The environmental bias of trade policy through the virtual water content of agri-food products

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Abstract

Considering the importance of virtual water trade in the sustainable transformation of the global agri-food industry and the critical importance of trade to face challenges on global food security, this paper aims to understand if trade barriers may drive or restrain the consumption of lower water intensive products in the agri-food sector. Using global data from years 2001, 2004, 2007 and 2010 it was found that the differences between trade policies for high water intensive products versus low water intensive products create an implicit subsidy benefiting the importation of agrifood products with high water footprint (green and blue).

Keywords: Trade policy, virtual water, water footprint, agri-food products

JEL codes: F13; Q56; Q17; Q18

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1 Introduction

In 2010, the United Nations recognized water as a fundamental human right and basic good, acknowledging its importance for social, economic, and environmental development. Despite this recognition, there remains a substantial lack of awareness and understanding regarding the water impact hidden on each consumed product.

Beyond the direct use of water in daily activities, the products consumed require substantial water amounts to be produced, transformed, and distributed, known as virtual water. Virtual water closely relates to the concept of water footprint (WFP), which denotes the cumulative virtual water content of goods or services consumed by individual(s) or countries (Brindha, 2017). This virtual water can be categorized into green water (derived from rain) and blue water (sourced from rivers, lakes, or underground water). The consumption of blue water raises concerns for water sustainability, considering the limited availability of water suitable for human consumption on the planet.

The distinction between blue and green water holds significance as its environmental and social impact is also different (Antonelli and Greco, 2015; Antonelli and Sartori, 2015). The food and agriculture industries play a key role, with approximately 90% of a country's water requirements depending on food consumption. Of this, 80% refers to green water, while 20% to blue water, with agriculture representing 70% of the latter's global use (Antonelli and Greco, 2015; Hatfield, 2015; Kayatz et al., 2019). With this regard, according to FAO (2018), agriculture is both the cause and the victim of water scarcity. And also, with almost a quarter of the world' population facing extremely high water stress, especially whether there are wheat, rice and maize, agricultural land projections are even worsened due to population growth, changes in income and in food preferences, resulting in higher food demand (Damerau et al., 2016; Dinar et al., 2019; Falkenmark, 2013).

The strong relationship between food and water security strengthens the importance of national policies for effective water resource management. Additionally, the environmental impact of food is strongly related to consumer preferences and dietary choices. The IPCC emphasizes the role of healthy and sustainable diets in mitigating the environmental impact of food systems (Mbow et al., 2020; Rosenzweig et al., 2020). Literature suggests that increasing the consumption of fruits, vegetables, legumes, and nuts, alongside reducing meat and sugar (particularly in countries with excessive consumption), is key for enhancing both health and environmental results (Willet et al., 2019). Notably, a significant concern is on the allocation of global crops to livestock, where the growth and feed phases contribute substantially to the total water footprint of meat, expanding its impact footprint, given that feed inputs are frequently grown from different countries than where the meat is consumed (Hokestra on Antonelli and Greco (2015)).

It is crucial to recognize that the water footprint depends not only on the product selected but also on the places of growth and transformation (Chapagain and Hoekstra, 2011; Hoekstra and Chapagain, 2011; Hoekstra and Hung, 2005). Nowadays, the food supply chains is spread all around the world, increasing the complexity and environmental influence of food. The international trade of agri-food products implies a high exchange of virtual water with potential benefits or detriments on global water resources. Unfortunately, water stress and negative impacts linked to current international supply chains and consumption trends are increasing the economies vulnerability to water related risks (such as droughts) and consequently to food insecurity. A special IPCC report states that climate change is already impacting food security through temperature changes, precipitation patterns, and an elevated frequency of natural disasters (Mbow et al., 2020). The strong relationship between water and food security explains the government's strategies on prioritizing access to free or subsidized water resources when it comes to food production; this is especially the case when considering the economic vulnerability of rural livelihoods against market pressures to sustain the production of more affordable items (Antonelli and Greco, 2015). Sadly, this may perpetuate cycles where global water resource managers lack sufficient economic resources to enhance water management techniques or, in some instances, drive the overexploitation of national water resources, incurring substantial social costs (Aw-Hassan et al., 2014; Caro et al., 2021; Javed et al., 2021).

Considering the importance of virtual water trade in the sustainable transformation of the global agri-food industry and the critical importance of trade in addressing challenges to global food security, this paper aims to understand whether trade barriers may encourage or hinder the consumption of less water-intensive products in the agri-food sector. Analysis and methodologies are based on Shapiro's work (Shapiro, 2021), including the application of instrumented variables to reduce measurement errors, the use of multi-regional input-output tables and the calculation of implicit "taxes" on environmental impact variables (CO2 emission in the case of Shapiro (2021), and WFP for this paper). Thus, the analysis will focus on the relation between trade policies and the water footprint of imported agri-food products. Following Shapiro (2021), the statistical linear regression uses trade policy differences between products within the same countries to identify implicit "taxes". This document looks for a better understanding of current trade policies and their influence on driving economic advantages to water intensive products and the possible explanations for this trend.

This paper is structured as follow: Section 2 presents the existing literature review, then methodology and data are explained in Section 3 and 4 respectively. The findings are discussed in Section 6 while conclusions in Section 7.

2 Virtual water trade: a review

Globalisation has spread the environmental impact of economic activities across borders, strengthening the importance of trade policies for the sustainable transformation of economies. Within this context, the significance of virtual water trade (VWT) is particularly noteworthy. In fact the total volume of water consumed to produce traded commodities is by far greater (and travels longer distances) than the volume of water that is physically transferred in the world (d'Odorico et al., 2019; Oki et al., 2017). Indeed, water remains a resource physically available mainly for local use (Hoekstra and Chapagain, 2011; Konar et al., 2016) as transporting crops is considerably easier than transporting the water required for their production. Over the last two decades, the VWT has become a crucial tool to show the amount of water driven, in particular, by the trade of agricultural products. It serves to establish a link between water and the availability of commodities within national economies (Chapagain et al., 2005).[1] Furthermore, the impacts of climate change and the subsequent use of land land use could potentially increase the Water Footprint (WFP) by up to 22%, by 2090 (Mekonnen and Gerbens-Leenes, 2020). This underscores a scenario where global-level actions are imperative for ensuring water sustainability and the protection of ecosystems.[2]

Several research works have been conducted to perform VWT analyses both at the global and regional level (Antonelli and Tamea, 2015; Chapagain et al., 2005; Chen and Chen, 2013; d'Odorico et al., 2019; Hoekstra and Hung, 2005; Serrano et al., 2016). Notably, in the global context, Duarte et al. (2019) tried to address the impact of globalisation on water through the use of panel data econometrics. Results highlight the fact that both institutional and geographic factors play a key role as drivers of virtual water bilateral trade flows between 1965 and 2010. Consequently, the impact of trade on water resources closely depends on the level of development exhibited by a country. In line with this last concept, a case study focusing on avocados investigates the relationship between international trade in avocados and the related virtual water trade over the period 2000-2006 (Caro et al., 2021). Using a Physical Trade Analysis, they show a rapid simultaneous growth in commercial and virtual water trade during the specified years. The analysis emphasizes a substantial disparity between developed and developing countries, with the former being a net importer of water and the latter a large net exporter. As a consequence, the over-exploitation of water associated with avocado trade flows may exacerbate environmental conditions in many relatively poor countries, where avocado exports are often seen as a crucial source of economic growth.

Other studies have explored VWT using various approaches, including an examination of network effects (Carr et al., 2013; d'Odorico et al., 2019) and the influence of different commodities (Tamea et al., 2014). Some studies on the role or potential solutions offered by the circular economy. Moreover, certain research emphasizes that bilateral VWT flows are affected not only by traditional trade determinants but also by national water endowments and the level of pressure on water resources (Fracasso, 2014).

[1] As revealed by Wu et al. (2019), the global trade volume of virtual water is around 30% of the global direct freshwater withdrawal.

[2] In this regards, see Sauvé et al. (2021) for a discussion on the concept of circularity of water.

With respect to the analysis we carry on in this research work, the literature at the baseline is linked with the seminal work by Shapiro (2021). Using statistical methods to better understand the relation between trade barriers and carbon footprint, he deeps on the potential causes of this behaviour. Defining a linear relation between trade policies - tariff and non-tariff measures (NTM) - to carbon footprint (measured in CO2 equivalent per dollar), he calculates the implicit "tax" imposed by tonne of CO2 equivalent emissions. Results present a negative and significant coefficient, implying the existence of a "carbon subsidy" derived from current trade policies. Moreover, based on this, the author introduces other political-economic explanatory variables finding that the upstream industries (frequently the most pollutants) experience lower trade barriers than downstream industries (the cleanest). Hence, the "implicit subsidy" may be caused by the lobbying power of upstream industries to reduce trade barriers. Extending this analysis to water, the international trade of agricultural commodities leads to the use and transfer of global virtual water resources. In our paper, we narrow the focus to the agrifood sector, concentrating the analysis on the trade and environmental impact within this specific domain. Importantly, the trade of virtual water depends on several variables beyond the water footprint of products, e.g. the availability of other natural resources, labour and capital, as well as the influence of importing taxes or domestic subsidies (Hoekstra and Chapagain, 2011). Hence, it is crucial to examine how current trade policies in the agri-food sector may either encourage or hinder the utilization of global water resources.

According to Konar et al. (2016), eliminating trade barriers may drive countries to import products from exporters where water is used more efficiently (e.g. countries with more rain or better irrigation techniques). This enhancement of water footprint could be a potential lever for climate change adaptation. One clear example of this statement is the case of Southern and Eastern Mediterranean countries (SEMED), where a strong correlation is observed between the decline of their water resources availability and the increase on imports of high-water intensive food products. In order to improve their balance, these countries should increase their export of high-water value products (high economic value per m3 of water consumed).

However it is importantly constrained by the tariffs of main trading partners, such as the EU (Zhang et al., 2018).

Another example is the case of China and USA. Yao et al. (2021) evaluate the impact of soybean trade flows changes from USA to China given trade tensions. The implementation of trade barriers between China and the USA and the consequent move of exports from the USA to other countries represent not only economic losses for the USA, but also an increase in blue water extraction at global level (even considering the water withdrawals of new exporters). Moreover, the critical role of the agri-food sector on national food security has driven the use of domestic subsidies which in return have increased the risks and vulnerabilities of countries on their national water resources in the medium and long term (Aw-Hassan et al., 2014; Caro et al., 2021; Javed et al., 2021). Current research also has reported potential negative effects of trade liberalisation on the use of global water resources. Duarte et al. (2019), analysed the different drivers on the increase of virtual water trade and identified that trade liberalisation increases not only the quantity of goods, but it also enables a higher demand on water intensive products. As highlighted by Berrittella et al. (2008), the impact of trade liberalisation depends strongly on the characteristics of the specific product under analysis. This often translates to a reduction in water usage in regions facing water scarcity and an increase in regions with abundant water resources. Alternatively, Gawel and Bernsen (2013) argues that the trade-related negativities on global water use go beyond trade policies and stem from market asymmetries, distorted water prices, and the omission f externalities costs. Consequently, improving trade regulations may not necessarily address the existing malfunctions within the sector.

Additionally, Flachsbarth et al. (2015) highlights the existence of trade-offs between environmental and food security goals, thus trade policies may consider but no limit to consider the use of natural resources for the sustainable transition of the sector.

In summary, the literature presents significant potential trade efficiencies on using global water resources. Nevertheless, there remains a gap in understanding the relationship between trade policies and demand implications, such as the implicit tax advantages associated with water-intensive products.

3 Econometric specification

Based on Shapiro (2021), the analysis of the relations between trade and water footprint can be defined as follows:

$$t_{jpy} = \alpha W_{jpy}^{Total} + \mu_j + \gamma_y + \nu_{jp} \tag{1}$$

The dependent variable t is the import tariff rate or *ad valorem* NTM that the importer country j imposes on agri-food product p during year y. The main explanatory variable is W representing the weighted total water footprint of imported product p during year y by county j and it is calculated as follows:

$$W_{jpy} = \frac{\Sigma_{i \neq j} W_{ipy} x_{ijpy}}{\Sigma_{i \neq jt} x_{ijpy}} \tag{2}$$

Hence, the WFP of importer j equals the WFP of all countries i exporting product p to country j on year y, weighted by the value of each trade flow.Finally, μ_j and γ_y are, respectively, country and year fixed effects. Thanks to these variables, the regression enables a comparison of trade policies across different agri-food products within a country-year framework. This facilitates a more in-depth analysis of the diverse trade policies applied to both more and less water-consuming products that are imported. In particular, the α coefficient will represent the implicit water tax (or subsidy) in trade policy. [3] Similar to Shapiro (2021), the calculation of WFP is based on multi-region input-output tables (IOTs) which implies potential measurement errors. To address this problem, the Total WFP is instrumented with the direct WFP of the 10 smallest countries ($\hat{i}$) from which each importer is trading the p specific product.[4] First stage of the instrumental variable (IV) equation is:

$$\hat{W}_{jpy}^{Total} = \beta \hat{W}_{jpy}^{Direct} + \mu_j + \gamma_y + \nu_{jp} \tag{3}$$

[3] As an example, if $\alpha = 1$, it means that current trade policy imposes an implicit tax of 1 euro per each m^3 of water used in imported products.

[4] This definition is used because importers have different combinations of exporters, depending on products.

where:

$$\hat{W}_{jpy}^{Direct} = \frac{\Sigma_{\hat{i}\neq j} W_{\hat{i}pt}^{Direct} x_{\hat{i}jpy}}{\Sigma_{\hat{i}\neq j,t} x_{\hat{i}jpy}} \tag{4}$$

$\hat{W}_{jpy}^{Direct}$ equals the direct WFP of the 10 smallest countries ($\hat{i}$) from which country j imports product p, weighted by the value of each trade flow. The second stage regression can be described as regression 1.

3.1 Other explanatory variables

Several factors can influence the increase or decrease of tariff measures, as it was mentioned before, and many of these factors are country specific. Since this paper focuses on comparing trade policies regarding various agri-food products within a single country, μ_j already incorporates those variables that rely solely on the country's specificity. Nevertheless, there may be additional relevant variables that could be considered to enhance comprehension of the results from previous regression analyses.

Upstreamness. The concept of upstreamness refers to the average distance of a product or industry from the final consumer. In this case major domestic industries, being well-organized, might lobby for low tariffs on their inputs, particularly in contrast to final consumers who are often less organized. Consequently, products that serve as inputs for other industries may encounter reduced tariffs and other trade barriers. Additionally, products that are distant from consumers may have heightened environmental impacts, as consumer awareness of environmental issues could diminish due to the complexity of value chains. Moreover, any policy implemented on upstream products could trigger cascading effects that amplify its impact and potentially lead to consumer dissatisfaction. Following Antràs et al. (2012) we measure upstreamness as follows:

$$U_{py} = [I - d_{ij} Y_j / Y]^{-1} 1]$$

where $d_{ij} Y_j / Y$ refers to the matrix describing the shares from the total output of product i that product j required for its own production. Therefore, values closer to one will be more downstream; meanwhile, greater values will refer to greatest upstreamness.[5]

Intra-industry trade. Intra-industry trade occurs when a country both imports and exports similar types of products. Within this framework, trade barriers for such goods may be complex due to divided lobbying efforts; in fact, firms producing these goods may push for higher trade barriers, while those purchasing them may aim for lower barriers. This division in lobbying efforts can complicate trade policy formulation (Shapiro, 2021). For its measurement, the common Grubel-Lloyd index was used (Grubel and Lloyd, 1975):

$$GLI_{jpy} = 1 - \frac{|ex_{ipy} - im_{ipy}|}{ex_{ipy} + im_{ipy}}$$

where ex_{ipy} and im_{ipy} refer respectively to the export and imports of country i of product p during year y. To calculate this value, we used bilateral trade data described in Section 4.

Import penetration. According to the OECD, import penetration is defined as the ratio of imports over total domestic demand (domestic production plus import minus exports). Shapiro (2021) considers that industries more exposed to international trade may have higher trade barriers. Import penetration was calculated annually at country-product level as follows:

$$IP_{jpy} = \frac{im_{ipy}}{X_{ipy} + im_{ipy} - ex_{ipy}}$$

where X_{ipy}, im_{ipy} and ex_{ipy} refer to output, exports and imports of country i respectively. Bilateral trade data for imports and exports and the EXIOBASE output (matrix x) were used.[6]

Average wage. Labour-related variables could also be potential explanations for higher trade barriers. Industries with high percentages of low-skilled or low-wage workers may seek public protection, such as trade barriers, as a tool for redistribution (Shapiro, 2021). The

[5] The calculation of this variable was made per each year at product level based on the flow matrix (Z) and the total output of each product (matrix x).

[6] As BACI database is in thousands USD and EXIOBAS in millions EUR, the conversion of currencies was made using the average annual exchange rate from the OECD.

labor-related variables used from EXIOBASE to calculate average wage include compensation of employees and employment. The first step of the data management was to calculate the total compensation and the total employment used per millions of euros of each product at country-year level. Total compensation equals the sum of the compensation given to three levels of skills (low, medium and high). Meanwhile, total employment is the sum of male and female employees involved in the production. To ensure that the indexes reflect the realities of each national product's production, the values used are from matrix S (direct stressors), meaning that labor production factors related to the inputs used in the product's production are not considered. The second step was devoted to obtaining the total number of employees working annually for each product-country and its total amount of compensation. To obtain this data, the employment and compensation factors were multiplied by their respective total output (matrix x). Therefore, the average wage was calculated as follows:

$$Averagewage_{jpy} = \frac{Compensation_{ipy}}{Employment_{ipy}}$$

Thus, products with low wages on their production processes may face higher trade barriers compared to products with higher wages.

Labour share and labour intensity. Similar to previous variables, the share of employment in specific industries may drive to higher trade barriers.[7] In this research work we used two different measures: i) the labour share which refers to the annual percentage of workers employed for the direct production of product p in country i over all workers employed in country i that year ($Labor\%_{jpy} = \frac{L_{ipy}}{L_{iy}}$);[8] ii) the second measure is the labour intensity and refers to the number of workers employed for the direct production of product p in country i over total output of product p in country i ($LaborIntensity_{jpy} = \frac{L_{ipy}}{x_{ipy}}$).[9]

Supply-Utilisation variables. The balance between the supply and utilization of each

[7] Shapiro (2021) suggest that industries with with a larger number of workers in a country may increase the public pressure for the implementation of stronger trade policies benefiting those industries.

[8] To calculate the total numbers of "workers employed" in i country and per p product we used the stressor from EXIOBASE "Total Employment" (thousand people/ME), multiplied by output (matrix x).

[9] Note that the value can be obtained directly from stressors matrix S in thousand workers by the value of shipments.

food item is measured by the FAO, and can be summarized by the following equation:

$$Prod. + Import + Stockvar. = Export + Feed + Processed + Seed + Otheruses + Food + Loss$$

On the left side of the equation, the net national supply consists of national production, imports, and variations in stock. Utilisation, on the right side of the equation, comprises exports, feed, products set aside for sowing or planting (seeds), items further processed to manufacture food items, food for direct human consumption, other uses, and losses. Considering the total utilisation as 100%, the share of food going to feed is calculated as the ratio between feeds and a value equal to the sum of export, feed, seed, processed food, other uses and loss. The paper considers and analyses two main uses of food that may be related to the use of lower trade barriers: food aimed for direct feeding and food intended for further processing. By including these variables, we can identify if the different uses of agri-food products can explain the presence of implicit taxes or subsidies.

This hypothesis originates from the fact that some water intensive products such as oil seeds, sugar beet/cane, wheat, and cereals grains are used as inputs for other industries rather than for direct human consumption.[10] Therefore, as these water-intensive products are critical inputs for the national food manufacturers of the importing country, these companies may try to influence trade policies to reduce their own costs. On the other hand, food imported specifically for direct consumption by consumers may not encounter this issue.

The relationship between lower trade barriers and percentage of food aimed to feed may be linked to the bargaining power of food manufacturers or livestock owners. Furthermore, analyzing the potential existence of preferential trade policies for feed products raises concerns in terms of resource use efficiency in consumer diets. As noted by Hoekstra and Chapagain (2011), several research papers have concluded that the larger water footprints of animal products versus plant-based products do not compensate for nutritional gains (e.g. water footprint per gram of proteins is greater on animal products versus pulses). A similar analogy can be extended to processed food, as technical damage may also compromise the nutritional value of products. However the analysis of calories efficiency may be harder to identify and

[10]For example, 48% of maize is used as an input to feed farm animals, meanwhile 92% of sugar beet is further processed to obtain sugar (FAO, 2023).

define at a general level, especially since food processing can add value beyond nutritional purposes from the consumer's perspective, such as convenience, increased shelf life, or the necessity of processing to make the product consumable for humans.

3.2 Level of water stress of the importer

Water stress is one of the main concerns when virtual water trade is discussed. As noted by Konar et al. (2016), the elimination of trade barriers may support the more efficient use of global water resources. Countries with high levels of water stress may benefit from importing water intensive products from other countries with higher water endowments. In contrast, policies discouraging the import of water intensive products for countries with high water stress levels may worsen the depletion of natural water sources.

For the analysis we categorise countries on three different levels of water stress: i) low water stress, if below 25%; ii) moderate water stress, if between 25% and 100%; iii) high water stress if above 100%.

Regressions based on equation 1 will be done by each level of water stress to identify how countries with higher water stress may be applying lower or higher trade policies to water-intensive products.

4 Data

In the next Section we describe the dataset used to create our four types of variables: water footprint, bilateral trade, trade policy, and other explanatory variables. Information refers to years 2001, 2004, 2007 and 2010 unless otherwise specified.

Water Footprint. Water footprint data was obtained from EXIOBASE3, which offers a time series of environmentally extended multi-regional input-output tables (IOTs) from 1995 to recent years for 44 countries (28 EU member states plus 16 major economies) and five regions in the rest of the world. The list of included countries and regions is provided in Annex A.2. The water-related information in EXIOBASE3 draws from various sources, including the Water Footprint dataset, the Water-GAP model, and data compiled by Pfister et al. (2009) (Stadler et al., 2018). Moreover, EXIOBASE3 incorporates trade data, macroeconomic parameters, and output estimates to provide a comprehensive global overview of the virtual water content of products.

Specifically, the EXIOBASE3 database consists of Monetary Supply-Use Tables (MSTUs), which, similar to IOTs, report the relationships and value added between industries' inputs and outputs, providing detailed information on product supply and demand (Eurostat, 2018). The presence of IOTs and MSTUs enables identifying of the indirect impacts of products and industries, i.e., the effects of their inputs, whose importance is growing with the increasing complexity of supply chains and product formulations. The compilation of final matrices involves: i) macroeconomic data sourced from the UN National Accounts Main Aggregates Database, supplemented by Taiwan National Statistics for balancing and filling gaps in final time series; ii) national industry and product input-output information, augmented with international databases like FAO for agrifood products and the International Energy Agency (IEA) for energy balances; iii) product-level trade data from BACI, IEA, and UN services trade databases; and iv) MSTU and IOT national statistics to construct actual technical relationships within value chains (Stadler et al., 2018). The final output comprises two main sets of data: i) product-by-product tables and ii) industry-by-industry tables. This project focuses on the former. Concerning direct water accounts, WFP can be retrieved from EXIOBASE3 as water consumption. [11] Specifically, it encompasses 13 categories for agricultural activities (both green and blue), 12 categories in livestock production (only blue), 7 in aggregated manufacturing sectors (only blue), 2 related to electricity production (only blue) and 1 on domestic use (only blue).

Following Shapiro (2021), the water footprint data used is at two levels: i) the direct water footprint, denoting the water directly utilized in the production of the analyzed product, and ii) the indirect water footprint, representing the water consumed in producing the inputs utilized by the analyzed products. The combination of both, direct and indirect water foot-

[11] In EXIOBASE3 there are also information on water withdrawals which are not used in this research work since they can return to their sources.

prints, yields the total water requirement of the product (Total Water Footprint, TWP). This study employs both direct and total water footprints for regressions and subsequent analyses. In particular, total water footprint (green + blue) is used to provide a comprehensive understanding of the virtual water content within products. Conversely, the blue water footprint is specifically employed due to its significant correlation with the depletion of fresh surface and groundwater resources.

Bilateral trade. Bilateral trade information, defined annually in thousands of US dollars for each bilateral trade relation and per product, was obtained from the BACI database. This database covers trade data from over 200 countries spanning from 1994 to recent years, with updates typically provided annually in January. Developed by the Centre d'Études Prospectives et d'Informations Internationales (CEPII), the database is compiled based on data reported to the UN Statistics Division via COMTRADE. For the analysis, the product list specified in Annex A.1 was utilized.

Trade Policy. This dataset comprises of Tariff and Non-Tariff measures applied, at product level, by each importer country per year. Tariff information is based on the MAcMap-HS6 database developed by the International Trade Centre (ITC) and the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII). The database covers preferential trade arrangements, ad valorem equivalent (AVE) for specific duties, and tariff-rate quotas, using reference groups of countries for aggregation methodology. For non-tariff measure, information is based on Niu et al. (2018) while the methodology is based on Looi Kee et al. (2009). Calculations cover 97 countries for the time period 1997-2005.[12] Total trade protection was calculated as the sum of both tariff and non-tariff measures, if data was available for both elements.

Water stress and food utilization. The level of Water Stress data was obtained from the official UN website dedicates to the SDG6. The indicator "[...]tracks how much freshwater

[12]Dataset includes: 1997, 2000, 2003, 2006, 2009, 2012, and 2015. Here, the value of NTM was calculated as the average of the two closest years to the year analysed (e.g., the mean between 2000 and 2003 is reported as 2001).

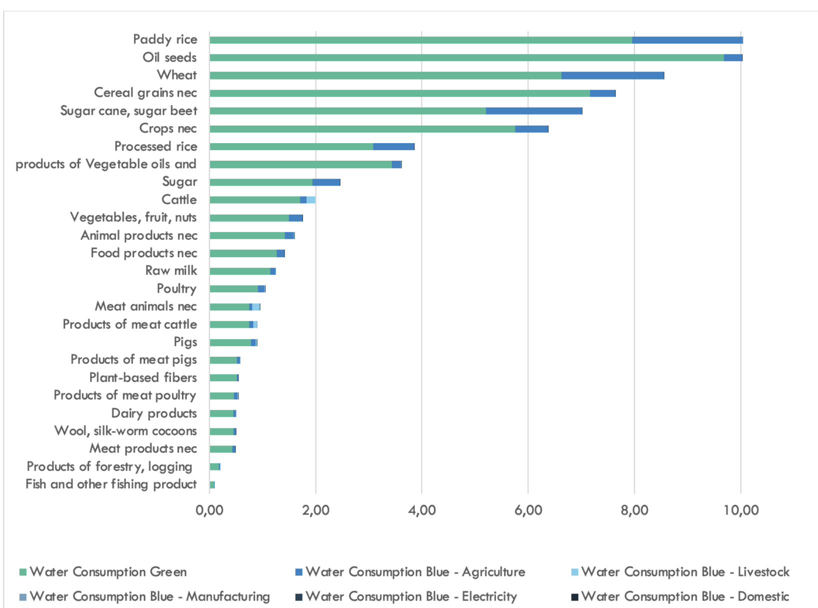
is being withdrawn by all economic activities, compared to the total renewable freshwater resources available, after considering environmental flow requirements" (UN-Water SDG 6 Data Portal). Data was used at country year level for 2001, 2004, 2007 and 2010. Data for the calculation of utilisation percentages was obtained from the Food Balances database on FAOSTAT. Data was used at country-commodity-year level for 2001, 2004, 2007 and 2010. Concordance was based on EXIOBASE supporting material 4. For products not found in EXIOBASE supporting material, the FAO product was categorised using HS tables, then concordance was made using HS-EXIOBASE 2.0 database. If product definition was not clear or identical to HS table, the FAO definitions were used to assure a correct categorization.

5 Data Analysis

5.1 Water Footprints at product and country level

In Figure 1 we present the weighted (blue + green) WFP by product to describe in detail the different water categories of water consumption per each product.

Figure 1: Total weighted WFP by product



Source: authors' elaboration

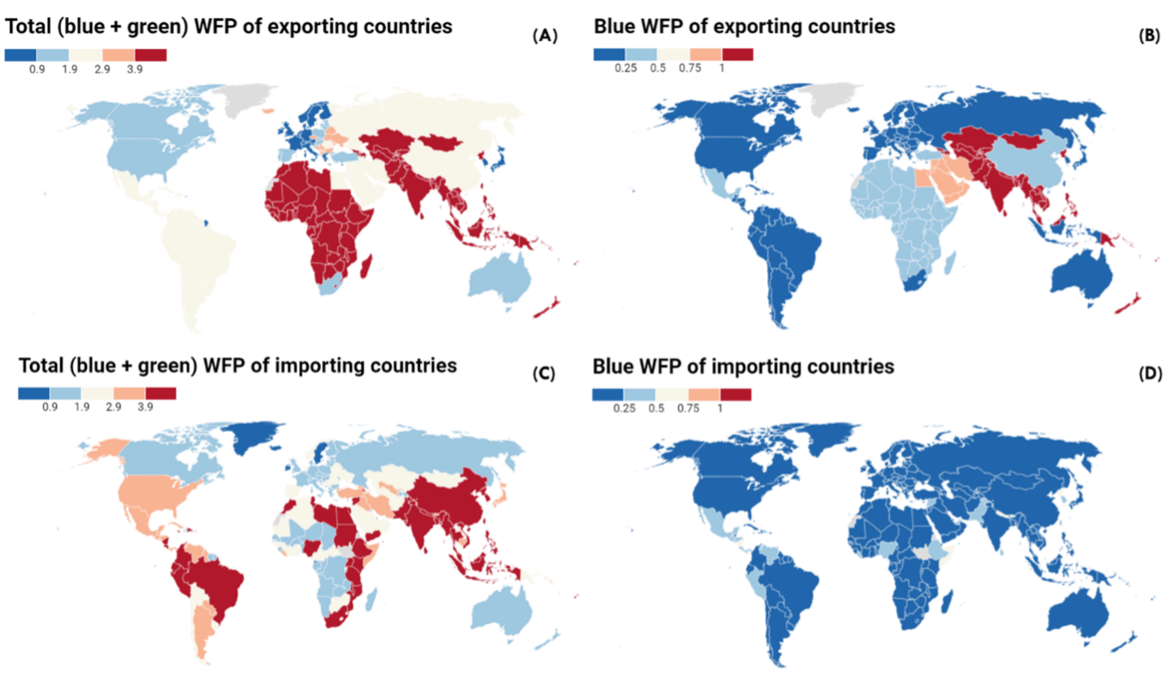
The majority of food production strongly depends on rainfall. This insight is very important given the potential impact of climate change and environmental degradation on rainfall patterns and temperatures. In terms of blue water consumption, paddy rice, wheat, and crops not elsewhere classified exhibit the highest footprints. The second most significant category of water consumption is blue water for agriculture, predominantly due to irrigation's key role in cultivating water-intensive crops. Additionally, irrigation usage is often associated with increased crop yields and climate adaptation, making it vital for addressing food security and other global challenges, with its importance expected to escalate. The third category comprises blue water used for livestock, particularly relevant for animal products, especially red meat. Water utilization for manufacturing and energy production represents the fourth and fifth categories, respectively, with their contributions relatively small, yet more significant for products with intensive processing and manufacturing. Conversely, domestic water values are small and negligible. However, water footprints for the same product can vary significantly among countries, influenced by national planting techniques, irrigation practices, and unique regional weather conditions (Chapagain and Hoekstra, 2011). For instance, major rice producers in Asia such as India and Indonesia rely primarily on rainfall, while rice production in countries like the USA or certain Middle Eastern nations heavily depends on irrigation, leading to increased blue water footprint and potential depletion of water sources. On the contrary, products with low water usage include wool, dairy products, plant-based fibers, forestry products, and fish. Although animal products, including dairy, might have been expected to exhibit higher water footprints, their market value often mitigates these values (measured as m3 per euro). Furthermore, it's important to analyze the percentage of direct water footprint (WFP). Animal and processed products using agrifood inputs often have a substantial proportion of indirect WFP. For instance, only 6% of the total water footprint of cattle is directly related to the consumption of water by livestock, while the remainder is associated with inputs, particularly feed.[13]

Water footprint at the country level was calculated first as the average WFP of agrifood

[13]For detailed information on water footprints (total and blue only), as well as the percentages of direct WFP for products, please refer to Annex A.3 and A.4.

products weighted on each country's production (export perspective). Then, the WFP was also calculated from the importer's perspective, this refers to the water footprint contained in the agrifood products imported. The water footprint of importer j is calculated as the water footprints of producer countries weighted by the volume exported from each producer to importer j.

Figure 2: Blue + Green and only Blue weighted WFP per country (exporter and importer perspective



Source: authors' elaboration. The following maps report the weighted total water footprints (direct + indirect) from exporter and importer perspectives as described before.

The analysis of the Total WFP from an exporter perspective (Figure 2 map A) identifies India and Indonesia as the countries with the highest WFP driven by the production of water intensive products like paddy rice, wheat, oil seeds, products of vegetable oils, and other cereals and crops. Including "rest of the world" (ROW) values, Africa and Asia Pacific are regions with high WFPs. Given the economic, environmental, and social characteristics of these regions, strong efforts and global support must be provided to increase their water use efficiency. When the importer perspective is used, the results change significantly. First, Total WFP of importing countries (Figure 2 map C) reports that China, India, the east coast of Africa, and the northwest of South America are the countries and regions with the highest WFP on their imports. There are no unique explanations for this, and it depends on the mix of products imported by each country and the places they are importing from. However, there are some interesting examples of countries importing a big amount of high-water intensive products like China, which imports an important number of cereals, oil seeds and vegetable oils compared to other countries. Another example is Egypt and its high import of wheat. Considering blue WFP (Figure 2 map B), the regions with higher water footprints are the Middle East and Asia Pacific, especially India whose blue water footprint is strongly driven by wheat and rice production. Kayatz et al. (2019) mention that the shift of Indian production to the dry season has increased the national area irrigated by groundwater, increasing the overall cereal production but without reducing the current pressure of current fresh water sources. Thus, the production of other cereals such as maize and the investments in new technologies for the increase of yields should play an important role in increasing food security while reducing the country's blue water footprint. If ROW regions are considered, the greatest values of blue WFP can be identified in Asia Pacific and the Middle East, the latter presenting at the same time high levels of water stress (WRI Aqueduct 2019). This confirms the observation of Mekonnen and Hoekstra (2011), who highlight that regions with high levels of water scarcity usually have higher blue water footprints. Finally, regarding blue WFP from imports perspective (Figure 2 map D), the values between countries are more balanced. This result is explained by the fact that big water importers are importing the products from countries with a strong dependence on rainfall and green water consumption. For example, China imports huge amounts of soybeans from Brazil which grows this product mainly using rain.

5.2 Trade policies and water footprint

This paper examines the correlation between trade policies and the water footprint (WFP) of agri-food products. As an initial step, we identify the top 5 products with the highest and lowest water footprints, alongside global tariffs and Ad Valorem Equivalents (AVEs) of Non-Tariff Measures (NTMs). Similar to Shapiro's approach, global tariffs refer to the values of all importers weighted by the value of imports. The analysis focuses on the year 2010. Unlike previous analyses that utilized total output, this study employs trade flows to weigh the water footprints of products. The weighted WFP of products based on agrifood imports is measured and compared with previous findings. Explanations for differences are provided. Results exhibit variations as trade leaders may not always be the largest producers. For instance, in 2010, the trade in oilseeds was dominated by the USA (43%) and Brazil (25%), despite Brazil not being as significant a producer as other major players like China, which ranks second in production but primarily for domestic consumption. Consequently, if we consider Brazil's high water footprint (33 m3/eur) compared to the rest of the world (e.g., USA's 8 m3/eur), oilseeds traded display a higher weighted WFP than the calculation based on total production. Conversely, in the case of paddy rice trade in 2010, the majority originated from the USA, which has a relatively low total water footprint (blue + green) compared to countries like India and China (only 1.8 m3/eur). Meanwhile, the WFPs of other significant producers such as India and China range between 8 and 10 m3/eur. Consequently, the weighted WFP of trade flows is lower than that based on production. Despite these differences, the top 5 highest water-consuming products remain largely unchanged (except for sugar cane/beet, where the WFP sharply declines when considering only trade flows), as does the list of the 5 least water-consuming products.

Trade policies on agri-food products have traditionally been defined to protect rural incomes and livelihood, and to protect consumers welfare by implementing food safety standards. At first sight, there is not an evident trend of higher or lower tariffs or non-tariff measures related to WFP (blue + green). This may be due to the different particularities of each importer, for example Japan tariffs on rice are extremely high in order to protect na-

Table 1: Total (blue + green) WFP and trade barriers for the most and the least water consuming products

Product	WFP based on trade flows (m3/eur)	WFP based on production (m3/eur)	Import tariff rate	Non-tariff measure
Panel A. Most water-consuming food products				
Oil seeds	14.4	10.0	0.1	0.6
Wheat	13.6	8.6	0.2	0.3
Crops nec	7.1	6.4	0.1	0.3
Cereal grains nec	6.3	7.6	0.5	0.5
Paddy rice	3.7	10.0	0.3	0.9
Average 5 most water-consuming	9.0	8.5	0.3	0.5
Panel B. Least water-consuming food products				
Products of meat poultry	0.4	0.5	0.5	0.6
Meat products nec	0.3	0.5	0.4	0.5
Products of meat pigs	0.3	0.6	0.4	0.1
Dairy products	0.3	0.5	0.3	0.5
Fish and other fishing product	0.1	0.1	0.1	0.7
Average 5 least water-consuming	0.3	0.4	0.3	0.4

tional rice producers. Something that can be identified is the strong importance of non-tariff measures versus tariffs. According to the OECD, non-trade measures are applied to address public concerns, such as the human and the planet health, however they may also create unnecessary barriers to trade, with potential impacts on least-developed countries. (ES Trade Team, 2017). Given the increasing importance of NTM on the agri-food sector, it is critical to analyse the relation between these measures and the environmental impact of products affected by them. The same analysis was applied for blue water footprint. Results were very similar. Given the intensive use of blue water for rice irrigation, this product is considered inside the top 5 of more water intensive products. Oil seeds rank decreases as it is irrigated mainly by rainfall. Beyond these differences, the conclusions about the relationships between trade policies and blue water footprints are similar to previous analysis. There is no evident trend of lower or higher trade barriers to more intensive water products.

Table 2: Total Blue WFP and trade barriers for the most and the least water consuming products

Product	WFP based on trade flows (m3/eur)	WFP based on production (m3/eur)	Import tariff rate	Non-tariff measure
Panel A. Most water-consuming food products				
Paddy rice	2.18	1.2	0.3	0.9
Cereal grains nec	0.45	0.5	0.5	0.5
Processed rice	0.36	0.8	0.4	1.6
Crops nec	0.35	0.6	0.1	0.3
Oil seeds	0.28	0.3	0.1	0.6
Average 5 most water-consuming	0.7	0.7	0.3	0.8
Panel B. Least water-consuming food products				
Poultry	0.0	0.1	0.1	0.1
Products of meat pigs	0.0	0.1	0.4	0.1
Meat products nec	0.0	0.1	0.4	0.5
Dairy products	0.0	0.0	0.3	0.5
Fish and other fishing product	0.01	0.0	0.1	0.7
Average 5 least water-consuming	0.0	0.1	0.3	0.4

6 Results

This section presents the results of the regression analysis and is divided into three subsections. The first subsection focuses on the relationship between trade policies and water footprints from a global perspective, aiming to provide insight into the potential bias of trade policies toward more water-intensive products within the same country. The second subsection analyzes how this potential bias may vary across different countries. Finally, the last section presents and analyzes the potential drivers of this bias.

6.1 Global level

Table 3 reports, in Panel A, the global results of regressions based on equation 1 for (blue + green) WFP; in Panel B results for the blue WFP only. Columns 1, 2 and 3 report results for the OLS estimation, while columns 4, 5 and 6 report the results considering the direct WFP as the instrumental variable for the 2SLS regression. In Panel A, all regressions describe a negative significant relation between trade policies and Total WFP on agri-food products. Thus, the inclusion of the instrument does not alter the result. The coefficients suggest an implicit negative tax (or subsidy) to water intensive products between 0.1 and 0.3 euros per thousand of m3. The negative sign of the coefficients of WFP would be further analysed to better understand what is driving the negative implicit "tax" on high water consumption products. Moreover, non-tariff measures have in general a greater implicit subsidy versus tariffs; this may be explained given the fact that high-water intensive products such as crops (including paddy rice, wheat, etc.) and oil seeds are affected by high non-tariff measures.

Table 3: OLS and 2SLS results considering Total (blue + green) WFP and Blue WFP

	OLS			2SLS		
	TTP (1)	Tariff (2)	NTM (3)	TTP (4)	Tariff (5)	NTM (6)
Panel A						
Total WFP	-0.282**	-0.064***	-0.217**	-0.327**	-0.078***	-0.249**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Importer FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-test				7.24e+05	7.24e+05	7.24e+05
R^2	.1005	.1558	.0956	.1005	.1558	.0956
Obs.	8288	8288	8288	8288	8288	8288
Panel B						
Blue WFP	134.619***	28.365**	106.253***	45.791*	-3.276	49.067*
	(0.024)	(0.013)	(0.019)	(0.027)	(0.008)	(0.025)
Importer FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-test				801.778	801.778	801.778
R^2	.1103	.1582	.1036	.1059	.1551	.1012
Obs.	8288	8288	8288	8288	8288	8288

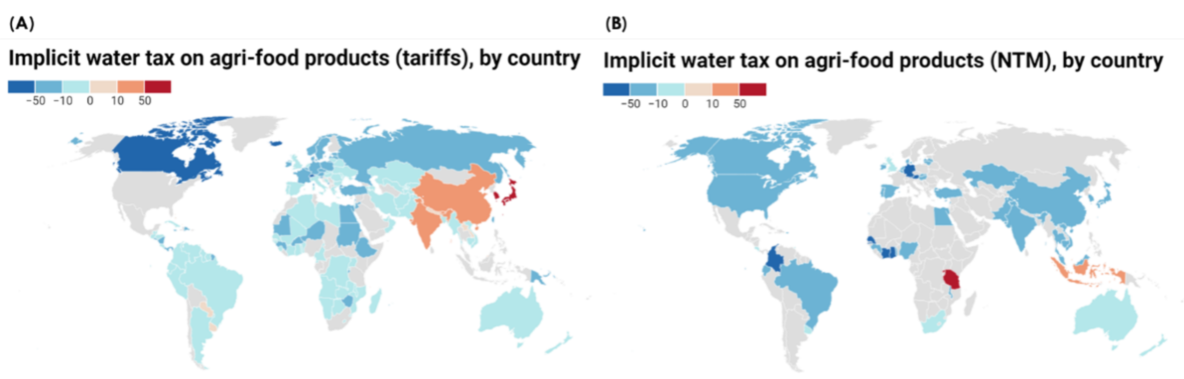
Notes: Robust standard errors in parentheses. All coefficients are reported as euros per thousand m^3.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Completed first-stage results are in Tables A.5 and A.6 in the Appendix.

In Panel B, the simple regression has positive strongly significant coefficients, implying a tax over more blue water intensive products. However, when corrected by the instrument, the significance level strongly diminishes. Some of the countries with the highest trade barriers for crops (e.g., Japan and South Korea on rice) import from countries with very high-water footprint, increasing the significance and value of the implicit "tax". Also, the results may be strongly affected by the high heterogeneity of blue WFP between exporters, especially for specific categories such as plant-based fibres. The positive implicit tax of non-tariff measures and total trade protection may help to the reduction of blue virtual water trade. However further analysis must be done on the increasing events of drought and rain variability, as this may increase the total amount of blue water content on goods, especially if trade is driven by lower tariffs on high water consuming foods and agricultural products. Finally, it is important to mention that the direct WFP is a strong instrument to describe Total (direct + indirect) WFP. First-stage results can be found in the Appendix A.5 and A.6.

6.2 Country level

This section makes a step forward in the analysis looking at the relationship between trade policies and WFP of imported agri-food products at the country level. The maps presented report coefficients for the regressions with tariffs and non-tariff measures (NTMs) as dependent variables. Negative coefficients would imply "subsidies."

Figure 3: Implicit tax (subsidy) by country on blue + green WFP



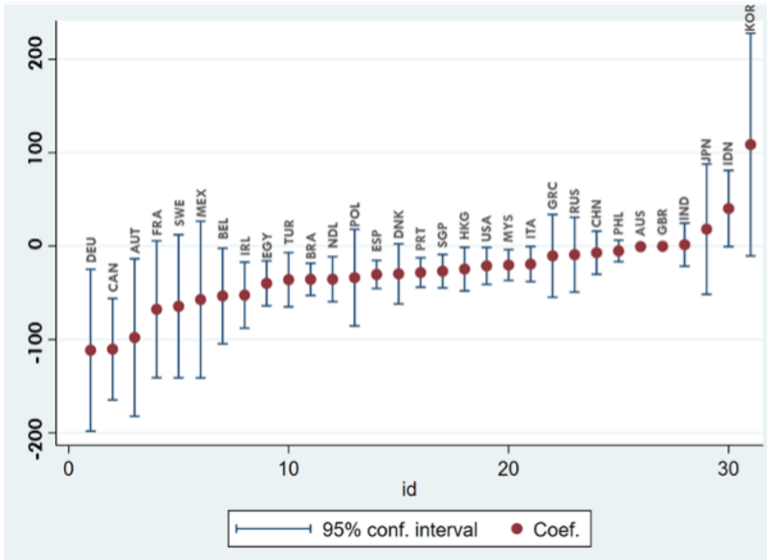
Notes: countries are coloured just in case their coefficients are significant (CI 90%).

Based on tariffs, Canada and Switzerland exhibit the most significant "subsidies" on high water consumption products, with coefficients of -62 and -155 euros per thousand m^3 respectively (CI 99%). This is primarily driven by high tariffs imposed on animal-related products compared to the tariffs applied to water-intensive products like cereals and oilseeds. Other countries, including the UK, the Netherlands, Italy, Russia, Poland, Taiwan, Portugal, Egypt, Iran, and Brazil, also exhibit strong, significant negative coefficients (CI 99%) ranging from -0.1 to -22 euros per thousand m^3. Furthermore, the majority of countries display negative coefficients spanning from 0 to -50 euros per thousand m^3, with approximately 80% of these coefficients significant at least at a 90% confidence interval. Specifically, China and South Korea demonstrate positive tariffs (CI 95%), primarily due to the high tariffs levied on high water-consuming products such as rice, wheat, other cereal grains, and oilseeds. Additionally, there are 27 more countries with positive coefficients (implying implicit taxes), but only 38% of them are significant at a confidence level of 90%. Based on non-tariff measures, Germany and Austria exhibit the lowest coefficients, -82 and -72 euros per thousand m^3 respectively (CI 95%). This is driven by the utilization of small or negligible NTMs on water-intensive foods compared to other agricultural and food products. Additionally, the UK, Spain, Malaysia, Portugal, Egypt, Singapore, and Brazil demonstrate significant negative coefficients ranging from -0.2 to -30 euros per thousand m^3 (CI 99%). Conversely, Cape Verde, Rwanda, Tanzania, and Indonesia are the only four countries with positive significant coefficients (CI 90%), influenced by the implementation of high NTMs on products such as oilseeds, wheat, and paddy rice.

Considering the combination of both trade policies, Figure 4 illustrates the implicit taxes per country using the Total Trade Protection (TTP), which is the sum of NTMs and tariffs. To simplify the graph, only countries responsible for 80% of global trade are included. TTP values are considered only if information on both tariffs and non-tariff measures is available. In this context, Germany, Canada, and Austria exhibit the most negative significant coefficients, ranging between -111 and -98 euros per thousand m3. Notably, for Germany and Austria, implicit tariffs represent approximately 3 to 4% of the national price for tap water in their main cities.[14] Additionally, the Figure displays the confidence interval (95%) of coefficients. Countries such as the Netherlands, Spain, Egypt, Turkey, and Brazil, among others, have coefficient ranges below zero. Interestingly, Canada and Germany have the smallest ranges, suggesting a strong trade policy bias towards subsidizing water-intensive products.

[14]This insight could be valuable for further analysis regarding the hidden costs of virtual water trade.

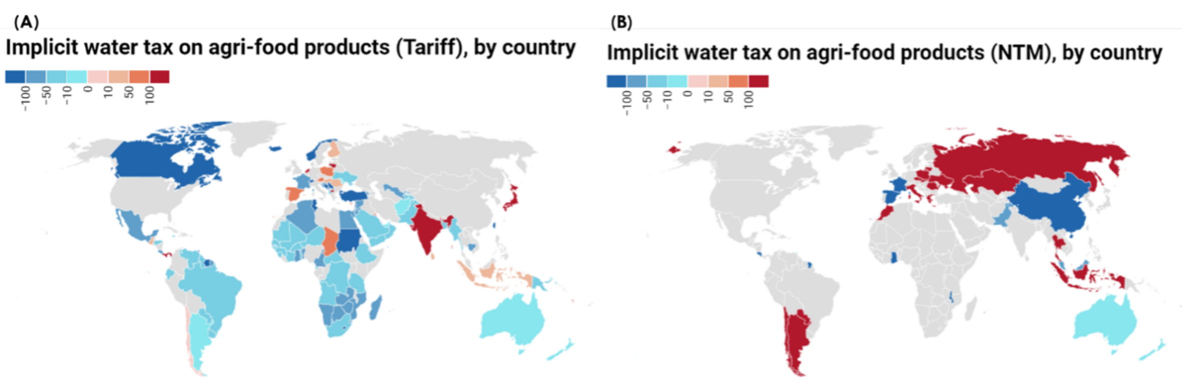
Figure 4: Implicit tax (subsidy) by country on blue + green WFP - TTP



Notes: the implicit taxes per country through the Total Trade Protection (TTP), which is the sum of NTMs and tariffs. Only countries responsible for 80% of global trade are included. TTP values are considered only if information on both tariffs and non-tariff measures is available.

Regarding Blue WFP, the same analysis was carried out. Similar to previous exercise, figure 5 illustrates the significant coefficients for tariffs and NTM.

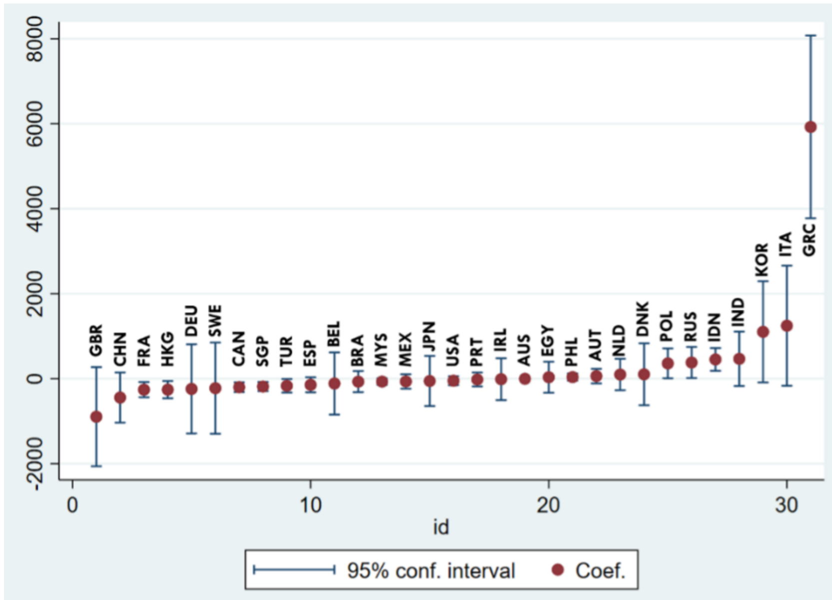
Figure 5: Implicit tax (subsidy) by country on blue WFP



Notes: countries are coloured just in case their coefficients are significant (CI 90%).

Based on tariffs, Tunisia, Serbia, Norway, and Switzerland are the countries with the highest significant "subsidy" on high water consumption products, exceeding 1 euro per m^3 (CI 99%), driven primarily by high tariffs on animal-related products. Among all countries with negative coefficients, two-thirds (66%) were significant (CI 90%), while the remaining 33% were not. Conversely, from countries with coefficients indicating a "tax" on water-intensive products, only 40% were significant (CI 90%). Among these significant countries, Japan has the highest coefficient, implying a tax of around 2 euros per m^3 (CI 99%). As previously mentioned, this can be strongly related to the high taxes imposed by the country on paddy rice. Regarding non-tariff measures (NTMs), China, Spain, Malawi, France, and Singapore demonstrate the lowest coefficients, ranging from -184 to -500 euros per thousand m3 (CI 95%). Various factors drive these measures; for instance, China implemented its lowest NTM on the most water-intensive product, namely sugar beet/cane. Nine countries, including Paraguay, Chile, and Ukraine, among others, exhibit significant coefficients implying taxes exceeding 200 euros per thousand m3 (CI 99%), with many of them imposing high NTMs on paddy rice. Less than half of the countries have coefficients that are statistically significant, whether positive or negative.

Figure 6: Implicit tax (subsidy) by country on blue WFP - TTP



Notes: the implicit taxes per country through the Total Trade Protection (TTP), which is the sum of NTMs and tariffs. Only countries responsible for 80% of global trade are included. TTP values are considered only if information on both tariffs and non-tariff measures is available.

Finally, as in Figure 4, the scatter graph reports that most of the countries leading trade does not have strong significant coefficients (Figure 6). Some countries like France, Canada, and Singapore present a “subsidy” if both tariffs and NTM are considered. In contrast Greece and India have implicit taxes, this results as in previous cases is strongly related with very high taxes on paddy rice.[15]

6.3 Analysis of other potential drivers

This part focuses on analysing the relationship between the possible drivers described on Section 3.1 and trade policies. Variables considered to explain the implicit “subsidy” of trade policies include upstreamness, intra-industry trade, import penetration, average wage, labour share, labour intensity, percentage of food going to feed, percentage of food going to further processing and the last two variables together. The regressions performed on this section are based on instrumented regression.

[15]Further analysis excluding paddy rice could verify this hypothesis.

Table 4: 2SLS results using other potential drivers. Blue + green WFP - Tariff

Dep. var.: Tariff	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Total WFP	-0.078***	-0.066***	-0.080***	-0.026*	-0.080***	-0.079***	-0.079***	-0.080***	-0.050***	-0.043***
	(0.020)	(0.017)	(0.022)	(0.014)	(0.021)	(0.021)	(0.020)	(0.019)	(0.019)	(0.015)
Upstreameness		-0.023**								
		(0.012)								
Import Penetration			-0.001							
			(0.001)							
Avg_wage				0.006***						
				(0.001)						
Labour Share					-2.460***					
					(0.340)					
Labour Intensity						-0.127***				
						(0.016)				
GLI							-0.003			
							(0.012)			
Feed								-0.079**		-0.078**
								(0.031)		(0.031)
Processing									-0.117***	-0.116***
									(0.025)	(0.025)
Importer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-test	7.24e+05	5.83e+05	4.96e+05	4.94e+05	4.92e+05	4.96e+05	7.16e+05	6.16e+06	3.77e+06	4.60e+06
R^2	.1558604	.1563543	.1232876	.1442469	.1271754	.1266458	.1557636	.178	.1800575	.1809067
Obs.	8288	8288	3766	3664	3766	3766	8288	7226	7226	7226

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: 2SLS results using other potential drivers. Blue + green WFP - NTM

Dep. var.: NTM	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Total WFP	-0.249**	-0.238**	-0.235***	-0.149***	-0.236***	-0.235***	-0.228**	-0.240**	-0.206**	-0.187*
	(0.111)	(0.109)	(0.085)	(0.049)	(0.083)	(0.082)	(0.112)	(0.103)	(0.101)	(0.096)
Upstreameness		-0.022								
		(0.023)								
Import Penetration			0.007***							
			(0.002)							
Avg_wage				0.010***						
				(0.001)						
Labour Share					-3.329***					
					(0.931)					
Labour Intensity						-0.225***				
						(0.056)				
GLI							0.149***			
							(0.026)			
Feed								-0.213***		-0.212***
								(0.034)		(0.034)
Processing									-0.166***	-0.165***
									(0.029)	(0.029)
Importer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-test	7.24e+05	5.83e+05	4.96e+05	4.94e+05	4.92e+05	4.96e+05	7.16e+05	6.16e+06	3.77e+06	4.60e+06
R^2	.0956463	.0956598	.0524407	.0783259	.0551344	.0568938	.0992764	.1013069	.1010447	.1027237
Obs.	8288	8288	3766	3664	3766	3766	8288	7226	7226	7226

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: 2SLS results using other potential drivers. Blue + green WFP - TTP

Dep. var.: TTP	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Total WFP	-0.327**	-0.304**	-0.314***	-0.175***	-0.316***	-0.314***	-0.307**	-0.321***	-0.256**	-0.230**
	(0.127)	(0.122)	(0.102)	(0.047)	(0.100)	(0.099)	(0.127)	(0.117)	(0.112)	(0.103)
Upstreameness		-0.045*								
		(0.026)								
Import Penetration			0.006***							
			(0.002)							
Avg_wage				0.016***						
				(0.001)						
Labour Share					-5.790***					
					-1.125					
Labour Intensity						-0.352***				
						(0.064)				
GLI							0.146***			
							(0.029)			
Feed								-0.291***		-0.290***
								(0.047)		(0.047)
Processing									-0.283***	-0.282***
									(0.037)	(0.037)
Importer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-test	7.24e+05	5.83e+05	4.96e+05	4.94e+05	4.92e+05	4.96e+05	7.16e+05	6.16e+06	3.77e+06	4.60e+06
R^2	.1005324	.1008279	.0659777	.1098345	.0721902	.0735275	.1031782	.110788	.1116327	.1140952
Obs.	8288	8288	3766	3664	3766	3766	8288	7226	7226	7226

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Concerning Table 4, it is evident that, overall, the implicit taxes associated with tariffs on agri-food products are not substantially affected by the potential explanatory variables included in the regressions. However, many of these variables hold significant importance in shaping trade policies.

For tariffs, all new variables introduced are significant except for intra-industry trade and import penetration. The presence of more upstream agri-food products, or those intended for use in feeding or further processing, could be related to critical supply chains within major food industries. This association may potentially lead to lobbying efforts aimed at reducing trade barriers and, subsequently, production costs. The three variables exhibit a significant negative correlation with trade barriers, yet they do not entirely explain the implicit subsidy on water use, which remains significant. Labour share and labour intensity also demonstrate a negative relationship with tariffs. This trend might stem from the substantial protection afforded to large manufacturing industries (such as those involved in meat processing, rice processing, and sugar production) through high tariffs, despite their lower reliance on labor. Conversely, businesses related to the production of labor-intensive goods (such as fish and vegetables) typically have less lobbying power, resulting in comparatively lower tariffs. Additionally, wages display a positive impact on tariffs. This phenomenon could be attributed to the fact that vulnerable workers, often those with lower compensation, engaged in the production of certain agri-food products, may benefit from redistribution initiatives and receive greater protection from international trade.

Concerning non-tariff measures (NTMs), as shown in Table 5, the results are very similar to those of tariffs. However, a notable distinction is the strong significance of intra-industry trade and import penetration for NTMs. These variables exhibit a positive relationship with tariffs, possibly indicating that products facing significant competition from international imports may receive higher protection from trade policies through the implementation of NTMs.

Finally implicit taxes related to total trade protection (TTP) are very similar to those of non-tariff measures (Table 6).[16]

[16]Further analysis can be done to better understand what else is driving the implicit subsidy on high water

Regarding the blue WFP, the regression results using other exponential variables are presented in Table 7. Here we focus only on the association between non-tariff measures (NTMs) and the blue water footprint, as it involves an implicit tax. The same analysis was conducted for tariffs and TTP, and the results are presented in the Appendix (Table A.9).

Regarding non-tariff measures, including new variables has varying effects on the implicit subsidy of blue water content, with most of them slightly increasing the significance of the coefficient for water footprint (WFP). Variables such as upstreamness, the share of food intended for feeding or further processing, labour share, and labour intensity exhibit significant negative coefficients, and their inclusion enhances the significance of the WFP coefficients.

This phenomenon may be attributed to products with high blue water footprint (WFP), such as paddy rice and sugarcane/beet, which face elevated non-tariff measures while simultaneously benefiting from low-tariff drivers like upstreamness. On the other hand, average wage and import penetration exhibit strongly positive and significant coefficients, augmenting the significance of the WFP coefficients. This can be explained by the fact that blue WFP is not always correlated with the GLI index or average wage. For instance, paddy rice and processed rice may have vastly different WFPs but share the same GLI index. Therefore, the impact of both variables is robust when analyzed individually, but if one is omitted, the significance of the other may diminish, given the characteristics of the sample used.

Finally import penetration is also strongly significant to NTM, but does not affect the significance of WFP coefficients.

consuming products and the impact of agrifood companies lobbying on the international water footprint of the sector. For example, the existence of an implicit subsidy on agrifood products aimed to feed may drive further analysis on the global efficiency of global value chains to create human nutritional value with less global water resources.

Table 7: 2SLS results using other potential drivers. Blue WFP - NTM

Dep. var.: NTM										
Total WFP	49.1*	66.976**	129.093*	171.609**	135.254**	133.664**	55.762**	49.087*	52.262*	54.673**
	(25.5)	-27.777	-66.271	-74.977	-67.091	-66.658	-25.595	-26.967	-27.068	-27.121
Upstreameness		-0.064***								
		(0.024)								
Import Penetration			0.007***							
			(0.002)							
Avg_wage				0.010***						
				(0.001)						
Labour Share					-3.300***					
					(0.861)					
Labour Intensity						-0.222***				
						(0.054)				
GLI							0.159***			
							(0.027)			
Feed								-0.224***		-0.224***
								(0.035)		(0.035)
Processing									-0.187***	-0.186***
									(0.030)	(0.030)
Importer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-test	801.778	646.863	99.352	80.530	98.354	99.616	792.288	745.793	735.000	730.923
R^2	.1012	.1034	.0644	.0955	.0672	.0689	.1059	.1067	.1069	.1090
Obs.	8288	8288	3766	3664	3766	3766	8288	7226	7226	7226

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.4 Heterogeneous effects

Concerning the water stress of importers and based on the analysis between trade policies and WFP of imported agri-food products, we replicate analysis based on equation 1 by the level of water stress. Results are disclosed in Table 8.

Countries with high levels of water stress tend to exhibit higher implicit subsidies for water-intensive agri-food imports, despite the majority of coefficients remaining strongly negative and significant. This indicates that the implicit subsidy persists regardless of the water stress level of the importing country.

Especially for NTMs, it becomes evident that the implicit subsidy increases with the water stress level of countries. For instance, countries utilizing more than 100% of their current available renewable freshwater sources exhibit an implicit subsidy of around 25 euros per thousand m^3, whereas countries withdrawing less than 25% have an implicit subsidy of just 0.19 euro per thousand m^3. In contrast, such a pattern cannot be identified for tariffs.

The same analysis was conducted for non-tariff measures (NTMs) and their impact on blue WFP (Table 9). We focused on NTMs only since they represent the trade policy with an implicit tax on blue WFP, and considering that for total WFP, NTMs yielded more insightful conclusions compared to other trade policies.

Contrary to previous findings, the relationship between non-tariff measures (NTMs) and blue WFP is negative for countries with high levels of water stress, indicating a subsidy of 81 euros per thousand m^3 for blue water-intensive products. In contrast, countries with low water stress suggest a tax of 85 euros per thousand thousand m^3 on such products.

This insight is crucial, given the direct relationship between blue WFP and water stress in producing countries. On the one hand, the implicit tax imposed by countries with low water stress may discourage the importation of water-intensive products from countries with higher levels of water stress. Conversely, the implicit subsidy provided by countries with high levels of water stress may encourage importing such products, alleviating pressure on national freshwater sources from domestic production.

As discussed in the introduction, these results could significantly influence further policy analysis and decision-making. By fostering the importation of more water-intensive products to countries with higher water stress, national water savings through trade could yield substantial social and environmental benefits. This approach could drive increased water efficiency and value creation, ultimately contributing to sustainability efforts on both local and global scales.

Table 8: 2SLS results by the level of water stress. Blue + green WFP

	TTP			Tariff			NTM		
	Low	Moderate	High	Low	Moderate	High	Low	Moderate	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Total WFP	-0.258**	-16.701***	-26.283***	-0.097***	-2.230	-0.083***	-0.192**	-15.719***	-25.441***
	(0.000)	(0.004)	(0.007)	(0.000)	(0.002)	(0.000)	(0.000)	(0.003)	(0.006)
Importer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-test	2.32e+06	26.194	65.313	1.95e+06	70.042	2.50e+07	2.32e+06	27.189	65.313
R^2	.0981	.0698	.0975	.2288	.1441	.2290	.0985	.0245	.0801
Obs.	5273	2124	364	9546	3353	1412	5343	2174	364

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: 2SLS results by the level of water stress. Blue WFP - NTM

	NTM		
	(1)	(2)	(3)
Total WFP	85.378**	14.466	-80.741*
	(0.036)	(0.028)	(0.046)
Importer FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
F-test	1014.928	90.590	113.941
R^2	.1074	.0865	.0707
Obs.	5343	2174	364

Notes: Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7 Conclusions

Based on the methodology used by Shapiro (2021), this research aims to understand better the relationships between trade policies and the water intensity of agri-food products. The main research questions are: Is there any trend for most water-intensive products to face higher or lower trade barriers? And why? To address these questions, the study first analyzes the water intensity of existing products, considering both total water footprints and solely blue water footprints. The water footprint is defined as the total or blue water consumed to produce €1 of output and strongly depends on the type of product analyzed and its place of production. Globally, the "most water-intensive" products with the highest water footprints are paddy rice, wheat, sugar, other cereals, grains, and oil seeds (if green water is considered). Meanwhile, the products with the lowest water footprints are meat, dairy, and fish products. When comparing the average trade barriers (tariffs and non-tariff measures) for the most and least water-intensive products, no clear trend of higher or lower trade barriers for the most water-intensive products can be identified. This result may be attributed to the high heterogeneity of trade policies between countries concerning the various agri-food products analyzed. Thus, the econometric analysis, which considers the country's particularities, identifies the potential implicit tax (or subsidy) that trade barriers impose on water consumption intensity. When analyzing total WFP, the coefficients suggest an implicit negative tax (or subsidy) to water-intensive products between 0.1 and 0.3 euros per thousand m3. In contrast, the coefficients obtained from the analysis of blue water footprint imply a positive tax on water-intensive products of around 49 euros per thousand cubic meters. However, this coefficient is significant (with a 90% confidence interval) only for non-tariff measures. These different conclusions may be attributed to the significance of green water consumption (from rainfall) for agri-food products, especially for highly water-intensive products, and for countries with high levels of rainfall. In contrast, the coefficient obtained by the analysis of blue water footprint implies a positive tax to water-intensive products of around 49 euros per thousand of m3; however, this coefficient is significant (CI 90%) just for non-tariff measures. These different conclusions may be caused by the importance of green water consumption (rain) for agrifood products, especially for high water-intensive products, and by countries with high levels of rainfall. When comparing total trade protection coefficients between countries for total water, it was found that Germany, Canada, and Austria have the highest implicit subsidies, going from 98 to 111 euros per thousand m3. Meanwhile, for blue water, most countries do not have strongly significant coefficients, and implicit taxes from tariffs are more positive on high water-intensive products than those implied by NTM. Finally, no specific driver or explanation for the implicit tax or subsidy on water-intensive products was identified. Some of the variables analyzed included water scarcity of importers and the share of food allocated to feed or aimed for further processing. However, neither of these new variables explained the results of the initial regression. Interestingly, water scarcity of importers was not a significant variable in trade policies for total water and blue water footprints. This finding is interesting, as several papers focusing on regions with high water stress recommend including trade policies to support importing water-intensive products rather than producing them domestically. Moreover, while the coefficients of shares going to feed and further processing are significant, they do not fully explain the implicit taxes. Nonetheless, they reduce the significance of implicit subsidies of non-tariff measures for products with high total water footprints (blue + green). This research found a significant heterogeneity in trade policy relationships towards water-intensive products, mainly depending on the different agrifood industry trends between countries and the significant heterogeneity in water endowments. The importance of international trade in the agri-food sector is unquestionable; however, there is still a huge heterogeneity in trade policies, especially concerning environmental aspects. Moreover, water availability is not a key decision factor for trade flows. Still, the asymmetry of water resources between countries and the increasing affectations of climate events on water availability and agrifood production may increase its importance on future trade flows. Therefore, it is strongly important to deepen the potential benefits of a more homogeneous and coordinated trade policy environment to improve the use efficiency of global water resources and enable a sustainable transition of the worldwide agrifood value chains.

References

Antonelli, M. and F. Greco (2015, 01). *The Water We Eat Combining Virtual Water and Water Footprints.*

Antonelli, M. and M. Sartori (2015). Unfolding the potential of the virtual water concept. what is still under debate? *Environmental science & policy 50*, 240–251.

Antonelli, M. and S. Tamea (2015). Food-water security and virtual water trade in the middle east and north africa. *International Journal of Water Resources Development 31*(3), 326–342.

Antràs, P., D. Chor, T. Fally, and R. Hillberry (2012). Measuring the upstreamness of production and trade flows. *American Economic Review 102*(3), 412–416.

Aw-Hassan, A., F. Rida, R. Telleria, and A. Bruggeman (2014). The impact of food and agricultural policies on groundwater use in syria. *Journal of hydrology 513*, 204–215.

Berrittella, M., K. Rehdanz, R. S. Tol, and J. Zhang (2008). The impact of trade liberalization on water use: A computable general equilibrium analysis. *Journal of Economic Integration*, 631–655.

Brindha, K. (2017). International virtual water flows from agricultural and livestock products of india. *Journal of Cleaner Production 161*, 922–930.

Caro, D., A. Alessandrini, F. Sporchia, and S. Borghesi (2021). Global virtual water trade of avocado. *Journal of Cleaner Production 285*, 124917.

Carr, J. A., P. D'Odorico, F. Laio, and L. Ridolfi (2013). Recent history and geography of virtual water trade. *PloS one 8*(2), e55825.

Chapagain, A., A. Y. Hoekstra, H. Savenije, and R. Gautam (2005). The water footprint of cotton consumption.

Chapagain, A. K. and A. Y. Hoekstra (2011). The blue, green and grey water footprint of rice from production and consumption perspectives. *Ecological Economics 70*(4), 749–758.

Chen, Z.-M. and G. Chen (2013). Virtual water accounting for the globalized world economy: National water footprint and international virtual water trade. *Ecological indicators 28*, 142–149.

Damerau, K., A. G. Patt, and O. P. Van Vliet (2016). Water saving potentials and possible trade-offs for future food and energy supply. *Global Environmental Change 39*, 15–25.

Dinar, A., A. Tieu, and H. Huynh (2019). Water scarcity impacts on global food production. *Global Food Security 23*, 212–226.

Duarte, R., V. Pinilla, and A. Serrano (2019). Long term drivers of global virtual water trade: A trade gravity approach for 1965–2010. *Ecological Economics 156*, 318–326.

d'Odorico, P., J. Carr, C. Dalin, J. Dell'Angelo, M. Konar, F. Laio, L. Ridolfi, L. Rosa, S. Suweis, S. Tamea, et al. (2019). Global virtual water trade and the hydrological cycle: patterns, drivers, and socio-environmental impacts. *Environmental Research Letters 14*(5), 053001.

Eurostat (2018). Statistics expalined. *Eurostat*.

Falkenmark, M. (2013). Growing water scarcity in agriculture: future challenge to global water security. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 371*(2002), 20120410.

FAO (2018). *Water for sustainable food and agriculture: A report produced for the G20 Presidency of Germany.* Food & Agriculture Org.

FAO (2023). *Food balance sheets 2010–2021. Global, regional and country trends.* Food & Agriculture Org.

Flachsbarth, I., B. Willaarts, H. Xie, G. Pitois, N. D. Mueller, C. Ringler, and A. Garrido

(2015). The role of latin america's land and water resources for global food security: environmental trade-offs of future food production pathways. *PloS one 10*(1), e0116733.

Fracasso, A. (2014). A gravity model of virtual water trade. *Ecological economics 108*, 215–228.

Gawel, E. and K. Bernsen (2013). What is wrong with virtual water trading? on the limitations of the virtual water concept. *Environment and Planning C: Government and Policy 31*(1), 168–181.

Grubel, H. and P. Lloyd (1975, 01). *Intra-Industry Trade: The Theory and Measurement of International Trade in Differentiated Products*. Macmillan Press, London.

Hatfield, J. L. (2015). Environmental impact of water use in agriculture. *Agronomy Journal 107*(4), 1554–1556.

Hoekstra, A. Y. and A. K. Chapagain (2011). *Globalization of water: Sharing the planet's freshwater resources*. John Wiley & Sons.

Hoekstra, A. Y. and P. Q. Hung (2005). Globalisation of water resources: international virtual water flows in relation to crop trade. *Global environmental change 15*(1), 45–56.

Javed, T., J. Zhang, N. Bhattarai, Z. Sha, S. Rashid, B. Yun, S. Ahmad, M. Henchiri, and M. Kamran (2021). Drought characterization across agricultural regions of china using standardized precipitation and vegetation water supply indices. *Journal of Cleaner Production 313*, 127866.

Kayatz, B., G. Baroni, J. Hillier, S. Lüdtke, R. Heathcote, D. Malin, C. van Tonder, B. Kuster, D. Freese, R. Hüttl, et al. (2019). Cool farm tool water: A global on-line tool to assess water use in crop production. *Journal of Cleaner Production 207*, 1163–1179.

Konar, M., T. P. Evans, M. Levy, C. A. Scott, T. J. Troy, C. J. Vörösmarty, and M. Sivapalan (2016). Water resources sustainability in a globalizing world: who uses the water? *Hydrological Processes 30*(18), 3330–3336.

Looi Kee, H., A. Nicita, and M. Olarreaga (2009). Estimating trade restrictiveness indices. *The Economic Journal 119*(534), 172–199.

Mbow, C., C. E. Rosenzweig, L. G. Barioni, T. G. Benton, M. Herrero, M. Krishnapillai, A. C. Ruane, E. Liwenga, P. Pradhan, M. G. Rivera-Ferre, et al. (2020). Food security. Technical report, IPCC.

Mekonnen, M. and W. Gerbens-Leenes (2020, October). The water footprint of global food production. *Water (Switzerland) 12*(10).

Mekonnen, M. M. and A. Y. Hoekstra (2011). The green, blue and grey water footprint of crops and derived crop products. *Hydrology and Earth System Sciences 15*(5), 1577–1600.

Niu, Z., C. Liu, S. Gunessee, and C. Milner (2018). Non-tariff and overall protection: evidence across countries and over time. *Review of World Economics 154*, 675–703.

Oki, T., S. Yano, and N. Hanasaki (2017). Economic aspects of virtual water trade. *Environmental research letters 12*(4), 044002.

Pfister, S., A. Koehler, and S. Hellweg (2009). Assessing the environmental impacts of freshwater consumption in lca. *Environmental science & technology 43*(11), 4098–4104.

Rosenzweig, C., C. Mbow, L. G. Barioni, T. G. Benton, M. Herrero, M. Krishnapillai, E. T. Liwenga, P. Pradhan, M. G. Rivera-Ferre, T. Sapkota, et al. (2020). Climate change responses benefit from a global food system approach. *Nature Food 1*(2), 94–97.

Sauvé, S., S. Lamontagne, J. Dupras, and W. Stahel (2021). Circular economy of water: Tackling quantity, quality and footprint of water. *Environmental Development 39*, 100651.

Serrano, A., D. Guan, R. Duarte, and J. Paavola (2016). Virtual water flows in the eu27: A consumption-based approach. *Journal of Industrial Ecology 20*(3), 547–558.

Shapiro, J. S. (2021). The environmental bias of trade policy. *The Quarterly Journal of Economics 136*(2), 831–886.

Stadler, K., R. Wood, T. Bulavskaya, C.-J. Södersten, M. Simas, S. Schmidt, A. Usubiaga, J. Acosta-Fernández, J. Kuenen, M. Bruckner, et al. (2018). Exiobase 3: Developing a time series of detailed environmentally extended multi-regional input-output tables. *Journal of Industrial Ecology 22*(3), 502–515.

Tamea, S., J. Carr, F. Laio, and L. Ridolfi (2014). Drivers of the virtual water trade. *Water Resources Research 50*(1), 17–28.

Willet, J., K. Wetser, J. Vreeburg, and H. H. Rijnaarts (2019). Review of methods to assess sustainability of industrial water use. *Water Resources and Industry 21*, 100110.

Wu, X., J. Guo, C. Li, L. Shao, M. Han, and G. Chen (2019). Global socio-hydrology: An overview of virtual water use by the world economy from source of exploitation to sink of final consumption. *Journal of Hydrology 573*, 794–810.

Yao, G., X. Zhang, E. A. Davidson, and F. Taheripour (2021). The increasing global environmental consequences of a weakening us–china crop trade relationship. *Nature food 2*(8), 578–586.

Zhang, Y., J.-H. Zhang, Q. Tian, Z.-H. Liu, and H.-L. Zhang (2018). Virtual water trade of agricultural products: A new perspective to explore the belt and road. *Science of the Total Environment 622*, 988–996.

Appendix

Table A.1: Product list

Product	prod_code
Sugar cane, sugar beet	c_b
Cattle	cttl
Products of forestry, logging	frs
Fish and other fishing product	fsh
Cereal grains nec	gro
Meat animals nec	m_a_n
Dairy products	mil
Animal products nec	oap
Crops nec	ocr
Food products nec	ofd
Meat products nec	omt
Oil seeds	osd
Processed rice	pcr
Paddy rice	pdr
Plant-based fibers	pfb
Pigs	pig
Poultry	pltr
Products of meat cattle	pmc
Products of meat pigs	pmp
Products of meat poultry	pmpl
Raw milk	rmk
Sugar	sgr
Vegetables, fruit, nuts	v_f
products of Vegetable oils and	vol
Wheat	wht
Wool, silk-worm cocoons	wol

Table A.2: EXIOBASE list of countries considered

Nbr	Code	Name	UN Region
1	AT	Austria	Western Europe
2	BE	Belgium	Western Europe
3	BG	Bulgaria	Eastern Europe
4	CY	Cyprus	Western Asia
5	CZ	Czech Republic	Eastern Europe
6	DE	Germany	Western Europe
7	DK	Denmark	Northern Europe
8	EE	Estonia	Northern Europe
9	ES	Spain	Southern Europe
10	Fl	Finland	Northern Europe
11	FR	France	Western Europe
12	GR	Greece	Southern Europe
13	HR	Croatia	Southern Europe
14	HU	Hungary	Eastern Europe
15	IE	Ireland	Northern Europe
16	IT	Italy	Southern Europe
17	LT	Lithuania	Northern Europe
18	LU	Luxembourg	Western Europe
19	LV	Latvia	Northern Europe
20	MT	Malta	Southern Europe
21	NL	Netherlands	Western Europe
22	PL	Poland	Eastern Europe
23	PT	Portugal	Southern Europe
24	RO	Romania	Eastern Europe
25	SE	Sweden	Northern Europe
26	SI	Slovenia	Southern Europe
27	SK	Slovakia	Eastern Europe
28	GB	United Kingdom	Northern Europe
29	US	United States	Northern America
30	JP	Japan	Eastern Asia
31	CN	China	Eastern Asia
32	CA	Canada	Northern America
33	KR	South Korea	Eastern Asia
34	BR	Brazil	South America
35	IN	India	Southern Asia
36	MX	Mexico	Central America
37	RU	Russia	Eastern Europe
38	AU	Australia	Australia and New Zealand
39	CH	Switzerland	Western Europe
40	TR	Turkey	Western Asia
41	TW	Taiwan	Eastern Asia
42	NO	Norway	Northern Europe
43	ID	Indonesia	South-Eastern Asia
44	ZA	South Africa	Southern Africa
45	WA	RoW Asia and Pacific	
46	WL	RoW America	
47	WE	RoW Europe	
48	WF	RoW Africa	
49	WM	RoW Middle East	

Table A.3: Total (blue + green) weighted WFP per product

Total Water Footprint	WFP (m3/eur)		Direct WFP as % of Total
Product	Total	Direct	
Paddy rice	10.04	6.43	64%
Oil seeds	10.03	9.40	94%
Wheat	8.55	7.59	89%
Cereal grains nec	7.64	6.81	89%
Sugar cane, sugar beet	7.01	5.65	81%
Crops nec	6.38	5.82	91%
Processed rice	3.86	0.00	0%
Products of Vegetable oils and	3.61	0.01	0%
Sugar	2.46	0.01	0%
Cattle	1.99	0.12	6%
Vegetables, fruit, nuts	1.75	1.64	93%
Animal products nec	1.60	0.00	0%
Food products nec	1.41	0.00	0%
Raw milk	1.25	0.00	0%
Poultry	1.05	0.01	1%
Meat animals nec	0.95	0.13	14%
Products of meat cattle	0.90	0.00	0%
Pigs	0.89	0.02	2%
Products of meat pigs	0.58	0.00	0%
Plant-based fibers	0.55	0.39	71%
Products of meat poultry	0.54	0.00	0%
Dairy products	0.51	0.00	0%
Wool, silk-worm cocoons	0.50	0.00	0%
Meat products nec	0.49	0.00	0%
Products of forestry, logging	0.21	0.00	0%
Fish and other fishing product	0.10	0.00	0%

Table A.4: Total (blue) weighted WFP per product

Total Water Footprint	WFP (m3/eur)		Direct WFP as % of Total
Product	Total	Direct	
Paddy rice	2.09	1.39	67%
Wheat	1.93	1.69	88%
Sugar cane, sugar beet	1.81	1.45	80%
Processed rice	0.77	0.00	0%
Crops nec	0.62	0.55	89%
Sugar	0.52	0.01	1%
Cereal grains nec	0.47	0.41	87%
Oil seeds	0.34	0.31	91%
Cattle	0.28	0.12	42%
Vegetables, fruit, nuts	0.25	0.24	94%
Meat animals nec	0.20	0.13	68%
Products of Vegetable oils	0.18	0.01	4%
Animal products nec	0.17	0.00	0%
Products of meat cattle	0.15	0.00	0%
Food products nec	0.14	0.00	1%
Poultry	0.13	0.01	5%
Pigs	0.11	0.02	16%
Raw milk	0.10	0.00	0%
Products of meat poultry	0.07	0.00	1%
Products of meat pigs	0.06	0.00	3%
Meat products nec	0.05	0.00	0%
Wool, silk-worm cocoons	0.05	0.00	0%
Dairy products	0.05	0.00	4%
Plant-based fibers	0.03	0.01	41%
Products of forestry, logging	0.02	0.00	0%
Fish and other fishing product	0.01	0.00	0%

Table A.5: First stage - Total WFP

	Total WFP TTP (1)	Total WFP Tariff (2)	Total WFP NTM (3)
WFP	0.998***	0.998***	0.998***
	(0.001)	(0.001)	(0.001)
R^2	0.977	0.977	0.977
Obs.	8288	8288	8288

Standard errors in parentheses

Notes:

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: First stage - Blue WFP

	Blue WFP TTP (1)	Blue WFP Tariff (2)	Blue WFP NTM (3)
WFP	0.944***	0.944***	0.944***
	(0.033)	(0.033)	(0.033)
R^2	0.661	0.661	0.661
Obs.	8288	8288	8288

Standard errors in parentheses

Notes:

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: 2SLS results using other potential drivers. Blue WFP - Tariff

Dep. var.: Tariffs										
Total WFP	-0.003	4.118	28.513	47.285	32.945	30.991	-3.413	-11.188	-8.545	-7.717
	(0.008)	-8.153	-32.701	-36.990	-32.983	-32.752	-8.707	-9.083	-9.173	-9.215
Upstreameness		-0.026**								
		(0.011)								
Import Penetration			-0.001							
			(0.001)							
Avg_wage				0.006***						
				(0.001)						
Labour Share					-2.454***					
					(0.336)					
Labour Intensity						-0.126***				
						(0.016)				
GLI							-0.003			
							(0.012)			
Feed								-0.077**		-0.077**
								(0.031)		(0.032)
Processing									-0.116***	-0.116***
									(0.025)	(0.025)
F-test	801.778	646.863	99.352	80.530	98.354	99.616	792.288	745.793	735.000	730.923
$\hat{R2}$	.1551813	.1571114	.1296046	.1547647	.1343137	.1334026	.155059	.1761626	.1786831	.1796547
Obs.	8288	8288	3766	3664	3766	3766	8288	7226	7226	7226

Table A.8: 2SLS results using other potential drivers. Blue WFP - TTP

Dep. var.: TTP										
Total WFP	0.046*	71.094**	157.607**	218.895**	168.199**	164.655**	52.349*	37.899	43.716	46.956*
	(0.027)	-29.110	-75.948	-87.397	-77.585	-76.568	-27.038	-28.438	-28.508	-28.546
Upstreameness		-0.091***								
		(0.027)								
Import Penetration			0.006***							
			(0.002)							
Avg_wage				0.016***						
				(0.001)						
Labour Share					-5.753***					
					-1.044					
Labour Intensity						-0.348***				
						(0.061)				
GLI							0.156***			
							(0.030)			
Feed								-0.302***		-0.300***
								(0.048)		(0.048)
Processing									-0.302***	-0.301***
									(0.039)	(0.039)
F-test	801.778	646.863	99.352	80.530	98.354	99.616	792.288	745.793	735.000	730.923
$\hat{R2}$	.1059532	.1095993	.0855918	.1382329	.0925843	.0935852	.1096014	.1149423	.1166462	.1196028
Obs.	8288	8288	3766	3664	3766	3766		7226	7226	7226

Table A.9: 2SLS results by the level of water stress. Blue + green WFP

	TTP			Tariff			NTM		
	Low	Moderate	High	Low	Moderate	High	Low	Moderate	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Total WFP	75.060**	45.941	-106.077**	-15.460***	61.557	-4.818	85.378**	14.466	-80.741*
	(0.037)	(0.053)	(0.043)	(0.003)	(0.041)	(0.010)	(0.036)	(0.028)	(0.046)
Importer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-test	987.677	89.633	113.941	67.594	284.233	154.191	1014.928	90.590	113.941
$\hat{R2}$	.1055	.1095	.0766	.2289	.1571	.2270	.1074	.0865	.0707
Obs.	5273	2124	364	9546	3353	1412	5343	2174	364