The impact of weather shocks on exports

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Abstract

Previous research provides ample evidence that on their own international trade and weather shocks can be important drivers of economic growth, but we know relatively little about how these two factors might interact. This paper brings together recent developments from the international trade and climate econometrics literatures to investigate the differential impact of weather shocks on exports relative to domestic sales. In contrast to previous empirical papers that study the impact of weather shocks on international trade, I use an empirical approach that includes domestic trade flows and controls robustly for multilateral resistance parameters. I find that agricultural exports are particularly sensitive to temperature increases relative to domestic market sales, especially in hot countries. Manufacturing sector exports are relatively resilient to weather shocks, except that precipitation increases in very rainy places lead to decreases in exports relative to domestic sales. Economists usually conceptualize the macroeconomic damages of climate change as productivity impacts, but these results provide some evidence that weather and potentially climate change can increase barriers to international trade, implying that the full economic damages of these shocks may entail not only productivity impacts at the farm or factory, but also disruptions along the supply chain once goods leave the site of production. I demonstrate the economic significance of these impacts using a standard sufficient statistic approach to translate my estimates into welfare losses from decreased gains from trade.

JEL codes: F13, F18, O13, Q17, Q54, Q56

Keywords: International trade, Exports, Weather variations, Climate change impacts

1 Introduction

A rapidly developing literature provides empirical evidence that extreme weather and climate change negatively impact economic outcomes (Dell et al. 2012; Burke et al. 2015; Kalkuhl and Wenz 2020). Such findings have led the IPCC to conclude with medium to high confidence that extreme weather and climate change have already impacted agricultural yields, labour productivity, and infrastructure around the world, and the risks of such impacts are likely to increase rapidly if global warming is not limited to 1.5°C (IPCC 2022). These risks highlight the importance of deepening our understanding of the potential economic impacts of further warming. Meanwhile, the literature on climate damages has paid relatively little attention to the role of international trade in the economic impacts of extreme weather and climate change; indeed, Dawson et al. (2020) undertake a quantitative textual analysis of recent IPCC assessments and find a lack of coverage of international trade in the reports. Nevertheless, international trade may interact with extreme weather and climate change in a range of potential ways; for example, access to international markets may help countries to adapt to climate change (Copeland et al. 2022), and changes in productivity across countries due to climate change may interact with international trade patterns to change the distribution of gains from trade across countries (Dingel et al. 2019). Another potential interaction between climate change and international trade is that extreme weather may impact countries' ability to trade internationally.

This paper tests empirically whether temperature and precipitation shocks impact barriers to international trade, shedding light on the extent to which extreme weather and climate change affect the accessibility of international markets. More specifically, I quantify the difference in the impact of weather shocks on the value of exports relative to sales in producers' domestic markets. In the terms of conventional models of international trade, this estimate can be understood as quantifying the impact of weather shocks on the iceberg trade costs parameter. While seminal contributions such as Dell et al. (2012) and Burke et al. (2015)

estimate the impact of weather shocks and climate change on productivity - that is, the "size of the output pie" - this paper focuses on the impact of weather shocks on the "division of the pie" between exports and domestic market sales. Moreover, unlike previous empirical studies of international trade and weather shocks, which do not disentangle impacts on underlying productivity from a potential particular sensitivity of exports to weather shocks, I use an empirical model that allows me to test specifically for a difference in the effect of weather shocks on exports versus sales in the domestic market. The results reveal the impact of weather shocks on barriers to international trade.

Several potential mechanisms could explain why changes in temperature or precipitation might affect barriers to international trade. First of all, international trade patterns often exhibit a "home bias", suggesting that if weather shocks disrupt production, export quantities reduce more than domestic sales; Jones and Olken (2010) discuss this hypothesis, pointing out that greater volatility of exports compared to domestic sales in the face of a production shock is consistent with standard trade models. Furthermore, international supply chains may be more sensitive to to weather shocks than domestic supply chains because they are longer and also rely more heavily on vulnerable infrastructure such as ports. Becker et al. (2013) explain how the vulnerability of seaports to extreme weather and climate change could negatively impact international trade. Railways are also vulnerable to the impacts of weather shocks: Chinowsky et al. (2019) find that increased temperatures have caused costly delays in the US rail networks. These potential impacts of weather shocks on transport infrastructure suggest that weather shocks may increase barriers to international trade. Real-life examples from Malaysia and Argentina help to illustrate this hypothesis further. In 2021, flooding in Malaysia caused significant disruptions to the semi-conductor industry; this flooding not only led to disruptions at the production plants, but also made roads inaccessible and caused congestion and delays at Port Klang, an important port for international trade.[1] In 2021, dry conditions in Argentina caused water levels of the Parana River to drop so much as to become impassable for barges, reportedly causing exports to be diverted to much more costly road transport routes.[2]

Finally, another potential mechanism through which weather shocks may affect exports differently from domestic sales is through price effects: existing trade barriers may allow domestic prices to respond to a domestic production shock more than export prices. For example, suppose weather shocks lead to a decrease in domestic production. Existing barriers to trade may allow domestic producers to raise prices in their domestic market, while international competition prevents them from doing so in the export market. In this case, the value of exports decreases relative to the value of domestic sales due to these price effects. An example from the Philippines illustrates these potential price effects. In 2019, unusually dry weather in the Philippines caused by the El Niño effect led to an oversupply of around 2 million kg of mangoes. According to local news reports, this excess supply was mainly absorbed by the domestic market, and local prices decreased by more than half. In this example, a weather shock led to a positive production shock and then a decrease in domestic prices relative to export prices.[3]

Although the hypotheses mentioned thus far suggest that exports may be more sensitive to weather shocks than domestic sales, a competing hypothesis suggests that the sign of this effect is actually ambiguous. That is, exports could be less vulnerable to weather shocks than domestic sales. A large literature on the propensity to export that tells us that firms that export are different from firms that do not (Atkin et al. 2017; Görg et al. 2012). Given that increased propensity to export is associated with mainly positive firm traits (e.g. higher productivity), this literature suggests that firms that export might be more resilient to weather shocks than firms that do not export. With this evidence in mind, we might expect that exports are less sensitive to weather shocks than domestic sales. The theoretical ambiguity of the effect of weather shocks on exports relative to domestic sales highlights the importance of investigating this question empirically, and also justifies the use of two-sided tests throughout this paper to do so.

[1] See `https://techwireasia.com/2021/12/malaysian-floods-devastate-workers-disrupts-semiconductor-supply-chain/`.

[2] See `https://www.bloomberg.com/news/articles/2021-08-06/the-argentine-river-that-carries-soybeans-to-world-is-drying-up#xj4y7vzkg` and `https://www.france24.com/en/live-news/20210901-south-america-s-parana-river-is-drying-up-baffling-experts`.

[3] See `https://www.bbc.co.uk/news/world-asia-48581857` and `https://www.aseantoday.com/2019/07/too-many-mangoes-a-bumper-harvest-puts-the-spotlight-on-filipino-supply-chains/`

To estimate of the differential effect of weather shocks on exports relative to domestic sales, I combine gravity model estimation techniques from the trade literature with developments from the climate econometrics literature. In some cases I also estimate the effect of weather shocks on the underlying levels of exports and domestic sales but in the most robust specifications I am unable to estimate this effect. Estimating the effect of weather shocks on trade is not straightforward given the potential biases inherent in empirical trade models. Models with international trade flows as the dependent variable are essentially cross-country comparisons and must inevitably deal with a myriad of potential confounding variables; how much two countries trade with each other is affected by complex array of factors many of which are difficult to measure and observe. Accordingly, a huge body of work in international trade has focused on the best techniques to mitigate potential omitted variable bias. A key development has been the use of importer and exporter fixed effects to properly control for 'multilateral resistance', which has now become part of best practice standards for empirical trade studies (Baldwin and Taglioni 2006). However, following these best practices means that country-specific variables such as weather shocks are absorbed into fixed effects.

To overcome these challenges I follow the innovations in Heid et al. (2017) and Beverelli et al. (2018) to control for the multilateral resistance parameters with a full set of importer-time and exporter-time fixed effects while still estimating the effect of country-specific variables (such as weather shocks) on exports relative to domestic sales. This approach includes domestic as well as international trade flows in the model and interacts the variables of interest (temperature and precipitation in this case) with a dummy indicator for international sales. Heid et al. (2017) apply this methodology to measure the effects of most favoured nation (MFN) tariffs and "Time to Export" on international relative to domestic trade. Beverelli et al. (2018) build on the methodology of Heid et al. (2017) to estimate the effect of institutional quality on exports relative to domestic sales. They find that poor institutions hinder exports and their GE simulation suggests that this effect translates into notable impacts on GDP. Ultimately, the approach developed in these papers provides a more robust basis for causal inference compared to methods used in previous papers exploring the relationship between temperature and trade.

Previous literature has demonstrated that weather and climate have notable economic impacts on a macroeconomic level. A rapidly expanding area of work uses historical weather data to estimate empirically the impact of weather and climate and economic outcomes. A particularly strong focus in this literature has been the effect of weather and climate on GDP. Seminal contributions include Dell et al. (2012), Burke et al. (2015), Kalkuhl and Wenz (2020), and Newell et al. (2021). Not only has this body of work contributed an empirical basis for the economic damages associated with climate change, but it has also made strides in developing an appropriate methodology for modelling the effects of weather on economic outcomes and linking weather effects with climate change impacts. Two key methodological developments have been the use of panel data techniques to deal with biases in cross-sectional analyses and functional forms that allow for non-linear effects of weather on economic outcomes. I follow these developments in the climate change economics literature, using a panel data setting and allowing for nonlinear effects of weather shocks; the main specification is a quadratic functional form for the effect of temperature on trade, but I also explore alternative functional forms based on higher-order polynomials and number of degree days in temperature bins.

A few papers have explored (ex-post) the relationship between weather shocks and trade and have found some evidence that increased temperatures are associated with a reduction in exports. An early contribution by Jones and Olken (2010) finds that increased temperatures are associated with reduced export growth in poor countries. The magnitude of their estimate is larger than the effect of temperature on GDP estimated in Dell et al. (2012), which they suggest may indicate that exports are more sensitive to temperature than GDP. More recently, Osberghaus (2019) reviews the literature on the effects of natural disasters and weather variation on international trade. He finds that most studies of the effect of temperature on trade find that increased temperatures reduces trade, with the agriculture sector particularly affected. The effect of precipitation on trade is ambiguous across the literature. These papers often focus on linear effects of temperature on trade, while the rapidly-developing climate change economics literature seems to have reached a consensus that nonlinear temperature effects are very important. Moreover, it's unclear if previous studies are just finding (through the lens of trade data) the effect of temperature on aggregate income, or if they are uncovering a particular sensitivity of international trade to weather shocks. Finally, these previous papers have often had to forgo a robust set of fixed effects to deal with potential confounding variables.

Dallmann (2019)'s contribution is the closest in this literature to this paper. She studies the effect of weather shocks on international trade using a gravity-like empirical model, finding that increased temperature in the exporting country tends to reduce bilateral trade. She suggests that this effect seems to be largely driven by the impact of temperature on production, but does not explore whether exports are more or less sensitive to these productivity impacts compared to domestic sales. Another recent paper that explores how international trade and climate can interact to have economic impacts is Dingel et al. (2019), which shows that climate change is likely to increase inequality between countries because it will increase the spatial correlation of productivities and therefore lead to higher gains from trade for rich countries compared to poor countries.

In short, we know from previous work that increased temperatures are associated with decreased productivity, and that this effect seems to translate into a decrease in international trade. This paper builds on this work by providing a clear answer on whether exports are particularly sensitive to weather shocks compared to overall income, while employing a strict set of controls to deal with potential omitted variable bias. The results imply that for the agricultural sector increases in temperature are associated with a shift in the balance of trade away from exports and towards domestic sales, particularly in already hot places. By comparison, manufacturing sector exports are relatively resilient to weather shocks, except that precipitation increases in very rainy places may decrease exports relative to domestic sales.

The remainder of the paper is organized as follows. The next section outlines the methodology used in this study, providing a brief theoretical background before describing the empirical model, and the following section describes the data. Then section 4 presents and discusses the empirical results, and section 5 uses a sufficient statistic approach to explore the implications of these results for economic welfare. Finally, section 6 concludes.

2 Methodology

The following section outlines the methodology used to estimate a differential effect of weather shocks on exports relative to domestic sales. First I outline a standard theoretical basis for the empirical trade model and explain the challenges of estimating the effects of unilateral variables such as weather shocks on bilateral trade. Then I present the estimating equations, and finally I explain how to interpret the coefficient estimates and how they relate to the marginal effects of interest.

2.1 Theoretical background

The structural gravity model, often dubbed the 'workhorse' of international trade analyses, can be derived from several different micro-foundations, all of which lead to the following standard expression for bilateral trade (Head and Mayer 2014):

$$X_{ij,t} = \frac{Y_{i,t}}{\Omega_{i,t}} \frac{E_{j,t}}{\Phi_{j,t}} \phi_{ij,t} \tag{1}$$

In this expression, $X_{ij,t}$ is the value of bilateral trade sold by exporter i to importer j in period t. $Y_{i,t}$ and $E_{j,t}$ are the value of the exporter i's total production and the value of importer j's total expenditure in period t, respectively. $\phi_{ij,t}$ is the bilateral accessibility of exporter i to importer j; this term includes the cost to transport goods from i to j as well as less-quantifiable trade barriers such as cultural and institutional differences between i and j.

$\Omega_{i,t}$ and $\Phi_{j,t}$ are the importer and exporter multilateral resistance parameters in year t; they describe how well-integrated buyers and sellers in a given country are into the global trade network in a given year. $\Omega_{i,t}$ summarizes how well sellers in country i can access buyers around the world, and $\Phi_{j,t}$ summarizes how well consumers in country j can access products from around the world (Head and Mayer 2014). These parameters are essential components of the model, and not controlling for them properly has been dubbed the "gold medal mistake" of estimating structural gravity models (Baldwin and Taglioni 2006). Standard practice in a panel data setting is to control for these terms using importer-time and exporter-time fixed effects, and Head and Mayer (2014)'s Monte Carlo simulations demonstrate the superiority of this approach over other ways to control for the multilateral resistances. However, these importer-time and exporter-time fixed effects absorb all country-specific characteristics that are invariant across trade partners, preventing the researcher from estimating the effect of country-specific variables such as GDP, national policies, institutions, and weather. This challenge is the main difficulty in studying the effect of weather shocks on trade; we have a trade-off between including country-specific variables such as temperature and precipitation in the above model and using best practices for robust gravity model estimation.

Head and Mayer (2014) review possible approaches to estimating country-specific effects in gravity models; given the potential pitfalls of the approaches they consider, they recommend that researchers estimate several different specifications since none of them are an ideal solution. One common way that papers deal with this challenge is forgoing the importer-time and exporter-time fixed effects. For example, Dallmann (2019) estimates the effect of temperature and precipitation on international bilateral trade by not including importer and exporter fixed effects and instead relying on observable country-specific variables (such as GDP) and country-pair fixed effects to deal with potential endogeneity. The benefit of this approach is that the researcher is able to identify the direct effect of weather variables on bilateral trade flows. The key disadvantage of this approach is that it cannot control for unobservable potential confounding variables which vary at the importer-time or exporter-time level and affect bilateral trade and are correlated with the weather variables. For example, an exporter's overall connections to the global trading network ($\Omega_{i,t}$ in Equation 1, known as outward multilateral resistance in the gravity literature), is an important determinant of bilateral trade. If weather shocks affect one bilateral relationship, this effect will spill over into the exporter's other bilateral relationships via their multilateral resistance. Without exporter-year fixed effects to control for outward multilateral resistance, we cannot isolate the direct effect of weather shocks on trade from the effect of outward multilateral resistance. Finally, weather shocks are certainly correlated with underlying productivity in a given year, so without exporter-year fixed effects we cannot identify whether exports are particularly sensitive to weather shocks relative to overall sales.

This paper takes a recently-developed approach to overcoming the challenges associated with estimating the effect of weather on trade. I follow the method developed in Heid et al. (2017) and Beverelli et al. (2018) to control for multilateral resistances with importer-time and exporter-time fixed effects and estimate the effect of temperature shocks on international *relative* to domestic trade. The cornerstone of this approach is to include domestic trade flows (i.e. $i = j$) in the model. Heid et al. (2017) show that this design enables the researcher estimate the interaction between a dummy variable indicating international (versus domestic) trade and the country-specific variable of interest (e.g. temperature). For a proof that the parameter of interest is identifiable (and not collinear with any other model parameters) see the appendix of Heid et al. (2017). Importantly, this method cannot provide an estimate of the direct effects of temperature and precipitation on all sales (domestic and international), because they are absorbed by the fixed effects. However, this model does provide an estimate of the differential effect of weather shocks on exports compared to domestic sales. This estimate provides insight into whether exports may be more or less sensitive to weather shocks compared to domestic sales, an issue that hasn't been addressed by Dallmann (2019) or other previous literature. As discussed in the Introduction of this paper, weather shocks may affect not simply how much is produced and sold overall, but also where these sales are made (domestic versus foreign markets).

2.2 Empirical model

To answer this question of whether temperature and precipitation differentially affect exports relative to domestic sales, I use an empirical counterpart to the theoretical gravity model in equation 1. A common approach to forming an estimating equation from a multiplicative model such as equation 1 is to log-linearize the expression and use OLS estimator. However, Silva and Tenreyro (2006) show that in the presence of heteroskedasticity (which is ubiquitous in trade data), the OLS estimator is biased when applied to a log-linear version of a multiplicative model. As a result, standard practice in the applied trade literature is to use the PPML estimator to estimate equation 1. The PPML estimator also has the advantage of being able to take account of zero trade flows, which are another prominent feature of trade data (Yotov et al. 2016).

I start with an empirical version of Equation 1 that is similar to the main specification in Dallmann (2019):

$$\begin{aligned} X_{ij,t} =& exp[h(T_{it}) + g(P_{it}) + +\rho_1 ln(GDP_{i,t}) + \rho_2 ln(GDP_{j,t}) \\ &+ \mu_{ij} + \alpha RTA_{ij,t} + YEAR_t] \times \varepsilon_{ij,t} \end{aligned} \tag{2}$$

$X_{ij,t}$ is the value of bilateral trade flows from exporter i to importer j in year t, and importantly this variable includes within-country sales - i.e. cases when $i = j$. The relationship between temperature and bilateral trade is given by:

$$h(T_{it}) = \theta_1 T_{it} + \theta_2 T_{it}^2 + INTL_{ij} \times (\theta_3 T_{it} + \theta_4 T_{it}^2)$$

T_{it} is annual mean temperature in country i in year t. Unlike previous papers, this model includes an interactive term with the INTL_{ij} dummy variable, which equals 1 if $i \neq j$; that is, it equals 1 when $X_{ij,t}$ represents international rather than domestic sales. θ_3 and θ_4 are the key coefficients of interest in this paper; they tell us if temperature shocks impact exports differently from domestic sales. A statistically significant estimate on this interactive term suggests that temperature affects not just how much is produced but also where that production tends to be sold.

Analogously, the relationship between precipitation and bilateral trade flows is given by $g(P_{it}) = \gamma_1 P_{it} + \gamma_2 P_{it}^2 + INTL_{ij} \times (\gamma_3 P_{it} + \gamma_4 P_{it}^2)$, where P_{it} is total annual precipitation in country i in year t. As with temperature, I allow for non-linear effects of precipitation on trade and I allow the effect of precipitation shocks to differ for exports compared to domestic sales.

The exporter-importer fixed effects in the equation above, μ_{ij}, control for time-invariant factors that affect the accessibility of import market j to exporter i. These controls absorb a myriad of factors that affect trade costs such as distance, geography, and cultural ties. Alongside these time-invariant drivers of trade costs, we would expect that changes in trade agreements over the sample period also affect trade costs, and I control for these effects with the $RTA_{ij,t}$ dummy variable, which indicates whether exporter i and importer j are part of a common regional trade agreement in year t. $YEAR_t$ is a year fixed effect, which controls for any global shocks in a given year such as a recession or the El Niño effect. $ln(GDP_{i,t})$ and $ln(GDP_{j,t})$ are the natural log of GDP in year t in the exporting and importing country respectively. These variables control for economic size, and are the empirical counterparts to $Y_{i,t}$ and $E_{j,t}$ in equation 1.

These choices for modelling the relationship between weather and trade flows follow developments in the climate econometrics literature. Following Dell et al. (2012), the use of panel data techniques to deal with the biases in cross-sectional analyses has become widespread in studies estimating the effects of weather and climate on economic outcomes. A panel specification with country fixed effects means that the model identifies the effects of weather shocks (deviations from countries' average weather) on economic outcomes; Kolstad and Moore (2020) explain that in a linear model these effects are short-run responses, and if adaptation opportunities are strong then extrapolating climate change effects from the effects of weather shocks is problematic. One way to deal with this issue to some extent is to introduce non-linearities into the effect of weather shocks on economic outcomes. Burke et al. (2015) make a seminal contribution demonstrating the importance of allowing for non-linearities in these relationships. Kolstad and Moore (2020) explain that allowing for non-linear effects means that the estimate is a mix of short- and long-run responses. The main specifications in this paper follow Burke et al. (2015) in using a quadratic functional form for $h(T_{it})$, but for robustness I also use specifications based on degree days. Compared to previous studies investigating the effect of weather on trade (which mainly use linear functional forms), this approach should help to address the challenge of connecting estimates of weather effects to climate change effects to some extent.

A key weakness in equation 2 is the lack of controls for multilateral resistance, $\Omega_{i,t}$ and $\Phi_{j,t}$. To address this issue, my preferred specification follows the approach in Beverelli et al. (2018), introducing exporter-year and importer-year fixed effects to control for these parameters:

$$\begin{aligned} X_{ij,t} = & exp[h(T_{it}) + g(P_{it}) + \pi_{i,t} + \chi_{j,t} + \mu_{ij} + \alpha FTA_{ij,t} \\ & + \eta INTL_{ij} \times YEAR_t] \times \varepsilon_{ij,t} \end{aligned} \tag{3}$$

In this specification, anything that varies at the exporter-year and importer-year level, such as GDP, is absorbed by the fixed effects. The direct effects of temperature and precipitation on trade are also absorbed into the exporter-year fixed effects, but the relative effects of weather on exports compared to domestic sales is identifiable. In other words, θ_1 and θ_2 as well as γ_1 and γ_2 are no longer identifiable but we can still obtain estimates for θ_3, θ_4, γ_3, and γ_4. The $INTL_{ij} \times YEAR_t$ dummy variables control for the average level globalization in a given year across all countries, an innovation which Bergstrand et al. (2015) find plays an important role in reducing bias in empirical gravity models.

In the results presented below, I present results based on equations 2 and 3 to enable comparisons with previous literature and also illustrate the impact that the various sets of fixed effects have on the results. Equation 3 is the preferred specification throughout this paper because it controls most robustly for the myriad of potential biases in trade models. Once again, this specification cannot deliver estimates of the effect of temperature and precipitation on total sales, but it can provide estimates of the effect of weather shocks on exports *relative* to domestic sales, which is the key parameter of interest in this study.

2.3 Interpreting model estimates

To compute full marginal effects of temperature or precipitation we must take into account the quadratic and interactive terms. First, note that since the empirical specification uses the PPML estimator, the coefficients are semi-elasticities: the proportional change in bilateral trade, $X_{ij,t}$, for a one unit change in the variable of interest. These semi-elasticities of bilateral trade with respect to temperature and precipitation are given by:

$$\beta_{Temp} = \theta_1 + 2\theta_2 T_{it} + INTL_{ij} \times (\theta_3 + 2\theta_4 T_{it})$$
$$\beta_{Precip} = \gamma_1 + 2\gamma_2 P_{it} + INTL_{ij} \times (\gamma_3 + 2\gamma_4 P_{it})$$

These parameters describe the $\beta \times 100\%$ change in bilateral trade associated with a 1 degree increase in annual mean temperature (ceteris parabis) and a 1 metre increase in total annual precipitation (ceteris parabis). For domestic sales ($\text{INTL}_{ij} = 0$), the semi-elasticities are simply $\beta_{Temp} = \theta_1 + 2\theta_2 T_{it}$ and $\beta_{Precip} = \gamma_1 + 2\gamma_2 P_{it}$, while for export sales the semi-elasticities include the interactive terms.

For the specification given by equation 2 we can identify estimates for the full semi-elasticities, but for the empirical model given by equation 3, we can only identify the interactive term, since θ_1 and θ_2 and γ_1 and γ_2 are absorbed into the fixed effects and not estimable (as explained above). These interactive terms, $INTL_{ij} \times (\theta_3 + 2\theta_4 T_{it})$ and $INTL_{ij} \times (\gamma_3 + 2\gamma_4 P_{it})$, are the difference (in percentage points) in the semi-elasticity for exports compared to domestic sales associated with 1 degree increase in temperature or a 1 metre increase in precipitation, ceteris parabis. They answer the central question of interest in this study: whether temperature and precipitation shocks have a differential effect on exports versus domestic sales. For ease of comparison across specification results, I report only the interactive terms of the estimated semi-elasticity estimates, regardless of whether or not the full elasticity is identified.

3 Data

The empirical model outlined above requires a cross-country panel dataset of bilateral trade flows, including domestic trade, plus data on regional trade agreements and data on weather in the exporting country. I outline the sources and construction of these variables below. The final dataset spans manufacturing and agriculture trade in 67 countries over 1991-2017; it is an unbalanced panel due to missing trade data for some years for some countries. Table 1 lists descriptive statistics for the model variables. See the appendix for a list of countries included in the model.

Table 1: Descriptive statistics for main variables

	Mean	St.Dev.	Min	Max
$\text{Trade}_{ij,t}$ (Billion USD)	5.0	125.52	0.0	14508.64
Manu. $\text{trade}_{ij,t}$ (Billion USD)	4.73	118.37	0.0	13647.25
Ag. $\text{trade}_{ij,t}$ (Billion USD)	0.31	8.55	0.0	901.78
$\text{Temperature}_{i,t}$ (°C)	15.45	5.7	3.5	27.95
$\text{Precipitation}_{i,t}$ (mm)	1088.51	752.15	14.58	5187.21
$\text{RTA}_{ij,t}$	0.24	0.42	0.0	1.0
Exporter $\text{GDP}_{i,t}$ (Billion USD)	671.92	1856.9	0.71	19519.35

International trade flows. Data on international bilateral trade flow comes from UN Comtrade for the manufacturing sector (United Nations 2021) and the FAO detailed trade matrix for the agriculture sector, which is part of the FAOSTAT database (Food and Agriculture Organization of the United Nations 2021). I mainly use reported imports, which should be more reliable than reported exports, but I check for instances when a country reports no imports but a partner country reports exports and fill in missing values with these reported exports. The FAOSTAT trade matrix does not include observations for FAO items 328 and 2631 (groundnuts and cotton), so I use bilateral trade data from Comtrade for these items. As is common practice in the international trade literature, I assume that missing bilateral trade represents zero trade and therefore obtain a complete matrix of international bilateral trade flows by filling in missing values with zero.

Domestic trade flows. The main challenge in compiling a data for this study is obtaining observations of domestic trade flows, which are not readily available. Following the approach in Beverelli et al. (2018), I construct domestic trade as the difference between output and total exports: $X_{ii} = Y_i - \sum_{i \neq j} X_{ij}$. Crucially, since international trade flows are observed in gross values, I use gross values of production (not value-added). Also, I use aggregate exports to all countries reported in the data, not just the 67 countries in my sample. For manufacturing I primarily use the UNIDO database for gross production data (UNIDO 2020), but where available I fill in missing values with data from the CEPII TradeProd dataset (Sousa et al. 2012). For agriculture, I use FAOSTAT's value of gross production data series. I use data starting from 1991 for all sources, since this is the earliest available year for the FAOSTAT value of gross production data. As explained above, observations of domestic trade are a cornerstone of the methodology used in this paper; however, the limited availability of data on domestic trade is the most significant data limitation faced by this paper and defines the coverage of countries and years in the sample.[4]

Regional trade agreements. I use the RTA dummy variable from the CEPII gravity database (Head and Mayer 2014). This variable indicates whether or not two countries have a regional trade agreement in a given year. For domestic trade observations, I set this this dummy equal to zero. For some specifications I also use GDP from this database.

Weather. Data on temperature and precipitation are from ECMWF's ERA5 database (Hersbach et al. 2020). Using the hourly gridded data for 2 metre surface temperature and for precipitation rate I compute the average annual temperature and total annual precipitation for each grid cell. I then spatially aggregate to the country-level by taking the population-weighted average across all grid cells in a given country, using the Gridded Population of the World v4 dataset for the year 2000 (Center for International Earth Science Information Network - CIESIN - Columbia University 2018). Figures 1 and 2 illustrate the average of these variables across the sample period. I test for unit roots in both the temperature and precipitation variables but do not find any evidence that either is non-stationary (see Table 6 in the Appendix for details of these

[4]For further details on how I construct domestic trade flows and select the sample of countries, see the appendix.

tests).

Figure 1: Average annual temperature in sample countries, 1991-2017

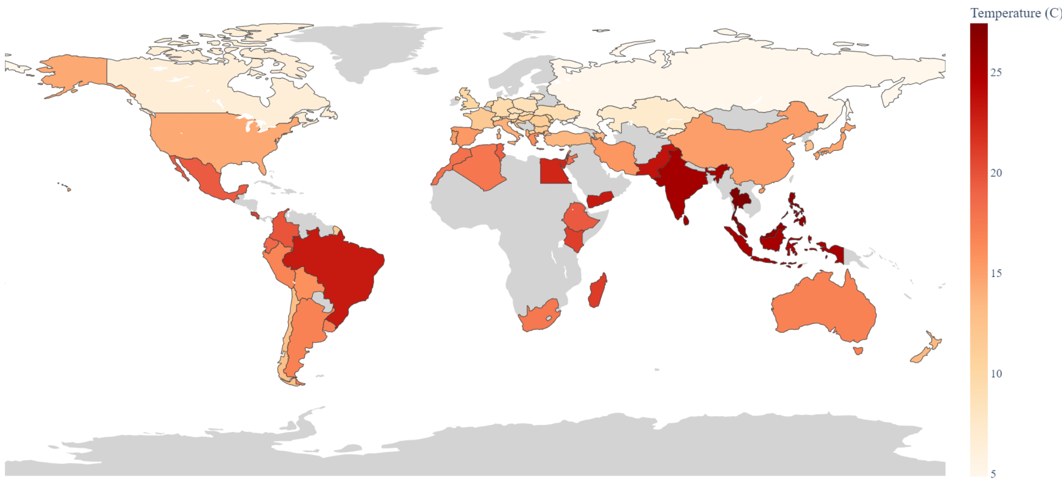
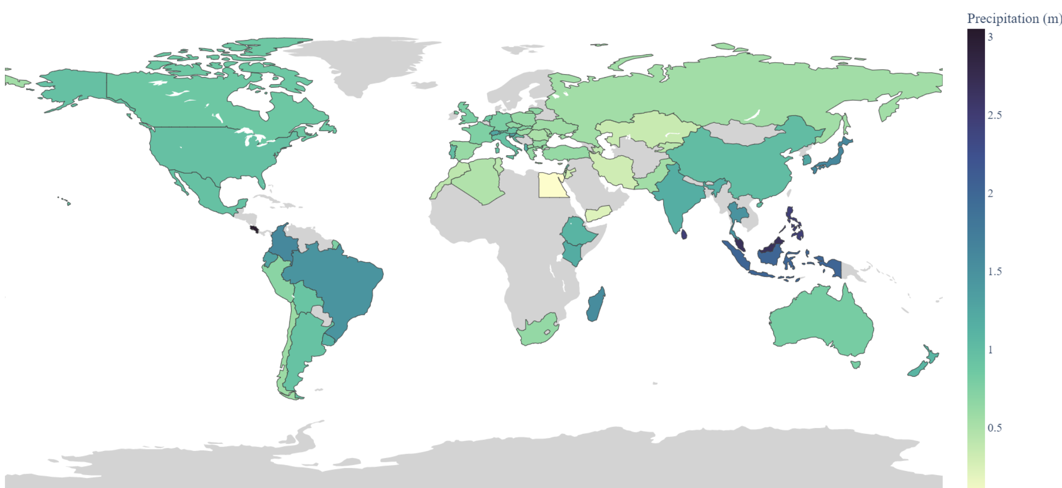


Figure 2: Average annual precipitation in sample countries, 1991-2017



Exporter characteristics. I explore heterogeneity in the effects of weather on trade according to a couple exporter characteristics: income and institutions. The Low income$_{i,t}$ dummy variable indicates whether country i was classified by the World Bank as 'Low income' or 'Lower middle income' in a given year (The World Bank 2022). The Weak institutions$_{i,t}$ dummy variable indicates whether country i is below the median observed value in year t for an institutional quality index. The institutional quality index is constructed as an unweighted average of the six variables in the World Governance Indicators dataset: control of corruption, government effectiveness, political stability and absence of violence, rule of law, regulatory quality, and voice and accountability (The World Bank 2020).

4 Results

The following discussion of results is organized as follows. First, I present estimation results for the effect of weather shocks on aggregate trade (manufacturing and agriculture combined). Next I break the analysis down to the sector level and show results for agriculture and manufacturing separately. Then I explore heterogeneity in the effect of weather shocks on trade according to exporter characteristics such as income and institutional quality. Finally, I explore alternative functional forms for the weather-trade relationships.

4.1 Main results

Table 2 shows coefficient estimates for the gravity model described in Section 2.2, with marginal effect estimates for each specification in the bottom panel of the table. The dependent variable is the total nominal value of bilateral trade in both the manufacturing and agriculture sectors. The marginal effects shown in the bottom panel are the estimated *difference* in the marginal effect of temperature or precipitation on exports relative to domestic sales, at a given level of temperature or precipitation. These estimates corresponds to the red and blue lines in the plots in Figures 3 and 4, which show the marginal effect estimates across levels of temperature and precipitation observed in the sample. The figure also includes the histogram of the annual mean temperature and total annual precipitation variables.

The results for aggregate trade indicate that mean temperature and total annual precipitation do not have a significantly different impact on exports relative to domestic sales, but exports are more sensitive to extreme weather than domestic sales. In particular, the estimated elasticity of aggregate exports to an additional extreme heat day is 0.5 percentage points lower than the elasticity of domestic sales.

Moving from left to right across Table 2, each column includes a progressively more strict set of controls for potential confounding variables. In column (1), I start with a specification similar to the main specification in Dallmann (2019), corresponding to Equation 2 above. Exporter-importer fixed effects absorb time invariant bilateral variables such as distance and sharing a border as well as any unobservable time invariant factors that affect bilateral accessibility. The $RTA_{ij,t}$ dummy controls for variation over the sample period in trade agreements. Although the results suggest that the effects of temperature and precipitation on trade are statistically insignificant on average across the sample, at 15°C (approximately the sample median of the temperature variable) the results indicate that the elasticity of exports to a temperature shock on exports is 13.2 percentage points higher than the elasticity of domestic sales. This results implies that at an annual mean temperature of 15°C, domestic sales are more sensitive to a temperature shock than exports. However, we should keep in mind that this specification controls for exporter and importer GDP, but otherwise does not control for the multilateral resistance faced by the exporter and importer. As explained above, this specification commits the 'gold medal mistake' of not properly controlling for exporter and importer multilateral resistances.

The estimates in columns (2) and (3) of Table 2 demonstrate that including a robust set of controls can have a notable impact on the coefficient estimates for the weather variables. Column (2) goes some way towards remedying the 'mistake' in column (1) by adding an importer-year fixed effects (FE) as well as time-invariant exporter FE. This specification reflects Table 22 in the appendix of Dallmann (2019). The importer-year FE control robustly for importer multilateral resistance, absorbing any factors affecting an importer's overall connection to the trading network in a given year. The exporter FE absorb any time invariant factors affecting an exporter's overall connection to consumer markets; these FE control imperfectly for exporter multilateral resistance but allow identification of the full effect of weather on trade (i.e. θ_1, θ_2, γ_1, and γ_2 are not absorbed into the FE). Column (2) also includes INTL-year dummies, as suggested by Beverelli et al. (2018) to account for the effects of increasing globalization over the sample period. In contrast to the results in column (1), in column (2) the estimated marginal effects of temperature are insignificant across the full distribution of the temperature variable. Meanwhile, precipitation has a statistically significant marginal effect on trade at upper levels of the precipitation distribution, as shown in the second panel of Figure 4. At 20 metres total annual precipitation, the semi-elasticity of exports in response to an additional metre of precipitation is 3 percentage points lower than the semi-elasticity of domestic sales.

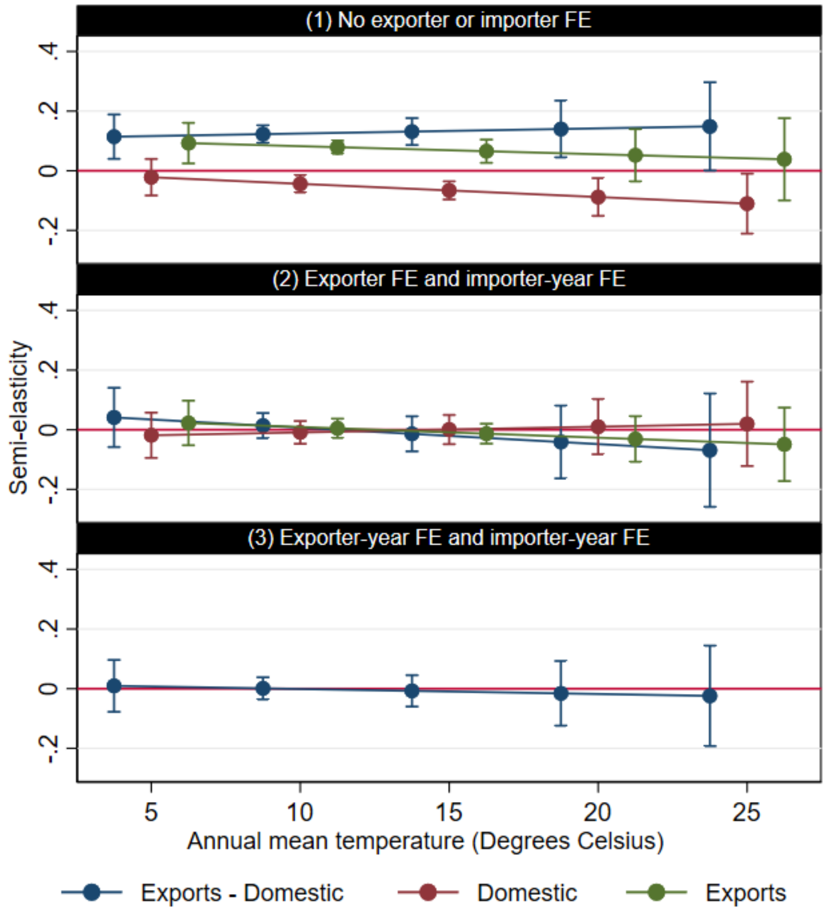
Table 2: Effects of weather shocks on aggregate trade

	(1)	(2)	(3)
$\text{Temp}_{i,t}$	1.2090	-0.5519	
	(1.1285)	(1.4879)	
$\text{Temp}^2_{i,t}$	-0.0022	0.0010	
	(0.0020)	(0.0026)	
$\text{INTL}_{ij}\times$ $\text{Temp}_{i,t}$	-0.3639	1.5718	0.4760
	(1.5696)	(2.0310)	(1.7891)
$\text{INTL}_{ij}\times$ $\text{Temp}^2_{i,t}$	0.0009	-0.0028	-0.0008
	(0.0028)	(0.0036)	(0.0031)
$\text{Precip}_{i,t}$	0.0010	-0.0115	
	(0.0137)	(0.0124)	
$\text{Precip}^2_{i,t}$	0.0001	0.0007^{*}	
	(0.0004)	(0.0004)	
$\text{INTL}_{ij}\times$ $\text{Precip}_{i,t}$	0.0048	0.0157	0.0135
	(0.0184)	(0.0134)	(0.0117)
$\text{INTL}_{ij}\times$ $\text{Precip}^2_{i,t}$	-0.0005	-0.0011^{***}	-0.0009^{**}
	(0.0005)	(0.0004)	(0.0004)
$\text{RTA}_{ij,t}$	0.2613^{***}	0.1640^{***}	0.1738^{***}
	(0.0509)	(0.0340)	(0.0398)
$\ln(\text{GDP}_{it})$	0.5804^{***}	0.5644^{***}	
	(0.0712)	(0.0551)	
$\ln(\text{GDP}_{jt})$	0.6717^{***}		
	(0.0502)		
Observations	109092	109092	109092
Difference in marginal effect on exports relative to domestic sales:			
Temp at 15°C	0.1314^{***}	-0.0138	-0.0073
	(0.0230)	(0.0300)	(0.0269)
Temp at 25°C	0.1486^{**}	-0.0688	-0.0241
	(0.0755)	(0.0969)	(0.0859)
Precip at 0.8 m	-0.0024	-0.0023	-0.0016
	(0.0121)	(0.0087)	(0.0085)
Precip at 2 m	-0.0133	-0.0292^{***}	-0.0242^{**}
	(0.0090)	(0.0096)	(0.0105)
Year FE	✓		
INTL-Year dummies		✓	✓
Importer-Year FE		✓	✓
Exporter FE		✓	
Exporter-Year FE			✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard errors (in parentheses) are clustered by exporter-importer pairs. All specifications control for exporter-importer FE.

Figure 3: Estimated marginal effect of temperature on aggregate trade

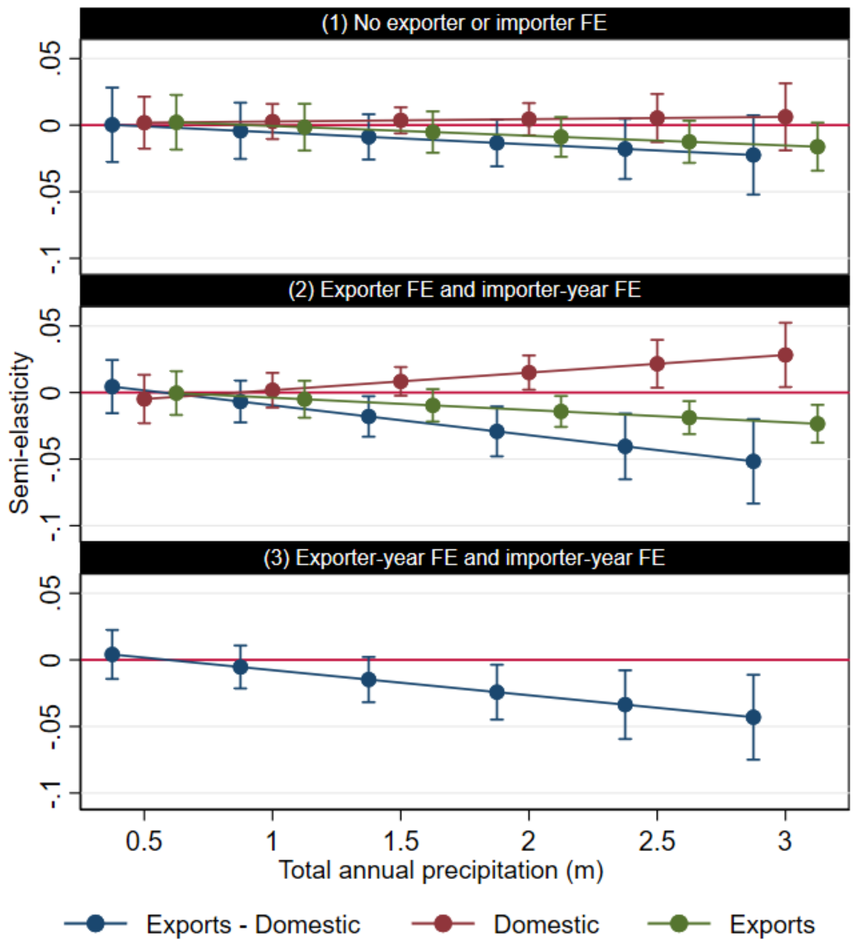


Notes: Marginal effect estimates shown here correspond to the estimates in the column of the same number in Table 2. 'Exports - Domestic' (the blue line) denotes the difference in the semi-elasticity for exports versus domestic sales - it is the main effect of interest in this study, telling us if weather shocks affect exports differently from domestic sales.

Finally, column (3) of Table 2 adds exporter-year FE. This specification corresponds to Equation 3. Note that the overall effect of weather is absorbed into these FE and only the interactive term with the INTL dummy can be estimated now. In other words, the effect of weather on exports *relative* to domestic sales is identified but we cannot identify the underlying level effects. However, this specification follows the consensus established in the literature to control for multilateral resistances with both importer-year and exporter-year FE. The results are similar to those in column (2). The impact of temperature on exports relative to domestic sales is statistically insignificant. Meanwhile, as illustrated in the bottom panel of Figure 4, in countries with already high levels of precipitation, an increase precipitation leads to a decrease in exports relative to domestic sales: the balance of trade shifts away from international markets and towards the domestic market.

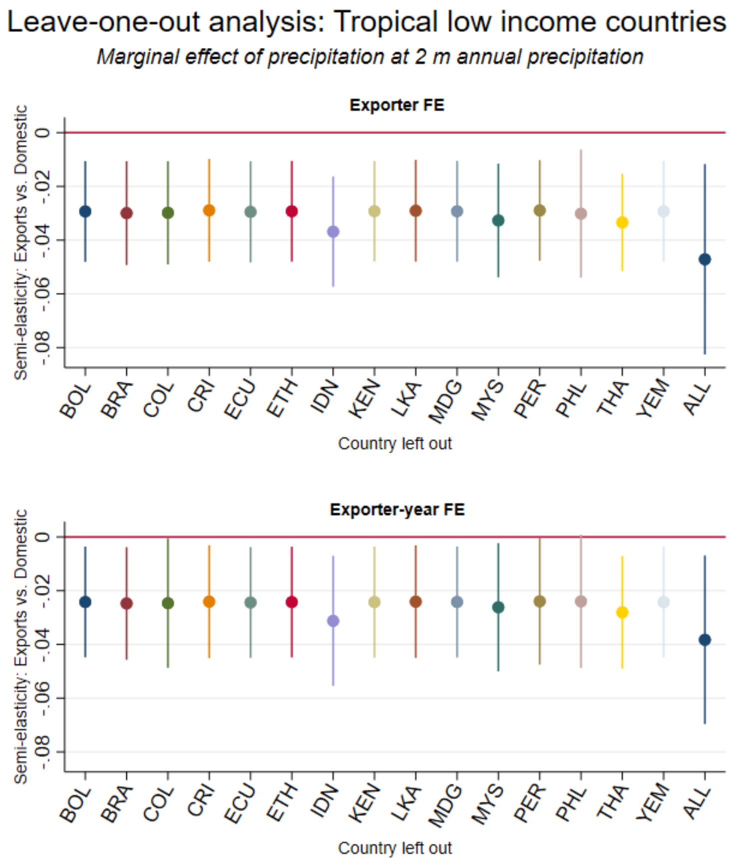
A notable feature of the precipitation variable is that its distribution is quite wide, with low income tropical countries dominating the upper tail. With this feature of the data in mind, I do a leave-one-out analysis to test whether the significant marginal effect of precipitation at 2 metres annual precipitation is driven by an outlier country in the precipitation distribution. I compile a list of tropical and low income

Figure 4: Estimated marginal effect of precipitation on aggregate trade



Notes: Marginal effect estimates shown here correspond to the estimates in the column of the same number in Table 2. 'Exports - Domestic' (the blue line) denotes the difference in the semi-elasticity for exports versus domestic trade - it is the main effect of interest in this study, telling us if weather shocks affect exports differently from domestic sales.

Figure 5: Robustness of precipitation effect to leaving out tropical low income countries



Notes: Countries labelled according to their 3-digit ISO codes; see the appendix for the correspondence between ISO3 codes and country names. 'ALL' denotes all tropical low income countries. Error bars represent 95% confidence intervals.

countries from within my sample countries according to the following characteristics: (i) the latitude of a country's capital is within the Tropic of Capricorn and Tropic of Cancer[5] and (ii) the country is classified as 'Low income' or 'Lower middle income' by the World Bank at any point during the sample period (The World Bank 2022). These criteria result in a list of 15 countries, which includes the countries at the very top of the distribution of the precipitation variable. Next, I iteratively re-estimate the model, each time leaving out one of the tropical low income countries, and then finally leaving out all of these countries. I do this procedure for both the model in column (2) of Table 2, which controls for exporter fixed effects, as well as the model in column (3), which controls for exporter-year fixed effects.

As Figure 5 illustrates, the estimated difference in the marginal effect of precipitation on exports relative to domestic sales at 2 m annual precipitation is fairly stable across each of these iterations, suggesting that the result is not driven by a single outlier country. The main potential exception occurs when the Philippines is left out of the model with exporter-year fixed effects; in this case the marginal effect of a precipitation shock at 2 metres annual precipitation does not have a significantly different effect on exports relative to domestic sales. This result suggests that the Philippines may be an important driver of the finding that exports are particularly sensitive to precipitation shocks in rainy countries. Nevertheless, when all tropical low income countries are left out of the analysis, the estimated marginal effect at 2 metres remains statisti-

[5]I obtain this data from the CEPII gravity database (Head and Mayer 2014).

cally significant (although standard errors widen, which is not surprising given that removing these countries eliminates all observations of annual precipitation above 2 meters and so the estimate is an out-of-sample prediction). Overall, the leave-one-out analysis suggests that the result that exports are relatively sensitive to precipitation shocks is fairly robust across samples and does not simply reflect a particular sensitivity of tropical low income countries to weather shocks. Moreover, the magnitude of the marginal effect of precipitation at 2 metres may be slightly larger when all tropical and low income countries are left out of the sample compared to when they are included, suggesting that exports from tropical low income countries may even be less sensitive to precipitation shocks compared to exports from other countries, perhaps because they are better adapted.

Overall, these estimates do not identify a significant effect of temperature shocks on aggregate trade. In very rainy places, exports may be more sensitive than domestic sales to additional precipitation, but otherwise these results do not indicate a particular sensitivity of exports to weather shocks. Moreover, these results demonstrate the importance of including a robust set of controls for multilateral resistances and globalization effects when estimating the effects of weather shocks on trade. Contrary to previous studies that have found a significant negative impact of temperature on trade, once a robust set of fixed effects are included, as is suggested by the gravity literature, this study finds that the effects of temperature on aggregate trade are statistically insignificant. Of course, including a demanding set of fixed effects reduces concerns of omitted variable bias, but it also reduces the identifying variation in the model, so these results could potentially reflect a lack of statistical power rather than true zero effects. Moreover, these results for aggregate trade may hide sector-specific effects of weather shocks on exports relative to domestic sales. Accordingly, the next section investigates these relationships separately for the agriculture and manufacturing sectors.

4.2 Results by sector

Previous studies, such as Dallmann (2019), have found that the sensitivity of international trade to weather shocks varies by sector, and Osberghaus (2019) notes that several studies on this topic have often found that agricultural trade is particularly affected by temperature shocks. Following this precedent, Table 3 presents results from estimating the model separately for the manufacturing and agricultural sectors. In columns (1) and (2) the dependent variable is the nominal value of bilateral trade in manufacturing goods and in columns (3) to (4) the dependent variable is the nominal value of bilateral trade in agricultural goods. For each sector, I estimate specifications with the set of controls corresponding to those used in columns (2) and (3) of Table 2. As with Table 2, the bottom panel of Table 3 shows the estimated difference in the semi-elasticity for exports versus domestic sales.

The results for manufacturing trade (columns (1) and (2) of Table 3) paint a similar picture as the results for aggregate trade in Table 2, which is unsurprising given the large size of manufacturing relative to the agriculture sector. Overall, these results do not identify a significant effect of temperature shocks on manufacturing exports relative to domestic sales. In very rainy places exports may be more sensitive to an increase in precipitation relative to domestic sales, but the standard errors on these estimates are large and this effect is significant only in the upper end of the precipitation distribution.[6] Of course within the manufacturing sector is a wide array of industries, and underneath these results could be significant effects for particular sub-sectors. Dallmann (2019)'s results suggest that trade in some manufacturing sub-sectors is more sensitive than others to weather shocks. Future work will aim to investigate potential heterogeneity within the manufacturing sector.

The results for agricultural trade (columns (3) and (4) of Table 3) confirm previous findings in the literature that this sector is particularly sensitive to temperature shocks. As shown in Figures 6, in relatively hot places, a temperature shock leads to decreases in exports relative to domestic sales. These results suggest that previous studies of the effect of weather on agricultural trade are not simply identifying - through the lens of trade - the effect of temperature shocks on underlying production. Export sales seem to be particularly sensitive to weather shocks, confirming the suggestive evidence of this effect in Jones and Olken (2010)'s results. At 15°C, the semi-elasticity of agricultural export sales with respect to a 1°increase in annual mean

[6]See the appendix for figures illustrating the estimated semi-elasticities for the manufacturing sector.

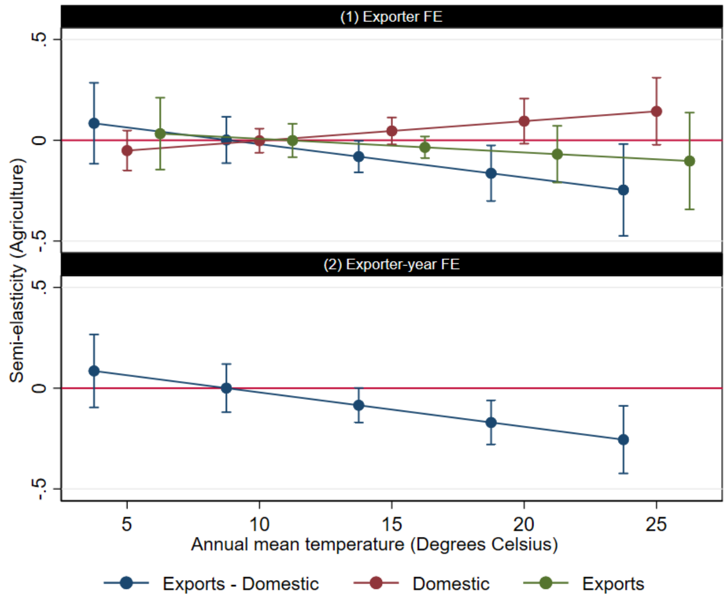
Table 3: Separating manufacturing and agricultural trade

	(1) Manu	(2) Manu	(3) Ag	(4) Ag
$\text{Temp}_{i,t}$	-0.6425		-2.7630	
	(1.4945)		(1.7394)	
$\text{Temp}^2_{i,t}$	0.0011		0.0049	
	(0.0026)		(0.0031)	
$\text{INTL}_{ij}\times\ \text{Temp}_{i,t}$	1.7192	0.5288	4.6851	4.8263**
	(2.0748)	(1.8177)	(2.9329)	(2.2375)
$\text{INTL}_{ij}\times\ \text{Temp}^2_{i,t}$	-0.0030	-0.0009	-0.0083	-0.0085**
	(0.0036)	(0.0032)	(0.0051)	(0.0039)
$\text{Precip}_{i,t}$	-0.0098		-0.0042	
	(0.0136)		(0.0131)	
$\text{Precip}^2_{i,t}$	0.0006		0.0003	
	(0.0004)		(0.0004)	
$\text{INTL}_{ij}\times\ \text{Precip}_{i,t}$	0.0135	0.0104	-0.0038	0.0017
	(0.0143)	(0.0118)	(0.0176)	(0.0193)
$\text{INTL}_{ij}\times\ \text{Precip}^2_{i,t}$	-0.0011**	-0.0009**	-0.0001	-0.0003
	(0.0004)	(0.0004)	(0.0004)	(0.0006)
$\text{RTA}_{ij,t}$	0.1635***	0.1779***	0.0160	0.0275
	(0.0362)	(0.0421)	(0.0904)	(0.0607)
$\ln(\text{GDP}_{it})$	0.6030***		-0.0617	
	(0.0586)		(0.0939)	
Observations	109092	109092	109092	109092
Difference in marginal effect on exports relative to domestic sales:				
Temp at 15°C	-0.0140	-0.0037	-0.0813**	-0.0849*
	(0.0323)	(0.0290)	(0.0399)	(0.0437)
Temp at 25°C	-0.0741	-0.0222	-0.2467**	-0.2553***
	(0.1007)	(0.0891)	(0.1163)	(0.0855)
Precip at 0.8 m	-0.0042	-0.0037	-0.0058	-0.0031
	(0.0094)	(0.0095)	(0.0126)	(0.0140)
Precip at 2 m	-0.0308***	-0.0249*	-0.0089	-0.0103
	(0.0103)	(0.0145)	(0.0106)	(0.0180)
Exporter FE	✓		✓	
Exporter-Year FE		✓		✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard errors (in parentheses) are clustered by exporter-importer pairs. All specifications control for exporter-importer FE, importer-year FE and INTL-year dummies.

Figure 6: Estimated marginal effect of temperature on agriculture trade



Notes: Marginal effect estimates shown here correspond to the estimates in columns (3) and (4) of Table 3. 'Exports - Domestic' (the blue line) denotes the difference in the semi-elasticity for exports versus domestic trade - it is the main effect of interest in this study, telling us if weather shocks affect exports differently from domestic sales.

temperature is 8.5 percentage points lower than the semi-elasticity for domestic sales. At 25°C, this gap widens to 25.6 percentage points.

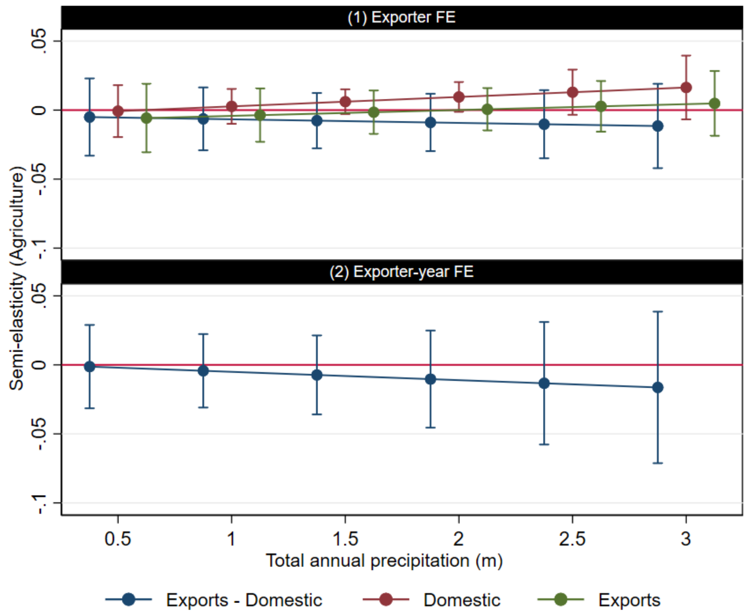
This reduced-form approach has the advantage of imposing limited assumptions on the data, but it does not uncover with certainty the mechanisms driving this relative sensitivity of agricultural exports to weather shocks. Nevertheless, knowing the sign of the effect helps to hone in on potential mechanisms. Recall that the dependent variable is the nominal value of trade, so mechanisms for this relative sensitivity of exports could be channeled through quantities or prices. That is, the decrease in exports relative to domestic sales could indicate that underlying quantities exported decrease relative to domestic quantities sold, and it could also reflect a decrease in the relative price of exports compared to domestically-sold goods.

In terms of potential mechanisms channeled through quantities sold, as hypothesized in the Introduction, producers may have a 'home bias' and prioritise their domestic markets, so when a weather shock negatively impacts production, they decrease exports more than domestic sales quantities. Another possibility is that international supply chains are more sensitive than within-country supply chains. In effect, weather shocks may act as an additional barrier to trade that increases the difficulty of getting goods to export markets.

Potential mechanisms via a decrease in the relative price of exports compared to the price of goods sold domestically imply that international trade barriers insulate producers from global competition and permit price fluctuations in domestic markets that do not occur in export markets. The results here are consistent with a potential mechanism in which agricultural producers are able to increase prices in their domestic market following a contraction in supply due to a weather shock, but export prices remain steady, so the value of exports decreases relative to the value of domestic sales.

Regardless of the exact mechanism driving the relative sensitivity of agricultural exports to weather shocks, we can expect that this effect may have implications for economic welfare. In neoclassical models of

Figure 7: Estimated marginal effect of precipitation on agricultural trade



Notes: Marginal effect estimates shown here correspond to the estimates in columns (3) and (4) of Table 3. 'Exports - Domestic' (the blue line) denotes the difference in the semi-elasticity for exports versus domestic trade - it is the main effect of interest in this study, telling us if weather shocks affect exports differently from domestic sales.

international trade, more openness to international trade is generally welfare-improving. Indeed, Arkolakis et al. (2012) show that underlying a wide class of structural trade models is a sufficient statistic in which a country's economic welfare increases as their share of expenditure on domestically-produced goods decreases. Accordingly, from the perspective of neoclassical trade models, we would expect that a shift towards domestic market sales due to a weather shock may decrease economic welfare in a country. Furthermore, given that export growth can be an import driver of economic growth, these results suggest that weather shocks can potentially undermine economic development through their effect on exports.

Finally, given that the relative sensitivity of exports to weather shocks occurs in the agricultural sector, these results could potentially have implications for domestic food security. However, without knowing whether the mechanism driving this effect is channeled through prices or quantities, we cannot say if this impact of weather shocks on export sales is good or bad for food security. If producers respond to weather shocks by keeping quantities sold at home relatively constant and decreasing exports instead, then this effect is not a threat to domestic food security. However, if these effects reflect an ability of producers to increase prices in their home markets, then this mechanism may undermine domestic food security.

4.3 Heterogeneity by exporter characteristics

Table 4 explores these results for bilateral agricultural trade based on characteristics of the exporting country. Column (1) interacts the temperature-trade function with a dummy variable indicating whether the exporter is a low income country, and column (2) interacts this function with a dummy variable indicating whether the exporter has weak institutions (see section **??** for a detailed description of these variables). The set of controls used in both specifications corresponds to those in columns (2) and (4) of Table 3: exporter-importer FE, importer-year and exporter-year FE, and INTL-year dummies. The bottom panel of Table 4 shows estimated difference in the marginal effects for exports versus domestic sales according to these exporter characteristics, and Figure 8 illustrates these estimates across the distribution of the temperature variable.

Table 4: Exploring heterogeneity by country characteristics

	(1)	(2)
$\text{INTL}_{ij} \times \text{Temp}_{i,t}$	3.5346*	5.2463***
	(1.9685)	(1.7744)
$\text{INTL}_{ij} \times \text{Temp}^2_{i,t}$	-0.0063*	-0.0093***
	(0.0034)	(0.0031)
$\text{Low income}_{i,t} \times \text{INTL}_{ij} \times \text{Temp}_{i,t}$	-0.0751***	
	(0.0186)	
$\text{Low income}_{i,t} \times \text{INTL}_{ij} \times \text{Temp}^2_{i,t}$	0.0003***	
	(0.0001)	
$\text{Weak institutions}_{i,t} \times \text{INTL}_{ij} \times \text{Temp}_{i,t}$		-0.0418**
		(0.0203)
$\text{Weak institutions}_{i,t} \times \text{INTL}_{ij} \times \text{Temp}^2_{i,t}$		0.0002**
		(0.0001)
$\text{INTL}_{ij} \times \text{Precip}_{i,t}$	0.0503**	0.0605
	(0.0253)	(0.0376)
$\text{INTL}_{ij} \times \text{Precip}^2_{i,t}$	-0.0028***	-0.0021*
	(0.0009)	(0.0012)
$\text{Low income}_{i,t} \times \text{INTL}_{ij} \times \text{Precip}_{i,t}$	-0.1110***	
	(0.0414)	
$\text{Low income}_{i,t} \times \text{INTL}_{ij} \times \text{Precip}^2_{i,t}$	0.0041***	
	(0.0011)	
$\text{Weak institutions}_{i,t} \times \text{INTL}_{ij} \times \text{Precip}_{i,t}$		-0.1149**
		(0.0544)
$\text{Weak institutions}_{i,t} \times \text{INTL}_{ij} \times \text{Precip}^2_{i,t}$		0.0031**
		(0.0015)
$\text{RTA}_{ij,t}$	0.0334	-0.0771
	(0.0591)	(0.0487)
Observations	109092	78584
Difference in marginal effect on exports relative to domestic sales:		
High income		
Temp at 15°C	-0.0835***	
	(0.0275)	
Temp at 25°C	-0.2091***	
	(0.0705)	
Precip at 0.8 m	0.0062	
	(0.0148)	
Precip at 2 m	-0.0601***	
	(0.0200)	
Low income		
Temp at 15°C	-0.0081	
	(0.0305)	

Temp at 25°C	-0.1284*	
	(0.0675)	
Precip at 0.8 m	-0.0400	
	(0.0256)	
Precip at 2 m	-0.0090	
	(0.0146)	
Strong institutions		
Temp at 15°C		-0.1215***
		(0.0405)
Temp at 25°C		-0.3078***
		(0.0762)
Precip at 0.8 m		0.0261
		(0.0216)
Precip at 2 m		-0.0254
		(0.0225)
Weak institutions		
Temp at 15°C		-0.0760**
		(0.0386)
Temp at 25°C		-0.2593***
		(0.0621)
Precip at 0.8 m		-0.0387*
		(0.0224)
Precip at 2 m		-0.0152
		(0.0121)

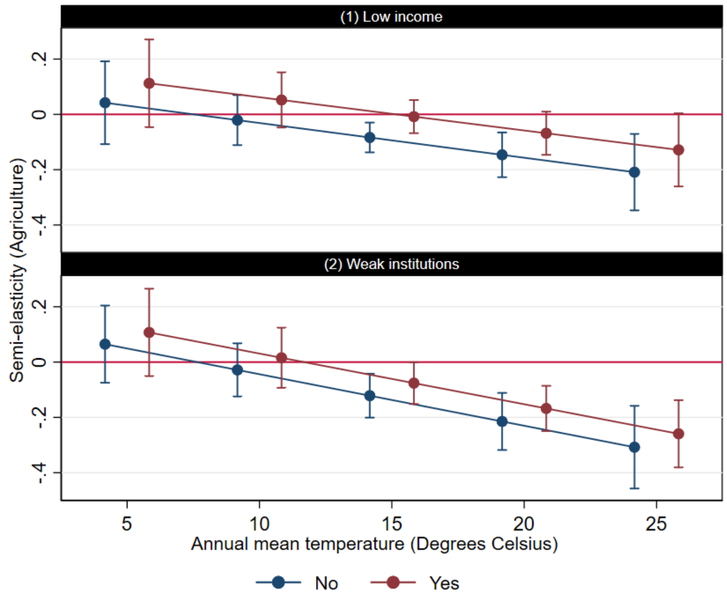
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable in both specifications is the value of agricultural trade. Standard errors (in parentheses) are clustered by exporter-importer pairs. All specifications control for exporter-importer FE, importer-year FE, exporter-year FE, and INTL-year dummies.

As shown in Column (1) of Table 4, temperature shocks lead to a shift in the balance of trade away from exports and towards domestic market sales for both high and low income countries. However, this effect may be slightly stronger and emerge at lower temperatures for high income compared to low income countries. At 25°C, the estimated marginal effect of a temperature shock on exports in high income countries is 21 percentage points lower than the effect on domestic sales; in low income countries this gap is 13 percentage points. The estimates in column (1) show even stronger heterogeneity between high and low income countries for the effect of precipitation shocks on exports relative to domestic sales: a statistically significant difference in the marginal effect on exports relative to domestic sales only emerges for high income countries. This result implies that in high income countries that are already fairly rainy, exports are more sensitive to an increase in precipitation than domestic sales, while in low income countries an increase in precipitation has a similar impact on exports as on domestic sales.

Several possible factors may explain this heterogeneity in the estimates for high versus low income exporters. Perhaps high versus low income countries tend to specialize in different agricultural sub-sectors, which leads to differing vulnerability of trade balances to weather shocks. Given that low income countries tend to be hotter (and to some extent wetter) than high income countries in the data, the weaker effect in these places may indicate some long term adaptation to typical weather conditions. Moreover, the fact that statistically significant effects emerge at lower levels of temperature and precipitation for high versus low income countries may indicate a lack of statistical power to identify the marginal effects outside the usual temperature ranges for these groups. Finally, less than a third of the sample of country-year observations are in the low income category, so this relatively low coverage of low income countries in the sample data may partly explain the lack of precise estimates for this group. Unfortunately this limitation is inherent in the data requirements of this research design, because data on the gross value of production (which is necessary

Figure 8: Heterogeneity in the marginal effect of temperature on agricultural trade



Notes: Marginal effect estimates shown here correspond to the estimates in the column of the same number in Table 4. The blue line, 'No', denotes the difference in the marginal effect for exports versus domestic sales for countries without the exporter characteristic in the plot title, and the red line, 'Yes', shows this effect for countries with this characteristic.

to construct observations of domestic sales) is less available for low income compared to high income countries.

Column (2) of Table 4 allows the effect of weather shocks on exports relative to domestic sales to vary based on whether the exporting country has strong versus weak institutional quality relative to the rest of the countries in the sample. Similar to the results for income, at high temperature levels, a marginal increase in temperature negatively impacts exports relative to domestic sales regardless of the institutional quality in the exporting country. This effect may be slightly stronger in countries with strong institutions, but the standard errors on these estimates are large so this heterogeneity is not precisely identified. Similarly, heterogeneity by institutional quality in the marginal effect of precipitation is not strongly identified.

Overall, neither low income levels nor weak institutions seem to increase the vulnerability of countries' export flows to weather shocks. Nevertheless, some heterogeneity based on income level and institutional quality of an exporting country may exist in the relative marginal effect curve. As mentioned above, this heterogeneity may reflect systematic differences in specialization in agricultural sub-sectors and/or in long-term adaptation. Future work on this topic should aim to understand this heterogeneity more thoroughly, though data limitations may present a challenge here.

4.4 Alternative functional forms for temperature

As a robustness check for the quadratic functional form assumption for the weather and trade relationships, Table 5 shows coefficient estimates for specifications based on alternative functional forms for the effects of temperature and precipitation on exports relative to domestic sales. Columns (1) and (2) introduce third-order and fourth-order polynomial terms, respectively, and columns (3) to (5) use flexible functional forms based on number of days in a year in a given temperature range. The dependent variable in all columns is the value of bilateral trade in agricultural products. All columns use the same set of controls as in column (5) of Table 3: exporter-importer FE, importer-year FE, exporter-year FE, and INTL-year dummies.

Table 5: Alternative functional forms

	(1)	(2)	(3)	(4)	(5)
$\text{INTL}_{ij}\times$ $\text{Temp}_{i,t}$	9.5303				
	(73.2664)				
$\text{INTL}_{ij}\times$ $\text{Temp}^2_{i,t}$	-0.0249	0.0247			
	(0.2538)	(0.1302)			
$\text{INTL}_{ij}\times$ $\text{Temp}^3_{i,t}$	0.0000	-0.0001			
	(0.0003)	(0.0006)			
$\text{INTL}_{ij}\times$ $\text{Temp}^4_{i,t}$		0.0000			
		(0.0000)			
$\text{INTL}_{ij}\times$ $\text{Precip}_{i,t}$	0.0479	0.0437	-0.0035	-0.0018	0.0154
	(0.0478)	(0.0608)	(0.0211)	(0.0192)	(0.0198)
$\text{INTL}_{ij}\times$ $\text{Precip}^2_{i,t}$	-0.0036	-0.0032	-0.0000	-0.0001	-0.0005
	(0.0030)	(0.0043)	(0.0005)	(0.0006)	(0.0005)
$\text{INTL}_{ij}\times$ $\text{Precip}^3_{i,t}$	0.0001	0.0000			
	(0.0000)	(0.0001)			
$\text{INTL}_{ij}\times$ $\text{Precip}^4_{i,t}$		0.0000			
		(0.0000)			
$D_{it,b}\times$ $\text{INTL}_{ij}, b \in (-\infty, -5]$°C			0.0043		
			(0.0046)		
$D_{it,b}\times$ $\text{INTL}_{ij}, b \in (-5, 0]$°C			-0.0101**		
			(0.0047)		
$D_{it,b}\times$ $\text{INTL}_{ij}, b \in (0, 5]$°C			0.0025		
			(0.0025)		
$D_{it,b}\times$ $\text{INTL}_{ij}, b \in (5, 10]$°C			0.0020		
			(0.0032)		
$D_{it,b}\times$ $\text{INTL}_{ij}, b \in (15, 20]$°C			-0.0057**		
			(0.0026)		
$D_{it,b}\times$ $\text{INTL}_{ij}, b \in (20, 25]$°C			0.0007		
			(0.0028)		
$D_{it,b}\times$ $\text{INTL}_{ij}, b \in (25, 30]$°C			-0.0059**		
			(0.0029)		
$D_{it,b}\times$ $\text{INTL}_{ij}, b \in (30, \infty)$°C			-0.0005		
			(0.0023)		
$D_{it,b}\times$ $\text{INTL}_{ij}, b \in (15, 25]$°C				-0.0025	
				(0.0021)	
$D_{it,b}\times$ $\text{INTL}_{ij}, b \in (25, \infty]$°C				-0.0052**	
				(0.0025)	
$D_{it,b}\times$ $\text{INTL}_{ij}, b \in (20, \infty]$°C					0.0014
					(0.0021)
$\text{RTA}_{ij,t}$	0.0274	0.0276	0.0161	0.0194	0.0212
	(0.0610)	(0.0610)	(0.0593)	(0.0608)	(0.0616)
Observations	109092	109092	109092	109092	109092

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable in all specifications is the value of agricultural trade. Standard errors (in parentheses) are clustered by exporter-importer pairs. All specifications control for exporter-importer FE, importer-year FE, exporter-year FE, and INTL-year dummies.

In column (3), the effect of temperature on exports relative to domestic sales is given by $h(D_{it}) = INTL_{ij} \times \sum_{b=0}^{B} \theta_b D_{it,b}$. The temperature distribution is divided into B 5 °C bins, and $D_{it,b}$ is the number of days during year t in which the mean temperature in country i falls into bin b. The coefficient estimate $\hat{\theta}_b$ indicates the marginal effect (relative to the reference bin of $(10, 15]$°C) of an additional day in bin b on the semi-elasticity of exports relative to domestic sales. The results are roughly consistent with a quadratic functional form for the effect of temperature, with stronger effects of temperature shocks on exports relative to domestic sales occurring at more extreme temperatures. This specification greatly reduces functional form assumptions compared to the polynomial specifications, but it has the disadvantage of requiring more statistical power to estimate all of the coefficients, and the prevalence of statistically insignificant results in column (3) may reflect a lack of power. I address this issue by estimating specifications with fewer bins in columns (4) and (5). Given that the results above suggest that the effect is occurs mainly in hot places, I focus on bins in the upper ranges of the temperature distribution. The results in these columns confirm that high temperature levels, particularly above 25°C, are a key driver of the relative sensitivity of exports to temperature shocks.

5 Counterfactual welfare simulation

As noted in Section 2, the theoretical expression for bilateral trade flows given by Equation 1 can be derived from a variety of micro-foundations. Arkolakis et al. (2012)'s seminal contribution demonstrates that this wide class of quantitative trade models share a common sufficient statistic for changes in welfare:

$$\Delta W_i = \left(\frac{\lambda_{ii}^{CFL}}{\lambda_{ii}^{BLN}} \right)^{\frac{1}{1-\sigma}}$$

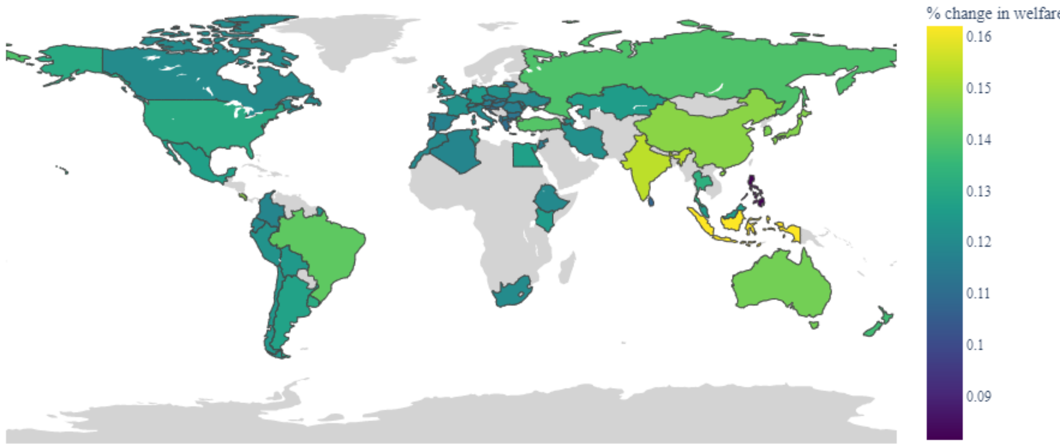
ΔW_i is the change in welfare for country i moving from the baseline (BLN) to counterfactual (CFL) scenario. $\lambda_{ii} = X_{ii}/E_i$ is country i's expenditure on domestically-produced goods as share of total expenditure. $\sigma > 1$ is the trade elasticity of substitution, and $1-\sigma$ is the elasticity of trade flows with respect to trade costs. In many demand-side derivations of the structural gravity model, a key assumption is that consumers prefer variety and each country produces a differentiated variety of the traded good, and the σ parameter, often called the Armington elasticity, is the representative consumer's elasticity of substitution between different varieties (Head and Mayer 2014). In supply-side derivations of the structural gravity model such as the Eaton and Kortum (2002) model, $1-\sigma$ reflects the degree of variation in the productivity of firms around the world.[7]

To assess the potential welfare implications of the differential impact of temperature on exports versus domestic market sales, I use this sufficient statistic alongside the coefficient estimates in column (3) of Table 2. First, I plug these coefficient estimates into equation 3 to predict bilateral trade ($\hat{X}_{ij}$) in a baseline and counterfactual scenario: the baseline scenario uses the average of the temperature and precipitation variables observed in each country from 2008 to 2018, and the counterfactual scenario takes these averages across 1980 to 1989. The median change in temperature observed in sample countries between these two decades is 0.92 degrees, and the median precipitation change is 0.02 metres. All other variables are constant across the baseline and counterfactual scenarios, and I use observed trade agreements as well as fixed effects estimates for 2017.

Next, I compute predicted total expenditure by summing up predicted bilateral trade across all exporters, $\hat{E}_{j,BLN} = \sum_i \hat{X}_{ij,BLN}$, and then I calculate the predicted share of expenditure on domestic goods:

[7] Regardless of the micro-foundations that underpin its interpretation, σ is a parameter from a static trade model and is distinct from the elasticity of marginal utility in the climate economics literature, which is sometimes denoted as σ, and which reflects social preferences for smoothing consumption levels across generations (Ramsey 1928; Drupp et al. 2018). With this in mind, the above sufficient statistic for welfare does not take into account the dynamics of decision making, in particular preferences for social discounting, and the results presented here should be interpreted with this caveat in mind.

Figure 9: Returning to 1980s weather: Estimated impacts on welfare via changes in trade flows, $\sigma = 6$



$\hat{\lambda}_{ii,BLN} = \hat{X}_{ii,BLN}/\hat{E}_{i,BLN}$. I do these calculations for both the baseline and counterfactual scenarios. Finally, I plug $\hat{\lambda}_{ii,BLN}$ and $\hat{\lambda}_{ii,CFL}$ into the equation above to compute $\Delta\hat{W}_i$ for each country. I use a value of 6 for σ, which is Head and Mayer (2014)'s preferred estimate after reviewing the literature on this parameter. As a robustness check, I also do this analysis with a value of 4 for σ, which is close to the median of the full sample of estimates in included in Head and Mayer (2014)'s meta-analysis of estimates of the trade elasticity.[8]

This simulation assesses the welfare impacts (via changes in trade flows) of returning to weather conditions of the 1980s but keeping international trade costs, policies, institutions, and all other bilateral and country-specific factors at 2017 conditions. Figure 9 illustrates the results of this simulation. Returning to weather conditions of the 1980s leads to a 0.08% to 0.16% increase in welfare across the sample countries. Note that this impact of weather changes on welfare reflects only changes due adjustment in trade flows; other impacts of changes in temperature and precipitation across this time period, such as health and productivity impacts, are not reflected in this simulation. These decreases in welfare due to temperature increases of around 1°since the 1980s are not huge, but given the underlying size of the economies in the sample, they are not negligible either. Comparing Figure 9 with Figure 12 (in the appendix) reveals that the calibration of the σ parameter affects the magnitudes of these results. The calibration of σ at the alternative value of 4 reflects an assumption that trade is less elastic to trade costs, so trade becomes more important to welfare compared to the calibration in Figure 9. Compared to the main results that assume $\sigma = 6$, in the alternative results for $\sigma = 4$ the magnitudes of the estimated trade-related welfare impacts of climate change increase, ranging from 0.13% to 0.27%. Nevertheless, the heterogeneity in these trade-related welfare impacts across countries is quite similar regardless of the calibration of σ. In general, countries in the north western quadrant of the map in Figure 9 tend to have seen relatively small trade-related impacts of climate change since the 1980s, while countries in the south eastern quadrant have seen relatively large impacts.

These welfare impacts of weather changes via changes in exports relative to domestic trade help to illustrate the potential economic significance of the empirical estimates presented above. Nevertheless, this simulation should be interpreted with a couple of important caveats in mind. First, the coefficient estimates from the empirical model are identified from weather shocks - that is, deviations from the usual tempera-

[8]See Figure 12 in the appendix for an illustration of the results with this alternative value for σ.

ture and precipitation experienced in a given country. The response of trade flows to a temperature shock may be different than the response to changes in temperature over 30 years because a gradual long-term change offers opportunities for exporters to learn and adapt. Accordingly, these simulated welfare impacts of changes in weather may overstate the impact of climate change. Finally, this sufficient statistic for welfare is derived from a stylized static framework for international trade which leads to a continuous monotonic relationship between changes in trade openness and changes in economic welfare; a more complex social welfare function that allows for dynamics, for example, or takes more account of distributional impacts within a country, may be more appropriate for a full assessment of the welfare implications of the results in this study.

6 Conclusion

This paper uses an approach that brings together developments from the international trade and climate econometrics literatures to investigate the differential impact of weather shocks on exports relative to domestic sales, shedding light on the effect of weather shocks on barriers to international trade. In contrast to previous empirical papers that study the impact of weather shocks on international trade, I include domestic trade flows in my model and control robustly for multilateral resistance using exporter-year and importer-year fixed effects. Not only does this approach provide a more robust basis for causal inference compared to previous papers, but it also allows me to separately identify the effect of weather shocks on the flow of trade from the effect on underlying productivity.

The results suggest that manufacturing exports are not affected by temperature shocks, but in particularly rainy places manufacturing exports decrease relative to domestic sales in response to an increase in precipitation. In other words, an increase in precipitation increases barriers to international manufacturing trade in rainy places. Meanwhile, in the agricultural sector increased temperatures lead to a decrease in exports relative to domestic sales, mostly in already hot countries. I do not find strong evidence of heterogeneity in this effect based on income levels or institutional quality. Finally, a simple sufficient statistics analysis to assess the welfare implications of these results suggests that returning to weather conditions of the 1980s but otherwise keeping the global trading network constant at recent conditions would increase welfare by 0.08% to 0.16% in sample countries due to decreases in weather-related trade barriers.

This paper contributes to our understanding of how to conceptualize the economic impacts of climate and weather. Climate change economists often model the economic damages associated with increased temperatures as part of the production function, which implies that these damages are productivity impacts. This paper brings some empirical insight into one aspect of how this assumption might be a simplification. More precisely, the economic damages of weather shocks likely do not stop when agricultural goods leave the factory or farm, but continue to have impacts along the supply chain. The results of this paper suggest that weather shocks are an additional barrier to international trade or exacerbate existing barriers to international trade.

Understanding the mechanisms underlying this effect as well as its economic significance are two key areas for future research on this topic. Several potential underlying mechanisms are consistent with these results, including that producers have a 'home bias', and that weather shocks create an additional barrier to international trade, perhaps through difficulties in transporting goods internationally or by increasing the gap between domestic and export prices. Future work could break the analysis down into more granular sub-sectors to try to get a better idea of what is driving these results. Moreover, given that these effects are identified from weather shocks, the economic significance of these results for long-term climate change is unclear. Understanding the mechanisms behind the effect will help to understand the extent to which exporters can adapt to these impacts in the long term. Alternative models and methods may also be useful for understanding how climate change may have economically significant impacts via impacts on trade flows.

Finally, a some policy takeaways arise from this paper. The results confirm findings in many other papers that the agricultural sector is particularly sensitive to weather shocks, and so climate and trade policy should take into account these sector-specific vulnerabilities. In particular, the results stress the importance of policy alignment. Climate and trade interact with each other in their effects on economic welfare, and so climate and trade policy should not exist in silos but instead take into account these interactions. For example, policy initiatives to support trade openness and export-driven growth may benefit from including climate change adaptation measures.

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7 Appendix

7.A List of countries in the model

ISO3 Codes in parentheses: Albania (ALB), Algeria (DZA), Argentina (ARG), Australia (AUS), Austria (AUT), Azerbaijan (AZE), Bolivia (Plurinational State of) (BOL), Brazil (BRA), Bulgaria (BGR), Canada (CAN), Chile (CHL), China (CHN), Colombia (COL), Costa Rica (CRI), Croatia (HRV), Cyprus (CYP), Czechia (CZE), Czechoslovakia (CZE), Ecuador (ECU), Egypt (EGY), Ethiopia (ETH), France (FRA), Germany (DEU), Greece (GRC), Hungary (HUN), India (IND), Indonesia (IDN), Iran (Islamic Republic of) (IRN), Israel (ISR), Italy (ITA), Japan (JPN), Jordan (JOR), Kazakhstan (KAZ), Kenya (KEN), Kyrgyzstan (KGZ), Lebanon (LBN), Lithuania (LTU), Madagascar (MDG), Malaysia (MYS), Mexico (MEX), Morocco (MAR), Netherlands (NLD), New Zealand (NZL), North Macedonia (MKD), Pakistan (PAK), Peru (PER), Philippines (PHL), Poland (POL), Portugal (PRT), Republic of Korea (KOR), Republic of Moldova (MDA), Romania (ROU), Russian Federation (RUS), Slovakia (SVK), Slovenia (SVN), South Africa (ZAF), Spain (ESP), Sri Lanka (LKA), State of Palestine (PSE), Switzerland (CHE), Thailand (THA), Tunisia (TUN), Turkey (TUR), Ukraine (UKR), United Kingdom (GBR), United States of America (USA), Uruguay (URY), Yemen (YEM)

7.B Additional notes on data cleaning

For the manufacturing sector, I calculate domestic trade at the country-year-sector level (I define country-specific sectors based on combinations of ISIC codes a given country reports production under over the sample period). Two potential issues lead to missing values for domestic trade: (i) production data is missing, and (ii) the production value is less than the value of exports and therefore domestic trade is negative, in which case I recode domestic trade to missing. I am unable to observe when missing production values indicate true missing values versus zero actual production. To avoid creating mechanical year-to-year variation in domestic trade based on what sectors are observed in a given country, after aggregating across ISIC codes to the country-year level, I recode domestic trade as missing if the number of sectors observed for a given country-year is more than 2 different than the mode number of sectors observed for that country.

I check for overlaps in the product coverage across FAOSTAT and Unido. I drop 254 such overlapping FAO items from the FAOSTAT data and instead use the observations in the Unido and Comtrade data and allocate these products to the manufacturing sector. I also drop FAO items that cannot be matched to an ISIC or HS code and items for which production data is unavailable despite the availability of trade data (e.g. live animals).

I drop countries from the sample if they are not in both UNIDO and FAO production data. To limit the prevalence of missing observations for domestic trade I drop addditional countries and settle on the sample of 67 countries listed above.

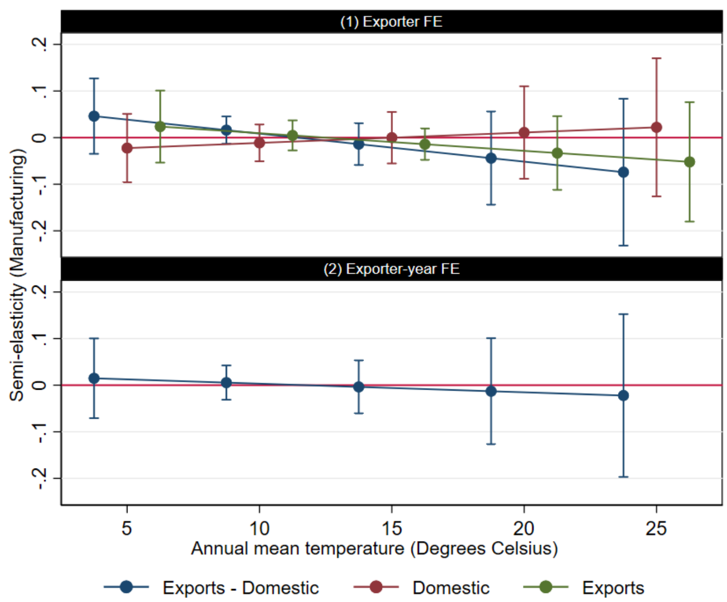
7.C Additional tables and figures

Table 6: Stationarity tests for temperature and precipitation variables

	Test statistic	P-value
IPS test with zero lags and a time trend		
Annual mean temperature	-28.478	≤ 0.01
Total annual precipitation	-30.881	≤ 0.01
Cross-sectionally-augmented IPS test with 2 lags and time trend		
Annual mean temperature	-3.06	≤ 0.01
Total annual precipitation	-3.214	≤ 0.01

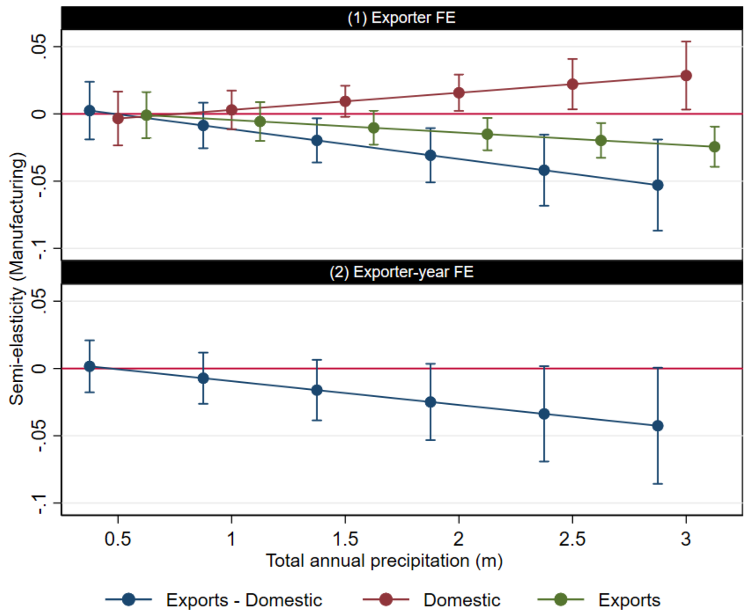
Notes: "IPS" refers to the Im, Pesaran, Shin test. The null hypothesis for both versions of this test is that the variable is non-stationary. For both the temperature and precipitation variables this null hypothesis is rejected at conventional levels.

Figure 10: Estimated marginal effects of temperature on manufacturing trade



Notes: Marginal effect estimates shown here correspond to the estimates in the column of the same number in Table 3 - i.e. the plot in first row, titled (1), corresponds to estimates from column (1) in Table 3. 'Exports - Domestic' (the blue line) denotes the difference in the marginal effect for exports versus domestic trade - it is the main effect of interest in this study, telling us if weather shocks affect exports differently from domestic sales.

Figure 11: Estimated marginal effect of precipitation on manufacturing trade



Notes: Marginal effect estimates shown here correspond to the estimates in the column of the same number in Table 3 - i.e. the plot in first row, titled (1), corresponds to estimates from column (1) in Table 3. 'Exports - Domestic' (the blue line) denotes the difference in the marginal effect for exports versus domestic trade - it is the main effect of interest in this study, telling us if weather shocks affect exports differently from domestic sales.

Figure 12: Returning to 1980s weather: Estimated impacts on welfare via changes in trade flows, $\sigma = 4$