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Abstract

Climate change and trade are closely related. Climate may alter the comparative advantages across countries, which may in turn trigger changes in trade patterns. Trade itself may constitute an adaptation strategy, moving excesses of agri-food supply to regions with shortages, and this in turn may explain changes in land-use. We investigate these linkages, showing that the changes in climate affect counties' trade value and contribute to reshaping trade patterns. First, we quantify the long-term impacts of climate on the value of agri-food exports, implicitly considering the ability of countries to adapt, and show that higher marginal temperatures and rainfall levels tend to be beneficial for countries' exports. Following a gravity model approach, we then link the evolving trade patterns to climate change adaptation strategies. We find that the larger the difference in temperatures and rainfall levels between trading partners, the higher the value of bilateral exports. Furthermore, while developed and developing exporters are both sensitive to climate change and to cross-countries heterogeneity in climate, we found their responses to changes in climate to be quite diverse.

Keywords

Climate normal; Climate heterogeneity; Export; Economic development

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Declaration

Senior authorship not assigned: the article has been thought, discussed, and written by the three authors and it is the result of their common commitment.

1. Introduction

The interest of policymakers and academics for climate change issues and trade dynamics, and their connections, is vivid and growing. The awareness that these two phenomena are closely related and have large impacts on the agri-food sector is increasingly common wisdom. Yet, understanding how climate change and trade are linked deserves deeper investigation at least for two reasons: the existing literature is relatively recent and not conclusive on how trade and climate change are related (e.g., Hsiang, 2016; Costinot et al., 2016; Janssens et al., 2020; Gouel and Laborde, 2021) and, even more important, understanding how the phenomena are related would help facing increasing challenges posed by climate change and planning adaptation and mitigation options (e.g., Burke and Emerick, 2016; Hochman and Zilberman, 2021; Shapiro, 2021), while feeding the world's growing population, which is expected to raise to almost 10 billion by 2050 (UNDESA, 2022).

By connecting economies, trade may be relevant for the adaptation to climate change-related challenges, such as the local climate becoming less suitable for crops traditionally produced and consumed, and for the reallocation of food from surplus to deficit regions, hence contributing to food security (FAO, 2017, 2018; Li et al., 2019)[1]. For instance, under varying climatic conditions, a country may decide to import a crop whose yield has fallen, and to produce more and to export another crop whose yield has increased or remained constant (Reimer and Li, 2009, 2010; Costinot et al., 2016). In sum, trade may constitute a climate change adaptation strategy. In addition, trade itself is likely to be impacted by climate change (Hsiang, 2016). These impacts are expected to be particularly relevant for the agri-food sector, which is one of the most sensitive and vulnerable sectors to the climate change (e.g., Deschenes and Greenstone, 2007; Mendelsohn and Massetti, 2017).

We investigate the potential impacts of climate change on the agri-food trade. First, we focus on the impacts that changes in climate normals have on the value of trade[2]. This part of the analysis builds upon cross-sectional studies of climate change, introduced by Mendelsohn et al. (1994) and extended to panel settings by Deschenes and Greenstone (2007), to examine the long-term impacts of climate on the value of trade at the country level, implicitly considering the ability of countries to adapt. The novelty here is that we move the focus from profits, the variable traditionally used in studies of climate change (e.g., Mendelsohn et al., 1994, 1996; Deschenes and Greenstone, 2007; Bozzola et al., 2018), to trade values so as to measure how the domestic trade patterns are affected by structural changes in climate. The rationale is simple: profits depend on countries' exports that are in turn affected by long-run changes in climate in the origin and/or destination regions (Dall'Erba et al., 2021). Second, aiming at a more holistic analysis of the impacts of climate change on global agri-food trade, we look at how the climate heterogeneity across trading partners impacts the value of bilateral trade. This second part of our analysis builds on the well-grounded strand of gravity-based research (e.g., Bergstrand, 1985; Eaton and Kortum, 2002), as the basis for our analysis on bilateral trade. In the gravity literature, this approach is traditionally used to quantify the impact of trade policies such as tariffs and non-tariff measures (e.g., Olper and Raimondi, 2008; Santeramo and Lamonaca, 2022a), or trade agreements (e.g., Heerman et al., 2015; Santeramo and Lamonaca, 2022b). Recently, the gravity approach has been used to investigate the nexus

[1] Feeding a growing global population in a changing climate presents a significant challenge to society (Challinor et al., 2014). World population and average income are rising and this, in turn, increases the demand for food. An increase in food production between 25-70% above 2014 levels will be required by 2050 to meet this growing demand and to prevent further food insecurity (Hunter et al., 2017).

[2] For the remainder of the paper, we refer to trade in agri-food products when we talk about "value of trade" with reference to our own empirical specifications, while the term "climate normals" (or climatologies) refer to long time averages (30-years) in climate variables (e.g., temperatures and precipitations) in a given location.

between trade and climate: Dall'Erba et al. (2021) assess the impact of weather conditions, specifically droughts, on interstate trade in the United States to mimic a free trade environment; Dallmann (2019) examines the effect of weather variations on bilateral trade flows worldwide but does not control for other determinant of bilateral trade such as trade barriers or market structure differences.

We build upon these approaches and introduce some novelties. First, we evaluate the role of long-term shifts in temperature or precipitation. Although previous studies consider past weather events (Dallmann, 2019; Dall'Erba et al., 2021), they miss the role of structural changes in climate as well as the future consequences of these climate trends. Second, we apply the gravity model to an international setting controlling for cofounding factors, such as trade policies.

We indirectly capture the fact that climate change, by altering comparative advantages of sectors across countries, may trigger changes in trade patterns (Zimmermann et al., 2018). Starting from the consideration that changes in climate may induce changes in land use and production choices and, as a consequence, may alter the agri-food supplies (Reilly and Hohmann, 1993), our focus is on the “excess of supply” (“excess of demand”) in exporting (importing) countries. Climate changes may affect countries' comparative advantages favouring a specialisation toward productions for which countries become more and more competitive. By altering the comparative advantages, climate change may reshape trade patterns allowing countries to exploit the beneficial opportunities (or to moderate the negative impacts) of climate change (Burke and Emerick, 2016). If changes in climate expand the export capacity of A country and the import demand of its trading partner, trade between them is likely to increase due to the changed climatic conditions. Differently, bilateral trade may reduce if, for instance, the changed climate conditions expand or shrink the export capacity of both countries.

For the reasons explained, we also investigate the impacts of climate change on the value of trade in agri-food products considering the level of economic development of exporting countries. Our empirical application considers a set of developed and developing economies covering two-third of global agri-food exports and located at different latitudes, in regions of the world characterised by different climate conditions.

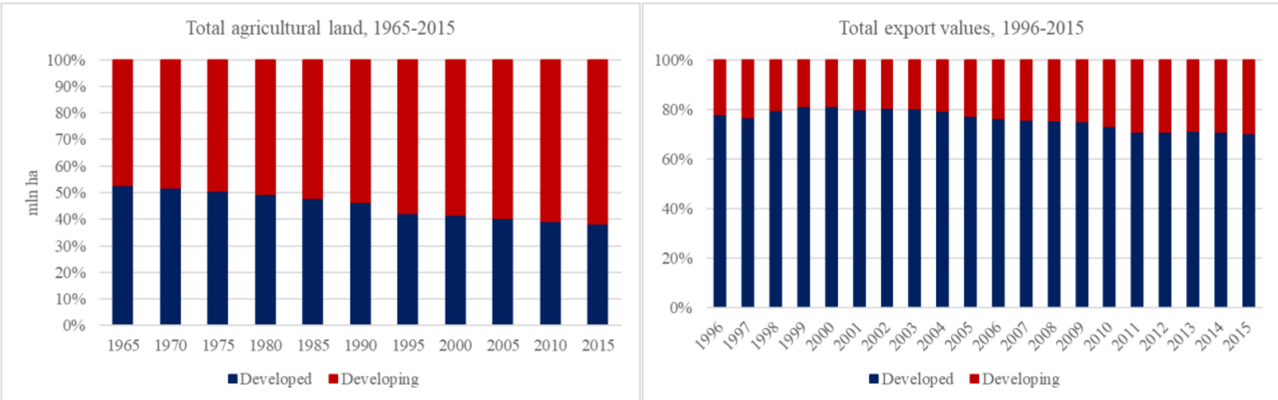
To the authors' knowledge, this is the first study that, using both a cross-sectional analysis of country-level value of exports and a panel regression of bilateral value of exports, investigates the role of *climate* (i.e., the weather conditions prevailing in a region over a long period) on trade values. Previous studies have focused on the impact that a country's *weather* in that year (i.e., its average temperature and precipitation) has on the annual growth rate of its exports (e.g., Jones and Olken, 2010) and on the effect of *weather variations* in the exporter and/or importer countries on bilateral trade flows (e.g., Dallmann, 2019). These are also needed analysis but there are important differences, because it is expected that long-run effects of climate change (when the adaptation may be fully adopted and thus implicitly captured) should be more stable than the short-run effects (when the adaptation is only partially adopted). One of the contributions of this paper is to show how trade capacities and trade patterns may have reflected the structural (i.e., long-run) climate changes that have occurred during the last few decades.

2. Current debate on climate change and international trade

Population and income growth, in low- and middle-income countries, is boosting agri-food demand and is hastening the demand for calories and dietary transition towards higher consumption of meat, fruit, and vegetables, relative to that of cereals (FAO, 2017; Gouel and Guimbard, 2019; Karimi Alavijeh et al., 2022). These trends are also fostering changes in land use and challenging the resilience of the agricultural system (e.g., Santeramo, Di Gioia, Lamonaca, 2021; Zhang et al., 2021). The expansion of agriculture and the production of traded goods are important drivers of global land use change (Böhringer et al., 2021; WTO, 2022). Most countries trade land-demanding products (Meyfroidt and Lambin, 2009) and large agricultural exports often are associated with high deforestation rates (DeFries et al., 2010). As compared to developed economies, the use of agricultural land (panel A) is raising in developing countries (figure 1, panel A). Such raising trend is also observed for agricultural exports (figure 1, panel B). the changes in land use and agri-food trade do not necessarily imply that trade is the driver of land-use transitions (Meyfroidt et al., 2010), but calls for attention on the trade-climate nexus, as one of the drivers of changes in land use. This link is specifically investigated in our analysis.

Figure 1. Trends of land use (panel A) and agri-food trade (panel B)

Panel A Panel B



Source: own elaboration on data from FAOSTAT and UN Comtrade.

Notes: Data includes countries in the sample described in section 3, divided according to the level of economic development.

The debate on the relation between climate change and international trade is also animated by findings showing that trade has a limited role in terms of adaptation to climate change (e.g., Costinot et al., 2016), and by contradicting conclusions that the link between trade and climate change adaptation is crucial (e.g., Janssens et al., 2020; Gouel and Laborde, 2021) and that trade plays an important role in distributing climate welfare impacts (Jones and Olken 2010).

The differences in impacts of climate change between countries with different levels of economic development are well documented (e.g., Mendelsohn et al., 2006; Dell et al. 2012; Global Commission on Adaptation, 2019). Developing countries are often located at warmer low latitudes whereas high-latitude countries are often developed economies (Zimmermann et al., 2018; IPCC 2019). In general, developing countries depend heavily on the agricultural sector, which is one of the sectors that is most susceptible to climate change (Mendelsohn, 2009). They may have less potential to adapt and thus may suffer the most from impacts of climate change (Reilly and Hohmann, 1993; Hertel and de Lima, 2020; Brenton et al., 2022).

For instance, in regions closer to the equator, the yields of cereal crops are declining as a result of climate change (IPCC, 2019). Adaptation measures, such as the choice of planting dates to avoid high temperatures or dry periods of the year, may be insufficient in already warm developing countries[3] where an increase in temperatures would increase the potential for drought stress (e.g., Brenton et al., 2022). They may also have lower capability to adapt to climate change due to infrastructure (e.g., roads, inland waterways and railway lines, storage and processing facilities) at higher risk of faster depreciation and damage (Koks et al., 2019; WTO, 2022), limited access to technology and weaker institutions (Acemoglu et al., 2002; Agemoglu and Dell, 2010; Guiso et al., 2015). For instance, supply chains that rely key infrastructure such as roads and ports can be disrupted by weather and climate extreme events (Attavanich et al., 2013; IPCC, 2022; WTO, 2022). Small Island developing nations or landlocked countries which trade through a limited number of ports and routes are especially vulnerable to impacts of climate change on transport infrastructure (WTO 2022)[4]. Moreover, less efficient processing, packaging, and storage facilities may increase costs (e.g., higher energy costs due to ventilation and temperature control mechanisms) and spoilage (e.g., more frequent bacterial foodborne diseases) (Brown et al., 2017).

Earlier studies by Reilly and Hohmann (1993) and Rosenzweig and Parry (1994) emphasise the role of international trade in the adjustment of the world food system to climate-induced changes in the agricultural production. The assumption is that, for open economies, climate change impacts on agriculture in any region cannot be considered in isolation from the rest of the world. More recent studies by Costinot et al. (2016) and Gouel and Laborde (2021) examine the role of trade in attenuating effects of climate change through new climate-induced pattern of comparative advantages. While Costinot et al. (2016) conclude that climate change impacts amount to a 0.26% reduction in global Gross Domestic Product (GDP) when trade and production patterns can adjust, Gouel and Laborde (2021) find larger welfare losses from climate change when adjustments in trade flows are constrained versus when they are not. Both studies by Costinot et al. (2016) and Gouel and Laborde (2021) investigate the contribution of adjustments through production and trade patterns to adaptation to climate change in agriculture, assuming that climate change may heterogeneously impact agricultural productivity both within and between countries. These heterogeneous impacts may alter countries' comparative advantages, because of changes in land use and production choices, and may consequently induce changes in international trade flows. The rationale is that, under climate change, regions with currently low temperatures may benefit from higher yields and improve their export capacity. In fact, a warmer climate allows these regions planting crops that could not grow under the current climate on existing fields and induces, as a result, changes in land use. For instance, with respect to the 30-years period 1961-1990, Russia became warmer in 1991-2020 (see figure A.1 in the Appendix A) and, according to the FAOSTAT statistics, its agricultural land increased by 4 million hectares over the same periods (i.e., from 551 to 555 million hectares). Differently, regions with currently high temperatures are exposed to the risk of a decrease in yields because of extreme temperatures and, as a consequence, to a reduction in their export capacity. Reimer and Li (2009, 2010) argue that climate change, by increasing the probability of extreme climate phenomena, may exacerbate yield variability and international trade favours the adaptation to yield variability through spatial

[3] As an example, consider India: the area near to Delhi has a typical tropical climate with maximum temperature reaching up to 45 °C during the summer months of April, May and June (see Sahay, 2018). Such temperatures are already prohibitive for growing wheat, whose yield tend to be negatively impacted by temperatures higher than 30 °C (e.g., Zampieri et al., 2017).

[4] Extreme weather events can affect key transport corridors and infrastructure, potentially disrupting regional and global trade network. According to WTO (2022) maritime transport which accounts for 80% of world trade by volume is particularly exposed to climate change. As an example the Paraná River transports 90% of Paraguay's international trade of agricultural goods, but recurrent droughts have in recent years frequently lowered water levels, diminishing the weight barges can carry, causing congestion and delays (WTO, 2022).

arbitrage. In sum, the literature on the nexus between climate change and international trade suggests that long-run changes in climate (i.e., climate change)[5] may have heterogenous impacts across countries, and the adjustments of trade patterns may smooth the consequences of these climate-induced changes.

3. Conceptual framework and empirical strategy

The empirical analysis starts from the concept that climate change, by affecting climate conditions in the exporting and importing countries, may alter their comparative advantage and, as a result, their trade capacity (see figure B.1 of the Appendix B). We investigate these dynamics adapting the approach traditionally used in cross-sectional studies of climate change (e.g., Mendelsohn et al., 1994, 1996; Deschenes and Greenstone, 2007; Bozzola et al., 2018; Bareille and Chakir, 2023). However, climate conditions between the exporting and importing countries may differ and potentially induce different specialisations of trading partners, with consequences on their bilateral trade relationships (see figure B.1 of the Appendix B). We capture these effects through a gravity-based analysis (e.g., Bergstrand, 1985; Eaton and Kortum, 2002; Dallmann, 2019; Dall'Erba et al., 2021).

3.1. Climate change impacts on country's agri-food trade value

We present a simple conceptual framework describing how shifts in the aggregate agri-food supply of countries due to changes in climate may alter their trade value in the agri-food sector. Climate is an exogenous factor typically affecting productivity (e.g., Mendelsohn et al., 1994, 1996; Knittel et al., 2020) and capable of altering comparative advantage, i.e., the relative ability of a country to produce a certain product at a lower cost than any other country, and as a consequence export (import) the excess of supply (demand) (French, 2017)[6]. Following Reimer and Li (2009, 2010), we assume that land is the principal factor of agricultural production and productivity (i.e., defined as output per area of land) shocks arise from the climate-induced randomness of agricultural production and from relatively permanent differences in climate across countries. The consequences of climate change may crucially depend on the ability of a country to change its trade levels (Costinot et al., 2016). Changes in land use and production choices are potential responses to the impacts of climate change (i.e., adaptation outcomes). For instance, a certain country (say Canada) may unlikely be a competitive exporter of a certain good (say grape) due to climate requirements for its production. However, warmer temperatures due to long-run changes in climate may give an advantage in producing that good to the country, increasing its competitiveness. In order to capture these features of trade, our model links the value of aggregate agri-food exports with climate conditions. Let us assume a country *i* to be a small open economy and a net exporter (importer) for the agri-food sector. Given its aggregate agri-food demand and supply (D_i and

[5] A related strand of empirical literature quantifies the effects of weather variations (i.e., short-run changes in climate) on international trade. Jones and Olken (2010) examine the impacts of temperature shocks on exports, concluding that higher temperatures have more substantial (detrimental) impacts on high-income countries, rather than on low-income ones. By examining the impacts of climate shocks on international trade in China, Li et al. (2015) compute high welfare losses induced by climate change. Dellmann (2019), investigates the effects of weather variations on bilateral trade and finds that the positive effects of temperature dominate. While short-run changes in climate may have relevant impacts on trade dynamics, this article focuses on the nexus between climate change and international trade and investigates the impacts induced by long-run changes in climate.

[6] As in Mendelsohn et al. (1994), we assume that climate affects, within each country, directly the productivity of different crops and indirectly the substitution of different inputs. As climate changes, economic agents (e.g. farmers) may even switch to different economic activities. This implies that relative autarky prices across sectors may also change. Accordingly, our framework considers implicitly adaptation across commodities within the same sector (e.g., across agri-food commodities) and also across different sectors (e.g., between the agri-food and the manufacturing sectors). This is in line with a growing body of evidence that indicates that climate change will affect manufacturing in addition to agriculture (e.g., Zhang et al., 2018).

S_i), the export (import) value of *i* (V_i) is a function of the exogenous market price (p^*) which depends on the conditions in the rest of the world, the known technology (z_i), the country's climate conditions (vector $\boldsymbol{C}_i$), and a set of country-specific characteristics (vector $\boldsymbol{X}_i$)[7]:

$$S_i - D_i = V_i = f(p^*, z_i, \boldsymbol{C}_i, \boldsymbol{X}_i, \cdot) \tag{1}$$

If p^* is higher (lower) than the domestic price, *i* is a net exporter (importer), thus $S_i - D_i > 0$ ($S_i - D_i < 0$); z_i is assumed to be constant in *i* (Mendelsohn et al., 1996); $\boldsymbol{C}_i$ is exogenous and reflects the long-run equilibria associated with the climate (Mendelsohn et al., 1994); $\boldsymbol{X}_i$ includes other relevant control factors at country level, such as geographic coordinates, development level, policy interventions.

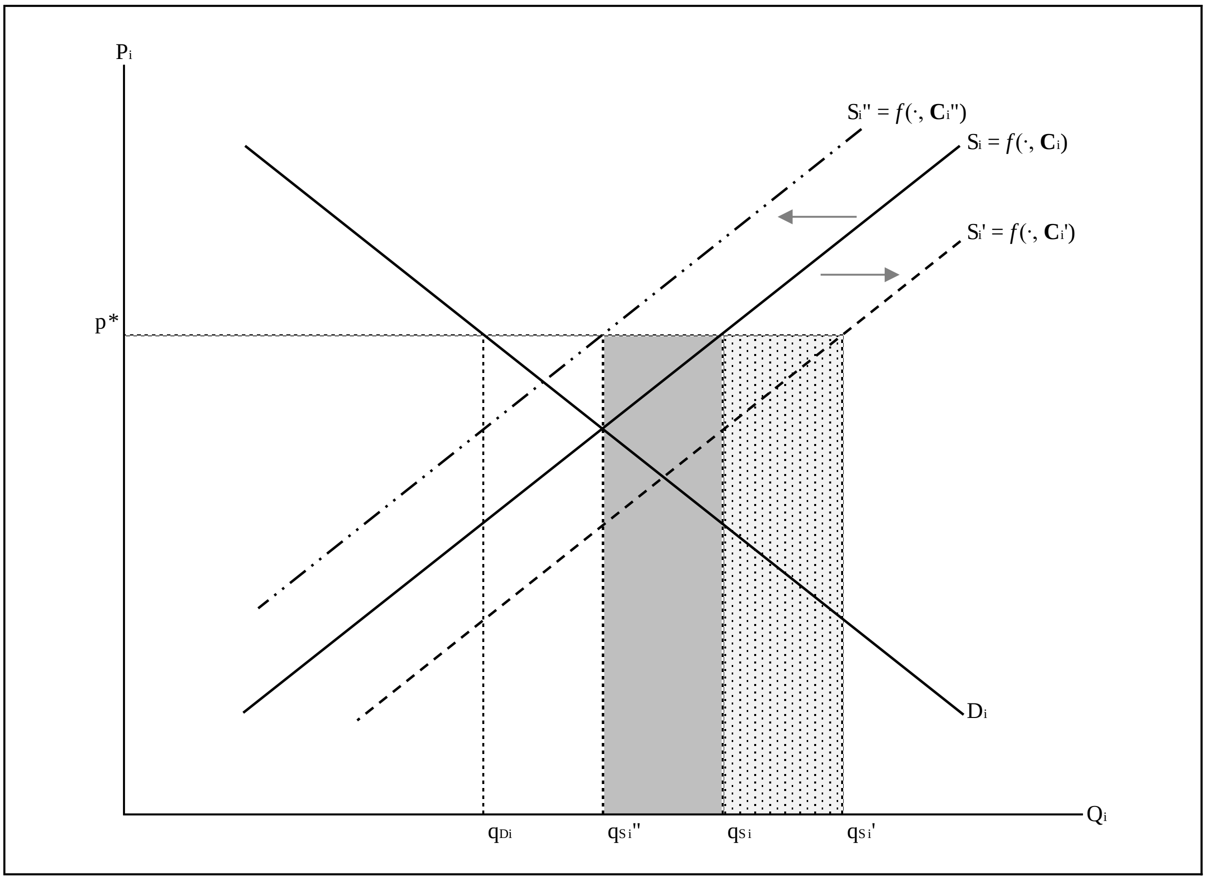
The rationale behind equation (1) is that climate may affect the trade value of *i*. For simplicity, suppose that long-run changes in climate shift S_i but leave D_i unaltered. A warmer (cooler) climate may favour (inhibit) the production of certain goods (say tropical fruits), shifting S_i but leaving unaltered D_i. If world price, p^*, is higher (lower) than the domestic price, then the changes in climate expand S_i (say from S_i to S_i') and increase (reduce) the excess of supply (demand) (say from $q_{S_i} - q_{D_i}$ to $q_{S_i'} - q_{D_i}$), and the value of exports (imports) of *i* increases (decreases) by $\left(q_{S_i'} - q_{S_i}\right) p^*$ (dotted area in figure 2); the opposite is true for a left-ward shift of the supply functions (grey area in figure 2). Climate change may determine changes in comparative advantages and result in increase or decrease of the trade values.

We build upon cross-sectional climate studies (e.g., Mendelsohn et al., 1994, 1996) to examine the long-term impacts of climate change on the agri-food sector, implicitly considering the ability of countries to adapt to changes in climate[8]. We use this approach to estimate how much climate explains observed cross-sectional variation of the value of countries' agri-food trade, controlling for confounding factors. One of the strengths of the method is its ability to measure the long run impacts of climate change taking into account (implicitly) the ability of each country to adapt. We estimate a log-linear specification[9] of the model in equation (1):

$$V_{it} = \beta_r + \beta_t + \boldsymbol{C}_i \gamma + \boldsymbol{X}_i \delta + u_{it} \tag{2}$$

[7] The subscript t for time varying variables is suppressed for ease of notation.
[8] In its traditional application, this cross-sectional approach (Mendelsohn et al., 1994) is a hedonic method that relies on a cross-sectional regression of farmland prices on fixed climate variables. Expected net revenues are also appropriate dependent variables often used in this stream of literature. We depart from this standard empirical application: our dependent variable is the value of total agri-food exports.
[9] We rely on a log-linear model since trade values tend to be log-normally distributed (Head and Mayer, 2014).

Figure 2. Changes in country's value of agri-food trade due to climate change



Notes: All else equal, shifts in country's aggregate agri-food supply (S_i) depend on changes in country's climate ($\boldsymbol{C}_i$). Given the exogenous market price (p^*) higher than domestic prices, $q_{D_i} - q_{S_i}$ is the baseline excess of supply, $\left(q_{S_i'} - q_{S_i}\right)p^*$ is the increase in the value of exports associated with an expanded supply (S_i') (dotted area), $\left(q_{S_i} - q_{S_i''}\right)p^*$ is the reduction in the value of exports associated with a shrunk supply (S_i'') (grey area).

The term V_{it} is a vector of the log value of agri-food total exports of country *i* at time *t*, expressed in USD. This dependent variable allows us to capture the impact of climate variables on trade values. The region fixed effects[10] (i.e., dummies equal to one if a country *i* belongs to a specific region, and zero otherwise), β_r, and time fixed effects (i.e., dummies taking the value one for each time t, and zero otherwise), β_t, control, respectively, for regional-level exogenous variables that we do not measure (Bozzola et al., 2018), such as similarities in climate conditions of neighbouring countries, and for exogenous technological progress (Kim and Moschini, 2018). The inclusion of spatial effects (i.e., region fixed effects), by controlling for some of the unobserved factors generating differences in trade across countries, also allows us to obtain consistent and unbiased parameter estimates in the presence of spatial autocorrelation (Chatzopoulos and Lippert, 2016)[11]. The term $\boldsymbol{C}_i$ is a matrix of country-specific climate normals of temperature (T, expressed in °C) and precipitation (P, expressed in mm per year) and γ is the corresponding vector of regression coefficients. Consistent with other cross-sectional climate studies (e.g., Mendelsohn et al., 1994, 1996), we posit a quadratic relationship between the dependent variable and the climate normals, hence $\boldsymbol{C}_i$ also includes the squares of these variables (i.e., T^2 expressed in °C and P^2 expressed in mm per year). Such a non-linear model delivers a relationship that largely reflects long-run outcomes for temperature effects and that is a weighted average of long-run and short-run responses for precipitation effects (Mérel and Gammans, 2021). The specification provides a matrix of country-specific characteristics, $\mathbf{X}_i$, and δ is the corresponding vector of regression coefficients. The matrix $\mathbf{X}_i$ includes countries' latitude and longitude (expressed in decimal degrees)[12] and a dummy indicating if i is a developed exporter to avoid bias upon the potential occurrence of the Yule-Simpson effect[13] (Pearl, 2009). Additional variables, included as proxies of technology and trade policies, and to control for differences across product categories are added in matrix $\mathbf{X}_i$ in alternative regressions for robustness analyses[14] (see section 3.3). A possible caveat, as in other econometric studies, concerns our inability to account for the positive effect of carbon fertilisation due to changes in CO2 concentrations, which are uniformly spread across the globe. The term u_{it} is a vector of random error terms which is assumed not to be correlated with climate. We rely on the pooled Ordinary Least Square (OLS) estimate of equation (2) to minimise the influence of random variation that could affect the coefficients in any one year.

Following the literature (e.g., Kurukulasuriya et al., 2011), we compute the percentage change in export values associated with a marginal increase in temperature and precipitation normals or climatologies (i.e., rolling 30-years averages) as follows:

$$\frac{\partial \hat{V}}{\partial T} \cdot \frac{1}{\hat{V}} = (\gamma_T + 2\gamma_{T^2}\bar{T}) * 100 \quad \text{and} \quad \frac{\partial \hat{V}}{\partial P} \cdot \frac{1}{\hat{V}} = (\gamma_P + 2\gamma_{P^2}\bar{P}) * 100 \qquad (3)$$

where γ_T, γ_{T^2}, γ_P, γ_{P^2} are coefficients estimated for long-run mean temperature and precipitation and their squares. $\bar{T}$ and $\bar{P}$ are sample means of 30-years rolling average temperature (in °C) and precipitation (in mm per year).

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[10] Table A.2 in the Appendix A provides information about which region each country belongs to.
[11] The countries in our samples are aggregated in seven regions. Further details are provided in Appendix A.
[12] Countries coordinates are time-invariant control factors.
[13] Also known as "reversal paradox", the Yule-Simpson effect is a phenomenon in which a certain relationship appears in subsamples of data but disappears or reverses when these subsamples are combined.
[14] Additional control variables are the percentage of population with access to electricity, the percentage of rural population with access to electricity, and variables capturing trade policies that are the average level of tariffs (in percentage) and the presence of multilateral non-tariff measures (i.e., a dummy equal to one if the country *i* implements a multilateral non-tariff measure, and zero otherwise).

3.2. Impacts of climate heterogeneity on bilateral trade

We wish to complement the analysis proposed in the previous sub-section by investigating also more specific impacts on bilateral trade. Changes in climate may alter comparative advantages and trade values of traders[15], which may be either beneficial or detrimental for bilateral trade. If trading partners are characterised by different climatic conditions, this leaves room for opposite specialisations of the exporter and of the importer in producing different goods. For instance, suppose that changes in climate enlarge the exporter's supply, increasing the value of agri-food exports, and limit the importer's supply, boosting the value of agri-food imports: the result would be an expansion of bilateral trade flows due to the new comparative advantages induced by the changes in climate. In contrast, as suggested in Dallman (2019) and Heerman (2020), countries with similar climatic characteristics tend to specialise in similar agri-food productions and to compete. We investigate if larger climate heterogeneity among trading partners increases bilateral trade flows.

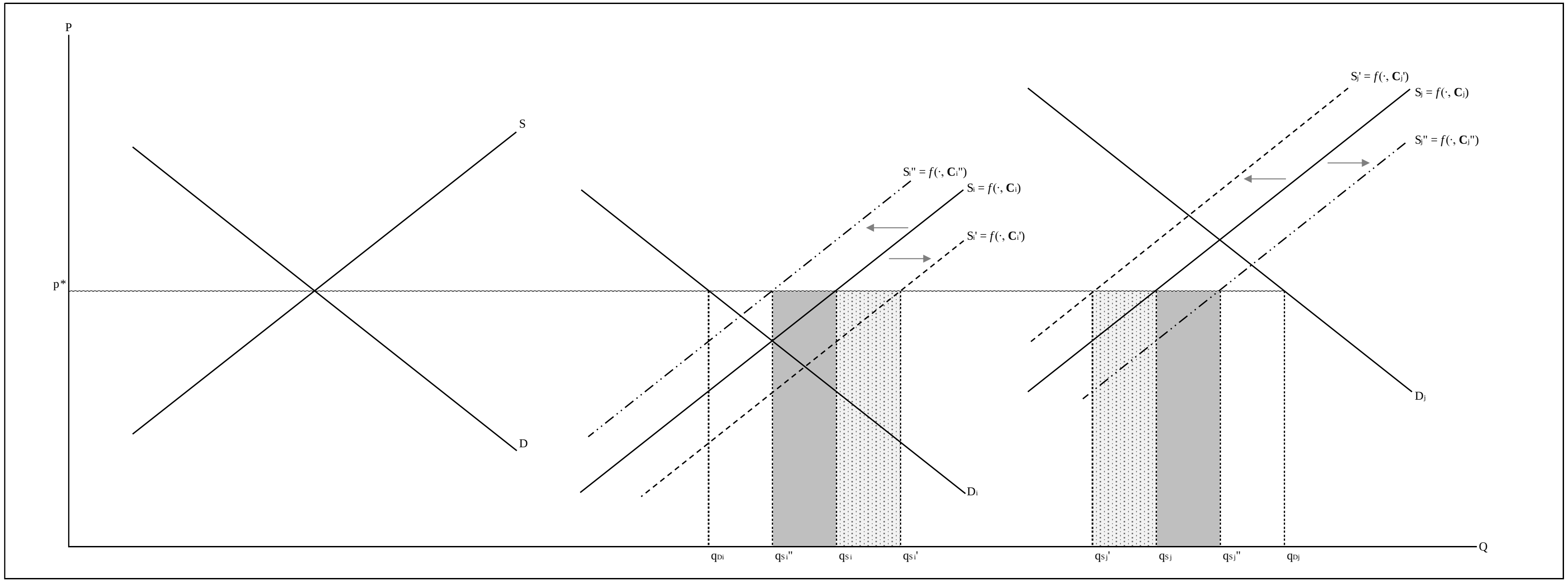
To clarify how climate heterogeneity between trading partners may induce changes in the value of bilateral agri-food trade, we introduce a baseline conceptual framework to justify the empirical specification. Let assume that i (exporting country) is engaged in bilateral trade with a partner j (importing country). The trade value of i is defined as in equation (1) and the trade value of j is described by $S_j - D_j = V_j = f\left(p^*, z_j, \boldsymbol{C}_j, \boldsymbol{X}_j\right)$, with S_j and D_j being the aggregate agri-food supply and demand of j. Countries differ in known technologies ($z_i \neq z_j$), climate conditions ($\boldsymbol{C}_i \neq \boldsymbol{C}_j$), and other specific characteristics ($\boldsymbol{X}_i \neq \boldsymbol{X}_j$).

Suppose that market price (p^*) higher than the domestic price in *i*, but lower than the domestic price in *j*, the excess of supply in *i* ($q_{D_i} - q_{S_i}$) matches the excess of demand in *j* ($q_{S_j} - q_{D_j}$) (figure 3). Assume that, all everything else equal, the long-run changes in climate conditions modify the composition of supply (leaving unaltered the demand) both in *i* and *j*: the trade value of *i* may increase or reduce[16] depending on the difference of the climatic conditions with respect to those of the trading partner j (i.e., $\boldsymbol{C}_i - \boldsymbol{C}_j$, hereinafter referred to as climate heterogeneity between *i* and *j*). For instance, suppose that the climate change expands exporter's supply (say from S_i to S_i') so that the value of exports increases by $\left(q_{S_i'} - q_{S_i}\right)p^*$ and \shrinks importer's supply (say from S_j to S_j') so that the value of imports increases by $\left(q_{S_j} - q_{S_j'}\right)p^*$ (dotted areas in figure 3). If different comparative advantages of *i* and *j*, due to climate change, allow compensation between the excess of supply in *i* and the excess of demand in *j*, bilateral trade may increase. Differently, if climate change shrinks *i*'s supply (say from S_i to S_i'') decreasing by $\left(q_{S_i} - q_{S_i''}\right)p^*$ the value of exports and expands *j*'s supply (say from S_j to S_j'') decreasing by $\left(q_{S_j''} - q_{S_j}\right)p^*$ the value of imports (grey areas in figure 3), bilateral trade is likely to shrink, due to changed climate conditions in *i* and *j*.

[15] Changes in climate have an impact on countries' domestic agri-food market, leading to changes in the terms of trade. Consequently, the level of bilateral trade between any two countries will not only depend on how climatic factors affect domestic supply and demand, but also on how climatic factors affect supply and demand in the trading partner.

[16] If changes in climate expand the export capacity of *i* and the import demand of *j*, trade between them is likely to increase due to the changed climatic conditions. Differently, bilateral trade may reduce if, for instance, the changed climate conditions expand or shrink the export capacity of both countries.

Figure 3. Changes in the value of bilateral agri-food trade due to changes in climate.



Notes: All else equal, shifts in aggregate agri-food supply of the exporter (S_i) and importer (S_j) depend on changes in countries' climate ($\boldsymbol{C}_i$ and $\boldsymbol{C}_j$). Given the exogenous market price (p^*) higher than domestic prices in the exporting market and lower than domestic price in the importing market, $q_{D_i} - q_{S_i}$ is the baseline excess of supply of the exporter and $q_{S_j} - q_{D_j}$ is the baseline excess of demand of the importer, $\left(q_{S_i'} - q_{S_i}\right)p^*$ is the increase in the value of exports associated with an expanded supply of the exporter (S_i') and $\left(q_{S_j} - q_{S_j'}\right)p^*$ is the increase in the value of imports associated with a shrunk supply of the importer (S_j') (dotted areas), $\left(q_{S_j} - q_{S_i''}\right)p^*$ is the reduction in the value of exports associated with a shrunk supply of the exporter (S_i'') and $\left(q_{S_j''} - q_{S_j}\right)p^*$ is the reduction in the value of imports associated with an expanded supply of the importer (S_j'') (grey areas).

Following the above mentioned framework, the bilateral trade between *i* and *j* may be described as follows: $V_{ij} = f\left(p^*, z_i, z_j, \boldsymbol{C}_i, \boldsymbol{C}_j, \boldsymbol{X}_i, \boldsymbol{X}_j, \cdot\right)$, and it may be related to the standard gravity framework (e.g., Bergstrand, 1985; Eaton and Kortum, 2002) according to which bilateral trade is explained by the distance (e.g., geographical, cultural, other transaction costs) and by the differences in economic conditions (e.g., production, income). We assume that trade from *i* to *j* imposes iceberg trade costs $\tau_{ij} \geq 1$[17]. Consistent with the theoretical gravity equation, bilateral trade, V_{ij}, is explained by the following structural gravity system[18]:

$$V_{ij} = \frac{V_i}{\Pi_i} \frac{E_j}{P_j} \tau_{ij} \tag{4}$$

The size term of equation (4), $V_i E_j$, includes the value of output in *i* (V_i)[19] and the total expenditure of *j* (E_j): large importing economies tend to import more from all sources; large producing economies tend to export more to all destinations; trading partners with a similar size tend to share larger trade flows. Π_i and P_j are multilateral resistances, as defined in Anderson and van Wincoop (2003) and proxy the competitiveness of *i* and j. Π_i and P_j depend on relative price indexes and on market clearing conditions. The term τ_{ij} includes proxies and determinants of transaction costs between *i* and *j*. These structural terms (Π_i and P_j) and the trade distance between *i* and j (τ_{ij}) form together the trade cost term of equation (4), i.e., $\frac{\tau_{ij}}{\Pi_i P_j}$.

Empirically, the structural form of the gravity model in equation (4) can be expressed as an exponential function:

$$V_{ijt} = e^{\{\boldsymbol{\beta}_{it} + \boldsymbol{\beta}_{jt} + \boldsymbol{\beta}_{ij} + \boldsymbol{C}_{ijt}\boldsymbol{\lambda} + \mathbf{W}_{ijt}\mu\}} \varepsilon_{ijt} \tag{5}$$

The term V_{ijt} is a vector collecting the value of exports of country *i* to country *j* at time *t*, expressed in USD. The term β_{it} is a vector of time-varying exporter fixed effects which control for outward multilateral resistances and countries' output shares at time *t*; the term β_{jt} is a vector of time-varying importer fixed effects which control for inward multilateral resistances and countries' total expenditure at time t. The use of β_{it} and β_{jt} (i.e., dummies taking the value one for each country *i* or *j* at a specific time *t*, and zero otherwise) allows us to control for observable and unobservable country-specific characteristics that vary over time (Yotov et al., 2016). The vector of country-pair fixed effects (i.e., dummies equal to one for each combination of *i* and *j*, and zero otherwise), β_{ij}, absorbs all bilateral time-invariant determinants of trade distance (e.g., geographic distance, common language, contiguity) without precluding the estimation of the effects of time-varying bilateral factors (Egger and Nigai, 2015). The terms $\boldsymbol{C}_{ijt}$ and $\boldsymbol{W}_{ijt}$ include time-varying control variables. Matrix $\boldsymbol{C}_{ijt}$, includes long-run absolute differences in mean temperature ($T_{it} - T_{jt}$, expressed in °C) and precipitation ($P_{it} - P_{jt}$, expressed in mm per year) between *i* and j at time *t* able to determine countries' output shares (i.e., V_i), and the vector λ includes the corresponding regression coefficients. The variable $T_{it} - T_{jt}$ ($P_{it} - P_{jt}$) explains how a higher temperature (precipitation) in exporting than in importing countries affects bilateral trade. Recall that the output share of *i* (a proxy of agricultural productivity, V_i) is defined as in equation (1), thus is a function of the climate conditions that

[17] Iceberg trade costs are additional costs *i* faces to sell one unit of its production in *j* (Melitz, 2003). As in Gouel and Laborde (2021), we neglect domestic trade costs and assume that all producers in a country receive the same price.
[18] The subscript *t* for time varying variables is suppressed for ease of notation.
[19] The term V_i should be equal to the total expenditure on *i*'s outputs in all countries in the world, including *i* itself ($V_i = \sum_J V_{ij} \ \forall j$).

may differ from the climate conditions of the trading partner *j*. Changes in climate conditions may have differential impacts on land use and production choices in the importing and exporting countries. These are only a few examples of potential channels through which changes in climate may impact agri-food markets of trading partners. This heterogeneity in climate impacts ($\boldsymbol{C}_i - \boldsymbol{C}_j$) may correlates with the bilateral trade flows. The matrix $\mathbf{W}_{ijt}$ includes the determinants of the transaction costs between *i* and *j* (i.e., bilateral tariff levels in percentage and dummies that control for the presence of non-tariff measures and regional trade agreements[20]); μ is the corresponding vector of regression coefficients. To test the robustness of the estimations, we also specify alternative models where matrix $\mathbf{W}_{ijt}$ includes the percentage of the population with access to electricity and the percentage of rural population with access to electricity. These variables are added as proxies for the economic development of *i* and *j*.

A challenge in the estimation of gravity-type models is the existence of heteroskedasticity and of zero trade flows which may cause inefficient and inconsistent estimates, thus undermining the validity of the inference. To overcome concerns related to heteroskedasticity, we follow the approach suggested by Silva and Tenreyro (2006) and use the Poisson Pseudo-Maximum-Likelihood (PPML) estimator. This estimator is robust to heteroskedastic errors and provides a natural way to deal with zeros in trade data. The use of the PPML estimator allows us to estimate the model in equation (5) in levels with a multiplicative error term (ε_{ijt}) and to assume proportionality between the conditional variance and conditional mean.

Finally, we translate the structural gravity estimates from the model in equation (5) into trade volume effects (TVE). To do this step, we follow the approach developed by Yotov et al. (2016). For continuous variables, such as climate variables[21], the estimated coefficient is the elasticity of the value of trade flows with respect to an increase in the long-run absolute differences in mean temperature and precipitation. The TVE, expressed in percentage, is computed as follows: $TVE = \hat{\lambda}_{\boldsymbol{W}} * 100$[22].

[20] The use of country-pair fixed effects allows us to account for the unobservable linkages between the endogenous trade policy covariates and the error term, solving for the problem of endogeneity of trade policy variables (Baier and Bergstrand, 2007).

[21] Absolute climate differences are expressed in log.

[22] Differently, for the dummy variables (e.g., presence of non-tariff measures, presence of regional trade agreements), the trade volume effect is calculated in percentage terms: $TVE_{dummy} = \left(e^{\widehat{\mu}} - 1\right) * 100$, where $\hat{\mu}$ is the estimate of the coefficient on the indicator variable of interest.

4. Data description

We compiled a rich dataset of historical annual data on trade flows (from 1996 to 2015) and on temperature and precipitation (from 1961 to 2015)[23] for twenty countries[24]. The timeframe of the empirical analysis is the period between 1996 and 2015. The stat date of the panel is conditioned to the availability of data on trade policies, used as control factors in the empirical analysis (see section 4.3); the end date of the panel depends on the update of climate and trade data at the time of the study planning[25]. Together these economies account in total for 57% of global agri-food exports in 2015[26]. The share of each country exports with respect to global exports in the agri-food sector is always lower than 10%. Our sample ensures representativeness in term of income group (developed and developing countries)[27] and geographical location (low-latitude and high-latitude regions). Countries are grouped as belonging to northern or southern hemisphere, based on the distribution of the majority of land respectively above or below the Equator: 65% of countries are located in northern hemisphere.

4.1. Trade data

We compile data on countries' total agri-food exports to the rest of world, and data on bilateral agri-food exports for each country-pairs in the sample from the UN Comtrade database. Trade data are aggregated at the one-digit level of the classification by Broad Economic Categories (BEC) and consider the category 'Food and beverages' (BEC 1996: 01). We also use trade data aggregated at the 2-digit level of the Harmonised System (HS) for robustness analysis: we consider exports of 24 agri-food sectors (both primary products and value added products).

Trade data for the selected countries over the period between 1996 and 2015 exhibit fractions of zeros and missing values. Country-pairs that do not trade with each other account in our dataset for 5.21%, of which only one tenth are zeros and the remaining are missing values. Missing values in total exports of countries account for 3.75%. A detailed analysis of zero trade flows shows that zeros in the sample are likely to be structural zeros (i.e., trade expected to be low), whereas missing trade values are likely to be associated with data recording issue (Head and Mayer, 2014). The presence of zero trade flows in the sample calls for the need of adjusting trade variables to accommodate zeros. To capture economically significant changes in trade, we replace zeros with the value of exports observed in the first year available[28].

Distinguishing between developed and developing exporters in our sample, table 1 and figure 4 provide summary statistics for trade variables and show trends in total and bilateral exports overtime.

[23] The longer time period used for climate data allows to build climate normal or climatologies (i.e., 30-years averages) of temperatures and precipitations. Climate normals are based on 30-years rolling averages, for the 30 years preceding the year the trade data refer to.

[24] The selected countries are Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Israel, Italy, Jordan, Morocco, New Zealand, Peru, Russian Federation, South Africa, Spain, the United Kingdom, the United States of America. Table A.2 in the Appendix A provides detailed information for each country in the sample.

[25] Thanks to a recent update of trade and climate data, we extend the timeframe of the analysis until 2021 as a sensitivity analysis. Details are provided in the Appendix F.

[26] The share of countries exports with respect to global exports in the agri-food sector is in Appendix A.

[27] We use the most recent country classification produced by the United Nation (2020) to associate each country to a group or the other. The list of countries by group is presented in Appendix A: 45% of the exporters in our sample are developed countries, 55% are developing countries.

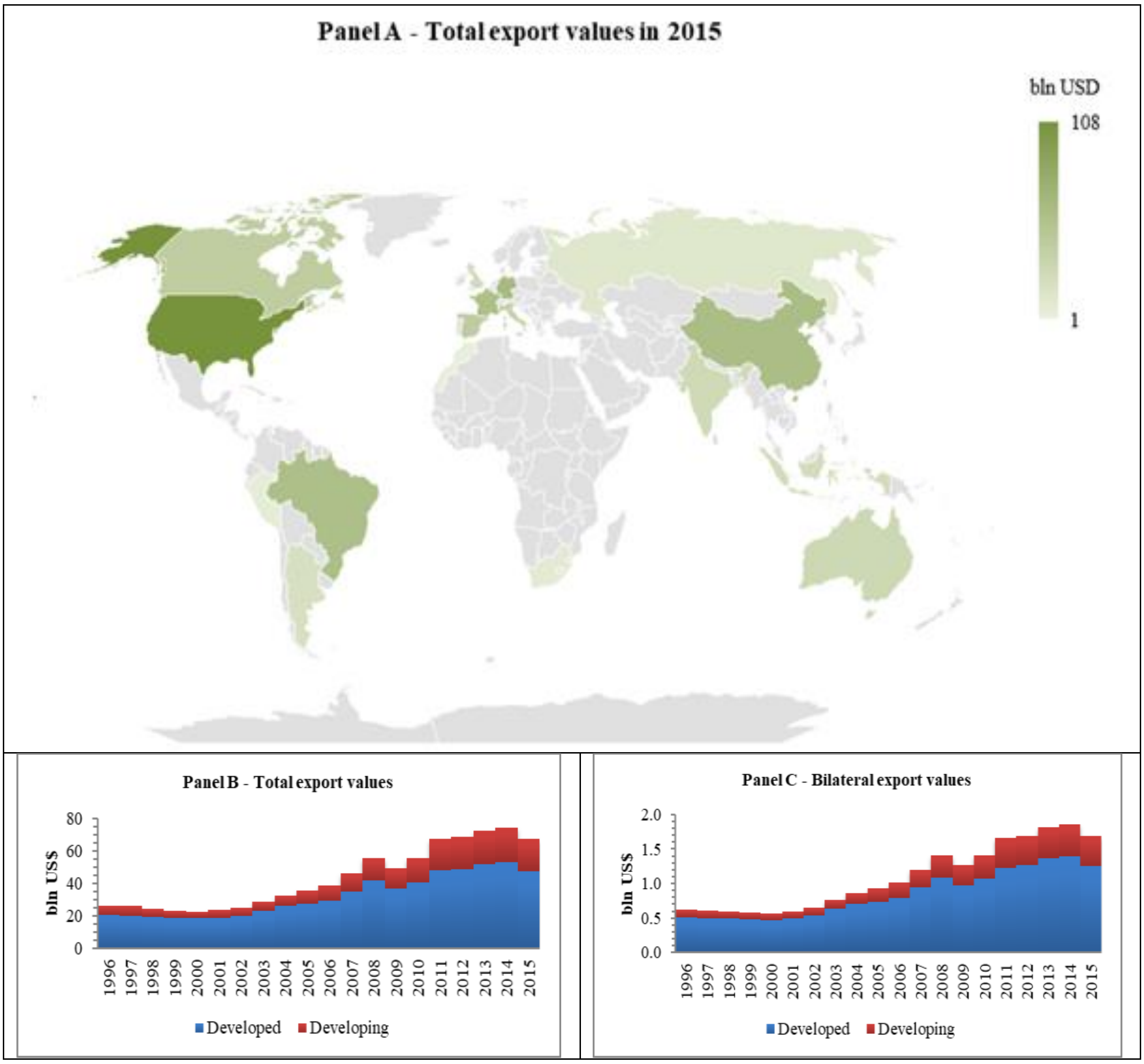
[28] This accommodation strategy is required for the cross-sectional analysis of climate change impacts on country's agri-food trade value (see equation 2), although not strictly necessary for the analysis of impacts of climate heterogeneity on bilateral trade based on the estimation of the model in equation (5) through the PPML. More details and robustness checks are provided in Appendix C.

Table 1. Averages and standard deviations for trade data

Trade (bln USD)	All	Developed	Developing
Total exports	20.27 ±(20.90)	32.03 ±(21.80)	10.65 ±(14.17)
Bilateral exports	0.51 ±(1.55)	0.85 ±(2.08)	0.23 ±(0.80)

Notes: Standard deviation in parentheses. Trade data aggregated at one-digit level of the classification by Broad Economic Categories (BEC) and consider 'Food and beverages' (BEC 1996: 01).

Figure 4. Summary statistics: total and bilateral export values



Source: own elaboration on data from UN Comtrade.

Notes: Trade data aggregated at one-digit level of the classification by Broad Economic Categories (BEC) and consider 'Food and beverages' (BEC 1996: 01). Exports from developing countries stacked over exports from developed countries in panels B and C. Total export values of developed countries are higher than total export values of developing countries (panels B and C). The growth rate of bilateral exports from developed countries is about twice larger than the growth rate of bilateral exports of developing countries (panel C).

The value of total exports of selected countries is 20.27 million USD on average. Although developed countries represent less than the half of exporters in the sample, they show higher export values (32.03 million USD of exports to the world) as compared to developing countries (10.65 million USD of exports to the world). Similarly, most of value in the food and beverage sector, traded bilaterally, originates in developed counties: they account for 846 million USD of bilateral exports (as compared to 0.23 million USD of bilateral exports originating in developing countries), with growth rate of exports about twice larger than developing countries (table 1, figure 4).

4.2. Climate data

Historical climate data are compiled from the Climatic Research Unit (CRU) of the University of East Anglia (Harris et al., 2014). This dataset provides observational and quality-controlled temperature and rainfall values from thousands of weather stations worldwide. The CRU datasets are widely accepted as reference datasets in climate research (World Bank, 2018). Observed data are presented at a spatial resolution of 0.5° latitude by 0.5° longitude grid (50 km by 50 km) over all land domains and aggregated at the national level for each variable. They consist of one annual mean value for temperature and one annual cumulative value for precipitation, established over the respective time windows. The temporal and spatial resolution of the dataset is summarised in table C.4 of the Appendix C.

Annual climatologies of temperature and precipitations are constructed using these historical weather data[29]. For each climate variable (i.e., temperature and precipitation), we built climatologies (or climate normals) as 30-year average of a weather variable for a given year. For instance, temperature normal (or precipitation normal) in 1996 is the average of annual temperatures (precipitations) of the interval 1966-1996; in 1997 the interval is 1967-1997; in 1998 the interval is 1968-1998; and so forth. Climatologies are derived from climate observations (i.e., absolute temperature and precipitation data) captured by weather stations.

The climate conditions affect productivity (i.e., defined as output per area of land) of both the exporters and the importers. Long-run changes in the climate conditions may determine changes in land use and production choices. A simple pairwise correlation between average changes in traders' agricultural land and climate normals or climatologies, both temperatures and precipitations suggests a potential link between climate change and land used for agricultural activities. This evidence is in line with the land statistics and indicators produced by the FAOSTAT for the period 2000-2020 that document a reduction of agricultural land associated with a decrease in the area of permanent meadows and pastures (-203 million ha) larger than the increase in cropland area (over 69 million ha) driven by trends in area of permanent crops (e.g., oil palm, cocoa and coffee, olives, orchards).

Climatologies and differences in climatologies between exporter and importers are reported in table 2 and figure 5; details are also provided according to the level of economic development of exporters. The annual 30-years average temperature in the exporting countries is 13.6 ºC (table 2). Annual average temperatures are about 7 ºC higher for developing than for developed exporters, reflecting the fact that developing countries are mostly located to lower latitudes (figure 5, panel A). Annual average temperatures in both developed and developing countries have increased in the past 20 years, with the difference between developed and developing exporters remaining rather constant over years (figure 5, panel C). The annual 30-years average precipitation of exporters is 73.4 mm (table 2). The annual level of precipitations is about 4 mm lower in developed than in developing exporters (figure 5, panel D). Changes in temperature normals over the 30-years periods 1961-1990 and 1991-2020 are in table A.1 in the Appendix A.

[29] The high correlation between one month and the next discourages the use every month of climate in the regression analysis.

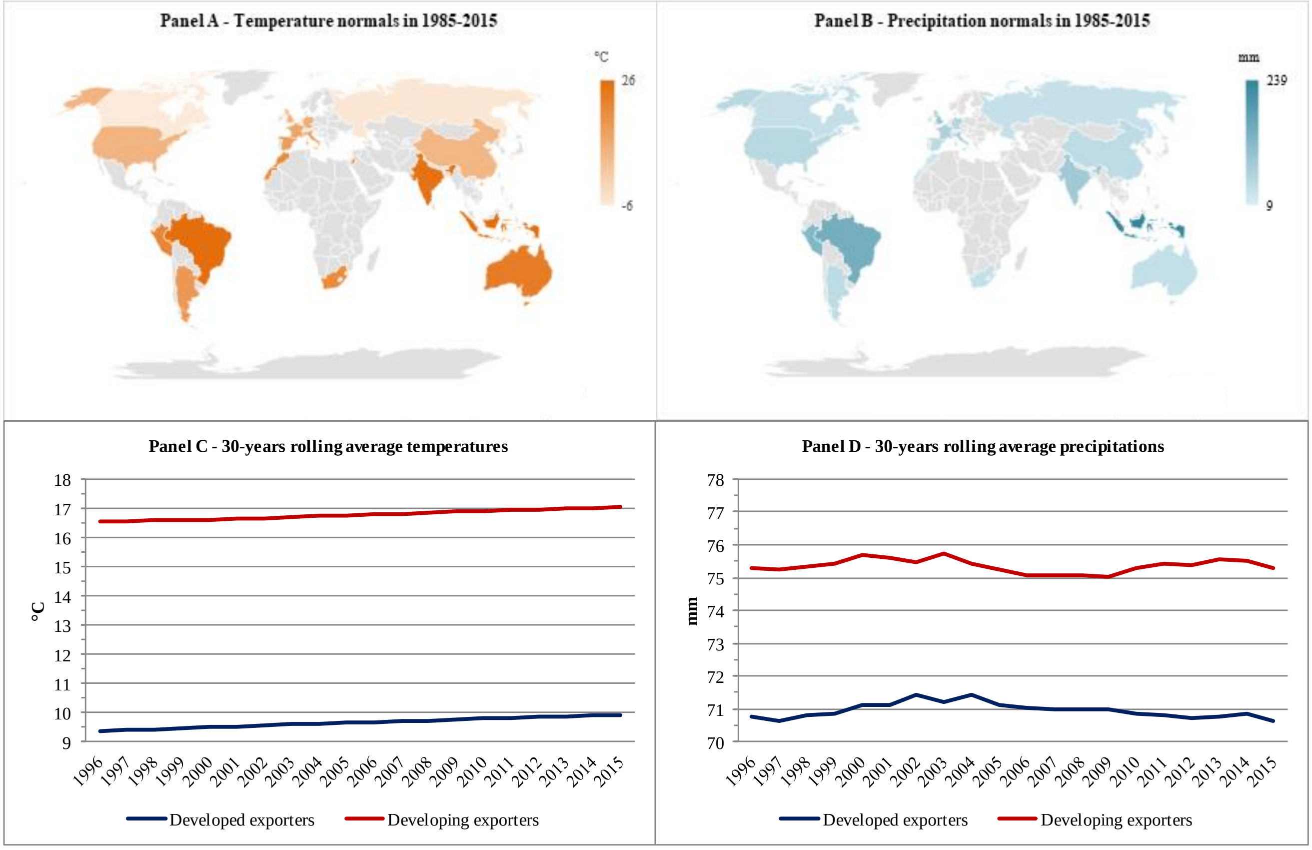
These statistics indicate a general tendency of the developed countries that, as also observed in our sample, tend to have a colder climate with respect to the developing countries. It should be kept in mind, however, that the strength of seasonality varies significantly across the globe, with seasons being more homogenous around the Equator.

Table 2. Averages and standard deviations for climatic variables

Variable	Unit of measure	All	Developed	Developing
Temperatures	°C	13.57 ±(8.79)	9.65 ±(6.99)	16.78 ±(8.83)
Absolute difference in temperatures	°C	10.15 ±(7.71)	9.78 ±(7.27)	10.45 ±(8.04)
Precipitations	mm	73.38 ±(53.81)	70.95 ±(31.93)	75.36 ±(66.58)
Absolute difference in precipitations	mm	57.91 ±(52.21)	48.04 ±(42.49)	65.98 ±(57.75)

Notes: Standard deviation in parentheses. Figures for absolute differences in temperatures and precipitations are the average of the year-on-year differences.

Figure 5. Summary statistics: 30-years average annual temperatures and precipitations



Source: own elaboration on data from Climatic Research Unit of University of East Anglia (Harris et al., 2014).

Notes: Rolling 30-years average annual temperatures and precipitation by exporter observed in 2015 (panels A and B). Rolling 30-years average annual temperatures and precipitation over exporters and years (panels C and D). Developed countries tend to have a colder (panels A and C) and drier (panels B and D) climate as compared to developing countries.

4.3. Other control factors

In the empirical application we account for other sources of heterogeneity across countries, which in turn may drive trade patterns. The inclusions of these variables reduce, to some extent, endogeneity concerns stemming from the omitted variables bias. Typical sources of heterogeneity are the geographical and economic preconditions of the affected country. We control for time-invariant characteristics, such as latitude and longitude, and for proxies of development, such as countries' access to electricity. The percentage of population with access to electricity and the percentage of rural population with access to electricity are retrieved for the analysed timeframe from the World Development Indicators database of the World Bank.

Another set of relevant covariates includes trade policy indicators, which are a source of transaction costs (Beghin and Schweizer, 2021). We compile annual data on number of multilateral and bilateral non-tariff measures implemented on agri-food products[30] from the UNCTAD's global database on non-tariff measures, which provides information on official measures implemented at country and product level. Information about the number of non-tariff measures is available at the HS 6-digit level since 1996; in order to facilitate the match between trade and non-tariff measures data, we aggregate the information on non-tariff measures at the one-digit level of the BEC classification. We control for average bilateral tariffs on agri-food products (aggregated at the BEC level), downloaded from the World Bank's World Integrated Trade Solution (WITS) database, and for the presence of Regional Trade Agreements (RTAs) between country-pairs, an information retrieved from the database of the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII).

5. Results and discussion

5.1. Results of the model of climate change impacts

We regress the value of countries' total exports on climate to estimate the best-value function across different countries. The regression results presented in table 3 are from the quadratic model presented in section 2.1 (equation 2), which includes the measures of climate: i.e., the annual average temperature and precipitation normals of the exporting countries and their squared values. Most of the climate coefficients are highly significant. The climate coefficients of the squared terms are also significant (at the 1% level), implying that the climate effects on the value of total export tend to be nonlinear, as shown in figure 6. The squared term of temperature is positive indicating that the value of trade displays a convex response to temperature normals. That is, the value of trade increases after a cut-off point (i.e., 5-6 °C) and a marginal change in temperature climatologies in the exporting country after that threshold would increase the value of total exports (figure 6, panel A). Differently, the positive first-degree and negative second-degree terms for precipitation indicate a concave response of exports' value to precipitation normals. Notably, there is an optimal level of precipitation in the exporting country (i.e., 95-100 mm per year). The value of agri-food exports increases at a declining rate up to this cut-off point, after which it decreases (figure 6, panel B).

[30] Multilateral non-tariff measures are implemented by a country against all its trading partners, bilateral non-tariff measures are country-pair specific (Santeramo and Lamonaca, 2019).

Table 3. Effects of climate change on countries' export values

	Temperature		Precipitation
γ_T	-0.09680***	γ_P	0.07398***
	(0.02121)		(0.00845)
γ_{T^2}	0.00795***	γ_{P^2}	-0.00039***
	(0.00117)		(0.00004)

Notes: Pooled OLS estimates of the model in equation (2) and coefficients explicated in equation (3) (observations = 400; R2 = 0.883). The dependent variable is the log value of total exports in food and beverage sector (BEC). Annual temperature of exporter is in degrees Celsius and annual precipitation of exporter is in units of mm per year. The specification includes a constant term, time and region fixed effects, latitude and longitude of the exporter, a dummy discriminating between developed and developing exporters. Robust standard errors are in parentheses.

*** Significant at the 1 percent level.

The impact of climate, measured as average marginal effects (table 4)[31], suggests that higher temperatures and rainfall levels in exporting countries favour exports[32]. A 1 °C increase (decrease) in annual temperature increases (decreases) export values by 11.91% (+2.41 billion USD on average)[33]. Increases (decreases) in precipitation have also positive (negative) effects: a 5 mm increase in rainfall levels increases export values by 8.73% (+1.77 billion USD on average). The positive correlations between the value of agri-food exports and both temperature and precipitation are indicative of the potential specialisation of trading partners in the production of certain goods. These positive impacts suggest the dependence of countries on trade, both in selling the excess of production in which they are specialised and in buying goods that they do not produce due to a missing specialisation.

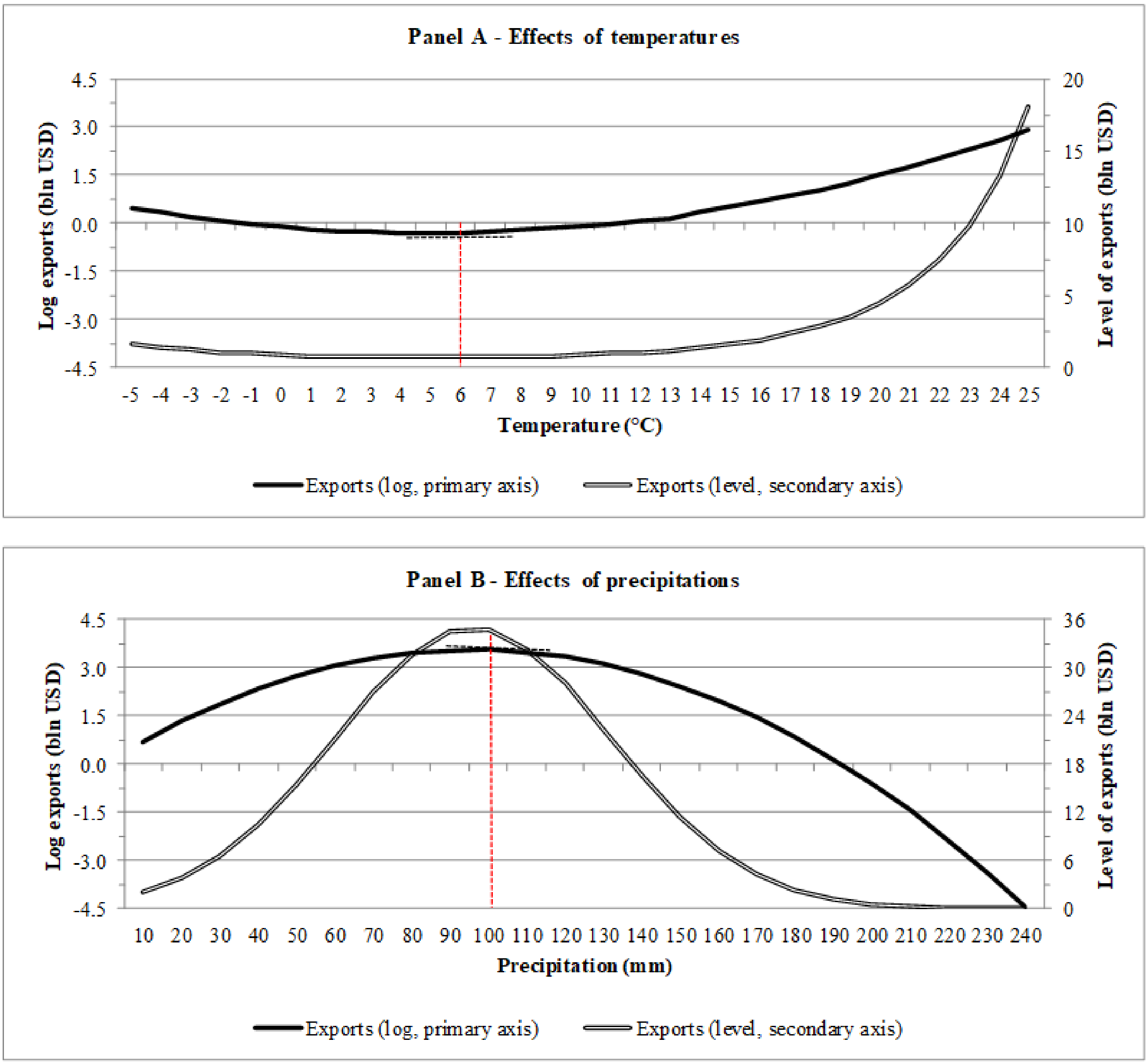
We run a set of robustness checks using more disaggregated trade data to address the concern that primary production is expected to be more sensitivity to value added products. We consider exports of 24 agri-food sectors (both primary products and value-added products) aggregated at the 2-digit level of the Harmonised System (HS). The results, reported in tables D.3 and D.4 of the Appendix D, confirm main results.

[31] The mean marginal impacts associated with a 1 mm increase in the rainfall levels are reported in table D.1 of the Appendix D.

[32] The results are robust to specifications that control for proxies of technology adoption and policy interventions in the exporting countries (table D.2 of the Appendix D).

[33] The increase in export values for a 1 °C increase in temperature is to be interpreted as the effect, ceteris paribus, of climate change on trade. Such an effect is easily achievable slightly changing the composition of the production. This may occur, for instance, if changes in climate move the specialisation of country from less to more valued products (e.g., from almons to grapes whose global exports account respectively to 1,600 million and 9,600 million USD in 2021 according to the FAOSTAT data). For instance, European countries, are benefitting of better growing season temperatures to produce (and consequently sell) high valued products, such as fruits. For instance, data from FAOSTAT shown that, from 2011 to 2021, the produced quantity and the export value of grapes increased respectively by 9% and 7% in Italy and even by 157% and 46% in Netherland.

Figure 6. Effects of climate normals on exports and turning points



Notes: The dependent variable is the value of total exports (both log and level) in food and beverage sector (BEC). Annual temperature of exporter is in degrees Celsius and annual precipitation of exporter is in units of mm per year. Turning points are 5-6 °C for temperatures of exporter and 95-100 mm for precipitations of exporter.

Table 4. Marginal impact of climate and change in countries' export values

	All		Developed		Developing	
	Marginal impact (%)	Change in average exports (bln USD)	Marginal impact (%)	Change in average exports (bln USD)	Marginal impact (%)	Change in average exports (bln USD)
Temperature (+1 °C)	11.91 [9.59; 14.22]	2.41	5.68 [4.75; 6.60]	1.82	17.01 [13.29; 20.73]	1.81
Precipitation (+5 mm)	8.73 [6.40; 11.05]	1.77	9.66 [7.15; 12.2]	3.09	7.96 [5.80; 10.15]	0.85

Notes: Marginal impacts are significant at the 1% level and obtained applying equation (3) on coefficients of variables in level and squared reported in table 3, evaluated at average temperature and precipitation of all, developed and developing exporters (see table 2); 95% confidence intervals are in brackets. Change in exports consider average exports of all, developed and developing exporters (see table 1).

Results are robust to sensitivity analyses on subsamples of exporters with different levels of economic development[34]. The impacts of climate are evaluated at average temperature and precipitation normals of developed (i.e., 9.65 °C, 70.95 mm) and developing (i.e., 16.78 °C, 75.36 mm) exporters (table 4). While the marginal impacts of change in annual precipitations (say +5 mm) in developed and developing countries are similar in magnitude (+9.66% and +7.96%, respectively), the effects of increases in temperature are about 11% higher than in developing countries. This may be because agri-food products exported from developing countries are generally better suited to warmer climates. This result supports the discussion in Gouel and Laborde (2021) who state that most of net-exporters of agricultural produce, such as most of the developing countries exporters in our sample, may benefit from climate change. According to the authors, this finding applies even to the countries suffering from productivity losses, due to the burden of the adjustments to climate change shifts to consuming countries through international prices. Another important factor to note is that, although Russia has a colder average temperature (i.e., -5.83 °C) than most of the other exporting countries in our sample (with the exception of Canada, i.e., -6.47 °C)[35], the country is not classified by the UN as developed one (United Nation, 2020). Apart from Russia and Canada, the average temperatures of the countries in our sample are higher than the turning point (i.e., 6.1 °C, figure 6, panel A). Conversely, the average annual rainfall quantity is for the majority of countries below the turning point (i.e., 98.85 mm, figure 6, panel B). That is, the majority of countries in our sample would benefit, keeping every other control factor constant, from a marginal increase in both temperature and precipitation normals. A few countries, with annual average rainfall above 98.85 mm, may have not benefitted from increases in annual precipitation: India, the United Kingdom, Peru, New Zealand, Brazil, and Indonesia.

In monetary terms, while the impact of higher temperatures is almost the same for developed and developing exporters (i.e., +1.8 billion USD on average for each additional °C), greater rainfall levels are more pro-trade for developed (i.e., +3.09 billion USD for a 5 mm increase) than for developing countries (i.e., +0.85 billion USD for a 5 mm increase).

These results pertain to the impact of climate change on the value of agri-food export. The estimated coefficients implicitly account for climate change adaptation measures undertaken within each country. These comprise a variety of decisions that farmers and other agents in

[34] The regression results are reported in the Appendix D (tables D.5 and D.6).

[35] For more details see the Appendix A. In a sensitivity analysis, we estimate the model in equation (2) excluding Russia and Canada from the sample: main results are confirmed.

the agri-food sector customarily make in response to changing economic and environmental conditions. They include, for example, switching to new crops production or even land conversion to very different productive uses such as the conversion of farmland to manufacturing plants, retirement homes, etc. (Mendelsohn et al., 1994). Our results capture the long-run effects of climate change (with a full adaptation implicitly captured), thus the estimates should be considered as upper-bounds with respects to those obtained through weather variations, which proxy the short-run effects (with limited adaptation) (Ortiz-Bobea, 2019). In the next section we look, more specifically, into how the value of bilateral exports is influenced by pair differences in climate between country pairs.

5.2. Results of the model of climate heterogeneity

In this second part of our analysis, we further investigate the impacts of climate change on trade in the agri-food sector, by looking at how pair differences in climate, here referred to as climate heterogeneity, influence the value of bilateral exports. All the gravity coefficients estimated for annual differences in temperatures and precipitations between trading partners are significant, evidence of a clear relationship between bilateral trade and country-pair differences in climate (table 5).

Table 5. Effects of differences in long-run climate on bilateral exports

Variables	All	Developed	Developing
Difference in temperatures	0.381***	0.499***	-0.443***
	(0.052)	(0.048)	(0.129)
Difference in precipitations	0.164***	0.076**	0.170***
	(0.059)	(0.034)	(0.033)

Notes: PPML estimates of the model in equation (5). The dependent variable is the value of bilateral exports in food and beverage sector (BEC). Differences in annual temperatures between the exporter and importer (log of absolute values) are in degrees Celsius; differences in annual precipitations between the exporter and importer (log of absolute values) are in units of mm per year. All specifications include a constant term, exporter-time, importer-time and country-pair fixed effects, level of tariffs (log), non-tariff measures (dummy), regional trade agreements (dummy). In the specification All, an additional control is a dummy discriminating between developed and developing exporters. All: observations = 7,580; $R2$ = 0.995. Developed: observations = 3,420; $R2$ = 0.997. Developing: observations = 4,160; $R2$ = 0.987. Robust standard errors are in parentheses.

*** Significant at the 1 percent level. ** Significant at the 5 percent level.

Our results suggest that, controlling for several confounding factors, the larger the differences in temperatures and rainfall levels between trading partners, the higher the value of bilateral exports[36]. The value of bilateral exports increases by 38.07% (+0.19 billion USD on average) for a 1 °C increase in differences in temperatures, and by 82.12% (+0.42 billion USD on average) for a 5 mm increase in differences in rainfall levels (table 6)[37]. The greater (lower) the specialisation of a trading partner exposed to high (low) levels of rainfall in the production of crops growing in a moist environment, the higher its ability to export (dependency on imports). Our conclusions support those provided by Dallmann (2019) who finds that higher differences in temperatures and precipitations between the exporting and importing countries are pro-trade. For each additional °C difference in the temperatures between trading partners, the author finds that bilateral trade increases by 2.8%, whereas we report a much larger effect.

[36] The results are robust to specifications that control for proxies of technology adoption in the exporting and importing countries. The results of the sensitivity analysis are in table E.1 of the Appendix E.

[37] The trade volume effect associated with a 1 mm increase in the rainfall levels are reported in table E.2 of the Appendix E.

These differences are partially explained by the different nature of the two studies: Dallmann (2019) refers to short-run changes in climate, while our analysis focuses on long-run differences in climate. As a result, our findings may be interpreted as long-run trade adjustments due to countries specialisation. As suggested by Gouel and Laborde (2021, p. 24), "trade plays a strong role in balancing the new domestic supply and demand schedules" and may induce a reallocation of productions among countries.

Table 6. Trade volume effect of climate heterogeneity and change in bilateral exports

	All		Developed		Developing	
	Trade volume effect (%)	Change in avg. exports (bln USD)	Trade volume effect (%)	Change in avg. exports (bln USD)	Trade volume effect (%)	Change in avg. exports (bln USD)
Difference in temperature (+1 °C)	38.07%	0.19	49.86%	0.42	-44.29%	-0.10
Difference in precipitation (+5 mm)	82.12%	0.42	37.87%	0.32	84.75%	0.20

Notes: Trade volume effect obtained from coefficients in table 5, evaluated at average differences in temperature and precipitation (table 2). Change in exports consider average bilateral exports of all, developed and developing exporters (table 1).

The analyses on subsamples of exporters with different levels of economic development show heterogeneous responses. Higher differences in annual temperatures (say +1 °C) are beneficial for developed exporters, whose bilateral export values increase by 49.86% (+0.42 billion USD on average), but detrimental for developing exporters that observe a 44.29% reduction in the value of bilateral exports (-0.10 billion USD on average). The effects estimated at the bilateral level are implicitly affected by mechanisms of changes in the extensive margin of trade (i.e., changes in trade routes, such as the opening of new bilateral relationships or the closing of old bilateral relationships) and of trade diversion (i.e., redirection of trade flows from one partner to the other). Higher annual differences in rainfall levels (say +5 mm) are especially beneficial for developing exporters, whose bilateral export values increase by 84.75% on average (as compared to +37.87% in bilateral export values of developed exporters), although the gain in monetary terms is comparable for developing (+0.20 billion USD) and developed (+0.32 billion USD) exporters. This is mostly due to marked differences in the magnitude of bilateral exports whose value, on average, is more than three times larger for developed (i.e., 0.85 billion USD) than for developing (i.e., 0.23 billion USD) countries.

Our results are consistent with findings of Dell et al. (2012) who conclude on substantial heterogeneity of climate impacts between developed and developing countries. They demonstrate that the net effect of a 1 °C rise in temperature decreases growth rates in developing countries by 1.39%. The large difference between the effect estimated in their study and in our analysis (i.e., -1.39% versus -44.29%) may be due to the diverse focus of the analyses: they examine the impact of temperature shocks (i.e., short-run effect of climate) on the economic growth (i.e., countries' total GDP), whereas we focus on the long-run effects of climate on trade in the agri-food sector. As argued by Jones and Olken (2010), by connecting countries, trade may transfer geographically limited climate effects on a global scale. They analyse the effects of climate shocks (similar to Dell et al., 2012) on export activities (similar to our analysis). They find that higher temperatures in developing countries lead to large, negative impacts on the growth of their exports (between -2.0% and -5.7%) and conclude that the negative impacts are substantial for agricultural products. Again, differences in the estimated effects may be due to a different focus of the analysis: all the economic activities in Jones and Olken (2010) and the agri-food sector in our analysis.

Our results assume a particular relevance considering that developing countries tend to have warmer temperatures and economic growth mostly based on agricultural activities. This reasoning may explain why developing exporters tend to be hardly affected by differences in climate.

5.3. Discussion and implications

A large strand of literature has modelled the implications of climate change for domestic markets (e.g., Mendelsohn and Massetti, 2017) and the role of international trade as a climate change adaptation strategy (e.g., Costinot et al., 2016; Gouel and Laborde, 2021). Another emergent strand of economic literature is quantifying the impacts of weather variations on international trade (e.g., Jones and Olken, 2010; Dallmann, 2019; Dall'Erba et al., 2021)[38]. The aim of this article has been to provide a more holistic view of the impacts of climate change on agri-food sector bridging these literatures, to understand of how long-run changes in climate impact countries' trade values as well as bilateral trade patterns in the agri-food sector. By deepening on the trade-climate nexus we feed the extant debate with a new potential channel to understand how climate change may influence land use.

Overall, our analysis suggests that higher temperatures, and larger differences in temperatures or precipitations are beneficial for trade. These findings reinforce the evidence provided by the recent literature and indicate that (i) the agricultural exports increase with (long-run) raises in temperature (e.g., Dallmann, 2019) and that (ii) the role of trade in fostering adaptation to climate change is likely to be crucial (Gouel and Laborde, 2021). Our findings are also coherent with the studies that have explicitly taken adaptation into account and allows us to conclude that relatively small and positive long-run effects due to the climate change that may be assessed through a cross-sectional approach are internally consistent with negative and large, short-run effects due to the weather shocks, as assessed through a panel approach (Ortiz-Bobea, 2019). However, climate impacts are likely to vary across countries with different levels of economic development, also due to heterogeneity in climate and trade levels between them. For instance, the marginal impact of climate is greater for developing exporters, but changes in export values and in bilateral exports is less pronounced than developed exporters. Moreover, larger differences in temperatures are beneficial for developed but not for developing exporters. As also shown in Jones and Olken (2010), climate change increases welfare in developed countries. Marked impacts of climate on international trade point out the potential of climate change: by lowering prices and increasing quantities of exported products, welfare of countries may take advantage from new dynamics in climate trends.

In this article, we analysed aggregate impacts on trade value in agri-food products, and we leave to future research a more specific analysis of intra-country variability of climatic conditions, which is more relevant in some of the countries in our sample than others.

Climate change will not only impact long term averages and precipitations, but also trigger more frequent and severe weather extremes. Our approach captures long-run effects of climate change, but it does not account for the cost of adaptation and extreme weather scenarios. Hence the findings cannot rule out sizable nor catastrophic damages on countries' export value under extreme climate change and weather shocks. Future research should complement our analysis by looking in more details at the impact of weather shocks on trade. Another complementary area of research relates to the role of trade in promoting or hindering climate change mitigation efforts. However, these efforts are left to future work.

[38] For a review see Santeramo, Miljkovic, Lamonaca (2021).

6. Conclusions

We asked what the impacts of climate change on the value of agri-food trade are. Taking implicitly into account climate change adaptation, we examined the long-term impacts of climate on the value of countries' exports. Findings revealed that, at the margins, higher temperatures and rainfall levels in the exporting countries are beneficial for their exports, strengthening evidence from previous studies (e.g., Janssens et al., 2020; Gouel and Laborde, 2021). The marginal impacts of changes in temperatures are higher in developing countries, but the gain in monetary terms associated with greater rainfall levels is higher for developed countries.

We complemented this analysis by investigating how climate heterogeneity between trading partners impacts bilateral trade relationships. The empirical analysis for this second part is based on the Gravity model of trade, and showed that bilateral trade grows as the climate heterogeneity between trading partners increases. The larger the heterogeneity in temperatures and rainfall levels, the higher the value of bilateral exports. This evidence complements the findings of Dallmann (2019) on the short-run impacts of weather heterogeneity on bilateral trade. Developed and developing exporters are both sensitive to climate differences but have diverse responses. Higher differences in temperatures between trading partners are beneficial for developed exporters but detrimental for developing exporters; larger differences in rainfall levels are especially beneficial for developing exporters, although the gain in monetary terms is almost comparable between developing and developed exporters.

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APPENDIX

A. Facts and figures

Figure A.1 depicts changes in temperature normals and in agricultural land over the 30-years periods 1961-1990 and 1991-2020, by country.

Figure A.1. Trends of land use change under climate change by country

Source: Authors' elaboration using climate normals from the Climatic Research Unit and agricultural land area from FAOSTAT.

Table A.1 shows changes in temperature normals over the 30-years periods 1961-1990 and 1991-2020.

Table A.2 describes the profile of countries in the sample.

Table A.1. Temperature normals in 1961-1966 and 2009-2015 (percent variation with respect to the first period) of countries in the sample

	Temperature normals		Precipitation normals	
Country	1961-1966 (°C)	2009-2015 (perc. var.)	1961-1966 (mm/year)	2009-2015 (perc. var.)
Developed				
Northern Hemisphere				
CAN	-7.2	15%	37.1	5%
FRA	10.5	11%	66.6	5%
DEU	8.2	13%	59.0	3%
ITA	11.8	8%	75.5	1%
ESP	13.3	7%	55.8	-11%
GBR	8.1	11%	93.8	10%
USA	6.7	10%	53.5	4%
Southern Hemisphere				
AUS	21.5	5%	33.9	18%
NZL	9.8	3%	144.4	-1%
Developing				
Northern Hemisphere				
CHN	6.3	8%	48.9	-2%
ISR	19.6	4%	21.8	-5%
JOR	18.8	4%	9.0	-3%
MAR	17.7	5%	27.3	-9%
RUS	-6.3	10%	37.6	-3%
Southern Hemisphere				
ARG	14.3	3%	44.5	10%
BRA	25.1	3%	140.4	6%
IND	23.9	8%	93.4	-7%
IDN	25.6	8%	226.5	6%
PER	19.6	0%	127.6	1%
ZAF	17.6	7%	39.5	-2%

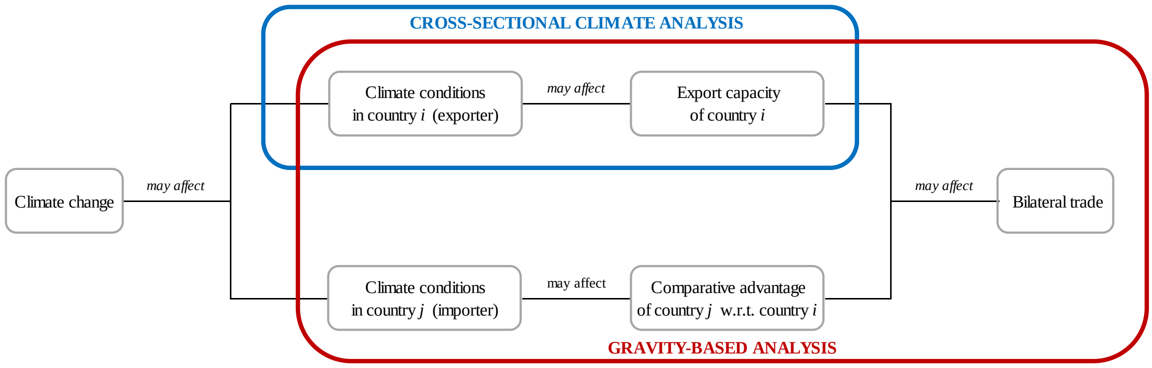
Table A.2. List and description of countries in the sample

Country	ISO 3	Economic development	Region	Hemisphere	30-years annual avg. temperature (°C)	30-years annual avg. precipitation (mm)	Export share (value) (%)	Avg. exports (mln USD)	Avg. bilateral exports (mln USD)
Argentina	ARG	Developing	Latin America and Caribbean	Southern	14.44	49.16	1.76	14,669	479
Australia	AUS	Developed	East Asia and Pacific	Southern	21.76	40.47	2.59	18,387	338
Brazil	BRA	Developing	Latin America and Caribbean	Southern	25.14	148.20	5.10	33,087	861
Canada	CAN	Developed	North America	Northern	-6.47	38.77	3.72	26,634	971
China	CHN	Developing	East Asia and Pacific	Northern	6.68	48.02	5.26	29,059	443
Germany	DEU	Developed	Europe and Central Asia	Northern	8.94	60.17	5.55	42,929	918
Spain	ESP	Developed	Europe and Central Asia	Northern	13.52	50.01	3.82	28,676	914
France	FRA	Developed	Europe and Central Asia	Northern	11.07	70.68	5.01	46,560	1,313
United Kingdom	GBR	Developed	Europe and Central Asia	Northern	8.72	101.15	2.37	20,088	481
Indonesia	IDN	Developing	East Asia and Pacific	Southern	26.04	237.17	2.12	11,164	262
India	IND	Developing	South Asia	Northern	24.33	86.81	2.39	12,249	181
Israel	ISR	Developing	Middle East and North Africa	Northern	19.65	21.50	0.15	1,272	42
Italy	ITA	Developed	Europe and Central Asia	Northern	12.14	77.45	3.27	25,960	852
Jordan	JOR	Developing	Middle East and North Africa	Northern	18.83	9.09	0.12	631	2
Morocco	MAR	Developing	Middle East and North Africa	Northern	17.75	24.88	0.38	2,597	90
New Zealand	NZL	Developed	East Asia and Pacific	Southern	9.99	144.46	1.72	12,064	314
Peru	PER	Developing	Latin America and Caribbean	Southern	19.61	128.42	0.53	2,635	87
Russia	RUS	Developing	Europe and Central Asia	Northern	-5.83	36.13	1.10	5,490	51
United Stated	USA	Developed	North America	Northern	7.24	55.42	9.62	66,959	1,515
South Africa	ZAF	Developing	Sub-Saharan Africa	Southern	17.91	39.56	0.68	4,341	73

Notes: Economic development groups assigned following United Nation (2017). Trade data aggregated at one-digit level of the classification by Broad Economic Categories (BEC) and consider 'Food and beverages' (BEC 1996: 01). The share of each country exports with respect to global exports in the agri-food sector (i.e., 1,122 billion USD) refers to 2015.

B. Conceptual framework and empirical strategy

Figure B.1. Conceptual framework and empirical strategy



C. Methodological choices

C1. Dealing with zero trade flows

Trade data collected for selected countries over the period between 1996 and 2015 exhibit fractions of zeros and missing values. In the sample, country pairs that do not trade with each other account for 5.21%, of which only one tenth are zeros and the remaining are missing values. Missing values in total exports of countries account for 3.75%. Zeros are associated with exports from Jordan[39]: if non-zero, exports from Jordan are missing or low in magnitude (i.e. never greater than few thousands of dollars). Thus, zeros in the sample are likely to be structural zeros: they may occur when bilateral trade is expected to be low (e.g. between distant and/or small countries, such in this case), as suggested in Head and Mayer (2014). Differently, missing trade values are likely to be associated with data recording issue. For instance, total exports of Brazil, Jordan, Morocco, Peru, Russian Federation and South Africa are missing in the first years of the dataset, but equal to hundreds of thousands of dollars in following years[40]. Similar considerations can be made for bilateral exports missing between Argentina and South Africa in 2003 and 2004; missing between Indonesia and Israel during the periods 1996-1997 and 2001-2007; missing from Israel to Indonesia in 1996, 1998, and 2007-2008, to Morocco in 2002-2005, 2010-2011, 2013, and 2015, to Peru in 1999-2000; or missing from Brazil, Jordan, Morocco, Peru, Russian Federation and South Africa to all trading partners and in different years of the sample. Missing data in the sample may be thus considered as statistical zeros (Head and Mayer, 2014).

The presence of statistical zeros (missing trade values) and structural zeros (trade expected to be low) in trade variables in the sample calls for the need of adjusting the empirical models in order to accommodate zeros, and revising the methods of estimation to allow for consistent estimates in the presence of a dependent variable assuming null values. In order to capture economically significant changes in trade, statistical zeros have been replaced with:

i. the 1st percentile of the distribution of exports,
ii. the 5th percentile of the distribution of exports,
iii. the 10th percentile of the distribution of exports,
iv. the value of exports observed in the first year available.

The graphical (figure C.1) and descriptive (table C.1) analysis shows that the greatest deviation between the collected (bilateral) data ('w/ zeros' in figure C.1) and adjusted (bilateral) trade variables ('1st pct', '5th pct', '10th pct', 'close values' in figure C.1) occurs in the first decade of the sample (since 1996 until 2005). Replacing statistical zeros with 1st, 5th, and 10th percentiles of the distribution of bilateral exports lowers the average trade values by 4.7% (and the variability by 2.1%): it implies assuming missing values as low trade values. Differently, replacing statistical zeros with the value of exports observed in the first year available is an approach based on a quasi-interpolation of data[41]: this approach lowers the average value of bilateral export by 4.4% (and the variability by 2.2%).

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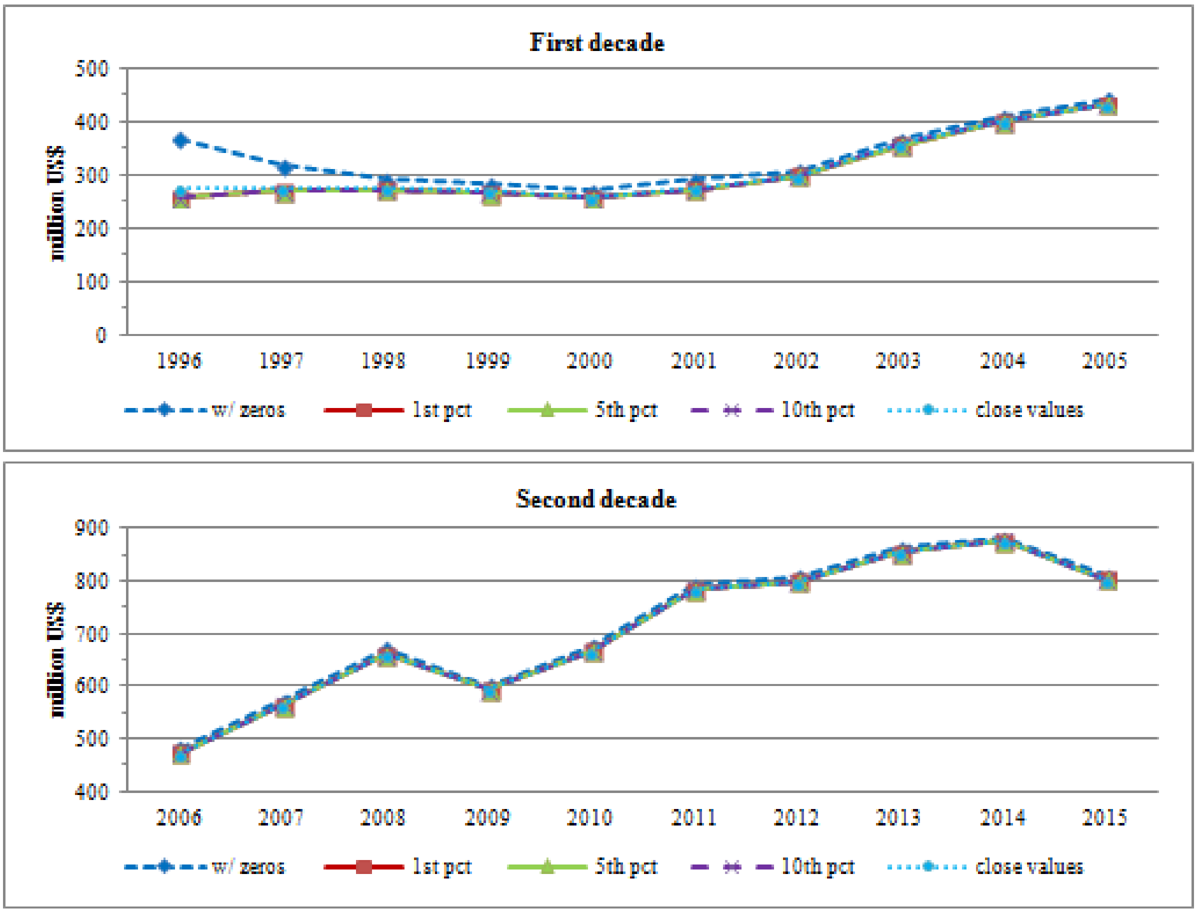
[39] Zero trade values are observed between Jordan and Argentina in 1999-2002, 2005-2006, 2008-2009, 2001-2012, 2014, between Jordan and Brazil in 1999-2000, 2004, 2007, 2009-2011, 2013-2014, between Jordan and China in 1999, 2002, 2005-2006, between Jordan and Indonesia in 1999-2001, 2013-2014, between Jordan and India in 1999, 2001-2002, between Jordan and Morocco in 1999, between Jordan and New Zealand 2006-2007, between Jordan and South Africa in 1999.

[40] Exports from Brazil and Russian Federation are missing in 1996, but respectively equal to 11,700 million US$ and 1,284 million US$ in 1997; exports from Jordan and Peru are missing in 1996 and 1997, but respectively equal to 208 million US$ and 916 million US$ in 1998; exports from Morocco are missing during the period between 1996 and 2001, but equal to 1,665 million US$ in 2002; exports from South Africa are missing during 1996-1998, but equal to 2,144 million US$ in 1999.

[41] Data interpolation is not possible due to missing values in the first years of the sample.

Figure C.1. Comparing trends in trade variables



Source: elaboration on data from UN Comtrade.

Notes: The figures report average annual values of bilateral exports. Statistical zeros (w/ zeros), 4.74% in the sample) are replaced with the 1st percentile (1st pct), the 5th percentile (5th pct), the 10th percentile (10th pct) of the distribution of exports, or with the value of exports observed in the first year available (close values). Trade data aggregated at one-digit level of the classification by Broad Economic Categories (BEC) and consider 'Food and beverages' (BEC 1996: 01).

Table C.1. Descriptive statistics of trade variables

Bilateral trade (1000 US$)	Obs.	Mean	Std. Dev.	Min	Max
with statistical zeros	7,240	532,724	1,582,390	0	22,500,000
statistical zeros = 1st pct	7,600	507,490	1,548,594	0	22,500,000
statistical zeros = 5th pct	7,600	507,502	1,548,590	0	22,500,000
statistical zeros = 10th pct	7,600	507,564	1,548,569	0	22,500,000
statistical zeros = close values	7,600	509,319	1,548,209	0	22,500,000

Notes: Structural zeros (i.e. zero trade flows) are 0.47%.

In order to disentangle the most appropriate method to accommodate statistical zeros in the empirical framework, the following model is estimated with Ordinary Least Squares (OLS):

$$X = \boldsymbol{Dt} + \boldsymbol{Dp} + \boldsymbol{Z}\phi + \nu \tag{C.1}$$

where X is a vector of observations on the dependent variable (i.e. value of bilateral exports from exporter *i* to importer *j* at time *t*), $\boldsymbol{Dt}$ is a matrix of time fixed effects, $\boldsymbol{Dp}$ is a matrix of country-pair fixed effects, $\boldsymbol{Z}$ is a matrix of exogenous variables (i.e. long-run differences in annual mean temperature and precipitation between exporter *i* and importer *j* at time *t* and their quadratic functions), ϕ is the corresponding vector of regression coefficients, ν is a vector of error terms assumed independently and identically distributed.

Different specifications of the model in equation (C.1) are estimated using, alternatively, as dependent variable bilateral exports with statistical zeros (specification i), with statistical zeros replaced with the 1st percentile of the distribution of exports (specification ii), with statistical zeros replaced with the 5th percentile of the distribution of exports (specification iii), with statistical zeros replaced with the 10th percentile of the distribution of exports (specification iv), with statistical zeros replaced with the value of exports observed in the first year available (specification v). The results are reported in table C.2.

The null hypothesis to test is the equality of coefficients ϕ estimated in different OLS regressions of the model in equation (C.1), against the alternative hypothesis of difference of coefficients ϕ:

$$H_0: \hat{\phi}_{(i)} = \hat{\phi}_{(ii)} = \hat{\phi}_{(iii)} = \hat{\phi}_{(iv)} = \hat{\phi}_{(v)} \quad \text{against} \quad H_1: \hat{\phi}_{(i)} \neq \hat{\phi}_{(ii)} \neq \hat{\phi}_{(iii)} \neq \hat{\phi}_{(iv)} \neq \hat{\phi}_{(v)} \tag{A.2}$$

where $\hat{\phi}_{(i)}$, $\hat{\phi}_{(ii)}$, $\hat{\phi}_{(iii)}$, $\hat{\phi}_{(iv)}$, and $\hat{\phi}_{(v)}$ are the regression coefficients estimated respectively for the specifications (i), (ii), (iii), (iv), and (v).

The outcomes of the tests are reported in table C.3. the null hypotheses $H_0: \hat{\phi}_{(i)} = \hat{\phi}_{(ii)}$, $H_0: \hat{\phi}_{(i)} = \hat{\phi}_{(iii)}$, $H_0: \hat{\phi}_{(i)} = \hat{\phi}_{(iv)}$, $H_0: \hat{\phi}_{(i)} = \hat{\phi}_{(v)}$ can be rejected: coefficients estimated in specification (i) are statistically different from coefficients estimated in specifications (ii), (iii), (iv) and (v) at the 1% significance level (and at 10% significance level for the coefficients estimated for differences in precipitation between exporter and importer). Similarly, regression coefficients significantly differ across specifications (ii), (iii), and (iv). Differently, we fail to reject the null hypotheses of equality between coefficients estimated in specification (v) and coefficients estimated in specifications (ii), (iii) and (iv). Exceptions are the coefficients estimated for differences in temperatures between exporter and importer: H_0: $\hat{\phi}_{(ii)} = \hat{\phi}_{(v)}$ can be rejected with χ2 = 7.49 (Prob > χ2 = 0.0062), H_0: $\hat{\phi}_{(iii)} = \hat{\phi}_{(v)}$ can be rejected with χ2 = 7.55 (Prob > χ2 = 0.0060), H_0: $\hat{\phi}_{(iv)} = \hat{\phi}_{(v)}$ can be rejected with χ2 = 7.90 (Prob > χ2 = 0.0050).

Statistical differences found between coefficients estimated in specification (i) and coefficients estimated in specifications (ii), (iii), (iv), and (v) suggest the importance of treating zero trade flows: using row trade data (with statistical zeros) as dependent variable may generate biased estimates, undermining the validity of results. Replacing statistical zeros with the value of exports observed in the first year available seems the most appropriate method: the resulted distribution of exports is less biased downward (as compared with variables obtained by replacing statistical zeros with first percentiles of the distribution of exports); the coefficients estimated in specification (v) are statistically equal to coefficients estimated in specifications (ii), (iii), and (iv). The main results of the study are based on this variable.

References

Head, K., Mayer, T., 2014. Gravity equations: Workhorse, toolkit, and cookbook, in: Head, K., Mayer, T. (Eds.), Handbook of International Economics, Vol. 4, Elsevier, pp. 131-195.

C.2 Climate data

Table C.2. Climate data

Dimension	Description
Temporal	Temperature (°C): annual mean value Precipitation (mm): annual cumulative value
Spatial	Grid: 0.5° latitude by 0.5° longitude grid (50 km by 50 km) Aggregation: national level

Source: Climatic Research Unit of University of East Anglia (Harris et al., 2020).

Table C.3. Comparing trade effects

Variables	Specification (i)	Specification (ii)	Specification (iii)	Specification (iv)	Specification (v)
$(Temp_i – Temp_j)$	-270,216.10 ***	-352,716.07 ***	-352,744.76 ***	-352,897.55 ***	-344,961.35 ***
	(88,681.11)	(82,238.60)	(82,238.77)	(82,239.69)	(82,129.00)
$(Temp_i – Temp_j)^2$	4,890.86	2,961.69	2,961.22	2,958.75	2,985.38
	(3,508.15)	(3,283.81)	(3,283.82)	(3,283.85)	(3,279.43)
$(Prec_i – Prec_j)$	-19,047.65 **	-15,941.99 **	-15,940.32 **	-15,931.43 **	-15,733.52 **
	(7,613.92)	(7,251.63)	(7,251.65)	(7,251.73)	(7,241.97)
$(Prec_i – Prec_j)^2$	-47.08	-55.39 *	-55.4 *	-55.45 *	-55.53 *
	(34.52)	(32.59)	(32.59)	(32.59)	(32.55)
Observations	7,240	7,600	7,600	7,600	7,600
R^2	0.80	0.80	0.80	0.80	0.80

Notes: Ordinary Least Square (OLS) estimation of equation (A.1) using annual climatic variables. The dependent variable is the value of bilateral exports with statistical zeros (specification i), with statistical zeros replaced with the 1st percentile of the distribution of exports (specification ii), with statistical zeros replaced with the 5th percentile of the distribution of exports (specification iii), with statistical zeros replaced with the 10th percentile of the distribution of exports (specification iv), with statistical zeros replaced with the value of exports observed in the first year available (specification v). All specifications include a constant term, time and country-pair fixed effects. Standard errors are in parentheses. Differences in temperature between exporter (*i*) and importer (*j*) are in degrees Celsius and differences in precipitation between *i* and *j* are in units of mm per year.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table C.4. Testing the equality of coefficients ϕ estimated in different Ordinary Least Square (OLS) regressions of equation (A.1)

	Specification (i)		Specification (ii)		Specification (iii)		Specification (iv)		Specification (v)
Specification (i)									
Specification (ii)	$(Temp_i - Temp_j)$	$(Temp_i - Temp_j)^2$							
	$\chi^2 = 27.99$	$\chi^2 = 11.03$							
	$(Prob > \chi^2 = 0.0000)$	$(Prob > \chi^2 = 0.0009)$							
	$(Prec_i - Prec_j)$	$(Prec_i - Prec_j)^2$							
	$\chi^2 = 15.95$	$\chi^2 = 6.15$							
	$(Prob > \chi^2 = 0.0001)$	$(Prob > \chi^2 = 0.0131)$							
Specification (iii)	$(Temp_i - Temp_j)$	$(Temp_i - Temp_j)^2$	$(Temp_i - Temp_j)$	$(Temp_i - Temp_j)^2$					
	$\chi^2 = 28.00$	$\chi^2 = 11.03$	$\chi^2 = 25.31$	$\chi^2 = 3.94$					
	$(Prob > \chi^2 = 0.0000)$	$(Prob > \chi^2 = 0.0009)$	$(Prob > \chi^2 = 0.0000)$	$(Prob > \chi^2 = 0.470)$					
	$(Prec_i - Prec_j)$	$(Prec_i - Prec_j)^2$	$(Prec_i - Prec_j)$	$(Prec_i - Prec_j)^2$					
	$\chi^2 = 15.96$	$\chi^2 = 6.16$	$\chi^2 = 15.12$	$\chi^2 = 26.37$					
	$(Prob > \chi^2 = 0.0001)$	$(Prob > \chi^2 = 0.0131)$	$(Prob > \chi^2 = 0.0001)$	$(Prob > \chi^2 = 0.0000)$					
Specification (iv)	$(Temp_i - Temp_j)$	$(Temp_i - Temp_j)^2$	$(Temp_i - Temp_j)$	$(Temp_i - Temp_j)^2$	$(Temp_i - Temp_j)$	$(Temp_i - Temp_j)^2$			
	$\chi^2 = 28.06$	$\chi^2 = 11.05$	$\chi^2 = 21.80$	$\chi^2 = 3.49$	$\chi^2 = 21.83$	$\chi^2 = 3.49$			
	$(Prob > \chi^2 = 0.0000)$	$(Prob > \chi^2 = 0.0009)$	$(Prob > \chi^2 = 0.0000)$	$(Prob > \chi^2 = 0.0616)$	$(Prob > \chi^2 = 0.0000)$	$(Prob > \chi^2 = 0.0616)$			
	$(Prec_i - Prec_j)$	$(Prec_i - Prec_j)^2$	$(Prec_i - Prec_j)$	$(Prec_i - Prec_j)^2$	$(Prec_i - Prec_j)$	$(Prec_i - Prec_j)^2$			
	$\chi^2 = 16.00$	$\chi^2 = 6.22$	$\chi^2 = 15.64$	$\chi^2 = 24.82$	$\chi^2 = 15.69$	$\chi^2 = 24.82$			
	$(Prob > \chi^2 = 0.0001)$	$(Prob > \chi^2 = 0.0127)$	$(Prob > \chi^2 = 0.0001)$	$(Prob > \chi^2 = 0.0000)$	$(Prob > \chi^2 = 0.0001)$	$(Prob > \chi^2 = 0.0000)$			
Specification (v)	$(Temp_i - Temp_j)$	$(Temp_i - Temp_j)^2$	$(Temp_i - Temp_j)$	$(Temp_i - Temp_j)^2$	$(Temp_i - Temp_j)$	$(Temp_i - Temp_j)^2$	$(Temp_i - Temp_j)$	$(Temp_i - Temp_j)^2$	
	$\chi^2 = 25.41$	$\chi^2 = 13.20$	$\chi^2 = 7.49$	$\chi^2 = 0.04$	$\chi^2 = 7.55$	$\chi^2 = 0.04$	$\chi^2 = 7.90$	$\chi^2 = 0.05$	
	$(Prob > \chi^2 = 0.0000)$	$(Prob > \chi^2 = 0.0003)$	$(Prob > \chi^2 = 0.0062)$	$(Prob > \chi^2 = 0.8506)$	$(Prob > \chi^2 = 0.0060)$	$(Prob > \chi^2 = 0.8476)$	$(Prob > \chi^2 = 0.0050)$	$(Prob > \chi^2 = 0.8318)$	
	$(Prec_i - Prec_j)$	$(Prec_i - Prec_j)^2$	$(Prec_i - Prec_j)$	$(Prec_i - Prec_j)^2$	$(Prec_i - Prec_j)$	$(Prec_i - Prec_j)^2$	$(Prec_i - Prec_j)$	$(Prec_i - Prec_j)^2$	
	$\chi^2 = 18.97$	$\chi^2 = 6.44$	$\chi^2 = 1.49$	$\chi^2 = 0.11$	$\chi^2 = 1.46$	$\chi^2 = 0.10$	$\chi^2 = 1.35$	$\chi^2 = 0.03$	
	$(Prob > \chi^2 = 0.0000)$	$(Prob > \chi^2 = 0.0111)$	$(Prob > \chi^2 = 0.2228)$	$(Prob > \chi^2 = 0.7378)$	$(Prob > \chi^2 = 0.2261)$	$(Prob > \chi^2 = 0.7564)$	$(Prob > \chi^2 = 0.2446)$	$(Prob > \chi^2 = 0.8579)$	

Notes: The specifications of equation (A.1) use, as dependent variable, the value of bilateral exports with statistical zeros (specification i), with statistical zeros replaced with the 1st percentile of the distribution of exports (specification ii), with statistical zeros replaced with the 5th percentile of the distribution of exports (specification iii), with statistical zeros replaced with the 10th percentile of the distribution of exports (specification iv), with statistical zeros replaced with the value of exports observed in the first year available (specification v). $(Temp_i - Temp_j)$ indicates differences in temperature between exporter (*i*) and importer (*j*) in degrees Celsius, $(Prec_i - Prec_j)$ indicates differences in precipitation between *i* and *j* in units of mm per year.

D. Sensitivity analyses on the cross-sectional model

The mean marginal impacts associated with a 1 mm increase in the rainfall levels are reported in table D.1.

Table D.1. Marginal impact of precipitation and change in countries' export values

	All		Developed		Developing	
	Marginal impact (%)	Change in average exports (bln USD)	Marginal impact (%)	Change in average exports (bln USD)	Marginal impact (%)	Change in average exports (bln USD)
Precipitation (+1 mm)	1.75 [1.28; .2.21]	0.35	1.93 [1.43; 2.44]	0.62	1.59 [1.16; 2.03]	0.17

Notes: Marginal impacts are significant at the 1 percent level and obtained from coefficients in table 3 evaluated at average precipitation of all, developed (45% of the sample) and developing (55% of the sample) exporters (see table 2); 95% confidence intervals are in brackets. Change in exports consider average exports of all, developed and developing exporters (see table 1).

In order to test the robustness of results, we introduce different control factors in the baseline cross-sectional model (table D.2, column [1]). In detail, we test for the effect of proxies of technology, i.e. alternatively access to electricity and access to electricity in rural areas (table D.2, columns [2]-[3]), and for the impact of policy interventions, i.e. tariff level and non-tariff measures (table D.2, column [4]). The results confirm findings of the baseline model with a low variability in the magnitude of estimated coefficients.

Table D.2. Robustness check of the cross-sectional estimation results: controlling for proxies of technology

Variables	Baseline [1]	Access to electricity rural [2]	Access to electricity [3]	Trade policies [4]
Temperature of exporter	-.09680***	-.04960**	-.08239***	-.11161***
	(.02121)	(.02001)	(.02015)	(.02104)
Temperature^2 of exporter	.00795***	.00544***	.00709***	.00832***
	(.00117)	(.00106)	(.00111)	(.00116)
Precipitation of exporter	.07398***	.06787***	.07339***	.07256***
	(.00845)	(.00788)	(.00835)	(.00843)
Precipitation^2 of exporter	0.00039***	-.00033***	-.00037***	-.00038***
	(.00004)	(.00004)	(.00004)	(.00004)
Access to electricity, rural	No	Yes	No	No
Access to electricity	No	No	Yes	No
Tariff levels	No	No	No	Yes
Non-tariff measures	No	No	No	Yes
Observations	400	395	395	400
R^2	.883	.901	.889	.891

Notes: Pooled OLS estimate of the model in equation (2). The dependent variable is the log value of total exports in food and beverage sector (BEC). Annual temperature of exporter is in degrees Celsius and annual precipitation of exporter is in units of mm per year. All specifications include a constant term, time and region fixed effects, latitude and longitude of the exporter, a dummy discriminating between developed and developing exporters. In the specifications *Access to electricity rural* [2] and *Access to electricity* [3], the lower sample size is due to missing observations in the control variables for Argentina in 1996-2000. Robust standard errors are in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

We run a set of robustness checks using more disaggregated trade data; we consider exports of 24 agri-food sectors aggregated at the 2-digit level of the Harmonised System (HS). The expanded dataset consists of 9,600 cross-sectional observations. Table D.3 compares the results of the baseline model (column [1]) with results of specifications that control for different product groups, i.e. animal-based, plant-based, and processed products (column [2]) or include product fixed effects (column [3]).

Table D.3. Robustness check of the cross-sectional estimation results: controlling for differences across product categories

Variables	Baseline [1]	Product groups [2]	Product fixed effects [3]
Temperature of exporter	-.06065***	-.06065***	-.06065***
	(.01417)	(.01415)	(.01160)
$Temperature^2$ of exporter	.00748***	.00748***	.00748***
	(.00070)	(.00070)	(.00058)
Precipitation of exporter	.07990***	.07990***	.07990***
	(.00576)	(.00577)	(.00487)
$Precipitation^2$ of exporter	-.00042***	-.00042***	-.00042***
	(.00003)	(.00003)	(.00002)
Animal-based products		.18021***	
		(.05408)	
Plant-based products		.35840***	
		(.04904)	
Product fixed effects	No	No	Yes
Observations	9,600	9,600	9,600
R^2	.415	.419	.635

Notes: Pooled OLS estimate of the model in equation (2). The dependent variable is the log value of total exports in 24 agri-food sectors (HS2-digit). Annual temperature of exporter is in degrees Celsius and annual precipitation of exporter is in units of mm per year. All specifications include a constant term, time and region fixed effects, latitude and longitude of the exporter, a dummy discriminating between developed and developing exporters. In the specifications Product groups [2], 'processed' is the base product group. Robust standard errors are in parentheses.

*** Significant at the 1 percent level.

Specular to results presented in table D.2 (dataset with BEC trade data), table D.4 (dataset with HS2-digit trade data) checks the robustness of the results controlling for proxies of technology and policy interventions, confirming main findings.

Table D.4. Robustness check of the cross-sectional estimation results: controlling for differences across product categories and proxies of technology

Variables	Baseline [1]	Access electricity rural [2]	Access electricity [3]	Trade policies [4]
Temperature of exporter	-.06065***	-.00512	-.04040***	-.06499***
	(.01160)	(.01172)	(.01159)	(.01170)
Temperature^2 of exporter	.00748***	.00457***	.00630***	.00762***
	(.00058)	(.00059)	(.00058)	(.00058)
Precipitation of exporter	.07990***	.07312***	.07927***	.07855***
	(.00487)	(.00484)	(.00487)	(.00489)
Precipitation^2 of exporter	-.00042***	-.00036***	-.00040***	-.00042***
	(.00002)	(.00002)	(.00002)	(.00002)
Access to electricity, rural	No	Yes	No	No
Access to electricity	No	No	Yes	No
Tariff levels	No	No	No	Yes
Non-tariff measures	No	No	No	Yes
Observations	9,600	9,480	9,480	9,600
R^2	.635	.643	.639	.637

Notes: Pooled OLS estimate of the model in equation (2). The dependent variable is the log value of total exports in 24 agri-food sectors (HS2-digit). Annual temperature of exporter is in degrees Celsius and annual precipitation of exporter is in units of mm per year. All specifications include a constant term, time, region and product fixed effects, latitude and longitude of the exporter, a dummy discriminating between developed and developing exporters. In the specifications *Access to electricity* [2] rural and *Access to electricity* [3], the lower sample size is due to missing observations in the control variables for Argentina in 1996-2000. Robust standard errors are in parentheses.

*** Significant at the 1 percent level.

The overall impact of climate is largely the same across the different models, although the quantitative estimates vary. All models suggest that annual temperatures are harmful and greater precipitations are beneficial for export values. The squared terms for temperature and precipitation are significant and opposed to the linear terms of same variables, implying that the observed relationships are nonlinear.

We regress the values of total exports of developed and developing countries on their climate to examine differences across exporters with different levels of economic development. The regression results, reported in table D.5, show that developed and developing exporters are both sensitive to climate but have diverse climate responses. The higher the annual temperatures, the greater the value of exports both of developed and developing countries. Differently from developed countries, the relation between climate normal and the value of export of developing countries is nonlinear (bell-shaped). The results also show that greater annual precipitations, up to a threshold, positively affect the value of exports. The evidence is verified for both developed and developing countries.

Table D.5. Effects of climate change on countries' export capacity

Variables	All exporters [1]	Developed exporters [2]	Developing exporters [3]
Temperature of exporter	-.09680***	-.03706***	-.05371**
	(.02121)	(0.00798)	(0.02604)
Temperature^2 of exporter	.00795***	-.01262***	.02013***
	(.00117)	(.00040)	(.00074)
Precipitation of exporter	.07398***	.13019***	.03293***
	(.00845)	(.00722)	(.01206)
Precipitation^2 of exporter	-.00039***	-.00096***	-.00040***
	(.00004)	(.00005)	(.00004)
Observations	400	180	220
R^2	.883	.982	.958

Notes: Pooled OLS estimate of the model in equation (2). The dependent variable is the log value of total exports in food and beverage sector (BEC). Annual temperature of exporter is in degrees Celsius and annual precipitation of exporter is in units of mm per year. All specifications include a constant term, time and region fixed effects, latitude and longitude of the exporter. In the specification *All exporters* [1], an additional control is a dummy discriminating between developed and developing exporters. Robust standard errors are in parentheses.

*** Significant at the 1 percent level.

The results of a sensitivity analysis on subsamples of exporters with different levels of economic development using more disaggregated data are reported in table D.6 and show climate responses of developed and developing exporters. The results on the restricted sample (see table D.5) are confirmed.

Table D.6. Robustness check of the cross-sectional estimation results: controlling for differences across product categories and level of development of exporters

Variables	All exporters [1]	Developed exporters [2]	Developing exporters [3]
Temperature of exporter	-.06065***	.01194	-.17725***
	(.01160)	(.01209)	(.03760)
Temperature^2 of exporter	.00748***	-.01736***	.01840***
	(.00058)	(.00076)	(.00083)
Precipitation of exporter	.07990***	.14382***	.12859***
	(.00487)	(.01080)	(.01761)
Precipitation^2 of exporter	-.00042***	-.00112***	-.00073***
	(.00002)	(.00007)	(.00006)
Observations	9,600	4,320	5,280
R^2	.635	.773	.607

Notes: Pooled OLS estimate of the model in equation (2). The dependent variable is the log value of total exports in 24 agri-food sectors (HS2-digit). Annual temperature of exporter is in degrees Celsius and annual precipitation of exporter is in units of mm per year. All specifications include a constant term, time, region and product fixed effects, latitude and longitude of the exporter. In the specification All exporters [1], an additional control is a dummy discriminating between developed and developing exporters. Robust standard errors are in parentheses.

*** Significant at the 1 percent level.

E. Sensitivity analyses on the gravity model

We test the robustness of the gravity-based estimated by introducing in the baseline model proxies of technology adoption in the exporter and importer. Table E.1 shows results of specifications that control, alternatively, for access to electricity in rural areas (column [2]) and access to electricity (column [3]) and compares results with findings from the baseline specification (column [1]).

Table E.1. Robustness check of the Gravity estimation results: controlling for proxies of technology

Variables	Baseline [1]	Access to electricity rural [2]	Access to electricity [3]
Difference in temperatures	.381***	.420***	.420***
	(.052)	(.050)	(.050)
Difference in precipitations	.164***	.184***	.184***
	(.059)	(.032)	(.032)
Access to electricity, rural in exporters (log)	No	Yes	No
Access to electricity, rural in importers (log)	No	Yes	No
Access to electricity in exporters (log)	No	No	Yes
Access to electricity in importers (log)	No	No	Yes
Observations	7,580	7,375	7,375
R^2	.995	.995	.995

Notes: PPML estimate of the Gravity model. The dependent variable is the value of bilateral exports in food and beverage sector (BEC). The difference in annual temperatures between the exporter and importer (log of absolute values) is in degrees Celsius; the difference in annual precipitations between the exporter and importer (log of absolute values) is in units of mm per year. All specifications include a constant term, exporter-time, importer-time and country-pair fixed effects, level of tariffs (log), non-tariff measures (dummy), regional trade agreements (dummy). In the specifications *Access to electricity rural* [2] and *Access to electricity* [3], the lower sample size is due to missing observations in the control variables for Argentina in 1996-2000. Robust standard errors are in parentheses.

*** Significant at the 1 percent level.

The trade volume effect associated with a 1 mm increase in the rainfall levels are reported in table E.2.

Table E.2. Trade volume effect of climate heterogeneity and change in bilateral exports

	All		Developed		Developing	
	Trade volume effect (%)	Change in avg. exports (bln USD)	Trade volume effect (%)	Change in avg. exports (bln USD)	Trade volume effect (%)	Change in avg. exports (bln USD)
Difference in precipitation (+1 mm)	16.42	.08	7.57	.06	16.95	.04

Notes: Trade volume effect obtained from coefficients in table 5, evaluated at average differences in temperature and precipitation (see table 2). Change in exports consider average bilateral exports of all, developed and developing exporters (see table 1).

F. Extending the timeframe of the analysis

Thanks to a recent update of trade and climate data, we extend the timeframe of the analysis until 2021 as a sensitivity analysis.

Due to an update in the methodology used by the Climatic Research Unit (CRU) of the University of East Anglia (UEA) to represent the historical climate, climate data collected from the Climate Change Knowledge Portal of the World Bank in 2019 (Harris et al., 2014) and in 2023 (Harris et al., 2020) are slightly different. For instance, recently collected temperatures tend to be about 0.5 °C higher (table F.1).

The cross-sectional climate model and the gravity model are run on different time periods (tables F.2 and F.3). The results of the models estimated over the period 1996-2015 with data collected in 2019 and in 2023 are comparable. Similar results are obtained considering both the more recent time period (i.e., 2016-2021) and the whole period (i.e., 1996-2021). As further analysis, we stop the analysis to the year 2019 to avoid potential biases due to the dynamics related to the COVID-19 pandemic: the results are robust.

Table F.1. Comparison of monthly data on temperature (°C) in 1970 in Argentina, Australia, China

	Argentina			Australia			China		
	WB 2019	WB 2023	Delta	WB 2019	WB 2023	Delta	WB 2019	WB 2023	Delta
Jan	20.35	20.74	0.39	27.83	27.88	0.05	-9.51	-8.76	0.75
Feb	21.01	21.49	0.48	27.89	27.93	0.04	-5.44	-4.69	0.75
Mar	18.00	18.62	0.62	25.21	25.31	0.10	-2.21	-1.48	0.73
Apr	16.32	16.99	0.67	21.68	21.80	0.12	7.05	7.43	0.38
May	10.75	11.36	0.61	17.09	17.25	0.16	13.23	13.51	0.28
Jun	7.59	8.00	0.41	15.74	15.83	0.09	16.74	16.90	0.16
Jul	7.91	8.38	0.47	13.73	13.85	0.12	19.37	19.57	0.20
Aug	8.80	9.35	0.55	15.13	15.28	0.15	18.73	18.94	0.21
Sep	13.40	13.91	0.51	17.97	18.18	0.21	13.65	14.00	0.35
Oct	14.43	14.98	0.55	22.94	23.08	0.14	7.03	7.50	0.47
Nov	16.91	17.43	0.52	24.72	24.84	0.12	-1.04	-0.44	0.60
Dec	19.71	20.23	0.52	26.92	27.03	0.11	-6.53	-5.82	0.71

Source: Data from the Climate Change Knowledge Portal of the World Bank in 2019 (WB 2019) and in 2023 (WB 2023).

Table F.2. Robustness check of the cross-sectional estimation results: extending the timeframe of the analysis

Variables	1996-2015 (old)	1996-2015 (updated)	2016-2021	1996-2021	2016-2019	1996-2019
Temperature of exporter	-0.0968***	-0.0083	0.0118	-0.0007	0.0140	-0.0083
	(0.0164)	(0.0248)	(0.0144)	(0.0314)	(0.0151)	(0.0248)
Temperature^2 of exporter	0.0080***	0.0035***	0.0024***	0.0032**	0.0023***	0.0035***
	(0.0008)	(0.0010)	(0.0006)	(0.0013)	(0.0006)	(0.0010)
Precipitation of exporter	0.0740***	0.0042***	0.0035***	0.0041***	0.0034***	0.0042***
	(0.0060)	(0.0007)	(0.0004)	(0.0009)	(0.0005)	(0.0007)
Precipitation^2 of exporter	-0.0004***	-0.000001***	-0.000002***	-0.000001***	-0.000002***	-0.000001***
	(0.0000)	(0.0000002)	(0.0000003)	(0.0000002)	(0.0000004)	(0.0000002)
Developed exporter	-6.4802***	-2.6594***	-1.9020***	-2.5321***	-1.8294***	-2.6594***
	(0.4804)	(0.4597)	(0.2741)	(0.5827)	(0.2875)	(0.4597)
Latitude	-0.0808***	-0.0319***	-0.0287***	-0.0296***	-0.0283***	-0.0319***
	(0.0062)	(0.0079)	(0.0047)	(0.0100)	(0.0049)	(0.0079)
Longitude	-0.0060**	-0.0191***	-0.0197***	-0.0184***	-0.0198***	-0.0191***
	(0.0025)	(0.0036)	(0.0021)	(0.0045)	(0.0022)	(0.0036)
N	400	380	140	520	100	480
R^2	0.88	0.84	0.88	0.85	0.88	0.85

Notes: Pooled OLS estimate of the model in equation (2). The dependent variable is the log value of total exports in food and beverage sector (BEC). Annual temperature of exporter is in degrees Celsius and annual precipitation of exporter is in units of mm per year. All specifications include a constant term, time and region fixed effects, latitude and longitude of the exporter, a dummy discriminating between developed and developing exporters. Robust standard errors are in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

Table F.3. Robustness check of the Gravity estimation results: extending the timeframe of the analysis

	1996-2015 (old, w/cf)	1996-2015 (old)	1996-2015 (updated)	2016-2021	1996-2021	2016-2019	1996-2019
Difference in temperatures	0.3807***	0.4258***	0.0675***	0.0040	0.0779***	0.0586	0.0834***
	(0.0516)	(0.0518)	(0.0135)	(0.0595)	(0.0137)	(0.0522)	(0.0145)
Difference in precipitations	0.1642***	0.1762***	0.1244***	-0.0656	0.1599***	-0.0791	0.1468***
	(0.0297)	(0.0310)	(0.0217)	(0.0518)	(0.0365)	(0.0512)	(0.0351)
CF (policy variables)	yes	no	no	no	no	no	no
N	7580	7580	7580	2260	9863	1504	9089

Notes: PPML estimate of the Gravity model. The dependent variable is the value of bilateral exports in food and beverage sector (BEC). The difference in annual temperatures between the exporter and importer (log of absolute values) is in degrees Celsius; the difference in annual precipitations between the exporter and importer (log of absolute values) is in units of mm per year. All specifications include a constant term, exporter-time, importer-time and country-pair fixed effects. Control factors (CF) are level of tariffs (log), non-tariff measures (dummy), regional trade agreements (dummy). Robust standard errors are in parentheses.

*** Significant at the 1 percent level.

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