The Impact of Water Resources on Trade under a Changing Climate*

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Abstract

Global warming induces significant changes in the global water cycle. Leveraging rich spatial and temporal variation in precipitation and sectoral bilateral trade between countries, this study examines the impact of water resources on international trade. The findings indicate that the abundance of water resources in the origin country relative to the destination country represents a comparative advantage. A 1% increase in relative precipitation per capita between the origin and destination leads to a 0.07% increase in exports. The impact is stronger for water-intensive industries and between trading partners with large differences in water endowment. We provide evidence on three underlying channels: productivity, trade structure, and transport. Long-term projections show that the aggregate gains and losses in exports due to changes in precipitation during 2080-2099 would amount to $660 and -$280 billion among winners and losers, respectively, relative to the 2015-2019 levels. The results highlight that the changing water resources play a critical role in shaping the impact of climate change on trade and the economy.

Keywords: water resource, international trade, comparative advantage, climate change

JEL codes: F14, Q25, Q54

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1 Introduction

Water resources are distributed unevenly worldwide, and the rapid reduction in these resources presents a significant threat to public health, political stability, and the environment (IPCC, 2022). As global warming continues to alter the global water cycle, the existing disparities in water distribution and the resulting economic crises are expected to worsen (World Bank, 2016). Changes in local water resources can be transmitted across regions through the trading of commodities that depend on water as an input. Virtual water trade has allowed countries with limited water resources to rely on the water supplies of other nations to meet their domestic needs. Despite the substantial growth of international trade in recent decades and the clear spatial redistribution of water resources caused by climate change, there is a lack of empirical evidence at the granular level regarding how water resources impact international trade in the context of a changing climate.

This paper aims to fill the gap in the literature by quantifying the impact of the spatial redistribution of water resources on international trade at a global scale. To that end, we compile rich datasets including bilateral trade, precipitation and other weather conditions, input usages, production, port logistics performance as well as future climate and population projections. Our empirical framework employs a gravity equation to examine trade flows while allowing for the Heckscher-Ohlin (HO) style interactions. Specifically, we investigate whether water-abundant countries export more in the sectors with higher water intensities. The identification leverages the variation in precipitation as the key driver for water resources. In addition, our model exploits the nature of sectoral bilateral trade flows between countries by incorporating a rich set of fixed effects.

Our regression analysis yields two key findings. First, relative precipitation abundance between the origin and the destination countries represents a comparative advantage. Relative precipitation abundance is measured as the exporter's precipitation per capita divided by the importer's precipitation per capita. On average, a 10-percent increase in relative precipitation leads to a 0.7-percent increase in trade flows. Second, the impact concentrates in water intensive industries such as food and livestock production as well as crude materials extraction. For example, the elasticity of the precipitation impact on agricultural trade is 0.3, more than four times larger than the average across industries. Additionally, the heterogeneous analyses reveal that the impact of water resources on trade is stronger between trading partners with large differences in water endowment. These findings are robust to a host of robustness checks including using alternative measures of water intensities and water resources.

Our analyses reveal three mechanisms of the precipitation impact on trade: productivity, trade structure, and transport disruption. First, the productivity mechanism encompasses the impacts of precipitation on outputs, TFP, and TFP growth rate. We find an inverted-U relationship between precipitation and agricultural production and a linear relationship between precipitation and industrial production. When evaluated at the mean of precipitation per capita, a one-unit increase (or 220%) in precipitation per capita increases agricultural value added per capita by 28.6%, which is about twice as large as that in industrial production. In addition, there is an inverted-U relationship between precipitation and agricultural TFP growth rate.

Second, in terms of trade structure, we examine the impact of precipitation on the existing number of industries that engage in trade as well as how the adjustment of these industries is correlated with industrial water intensity. The findings indicate that when relative water resources increase, export sectors tend to concentrate on the industries with higher levels of water intensity; when relative water resources decrease, export sectors become more diversified to offset potential losses in comparative advantage. The findings suggest that the lack of diversification in domestic industries can exacerbate vulnerabilities to climate change.

Third, the transport mechanism focuses on the impact of precipitation on marine transport by linking the precipitation at the port level with trade logistics performance index. The index measures a port's key logistics performances including the efficiency of the customs clearance process and frequency with which shipments reach the consignee within the scheduled time. The findings reveal that when droughts lower water levels, significant congestion and delays arise in canals and ports, leading to higher transportation costs and reduced trade flows.

Based on our empirical estimates, we then quantify the overall impact of changes in precipitation on international trade during 2000-2019 and project the long-run impact at the end of the century under different climate scenarios. We find that the distributional effects of water resources on trade are substantial across countries and regions. Countries in Africa, South America, and East Asia experience the largest decreases in export, while countries in North America, Europe, and Oceania observe the largest decreases in imports during 2000-2019, relative to the average in 1995-1999. In projecting the long-run impacts, our simulations account for the role of adaptation by allowing the effects of precipitation on trade to evolve based on the water endowment following the recent climate impact literature (Auffhammer, 2022; Carleton et al., 2022; Heutel et al., 2021). The simulations show that the gains in exports due to changes in precipitation are expected to gradually outweigh the losses during the period of 2020-2099. In the years 2080-2099, the aggregate gains and losses in exports are projected to be $660 and -280 billion, respectively, relative to the average trade flows during 2015-2019.[1]

Our study makes two significant contributes to the literature. First, although there is a substantial body of literature on the economic impacts of weather shocks and climate change (see Carleton and Hsiang (2016) for a review), the research has largely focused on temperature, with precipitation and water resources receiving less attention.[2] In addition, few studies examined the effects of water on international trade. Our work contributes to the literature by examining how the changes in the spatial distribution of water affects trade flows while emphasizing the role of water intensity across various sectors at a global scale.

Second, this study contributes to a large empirical literature that examines the sources of comparative advantage in the HO tradition. This literature has identified various factors of comparative advantage, including the traditional factors, such as capital and skilled labor (Romalis, 2004), and a number of non-traditional factors, such as institutions (Levchenko, 2007; Nunn, 2007; Bombardini

[1] Our key variable of interest is relative precipitation between trade partners. A country might experience greater precipitation growth than certain trade partners but less precipitation growth than others. Consequently, this can lead to an increase in exports to some partners while decreasing exports to others. Therefore, we can simultaneously observe both the gains and losses for each country.

[2] Dell et al. (2012) and Burke et al. (2015b) have examined the joint effects of rainfall and temperature changes on aggregate economic outcomes. The World Bank has also produced several reports that analyze the effects of water and rainfall on outcomes including agricultural production, economic activity, and migration (Damania et al., 2020; Russ, 2020; Zaveri et al., 2021).

et al., 2012) and demographic composition (Cai and Stoyanov, 2016). Our analysis demonstrates that water represents an important source of comparative advantage in international trade. Our study is closely related to the seminal work by Debaere (2014), which showed that countries rich in water resources export more water-intensive products. However, our work differs from his in three important ways. First, while Debaere (2014) relies on cross-sectional data, our analysis is conducted in a panel setting to leverage both cross-sectional and temporal variation in precipitation and trade flows. Second, our findings suggest that relative abundance of water resources between the origin and destination countries, rather than a country's own water resources as modeled in Debaere (2014), provides a comparative advantage. Third, we provide the first set of projections to examine the long-run impact of climate change on trade flows via changes in water resources. As climate change would lead to substantial changes in water availability and redistribution over time, understanding the long-run impacts is crucial for formulating mitigation and adaption policies.

The rest of the paper is organized as follows. Section 2 introduces the data and background. Section 3 describe the empirical strategies. Section 4 presents the empirical results and robustness tests. Section 5 explores the mechanisms. Sections 6 projects the long-run impacts. Section 7 concludes.

2 Data and Background

2.1 Data Description

This section describes the data used in the analyses. Table A1 reports the summary statistics for the main variables.

Trade data. Bilateral trade data by industry at the country level are from the CEPII BACI.[3] The database is built from data directly reported by each country to the United Nations Statistical Division. The CEPII developed a procedure that reconciles the declarations of the exporter and the importer, which may be different in the original data. CEPII is widely used in economic research. The raw data are defined as items from the Harmonized System (HS) nomenclature at the 6-digit

[3] http://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele.asp

level. We convert the 6-digit HS codes to the 5-digit Standard International Trade Classification (SITC) Revision 4, following the guidance from the United Nations Statistics Division (UNSD).[4] Then we aggregate the products from the SITC 5-digit level (2971 industries) to the 2-digit level (67 industries). The data range from 1995 to 2019. In the model, we average the variables on a 5-year basis (1995-1999, 2000-2004, 2005-2009, 2010-2014 and 2015-2019). The 5-year average allows for adjustments in bilateral trade flows (Olivero and Yotov, 2012) and also minimizes the impact of potential measurement errors.

Precipitation data. The precipitation data are from the ERA5. The ERA5 is the latest fifth-generation reanalysis of the global atmosphere, produced by the European Centre for Medium-Range Weather Forecasts (ECMWF), covering the period from 1970 to the present. The original data are recorded at hourly intervals, but we aggregate them to the annual level, and then average annual precipitation over 5-year periods to match the frequency of the trade data. The spatial resolution of ERA5 is 31 x 31 km. To construct precipitation data at the country level, we use population density in each grid cell as the weight, accounting for the mismatch between water distribution and human activities. To assess the robustness of our results, we also construct unweighted precipitation in our alternative specification.

Other inputs. Other inputs include labor, capital and land, following the specification in Debaere (2014). The input data used in Debaere (2014) are cross-sectional and we obtain the panel data from the recent version of the Penn World Table 10 (PWT). The earlier version of PWT data is the original data source in Debaere (2014). Skilled labor stocks are measured as the ratio of workers completing high school to those not completing high school. Physical capital stocks are the average capital stock per worker. Land stock is measured as a country's land area. Note that all inputs in our following analysis are on a per capita basis, i.e., dividing the inputs by the country's population. The population data come from the World Bank.

Input intensities. The measures of water intensity, skill intensity, capital intensity and land intensity come directly from Debaere (2014). Water intensity is measured as the ratio of the cost

[4] http://unstats.un.org/unsd/classifications/Econ

of water use over value added plus the cost of water use. Skill intensity is the wage share of nonproduction workers to the total number of workers. Capital intensity is the sectoral capital stock divided by the value added in each sector. Land intensity is measured as the ratio of land use to total factor use for a sector. The products in Debaere (2014) follow IO1997-10 digit HTS concordance. We convert the IO1997 codes to the 5-digit SITC codes and then the SITC 2-digit level, following the guidance from the US Bureau of Economic Analysis (BEA) and UNSD. Note that all intensities only have variations at the sector level and remain constant across countries and over time. Such practice follows the HO literature and allows us to see how the resource differences, instead of technology differences, affect trade.

Climate projections. The projected precipitation data for the long-run simulations are from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP). The NEX-GDDP dataset is derived from the general circulation models (GCM) conducted under the Coupled Model Intercomparison Project Phase 5. The NEX-GDDP dataset provides daily downscaled projections under RCP4.5 and RCP8.5 from 21 GCMs at a spatial resolution of 0.25 degrees from 1950 to 2100. Temporally, we sum up the daily precipitation to the annual level. Geographically, similar to our baseline analysis, we construct the precipitation at the country level using the population density (year 2020) in the grid of NEX-GDDP as the weight. Our main results are produced using the median projected precipitation and climate from the 21 GCMs. We assess the uncertainty by using the 75th and 25th of the projected precipitation from 21 GCMs.

Population projections. The future population projections are from the Shared Socioeconomic Pathways (SSPs). The SSPs depict a set of plausible scenarios of socio-economic development over the twenty-first century that are predicted by integrated assessment modelling (Riahi et al., 2017). The population projection is produced by the International Institute for Applied Systems Analysis (IIASA) in the SSP database. We obtained SSP2, SSP3 and SSP4 projections that yield carbon emissions that fall between RCP4.5 and RCP8.5 in integrated assessment modelling exercises (Carleton et al., 2022). Projected population does not differ between the RCP4.5 and RCP8.5 scenarios, as this practice does not provide additional information in our context. Population data are originally in five-year increments and we use the implied annual growth rate to construct the projected population in each future year.

Auxiliary data. The production data are from the World Bank. The variables include value added per capita in agricultural and industrial sectors. The unit of observation is country by year and the data range from 1999 to 2019. Agricultural TFP and its growth rate are from the U.S. Department of Agriculture. The data range from 1995 to 2019. The data have been used in other climate impact studies such as Ortiz-Bobea et al. (2021).

Trade logistics are assessed using the logistics performance index (LPI), which is derived from the Logistics Performance Survey conducted by the World Bank in collaboration with private companies and individuals involved in international logistics. This survey has been conducted in the years 2007, 2010, 2012, 2014, 2016, and 2018. LPI evaluates a country's port logistics performance based on six dimensions: the efficiency of the customs clearance process, quality of trade related infrastructure, ease of arranging competitively priced international shipments, quality of logistics services, ability to track and trace consignments, and frequency with which shipments reach the consignee within the scheduled time. The index ranges from one to five, with a higher score representing better performance.

While the logistics evaluation is conducted at the port level, the public version of LPI varies by country and year. Our precipitation at the national level may not capture the water resources at the port locations. Therefore, we first identify the port locations as a point feature from the World Port Index.[5] Next, we extract the monthly precipitation depth (unit: meter) in the ERA5 grid in which the ports locate. To merge LPI with the precipitation data, we average the precipitation at the port level to form the country by year panel.

2.2 Data Pattern

Climate change is expected to cause increased variability and reduced predictability of precipitation, resulting in the redistribution of water resources. Figure 1 shows the average annual changes

[5] https://msi.nga.mil/Publications/WPI

in precipitation by country during 2000-2019 in Panel A, and the projected changes in RCP8.5 scenario during 2080-2099 in Panel B. Panel A shows that relative to the annual average in 1995-1999, precipitation dropped in most countries during 2000-2019. The magnitude is particularly large in Africa, with a decrease of 65% relative to the baseline. Panel B shows a different pattern for the end of the century: the areas around the Mediterranean Sea are projected to experience the largest decrease in precipitation in 2080-2099, relative to the annual average in 2015-2019. Most countries in Latin America and some countries in southern Africa and Oceania are projected to experience losses in precipitation. The comparison between Panels A and B highlights that the pattern of water redistribution changes over time: many of the countries in Asia, North America, and Africa experienced losses in precipitation during 2000-2019 will see increases during 2080-2099, relative to the baseline levels in 1995-1999.

The demand for water resources will increase dramatically due to the rising population and income. Within the next 30 years, the demand for water in agriculture could rise by 50%, and demand for urban use could increase by 80% (Flörke et al., 2018). Figure 2 illustrates the percentage changes in precipitation per capita by region over time. Panel A shows that, compared to the annual average in 1995-1999, precipitation per capita decreased and fluctuated in all regions during 2000-2019. The population growth drove the overall decreasing trends, while changes in precipitation explained the fluctuations. The fluctuations are much larger when we examine the precipitation pattern for each individual country. Panel B projects that the Middle East and Africa will experience a drop in precipitation per capita by up to 50% by the end of the century under the RCP8.5 (business-as-usual) scenario, whereas Europe and Asia will experience an increase of about 50% relative to the annual average in 2015-2019.

The pattern of water redistribution becomes more apparent when considering changes in the relative precipitation. The relative precipitation between regions A and B is the ratio of precipitation per capita in region A relative to that in region B.[6] Figure A2 shows the average annual changes

[6]To better understand the trends of relative precipitation over time, Figure A1 reports the changes (%) of relative precipitation per capita over year. Relative precipitation per capita fluctuates drastically over year in 2000-2019 and gradually increases in 2020-2099. The increasing trends of relative precipitation per capita over time is driven by the current trade structure and population distribution. Higher proportion of current exporters (importers) is developed

(in %) in relative precipitation per capita by region in 2000-2019 and 2080-2099 in RCP8.5 scenario. Blue colors indicate increases while red colors indicate decreases. For example, the first grid (row 1, column 1) in Figure A2A shows that compared to the 1995-1999 baseline, the relative precipitation between "Sub-Saharan Africa" and "East Asia and Pacific" decreased by 18% in 2000-2019.

Three observations emerge from Figure A2. First, exports from "Sub-Saharan Africa" and "Europe to Central Asia" experienced the largest decrease (-26%) in relative precipitation in 2000-2019. Second, "Sub-Saharan Africa" and "Middle East and North Africa" experienced declines in relative precipitation compared to most regions, while "Europe and Central Asia" and "North America" gained in relative precipitation compared to most regions. Third, the patterns of relative changes in precipitation between 2000-2019 and 2020-2099 in RCP8.5 scenario are quite similar, which contrasts with the differing patterns of changes in absolute precipitation shown in Figure 1 between the two time periods. Both Figures A2A and A2B have more red colors in the upper triangular areas and blue colors in the lower triangular areas, indicating decreasing and increasing precipitation, respectively, in row regions relative to column regions. However, the magnitude of the changes in Figure A2B is much larger than those in Figure A2A in absolute values.

Since water is a key input for production, relative precipitation and its induced water redistribution is likely to affect international trade, particularly for the industries that are more water dependent. As demonstrated in the HO literature, comparative advantage stems from the country-industry matches because industries vary in the factors needed for production and countries differ in these factor endowments. We follow the terminology in Chor (2010) and designate the interaction between relative precipitation and water intensity as the comparative advantage of water. Figure A3 shows the correlation between trade and the comparative advantage of water, which motivates our empirical specification in the next section. In Figure A3A, the y-axis denotes the residuals from regressing logarithmic trade volume on various fixed effects in Equation (1), and the x-axis denote the residuals from regressing comparative advantage of water on the same set of

(developing) countries whose populations are projected to grow slower (faster); higher proportion of current importers is developing countries whose populations are projected to grow faster.

fixed effects. The positive correlation suggests that trade volume increases as the comparative advantage of water increases. Figure A3B further demonstrate that the positive correlation between trade volume and relative precipitation is mainly driven by industries with high water intensity.[7]

3 Empirical Strategy

To estimate the effect of precipitation on bilateral trade, we specify the following equation based on the gravity model in the trade literature:

$$\log\left(y_{ijkt}\right) = \sum_{h=1}^{4}\left(\alpha_h RF_{ijt}^{h} + \beta_h FI_k^h * RF_{ijt}^{h}\right) + \tau_{ij} + \delta_{it} + \mu_{jt} + \pi_{kt} + \zeta_{ik} + \eta_{jk} + \varepsilon_{ijkt}, \qquad (1)$$

where y_{ijkt} measures the value of trade flows from exporter i to importer j in industry k during a 5-year period t. RF_{ij}^{h} measures the relative factor endowment h per capita in exporter i divided by the importer j's factor per capita. We include four factors: precipitation, skilled labor, capital, and land indexed by $h = 1,2,3,4$, respectively. Our key variable of interest is the relative precipitation per capita. The relative measure accounts for the fact that bilateral trade flows are inherently influenced by the determinants of both exporting and importing countries. It also captures the intuition of comparative advantage that trade volume and trade structure remain unchanged when the inputs and outputs in all countries change proportionally. FI_k^h is the sectoral intensity of factor h in industry k, defined as the ratio of the cost of factor h over value added plus the cost of factor use as defined in Debaere (2014).

Since the factor endowments vary over time in our model, the interaction terms between the factor intensity and relative factor endowment capture the Rybczynski effects in the HO framework. In the case of water, the Rybczynski theorem predicts a positive coefficient on the interaction term, implying that water-abundant countries export more in the sectors with a high water intensity; and that water-scarce countries import more in the sectors with a high water intensity. Coefficients α_h capture the effect of factor endowment when the corresponding intensities of water, skilled labor,

[7] Industries with high water intensity include the sectors of "food and live animals", "Beverages and tobacco", "Crude materials, inedible" and "Mineral fuels etc". Industries with low water intensity include the other sectors.

capital and land in an industry equal zero.

To address the endogeneity concern due to unobservables, Equation (1) controls for a rich set of fixed effects in various dimensions following the literature (Bombardini et al., 2012; Cai and Stoyanov, 2016; Nunn, 2007; Romalis, 2004). The country-pair fixed effects (τ_{ij}) control for bilateral time-invariant components of trade costs, including distance and various trade polices (Baier and Bergstrand, 2007) as well as other factors proposed by the HO literature, such as contract enforcement (Nunn, 2007) and skill distribution (Bombardini et al., 2012). The exporter-by-time fixed effects (δ_{it}) and importer-by-time fixed effects (μ_{jt}) control for exporter or importer specific time varying confounders such as production costs and destination prices (Egger and Nigai, 2015; Shapiro, 2016). Furthermore, industry-by-time fixed effects (π_{kt}), industry-by-exporter fixed effects (ζ_{ik}), and industry-by-importer fixed effects (η_{jk}) are also included to control for industrial specific time shocks as well as the changes in industrial structures. Our analysis uses precipitation as a proxy for water resources. Precipitation is likely exogenous to the unobservables conditional on this rich set of fixed effects.

Anderson and Van Wincoop (2003) emphasize the role of multilateral resistance (MR) in the gravity model in that changes in trade costs on one bilateral route can impact trade flows on all other routes due to relative price effects. To address the MR issue, various approaches have been proposed, but the fixed effect models, as recommended by Head and Mayer (2014), are preferred in the literature. As trade costs may potentially vary by industry and time, we evaluate the robustness of our findings by progressively including additional fixed effects not shown in Equation (1), including exporter-by-importer-by-time FEs, exporter-by-industry-by-time FEs, and importer-by-industry-by-time FEs.

Our empirical framework differs from that of Debaere (2014) and previous empirical HO studies in three aspects. First, we incorporate time-varying precipitation by utilizing changes in the hydrological cycle to capture the Rybczynski effects. Earlier HO studies usually rely on cross-sectional data, and as such, their findings represent the long-run effects driven by factor endowment differences, instead of changes in factor endowments.

Second, our data structure is disaggregated at both the exporter and importer levels, whereas previous studies utilized data at either the exporter or importer level. Our data structure not only enables us to evaluate the comparative advantage of water, as typically done in the literature, but also provides the opportunity to examine the trade flow matrix for each exporter-importer pair. Such an approach offers valuable insights to policymakers, as the role of exports and imports may differ across countries.

Third and most importantly, different from absolute water resources studied in the literature, we utilize the relative precipitation per capita, accounting for water resources in both exporters and importers. The relative measure is consistent with the Rybczynski theorem which highlights the changes in exporters' factor endowments while implicitly assuming that factor endowments in trade partners remain unchanged. The theorem implies that when an exporter's factor endowment increases but an importer's factor endowment increases to a larger extent, the factor prices of the exporter may not decrease, and the production and export of the exporter may not increase. While a country's absolute water resources influence trade flows as shown in Debaere (2014), our findings highlight the important role of relative water resources that cannot be captured by absolute water resources. In our empirical specifications, the exporter by time fixed effects fully absorb the variation in absolute water sources.

4 Estimation Results

4.1 Main Results

Marginal effects. Table 1 presents the estimate of the effect of relative precipitation on trade flows from Equation (1). Column 1 starts with a specification with the fixed effects in three dimensions, country-pair fixed effects, industry fixed effects and time (5-year period) fixed effects. Columns 2 and 3 gradually allow the interactions of fixed effects in the previous three dimensions, to control for unobservables in various dimensions as discussed in the previous section. Column 4 controls for the multilateral resistance by including the exporter-by-importer-by-time fixed effects, exporter-by-industry-by-time fixed effects and importer-by-industry-by-time fixed effects.

Overall, starting from column (2), the results are robust to adding further fixed effects. Because specification (2) can identify the main effect of precipitation, which is necessary for predicting the overall impacts of precipitation in the next section, we use specification (2) as the benchmark specification.

Specification (2) shows a positive coefficient estimate for the interaction term, implying that relative precipitation is a determinant of a country's comparative advantage. The coefficient estimates imply that a one-unit increase in relative precipitation per capita boosts trade flows by 1.4% for an average industry with water intensity of 0.016. For the industry with the highest water intensity of 0.465, a one-unit increase in relative precipitation per capita boosts trade flows by 40.5%. The coefficient estimate on the relative precipitation variable itself is insignificant and small, suggesting that changes in water resources may not have any trade impact on industries that do not use water.

To aid interpretation, we transform the estimates into elasticities. Given the mean of the relative precipitation per capita being 4.7, the elasticity of trade with respect to relative precipitation is 0.07, implying that a 10% increase in relative precipitation results in a 0.7% increase in trade flows. To provide more detailed information, we report the elasticities separately for each 2-digit SITC industry in Figure 3 evaluated at the mean of the relative precipitation level. The elasticities are higher for industries with higher water intensities. For example, the elasticities are approximately 0.3 for the industries of "Food and live animals" and "Crude materials, inedible, except fuels". For the industries of "Beverages and tobacco" and "Mineral fuels, etc.", the elasticities are approximately 0.07. However, the effects in other industries are negligible.

To our knowledge, our study is the first to estimate the elasticity of trade flows with respect to relative precipitation per capita. The closest counterpart in the literature is the average elasticity of exports with respect to (absolute) precipitation per capita in Debaere (2014). Our estimate of 0.07 is larger than his estimate of 0.018, but they are largely comparable in magnitude, despite significant differences in data structure and the estimation framework.[8] Conceptually, it is not

[8] In table A6, we also compare the trade effects of different inputs.

clear *a priori* which estimate should be larger between ours and Debaere (2014). On the one hand, the results from the cross-sectional data as in Debaere (2014) are usually interpreted as the long-term effects, which are likely to be larger than the shorter-term impact in our study. On the other hand, our data structure at the country-pair level is more disaggregated with an additional dimension in importers. The substitutes among different importers for a given exporter could lead to larger estimates in elasticities.

Overall effects. We compute the overall effect of precipitation changes on trade flows from 2000 to 2019 relative to the period of 1995-1999 by combining the estimated coefficients in Equation (1) with the actual changes in precipitation. Although our estimated elasticities are largely comparable in magnitude to those found in Debaere (2014), the overall effects of precipitation on trade vary significantly when we account for the varying bilateral strength in precipitation per capita. In Debaere (2014), the model only considers the exporters and the findings imply that the overall effects of precipitation per capita on trade would be negative as the population growth would result in a decrease in precipitation per capita in most countries. However, if precipitation per capita in all countries decreases proportionally, comparative advantage across countries as measured by the relative precipitation would stay the same, and hence trade flows would stay the same in our framework.[9]

Our empirical framework considers not only the water resources of the exporter but also those of the importer as well as the number of importers, all of which can affect trade flows. Therefore, the trade effect of changes in precipitation per capita within an exporter's own country is ambiguous a priori. To illustrate the point, let's consider China as an exporter, which had 201 trade partners in 2010. Even though China's precipitation per capita decreased in 2010 relative to the average in 1995-1999, the precipitation per capita in 92 of its trade partners decreased at a faster rate than in China, while the precipitation per capita in 109 trade partners decreased at a slower rate. As a result, the effect of relative precipitation on trade flows increased in some trade pairs but

[9] If comparative advantage cannot be adequately captured by the relative precipitation as constructed in our paper (e.g., due to a threshold effect in production), trade patterns could still change even if the water resources change proportionally across countries.

decreased in others. Therefore, the overall effect of precipitation per capita on China's trade needs to take into account the changes in precipitation per capita in all the trading partners.

Figure 4A reports the predicted trade flows driven by the spatial changes of precipitation at the global level during 2000-2019 relative to those in 1995-1999. The blue line indicates the aggregate gains in exports among the exporter-importer pairs that would see an increase in export, and the red line indicates the aggregate losses in exports among the exporter-importer pairs that would see a decrease in export. The grey line indicate the net effects by adding the changes across these two groups of the country pairs. Specifically, Figure 4A shows that the trade gains and losses are $3.78 and -3.87 billion in 2019, respectively, relative to the export levels in 1995-1999. In total, from 2000 to 2019, the trade gains and losses are $65 and -50 billion, respectively.

The agricultural sector is the single largest anthropogenic water user, consuming over 70% of the available freshwater (Flörke et al., 2018). With rising population and income, it is expected that by 2050, global demand for agricultural production will increase by 70% (FAO 2021). Our analysis reveals that from 2000 to 2019, the total trade gains and losses in agriculture (represented by the sector of "food and live animals") were $16 and -13 billion, respectively, accounting for about 25% of the overall effects of precipitation on trade.

Figure 5 reports the precipitation effects on agricultural trade from 2000 to 2019 for individual countries. Three observations arise. First, Figure 5A shows that there is heterogenous impacts within each continent where some countries gain while others lose. Some countries in Africa, South America and East Asia are associated with the largest losses in export. Second, Figure 5B depicts that the countries that observe increases in import during this period concentrate mostly in Africa, South America and East Asia. In contrast, countries in North America, Europe and Oceania see decreases in imports. Third, the effect may be asymmetric: countries with an increase in export may not necessarily see a reduction in import. For example, both exports and imports dropped in Vietnam but grew in France.

The observations of both gains and losses depicted in Figure 4A reflect the trade adjustment owing to changes in precipitation. To further examine the adjustment, Figure A4A reports the estimated bilateral trade flows driven by precipitation changes in seven regions for all industries. Looking at the bilateral trade reveals significant heterogeneity in impacts across regions. The grids show the annual average changes in trade between two regions in 2000-2019, relative to the level during 1995-1999. The directions of trade are from the horizontal regions, i.e., exporters, to the vertical regions, i.e., importers. The diagonal cells represents the trade response within regions while the non-diagonal cells between regions. Blue color is associated with positive numbers while the red indicates negative numbers, indicating increases and decreases in trade flows, respectively. Summing up all columns in each row produces the changes in overall exports from the row regions; Summing up all rows in each column produces the changes in overall imports to the column regions.

Two findings emerge. First, some regions gain but others lose from the changes in precipitation. The largest gains in trade are observed between "Europe and Central Asia" (ECA) and "Middle East and North Africa" (MENA) while the largest losses in trade are observed between "East Asia and Pacific" (EAP) and "Europe and Central Asia" (ECA). Take the cell of "EAP - ECA" for example, the average annual trade from EAP to ECA decreased by $181 million from 2000 to 2019, relative to the grid's average annual trade during 1995-1999. This implies that total exports from EAP to ECA decreased by $3.6 billion in total during 2000-2019 due to the change of comparative advantages in water resources.

Second, trade adjustments occur both within region and across regions. Within the region, we take the EAP-EAP cell for example. The annual net exports from EAP to EAP increased $138 million as depicted in Figure A4A, but the annual exports within EAP increased $441 million and decreased $303 million due to changes in trade partners and industries as shown in the corresponding EAP-EAP cells in Figure A5A and A5B. To understand the changes across the regions, we take the row of EAP for example. While the EAP region saw the largest losses in exports to ECA, the EAP region increased exports to other five regions such that the net effects on trade in EAP is positive. Particularly, the annual exports within EAP as well as from EAP to MENA increased by $138 and 151 million, respectively.

4.2 Robustness

Zero trade. Trade data at a granular level often includes a substantial number of observations with a value of zero, as is the case in our study. Removing these observations runs the risk of introducing sample selection bias. Furthermore, excluding trade flows with a zero value may lead to an incomplete evaluation of the trade adjustment process. To assess the robustness of our findings, we include the observations with zero value. The zero-trade sample is constructed by expanding the trade flow to all possible trade partners in all years as long as a trade flow in a country-pair is recorded in the data in any year. This data filling nearly triples the sample size to about 9 million observations.

In Table A2, we estimate a Poisson model following Silva and Tenreyro (2006) where the dependent variable is specified as trade flows in levels rather than in logarithms. The interpretation of the coefficients from the Poisson model is exactly the same as under OLS. The results show that the coefficients across different models are robust. The magnitudes are comparable with the main results in Table 1. These results suggest that our key findings are unlikely driven by the observations with zero value.

Alternative measures of water intensity. We examine the robustness of our findings to alternative measures of water intensities. The results presented in Table 1 employ the measure of direct and blue water following the main specification in Debaere (2014). Alternatively, the measure of water intensity could encompass both blue and green water, with blue water being composed of surface and groundwater, and green water being stored in soil or vegetation. Additionally, water intensity could include direct water as well as indirect water, the latter of which is calculated using Input-Output tables and represents the water used in the intermediate inputs of a good.

Table A3 assesses the robustness of our results to different measures of water intensity following Debaere (2014). Column 1 focuses on the direct and indirect water as well as the blue water. Column 2 uses direct water as well as the green and blue water. Column 3 uses the direct and indirect water as well as green and blue water. Column 4 takes the average of the previous four measures of water intensity. The results are robust to different measures of water intensity.

Another concern of water intensity is the underpricing of water. Recall that factor intensity is measured as the ratio of the cost of factor use over value added plus the cost of factor use. This practice is reasonable for labor or capital intensities when market prices exist for labor and capital. In case of water, the usage intensity may be misleading because the observed water prices are usually free, subsidized or systematically below its true prices such that some sectors, such as agriculture, may be considered as non-water-intensive sectors. While we acknowledge this caveat, we note that the water price we adopt is constructed based on the data from the U.S. as in Debaere (2014) where the prices are less underpriced. Additionally, following the HO literature, the input intensity does not vary over countries and what matters for identification is the ranking of water intensities across different sectors.

Alternative measures of water resources. One concern with the measure of per capita precipitation is that population movements across countries could be affected by precipitation, water endowments, and economic activities. If the positive effects of trade owing to increased water resources create more jobs and attract more migrants, the per capita measures that we use will become endogenous. Given that migrants account for only a small portion of the total population, our results are less likely to be affected by population migration. Nevertheless, we further examine this issue by constructing the precipitation per capita using the population in 1994, the year before our data start. This measure alleviates the concern of migration as the population measure is pre-determined and held constant. Column 1 in Table A4 shows that the estimates remain robust. Lastly, migration varies at the exporter-importer-year level so models with the exporter-importer-year FE are able to absorb the effects driven by migration. Our results are robust to controlling the exporter-importer-year FE in Column 2, suggesting that migration is not a driving factor in our analysis.

Second, we examine the robustness of our findings to the weight we use to aggregate the precipitation data. The raw precipitation data is at a 30 km by 30 km resolution, and we aggregated the data to the country level, with the grid population serving as the weight. This method accounts for the distribution of water resources and human activities within each country. In Columns 3 and 4 of Table A4, we examine the robustness of our findings by using an unweighted version of precipitation in models with different fixed effects. The results remain largely the same.

Third, precipitation is only one part of water resources. Countries with less precipitation may rely on other sources of water, such as upstream transboundary water, melt glaciers and ground water. Regarding upstream transboundary water, it may bring large measurement errors when the country size is small. We address this concern by excluding countries that are small. A small country refers to a country whose size is less than 10% or 25% of the country size distribution (9 or 54 thousand square kilometer). Columns 5 and 6 of Table A4 report the findings by excluding country pairs with the size of either exporters or importers less than 10% or 25%, respectively. The findings remain stable.

Regarding melt glaciers and ground water, we address this concern by showing that precipitation, as a proxy for water resource, can capture changes in melt glaciers and ground water.[10] Specifically, we examine the effects of precipitation on terrestrial water changes by using the data from the Gravity Recovery and Climate Experiment (GRACE) mission. Changes in total water storage monitored by the GRACE satellites include changes in snow water storage, surface water reservoir storage, soil moisture storage, and groundwater storage. Figure A7 shows that the relationship between precipitation and water resources is close to linear. On average, a one-standard-deviation increase in precipitation per capita increases changes in terrestrial water storage by 0.9 standard deviation.[11] The findings confirm that precipitation itself is the key driver of terrestrial water changes.

Relative precipitation and absolute precipitation. We compare the effects of relative precipitation and absolute precipitation. Column 1 in Table 2 corresponds to Column 1 in Table 1

[10]We do not estimate the effects of relative terrestrial water changes on trade because trade flows and terrestrial water changes are mutually determined, which leads to biased estimates. In contrast, relative precipitation is exogenous after including a large set of fixed effects. Additionally, one of our goals is to simulate future impacts of water changes under different climate scenarios. The future projection requires future water resources as inputs. The project changes in terrestrial water storage are not available in the climate simulations but the projected precipitation under different RCP scenarios are readily available.

[11]Note that it is not feasible to estimate the effects of relative terrestrial water changes on trade with the relative precipitation as an instrument because terrestrial water changes contain both positive and negative values such that relative terrestrial water changes, i.e. terrestrial water change per capita in exporter divided by terrestrial water changes per capita in importer, is not a meaningful measurement.

but includes the interaction term between water intensity and exporters' precipitation per capita, as well as the interaction term between water intensity and importers' precipitation per capita. Our findings generally align with our expectations, as water-abundant exporters tend to export more in sectors with higher water intensities, while water-scarce importers tend to import less. However, there is one exception with a positive coefficient estimate for precipitation in importers, which may be attributed to omitted variable bias. In Column 2 of Table 2, we introduce additional fixed effects as in Column 2 of Table 1. The coefficient estimate for the interaction term with exporters turns negative and becomes statistically insignificant, whereas the coefficient estimates for the interaction term with importers retain the same sign.

Moving to Column 3, we focus on the precipitation in exporters and fully absorb the interaction term with importers by including importer by industry by time fixed effects. The coefficient estimates for the interaction term with exporters continue to lack significance. Similarly, in Column 4, we emphasize the precipitation in importers and absorb the interaction term with exporters through exporter by industry by time fixed effects. The coefficient estimate for the interaction term with importer becomes insignificant. Overall, the coefficient estimates for relative precipitation remain stable across different specifications, whether including or excluding absolute precipitation. However, the coefficient estimates for absolute precipitation in both exporters and importers exhibit instability. These results suggest that the relative abundance of water resources, rather than the absolute level, serves as the key determinant of comparative advantage.

Alternative model specifications. Lastly, we examine the robustness of our results to different model specifications and trade measurement. The results are reported in Table A5. Column 1 removes all other inputs as control variables. The findings remain robust, further suggesting that our results are unlikely to be confounded by unobservables. Column 2 uses the level of trade (rather than the logarithm scale) as the dependent variable. Column 3 uses the trade quantity (rather than in monetary terms) in logarithm as the dependent variables. The qualitative results are robust to these different specifications.

5 Mechanisms

This section explores three mechanisms underlying the estimated impact of water resources on trade: productivity, trade structure, and transport disruption.

5.1 Production Effects

To examine the effect of precipitation on agricultural and industrial production as well as TFP, we regress measures of output in logarithm and TFP on precipitation per capita at the country by year level. Table 3 reports the estimation results. Panel A reports the estimation results for agricultural and industrial value added per capita in Columns 1-2 and Columns 3-4, respectively. Columns 1 and 3 include the linear term of precipitation per capita while Columns 2 and 4 include quadratic terms. All regressions control for country fixed effects and year fixed effects.

Column 2 shows an inverted-U relationship between precipitation and agricultural production. On average, a one-unit increase (or 220%) in precipitation per capita increases agricultural value added per capita by 28.6% when evaluated at the mean of precipitation per capita. The nonlinear effects are consistent with existing literature that shows that agricultural production increases with precipitation first and then decrease (Auffhammer et al., 2006; Damania et al., 2020; Fishman, 2016). The nonlinearity also resonates with the destructive effects of drought and floods on agriculture and economic growth in recent literature (Kotz et al., 2022; Lesk et al., 2016).

Columns 3-4 in Panel A shows the precipitation effects on industrial value added per capita. While the results in Column 4 also show the inverted-U shape, the estimates of the squared term are not significant at the conventional significance. Therefore, we use the results in Column 3 for interpretation. A one-unit increase (220%) in precipitation per capita increases industrial value added per capita by 14%. The different findings in Columns 2 and 4 may reflect the fact that agriculture, as the biggest water user, usually locates close to water such that the negative effects from flood are larger than that in the industrial sector. As a result, we do not observe significant reduction in industrial production when the precipitation is at the right tail of its distribution. It is also possible that the country-level analyses lacks the statistical power to identify the nonlinear effects for the industrial sector.

Since agriculture is the key industry for water usage, we further explore the precipitation effects on agricultural TFP and the results are shown in Panel B in Table 3. Columns 1-2 and Columns 3-4 report the results for agricultural TFP and agricultural TFP growth rate, respectively. Columns 1-2 show that relationship between precipitation and agricultural TFP is close to linear and the estimates are not as precise as those in Panel A. However, there is a precisely estimated inverted-U relationship between precipitation and agricultural TFP growth rate. On average, a one-unit increase (220%) in precipitation per capita increases agricultural TFP growth rate by 3.3 percentage point evaluated at the mean of precipitation per capita. The marginal effect is equivalent to 0.5 standard deviation of agricultural TFP growth rate. The nonlinear effects are consistent with Ortiz-Bobea et al. (2021) which documents that climate change has slowed down the productivity growth in the agricultural sector.

5.2 Trade Structure

The second potential underlying channel of impact is the changes in trade structure in response to changes in precipitation. To examine this, we conduct linear regressions with the dependent variable being the number of industries in trade, obtained by counting the unique industry identifier in each exporter-importer pair. Table 4 reports the estimated effects of relative precipitation per capita on the existing number of industries that engage in trade. Columns 1 and 2 use the digit-2 SITC industries and Columns 3 and 4 use the digit-5 SITC industries. There are 67 industries for the digit-2 SITC and 2971 industries for the digit-5 SITC. Columns 1 and 3 include exporter fixed effects, importer fixed effects and time fixed effects, while Columns 2 and 4 include exporter-by-time fixed effects and importer-by-time fixed effects.

The results show that an increase in relative precipitation per capita reduces the number of industries engaged in trade. The elasticities of the number of industries in trade with respect to relative precipitation are -0.001 and -0.02 for the 2-digit and 5-digit levels, respectively. It is intuitive that the elasticity for the 5-digit level is larger than that for the 2-digit level because the finer industries have more substitutes. These findings are robust to the inclusion of different fixed effects. The findings suggest that when relative precipitation increases, trade would concentrate among fewer industries. In contrast, when relative precipitation decreases, trade become more diversified potentially as a way to mitigate the potential losses driven by changes in comparative advantage. Put it differently, the lack of diversification in industrial structure could exacerbate vulnerabilities to climate change. This underscores the need to support efforts to accelerate economic diversification.

Next, we further explore how the adjustment of industries discussed above is correlated with industrial water intensity. Our raw trade data are at the 5-digit level and our main analysis aggregate the data to the 2-digit level. Correspondingly, we derive a measure of water intensity at the 2-digit level by calculating the simple average of the water intensities from the more detailed 5-digit level. This construction method yields the 2-digit water intensity that varies across exporters, importers, industries, and years, solely reflecting changes in the composition of 5-digit industries engaged in trade (i.e. industrial change) rather than productivity. Following the same framework in Equation (1), we instead employ this 2-digit water intensity as the dependent variable to investigate whether countries with abundant water resources adjust their exports toward water-intensive industries.

Table 5 reports the estimation results and we focus on Column 2 for interpretation. Controlling for water intensity, a one-unit increase in precipitation per capita (equivalent to a 21% increase) leads to a 0.019 unit (or 133%) increase in water intensity resulting from sectoral changes in trade. The elasticities of sectoral water intensity with respect to precipitation is 0.1 on average. The response is larger in the "Food and live animals" industry, with the elasticity being 0.38. The results are robust to different specifications. In sum, the findings in Tables 8 and 9 show that changes in relative precipitation lead to adjustments in the composition of industries engaged in trade.

5.3 Transport Disruption

Marine transport accounts for 80% of world trade by volume (WTO, 2022). Key transport corridors and infrastructures can be affected by changes in water resources, potentially creating vulnerabilities in the global trade network. One the one hand, severe droughts lower water levels. Shallow water forces cargo ships to operate at lower capacity in order to navigate and transport commodities, causing significant congestion and delays around ports. This is highlighted in the recent severe delay in the Panama Canal, which is responsible for moving 40% of the world's cargo ship traffic, due to a historical drought in the area around the canal.[12] On the other hand, floods directly damage critical infrastructure, including roads, bridges and ports, which hurt firm productivities and disrupt global value chains.

This section examines the effects of water resources on transport by estimating the effects of precipitation on trade logistics performance index (LPI). Figure A6 shows the relationship between precipitation and LPI. As precipitation increase, the logistics performance first improves and then worsens. This analysis provides some initial evidence that both droughts and floods disrupt a country's port logistics performance. Table 6 shows the regression results with the dependent variable being LPI. To flexibly capture the nonlinear relationship between precipitation and LPI as shown in Figure A6, we implement a spline function with the knot at the 25% quantile of precipitation. Our findings are robust when gradually including control variables and region by year fixed effects.

Two findings emerge from Column 3. First, at the left distribution of precipitation (0-25%), a one-meter decrease in precipitation (925%) reduces logistics performance by 2.2 units (74%). The findings are consistent with the World Trade Report (2022) that recurrent droughts in recent years have frequently lowered water levels, diminishing the weight barges can carry, causing congestion and delays in the Paraná River, which transports 90% of Paraguay's international trade of agricultural goods.[13] Second, at the right distribution of precipitation (25%-100%), a one-meter increase

[12] See the report on the delay by the NPR here: https://www.npr.org/2023/08/27/1196219611/a-historic-drought-is-causing-a-huge-traffic-jam-at-the-panama-canal.

[13] https://www.wto.org/english/res_e/publications_e/wtr22_e.htm

in precipitation (925%) decreases logistics performance by 0.35 units (12%). Since this estimate is not significant at the conventional level, the results are suggestive and should be interpreted with caution.

6 Long-run Projections

This section projects the long-run impact of relative precipitation on trade flows. A key challenge is that the short-run effects of precipitation may not fully account for adaptation to future climate change. Adaptation could take place through a variety of human behavior adjustments. To capture adaptation, our strategy follows the recent studies that account for the role of adaptation in predicting future climate impacts on various outcomes including energy demand, mortality and household consumption (Auffhammer, 2022; Carleton et al., 2022; Heutel et al., 2021; Lai et al., 2022). Our model allows the main effect of precipitation and the HO interaction effect to evolve based on the water endowment. We estimate the following equation:

$$
\begin{aligned}
\log\left(y_{ijkt}\right) &= \alpha_{1s} \cdot RPrec_{ijt} \cdot \sum_{s=1}^{3} I_s\left(ED_{ij}\right) + \beta_{1s} \cdot WI_k \cdot RPrec_{ijt} \sum_{s=1}^{3} I_s\left(ED_{ij}\right) \\
&+ \sum_{h=2}^{4}\left(\alpha_h RF_{ijt}^{h} + \beta_h FI_k^{h} * RF_{ijt}^{h}\right) + \tau_{ij} + \delta_{it} + \mu_{jt} + \pi_{kt} + \zeta_{ik} + \eta_{jk} + \varepsilon_{ijkt}
\end{aligned}
\tag{2}
$$

where the $RPrec_{ijt}$ represents relative precipitation per capita between exporter i and importer j at time t. ED_{ij} is a proxy of relative strength in water endowment in the long term. Specifically, it is measured using the average relative precipitation per capita during a 30-year period between exporters and importers from 1970 to 1999. The assumption is that the long-term water endowment affects the adaptive behavior through various channels. Intuitively, if the relative water endowment of the US-China pair in the future converges to the US-Germany relative water endowment now, the future precipitation effects between the US and China will follow the precipitation effects between the US and Germany now. The relative water endowment enters Equation (2) in a non-parametric form, accounting for the fact that adaptation behaviors may have an accumulating stage and take place nonlinearly. Specifically, $I_s\left(ED_{ij]}\right)$ is a dummy variable indicating the top 30%, middle 40%

and bottom 30% of the relative strength in water endowment.

Table 7 shows the effect of relative precipitation on trade flows for the three levels of relative water endowment. The results are robust to different fixed effects. We focus on the results in column 2 for interpretation. The coefficient estimates for the interaction term between sectoral water intensity and relative precipitation per capita show that the precipitation effects become stronger when there are larger differences in water endowment between countries, suggesting that the precipitation effects vary with the relative water endowment.

Next, we define two measures of future precipitation impacts on trade flows relative to the base year 2015-2019, utilizing the estimated coefficients in Table 7 as well as the future precipitation and water endowments. In the projection without adaptation, the change of trade flow in a future year t relative to the base year 2015-2019 is:

$$\Delta\hat{y}_{ijkt}^{\text{NoAdapt}} = e^{f\left(RPrec_{ijt}, WI_{k,15-19}, ED_{ij,15-19}; \theta\right)} - e^{f\left(RPrec_{ij,15-19}, WI_{k,15-19}, ED_{ij,15-19}; \theta\right)} \tag{3}$$

In the projection with adaptation to water endowment, the change of trade flow in a future year t relative to the base year 2015-2019 is:

$$\Delta\hat{y}_{ijkt}^{\text{Adapt}} = e^{f\left(RPrec_{ijt}, WI_{k,15-19}, ED_{ijt}; \theta\right)} - e^{f\left(RPrec_{ij,15-19}, WI_{k,15-19}, ED_{ij,15-19}; \theta\right)} \tag{4}$$

Where ED_{ijt} is the predicted relative water endowments, i.e., the 30-year moving average of precipitation per capita during year $t-1$ to $t-30$.

Figure 4B shows the projected changes in trade flows over time with adaptation in the RCP8.5 scenario (the business-as-usual scenario) at the global level.[14] The blue line indicates increase in trade among the exporter-importer pairs which would observed a growth in export compared to the base year and the red line indicates reduction in trade among the exporter-importer pairs which

[14]Our main results focus on the case of adaptation because the projection of no adaptation and the projection of adaptation are very close, as shown in Panel A in Figure A8. The findings are consistent with the pattern in Panel B in Figure A1 that the relative precipitation in RCP8.5 and RCP4.5 scenarios are very close. The underlying reason is that the measure of relative precipitation account for the interactions among countries, instead of precipitation changes purely in each single country.

would observed a drop in export relative to the base year. The grey line indicate the aggregate effects among all country pairs. We find that trade gains gradually dominate the losses over time, which is consistent with the trends of relative precipitation per capita over year in Figure A1. The average annual trade gains and losses during 2080-2099 are $33 and -14 billion, respectively, relative to the average during 2015-2019. In total, from 2080 to 2099, the trade gains and losses are $660 and -280 billion, respectively, relative to the average during 2015-2019.

For the agricultural sector, the average annual trade gains and losses during 2080-2099 are $11.2 and -1.1 billion, respectively, relative to the annual average during 2015-2019. Figure 6 reports the average precipitation effects on agricultural trade from 2080 to 2099 for each individual country. First, Panel A shows that many countries in South America and East Asia, including Brazil and China, experience gains in net exports in 2080-2099, relative to the average during 2015-2019. In contrast, Australia and New Zealand experience losses in net exports. These patterns seem to run counter to those in Figure 5, highlighting the important role of adaptation. Second, high-latitude areas in the northern hemisphere, including America, Canada and many countries in Europe see increase in exports during both 2000-2019 and 2080-2099, relative to their corresponding baseline levels. Third, the impact on export is opposite to that on import in direction for most countries but there are some exceptions. For example, India gains in both exports and imports but Australia loses in both exports and imports.

The key driving forces underlying these comparisons between 2000-2019 and 2080-2099 are relative changes in population, precipitation and existing trade networks. First, countries that gain in 2000-2019 but lose in 2080-2099, such as Brazil and China, are usually those with fast population growth recently but will experience population decline at the end of century. Therefore, relative precipitation per capita decreases in 2000-2019 but increases in 2080-2099, leading to exports decrease during the first two decades of the century and then increase during the last two decades of the century. For the same reason, many developed economies in the northern hemisphere are slow in population changes both in 2000-2019 and 2080-2099, so the exports remain positive in both periods. Second, relative changes in precipitation also play a key role. Take Australia-Canada pair for example. These two countries have a similar population growth in 2080-2099, relative to the baseline 2015-2019, such that the trade flows in this pair are mainly driven by precipitation changes. As indicated in Figure 1B, projected precipitation in 2080-2099 would decrease in Australia but increase in Canada, hence the agricultural trade flows from Australia to Canada would decrease by 1.2 million. In additional, since the net trade impact in one country is determined by its trade with all its trading partners, some countries are projected to have gains (losses) in both exports and imports, such as India (Australia).

To further understand the directions and magnitudes of changes in trade flows in Figure 4B, we examine the predicted bilateral trade responses (in $10 million) for all sectors during 2080-2099 in Figure A4B. There are two differences from the changes during 2000-2019 depicted in Figure A4A. First, more areas in Figure A4B are in blue, indicating the trade gains surpassing the losses over time. Second, "South Asia (SA)", ECA and EAP continue to increase exports to "Middle East and North Africa". The magnitudes increase by nearly 10 folds by the end of the century. Meanwhile, SA and "North America (NA)" maintain similar losses in exports to ECA.

Uncertainty. Uncertainty is inherent in future projections of climate impacts so the projected average impacts should be interpreted with caution. There are three sources of uncertainty: regression uncertainty, emission uncertainty, and climate uncertainty (Burke et al., 2015a). Regression uncertainty stems from the econometric estimates of response functions using historical data, i.e., uncertainty in the regression coefficients. Emission uncertainty refers to the imperfect knowledge in the future trajectory of anthropogenic activities that might affect the climate system (e.g., RCP4.5 or RCP8.5). Climate uncertainty refers to the uncertainty in how the climate system responds to a given level of emissions. There is an ensemble of 21 GCMs typically used in national and international climate assessments.

To account for regression uncertainty, we follow the procedure in Carleton et al. (2022) and Hsiang (2010) to randomly draw a set of parameters 200 times, from a multivariate normal distribution characterized by the covariance matrix for the parameter estimates in Equation (2). Next, we construct a predicted response function by combining these parameter draws with the median values of precipitation and climate provided by 21 climate projections. Last, we take the 2.5th and 97.5th percentiles from the distribution of the outcomes to construct the 95% confidence interval. This is how we obtain the confidence intervals (grey areas) in Figure 4B.

To account for emission uncertainty, we report results under both RCP4.5 and RCP8.5 scenarios. Panel B in Figure A8 shows the projected trade changes in 2020-2099 in the cases of adaptation under climate scenarios of RCP4.5 and RCP8.5. The results from scenarios RCP4.5 and RCP8.5 are very close. Therefore, our main findings focus on the case of adaptation in RCP8.5.

To account for climate uncertainty, we discuss our key results using the 25th and 75th percentile values of precipitation and climate variables provided by 21 climate projections in Panel C in Figure A8. The global aggregate trade changes using 25th and 75th quantile values are in the same order of magnitudes with the main results based on median values of precipitation and climate. Specifically, global trade changes in 2080-2099 are projected to be $29, $19 and $12 billion for the 25th, 50th and 75th quantiles of precipitation and climate variables, respectively. Overall, our findings under different climate scenarios are largely comparable.

7 Conclusions

This paper examines the effects of water resources on international trade at a global scale. By exploiting the time variation in precipitation and sectoral bilateral trade flows, our analysis shows that relative abundance in water resources between the origin and destination countries is a crucial factor in determining a country's comparative advantage: water-abundant countries export more in sectors with a high water intensity while water-scarce countries import more in those sectors. We show that changes in water resources affect trade flows through at least three channels: productivity, trade structure, and transport. Based on climate projections, we estimate the long-run effects of relative water resources on trade flows by the end of century, and find substantial heterogeneity in the impacts across regions. The results indicate that the net global trade is likely to increase as a result of the changes in the spatial distribution of water resources from 2020 to 2099.

Our findings suggest that although climate shocks will continue to be costly and disruptive, trade could aid countries in enhancing their long-term preparedness and response, ultimately resulting in increased resilience against localized shocks. Nonetheless, when water is undervalued, particularly with the widespread water subsidies, whether implicit or explicit, trade may not provide an effective solution to the challenge of water scarcity.

While our analysis is conducted at the country level, recent studies have shown that using aggregated statistical models might underestimate the impact of precipitation due to the large cross-region heterogeneity within a country (Damania et al., 2020; Lobell and Asseng, 2017). To account for within-country variation in precipitation, future analysis on the impact of water resources on trade could leverage more granular trade data at the subnational level, where available.

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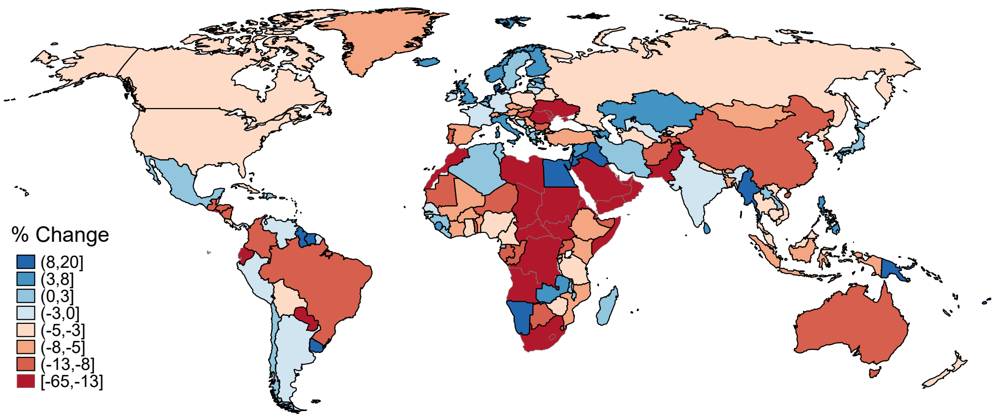
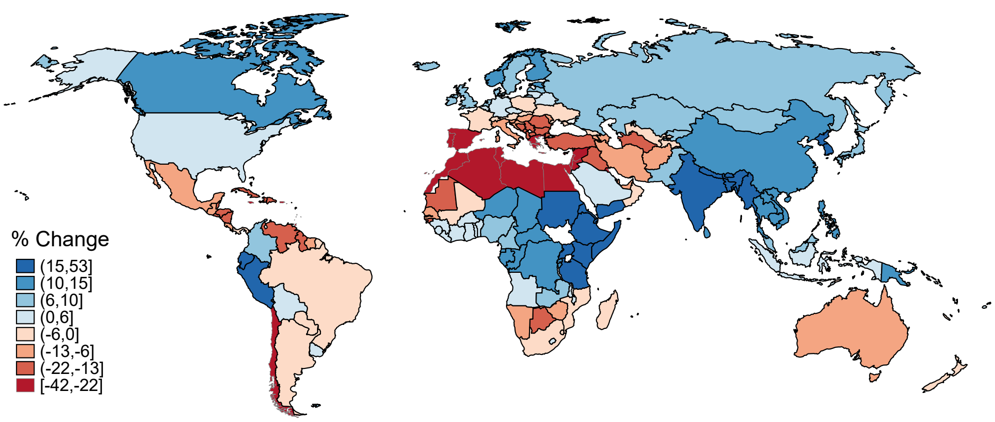
Figure 1: Changes (%) in precipitation by country



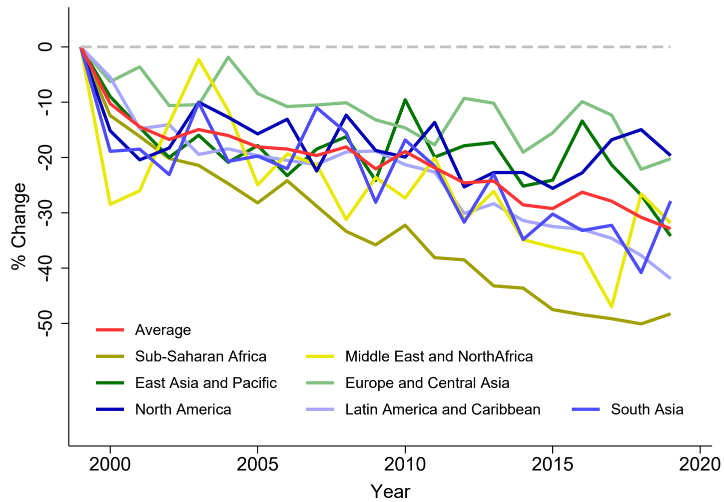
(A) 2000-2019



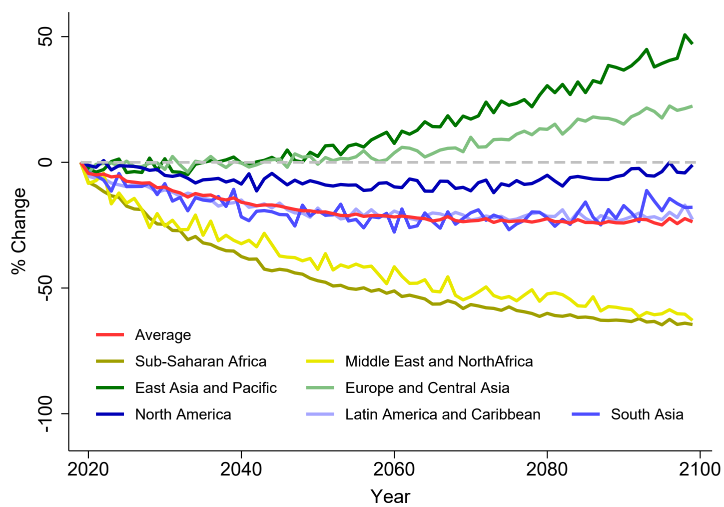
(B) 2080-2099

Notes: This figure shows the average annual changes (%) in precipitation by country in 2000-2019 and 2080-2099 in RCP8.5 scenario. Panel A shows the changes (%) in precipitation in 2000-2019, relative to the annual average in 1995-1999. Panel B shows the changes (%) in precipitation in 2080-2099, relative to the annual average in 2015-2019.

Figure 2: Changes (%) in precipitation per capita by regions over year



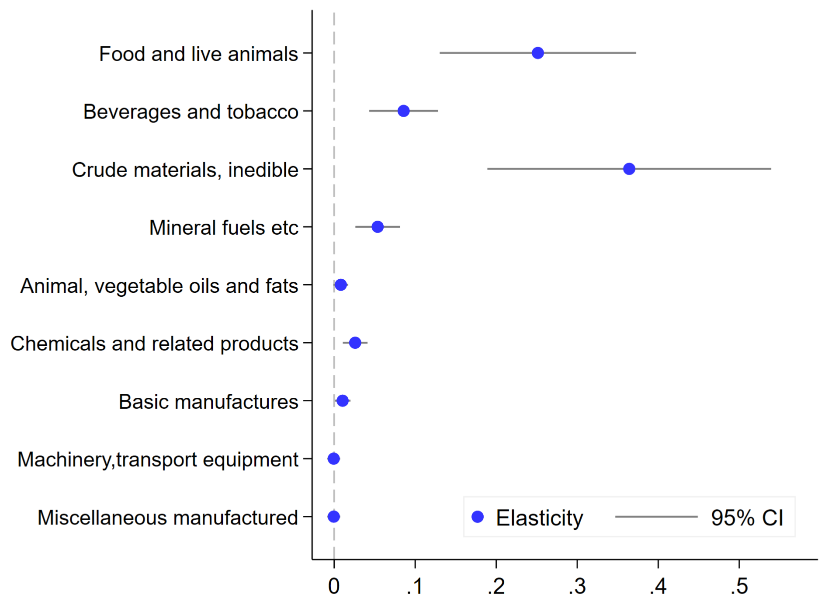
(A) 2000-2019



(B) 2020-2099

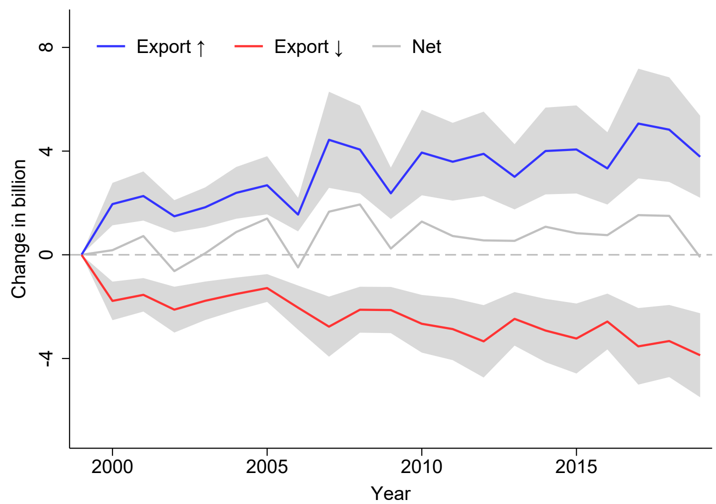
Notes: This figure shows the average annual changes (%) in precipitation by region over year. Panel A shows the changes (%) in precipitation in 2000-2019, relative to the annual average in 1995-1999. Panel B shows the changes (%) in precipitation in 2020-2099, relative to the annual average in 2015-2019 under the RCP8.5 (business-as-usual) scenario.

Figure 3: The effects of relative precipitation on trade by industry

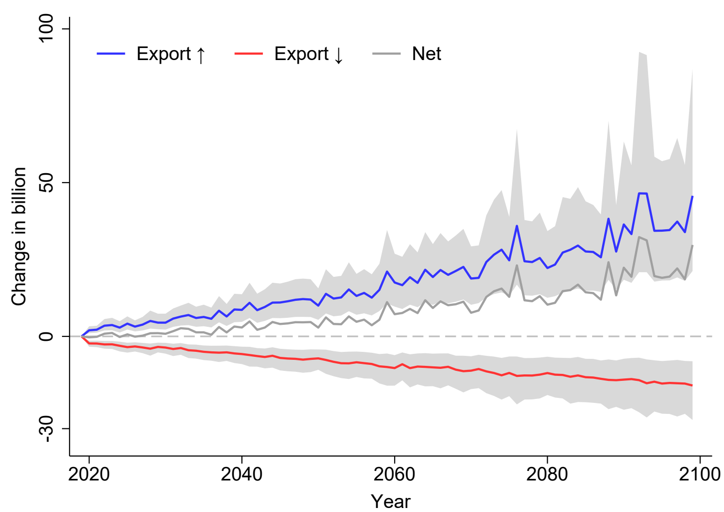


Notes: This figure shows the elasticities of trade flows with respect to relative precipitation per capita by 2-digit SITC industries from Equation (1). The grey bar shows the 95% confidence interval.

Figure 4: Projected trade changes



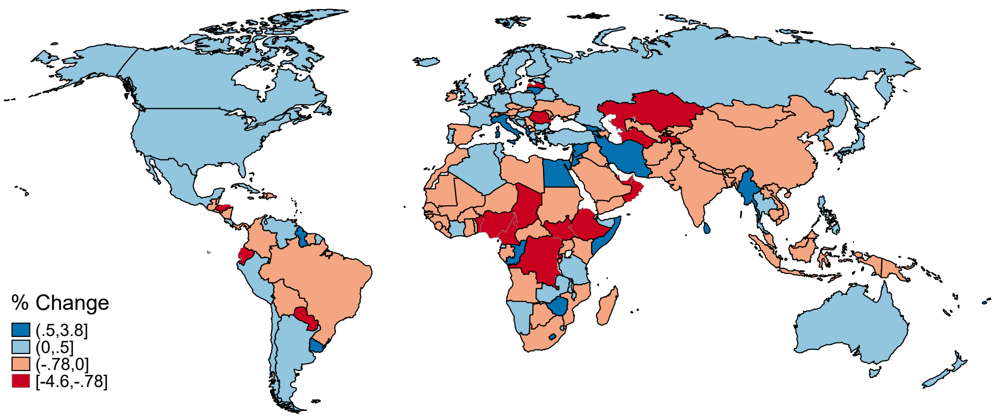
(A) 2000-2019



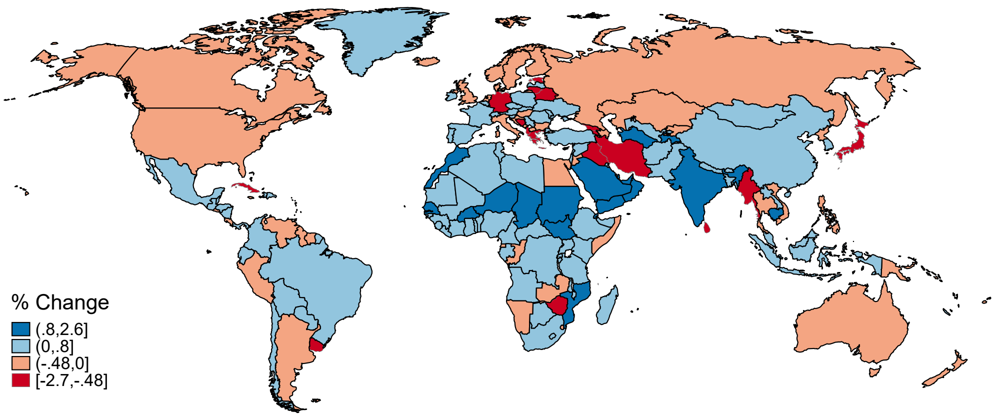
(B) 2080-2099

Notes: Panel A shows the predicted global trade flows driven by precipitation changes in 2000-2019, relative to the trade flows in 1995-1999, by combining the estimated coefficients in Equation (1) and the actual changes in precipitation across the countries. Panel B shows the predicted trade flows driven by precipitation changes in 2020-2099, combining the estimated coefficients in Equation (2) and the projected changes in precipitation in the case of adaptation under RCP8.5. The blue line indicates the gains in trade; the red line indicate the losses in trade; and the grey line indicate the net effects. The grey areas are 95% confidence intervals.

Figure 5: Projected agricultural trade changes (%) in each country, 2000-2019



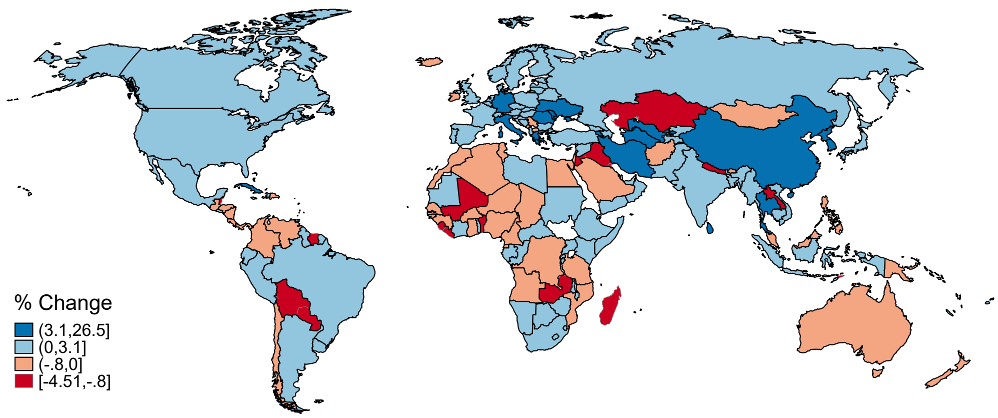
(A) Export



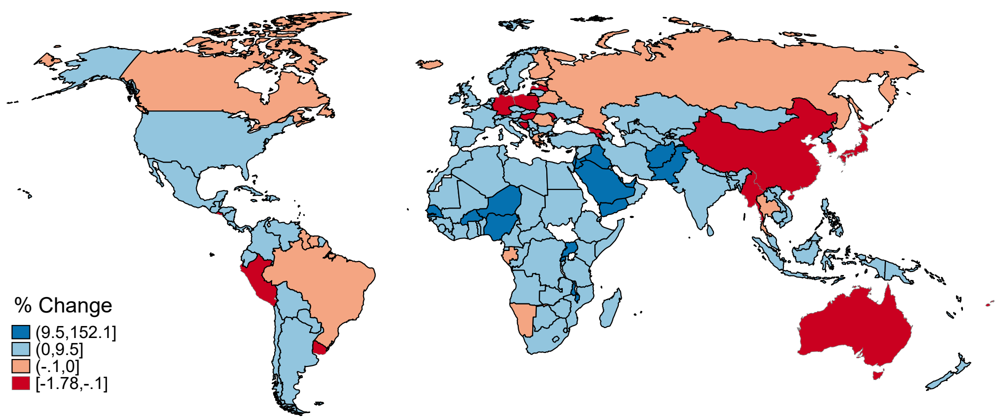
(B) Import

Notes: This figure shows the projected precipitation effects on agricultural trade flows from 2000 to 2019 for each individual country, combining the estimated coefficients in Equation (1) and the actual changes in precipitation. Panels A and B show the changes (%) for export and import, respectively.

Figure 6: Projected agricultural trade changes (%) in each country, 2080-2099



(A) Export



(B) Import

Notes: This figure shows the average precipitation effects on trade flows from 2080 to 2099 for each individual country, combining the estimated coefficients in Equation (2) and the projected changes in precipitation under RCP8.5. Panels A and B show the changes for export and import, respectively.

Table 1: The effect of relative precipitation on trade flows

	(1)	(2)	(3)	(4)
Variables		log(trade flow)		
WaterIntensity * RPrec	2.0075***	0.8735***	0.8561***	0.8802***
	(0.5009)	(0.2133)	(0.2148)	(0.2199)
RPrec	0.0094***	-0.0001		
	(0.0022)	(0.0009)		
Observations	3,441,109	3,441,109	3,441,109	3,441,109
Adjusted R2	0.5554	0.6929	0.7048	0.7149
Other inputs	Yes	Yes	Yes	Yes
Industry FE	Yes			
Time FE	Yes			
Exporter by importer FE	Yes	Yes		
Exporter by time FE		Yes		
Importer by time FE		Yes		
Industry by time FE		Yes	Yes	
Exporter by industry FE		Yes	Yes	
Importer by industry FE		Yes	Yes	
Exporter by importer by time FE			Yes	Yes
Exporter by industry by time FE				Yes
Importer by industry by time FE				Yes

Notes: This table reports the effect of relative precipitation on trade flows from Equation (1). The unit of analysis is exporter by importer by industry by each 5-year from 1995 to 2019. *RPrec* denotes relative precipitation per capita. Columns 1-4 gradually increase the dimensions of fixed effects. Control variables include labor, capital and land as well as their interactions with corresponding sectoral intensities. The standard errors in parentheses are clustered at the exporter by importer level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: The effect of relative precipitation and absolute precipitation

	(1)	(2)	(3)	(4)
Variables		log(trade flow)		
WaterIntensity * RPrec	1.8190***	0.8771***	0.9079***	0.8826***
	(0.4753)	(0.2137)	(0.2171)	(0.2187)
RPrec	0.0093***	-0.0002	-0.0005	-0.0003
	(0.0022)	(0.0009)	(0.0008)	(0.0009)
WaterIntensity * Prec in exporter	1.9902*	-0.8601	-1.3001	
	(1.0271)	(0.8304)	(0.8792)	
Prec in exporter	0.0089*			
	(0.0053)			
WaterIntensity * Prec in importer	-0.0015**	-0.0017*	-0.1042	
	(0.0006)	(0.0010)	(0.2367)	
Prec in importer	0.0040***			
	(0.0002)			
Observations	3,441,109	3,441,109	3,441,109	3,441,109
Adjusted R2	0.5555	0.6929	0.6959	0.7000
Other inputs	Yes	Yes	Yes	Yes
Industry FE	Yes			
Time FE	Yes			
Exporter by importer FE	Yes	Yes	Yes	Yes
Exporter by time FE		Yes	Yes	No
Importer by time FE		Yes	No	Yes
Industry by time FE		Yes	Yes	Yes
Exporter by industry FE		Yes	Yes	No
Importer by industry FE		Yes	No	Yes
Exporter by importer by time FE			Yes	Yes
Exporter by industry by time FE			Yes	No
Importer by industry by time FE			No	Yes

Notes: This table compares the effects between relative precipitation and absolute precipitation from estimating Equation (1). The outcome variable is trade flows in logarithms. The unit of analysis is exporter by importer by industry by each 5-year from 1995 to 2019. *RPrec* denotes relative precipitation per capita between the exporting and importing countries while *Prec* denote (absolute) precipitation per capita in the exporting country. Columns 1-4 gradually increase the dimensions of fixed effects. Control variables include labor, capital and land as well as their interactions with corresponding sectoral intensities. The standard errors in parentheses are clustered at the exporter by importer level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: The effect of precipitation on production and TFP

	(1)	(2)	(3)	(4)
	log(value added per capita)			
Variables	Agriculture		Industry	
Panel A				
Prec	0.117***	0.297***	0.139**	0.231*
	(0.035)	(0.066)	(0.066)	(0.139)
Prec * Prec		-0.023***		-0.012
		(0.006)		(0.012)
Observations	3,402	3,402	3,275	3,275
Adjusted R2	0.981	0.982	0.962	0.962
	Agri TFP		Agri TFP growth rate	
Panel B				
Prec	4.072*	6.981	0.0087*	0.0353**
	(2.262)	(5.898)	(0.0052)	(0.0139)
Prec * Prec		-0.458		-0.0042**
		(0.669)		(0.0016)
Observations	4,235	4,235	4,183	4,183
Adjusted R2	0.578	0.578	0.014	0.015
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: This table examines the precipitation effects on production and total factor productivity in panel A and panel B, respectively. The unit of analysis is country by year from 1999 to 2019 in Panel A and from 1995 to 2019 in Panel B. *Prec* denotes precipitation per capita. Columns 1 and 3 report the linear effects and Columns 2 and 4 report the quadric effects. The dependent variables from Columns 1-2 and Columns 3-4 in panel A are agricultural and industrial value added per capita in logarithms, respectively; the dependent variables from Columns 1-2 and Columns 3-4 in panel A are agricultural TFP and agricultural TFP growth rate, respectively. The standard errors in parentheses are clustered at the country level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: The effect of relative precipitation on the number of trade industries

	(1)	(2)	(3)	(4)
	Number of Industries			
Variables	SITC level 2		SITC level 5	
RPrec	-0.024**	-0.028***	-0.929***	-1.053***
	(0.009)	(0.010)	(0.265)	(0.287)
Observations	159,036	159,036	159,036	159,036
Adjusted R2	0.669	0.682	0.604	0.614
Other inputs	Yes	Yes	Yes	Yes
Exporter FE	Yes		Yes	
Importer FE	Yes		Yes	
Time FE	Yes		Yes	
Exporter by time FE		Yes		Yes
Importer by time FE		Yes		Yes

Notes: This table reports the effects of relative precipitation on the existing number of industries in trade. The dependent variable, the number of industries, is obtained by counting the unique industry identifier in each exporter-importer pair. The unit of analysis is exporter by importer by each 5-year from 1995 to 2019. *RPrec* denotes relative precipitation per capita. Columns 1 and 2 use the digit-2 SITC industries and columns 3 and 4 use the digit-5 SITC industries. Columns 1 and 3 include exporter FE, importer FE and time FE; columns 2 and 4 include exporter-by-time FE and importer-by-time FE. Control variables include relative labor, capital and land. The standard errors in parentheses are clustered at the exporter by importer level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: The effect of relative precipitation on average water intensity

	(1)	(2)	(3)	(4)
Variables	Time varying water intensity			
WaterIntensity * RPrec	0.0874***	0.0185**	0.0196**	0.0197**
	(0.0159)	(0.0076)	(0.0077)	(0.0078)
RPrec	0.0000	0.0000		
	(0.0000)	(0.0000)		
Observations	3,441,109	3,441,109	3,441,109	3,441,109
Adjusted R2	0.5488	0.6576	0.6596	0.6781
Other inputs	Yes	Yes	Yes	Yes
Industry FE	Yes			
Time FE	Yes			
Exporter by importer FE	Yes	Yes		
Exporter by time FE		Yes		
Importer by time FE		Yes		
Industry by time FE		Yes	Yes	
Exporter by industry FE		Yes	Yes	
Importer by industry FE		Yes	Yes	
Exporter by importer by time FE			Yes	Yes
Exporter by industry by time FE				Yes
Importer by industry by time FE				Yes

Notes: This table explores how the adjustment of industries is correlated with industrial water intensity by estimating the effects of relative precipitation on the average water intensity. The unit of analysis is exporter by importer by industry by each 5-year from 1995 to 2019. *RPrec* denotes relative precipitation per capita. The water intensity varies by exporter, importer, industry and year. The variation is purely driven by the industry compositional change in trade, instead of productivity changes. Columns 1-4 gradually increase the dimensions of fixed effects. Control variables include labor, capital and land as well as their interactions with corresponding sectoral intensities. The standard errors in parentheses are clustered at the exporter by importer level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: The effects of precipitation on logistics performance

	(1)	(2)	(3)
Variables	Logistics performance index		
Prec * I(Prec 0-25%)	2.083**	2.242***	2.156**
	(0.844)	(0.839)	(0.893)
Prec * I(Prec 25-100%)	-0.235	-0.196	-0.351
	(0.326)	(0.327)	(0.375)
Observations	715	715	715
Adjusted R2	0.909	0.909	0.908
Controls	No	Yes	Yes
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Region by year FE	No	No	Yes

Notes: This table reports the effects of precipitation on logistics performance. The dependent variable, logistics performance index, is obtained from the World Bank Logistics Performance Survey. The unit of analysis is country by year from 2007 to 2018. *Prec* denotes precipitation per capita. Columns 1-3 gradually include control variables and region by year fixed effects. Control variables include temperature bins. The standard errors in parentheses are clustered at the country level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

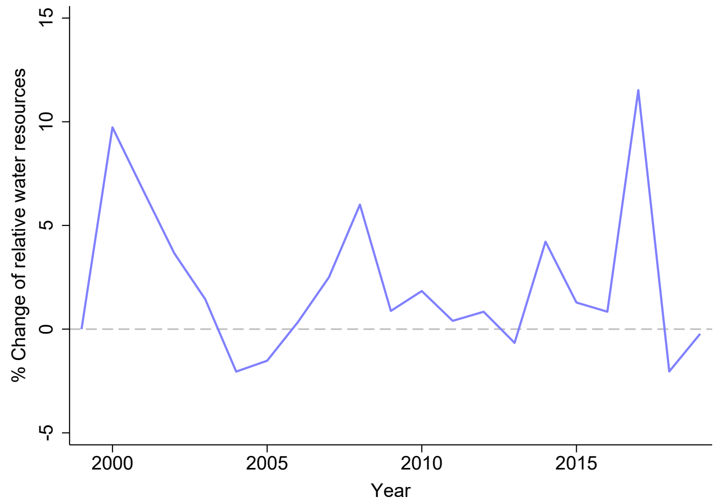
Table 7: The effect of relative precipitation on trade flows by water endowment

	(1)	(2)	(3)	(4)
Variables	log(trade flow)			
WaterIntensity * RPrec * I(ED 0-30%)	2.5779**	0.3712	0.3880	0.4548
	(1.2082)	(0.5090)	(0.5077)	(0.5126)
RPrec * I(ED 0-30%)	-0.2006**	-0.0557		
	(0.0944)	(0.0427)		
WaterIntensity * RPrec * I(ED 30-70%)	2.0147***	0.6247**	0.6198**	0.6638**
	(0.5929)	(0.2805)	(0.2807)	(0.2958)
RPrec * I(ED 30-70%)	0.0039	0.0080		
	(0.0191)	(0.0077)		
WaterIntensity * RPrec * I(ED 70-100%)	2.0283***	0.9297***	0.9108***	0.9214***
	(0.6194)	(0.2215)	(0.2228)	(0.2225)
RPrec * I(ED 70-100%)	0.0095***	-0.0002		
	(0.0021)	(0.0009)		
Observations	3,441,109	3,441,109	3,441,109	3,441,109
Adjusted R2	0.5554	0.6929	0.7048	0.7149
Other inputs	Yes	Yes	Yes	Yes
Industry FE	Yes			
Time FE	Yes			
Exporter by importer FE	Yes	Yes		
Exporter by time FE		Yes		
Importer by time FE		Yes		
Industry by time FE		Yes	Yes	
Exporter by industry FE		Yes	Yes	
Importer by industry FE		Yes	Yes	
Exporter by importer by time FE			Yes	Yes
Exporter by industry by time FE				Yes
Importer by industry by time FE				Yes

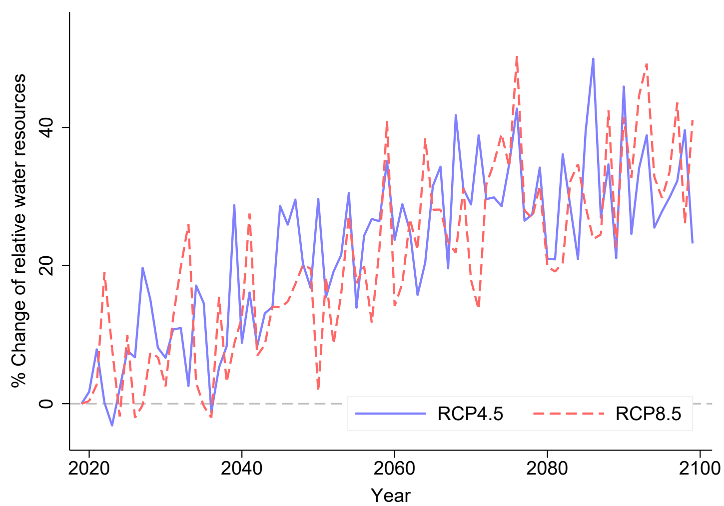
Notes: This table reports the effects of relative precipitation on trade flows by water endowment. The unit of analysis is exporter by importer by industry by each 5-year from 1995 to 2019. *RPrec* denotes relative precipitation per capita. Water endowment is the 30 years' average relative precipitation per capita between exporters and importers from 1970 to 1999. Water endowment enters the equation as three dummy variables indicating the top 30%, middle 40% and bottom 30% of the relative strength in water endowment. Columns 1-4 gradually increase the dimensions of fixed effects. Control variables include labor, capital and land as well as their interactions with corresponding sectoral intensities. The standard errors in parentheses are clustered at the exporter by importer level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix

Figure A1: Changes (%) of relative precipitation per capita over year



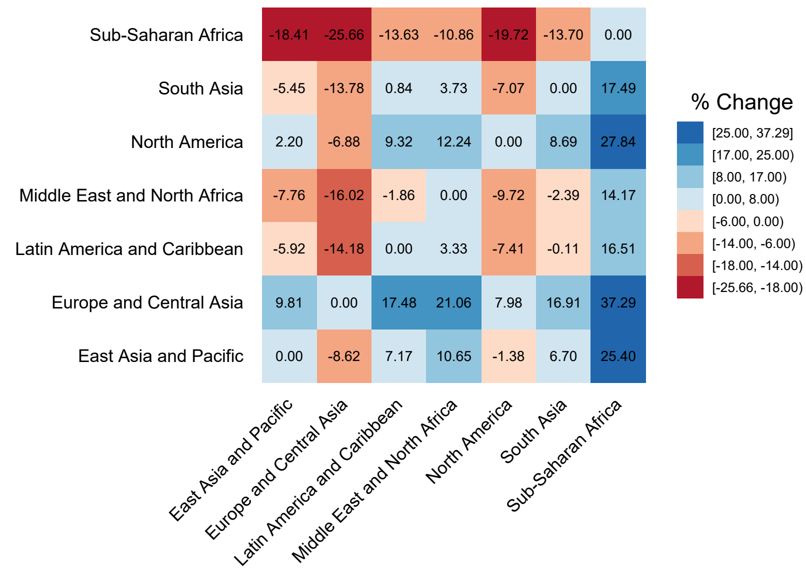
(A) 2000-2019



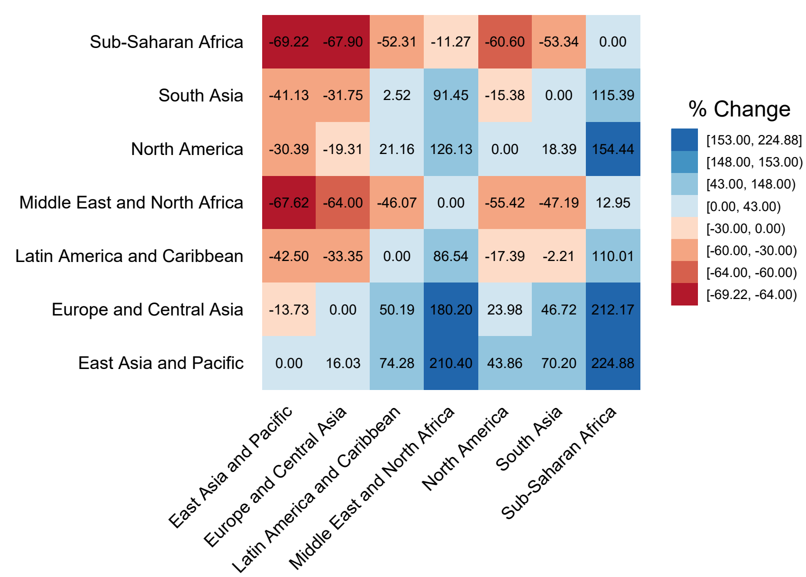
(B) 2020-2099

Notes: This figure shows the changes (%) of relative precipitation per capita over year. Panel A shows the changes (%) of relative precipitation per capita in 2000-2019, relative the annual average in 1995-1999. Panel B shows the changes (%) of relative precipitation per capita in 2020-2099, relative the annual average in 2015-2019 in both RCP4.5 and RCP8.5 scenarios.

Figure A2: Changes (%) of relative precipitation per capita by region



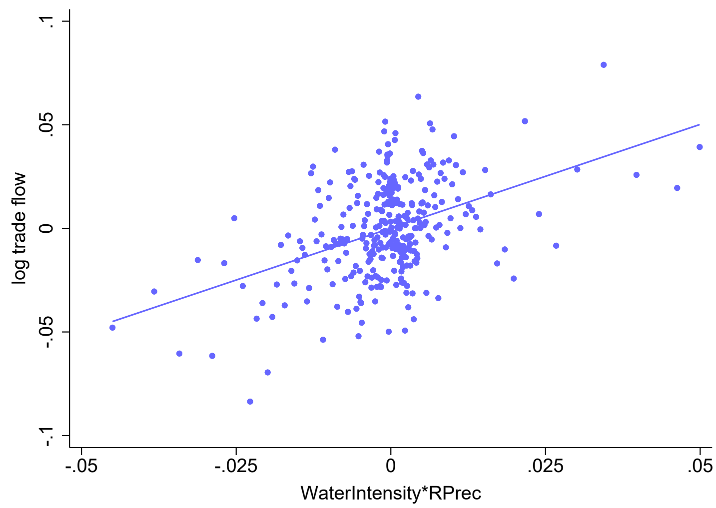
(A) 2000-2019



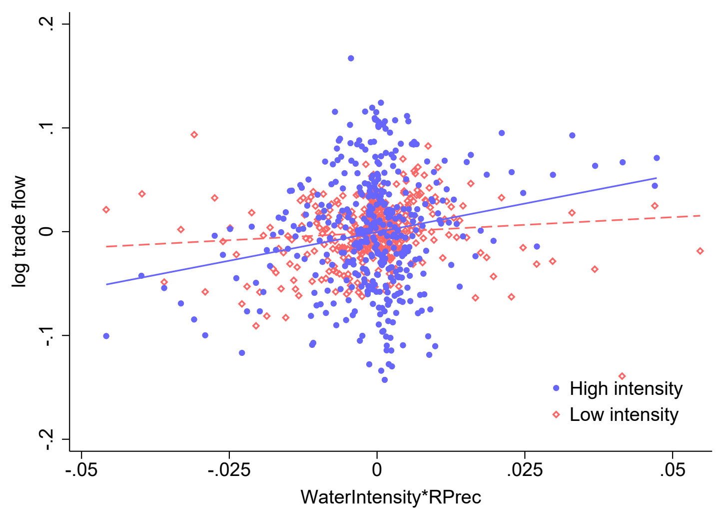
(B) 2080-2099

Notes: This figure shows the bilateral average annual changes (%) in precipitation by region during 2000-2019 and 2080-2099. Panel A shows the bilateral changes (%) in precipitation during 2000-2019, relative to the annual average during 1995-1999. Panel B shows the bilateral changes (%) in precipitation during 2080-2099, relative to the annual average during 2015-2019, under the RCP8.5 scenario.

Figure A3: Correlation between trade and comparative advantage of water



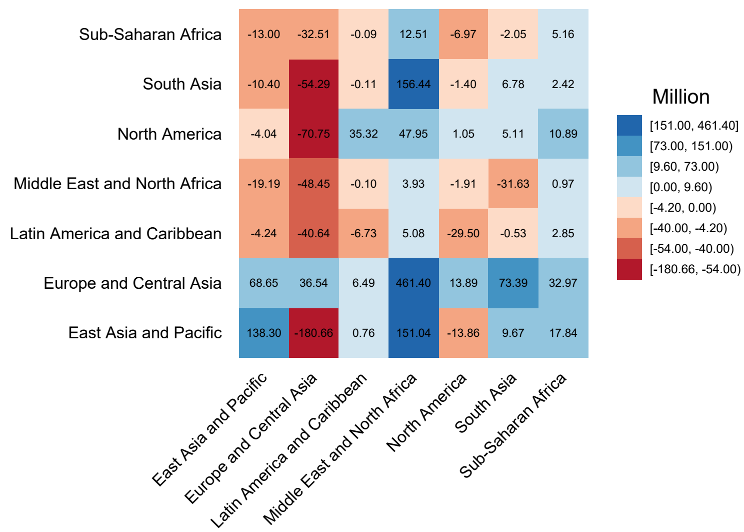
(A) Residualized correlation



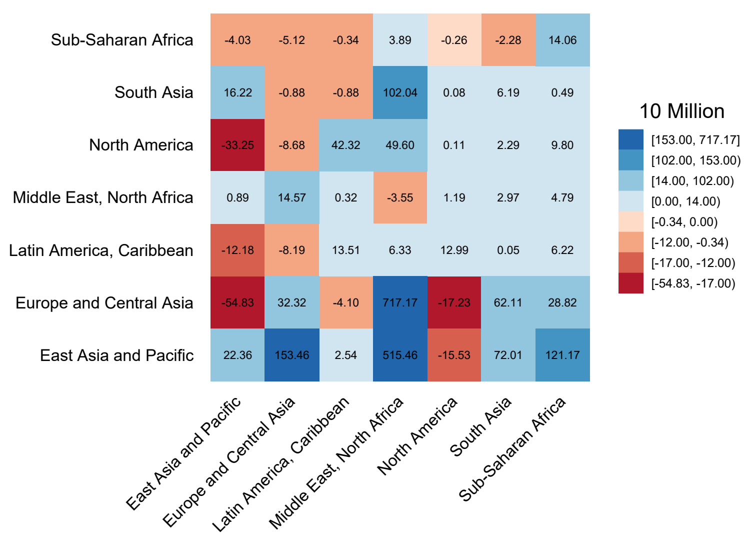
(B) Residualized correlation by water intensity

Notes: This figure shows the correlation between trade and comparative advantage of water using the sectoral bilateral trade data from 1995 to 2019 on a 5-year basis. Comparative advantage of water is defined as the interaction between relative precipitation and water intensity. The y-axis is the residuals obtained from regressing logarithmic trade value on various fixed effects in Equation (1). The x-axis is the residuals obtained from regressing comparative advantage of water on various fixed effects in Equation (1). Industries with high water intensity include the sectors of "food and live animals", "Beverages and tobacco", "Crude materials, inedible" and "Mineral fuels etc". Industries with low water intensity include the other sectors.

Figure A4: The overall effects of relative precipitation on trade by region



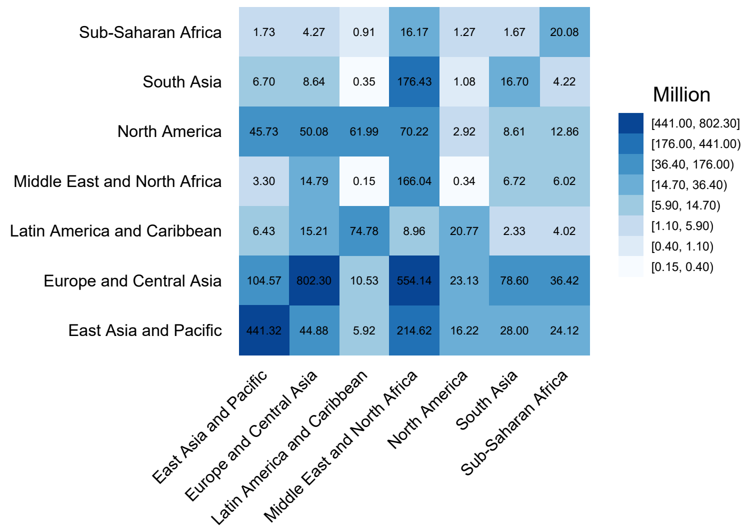
(A) 2000-2019



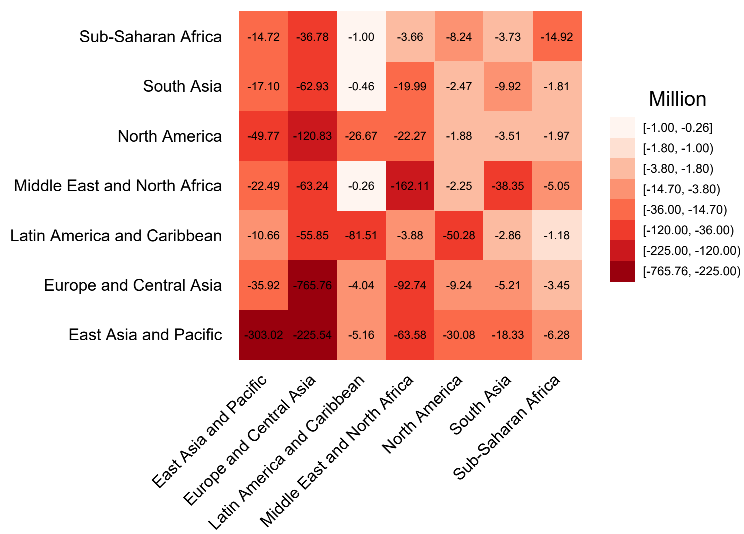
(B) 2080-2099

Notes: Panel A shows the predicted annual average changes in bilateral trade flows driven by changes in relative precipitation between two regions during 2000-2019, relative to the average during 1995-1999. Panel B shows the predicted annual average changes in bilateral trade flows driven by changes in relative precipitation between two regions in 2080-2099, relative to the average during 2015-2019, under RCP 8.5. The directions of trade are from the vertical regions (exporters) to the horizontal regions (importers). The diagonal cells represents the trade response within regions while the non-diagonal cells between regions. Blue color is associated with positive numbers while the red indicates negative numbers, indicating increases and decreases in trade flows, respectively. Summing up all columns in each row produces the changes in overall exports from the row regions; Summing up all rows in each column produces the changes in overall imports to the column regions.

Figure A5: The gains and losses in trade by region, 2000-2019



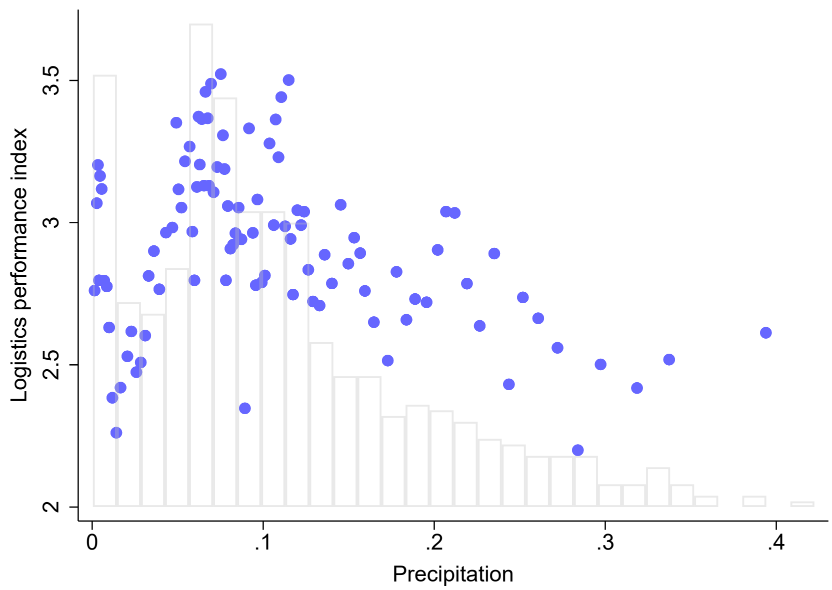
(A) Positive effects



(B) Negative effects

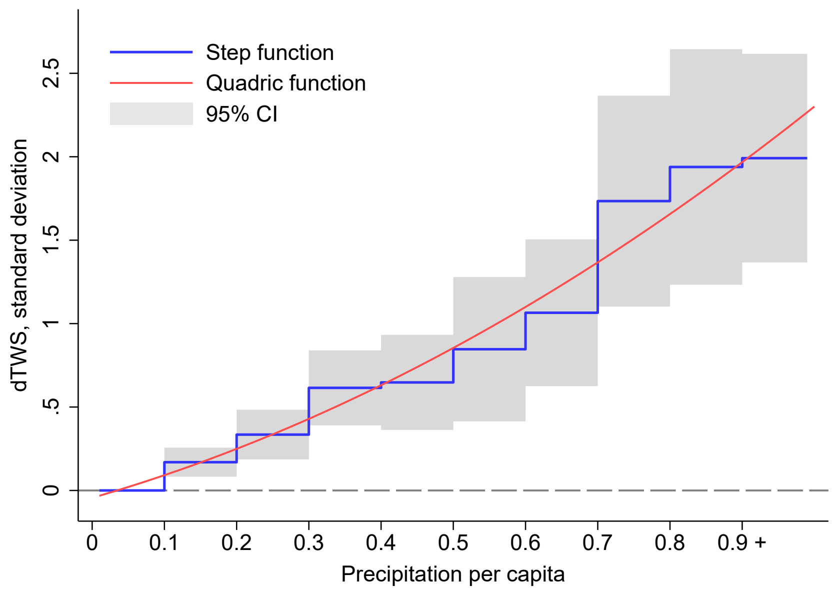
Notes: This figure shows the predicted annual average changes in bilateral trade flows driven by precipitation between two regions in 2000-2019, relative to year 1995-1999. Panel A sums up the positive changes in trade flows in each exporter-importer-industry-year observation. Panel B sums up the negative changes in trade flows in each exporter-importer-industry-year observation. Combining each grids in Panel A and B produces the grids in Figure 8. The directions of trade are from the vertical regions (exporters) to the horizontal regions (importers). The diagonal (non-diagonal) represents the trade response within (between) regions. Summing up all columns in each row produces the changes in overall exports from the row regions; Summing up all rows in each column produces the changes in overall imports to the column regions.

Figure A6: The relationship between precipitation and logistics performance index



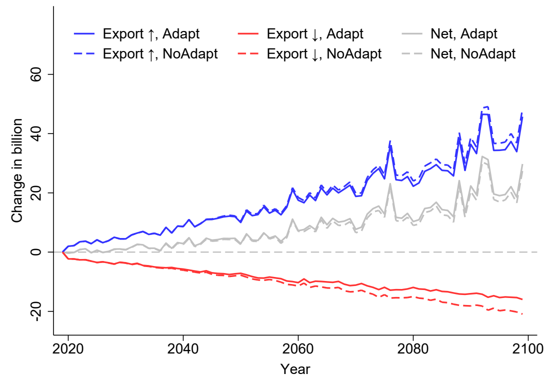
Notes: This figure shows the relationship between precipitation and logistics performance index. Logistics performance index, is obtained from the World Bank Logistics Performance Survey. Precipitation is obtained from extracting the value in the ERA5 grid in which the ports locate. The grey bars represent the distribution of precipitation.

Figure A7: The effects of precipitation on water resources

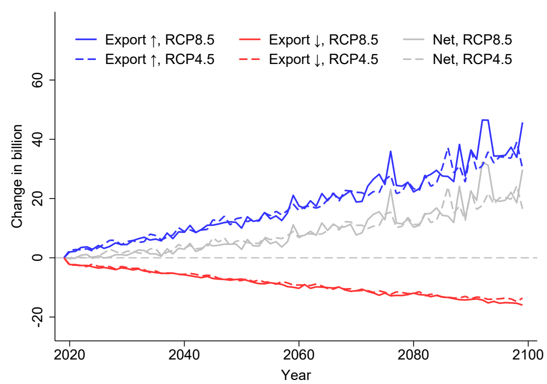


Notes: This figure shows the effects of precipitation per capita on terrestrial water change per capita from estimating the following equation: $dTWS_{it} = \sum_2^9 \gamma_{b1}$ PrecBin $_{it} + \sum_2^9 \gamma_{b2}$ TempBin $_{it} + \tau_i + \delta_t + \mu_{rt} + v_{it}$, where $dTWS$ measures the z-score of the annual changes in terrestrial water storage per capita in country i from year $t-1$ to t. *PrecBin* is a vector of precipitation bins for each 10 thousands m3 precipitation per capita. *PrecBin* equals one if the precipitation per capita falls into the bth precipitation bin and zero otherwise. The bin with the least precipitation (the first bin) is set as the reference group. Similarly, *TempBin* is a vector of 5 degree Fahrenheit temperature bins. τ_i is the country fixed effects, controlling for time-invariant confounders such as geographical conditions. δ_t is the year fixed effects, controlling for common trends in the hydrographical cycle. μ_{rt} is the region by year fixed effects, controlling for the time-varying factors in each region by year. The blue line is the step function and the red line is the quadric function. The grey area shows the 95% confidence interval.

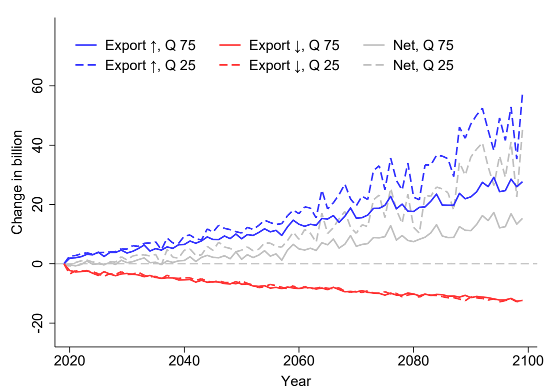
Figure A8: Projected trade changes in 2020-2099



(A) With and without adaptation in RCP8.5



(B) Adaptation in RCP4.5 and RCP8.5



(C) Adaptation in RCP8.5, quantile 75 and 25

Notes: This figure shows the predicted trade flows due to precipitation changes in 2020-2099 at the global level based on the estimated coefficients in Equation (2) and the actual changes in precipitation. The blue line indicates the gains from trade and the red line the losses from trade. The grey line indicates the net effects. Panel A shows the cases of with and without adaptation in RCP8.5. Panel B shows the cases of adaptation in RCP4.5 and RCP8.5. Panel C shows the cases of adaptation in RCP8.5 using the 75th and 25th of the projected precipitation from 21 GCMs.

Table A1: Summary statistics

Variables	(1) Obs.	(2) Mean	(3) Std. Dev.	(4) Min.	(5) Max.
Trade					
Trade flow (thousand dollars)	3,441,109	6420.6	32228	0.0010	528332.7
Relative inputs					
RPrec, relative precipitation (ratio)	3,441,109	4.728	14.547	0.0000	194.481
RLabor, relative labor (ratio)	3,441,109	2.017	2.699	0.0029	76.106
RCapital, relative capital (ratio)	3,441,109	3.985	8.635	0.0020	204.138
RLand, relative land (ratio)	3,441,109	4.492	21.824	0.0000	3104.950
Input intensities					
Water intensity (ratio)	3,441,109	0.016	0.052	0.0000	0.465
Labor intensity (ratio)	3,441,109	0.387	0.106	0.0924	0.645
Capital intensity (ratio)	3,441,109	0.829	0.409	0.2396	3.568
Land intensity (ratio)	3,441,109	0.019	0.043	0.0000	0.245

Notes: This table reports the summary statistics. The unit of analysis is exporter by importer by industry by 5-year period. The data range from 1995 to 2019. Relative inputs are defined by dividing the input per capita in the exporter by the input per capita in the importer. Water intensity is measured as the ratio of the cost of water use over value added plus the cost of water use. Skill intensity is the wage share of nonproduction workers to the total. Capital intensity is the sectoral capital stock divided by the value added in each sector. Land intensity is measured as the ratio of land use to total factor use for a sector.

Table A2: Robustness tests on the zero trade

	(1)	(2)	(3)	(4)
Variables	Trade flow with zero value			
WaterIntensity * RPrec	2.1680***	0.7965***	0.8332***	0.8815***
	(0.6021)	(0.2387)	(0.2336)	(0.2655)
RPrec	0.0046***	0.0018**		
	(0.0015)	(0.0008)		
Observations	9,365,871	9,365,871	9,365,871	9,365,871
Other inputs	Yes	Yes	Yes	Yes
Industry FE	Yes			
Time FE	Yes			
Exporter by importer FE	Yes	Yes		
Exporter by time FE		Yes		
Importer by time FE		Yes		
Industry by time FE		Yes	Yes	
Exporter by industry FE		Yes	Yes	
Importer by industry FE		Yes	Yes	
Exporter by importer by time FE			Yes	Yes
Exporter by industry by time FE				Yes
Importer by industry by time FE				Yes

Notes: This table assesses the robustness of our results to the zero-trade issue by including the observations with zero trade. We follow Silva and Tenreyro (2006) by estimating the Poisson model with the dependent variable specified as trade flows in levels rather than in logarithms. The unit of analysis is exporter by importer by industry by each 5-year from 1995 to 2019. *RPrec* denotes relative precipitation per capita. Columns 1-4 gradually increase the dimensions of fixed effects. Control variables include labor, capital and land as well as their interactions with corresponding sectoral intensities. The standard errors in parentheses are clustered at the exporter by importer level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: Robustness tests of alternative water intensity

	(1)	(2)	(3)	(4)
	log(trade flow)			
Variables	Direct & indirect, blue	Direct, green & blue	Direct & indirect, green & blue	Average
WaterIntensity * RPrec	0.6864***	0.1782***	0.0656***	0.0548***
	(0.1733)	(0.0522)	(0.0158)	(0.0126)
RPrec	-0.0001	-0.0010	-0.0007	-0.0009
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Observations	3,441,109	3,441,109	3,441,109	3,441,109
Adjusted R2	0.6929	0.6929	0.6929	0.6929
Other inputs	Yes	Yes	Yes	Yes
Exporter by importer FE	Yes	Yes	Yes	Yes
Exporter by time FE	Yes	Yes	Yes	Yes
Importer by time FE	Yes	Yes	Yes	Yes
Industry by time FE	Yes	Yes	Yes	Yes
Exporter by industry FE	Yes	Yes	Yes	Yes
Importer by industry FE	Yes	Yes	Yes	Yes
Exporter by importer by time FE	Yes	Yes	Yes	Yes
Exporter by industry by time FE	Yes	Yes	Yes	Yes
Importer by industry by time FE	Yes	Yes	Yes	Yes

Notes: This table assesses the robustness of our results to alternative measures of water intensities. The outcome variable is trade flows in logarithms. The unit of analysis is exporter by importer by industry by each 5-year from 1995 to 2019. *RPrec* denotes relative precipitation per capita. Columns 1 focuses on the direct and indirect water as well as the blue water. Column 2 uses direct water as well as the green and blue water. Column 3 uses the direct and indirect water as well as green and blue water. Column 4 takes the average of the previous four measures of water intensities. Control variables include labor, capital and land as well as their interactions with corresponding sectoral intensities. The standard errors in parentheses are clustered at the exporter by importer level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: Robustness tests of alternative water resources

	(1)	(2)	(3)	(4)	(5)	(6)
Variables			log(trade flow)			
WaterIntensity * RPrec	0.7769***	0.8953***	0.7069***	0.6941***	0.8907***	1.0812***
	(0.2434)	(0.2287)	(0.1581)	(0.1625)	(0.2609)	(0.3182)
RPrec	0.0012		-0.0002		0.0002	0.0013
	(0.0013)		(0.0005)		(0.0010)	(0.0013)
Observations	3,441,109	3,441,109	3,441,109	3,441,109	2,803,268	1,931,586
Adjusted R2	0.6929	0.7149	0.6929	0.7149	0.6984	0.7023
Other inputs	Yes	Yes	Yes	Yes	Yes	Yes
Exporter by importer FE	Yes		Yes		Yes	Yes
Exporter by time FE	Yes		Yes		Yes	Yes
Importer by time FE	Yes		Yes		Yes	Yes
Industry by time FE	Yes		Yes		Yes	Yes
Exporter by industry FE	Yes		Yes		Yes	Yes
Importer by industry FE	Yes		Yes		Yes	Yes
Exporter by importer by time FE		Yes		Yes		
Exporter by industry by time FE		Yes		Yes		
Importer by industry by time FE		Yes		Yes		

Notes: This table assesses the robustness of our results to alternative measures of water resources. The outcome variable is trade flows in logarithms. The unit of analysis is exporter by importer by industry by each 5-year from 1995 to 2019. *RPrec* denotes relative precipitation per capita. Columns 1 and 2 use the population in 1994, the year before our data start, to construct the precipitation per capita. Columns 3 and 4 use the unweighted precipitation when aggregating the precipitation at the 30 km resolution to the country level. Columns 5 and 6 exclude country pairs with the size of either exporters or importers less than 10% or 25% of the country size distribution (9 or 54 thousand square kilometer), respectively. Control variables include labor, capital and land as well as their interactions with corresponding sectoral intensities. The standard errors in parentheses are clustered at the exporter by importer level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: Robustness tests of alternative model specifications and measurement

Variables	(1) log(trade flow)	(2) trade	(3) log(quantity)
WaterIntensity * RPrec	0.8974***	9,129.29**	0.8867***
	(0.2110)	(4,079.16)	(0.2521)
RPrec	-0.0001	-31.252**	0.0002
	(0.0008)	(13.944)	(0.0011)
Observations	3,441,109	3,441,109	3,441,109
Adjusted R2	0.6928	0.4199	0.6903
Other inputs	No	Yes	Yes
Exporter by importer FE	Yes	Yes	Yes
Exporter by time FE	Yes	Yes	Yes
Importer by time FE	Yes	Yes	Yes
Industry by time FE	Yes	Yes	Yes
Exporter by industry FE	Yes	Yes	Yes
Importer by industry FE	Yes	Yes	Yes

Notes: This table assesses the robustness of our results to alternative model specifications and measurements. The unit of analysis is exporter by importer by industry by each 5-year from 1995 to 2019. *RPrec* denotes relative precipitation per capita. Column 1 removes all other inputs as control variables. Column 2 uses the level of trade as the dependent variable. Column 3 uses the trade quantity in logarithms as the dependent variables. Control variables include labor, capital and land as well as their interactions with corresponding sectoral intensities. The standard errors in parentheses are clustered at the exporter by importer level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6: The effect of different inputs on trade flows

	(1)	(2)	(3)	(4)
Variables	log(trade flow)			
WaterIntensity * RPrec	0.0178***	0.0077***	0.0076***	0.0078***
	(0.0044)	(0.0019)	(0.0019)	(0.0019)
RPrec	0.0377***	-0.0006		
	(0.0088)	(0.0034)		
LaborIntensity * RLabor	0.0547***	0.0003	-0.0025	-0.0012
	(0.0127)	(0.0068)	(0.0079)	(0.0098)
RLabor	-0.0512***	0.0167**		
	(0.0129)	(0.0065)		
CapitalIntensity * RCapital	0.0478***	-0.0203***	-0.0193***	-0.0227***
	(0.0094)	(0.0063)	(0.0065)	(0.0067)
RCapital	-0.0722***	0.0089		
	(0.0147)	(0.0077)		
LandIntensity * RLand	0.0136**	0.0018	0.0018	0.0006
	(0.0063)	(0.0020)	(0.0020)	(0.0021)
RLand	-0.0077	-0.0001		
	(0.0048)	(0.0013)		
Observations	3,441,109	3,441,109	3,441,109	3,441,109
Adjusted R2	0.5554	0.6929	0.7048	0.7149
Other inputs	Yes	Yes	Yes	Yes
Industry FE	Yes			
Time FE	Yes			
Exporter by importer FE	Yes	Yes		
Exporter by time FE		Yes		
Importer by time FE		Yes		
Industry by time FE		Yes	Yes	
Exporter by industry FE		Yes	Yes	
Importer by industry FE		Yes	Yes	
Exporter by importer by time FE			Yes	Yes
Exporter by industry by time FE				Yes
Importer by industry by time FE				Yes

Notes: This table reports the effect of relative precipitation on trade flows from estimating Equation (1). All right-hand-side variables are normalized (z score) such that the coefficients among different inputs can be compared. The unit of analysis is exporter by importer by industry by each 5-year from 1995 to 2019. *RPrec*, *RLabor*, *RCapital* and *RLand* denote per capita measures of relative precipitation, relative labor, relative capital and relative land, respectively. Column 1 includes the fixed effects similar with the main model in Debaere (2014) and the findings are largely consistent. Specifically, all interactions (precipitation, labor, capital and land) are significantly positive, suggesting all inputs are key determinants of comparative advantages. The marginal effects of precipitation and land are close; the marginal effects of labor and capital are close; the marginal effects of labor and capital are about three times as large as those of precipitation and land. However, after Columns 2-4 gradually increase the dimensions of fixed effects, the effects of precipitation remain robust but the effects of other inputs are not stable. The instability in the coefficients of other inputs is likely due to insufficient variation conditional on various fixed effects. The findings are consistent with Cai and Stoyanov (2016) that, after the utilize the time variation to estimate the Rybczynski effects of aging, the coefficients in front of labor interaction and capital interaction become unstable. The standard errors in parentheses are clustered at the exporter by importer level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.