

RESEARCH ARTICLE Trade Openness and Domestic Water Use

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Special Section:
Socio-hydrology: Spatial and Temporal Dynamics of Coupled Human-Water Systems

Key Points:

We determine the causal impact of trade openness on domestic water withdrawals in agriculture and industry
Trade openness leads to less water withdrawals in agriculture but does not significantly impact industrial or total withdrawals
Trade openness reduces water use in agriculture primarily through the intensive margin effect

Supporting Information:
Supporting Information S1

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Abstract We contribute to the debate over globalization and the environment by asking, what is the impact of trade on national water use? To address this question, we employ econometric methods to quantify the causal relationship between trade openness and water use. Specifically, we use the instrumental variables methodology to evaluate the impact of trade openness on domestic water withdrawals in agriculture and industry. We find that trade openness does not have a significant impact on total or industrial water withdrawals. However, we show that one percentage point increase in trade openness leads to a 5.21% decrease in agricultural water withdrawals. We find that trade openness reduces water use in agriculture primarily through the intensive margin effect, by leading farmers to produce more with less water, such as through the adoption of technology. We do not find evidence for extensive margin or crop mix impacts on agricultural water withdrawals. Significantly, these results demonstrate that trade openness leads to less water use in agriculture. This finding has broad scientific and policy relevance as we endeavor to untangle causal relationships in the complex global food system and develop policies to achieve water and food security.

1. Introduction

There has been a recent explosion in research on the water-trade nexus. An extensive literature has developed on the water resources embodied in traded goods (i.e., virtual water trade”) (Hoekstra & Hung, 2005; Hoekstra & Mekonnen, 2012). Work in this area began with the observation that trade may “save” local water resources of the importing country (Allan, 1993). This idea generated extensive work on trade-based global water savings (GWS) (Chapagain et al., 2006; Dalin et al., 2012; de Fraiture et al., 2004). GWS determines the theoretical volume of water that would have been consumed in the absence of trade (i.e., autarky, or if all importing nations instead produced the goods that they import themselves) compared with how much water was actually consumed under the existing trade system (Konar et al., 2016). The global trade system has been shown to save (virtual) water resources (Chapagain et al., 2006). Now there is a critical need to better understand the implications of trade for domestic (physical) water use.

The impact of trade on water use remains an open question. Dang et al. (2016) present a theoretical model of trade and domestic water resources showing the conditions under which trade liberalization will impact water use. Reimer (2014) shows that trade liberalization may be neutral from a water resources perspective but improves welfare and may enable countries to better deal with shocks. Berrittella et al. (2008) show that the impacts of trade liberalization are likely to be nonlinear and reduce water use in water scarce countries but increase water use in water rich countries. Liu et al. (2014) find that international trade buffers the impacts of the projected future shortfalls in irrigation. Konar et al. (2016) determine that free trade leads to greater GWS under a changing climate. On the other hand, Hoekstra (2009) suggests that the export of water-intensive commodities will increase water use and scarcity in exporting nations. Zhao et al. (2015) find that virtual water flows exacerbate water stress in China. Metulini et al. (2016) show that trade induced by human migration is detrimental to the water resources of some countries.

The goal of this paper is to understand the impact of trade openness on national water use. Trade openness is typically measured as total imports and exports as a fraction of economic activity (GDP). Importantly, we are interested in the causal impact of trade openness on domestic water use. A cross-country regression of water use on trade openness may not reflect the causal impact of trade openness on water use. There are two main problems with inferring causality from a cross-sectional regression. First, reverse causality may exist. Access to abundant water resources may enable countries to produce and trade more. Second, endogeneity distorts our interpretation of regression results.

A common cause of endogeneity is that a confounder variable is impacting both the independent (trade openness) and dependent (water use) variables. For example, wealthy countries are more likely to be both more open to trade (as predicted by the gravity model of international trade; Tinbergen, 1962) and to use advanced production technologies that enable them to use water more efficiently, potentially using less. This would lead us to underestimate the impact of trade on water use. Conversely, if these wealthy countries implement policies such as agricultural subsidies, they are likely to boost their agricultural production, leading to more trade and more water use. In this case, the correlational relationship between trade and water withdrawals will be overestimated. Using country trade policies instead of trade openness does not solve the problem. This is because countries that adopt free trade policies may do so precisely because they have the water resources required to meet the increased production demands that will come with trade liberalization.

To understand the causal impact of trade openness on domestic water use, we turn to instrumental variables (IV). Frankel and Romer (1999) introduced the use of the geographical determinants of trade to “instrument” for trade and establish the causal impact of trade on economic growth. Geographic factors determine trade, as given by the gravity model of trade (Tinbergen, 1962). Yet geographic attributes are likely to be exogenous to outcome variables of interest (Frankel & Romer, 1999). This makes geographic variables a suitable instrument for trade openness. Levin and Tervi (2002) employ the same IV approach for a larger sample of years to establish the impact of trade on income, corroborating earlier findings of Frankel and Romer (1999). Geographical determinants of trade are also used to infer the causal impact of trade on air pollution (Frankel & Rose, 2005; Managi et al., 2009). These studies explicitly address the endogeneity of trade and the outcome variable of interest.

Kagohashi et al. (2015) estimate the impact of trade on water use with an IV approach to address endogeneity between trade and water use. However, Kagohashi et al. (2015) use panel data which includes time-varying GDP which might bias their results. Generally, panel data are inappropriate to use when the geographic determinants of trade are used as an instrument for trade. This is because the geographic determinants do not change in time. For this reason, a cross-sectional study is more appropriate. Specifically, GDP is the only time-varying variable in the set of instruments in Kagohashi et al. (2015). For this reason, GDP might dominate the constructed trade openness and thus dominate the estimate of the causal effect. An IV approach that uses cross-sectional data rather than panel data would improve upon the estimate provided by Kagohashi et al. (2015). Additionally, Kagohashi et al. (2015) determine the impact of trade openness on total water withdrawals, ignoring potential differences in withdrawals by economic sector.

We contribute to the debate over globalization and the environment by asking what is the impact of trade on national water use? Importantly, we use an IV methodology to determine the causal impact of trade openness on domestic agricultural and industrial water use. Our IV methodology follows the approach first employed in the seminal work of Frankel and Romer (1999), which geographic variation is used to instrument for trade, based on the gravity model of trade. Here we build upon the work of Kagohashi et al. (2015) in three important ways. First, we use cross-sectional rather than panel data. Second, we distinguish between agricultural and industrial water use. Third, we evaluate the mechanisms driving agricultural water use. We detail our data and methods in section 2. Our results are presented in section 3. We conclude in section 4.

2. Methods

Here we describe our methods. In section 2.1 we detail the data we use on international trade, geographic attributes, agricultural production, and water use. Table 1 lists all data sources used in this study. In section 2.2, we explain the instrumental variables (IV) technique for causal inference.

2.1. Data

We collect data from a variety of sources. This is because we require information on bilateral trade, international trade openness, geographic attributes, agricultural production, and water use. For all variables, we collect country level cross-sectional information for the year 2002, or as close as possible when 2002 is not available. We restrict our analysis to a single year due to limitations in the water use database. The year 2002 is the most recent year with the largest available sample size for water withdrawal data.

Table 1
Sources of Data Used in This Study

Category	Variable	Variable label	Data source
Trade	t_{ij}	Bilateral trade between countries i and j	IMF
	T_i	(export + import value for country i)/GDP	World Bank
Geographical features	D	Distance	CEPII
	A	Area	
	LL	Landlocked dummy	
	B	Border dummy	
Latitude	L	Latitude	World Bank
Dummy variable for region	ECA	Europe and Central Asia	World Bank
	LAC	Latin America and Caribbean	
	MENA	Middle East and North Africa	
	NA	North America	
	SA	South Asia	
	SSA	Sub-Saharan Africa	
	EAP	East Asia and Pacific	
	P	Population	
Population	P	Population	UNPD
	apre	Area-weighted annual average precipitation	Dell et al. (2012)
atem	Area-weighted annual average temperature		
Weather	wpre	Population-weighted annual average precipitation	
	wtem	Population-weighted annual average temperature	
Climate zone	kgatrstr	% land area in Koeppen-Geiger tropics and subtropics	PSU
	kgatemp	% land area in Koeppen-Geiger temperate zones	
	kgptrstr	% 1995 pop in Koeppen-Geiger tropics and subtropics	
	kgptemp	% 1995 pop in Koeppen-Geiger temperate zones	
Crop-specific variables		Agricultural production	FAOSTAT
		Agricultural harvested area	
		Yield	
Water	W	Water withdrawals	AQUASTAT
Industry-related variables	K	Net fixed standardized capital stock	EPWT
	L	Number of employed workers	EPWT
	Patent	Total count of patents in force by applicant origin	WIPO

Bilateral trade. Data on bilateral trade are collected from the International Monetary Fund (IMF) Direction of Trade Statistics (DOTS) (International Monetary Fund, 2016). DOTS data are available at <http://data.imf.org/>. The DOTS reports bilateral trade in value (\$) among all IMF member states, some nonmember countries, the world, and major areas. Imports are reported on a cost, insurance, and freight (CIF) basis and exports are reported on a free on board (FOB) basis, with the exception of a few countries for which imports are also available FOB. Data are available with monthly and quarterly temporal frequency starting in 1960. Annual data are available from 1947 to 1960. Time series data include estimates derived from reports of partner countries for nonreporting and slow-reporting countries. We select the year 2002 in which bilateral trade data is reported for 185 countries.

Trade openness. The classic definition of trade openness is total trade as a fraction of total economic activity. Total economic activity is typically measured by gross domestic product (GDP). Thus, trade openness is typically defined to be

$$T_c = \frac{\text{Imports}_c + \text{Exports}_c}{\text{GDP}_c} \quad (1)$$

where T refers to trade openness, "Imports" refers to gross imports of goods and services in value terms, "Exports" refers to gross exports of goods and services in value terms, and total economic activity is proxied with GDP, and c serves as an index for country c. Trade openness measures the proportion of economic activity encapsulated in trade. For this reason, trade openness is sometimes referred to as the "trade share" or "trade intensity." To quantify trade openness, we obtain data on total import value, total export value, and GDP (all in \$) for each country from the World Bank data portal (World Bank data are available at <http://data.worldbank.org/indicator>). We map our log trade openness variable in Figure 1.

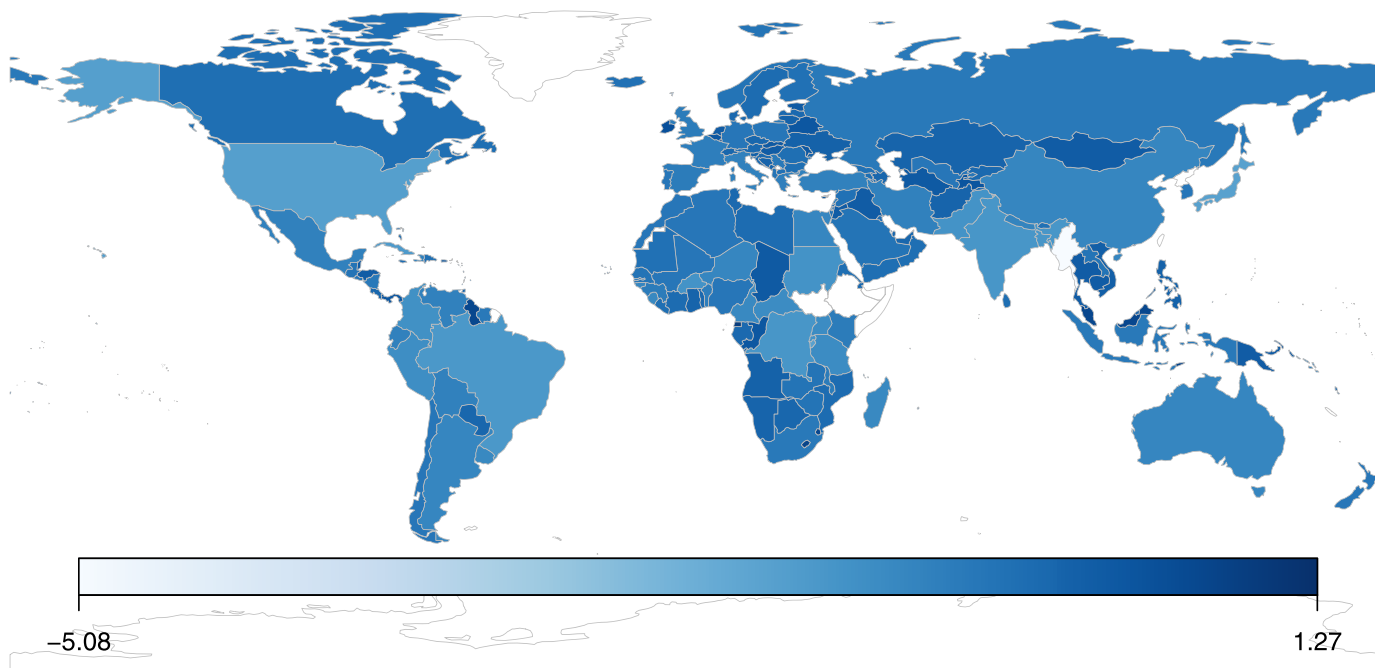


Figure 1. World map for log trade openness in year 2002.

GeographyThe primary source for geographical variables are from the GeoDist database (Mayer & Zignago, 2011) accessed through CEPR Research and Expertise on the World economy (CEPR). Data are available at <http://www.cepii.fr/CEPII/en>. CEPII produces data on the world economy and provides a database of geographic variables for the estimation of the gravity model of international trade. Variables provided include geographic bilateral distances, border indicator, trade and money agreements, cultural data, language, and colonial history from 1948 to 2015. From GeoDist, we collect information on national area, landlocked dummy variable, border dummy variable and the distance between pairs of countries. We also use latitude and dummy variables for region from the World Bank data portal. World Bank data are available at <http://data.worldbank.org/indicator>.

PopulationOur data on population come from United Nations Population Division (United Nations Population Division data are available at <https://esa.un.org/unpd/wpp/Download/Standard/Population/>), which we access from the World Bank data portal. Total population (thousands) are collected.

WeatherWe use both the area-weighted and population-weighted annual average precipitation and temperature data from Dell et al (2012). Dell et al. (2012) aggregate high resolution monthly historical weather data to the country-year level. Their weather data are taken from the Terrestrial air temperature and precipitation: 1900–2006 gridded monthly time series, version 1.01 (Matsuura & Willmott 2007). These weather data are aggregated to the country-year level using either population or area as the weights.

ClimateThe climate data are from Portland State University (PSU data are available at <https://www.pdx.edu/econ/country-geography-data>). PSU takes the Koeppen-Geiger climate zones map from Strahler and Strahler (1992). Then, they calculate the percent land area and population in each climate zone at the country-year level in equal area projection.

Agricultureproduction Information on agriculture is collected from the Food and Agriculture Organization of the United Nations Statistics Division (FAOSTAT data are available at <http://faostat3.fao.org/>). In particular, we collect data on the agricultural production (t), harvested area (ha), and yield ($hg\ ha^{-1}$) from FAOSTAT. We select five major crops due to data limitation, i.e., wheat, barley, maize, and oats. We also use the production data for total cereal value. Data on the value of total agricultural production in each country are collected from the World Bank data portal. We select information on all agricultural commodities for our analysis.

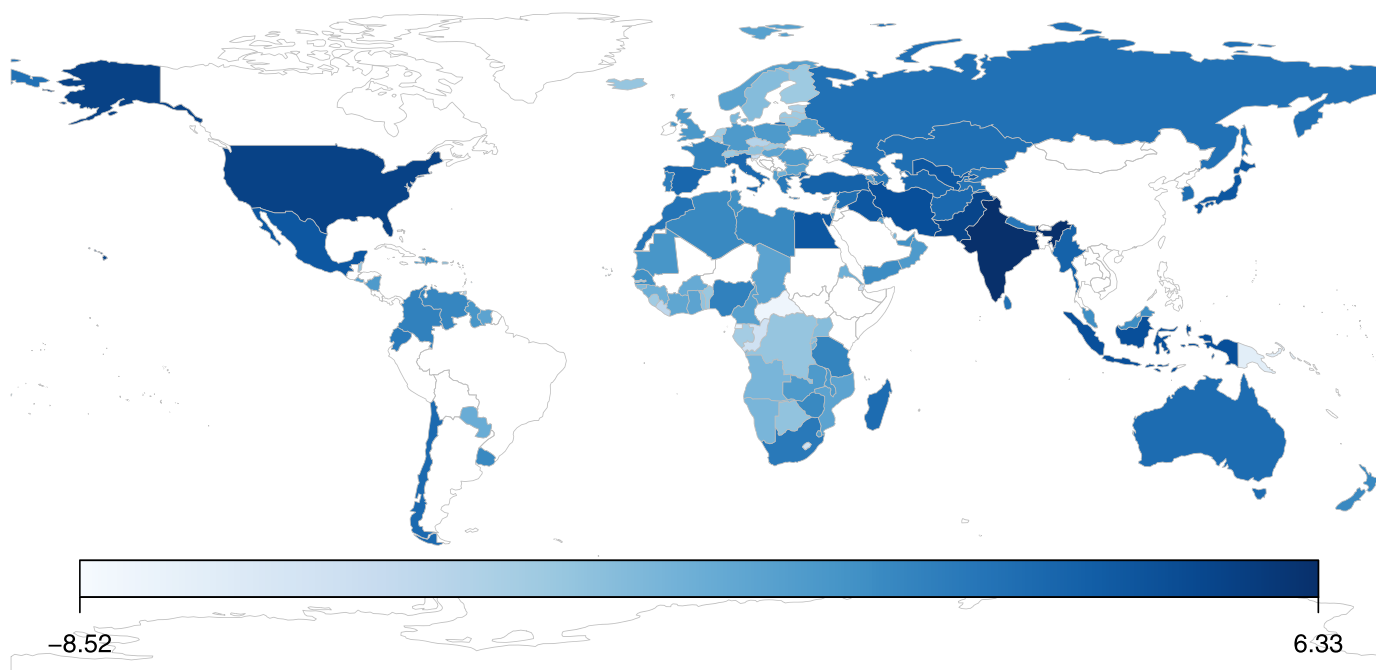


Figure 2. World map for log agricultural water withdrawals ($3 \times 10^3 \text{ m}^3$) in year 2002.

Water use. To measure water use, we use information on water withdrawals provided by the AQUASTAT database of the FAO (AQUASTAT data available at <http://www.fao.org/nr/water/aquastat/data/query/index.html?lang=en>), which we access from the World Bank data portal. AQUASTAT is the global water information system of the FAO. AQUASTAT collects, analyzes, and disseminates data and information by country on water resources, water uses, and agricultural water management. Aquastat provides information on water withdrawals by source (i.e., surface and groundwater). Aquastat also provides information on water withdrawals by sector (i.e., agriculture and industry). Unfortunately, the combined classification is not available (i.e., fraction of agricultural withdrawals from surface supplies).

Annual freshwater withdrawals refer to total water withdrawals not counting evaporation losses from storage basins. Withdrawals also include water from desalination plants in countries where they are a significant source. It is possible for withdrawals to exceed total renewable resources. This could occur if there is extraction from nonrenewable aquifers, desalination plants produce considerable water resources, or where there is significant water reuse. Withdrawals for agriculture are total withdrawals for irrigation and livestock production. Withdrawals for industry are for direct industrial use, which includes withdrawals to cool thermoelectric power plants. AQUASTAT also provides information on withdrawals for domestic use, including drinking water, municipal use or supply, and use for public services, commercial establishments, and homes.

We select data on annual freshwater withdrawals by sector (i.e., agriculture and industry). Unfortunately, water withdrawals data by source are too sparse for our analysis. For each country, we choose information for the most recent year available from 1987 to 2002. This is because 2002 is the year with the most countries provided in the database. We map log water withdrawals for agriculture in Figure 2.

Industry-related variables. We collect variables to estimate the level of industrial development of a nation. We collect number of employed workers and estimated net fixed standardized capital stock in 2005 purchasing power parity from Extended Penn World Tables (Marquardt, 2012). The total count of patents in force by application origin for year 2004 is from World Intellectual Property Organization (WIPO) are available at <https://www3.wipo.int/ipstats/index.htm?tab=5patent>. We select these years since they are the closest available years to 2002 (i.e., the year of most complete water withdrawal data).

2.2. Causal Inference With Instrumental Variables

The relationship between trade openness and water withdrawals is shown in the following regression equation:

$$W_{c,s} = \beta T_c + \gamma X_{c,t} + \epsilon_t \tag{2}$$

where $W_{c,s}$ is water withdrawals of economic sector s in country c , T_c is the trade openness of country c , $X_{c,t}$ is a set of control variables, and ϵ_t is the error term, which is assumed to be independent, identical, and normally distributed. The coefficient of interest is β , which is a scalar and corresponds to trade openness. γ is a vector and represents the coefficients corresponding to the set of control variables for country c . National level values of T and W are mapped in Figures 1 and 2, respectively. Visually, it is not clear how trade openness and agricultural water withdrawals are correlated.

An ordinary least squares (OLS) regression approach is used in many empirical studies to explore the relationship between two variables. OLS estimates the partial correlation between the two variables of interest. In many cases, simply knowing the correlation between two variables is insufficient for understanding their causal relationship. This is true even with carefully chosen control variables. This is because there may be reverse causality or an unobserved confounding factor that is driving both outcomes. For the case of trade openness and water withdrawals, wealthy countries are more likely to be more open to trade. These countries are also more likely to adopt water-saving technologies which may enable them to withdraw less water. This will result in a downward OLS estimate for the relationship between trade openness and domestic water withdrawals. Conversely, policies such as agricultural subsidies in wealthy nations may boost agricultural production, leading to more trade and more water withdrawals. In this case, the OLS relationship between trade openness and water withdrawals will be overestimated. It is essential to isolate the trade share that is correlated with water withdrawals yet uncorrelated with other unobservable determinants of water use.

In order to isolate the causal impact of trade openness on water withdrawals, we use an “instrumental variables” (IV) or “two-stage least squares” approach (Angrist & Pischke, 2009; Wooldridge, 2010). For this approach to work, a variable must be identified that is (1) strongly correlated with trade openness and (2) uncorrelated with any unobservable determinants of the outcome of interest, in this case, water withdrawals, except through trade. Such a variable is known as an “instrument.” In the “first stage” of an instrumental variables estimation, the variation in the endogenous variable that is driven by another variable that is only related to the ultimate outcome of interest through the endogenous variable is isolated. In the “second stage,” the predicted value of the endogenous variable from the first stage is used as the independent variable to obtain a causal estimate.

To construct an instrument for trade openness, we follow Frankel and Romer (1999) and employ information about the geographic attributes of a country. Frankel and Romer (1999) used the geographic factors of a country, such as area, population, and distance to neighbors, to determine the impact of trade openness on income. Geographic factors determine trade, as given by the gravity model of trade. Yet these geographic attributes are exogenous to outcome variables of interest (Frankel & Romer, 1999). So geographic variables are a suitable instrument for trade openness. For this reason, geographic variables have been used in an IV framework to determine the impact of trade on several outcome variables of interest, including air pollution (Frankel & Rose, 2005) and environmental policy (Andonova et al., 2007).

First, we estimate the log transform of the bilateral trade share ($s_{ij} = \log \frac{t_{ij}}{GDP_i}$) using geographic factors. We use bilateral trade between country i and j (t_{ij}) over GDP in country i (GDP_i) as the bilateral trade share, then we take the log transform to get the dependent variable (s_{ij}). We use GDP_i because we want to get an instrument for $Openness_i$ ($5T_i = GDP_i$). So we estimate $T_{ij} = GDP_i$ first. Then, we sum this for all j to get $Openness_i$. For predictors, we follow those introduced by Frankel and Romer (1999), which stems from the gravity model of international trade, in which the bilateral trade between countries is proportional to the GDP of the two countries and negatively correlated with the distance between the countries. In this instrument, only geographic attributes are used as predictors and GDP is omitted because of potential endogeneity with the outcome variable of interest. To specify, the log transform of the bilateral trade share between country i and j for country i (s_{ij}) is estimated by the following equation:

$$s_{ij} = \log \frac{t_{ij}}{GDP_i} \quad (3)$$

$$= \alpha_0 + \alpha_1 \log D_{ij} + \alpha_2 \log P_i + \alpha_3 \log A_i + \alpha_4 \log L_{ij} + \alpha_5 \log B_{ij} + \alpha_6 \delta_{ij} + \alpha_7 B_{ij} + \alpha_8 B_{ij} \log D_{ij} + \alpha_9 B_{ij} \log P_i + \alpha_{10} B_{ij} \log A_i + \alpha_{11} B_{ij} \log P_i + \alpha_{12} B_{ij} \log A_i + \alpha_{13} B_{ij} \delta_{ij} + \alpha_{14} B_{ij} \log L_{ij} + \alpha_{15} B_{ij} \log P_i + \alpha_{16} B_{ij} \log A_i + \alpha_{17} B_{ij} \log D_{ij} + \alpha_{18} B_{ij} \log P_i + \alpha_{19} B_{ij} \log A_i + \alpha_{20} B_{ij} \log L_{ij} + \alpha_{21} B_{ij} \log P_i + \alpha_{22} B_{ij} \log A_i + \alpha_{23} B_{ij} \log D_{ij} + \alpha_{24} B_{ij} \log P_i + \alpha_{25} B_{ij} \log A_i + \alpha_{26} B_{ij} \log L_{ij} + \alpha_{27} B_{ij} \log P_i + \alpha_{28} B_{ij} \log A_i + \alpha_{29} B_{ij} \log D_{ij} + \alpha_{30} B_{ij} \log P_i + \alpha_{31} B_{ij} \log A_i + \alpha_{32} B_{ij} \log L_{ij} + \alpha_{33} B_{ij} \log P_i + \alpha_{34} B_{ij} \log A_i + \alpha_{35} B_{ij} \log D_{ij} + \alpha_{36} B_{ij} \log P_i + \alpha_{37} B_{ij} \log A_i + \alpha_{38} B_{ij} \log L_{ij} + \alpha_{39} B_{ij} \log P_i + \alpha_{40} B_{ij} \log A_i + \alpha_{41} B_{ij} \log D_{ij} + \alpha_{42} B_{ij} \log P_i + \alpha_{43} B_{ij} \log A_i + \alpha_{44} B_{ij} \log L_{ij} + \alpha_{45} B_{ij} \log P_i + \alpha_{46} B_{ij} \log A_i + \alpha_{47} B_{ij} \log D_{ij} + \alpha_{48} B_{ij} \log P_i + \alpha_{49} B_{ij} \log A_i + \alpha_{50} B_{ij} \log L_{ij} + \alpha_{51} B_{ij} \log P_i + \alpha_{52} B_{ij} \log A_i + \alpha_{53} B_{ij} \log D_{ij} + \alpha_{54} B_{ij} \log P_i + \alpha_{55} B_{ij} \log A_i + \alpha_{56} B_{ij} \log L_{ij} + \alpha_{57} B_{ij} \log P_i + \alpha_{58} B_{ij} \log A_i + \alpha_{59} B_{ij} \log D_{ij} + \alpha_{60} B_{ij} \log P_i + \alpha_{61} B_{ij} \log A_i + \alpha_{62} B_{ij} \log L_{ij} + \alpha_{63} B_{ij} \log P_i + \alpha_{64} B_{ij} \log A_i + \alpha_{65} B_{ij} \log D_{ij} + \alpha_{66} B_{ij} \log P_i + \alpha_{67} B_{ij} \log A_i + \alpha_{68} B_{ij} \log L_{ij} + \alpha_{69} B_{ij} \log P_i + \alpha_{70} B_{ij} \log A_i + \alpha_{71} B_{ij} \log D_{ij} + \alpha_{72} B_{ij} \log P_i + \alpha_{73} B_{ij} \log A_i + \alpha_{74} B_{ij} \log L_{ij} + \alpha_{75} B_{ij} \log P_i + \alpha_{76} B_{ij} \log A_i + \alpha_{77} B_{ij} \log D_{ij} + \alpha_{78} B_{ij} \log P_i + \alpha_{79} B_{ij} \log A_i + \alpha_{80} B_{ij} \log L_{ij} + \alpha_{81} B_{ij} \log P_i + \alpha_{82} B_{ij} \log A_i + \alpha_{83} B_{ij} \log D_{ij} + \alpha_{84} B_{ij} \log P_i + \alpha_{85} B_{ij} \log A_i + \alpha_{86} B_{ij} \log L_{ij} + \alpha_{87} B_{ij} \log P_i + \alpha_{88} B_{ij} \log A_i + \alpha_{89} B_{ij} \log D_{ij} + \alpha_{90} B_{ij} \log P_i + \alpha_{91} B_{ij} \log A_i + \alpha_{92} B_{ij} \log L_{ij} + \alpha_{93} B_{ij} \log P_i + \alpha_{94} B_{ij} \log A_i + \alpha_{95} B_{ij} \log D_{ij} + \alpha_{96} B_{ij} \log P_i + \alpha_{97} B_{ij} \log A_i + \alpha_{98} B_{ij} \log L_{ij} + \alpha_{99} B_{ij} \log P_i + \alpha_{100} B_{ij} \log A_i$$

where t_{ij} is the bilateral trade in value (the sum of import value and export value) between country i and country j . D is for distance, P is for population, A is for land area, L is a landlocked dummy which indicates whether the country is landlocked or not, B is a border dummy which indicates whether the two countries share a common border or not. The interaction terms between the border dummy and all of the other explanatory variables are included in this model. The subscripts i and j refer to country i and country j , respectively.

In this way, s_{ij} refer to element i, j in a matrix of all estimated bilateral trade shares. Based on equation (3), we get the estimated bilateral trade shares s_{ij} for all pairs of i and j ($i \neq j$), which forms matrix \hat{s} . Note that the matrix \hat{s} is not symmetric (i.e., $s_{ij} \neq s_{ji}$). $s_{ij} = \log \frac{t_{ij}}{GDP_i}$, while $s_{ji} = \log \frac{t_{ji}}{GDP_j}$. The numerators are the same (i.e., $t_{ij} = t_{ji}$) because they are the total bilateral trade flow between country i and j . Yet the denominators are GDPs for country i and j respectively, which are different.

Our bilateral equation differs from the method employed in Kagohashi et al. (2015) in both dependent and independent variables. Kagohashi et al. (2015) include GDP as a predictor variable, which is potentially endogenous and might dominate the prediction. In our specification, we omit GDP to ensure that the predicted trade share only depends upon geographic characteristics (i.e., not GDP). For the dependent variable, unlike Kagohashi et al. (2015), in which bilateral trade flow is predicted, we predict the bilateral trade share directly. Our method allows us to directly construct trade openness based on this bilateral trade share. Kagohashi et al. (2015) estimate total trade based on the predicted bilateral trade flow and then divide by GDP to obtain trade openness. However, their inclusion of GDP in the denominator might introduce bias due to its potential endogeneity. In this way, our methodology builds and improves upon the methodology used in Kagohashi et al. (2015), by using geographic attributes to construct an instrument for trade openness following Frankel and Romer (1999).

Second, as in Frankel and Romer (1999), the instrument for trade openness for country i is constructed by summing the estimated bilateral trade share between country i and all other countries:

$$\hat{\tau}_i = \sum_{j \neq i} \hat{s}_{ij} \quad (4)$$

where $\hat{\tau}_i$ is the constructed trade openness, which is the instrument in our model.

As pointed out by Frankel and Romer (1999), the instrument should be

$$\hat{\tau}_i = \sum_{j \neq i} \frac{t_{ij}}{GDP_i} = \sum_{j \neq i} \frac{E \exp(\alpha_0 + \alpha_1 D_{ij} + \alpha_2 P_i + \alpha_3 A_i + \alpha_4 L_{ij} + \alpha_5 B_{ij} + \alpha_6 \delta_{ij} + \alpha_7 B_{ij} + \alpha_8 B_{ij} \log D_{ij} + \alpha_9 B_{ij} \log P_i + \alpha_{10} B_{ij} \log A_i + \alpha_{11} B_{ij} \log P_i + \alpha_{12} B_{ij} \log A_i + \alpha_{13} B_{ij} \delta_{ij} + \alpha_{14} B_{ij} \log L_{ij} + \alpha_{15} B_{ij} \log P_i + \alpha_{16} B_{ij} \log A_i + \alpha_{17} B_{ij} \log D_{ij} + \alpha_{18} B_{ij} \log P_i + \alpha_{19} B_{ij} \log A_i + \alpha_{20} B_{ij} \log L_{ij} + \alpha_{21} B_{ij} \log P_i + \alpha_{22} B_{ij} \log A_i + \alpha_{23} B_{ij} \log D_{ij} + \alpha_{24} B_{ij} \log P_i + \alpha_{25} B_{ij} \log A_i + \alpha_{26} B_{ij} \log L_{ij} + \alpha_{27} B_{ij} \log P_i + \alpha_{28} B_{ij} \log A_i + \alpha_{29} B_{ij} \log D_{ij} + \alpha_{30} B_{ij} \log P_i + \alpha_{31} B_{ij} \log A_i + \alpha_{32} B_{ij} \log L_{ij} + \alpha_{33} B_{ij} \log P_i + \alpha_{34} B_{ij} \log A_i + \alpha_{35} B_{ij} \log D_{ij} + \alpha_{36} B_{ij} \log P_i + \alpha_{37} B_{ij} \log A_i + \alpha_{38} B_{ij} \log L_{ij} + \alpha_{39} B_{ij} \log P_i + \alpha_{40} B_{ij} \log A_i + \alpha_{41} B_{ij} \log D_{ij} + \alpha_{42} B_{ij} \log P_i + \alpha_{43} B_{ij} \log A_i + \alpha_{44} B_{ij} \log L_{ij} + \alpha_{45} B_{ij} \log P_i + \alpha_{46} B_{ij} \log A_i + \alpha_{47} B_{ij} \log D_{ij} + \alpha_{48} B_{ij} \log P_i + \alpha_{49} B_{ij} \log A_i + \alpha_{50} B_{ij} \log L_{ij} + \alpha_{51} B_{ij} \log P_i + \alpha_{52} B_{ij} \log A_i + \alpha_{53} B_{ij} \log D_{ij} + \alpha_{54} B_{ij} \log P_i + \alpha_{55} B_{ij} \log A_i + \alpha_{56} B_{ij} \log L_{ij} + \alpha_{57} B_{ij} \log P_i + \alpha_{58} B_{ij} \log A_i + \alpha_{59} B_{ij} \log D_{ij} + \alpha_{60} B_{ij} \log P_i + \alpha_{61} B_{ij} \log A_i + \alpha_{62} B_{ij} \log L_{ij} + \alpha_{63} B_{ij} \log P_i + \alpha_{64} B_{ij} \log A_i + \alpha_{65} B_{ij} \log D_{ij} + \alpha_{66} B_{ij} \log P_i + \alpha_{67} B_{ij} \log A_i + \alpha_{68} B_{ij} \log L_{ij} + \alpha_{69} B_{ij} \log P_i + \alpha_{70} B_{ij} \log A_i + \alpha_{71} B_{ij} \log D_{ij} + \alpha_{72} B_{ij} \log P_i + \alpha_{73} B_{ij} \log A_i + \alpha_{74} B_{ij} \log L_{ij} + \alpha_{75} B_{ij} \log P_i + \alpha_{76} B_{ij} \log A_i + \alpha_{77} B_{ij} \log D_{ij} + \alpha_{78} B_{ij} \log P_i + \alpha_{79} B_{ij} \log A_i + \alpha_{80} B_{ij} \log L_{ij} + \alpha_{81} B_{ij} \log P_i + \alpha_{82} B_{ij} \log A_i + \alpha_{83} B_{ij} \log D_{ij} + \alpha_{84} B_{ij} \log P_i + \alpha_{85} B_{ij} \log A_i + \alpha_{86} B_{ij} \log L_{ij} + \alpha_{87} B_{ij} \log P_i + \alpha_{88} B_{ij} \log A_i + \alpha_{89} B_{ij} \log D_{ij} + \alpha_{90} B_{ij} \log P_i + \alpha_{91} B_{ij} \log A_i + \alpha_{92} B_{ij} \log L_{ij} + \alpha_{93} B_{ij} \log P_i + \alpha_{94} B_{ij} \log A_i + \alpha_{95} B_{ij} \log D_{ij} + \alpha_{96} B_{ij} \log P_i + \alpha_{97} B_{ij} \log A_i + \alpha_{98} B_{ij} \log L_{ij} + \alpha_{99} B_{ij} \log P_i + \alpha_{100} B_{ij} \log A_i}{GDP_i} \quad (5)$$

where $\hat{\alpha}^0$ is the vector of the estimated coefficients in equation (3), X_{ij} is the vector of all the independent variables between country i and country j as in equation (3) (i.e., D_{ij} , P_i , A_i , P_j , A_j , L_{ij} , L_j , B_{ij} , and the interaction terms). Since we are assuming $\hat{\alpha}^0$ to be homoscedastic, $E \exp(\hat{\alpha}^0 X_{ij})$ is a constant for all the observations. In this case, the instrument equals $\sum_{j \neq i} \exp(\hat{\alpha}^0 X_{ij})$ times a constant. We ignore this constant term since it makes no difference in the following IV methodology.

We use the constructed trade openness $\hat{\tau}_i$ as the instrument for trade openness and apply the IV method to estimate the causal effect of trade openness on water withdrawals. The second stage of the estimation takes the predicted values for $\hat{\tau}_i$ and uses those as the independent variable.

The IV procedure is provided in equations (6) and (7). The first stage is provided in equation (6). In equation (6), the endogenous variable, i.e., the real trade openness (T), is regressed on the constructed trade openness variable (\hat{T}) and control variables. The second stage is provided in equation (7). In equation (7), log water withdrawals (W) are regressed on predicted values of real trade openness, denoted as \hat{T}_i .

$$T_i = b_0 + b_1 \hat{T}_i + b_2 X_{c1i} + u_i \tag{6}$$

$$\log(W_i) = c_0 + c_1 \hat{T}_i + c_2 X_{c1i} + v_i \tag{7}$$

We apply the statistical test to determine if the coefficient t is significant. This requires that we estimate the standard errors for coefficients. To estimate the standard errors we use the variance-covariance matrix, in which the elements in the diagonal ($\hat{\sigma}_{ii}$) provide the variance of the corresponding coefficient ($\hat{\beta}_i$, i.e., $\hat{\sigma}_{ii}$ is the variance of $\hat{\beta}_i$). The usual IV standard error formula is the estimated variance-covariance matrix from 2SLS. However, we also need to account for the fact that our instrument depends on the parameters of the bilateral trade equation (i.e., equation (3)) as pointed out by Frankel and Romer (1999). As such, we estimate the variance-covariance matrix as the usual IV formula plus the variance-covariance coming from the instrument construction. Specifically, the estimated variance-covariance matrix of the coefficients equals the usual IV formula plus $\hat{\sigma}_{ii} \hat{\beta}_i \hat{\beta}_i' + \hat{\sigma}_{ii} \hat{\beta}_i \hat{\beta}_i'$, where $\hat{\beta}$ is the vector of estimated coefficients in equation (3) and $\hat{\sigma}$ is the vector of estimated coefficients in equation (3) and $\hat{\sigma}$ is the estimated variance-covariance matrix of $\hat{\beta}$ (Frankel & Romer, 1999).

3. Results and Discussion

Here we present and discuss results on the relationship between trade openness and water withdrawals. First, we present the results of our bilateral trade share equation. Then, we check the quality and robustness of our IV estimate. Next, we compare the correlational (OLS) and causal (IV) estimates of the relationship between trade openness and water withdrawals. Finally, we examine a few potential mechanisms for the impact of trade openness on agricultural water withdrawals.

3.1. Bilateral Trade Share

Table 2 presents results for the bilateral trade share (equation (3)), which only geographic attributes are used as predictors and GDP is omitted due to potential endogeneity concerns. Table 2 provides evidence that most of the geographic attributes included in the model are statistically significant determinants of trade openness. The coefficient for log transform of distance ($\log(D_{ij})$, 21.430) is negative. This is consistent with the gravity model of international trade, in which bilateral trade between countries is negatively correlated with the distance between the two countries (Frankel & Romer, 1999).

The size of a country is measured using both its area (A) and its population (P). These scale factors exhibit negative coefficients in Table 2. Note that the dependent variable in Table 2 is the log transform of bilateral trade share (i.e., $t_{ij} = \text{GDP}$) instead of bilateral trade (i.e., t_{ij}), in which we would expect country size measures to exhibit positive coefficients. Bilateral trade share, which measures the trade openness for the home with respect to a foreign country, is highly correlated with the relative border length with respect to country area. Larger countries have a relatively shorter border length, and thus have a smaller bilateral trade share with other countries. This is consistent with the fact that, all else equal, larger countries tend to have more intranational trade and less international trade (Frankel & Romer, 1999). However, when the trading partner country j has a higher population, then trade tends to increase ($\log(P_j)$, 51.104). This makes sense since trading partners with larger populations typically have

	Dependent variable $\log(\text{Bilateral trade share for country } i)_j$ (\$)
Constant	210.374*** (0.309)
$\log(D_{ij})$	21.430*** (0.025)
$\log(P)$	20.008 (0.016)
$\log(A)$	20.039*** (0.012)
$\log(P)$	1.104*** (0.016)
$\log(A)$	20.249*** (0.012)
LL_i , $1LL_j$	20.953*** (0.037)
B_{ij}	5.766*** (1.851)
$\log(D_{ij})$ 3 B_{ij}	0.430** (0.214)
$\log(P)$ 3 B_{ij}	20.282** (0.131)
$\log(A)$ 3 B_{ij}	20.002 (0.126)
$\log(P)$ 3 B_{ij}	20.211 (0.131)
$\log(A)$ 3 B_{ij}	0.027 (0.126)
$(LL_i, 1LL_j)$ 3 B_{ij}	0.473** (0.186)
Observations	19,948
R^2	0.383
Adjusted R^2	0.383
Residual std. error	2.642 (df 5 19,934)
F-statistic	952.381*** (df 5 13; 19,934)

Note. Notations of variables are the same as those in equation (3).
 **Significance at the 5% level.
 ***Significance at the 1% level.

larger demands and/or supplies, which is likely to lead to larger openness in country i . Landlocked countries tend to be less open to trade (LL520:953). If two countries share a common border then they are much more likely to trade more (B55:766).

These results are broadly consistent with results presented in Frankel and Romer (1999) and Kagohashi et al. (2015). For example, all studies find that being further apart and landlocked decreases bilateral trade, while countries that share a common border see their bilateral trade increase. Importantly, note that our bilateral trade share equation and table does NOT include GDP. However, time-varying GDP is used to predict the bilateral trade share by Kagohashi et al. (2015, equation (1) and Table 2). This is potentially problematic because GDP is likely to be endogenous to trade and water withdrawals of a nation. So our empirical specification improves upon the approach used by Kagohashi et al. (2015), since we do not include time-varying values of GDP, which may be subject to endogeneity concerns.

3.2. Instrument Quality

The quality of the instrument is very important in the IV methodology. To ensure a high quality instrument, two assumptions must be satisfied: (1) the instrument must be highly correlated with the instrumented variable and (2) the instrument must not be correlated with other determinants of the outcome variable in the error term.

To test the first assumption, we evaluate the relationship between the instrument (constructed trade openness, $\hat{\tau}_i$) and the instrumented variable (actual trade openness, τ_i). Figure 3 plots the relationship between the actual and constructed trade openness for each country. This relationship appears to be roughly linear and increasing, which provides evidence that the first assumption for a high quality instrument is satisfied. To quantify the relationship between the actual and constructed trade share we use the Kleibergen-Paap statistic (rk Wald F-statistic ("First stage F-statistic")). The first stage F-statistic is greater than the rule-of-thumb

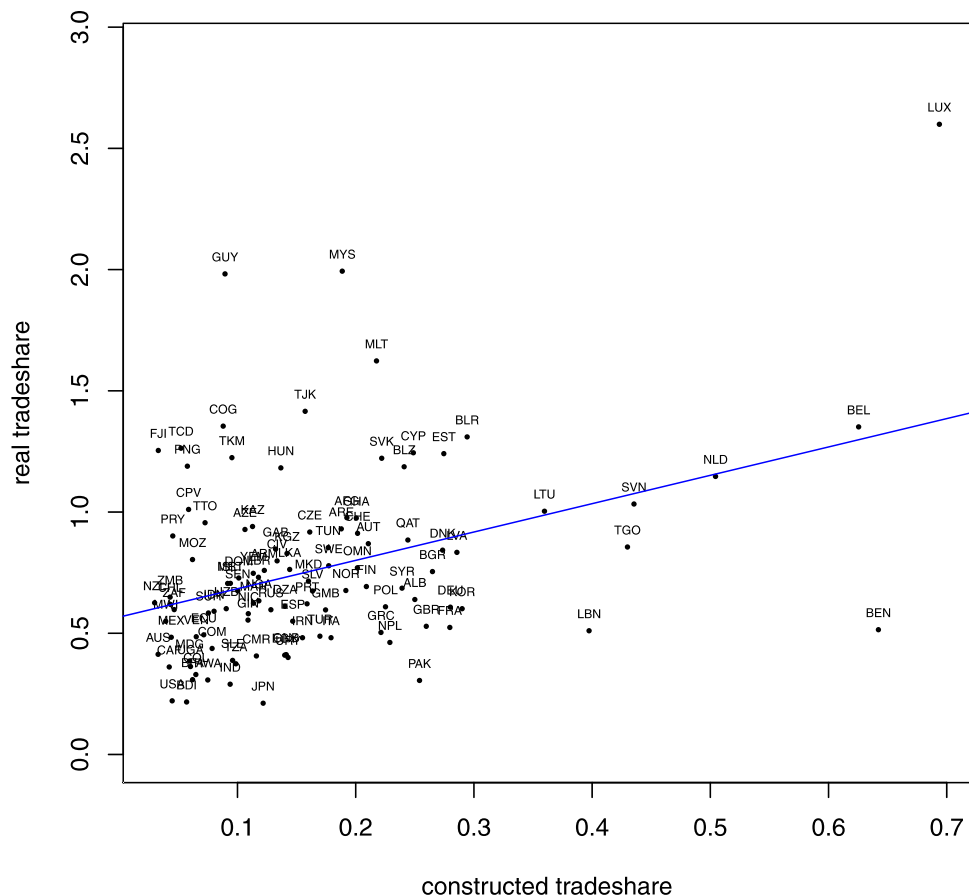


Figure 3. Actual versus constructed trade share.

Table 3
Robustness of Instrumental Variables Estimates for Agricultural Water Withdrawals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A: Log agricultural water withdrawals (second stage)									
Real trade openness	25.21** (2.52)	25.15** (2.38)	25.44** (2.39)	24.88** (2.15)	24.39** (2.03)	25.32** (2.22)	25.41** (2.56)	24.6** (1.83)	24.63** (1.79)
B: Real trade openness (first stage)									
Constructed trade openness	1.03*** (0.31)	1.11*** (0.32)	1.12*** (0.31)	1.22*** (0.33)	1.22*** (0.32)	1.03*** (0.3)	1.02*** (0.31)	1.27*** (0.33)	1.25*** (0.32)
Fstat	11.3***	12.4***	12.9***	14***	14.1***	11.8***	11.1***	15.1***	15.3***
N_obs	108	106	107	104	104	108	108	103	104
Other controls	No	Weather(A)	Weather(P)	Climate(A)	Climate(P)	Region	fraction_agr	All(A)	All(P)

Notes. Standard errors in parentheses. Dependent variable indicated in the title. Other controls specify the control variables besides log(population), log(land area), and latitude. Weather(A), area-weighted measurements for weather including log(apre) and log(atem); weather(P), population-weighted measurements for weather including log(wpre) and log(wtem); climate(A), area-weighted measurements for climate zone including kgatrstr and kgatemp; climate(P), population-weighted measurements for climate zone including kgptrstr and kgptemp; region, dummy variables for region including ECA, LAX, MENA, NA, SA, SSA, and EAP; fraction_agr, agricultural fraction of GDP; all(A), area-weighted measurements for weather, climate zone, and region; all(P), population-weighted measurements for weather, climate zone, and region. The full results including all the independent variables are reported in Table S1–S2.

**Significance at the 5% level.
***Significance at the 1% level.

threshold of 10 for weak instruments for all results (refer to Table 3) which suggests that our instrument is not weak.

To check the second assumption, we evaluate the impact of geographic control variables on our outcome variable of interest, water withdrawals. This is because the major assumption for this IV approach is that the geographic attributes in the bilateral trade equation (equation (3)) are uncorrelated with other determinants of water withdrawals besides control variables (i.e., X_c in equations (6) and (7)). That is, the instrument will influence water withdrawals only through trade besides controlled channels, X_c .

We control for variables which are likely to be correlated with both trade openness (T) and water withdrawals (W). We control for national size by controlling for both area (A) and population (P). Additionally, we control for latitude (L) because global geographic position may impact both T and W. This is because countries in lower latitudes tend to be less involved in global trade and also have higher evaporative demands of crops. That is to say, latitude likely affects water withdrawals through nontrade channels and would thus bias our results if we do not control for it. So we control for log transform of area, log(A), log transform of population, log(P), and latitude, L.

However, it is still unclear if there are other channels—such as climate, weather, and geographic region—through which the constructed trade openness will impact water withdrawals in agriculture. To check the robustness of our model, we systematically determine the impact of various sets of control variables on our IV specification in Table 3. Note that we control for region to eliminate the factors clustered by region such as culture and development level.

The structural composition between countries may impact their water use in agriculture and industry. For example, wealthy nations might have larger industrial production and trade more secondary and tertiary sectors (i.e., rather than agriculture). For this reason, we control for agricultural fraction of GDP in Table 3 and industrial fraction of GDP in Table 4. We control for both the agricultural and industrial fraction of GDP in Table 5. Please refer to the Supporting Information S1 document for full results. Capital and labor are two of the main determinants of industrial production that might influence both trade and water withdrawals and thus need to be controlled for in our industrial specification. Countries with more patents might participate in trade with more technology-oriented products and thus have larger exports and lower water withdrawals. For this reason, we control for capital, labor, and total number of patents in Table 4. When we add these sector specific controls to our specification, the results are robust. These tests give us confidence that our preferred specification is measuring the impact of trade openness on water withdrawals in a way that is robust to the varying structural composition of countries.

Table 4
Robustness of Instrumental Variables Estimates for Industrial Water Withdrawals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A: Log industrial water withdrawals (second stage)							
Real trade openness	1.09 (1.18)	0.79 (1.12)	0.3 (1.17)	1.76 (1.17)	1.36 (1.05)	1.02 (1.22)	1.47 (0.99)
B: Real trade openness (first stage)							
Constructed trade openness	1.03*** (0.31)	1.08*** (0.33)	1.06*** (0.34)	1.03*** (0.3)	1.48*** (0.38)	0.99*** (0.3)	2.02*** (0.45)
Fstat	11.3***	10.8***	9.8***	11.8***	15***	11.2***	20***
N_obs	108	92	92	108	86	108	71
Other controls	No	log(K) log(L)	K/L	Region	Patent	fraction_ind	All

Notes. Standard errors in parentheses. Dependent variable indicated in the title. Other controls specify the control variables besides log(population), log(land area), and latitude. K, capital; L, labor; region, dummy variables for region including ECA, LAX, MENA, NA, SA, SSA, and EAP; patent, total count of patents in force by applicant origin; fraction_ind, industrial fraction of GDP; all, all the control variables in columns (2)–(5). The full results including all the independent variables are reported in Table S3.

***Significance at the 1% level.

Table 3 suggests that the second stage coefficients are approximately the same across models. This is because the second stage coefficient is relatively stable around 25.00 and is statistically significant at the 5% level across all specifications. From Table 3, we determine that the model for agricultural water withdrawals is robust if we control for log(A), log(P), and L in our specification. Similarly, Tables 4 and 5 suggest that our model for industrial and total water withdrawals is robust. Our robustness checking results suggest that although there might be some covariates correlated with trade and water withdrawals by sectors, they are not correlated with our instrument (i.e. constructed trade openness) and thus do not need to be controlled for in our model specification. We estimate the following first and second stage equations accordingly:

$$T_i = \beta_0 + \beta_1 \ln A_i + \beta_2 \ln P_i + \beta_3 \ln L_i + u_i \quad (8)$$

$$\ln W_i = \gamma_0 + \gamma_1 T_i + \gamma_2 \ln A_i + \gamma_3 \ln P_i + \gamma_4 \ln L_i \quad (9)$$

Thus, our preferred first and second stage specifications include land area (A), population (P), and latitude (L) as controls. Our preferred specification is shown in column (1) of Table 4. We use this robust model for all analysis that follows.

Table 5
Robustness of Instrumental Variables Estimates for Total Water Withdrawals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A: Log industrial water withdrawals (second stage)												
Real trade openness	21.08 (1.16)	20.88 (0.92)	20.99 (1.11)	21.24 (1.2)	21.2 (1.13)	21.3 (1.13)	21.48 (1.11)	21.25 (1.04)	20.93 (0.86)	20.47 (0.83)	21.44 (0.99)	21.19 (0.87)
B: Real trade openness (first stage)												
Constructed trade openness	1.03*** (0.31)	1.08*** (0.33)	1.06*** (0.34)	0.99*** (0.3)	1.11*** (0.32)	1.12*** (0.31)	1.22*** (0.33)	1.22*** (0.32)	1.03*** (0.3)	1.48*** (0.38)	1.23*** (0.39)	1.27*** (0.38)
Fstat	11.3***	10.8***	9.8***	11.2***	12.4***	12.9***	14***	14.1***	11.8***	15***	10.1***	11.2***
N_obs	108	92	92	108	106	107	104	104	108	86	88	88
Other controls	No	log(K) log(L)	K/L	fraction_ind fraction_agr	Weather(A)	Weather(P)	Climate(A)	Climate(P)	Region	Patent	All(A)	All(P)

Notes. Standard errors in parentheses. Dependent variable indicated in the title. Other controls specify the control variables besides log(population), log(land area), and latitude. Control variables are the same as those in Table 3 and Table 4. The full results including all the independent variables are reported in Table S4–S5.

***Significance at the 1% level.

Table 6
Causal Effect of Trade on Log Water Withdrawals

	Total	Agricultural	Industrial
Openness	21.08 (1.16)	25.21** (2.52)	1.09 (1.18)
Fstat	11.3***	11.3***	11.3***
N_obs	108	108	108

Notes. Second stage results are provided for log total water withdrawals, log agricultural water withdrawals, and log industrial water withdrawals. The geographic controls are land area (A), population (P), and latitude (L). The full results including all the independent variables are reported in Table S6.

**Significance at the 5% level.
***Significance at the 1% level.

3.3. Causal Impact of Trade Openness on Water Withdrawals

Trade openness does not have a statistically significant causal impact on total water withdrawals (i.e. water withdrawals in both agriculture and industry; refer to Table 6). From Table 6, trade openness illustrates a positive, but statistically insignificant impact on water withdrawals in industry ($\beta = 1.09$). The impact of trade openness on total water withdrawals is negative, but also statistically insignificant ($\beta = -21.08$). However, the impact of trade openness on water withdrawals in agriculture is negative and statistically significant at the 5% level ($\beta = -25.21$).

Table 7 compares the OLS and IV estimates of the relationship between trade openness and agricultural water withdrawals. OLS estimates reveal that there is a negative and statistically significant relationship between trade openness and water withdrawals in

agriculture ($\beta = -20.96$; refer to column 1 of Table 7). However, simply looking at the correlation between trade openness and water withdrawals is uninformative about the causal relationship between the variables. In column 1 of Table 7, water use is treated as the dependent variable, but countries may choose how much to trade based on their expected water use, implying that causality also runs in the opposite direction. For scientific understanding and policy purposes, we are most interested in the causal impact of trade on water use.

IV results, which enable us to identify the causal impact of trade openness on water use, are provided in column 2 of Table 7. The coefficient of interest ($\beta = -5.21$; refer to section 2) is negative and statistically significant at the 5% level. The results indicate that one percentage point increase in trade openness leads to a 5.21% reduction in agricultural water withdrawals. Significantly, this relationship has a causal interpretation. It is also about five times larger than the corresponding OLS estimate, suggesting considerable bias in the latter.

The goal of causal inference is to obtain an unbiased estimate of the coefficient of interest, the coefficient on trade openness, c_1 . We are not directly concerned with the other coefficients in the regression model. For this reason, we are most concerned that the coefficient on trade openness is robust across specification. We perform an extensive check of the robustness in Tables (3–5) and find that the coefficient of interest is relatively constant. This gives us confidence that we are accurately estimating the impact of trade openness on water withdrawals (in agriculture, industry, and total).

Kagohashi et al. (2015) find that the overall effect of a 1% increase in trade openness reduces total water withdrawals and/or consumption by roughly 1.0–1.5% on average. Note that Kagohashi et al. (2015) do not separate water withdrawals by economic sector (i.e., agriculture and industry) as we do in this paper. So we go one step further than Kagohashi et al. (2015), by evaluating the impacts of trade openness on agricultural and industrial withdrawals separately. This enables us to conclude that trade openness reduces agricultural water withdrawals but does not impact industrial water withdrawals.

Table 7
The Effect of Trade Openness on Agricultural Water Withdrawals, OLS Versus Instrumental Variables

	Log agricultural water withdrawals		Real trade openness
	OLS	IV (second stage)	IV (first stage)
Real trade openness	20.96* (0.48)	25.21** (2.52)	
Constructed trade openness			1.03*** (0.31)
Observations	129	108	108
First stage F-statistic			11.3

Notes. Standard errors in parentheses. Dependent variable indicated at the top of the columns. All regressions include log population, log area, and latitude as controls.

*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

3.4. Why Does Trade Openness Lead to Less Water Withdrawals in Agriculture?

The results in Table 6 suggest that the causal effect of trade openness on water withdrawals in agriculture is different than in industry. So there are unique characteristics of agriculture that determine these mechanics. What are they? Why does trade openness lead to less water withdrawals in agriculture? Here we empirically determine the mechanism driving changes in water use in agriculture. To do this, we follow Debaere and Kurzenoerfer (2015), who highlight three mechanisms through which water use in an economy may be impacted. Debaere and Kurzenoerfer (2015) decompose water use impacts by the “scale” of the economy, “water productivity” at the sectoral level, and “composition” of the economy. We follow this decomposition, but restricted to agriculture. In the agricultural setting, water withdrawals may be impacted by “extensive margin” effects, “intensive margin” effects, or “crop mix” effects.

Table 8
Causal Effect of Trade Openness on the Value of Output (\$) and Log Water Withdrawal Productivity

	Total	Agricultural	Industrial
log(Value of output)			
Openness	1.21 (1.34)	0.15 (0.61)	1.37 (1.51)
log(Water withdrawal productivity)			
Openness	2.29 (1.72)	5.37** (2.6)	0.28 (1.49)
Fstat	11.3***	11.3***	11.3***
N_obs	108	108	108

Notes. Second stage results are provided for log total water withdrawals, log agricultural water withdrawals, and log industrial water withdrawals. The geographic controls are land area (A), population (P), and latitude (L). The full results including all the independent variables are reported in Table S7.

**Significance at the 5% level.
***Significance at the 1% level.

First, trade openness may lead farmers to expand the area on which they grow crops, which is defined as an extensive margin effect. To estimate the extensive margin effect, we change the outcome variable in equation (9). We use log transform of harvested area, log transform of agricultural production, and log transform of the value of agricultural output. Table 9 suggests that trade openness has no significant effect on the harvested area of crops. Similarly, Table 9 suggests that trade openness does not significantly impact crop production. Table 8 shows that trade openness does not impact the value of agricultural output. We also evaluate the impact of trade openness on the value of industrial output to compare potential extensive margin effects between agriculture and industry. For both economic sectors, there is no impact of trade openness on the value of production. These results in unison suggest that trade openness does not impact water withdrawals through the extensive margin of production.

Second, trade openness might stimulate farmers to introduce more advanced technology and thus produce more per unit of water. This is defined as the intensive margin effect. We use two measures of the intensive margin: crop yield and water withdrawal productivity. We

define water withdrawal productivity to be the value of production per water withdrawals. Table 9 shows that trade openness does not impact the yield of crops in a statistically significant way. Table 8 shows that trade openness does not impact total or industrial water withdrawal productivity. However, one percentage point increase in trade openness leads to a 5.37% increase in agricultural water withdrawal productivity and is statistically significant at the 5% level. Table 8 provides evidence that trade openness leads to less water withdrawals in agriculture due to gains in water withdrawal productivity, an intensive margin effect.

Finally, an increase in trade openness might cause farmers to change their crop mix in a manner that uses less water. They might switch to produce higher-value but less water-intensive crops for export. For example, we consider five major crops (ryewheat, barley, maize, and oats) in this paper due to limitations in data availability for other crops. We consider the causal effect on crop-specific log agricultural production, harvested area, and yield to examine the crop mix effect. Table 9 suggests that trade openness does not

Table 9
Causal Effect of Trade Openness on Crop-Specific Log Transform of Agricultural Production, Agricultural Harvested Area, and Yield

	(1) Total cereal	(2) Rye	(3) Wheat	(4) Barley	(5) Maize	(6) Oats
log(Production)						
	(\$)	(t)	(t)	(t)	(t)	(t)
Openness	2.01 (1.23)	1.93 (2.64)	22.02 (2.36)	20.58 (1.8)	0.95 (1.63)	0.17 (2.07)
log(Harvested area)						
	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)
Openness	1.82 (1.32)	1.2 (2.63)	22.37 (2.38)	20.75 (1.69)	0.38 (1.69)	20.03 (1.81)
log(Yield)						
	(\$/ha)	(hg/ha)	(hg/ha)	(hg/ha)	(hg/ha)	(hg/ha)
Openness	0.16 (0.5)	0.73 (0.52)	0.33 (0.6)	0.18 (0.66)	0.51 (0.57)	0.2 (0.66)
Fstat	18.2***	12.5***	15.5***	13.1***	17.7***	15.3***
N_obs	153	57	105	88	136	68

Note. The geographic controls are land area (A), population (P), and latitude (L). The full results including all the independent variables are reported in Table S8.

***Significance at the 1% level.

lead growers to switch between the major crop types, suggesting that crop switching amongst major crops does not explain the reduction in water withdrawals in agriculture with increased openness to trade.

So these results contribute to our understanding as to why increased trade openness leads to less water withdrawals in agriculture. The results presented in this section indicate that trade openness leads to less water withdrawals in agriculture primarily through the intensive margin. Our results confirm findings presented in Kagohashi et al. (2015) that an expansion in trade openness encourages producers to adopt water-saving technologies. In other words, it appears that openness to trade leads agricultural producers to generate higher-value agricultural production per unit water withdrawn. These results are consistent with the explanation that trade openness leads farmers to adopt advanced technologies such as improved crop varieties and irrigation technology that enable them to both generate more agricultural revenue and use less water.

4. Conclusion

This paper contributes to the debate over globalization and water resources. The major question that this paper addressed is what is the impact of trade openness on national water use? Much work published on the water-trade nexus has focused on links between trade and virtual water resources and has used these results to infer the implications of trade for water use. We contribute to this literature by explicitly considering the impact of trade for domestic, physical water use. Importantly, we use the instrumental variables technique to evaluate the causal impact of trade openness for domestic agricultural and industrial water withdrawals.

Our results suggest that one percentage point increase in trade openness leads to a 5.21% decrease in agricultural water withdrawals. However, trade openness does not have a significant impact on total industrial water withdrawals. Why does trade openness lead to less water withdrawals in agriculture? Our results suggest that trade openness reduces water use in agriculture primarily through the intensive margin. For example, by leading farmers to adopt technologies such as advanced irrigation technology. We do not find evidence for extensive margin or crop mix impacts on agricultural water withdrawals. However, improved water use data by source, crop, and industry would enable future research to refine our analysis.

Future work that incorporate trade directionality into the trade openness metric (i.e., as in the directed gravity models in Tamea et al. (2014)) may yield new understanding. This is because trade openness may have different impact for the country of import than it does for the country of export. Additionally, probing heterogeneity in the trade-water relationship of economic sectors is an important avenue for future research. Our IV approach assumes that the treatment effects of trade openness are homogeneous across economic sectors (i.e., identical regardless of what mechanism led to the change in trade openness). Future work could explore the development of different instruments to evaluate if the treatment effects are heterogeneous across sectors.

This paper shows that one unintended consequence of increased globalization is to use less (physical) water to produce food. These results complement the recent literature that shows that international trade saves (virtual) water resources. This work highlights the need for future research to continue to refine our understanding of the trade-water nexus. In an era of increasing antiglobalization sentiment, this work highlights one potential beneficial but unintended consequence of trade: using less water to grow our food.

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