	-0.458*** (0.163)	-0.453*** (0.161)	-0.447*** (0.162)	-0.450*** (0.162)	-0.449*** (0.162)	-0.456*** (0.163)
Gov. health expenditure (%)	-0.020* (0.011)	-0.020* (0.011)	-0.020* (0.011)	-0.020* (0.011)	-0.020* (0.011)	-0.020* (0.011)	-0.020* (0.011)
Financial globalization	0.379* (0.199)	0.374* (0.200)	0.376* (0.197)	0.377* (0.197)	0.378* (0.199)	0.376* (0.197)	0.369* (0.198)
Incoming FDI	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
Temperature	0.367** (0.184)					0.358* (0.190)	
Temperature increase		0.065** (0.032)					0.062 (0.039)
Heat wave			0.156* (0.080)				0.151* (0.081)
Precipitation anomalies				0.269 (0.238)		0.264 (0.238)	
Increasing precipitation anomalies					0.101** (0.050)		0.103** (0.050)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1721	1721	1721	1721	1721	1721	1721
R ²	0.292	0.291	0.293	0.292	0.293	0.293	0.296
R ² _adjusted	0.281	0.281	0.282	0.282	0.283	0.282	0.285
F	2.372	2.201	2.475	2.239	2.292	2.336	2.383

Note: the dependent variable is the Gini index for disposable income. Robust standard errors clustered at the country-level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

1 **Table B.2 Climate change indicators (GMM estimation)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gini index _{t-1}	0.850*** (0.062)	0.885*** (0.044)	0.838*** (0.050)	0.864*** (0.055)	0.810*** (0.048)	0.858*** (0.043)	0.998*** (0.012)
ln(GDP pc)	0.247 (1.367)	-0.711 (0.888)	-0.050 (1.278)	-0.533 (1.598)	-2.254 (1.647)	-0.529 (1.036)	-1.496 (1.265)
ln(GDP pc) ²	-0.019 (0.082)	0.033 (0.051)	-0.019 (0.073)	0.020 (0.092)	0.100 (0.092)	0.020 (0.059)	0.083 (0.071)
Temperature	0.665** (0.287)					0.534** (0.234)	
Temperature increase		0.102** (0.042)					-0.060 (0.096)
Heat wave			0.200*** (0.077)				-0.099 (0.069)
Precipitation anomalies				0.493* (0.281)		0.666*** (0.220)	
Increasing precipitation anomalies					0.064* (0.037)		0.080* (0.045)
Observations	1471	1471	1471	1322	461	1322	461
AR(1)	-3.724 0.000	-3.690 0.000	-3.830 0.000	-3.349 0.001	-2.583 0.010	-3.544 0.000	-2.943 0.003
AR(2)	-1.351 0.177	-1.578 0.115	-1.428 0.153	-1.350 0.177	0.724 0.469	-1.583 0.113	0.579 0.563
Hansen	29.088 0.177	28.962 0.182	25.147 0.196	25.636 0.318	19.369 0.622	24.557 0.319	23.548 0.429

2 Note: the dependent variable is the Gini index for disposable income. System GMM two-step estimator, including finite sample
3 correction (Windmeijer, 2005). Time trend included. The lagged dependent variable, GDP per capita and its square are treated
4 as endogenous. AR(#) tests on the serial correlation of residuals. Hansen tests of overidentification of restrictions. Robust
5 standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
6
7

1 **Table B.3 The agricultural channel**

	(1)	(2)	(3)	(4)
ln(GDP pc)	9.440** (4.373)	9.249** (4.301)	9.739** (4.347)	10.612** (4.277)
ln(GDP pc)^2	-0.557** (0.247)	-0.536** (0.243)	-0.573** (0.245)	-0.612** (0.241)
Rural electricity access	-0.048*** (0.017)	-0.046*** (0.017)	-0.048*** (0.017)	-0.045** (0.018)
Industry share (%)	-0.008 (0.019)	-0.009 (0.018)	-0.009 (0.018)	-0.009 (0.018)
Mobile subscription	-0.273* (0.148)	-0.283* (0.149)	-0.267* (0.149)	-0.309** (0.149)
GFCF over GDP (%)	-0.005 (0.011)	-0.005 (0.011)	-0.004 (0.011)	-0.005 (0.011)
Schooling	-0.409*** (0.147)	-0.408*** (0.146)	-0.405*** (0.144)	-0.449*** (0.164)
Gov health expenditure (%)	-0.016 (0.011)	-0.017 (0.011)	-0.016 (0.011)	-0.018 (0.011)
Financial globalization	0.345* (0.208)	0.389** (0.195)	0.338* (0.200)	0.372* (0.197)
Incoming FDI	0.001*** (0.000)	0.001*** (0.001)	0.001*** (0.001)	0.001*** (0.000)
Low rural pop.	0.332 (0.394)	-0.928* (0.505)	0.120 (0.447)	
High rural pop.	-5.187*** (1.908)	-0.575 (0.526)	-4.909*** (1.838)	
Temperature		0.178 (0.254)		0.340* (0.176)
Precipitation anomalies	0.343 (0.248)			0.265 (0.248)
Temperature in Low rural pop.	0.083 (0.236)		0.108 (0.237)	
Temperature in Mid rural pop.	0.489* (0.311)		0.501* (0.313)	
Temperature in High rural pop.	2.023*** (0.667)		1.961*** (0.649)	
Precipitation anomalies in Low rural pop.		0.846** (0.396)	0.842** (0.392)	
Precipitation anomalies in Mid rural pop.		-0.185 (0.346)	-0.094 (0.346)	
Precipitation anomalies in High rural pop.		-0.343 (0.520)	-0.315 (0.523)	
Agric. empl.				0.005 (0.029)
Agric. empl.* Temperature				0.002*** (0.001)
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1721	1721	1721	1714
R ²	0.311	0.307	0.316	0.290
R ² _adjusted	0.299	0.295	0.303	0.279
F	2.394	2.095	2.387	2.454

2 Note: the dependent variable is the Gini index for disposable income. Robust standard errors clustered at
3 the country-level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
4

1 **Table B.4 FDIIs and the functional diversification in FDI as mediating factor**

	(1)	(2)	(3)	(4)	(5)
ln(GDP pc)	9.720** (4.111)	9.657** (4.137)	9.510** (4.138)	9.364** (4.130)	9.366** (4.113)
ln(GDP pc) ²	-0.565** (0.233)	-0.559** (0.234)	-0.552** (0.234)	-0.542** (0.234)	-0.542** (0.233)
Rural electricity access	-0.047*** (0.018)	-0.046** (0.018)	-0.047** (0.018)	-0.047** (0.018)	-0.048*** (0.018)
Industry share (%)	-0.008 (0.018)	-0.007 (0.018)	-0.008 (0.018)	-0.007 (0.018)	-0.007 (0.018)
Mobile subscription	-0.344** (0.149)	-0.349** (0.148)	-0.344** (0.149)	-0.341** (0.148)	-0.341** (0.147)
GFCF over GDP (%)	-0.005 (0.010)	-0.005 (0.011)	-0.005 (0.010)	-0.006 (0.011)	-0.006 (0.010)
Rural pop. (%)	-0.052 (0.054)	-0.055 (0.055)	-0.052 (0.055)	-0.056 (0.055)	-0.055 (0.055)
Schooling	-0.454*** (0.162)	-0.457*** (0.162)	-0.456*** (0.162)	-0.457*** (0.162)	-0.459*** (0.162)
Gov. health expenditure (%)	-0.020* (0.011)	-0.019* (0.011)	-0.020* (0.011)	-0.020* (0.011)	-0.020* (0.011)
Financial globalization	0.356* (0.198)	0.361* (0.199)	0.371* (0.198)	0.366* (0.195)	0.372* (0.195)
Incoming FDIIs	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
Temperature increase	0.065* (0.039)	0.065* (0.038)	0.062 (0.039)	0.060 (0.038)	0.060 (0.037)
Heat wave	0.145* (0.081)	0.148* (0.080)	0.150* (0.080)	0.148* (0.081)	0.147* (0.081)
Increasing precip. anomalies	0.099** (0.049)	0.104** (0.050)	0.103** (0.050)	0.111** (0.050)	0.327*** (0.107)
FDI sh. in Upstream activities	-0.647** (0.314)				
FDI sh. in Production activities		0.290** (0.136)			
FDI sh. in Downstream activities			0.071 (0.118)		
Functional diversification in FDI				-0.003*** (0.001)	-0.002** (0.001)
Func. diversification in FDI * Increasing precipitation anomalies					-0.003** (0.001)
Country FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	1721	1721	1721	1721	1721
R ²	0.300	0.299	0.296	0.302	0.304
R ² _adjusted	0.288	0.287	0.284	0.290	0.291
F	2.396	2.286	2.405	2.419	2.381

2 Note: the dependent variable is the Gini index for disposable income. Robust standard errors clustered at the
3 country-level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
4

5

APPENDIX C: Robustness with lagged variables (y-1)

Table C.1 Climate change indicators (lagged variables, y-1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L.ln(GDP pc)	8.941** (4.133)	8.809** (4.116)	9.526** (4.096)	8.989** (4.146)	8.888** (4.098)	9.115** (4.164)	9.575** (4.084)
L.ln(GDP pc) ²	-0.546** (0.235)	-0.539** (0.234)	-0.578** (0.233)	-0.551** (0.236)	-0.540** (0.233)	-0.558** (0.237)	-0.580** (0.232)
L.Rural electricity access	-0.045** (0.018)	-0.045** (0.018)	-0.044** (0.018)	-0.045** (0.018)	-0.045** (0.018)	-0.045** (0.018)	-0.044** (0.018)
L.Industry share (%)	-0.015 (0.018)	-0.015 (0.018)	-0.014 (0.018)	-0.015 (0.018)	-0.015 (0.018)	-0.015 (0.018)	-0.015 (0.018)
L.Mobile subscription	-0.328** (0.139)	-0.330** (0.139)	-0.327** (0.137)	-0.321** (0.139)	-0.328** (0.137)	-0.319** (0.139)	-0.324** (0.136)
L.GFCF over GDP (%)	-0.004 (0.011)	-0.004 (0.011)	-0.004 (0.011)	-0.004 (0.011)	-0.004 (0.011)	-0.004 (0.011)	-0.004 (0.011)
L.Rural pop. (%)	-0.057 (0.054)	-0.055 (0.054)	-0.057 (0.054)	-0.053 (0.053)	-0.054 (0.054)	-0.054 (0.053)	-0.055 (0.054)
L.Schooling	-0.446*** (0.167)	-0.451*** (0.168)	-0.449*** (0.165)	-0.434*** (0.166)	-0.444*** (0.167)	-0.434*** (0.166)	-0.452*** (0.167)
L.Gov. health expenditure (%)	-0.018* (0.010)	-0.018* (0.010)	-0.018* (0.010)	-0.018* (0.010)	-0.019* (0.010)	-0.018* (0.010)	-0.018* (0.010)
L.Financial globalization	0.371** (0.182)	0.367** (0.183)	0.369** (0.180)	0.370** (0.179)	0.370** (0.182)	0.369** (0.179)	0.363** (0.180)
L.Incoming FDI	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)
L.Temperature	0.302* (0.172)					0.297* (0.172)	
L.Temperature increase		0.056* (0.032)					0.053 (0.040)
L.Heat wave			0.200** (0.077)				0.194** (0.078)
L.Precipitation anomalies				0.382 (0.240)		0.381 (0.240)	
L.Increasing precip. anomalies					0.117** (0.049)		0.117** (0.049)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1590	1590	1590	1590	1590	1590	1590
R ²	0.304	0.304	0.308	0.307	0.307	0.307	0.312
R ² _adjusted	0.293	0.293	0.297	0.296	0.296	0.296	0.300
F	2.391	2.224	2.519	2.232	2.415	2.335	2.466

Note: the dependent variable is the Gini index for disposable income. Robust standard errors clustered at the country-level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

1 **Table C.2 The agricultural channel (lagged variables, y-1)**

	(1)	(2)	(3)	(4)
L.ln(GDP pc)	9.664** (4.334)	9.450** (4.228)	10.012** (4.273)	10.568** (4.298)
L.ln(GDP pc)^2	-0.596** (0.246)	-0.573** (0.241)	-0.614** (0.242)	-0.634** (0.244)
L.Rural electricity access	-0.047*** (0.017)	-0.044*** (0.016)	-0.046*** (0.017)	-0.042** (0.018)
L.Industry share (%)	-0.015 (0.018)	-0.016 (0.018)	-0.016 (0.018)	-0.016 (0.018)
L.Mobile subscription	-0.249* (0.138)	-0.264* (0.140)	-0.245* (0.140)	-0.288** (0.138)
L.GFCF over GDP (%)	-0.004 (0.011)	-0.004 (0.011)	-0.003 (0.011)	-0.004 (0.011)
L.Schooling	-0.392** (0.153)	-0.390** (0.151)	-0.387** (0.149)	-0.428** (0.169)
L.Gov health expenditure (%)	-0.014 (0.010)	-0.015 (0.010)	-0.014 (0.010)	-0.016 (0.010)
L.Financial globalization	0.342* (0.187)	0.386** (0.175)	0.338* (0.179)	0.366** (0.179)
L.Incoming FDI	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)
L.Low rural pop.	0.426 (0.403)	-0.757 (0.466)	0.213 (0.441)	
L.High rural pop.	-5.184*** (1.799)	-0.632 (0.539)	-4.914*** (1.723)	
L.Temperature		0.244 (0.202)		0.251 (0.173)
L.Precipitation anomalies	0.465* (0.253)			0.395 (0.255)
L.Temperature in Low rural pop.	0.126 (0.195)		0.146 (0.196)	
L.Temperature in Mid rural pop.	0.510* (0.282)		0.515* (0.284)	
L.Temperature in High rural pop.	2.042*** (0.645)		1.987*** (0.620)	
L.Precipitation anomalies in Low rural pop.		0.989** (0.405)	0.990** (0.402)	
L.Precipitation anomalies in Mid rural pop.		-0.061 (0.371)	0.028 (0.371)	
L.Precipitation anomalies in High rural pop.		-0.318 (0.460)	-0.294 (0.463)	
L.Agric. empl.				0.009 (0.027)
L.(Agric. empl.*Temperature)				0.002** (0.001)
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1590	1590	1590	1583
R ²	0.323	0.321	0.330	0.304
R ² _adjusted	0.311	0.308	0.317	0.292
F	2.364	2.179	2.342	2.241

2 Note: the dependent variable is the Gini index for disposable income. Robust standard errors clustered at the
3 country-level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

1 **Table C.3 FDIIs and the functional diversification in FDI as mediating factor (lagged**
2 **variables, y-1)**

	(1)	(2)	(3)	(4)	(5)
L.ln(GDP pc)	9.807** (4.073)	9.655** (4.135)	9.452** (4.117)	9.593** (4.103)	9.629** (4.095)
L.ln(GDP pc) ²	-0.594** (0.232)	-0.583** (0.234)	-0.573** (0.234)	-0.579** (0.233)	-0.580** (0.232)
L.Rural electricity access	-0.045** (0.018)	-0.043** (0.018)	-0.044** (0.018)	-0.044** (0.018)	-0.044** (0.018)
L.Industry share (%)	-0.015 (0.018)	-0.015 (0.018)	-0.015 (0.018)	-0.013 (0.018)	-0.013 (0.018)
L.Mobile subscription	-0.322** (0.136)	-0.331** (0.134)	-0.323** (0.136)	-0.320** (0.135)	-0.321** (0.135)
L.GFCF over GDP (%)	-0.004 (0.010)	-0.003 (0.011)	-0.004 (0.010)	-0.004 (0.011)	-0.004 (0.010)
L.Rural pop. (%)	-0.054 (0.054)	-0.059 (0.054)	-0.055 (0.054)	-0.058 (0.054)	-0.058 (0.054)
L.Schooling	-0.450*** (0.167)	-0.452*** (0.166)	-0.452*** (0.167)	-0.450*** (0.167)	-0.451*** (0.167)
L.Gov. health expenditure (%)	-0.018* (0.010)	-0.017* (0.010)	-0.018* (0.010)	-0.018* (0.010)	-0.018* (0.010)
L.Financial globalization	0.348* (0.180)	0.357** (0.180)	0.364** (0.180)	0.351** (0.176)	0.352** (0.177)
L.Incoming FDIIs	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
L.Temperature increase	0.056 (0.040)	0.056 (0.038)	0.053 (0.040)	0.049 (0.039)	0.049 (0.039)
L. Heat wave	0.189** (0.078)	0.192** (0.077)	0.192** (0.077)	0.190** (0.078)	0.189** (0.078)
L.Increasing precip. anomalies	0.113** (0.047)	0.119** (0.049)	0.117** (0.049)	0.128*** (0.048)	0.306** (0.129)
L.FDI sh. in Upstream activities	-0.610* (0.342)				
L.FDI sh. in Production activities		0.356*** (0.132)			
L.FDI sh. in Downstream activities			0.076 (0.103)		
L.Functional diversification in FDI				-0.003*** (0.001)	-0.002* (0.001)
L.(Func. diversification in FDI * Increasing precipitation anomalies)					-0.003* (0.002)
Country FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	1590	1590	1590	1590	1590
R ²	0.316	0.317	0.312	0.321	0.324
R ² _adjusted	0.304	0.305	0.300	0.309	0.311
F	2.542	2.333	2.496	2.511	2.616

3 Note: the dependent variable is the Gini index for disposable income. Robust standard errors clustered at the
4 country-level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
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