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DISCUSSION PAPER

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International Trade and the Transmission of Temperature Shocks

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Abstract

We examine how the adverse impacts of weather shocks are distributed through the trade network. Exploiting a rich, theoretically derived, fixed effects structure, we find significant negative short-run effects of high temperature on exports. A month with an average temperature above 30 °C implies export losses of around three percent. These effects are increasing in the labour-intensity of exports. Using our structural Gravity model, we assess the general equilibrium incidence of these temperature shocks. We find that equilibrium adjustments reduce the economic costs by around 20 percent, but significant costs arise also for countries not directly exposed to high temperatures.

Keywords: International trade, Temperature, Extreme weather, Structural Gravity
JEL Codes: F14; F18; Q54

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1 Introduction

Climate change is a global problem. The emission of greenhouse gases impacts ecosystems and economies around the globe, independently of the location of the emitter. In order to infer the sensitivity of economic activities to climate change a growing literature studies how weather in general, and temperature in particular, affects aggregate economic outcomes.

Most studies in this field analyse local outcomes of local weather variation (Dell et al., 2012; Burke et al., 2015). But economies are not isolated from each other. As international trade links the fortune of economies, the economic impacts of local weather events may spillover and disseminate through the global trade network, creating a spatial disentangling of the occurrence of weather events and their full economic consequences. In order to comprehensively assess the economic costs of weather events, we need to understand the propagation of the costs of these events across borders.

International trade is an important source of welfare for both exporting and importing countries. However, if extreme weather events disrupt the production of goods and subsequently exports and if international trade creates economic gains for both trading parties — as, at least in the aggregate, standard economic theory suggests — then these weather events may have economic consequences for the importing country, potentially far away from the actual geographic location of the event. But standard economic theory also suggests that, in order to minimize economic costs of the shock, consumers are able to adjust and substitute, at least partially, towards suppliers not directly exposed to the extreme event. An analysis of the transmission of these costs needs to take into account substitution options, the subsequent price changes and new market equilibria. Our study is — at least to our knowledge — the first that provides robust ex-post empirical evidence of the international transmission of the costs of extreme weather events. Based on a refined structural Gravity model we show that high temperature events in one country cause economically and statistically significant costs also in countries not directly exposed to the event.

Understanding the spatial spillovers of local weather events has important consequences for cost-assessments of climate change and thus the decision-making of policy makers. As the frequency and severity of extreme weather events is likely increasing with further global warming — a relatively undisputed argument in particular regarding heat waves (IPCC, 2021) — the propagation of the costs of extreme weather events through the global trade network is relevant for a comprehensive account of the social cost of carbon (SCC), a key figure used in cost-benefit analysis that puts a monetary value on the impacts of climate change caused by one ton of carbon (Wagner et al., 2021). In the U.S., the former Trump administration revised the official, formerly global, SCC figures, considering only climate impacts that occurred domestically in continental United States. This has been reversed by the Biden administration, mainly based on ethical and fairness arguments. But if costs of climate change are propagated through international trade and hence also borne by countries not directly affected, this provides an argument to take into account global climate impacts for the SCC calculation even from a pure selfish perspective.[1] It is therefore important to measure the extent of climate impacts on trade flows and their propagation through the global trade system.

Many individual weather shocks are probably transient and are potentially difficult to identify in annual data. Typically, GDP data is available on a quarterly-level at best. In addition, output and GDP data are often imprecise and suffer from substantial measurement error in many countries (Jerven, 2013), some of which might be highly exposed to climate and weather impacts. International trade data is known to be more accurate as the value of trade is often recorded by both, the exporting and importing country. As bilateral trade data is increasingly available with higher temporal frequency, looking at international trade provides a promising avenue to gauge the impact of weather shocks on aggregate economic outcomes.

This paper therefore aims at answering three research questions: (i) Do extreme weather events affect exports? (ii) If so, through which channels do these events affect bilateral trade and which characteristics govern the effects? (iii) And, finally, what is the spatial incidence of the costs of these events and how much of these costs arise in not directly exposed countries?

In order to identify both partial and general equilibrium effects of weather events on international trade, we build a structural Gravity model, where weather events affect monthly output and, consequently, importers face supply losses from affected exporters. The model explicitly describes demand and price shifts, as importers respond with substitution from other sources.

[1] See Kotchen (2018) for a theoretical analysis of this argument.

This model is then estimated using five decades of monthly observations of bilateral trade and weather data, including more than 20,000 country pairs and about 4.5 million observations. Estimating a structural Gravity model provides a well-suited framework to identify the impact of weather on aggregate economic outcomes as the identification builds on established trade theory and a robust empirical relationship. While we perform the empirical analyses for various types of extreme weather events, we focus on episodes of high ambient temperature in the main part of the analysis. Theoretically consistent with our derived general equilibrium model, we are able to exploit a rich and theory-derived fixed effects structure that allows to tightly estimate the temperature impacts on monthly bilateral exports.

We find highly significant negative non-linear effects of high absolute temperature and extreme temperature deviations in the exporting country on the value of contemporaneous gross exports. In a month when the average temperature is at least 30 °C, exports decrease by 3.4 percent relative to a month with an average temperature below this threshold. Using an alternative specification of extreme deviations from country-specific mean temperatures, we find that a top-percentile temperature shock in the export country reduces the export value by 2.1 percent.

We then examine if specific exporter characteristics govern the effect size and find that the impact rises with the labour-intensity of the exports. This is consistent with the notion that short-run temperature impacts on exports might be governed by labour productivity or labour supply effects in the exporting country due to of physiological heat stress, as suggested by substantial micro-empirical evidence.

Equipped with these estimates, which inform our structural Gravity model, we compute the counterfactual global trade equilibria in absence of a high temperature event. This allows us to calculate the cost-incidence of such an event for the country directly exposed to the temperature shock as well for countries only indirectly exposed through trade links with the affected location. Measuring costs as losses in trade relative to the counterfactual scenario without temperature shock, we find that the mean high temperature shock has statistically significant global costs of 360 million USD. About two-thirds of these costs appear in countries not directly exposed to the temperature event, suggesting that substantial parts of the costs of these shocks are transmitted and propagated through the trade network.

In a final step, we analyse the magnitude of these spillovers under climate change projections based on twenty-year monthly temperature averages from global climate models. We find that under a middle-of-the-road climate projection of the period 2020-2039, annual global trade is reduced by about 735 million USD due to additional high temperature events relative to 2015.

Literature review. Growing micro- and plant-level evidence suggests that high ambient temperature has detrimental impacts on labour productivity and supply. Using survey data on time allocation of individuals, Zivin and Neidell (2014) find evidence for a substantial reduction of labour supply in climate-exposed industries such as agriculture, construction and manufacturing in non-climate-controlled facilities on days with maximum temperature above 85 °F (29.4 °C). However, over time, humans seem to be able to adapt physiologically to higher temperatures, mitigating performance losses, at least in certain environments. Analysing the performance of track and field athletes, Sexton et al. (2022) find that acclimatization can reduce temperature-induced performance losses by at least 50 percent.

Given the evidence on the temperature-productivity relationship of individuals, one might suggest that such temperature effects prevail also on plant-level. Looking at the near-universe of Chinese manufacturing plants from 1998 to 2007, Zhang et al. (2018) find an inverted U-shape relationship between temperature and total factor productivity (TFP). Their estimates show that for the average plant on a day with maximum temperature above 90 °F (32.24 °C), TFP decreases by 0.56 percent relative to a day with 50-60 °F (10-15 °C), translating into an estimated output loss of 0.45 percent for the average plant. Similar findings are documented using firm-level data from India. Somanathan et al. (2021) provide evidence that annual plant output falls by about 2 percent if every day would warm by 1 °C. This loss appears to be driven by a reduction in the output elasticity of labour due to an increasing rate of absenteeism and a decrease in labour productivity.

This research provides the micro-economic foundation of the macro-level impact of high ambient temperatures on economies. Measuring aggregate impacts of temperature changes on economic growth rates has been the aim of a number of influential studies such as Dell et al. (2012) and Burke et al. (2015). Assuming a log-linear relationship of temperature and economic activities, Dell et al. (2012) find a substantial negative effect of temperature changes on GDP growth, but only in poor countries: a 1 °C rise in annual average temperature reduces economic growth by about 1.3 percentage points. Burke et al. (2015) argue that the aggregate impact of temperature on economic outcomes is non-linear, suggesting a concave function with economic productivity peaking at 13 °C. Based on sub-national data, Kalkuhl and Wenz (2020) support the evidence that temperature variation affects aggregate outcomes in a non-linear fashion.

However, this literature focuses on local effects of local events. Given the economic relevance of international trade, focusing on local temperature might provide an incomplete picture of the impacts of weather events on the economy. As Jones and Olken (2010) say: "international trade links the fortunes of countries providing important conduits for geographically limited climatic impacts to have global economic effects." Using reduced-form regressions with product-level export panel data they find that export growth is reduced by 2.0-5.7 percentage points in poor countries if annual temperature increases by 1 °C. Product-level analyses show that this is driven in particular by adverse effects on agriculture and light manufacturing. This finding has been confirmed by Dallmann (2019), who additionally controls for temperature (and precipitation) impacts at the importer location. Also using a linear temperature specification in an annual time-scale, she finds that each 1 °C warming in the exporter country reduces bilateral exports by 3.1 percent, but does not find significant effects of the importer's temperature.

Our paper differs in five important aspects from these previous studies. First, our estimation is derived from a theoretically consistent general equilibrium trade model. The derived estimated Gravity equation has been proved to be empirically robust in many applications in international economics. Jointly with our tight, theoretically derived, high-dimensional fixed effects structure, this should minimize omitted variable bias, improve identification and generate robust estimates of the weather variation effects on an aggregate economic outcome such as exports.

Second, we use data with a monthly temporal resolution while most of the previous macro-level studies rely on annual data. Heat waves typically last only for a few weeks. But as aggregate statistics such as GDP are only available on a quarterly or even annual basis, it may be challenging to identify the effects of those events in aggregate data. The few existing studies using monthly trade data do either not analyze global data (such as Karlsson (2021), focusing on U.S. exports), or do not study temperature effects (Tembata and Takeuchi, 2019; Felbermayr et al., 2020).

Third, previous studies show that the functional relationship between aggregate economic outcomes and temperature remains heavily debated. Newell et al. (2021) test several hundred functional forms and find that non-linear temperature specifications dominate the model set in terms of predictive ability. Based on our large data set, we estimate the effects of single °C bins, thereby allowing for a high degree of flexibility in the functional form.

Fourth, while we, similar to Jones and Olken (2010), find evidence for larger effects of high temperature events on exports of manufactured goods, we use a more direct approach to identify labour-productivity effects as a key channel. Using input-output data we find that high labour-intensity of exports correlates with a stronger negative impact of high temperature events on exports.

Fifth, and of particular relevance, by exploiting our estimated structural model, we simulate the equilibrium adjustments caused by a high temperature episode. This enables us to estimate the cost-incidence of such events also for countries only indirectly affected, taking into account their opportunities to adjust imports in response to a shock abroad.

Besides contributing to literature on weather effects on international trade, our paper adds to a growing literature that studies the spatial transmission of natural shocks such as disasters or weather extremes more explicitly. This is particularly relevant as impacts of climate change are and will be unevenly spread across countries and, as Costinot et al. (2016) point out: "[i]n a globalized world, the impact of micro-level shocks depends not only on their average but also on their dispersion over space." Using a spatially highly-resolved crop field model, they study general equilibrium adjustments of crop productivity shocks from climate change. They show that adjusting planted crop types in response to changes in comparative advantage is an important force to reduce costs of climate change in agriculture. Relative to this, international trade plays only a minor role in alleviating the consequences of climate change. However, we do not address this margin explicitly as in our model each country produces a specific, non-homogeneous good. Thereby, we implicitly abstract from adjustments in the domestic production processes.

At the firm level, Barrot and Sauvagnat (2016) find that when one of their suppliers is hit by a large natural disaster, firms experience an average drop of 2-3 percentage points in sales growth. This is supported by findings of Pankratz and Schiller (2019) who show that firm-performance is negatively affected if large suppliers of these firms have been exposed to extreme weather events but also that the downstream firms respond and adjust their supply chains to less exposed suppliers. While these papers study firm-level responses to exogenous shocks, we focus on aggregate impacts on the macro-level.

Also using a computable general equilibrium (CGE) model informed by climate impact projections, Schenker (2013) points out that international trade may redistribute parts of the climate impact costs such that for some regions these imported impacts can be responsible for one-sixth of the total cost of climate change. This is in line with Knittel et al. (2020) who apply a CGE model in order to study how German trade would be affected by future climate-change-induced labour productivity losses. They find that although Germany is relatively less affected by these impacts and thus gains relative comparative advantages in labour-intense manufacturing, the total absolute impact on welfare is negative due to absolute import losses. Different to these studies, which rely on carefully calibrated models of future climate conditions, we exploit past weather and trade data to estimate the dispersion of these effects across space.

The remainder of the paper develops in section 2 the analytical general equilibrium Gravity model from which we derive our estimation equation. Section 3 discusses the empirical approach and introduces the estimation framework. Section 4 presents the data and the construction of the variables. Section 5 shows the estimated temperature effects on bilateral trade. These estimates lay the groundwork for the counterfactual simulations, presented in Section 6, including ex-ante simulations based on future climate projections. Finally, section 7 concludes the analysis.

2 Model

We build on a simple general equilibrium trade model where each country produces a specific variety which is traded with the rest of the world — i.e. goods are differentiated by origin as in Armington (1969). Consumers have constant elasticity of substitution (CES) preferences for these country-specific goods. The CES-Armington general equilibrium model, whose theoretical underpinning goes back to Anderson (1979), is the workhorse model in structural Gravity research (Head and Mayer, 2014). We extend this model in two important dimensions: First, we model how weather shocks can affect the production of output. Second, we take into account intra-annual variation in production and consumption.

Consumption. Each point in time can be characterized by the set union of year index $t \in \{1, T\}$ and calendar month $m \in \{1, 12\}$. Each country $j \in \{1, N\}$ is populated by a representative agent with CES utility. As we explain below, the model controls for important known determinants of weather shocks such as the geography and intra-annual climate variation. Thus, the realisation of a weather shock is ex-ante unknown and economic agents are myopic with respect to the occurrence of these idiosyncratic weather shocks. Hence, we assume that the representative agent maximizes her utility at each point in time independently of past or future expectations or decisions.

Thus, utility of the representative agent in country j in year t and month m is described by

$$U_{jtm} = \left(\sum_{i=1}^{N} \lambda_i^{\frac{1-\sigma}{\sigma}} C_{ijtm}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where C_{ijtm} denotes country j's consumption of the specific variety imported from country i at point in time $\{t, m\}$. This consumption expression can be decomposed in two components: First, there is aggregate annual consumption of good i in j in year t, C_{ijt}. Second, holiday seasons, accounting or exogenous inventory management motivations, as well as other factors shape the intra-annual demand variation, captured by the exogenous consumption shifter ϕ_{jm}, which is normalized such that $\sum_{m=1}^{12} \phi_{jm} = 1$. Hence, $C_{ijtm} = C_{ijt}\, \phi_{jm}$. $\lambda_i > 0$ describes an exogenous preference parameter for goods from country i and $\sigma > 1$ is the elasticity of substitution among varieties of different origins.

While trade balances are exogenously fixed across years, we assume that intra-annually countries can run trade balance surpluses or deficits. Thus, consumers in j maximize equation (1) subject to the annual budget constraint $\sum_i \tau_{ijt}\, p_{it}\, C_{ijt} = E_{jt}$, where E_{jt} is total annual expenditure for consumption, p_{it} denotes factory-gate prices of good i and τ_{ijt} are iceberg trade costs. Important determinants of these trade costs are time-invariant characteristics such as the geographical distance between exporter and importer and common cultural attributes. In addition, trade costs may also have a time-varying component as new trade agreements come into force or improvements in infrastructure reduce transport costs. Note that we assume that bilateral trade costs change only annually rather than monthly. While in reality, trade agreements or infrastructure improvements come into force in a particular month, this assumption simplifies our identification strategy.[2] We also assume that factory-gate prices p_{it} are sticky and change only annually as menu costs impede price adjustments and contractual agreements fix prices for certain periods.[3]

Solving the representative agents optimization problem yields annual demand

$$C_{ijt} = \left(\frac{\lambda_i\, \tau_{ijt}\, p_{it}}{P_{jt}} \right)^{1-\sigma} E_{jt}, \tag{2}$$

where the associated consumer price index in country j is given by

$$P_{jt} = \left(\sum_{i=1}^{N} (\lambda_i\, \tau_{ijt}\, p_{it})^{1-\sigma} \right)^{\frac{1}{1-\sigma}}. \tag{3}$$

For given prices, we can thus define the propensity of country j to spend on imports of good i at date $\{t,m\}$ with $\theta_{ijtm} = p_{it}\, \tau_{ijt}\, C_{ijt}\, \phi_{jm}$.

Output and weather shocks. But j's import spending propensity for good i cannot be satisfied in any case. First, also the production in i is exposed to exogenous, intra-annual shifts

[2]Most trade costs changes are long-term and their temporal implementation probably uncorrelated to monthly weather variations. This assumption should therefore not lead to biased estimates of weather impacts.

[3]As seen below, presumably temperature-induced labour-productivity effects in the manufacturing sector are a key determinant of the measured aggregate impact on trade. These goods are often relatively specific and are not traded on global spot markets but have rather sticky prices. For instance, Apel et al. (2005) find that the median Swedish firm in their sample adjusts prices just once a year.

and subject to seasonal variation. This is most obvious in the case of agricultural production which depends on harvesting cycles. Other drivers of these country-specific intra-annual cycles are holiday seasons or annual cyclical weather impacts which also affect production and transport infrastructure such as tropical cyclones. This is captured by the weight parameter φ_{im}, which describes the exogenous monthly country-specific variation of output, normalized such that $\sum_{m=1}^{12} \varphi_{im} = 1$.

Second, there are potential weather shocks affecting output beyond these cyclical patterns. Let us assume that $W_{itm} = exp(\rho \, \mathbb{1}_{itm}(D_{itm}))$ describes the potential weather shock affecting output in country i in year t and calendar month m. If the indicator $\mathbb{1}_{itm}(D_{itm})$ is equal to one a weather shock materialises and production of good i is exposed to the extreme weather event D_{itm}. In general, this could be a month of extreme high or low temperature, heavy or poor rainfall, or high wind speed. Otherwise, $\mathbb{1}_{itm}(D_{itm}) = 0$. The parameter ρ measures then the weather shock's impact on output. Identifying ρ is one of the key aims of our empirical exercise.

Let us denote X_{itm} as the total free on board (f.o.b) value of exports of i. Then, $X_{itm} = \sum_j X_{ijtm}$, where X_{ijtm} is the value of actual bilateral exports net of intra-annual supply shifts and weather shocks from country i to j.

International trade. Hence, for given prices, actual exports of country i to j at time $\{t,m\}$ can be expressed as $X_{ijtm} = \theta_{jitm} \, \varphi_{im} \, W_{itm}$. Solving for θ_{jitm} and plugging this into the demand equation (2) leads to

$$X_{ijtm} = \left(\frac{\lambda_i \, \tau_{ijt} \, p_{it}}{P_{jt}} \right)^{1-\sigma} E_{jt} \, \phi_{jm} \, \varphi_{im} \, W_{itm}. \tag{4}$$

Annual total exports of country i in year t are thus

$$X_{it} = \sum_{j=1}^{N} \sum_{m=1}^{12} \varphi_{im} \, W_{itm} \left(\frac{\lambda_i \, \tau_{ijt} \, p_{it}}{P_{jt}} \right)^{1-\sigma} E_{jt} \, \phi_{jm}.$$

After rearranging this expression and dividing by $(\lambda_i p_{it})^{1-\sigma}$, following Anderson and Van Wincoop (2003), we define the term on the right hand side as

$$\Pi_{it}^{1-\sigma} = \sum_{j=1}^{N} \sum_{m=1}^{12} \left(\frac{\tau_{ijt}}{P_{jt}} \right)^{1-\sigma} E_{jt}\, \phi_{jm} \varphi_{im}\, W_{itm}, \tag{5}$$

the so-called outward multilateral resistance term. Since $(\lambda_i p_{it})^{1-\sigma} = X_{it}/\Pi_{it}^{1-\sigma}$, we plug this into equation (4) and get the Gravity equation that describes the monthly exports of country i to j:

$$X_{ijtm} = X_{it}\, \varphi_{im}\, W_{itm}\, E_{jt}\, \phi_{jm} \left(\frac{\tau_{ijt}}{\Pi_{it} P_{jt}} \right)^{1-\sigma}. \tag{6}$$

Equation (6) is the equation we are going to estimate.It is this equation that transmits the weather shock from the exporters location to the importer, affecting the availability of goods from i. Assuming that $\rho < 1$, the occurrence of a weather shock in i reduces bilateral import of j by $exp(\rho)$ at that particular point in time. Ceteris paribus, households in j face a potential import loss. But ignoring the general equilibrium response from substitution and price adjustments may be misleading. With a positive σ, consumers in j are able to substitute goods of different origin, so a weather-caused shortage of supply from one country can, at least partially, be compensated by imports from other locations.

Similarly, we can derive the inward multilateral resistance term $P_{jt}^{1-\sigma}$ by plugging in $(\lambda_i p_{it})^{1-\sigma} = X_{it}/\Pi_{it}^{1-\sigma}$ into equation (3).

$$P_{jt}^{1-\sigma} = \sum_{i=1}^{N} \sum_{m}^{12} \left(\frac{\tau_{ijt}}{\Pi_{it}} \right)^{1-\sigma} X_{it}\, \varphi_{im}\, W_{itm}\, \phi_{jm}. \tag{7}$$

As shown by Fally (2015) and others, accurate estimates of equation (6) allow to consistently reveal a comprehensive specification of the model described by the equations (5)–(7). This system of equations captures the effect of weather shocks on exports via two channels. First, as a first-order effect weather shocks affect bilateral trade since the shock affects output and thus directly exports of country i to j as can be seen in (6). Second, important components of (6) are the multilateral resistance terms (5) and (7). An adverse weather shock in country i lowers outward multilateral resistance, thereby having a diminishing effect on exports to all other trading partners of i, and, holding everything else constant, raising bilateral trade between i and j.

Model closing. Equations (5)–(7) already take into account that a weather shock in a third country affects bilateral trade of not directly exposed countries via the multilateral resistance terms, taking prices and income as given. But as the weather shock reduces supply and shifts demand, the prices of country-specific varieties p_{it} need to adjust in a new equilibrium. As annual trade balances must hold, aggregate expenditure needs to adjust, leading to a ripple effect of the weather shock through the trade network.

Market clearing demands that good prices p_{it} are equal to

$$p_{it} = \left(\frac{X_{it}}{X_t}\right)^{\frac{1}{1-\sigma}} \frac{1}{\lambda_i \Pi_{it}}. \tag{8}$$

Note that prices depend on aggregate exports X_{it} and the power-transformed outward multilateral resistance term Π_{it}, two terms which are both affected by weather shocks in country i. On the one hand, a weather shock-induced reduction in relative exports of country i pushes up the price of the country-specific variety. On the other hand, it raises the power-transformed outward multilateral resistance term in the denominator, pushing prices downwards.

The price adjustment then also affects aggregate expenditure expressed in terms of nominal income. Similar to Dekle et al. (2008), annual trade deficits and surpluses are treated as exogenous.

$$X_{it} = \eta_{it} E_{it}, \tag{9}$$

where η_{it} captures the trade balance position. If exports X_{it} changes due to a weather shock, aggregate expenditure must adjust as well. Hence, (5) – (9) define the system of equation that characterize the general equilibrium system.

3 Estimation

Silva and Tenreyro (2006) propose the Poisson pseudo-maximum-likelihood (PPML) estimator for Gravity equations such as (6) due to its robustness to heteroscedasticity and consistency in case of zero bilateral trade flows. Building on the properties of the PPML estimator, Fally (2015) shows that using importer×year, exporter×year, and country pair fixed effects allow for an unbiased identification of the structural Gravity model and its equilibrium constraints. Based on these considerations, we extend this framework to our model.

Let us define the following expressions for the exporter×year and importer×year fixed effects, respectively:[4] $exp(\pi_{it}) \equiv \left(\frac{Y_{it}}{\Pi_{it}^{1-\sigma}}\right) \times E_{Rt}$ and $exp(\xi_{jt}) \equiv \left(\frac{E_{jt}}{P_{jt}^{1-\sigma}}\right) \times \frac{1}{E_{Rt}}$. As noted by Anderson and Yotov (2010), the solution to the structural model is determined up to a scalar. We thus impose $P_{Rt} = 1$ for an arbitrary benchmark importer R. The benchmark importer has expenditure E_{Rt} in year t.

Hypothetically, most weather shocks have only a short-term impact on trade which might be difficult to detect in annual data. Thus, our identification relies strongly on the exploitation of monthly variation in bilateral trade. As we rely on monthly weather and trade data, this enables us to employ a country-pair×year-fixed effects term.We define the country-pair×year-fixed effects as $exp(\mu_{ijt}) \equiv \tau_{ijt}^{1-\sigma}$. Note that we can summarise $exp(\zeta_{ijt}) = exp(\mu_{ijt} + \pi_{it} + \xi_{jt})$ for the Gravity estimations in cases we are not interested in the consistent estimates of the specific fixed effects but aim to benefit from computational efficiency. However, in order to specify the general equilibrium model for the counterfactual simulations later in the paper, individual estimates of μ_{ijt}, π_{it} and ξ_{jt} are needed.

In contrast to most other Gravity models that aim at explaining annual variation in bilateral trade, we extend this framework by employing exporter×calendar month and importer×calendar month fixed effects, respectively, in order to account for specific seasonal supply and demand effects: $exp(\delta_{im}) \equiv \varphi_{im}$ and $exp(\psi_{jm}) \equiv \phi_{jm}$, hence, φ_{im} and ϕ_{jm} describe exporter- and importer-specific calendar month fixed effects.

We are in particular interested in the transmission of weather shocks from the exporting to the importing country. But as the volume of bilateral trade is negatively correlated with distance of the two countries, a substantial amount of trade occurs over short distances such as between neighboring countries. Since the correlation of the weather in two countries is also decreasing with increasing distance, it might be useful to control for the state of the weather at

[4]In Appendix A.1, we show how these fixed effect definitions can be consistently derived from equation (6) such that it reflects the information captured in the system of equations (5) – (7).

the importing country, $exp(\rho\, \mathbb{1}_{jtm}(D_{jtm}))$, the only control variable in our main specification.[5]

Armed with these expressions, we are able to define

$$X_{ijtm} = exp\left(\zeta_{ijt} + \delta_{im} + \psi_{jm} + \rho\, \mathbb{1}_{itm}(D_{itm}) + \rho\, \mathbb{1}_{jtm}(D_{jtm})\right) \times \varepsilon_{ijtm}, \tag{10}$$

where ε_{ijtm} is an error term. Note that this is a simple log-transformation and stochastic representation of the previously derived Gravity equation (6). In order to identify the full general equilibrium Gravity model we also estimate

$$X_{ijtm} = exp\left(\mu_{ijt} + \pi_{it} + \xi_{jt} + \delta_{im} + \psi_{jm} + \rho\, \mathbb{1}_{itm}(D_{itm}) + \rho\, \mathbb{1}_{jtm}(D_{jtm})\right) \times \varepsilon_{ijtm}, \tag{11}$$

which provides fixed-effects estimates that are used for a consistent identification of the general equilibrium model. However, these differences have no impact on the estimation of ρ. The country-pair$\times$year and the calendar month$\times$exporter and -importer fixed effects absorb potential impacts of long-run climate trends, as well as the long-run adaptation to these trends. Hence, the estimated effects need to be interpreted as almost immediate, short-run effects of temperature on contemporaneous exports.

But it is possible that the weather shocks become effective only with a time lag, as the shipment of the exposed goods needs time or storage and inventory delay the materialisation of the effect. Possibly, the slump in bilateral trade due to a weather shock can also be compensated over time. We therefore estimate also a lagged model up to L months after the event.

$$X_{ijtm} = exp[\sum_{l=0}^{L}(\rho_l\, \mathbb{1}_{itm-l}(D_{itm-l}) + \rho_l\, \mathbb{1}_{jtm-l}(D_{jtm-l})) + \zeta_{ijt} + \delta_{im} + \psi_{jm}] \times \varepsilon_{ijtm}. \tag{12}$$

The multiple high-dimensional fixed effect structure of the model aggravates the estimation using standard Poisson regression estimation packages. Thus, we use the `ppmlhdfe`-package (Correia et al., 2020) that allows for a fast estimation of PPML models in the presence of high-dimensional fixed effects.Standard errors are three-way clustered (at the levels of importer,

[5]Thereby, we account for potential demand effects of weather. In presence of demand effects and positive correlations of weather in the two trade partners, the estimation of supply-side effects on exports would be biased upwards.

exporter, and time step $\{t,m\}$), as proposed by Egger and Tarlea (2015).

4 Data

We measure international trade as the value of bilateral exports in current USD, excluding freight and insurance (f.o.b.). We use publicly available data from the IMF's Direction of Trade Statistics (DOTS) (International Monetary Fund, 2022). The data set contains bilateral export values of more than 20,000 country pairs from January 1960 to December 2016. We use only monthly reported observations by the exporting country, i.e. we exclude estimated values deducted from quarterly or annual data and entries which are reported only by the importing country.[6]

Given the prior empirical literature on weather impacts on economic outcomes, we focus our analysis on high temperature. Our main source of historical temperature data is the World Bank's Climate Change Knowledge Portal (CCKP) (World Bank, 2022a). The CCKP data is based on the latest version of the global observational data sets from the Climate Research Unit of the University of East Anglia (Harris et al., 2014) where the gridded data of monthly mean temperatures are aggregated at country level.

The functional form describing how temperature realisations affect economic outcome is still heavily disputed. Most of the previous literature that focused on aggregated outcomes such as GDP has been assuming quadratic or other polynomial functions. However, this relationship does not seem to be very robust, as Newell et al. (2021) note. In contrast, most of the modern plant and micro level studies use temperature bins of usually 5 °C width. Our large data set allows for even more flexibility. In our initial model specification, we estimate the temperature elasticity of exports (and imports, added as a control) using 1 °C bins of monthly mean temperature, starting from -15 °C and below to +35 °C and more. Informed by the estimation results of this very flexible model specification, we conclude that we are able to capture great parts of the estimated effect by defining a simple threshold of 30 °C for identifying adverse tem-

[6]Based on personal communication with the IMF staff, we differentiate carefully between missing observations and zero exports. For the period after 1999, missing values can be interpreted as non-existent trade except for country pairs without positive trade over the entire sample period. Hence, we can safely identify zero trade flows after 1999, but have to drop non-positive observations in the period until 1999. Figure A.1 in the Appendix shows the value of exports and number of exporting countries over time in the data set.

perature events. Therefore, in the subsequent estimations, we use a single binary variable to identify these episodes of high absolute temperature. That definition of hot months in absolute terms applies to ca. 1.5 percent of the estimation sample.

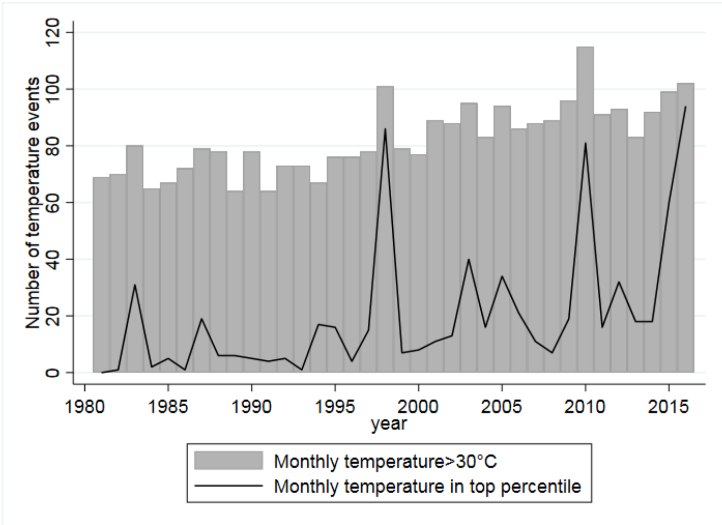
However, countries might be able to adapt to hot ambient temperatures — e.g. by adjusting the sectoral composition of the economy or by adjusting production processes such as an increased use of air conditioning. In effect, countries which are frequently exposed to high temperatures may be more able to cope with these shocks. Moreover, only a subset of countries (those in warm world regions) may actually experience such high average temperature levels. In a complementary specification, we therefore identify for each country those months which belong to the top-percentile of the country-specific temperature distribution. This temperature variable is evenly distributed on world regions by construction.[7] These events are interpreted as abnormally hot months, given the country-specific temperature distributions. Consequently, we estimate the impacts of months with abnormally hot temperatures, using months in the 1^{st} to the 99^{th} percentiles as baseline category.

Figure 1 depicts the frequency of both types of temperature events over time for a balanced sub-sample of our data set. Due to global warming, the probability that a given month is defined as a high temperature event is increasing in the last decades. In the Appendix, we also depict the distribution of both temperature events over calendar months (Figure A.2).

As our empirical strategy relies heavily on fixed effects, the two data sets on trade (IMF DOTS) and temperature (CCKP) are generally sufficient for estimating the overall effects of temperature on bilateral exports. However, we are also interested in identifying potential mechanisms that affect the magnitude of the temperature shock on exports. For this, we add various additional data. First, as weather is particularly important in the production of primary goods, we include the value added of agriculture, forestry, hunting and fishing as percentage of GDP, provided on an annual basis by the World Development Indicators (World Bank, 2022b). Second, we add data on the product composition of annual exports in the four preceding years to approximate the relative importance of economic sectors for exports (UN Comtrade, 2022). Third, we match our data with the annual ND-GAIN index which summarizes a country's

[7] Given the structure of the data set, there are mostly seven such temperature events per country.

Figure 1: Temperature events 1981-2016



Number of months with mean temperature of at least 30 °C and top-percentile temperatures. The graph is restricted to a balanced sample of 155 countries with non-missing temperature data in 1981-2016.

vulnerability to climate change (Notre Dame Global Adaptation Initiative, 2022). Finally, we approximate the labour intensity of annual exports using input-output data from GTAP (Aguiar et al., 2019). In more detail, we combine the exporter- and sector-specific labour intensities (measured as shares of labour input to total inputs) and the importer-specific sector shares of total exports for each country-pair-year combination.[8]

Table A.1 in the Appendix provides an overview on the descriptive statistics of key variables used in the empirical analysis.

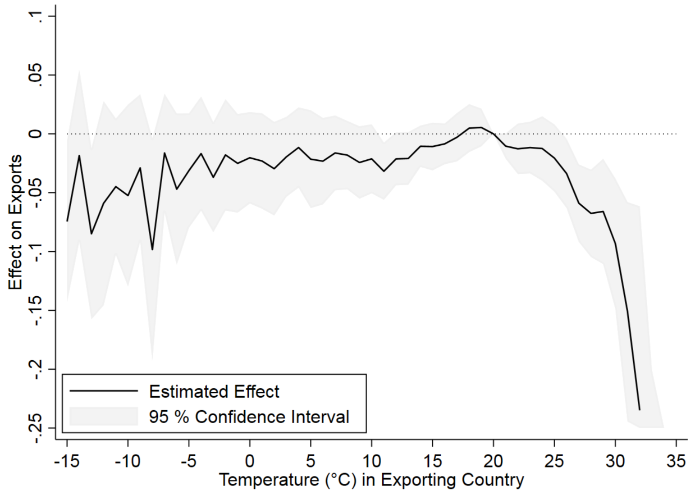
5 Estimation Results

The results section is structured as follows. First, we estimate the contemporaneous effects of temperature on exports, using various specifications of the temperature impact. Second, going beyond short-term impacts, we estimate finite distributed lag models. Subsequently, we employ interaction models in order to study potential heterogeneous effects of high temperature to better understand the underlying impact channels. Finally, we briefly present results on the effects of other weather phenomenons, such as extreme precipitation and wind speed.

[8]GTAP data is only available for the years 2004, 2007, 2011, and 2014. Therefore, the number of observations is considerably smaller when labour-intensity is included in the estimation.

5.1 Contemporaneous temperature effects

Figure 2: Contemporaneous effects of temperature on exports per 1 °C.



Estimated coefficients for each individual °C realisation in the exporting country with its 95 percent confidence interval, using 20 °C as baseline (N=3,821,155). For reasons of clarity, the plot is restricted on shown range of effect sizes; the unrestricted plot (also showing estimated temperature effects at the importer location) is depicted in Figure A.3 in the Appendix.

Figure 2 shows the non-linear impact of country-wide average monthly temperature on exports, accounting for each possible temperature realisation from -15 °C and colder to +35 °C and warmer. We use 20 °C as baseline category as at this temperature no substantial effects (e.g., on labour productivity) are expected based on prior literature, and there is a sizable number of observations in this category. In an alternative specification, we aggregate the temperature data into ten bins each spanning 5 °C, using 15-20 °C as the baseline category (see Figure A.4).

Inspired by these results, we conclude that absolute temperature effects on exports may predominantly occur during months which are characterised by average temperature at 30 °C and higher. Therefore, we estimate a more parsimonious specification where a single binary variable indicates whether such an event occurred (D^{t30}_{itm}) that we define as a temperature shock subsequently. Based on this model, hot months with average temperature equal or above 30 °C face a reduction in exports by 3.4 percent ($p = 0.001$), compared to mean temperature below 30 °C (see column (1) in Table 1). There are also statistically significant effects of weather at the importer location, which corroborates our strategy to control for the importer's weather.

Table 1: Contemporaneous temperature effects on exports

	(1) Abs. Temp.	(2) Abn. Temp.	(3) Both	(4) Interaction
D_{itm}^{t30}	-0.0336		-0.0253	-0.0166
	(0.0100)		(0.0124)	(0.0140)
D_{jtm}^{t30}	-0.0124		-0.0092	-0.0095
	(0.0056)		(0.0058)	(0.0059)
D_{itm}^{p99}		-0.0210	-0.0206	-0.0203
		(0.0076)	(0.0076)	(0.0077)
D_{jtm}^{p99}		-0.0149	-0.0148	-0.0149
		(0.0064)	(0.0064)	(0.0063)
$D_{itm}^{t30} \times D_{itm}^{p99}$				-0.0236
				(0.0190)
$D_{jtm}^{t30} \times D_{jtm}^{p99}$				0.0019
				(0.0089)
Observations	3821155	3821155	3821155	3821155

The dependent variable is bilateral exports in current USD. Index i (j) indicates the exporting (importing) country. Standard errors in parentheses.

Nevertheless, temperatures at the exporter location exhibit larger and — regarding different model specifications — more robust effects on trade.

The effect on exports is about an order of magnitude greater than the plant-level effect estimated by Zhang et al. (2018) from a day hotter than 32 °C. Reasons for this difference could be either an increasing impact of longer episodes of hot temperature as we only take into account entire months with high temperatures, or it could be that ripple effects through supply chains amplify the impact. However, the results are broadly in range with Jones and Olken (2010), estimating a decline of exports of 2 to 5.7 percent per 1 °C increase, as well as with Burke et al. (2015) who discuss significant negative effects of temperatures above 30 °C on GDP growth, labour supply and labour productivity.

As discussed in section 4, episodes with a monthly and country-wide mean temperature of at least 30 °C may occur only in specific regions. Therefore, we assess the effects of abnormally high temperature shocks, identified by observations in the highest percentile of the country-specific temperature distributions. This specification, presented in column (2) in Table 1, confirms a contemporaneous short-run non-linear temperature effect on exports.

Comparing columns (1) and (2) in Table 1, the question arises whether the two specifications describe the same economic processes, or whether the effects of absolutely and abnormally high temperatures are independent impacts. In the latter case, the underlying impact channels may differ, indicated by significant marginal effects in an estimation including both temperature specifications. Therefore, in column (3), we include both absolutely and abnormally high temperature, and in column (4) we additionally study the interaction between them. For exporters, both temperature variables (D^{t30}_{itm} and D^{p99}_{itm}) remain individually significant. Moreover, the effects are independent from each other as there is no statistically significant interaction effect. Hence, both effects can be observed in the short term: a substantial effect on exports from episodes of absolute hot temperature, and a somewhat smaller effect of months of abnormally high temperatures, given the country-specific temperature distribution.

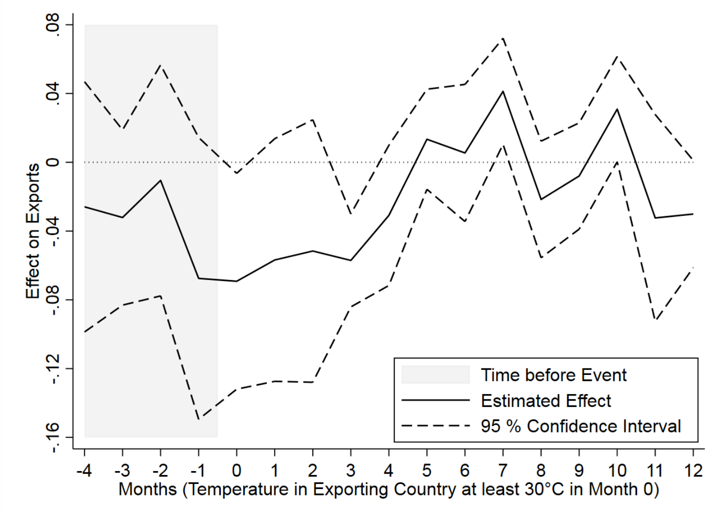
In the Appendix, we also test a temperature impact model with a linear, as well as a quadratic specification, as often assumed in the literature — see, for example, Missirian and Schlenker (2017) or Burke et al. (2015). The results, presented in columns (1) and (2) in Table A.2 in the Appendix, confirm a non-linear effect of temperature on exports. Moreover, we assess the question whether the effects of absolute and abnormally hot months affect the extensive or intensive margin or both.Therefore, we estimate linear probability models of the binary variable whether there is trade between countries (columns 3 and 4), and restrict the sample to positive export flows (columns 5 and 6). The results (see Table A.2 in the Appendix) suggest that the effects stem from changes at the intensive margin: Temperature events have no significant impact on the decision whether exports occur or not, but reduce the value of exports in the subsample of positive export flows.

Equipped with this series of estimation results for contemporaneous effects of temperature, we obtain one robust finding: Months with high temperatures, either measured in absolute or relative terms, lead to a statistically and economically significant reduction of exports relative to months facing lower (or less extreme) temperature levels. This effect is well captured by the parsimonious models focusing on D^{t30}_{itm} or D^{p99}_{itm} (columns (1) and (2) in Table 1). Reviewing the prior literature on temperature effects on macro-economic outcomes (see literature review in section 1), reveals a clear focus on absolute temperature specifications, as there is a sound and robust micro-economic and physiological empirical foundation of these effects, while there is less theoretical and micro-econometric support for economic impacts from abnormally high temperatures. Therefore, in the remainder of the analysis, we are going to focus on impacts of high absolute temperature (D^{t30}_{itm}). However, we replicate all analyses with specifications based on abnormally high temperatures, report the results in the Appendix, and highlight potential qualitative differences.

5.2 Lagged temperature effects

We have shown that months of high temperatures have a detrimental effect on exports in the month of their occurrence. However, it is important to understand the duration of these impacts. Are they only short-lived or do they have longer term consequences? For assessing this question, we estimate a finite distributed lags model with four months before and twelve after the temperature event. To reduce computational complexities, we rely on the parsimonious model with a dummy for months with average temperature greater or equal 30 °C. Figure 3 depicts the estimated coefficients, relative to a month where temperature has been below 30 °C.

Figure 3: Lagged impact on exports of an average monthly temperature of at least 30 °C



Estimated effects of a hot month on exports, including 95-percent confidence intervals. The effects are relative to a month with a temperature below 30 °C. Lagged impacts of hot months at the importer location are depicted in Figure A.5.

The estimation confirms the contemporaneous effect of a temperature shock on exports in the month of the event (-6.7 percent, $p = 0.031$). We also find a lagged negative effect three months after the event (-5.5 percent, $p < 0.001$) and a positive effect after seven months (+4.2

percent, $p = 0.009$). The estimated effects prior to the temperature event, serving as placebos, are statistically non-significant. The cumulative effect over the period of one year after the event remains negative, albeit at non-significant levels (see Figure A.6 in the Appendix). We conclude that temperature shocks on exports manifest mainly in the short term during and directly after the event. The effect is neither substantially aggravating over time nor is there any evidence of a substantial catching up or compensation for lost exports in post-event months, such that the cumulative effect after one year is in the same order of magnitude as after a few months. For abnormally high temperatures, the analysis of lagged effects yields similar results: The effect proofs to be short-lived and only existent for exporters (see Figures A.7 and A.8 in the Appendix). However, the initially negative effect of abnormally hot months is followed by some (statistically non-significant) positive lagged effects, such that the cumulative effect after one year of the event is not statistically different from zero.

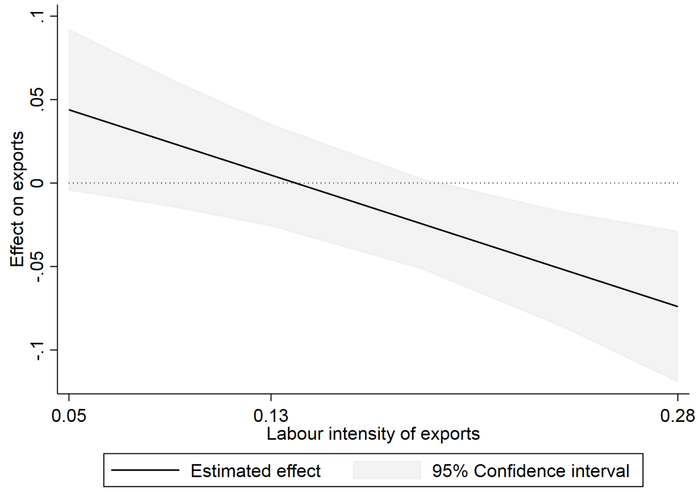
In summary, it can be stated that across all model specifications the temperature shock in the exporting country is more relevant than in the importing country, supporting similar findings based on reduced-form, parsimonious estimates with annual trade data (Dallmann, 2019). These identified temperature impacts are relatively short-lived. Consequentially, we focus in the remainder of the analysis on the contemporaneous temperature effects in the exporting country. However, we keep the temperature in the importing country as a covariate in all estimations.

5.3 Heterogeneous effects of temperature

So far, we estimated average effects of high temperature events on exports across the full sample. But the effect magnitude might be conditional on country or trade flow characteristics. Understanding these differences allows us to infer more precisely about impact channels and economic mechanisms translating the temperature shock in economic outcomes.

One important impact channel identified by prior micro- and plant-level evidence suggests that high absolute ambient temperature reduces productivity and supply of labour (Somanathan et al., 2021; Zhang et al., 2018; Zivin and Neidell, 2014). Hence, we incorporate the labour intensity of year- and importer-specific exports ($labourint_{ijt}$). If labour productivity (or sup-

Figure 4: Estimated effect of an average monthly temperature of at least 30 °C on exports for different levels of labour intensity



Estimated contemporaneous effects of D_{itm}^{t30} on exports for given levels of labour intensity, including 95-percent confidence intervals. The effects are relative to a month with temperature below 30 °C. Labelled values at the x-axis are the 5^{th}, 50^{th}, and 95^{th} percentile of $labourint_{ijt}$

ply) is a major determinant for the magnitude of the adverse temperature effect on exports as suggested, the estimated effect should vary with the labour intensity of bilateral exports.[9]

We augment the basic estimation equation (10) with interaction terms of the heterogeneity variable with D_{itm}^{t30}. Direct effects of labour intensity and other heterogeneity variables are not estimated as they are perfectly collinear with fixed effects at country pair-year level.

We estimate marginal effects of D_{itm}^{t30} on exports over different levels of the heterogeneity variable. Figure 4 depicts the results for labour intensity, and Figure A.10 in the Appendix summarizes similar plots for the other potential heterogeneity variables.

The results suggest that the contemporaneous effects of absolutely hot months is indeed governed by the labour intensity of exports. The interaction effect shown in Figure 4 is highly significant ($p = 0.003$). A 10 percentage points increase in labour intensity of exports is associated with an increase of the adverse impact by approximately 5 percentage points. On the

[9] While we focus here on labour intensity given the micro-economic evidence, we similarly test for other potential sources of effect heterogeneity in the Appendix. Inspired by Dell et al. (2012), we interact the temperature effect with the annual income in the exporting country (gdp_{it}) and the annual share of agricultural production in the exporter's GDP (including forestry, fisheries and hunting, $agri_{it}$). We further hypothesize that the exporter's resilience towards climate change (measured by the annual ND-GAIN index, $ndgain_{it}$) may govern the response to a temperature shock. Finally, effects may vary with the product composition of total exports (Jones and Olken, 2010). Therefore, we interact the temperature shock with product-specific shares of total exports in the preceding four years (e.g., $prFood_{ijt}$ for food and live animal products).

contrary, there is no significant interaction effect with relative temperature extremes (D_{itm}^{p99}, see Figure A.9 in the Appendix). This is broadly in line with prior micro-economic and physiological literature (see e.g., Dunne et al. (2013)), which postulates that absolute temperature levels are crucial for potential declines of work capacity.[10] Hence, an unusually warm summer in a cold environment would be treated as an extreme temperature event in D_{itm}^{p99}, but has no expected adverse impact on labour productivity. In a similar vein, Jones and Olken (2010) detect a negative effect of high temperatures on exports of light manufacturing goods and speculate that productivity effects of workers might be responsible. Our results provide further evidence that labour productivity or supply is key for understanding the mechanism behind the identified effects of temperature shocks on aggregated exports.

Most of the other analyzed variables show no significant interaction with the temperature effect (Figure A.10 in the Appendix). In our structural Gravity model, the temperature effects on exports do not significantly vary with economic development, the share of agricultural goods in the exporting country's production, or the exporter's assessed resilience to climate change. Similarly, most of the product category shares do not interact with temperature impacts — with the exceptions of exports characterized by high shares of Crude Materials (more adversely affected) and Mineral Fuels (less affected). These results, however, are compatible with the interpretation that labour productivity is the underlying channel of temperature effects — as labour intensity is relatively high for the former and low for the latter.

5.4 Extensions: Impacts of precipitation and storms

While we focus on the effects of high temperature, the data and the employed empirical methodology generally allow for an equivalent analysis of the impacts of other weather phenomena. We are particularly interested in weather events that may be affected by climate change, and therefore additionally assess impacts of extreme precipitation and storms. The employed data and obtained results are summarized in Appendix A.4.

Regarding precipitation, we do not find any contemporaneous effects on exports or imports. Considering the potential impact channels of hydrological events on production processes, this

[10]While other factors such as wind speed and humidity are important, substantial losses of work capacity are generally only observed at absolute temperature levels of higher than 25 °C.

non-effect may be plausible: precipitation is most relevant for the production of primary goods. But these goods have certain growing periods, and their processing also needs time, such that a contemporaneous effect of a lack of precipitation on the production and hence on exports is unlikely. Extreme high precipitation, in contrast, may have adverse effects on trade, e.g. by flooded transport infrastructure or production facilities. The fact that we do not find such an effect may be due to an inaccurate measure of flood intensity. As a monthly mean value, our precipitation measure may not properly indicate short-term extreme events which last only for one or two days. Furthermore, for being harmful to the economy, the occurrence of intense precipitation events must coincide with the location of vulnerable assets or infrastructure — issues that are not sufficiently detectable by country-month averages.

Similarly, we find only limited evidence for the existence of storm impacts on exports. Linear and quadratic specifications of monthly maximum wind speed values yield insignificant effects. Extreme wind speed events, defined as being in the country-specific top percentile of wind speeds, are without effect as well. However, we find non-linear effects of very intense storms in absolute terms (of 140 knots maximum wind speed and higher) when analyzing a flexible model using wind speed bins. In these months, exports decrease substantially (up to 7 percent), which may hint to impaired transport infrastructure or production facilities.

6 Counterfactual Simulations

Our previous analysis revealed that exports are negatively affected by extreme temperature events. A high temperature episode in the exporting country reduces trade in the month of the event. But the global costs of such an event remain unclear since importers are able to either source goods from somewhere else or compensate for lost imports by purchasing more in later periods from the same source. We studied possible compensation across time using distributed lag models but did not find robust evidence for this (see section 5.2).

But importers could also seek for compensation across space. Although in our model imports of different origin are imperfect substitutes only, buyers can adjust the source of their imports and, at least partially, recoup losses on one trade link by additional imports from other sources. This demand adjustment has, of course, repercussions on relative prices and available income, changing the world trade equilibrium.

Therefore, we compute the new global trade equilibrium resulting from a temperature shock, the global costs, and their distribution on directly and indirectly affected countries. Finally, we approach the question how these global costs will evolve under climate change.

6.1 Methodology

As discussed above, and as shown by Fally (2015), we are able to retrieve from our PPML fixed effects estimation of (10) the underlying structural Gravity model, described in equations (5) – (9). See Appendix A.1 for the derivation of the model from the fixed effect estimation.

However, there are two parameters which we do not observe. One is the preference parameter λ_i, which informs the pricing equation (8). But we can rewrite equation (8) such that it provides the price change relatively to the estimated baseline which is independent of this structural parameter.

$$\Delta p_{it} = \left(\frac{X_{it} \hat{X}_t}{\hat{X}_{it} X_t} \right)^{\frac{1}{1-\sigma}} \frac{\hat{\Pi}_{it}}{\Pi_{it}},$$

where the hat ˆ denotes estimated parameters, i.e. the predicted exports and the estimated outward multilateral resistance terms.

The second not retrievable key parameter is the elasticity of substitution between varieties of different origin, σ. We take this from the literature and inform our model by the elasticity estimate of Simonovska and Waugh (2014), who estimate it using disaggregate price and trade-flow data. Their estimate yields an elasticity of roughly four. However, we are going to conduct extensive sensitivity analyses and test the robustness of our findings with respect to σ. Obviously, the ease of substitution from one good to another substantially influences the magnitude of the effects.

Equipped with our estimated model and the additional parameter, we run counterfactual simulations, computing the hypothetical trade equilibrium in absence of a high absolute temperature event. This allows to assess the full international trade costs of a temperature shock, accounting for equilibrium adjustments in the trade network. However, as we only observe international trade flows without the full local economic impact in the affected country, we are not able to derive comprehensive welfare consequences of temperature shocks from our simulations. Rather, our calculations provide the costs of temperature shocks in terms of lost trade.[11]

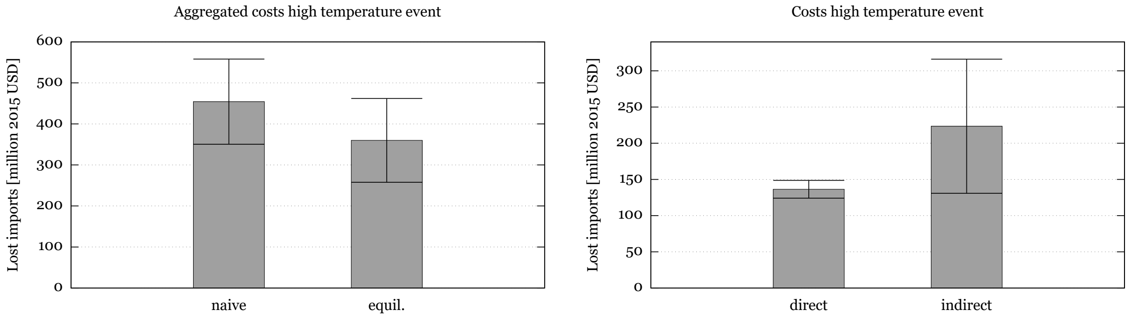
To administer the counterfactual simulations and compute the new equilibria we need to reduce the model dimensionality in terms of spatial and temporal coverage. First, we reduce the number of countries incorporated in the analysis. This more parsimonious model covers the bilateral monthly trade of 43 countries (listed in Table A.6 in the Appendix). The trade within this sub-sample makes up roughly 90 percent of the global trade volume. With this reduced data set we bootstrap 100 times the estimation of the structural Gravity equation (11) with specific exporter×year, importer×year, and country-pair×year fixed effects. The mean coefficient of the weather shock D^{t30}_{itm} on exports estimated with this smaller data set spanning 43 countries only is almost identical to the point estimator based on the full data set in our preferred specification reported in column (1) of Table 1. In the next step, we select the year 2015 — the year where we have the best data coverage of monthly bilateral trade — for our assessment.[12]

The bootstrapped fixed effects for 2015 plus the estimated temperature shock coefficient calibrate our CES-Armington monthly-trade model described in section 2. As these estimated coefficients, jointly with our assumed trade elasticity, fully and consistently specify our trade model, we are ready to conduct counterfactual analyses. For each set of bootstrapped estimates, we randomly draw an observed high temperature event in 2015, and compute the counterfactual global trade equilibrium assuming this event would not have happened. We report the mean loss of imports as well as the 95 percent-confidence interval for the country experiencing the temperature shock (directly affected) and all other countries (indirectly affected).

[11]Note that in welfare terms — ignoring any frictions and rigidities — the maximum costs at stake for the importing country are the total welfare gains from trade with the exporting country exposed to the weather event.

[12]The global climate in 2015 has been characterized by an El Niño situation — a phase of the El Niño–Southern Oscillation (ENSO) climate phenomena that influences sea temperatures and weather in large parts of the globe (Blunden and Arndt, 2016). As a consequence, 2015 saw heatwaves in France, high temperatures and drought in South America, in particular in Argentina, Brazil, and Colombia, as well as severe drought in South Africa.

Figure 5: General equilibrium trade losses of average high temperature event



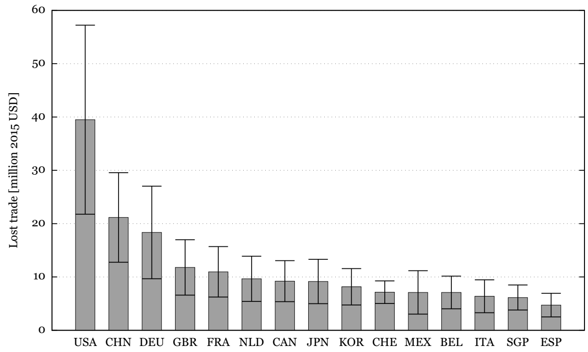
The left panel shows the aggregated global trade loss (summing up directly and indirectly affected countries) of the average high temperature event (monthly mean temperature at least 30 °C). The left bar depicts the mean estimate of lost imports before equilibrium adjustments (naïve). The right bar shows estimated lost imports after the equilibrium-adjustment (equil.). The right panel splits the aggregated losses into average losses for the directly affected country and average aggregated losses for the indirectly affected countries. Bootstrapped 95 percent confidence interval.

6.2 Global trade-loss incidence of local temperature shocks

Equipped with our estimated structural Gravity model, we aim at answering how a single high temperature event changes the world trade equilibrium and impacts directly and indirectly affected countries. As a first approximation for computing the global international trade losses of the average temperature shock, an analyst could just sum up the reduction of imports from the directly affected exporter across all importers, ignoring substitution and income effects. This is shown in the left bar in the left panel of Figure 5. This ”naïve” approach leads to aggregated international trade losses of 2015-USD 454 million for the average high temperature event. However, as the right bar in the same panel of Figure 5 shows, when equilibrium adjustments are taken into account, importers are able to partially substitute their purchases from the directly exposed country to other sources, and global trade losses decrease to 360 million USD, a reduction of about 20 percent relative to an assessment that ignores equilibrium effects.

This total amount of import losses appears in directly and indirectly affected countries. Indirectly affected importers can only partially substitute their import losses via alternative sources. In this sense, international trade transmits a share of the costs of the temperature event. A cost assessment of these events not including these cross-border effects is therefore incomprehensive. The right panel of Figure 5 shows this. Of the 360 million USD total international trade losses appear 136 million USD in the directly affected exporting country due to

Figure 6: Distribution of indirect costs



Distribution of average costs of the top-15 indirectly affected countries in decreasing order. Bootstrapped 95 percent confidence interval

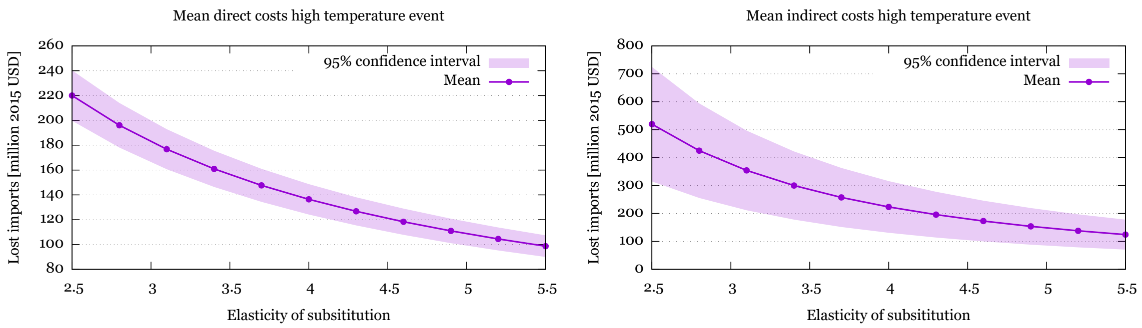
losses in purchasing power caused by the temperature-induced export reduction. This means that the group of countries that have not been directly experienced the temperature event bear import losses of 224 million USD from the average single temperature shock. This are average costs of about 5.3 million USD per temperature shock for an indirectly affected country via these trade spillovers. While this effect is not huge, our bootstrapped confidence interval suggests that these costs are statistically significant different from zero given a five percent significance level.

But these indirect costs are distributed unevenly across countries. As Gravity theory tells us, absolute indirect costs of temperature shocks are governed by the total value of imports and therefore depend on the size of the importing country, as well as the trade costs of shipping a good to the importing country. Thus, larger importing countries and countries with lower costs of trade with the directly affected country have to burden larger absolute costs. Figure 6 ranks the average indirect costs in a decreasing order. While the country at the 25$^{\text{th}}$ percentile faces costs of about 8.6 million USD, the country at the 75$^{\text{th}}$ percentile faces costs of 2.3 million USD.

6.3 Sensitivity analysis

The magnitude of the general equilibrium effects is fully specified by the estimates of the underlying Gravity model with one degree of freedom: The estimation of the Gravity system does not identify the elasticity of substitution σ which governs the ease to adjust demand and source goods from somewhere else. As discussed above, in our central estimates we set $\sigma = 4$, following Simonovska and Waugh (2014). However, it is key to understand how sensitive our results are depending on the choice of σ.

Figure 7: Sensitivity analysis – elasticity of substitution σ



Sensitivity analysis of general equilibrium effects conditional on elasticity of substitution σ ranging from 2.5 to 5.5. The left panel shows the trade losses of the mean > 30 °C event on directly affected countries. The right panel shows the losses on indirectly affected countries. Confidence intervals are bootstrapped.

Figure 7 plots the effect of the mean high temperature event for values of σ ranging from 2.5 to 5.5. The right panel shows the aggregate import losses for only indirectly affected countries. Assuming an elasticity of substitution of 2.5 leads on average to an import loss of about 520 million USD. These losses decrease with a substitution elasticity of 5.5 to about 124 million USD for all importing countries. It is also important to note that the point estimator of the mean temperature event on the average indirectly affected country, although being small (2.9 million USD at $\sigma = 5.5$), is statistically different from zero with 95 percent confidence over the whole range of the tested elasticities. As theory suggests, the costs are lower for higher elasticities as costs can be more easily mitigated by adjusting the sourcing of goods.

The left panel of Figure 7 shows the effects for directly affected countries. If cost-sharing is limited under a low elasticity of substitution of 2.5, the average directly affected country faces mean losses 220 million USD. Assuming an elasticity of substitution of 5.5, these losses decrease to about 100 million USD.

6.4 Costs under future climate projections

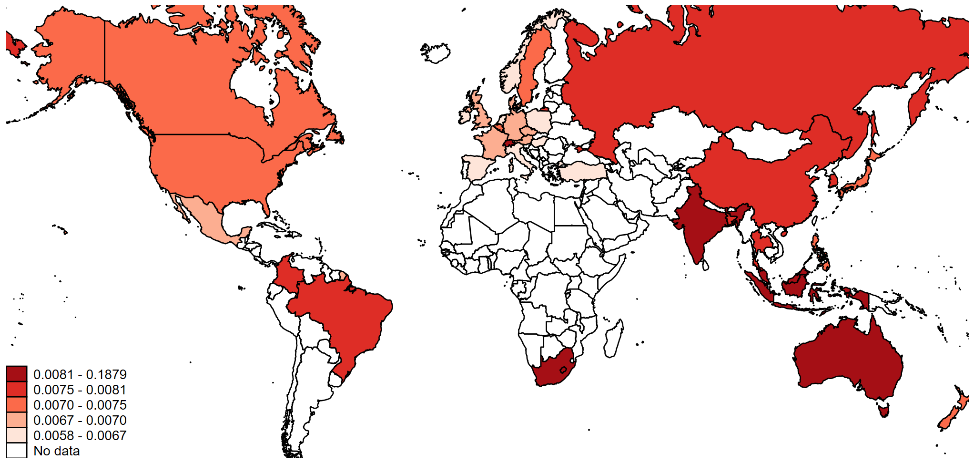
So far, our estimated structural Gravity model has been applied to compute ex-post general equilibrium effects of high temperature events. However, the model allows also to compute the impacts on international trade — of both, directly and indirectly affected countries — under future climate projections. We thus compute the counterfactual impact a projection of the future climate would have on our estimated world economy of 2015 and compare it with the historic climate means. There is therefore an important caveat: Our simulations assume that the future climate happens in the world economy of 2015, ignoring any socio-economic adjustments and changes that will happen. But trade costs, total expenditures but also the vulnerability to high temperature might change substantially in future. We therefore believe that this is a sensible approach, and are fully aware of its limits.

We use data provided by World Meteorological Organization in the KNMI Climate Change Atlas. This database provides modelled mean temperatures at the country-month level, both for the past and for projections up to the year 2100. We rely on the median output of the multi-model ensemble CMIP5 (Coupled Model Inter-comparison Project Phase 5 used in the 5^{th} IPCC Assessment Report), and focus on projections based on the Representative Concentration Pathway (RCP) 4.5. RCP4.5 is a rather ”optimistic” emission scenario which assumes that global emissions peek before 2050, and radiative forcing stabilizes by 2080-2100. However, due to the inertia of the climate system, projections for the near future do not vary substantially across RCPs.

In our analysis, we examine the consequences of the average climate of 2020-2039 due to the reasons discussed above. We compare this period to the latest available historic 20-year period in the data, which is 1980-1999. Thus, the differences to the historic climate are not substantial. For both 20-year periods, we compute for each country and calendar-month the probability that the monthly mean temperature exceeds 30°C.

We then compute the difference in annual import expenditures, comparing a scenario with the historical distribution of high temperature events to a scenario with the expected distribution of heat events given the climate projection for 2020-2039. We express these changes in percent of the historical baseline.

Figure 8: Import expenditure losses in percent, historic climate versus climate projection mean RCP4.5 2020-2039



Change of annual import expenditures of countries covering 90 percent of world trade assuming a distribution of hot months as projected under a climate change scenario for 2020-2039, compared to a scenario with the historic (1980-1999) distribution of hot months. Changes between the two scenarios expressed in percent of annual import expenditures. Table A.7 in the Appendix shows individual country-level means and 95 percent-confidence intervals from the bootstrapped estimations and simulations.

While the differences depicted in Figure 8 are small, we observe additional trade losses in all countries that are part of the simulated world trade equilibrium. While these additional losses are small in Europe, they become substantially higher in Asia (in particular India) and Oceania, as well as in South Africa.

If we sum this up across countries, we find that annual global trade is reduced by 735 million USD due to additional months with high temperatures in a projection of the average climate 2020-2039 relative to today's climate. This figure gives only limited insights about the welfare consequences, which cannot be properly calculated due to the lack of data on domestic monthly output.

Of course, this is by no means a complete assessment of the economic costs of climate change as it only covers trade losses from very hot months, thereby ignoring moderate and long-term temperature changes, temperature effects on the domestic production and human health, and all impacts from other hazards, ranging from losses due to more frequent and more severe flooding, tropical cyclone activities, agricultural productivity or biodiversity losses.

7 Conclusion

This paper aims at empirically identifying the short-run impact of temperature shocks on exports and estimating its equilibrium costs, using a structural Gravity framework with high temporal resolution. Our large data set enables a high-dimensional fixed effects structure which controls for unobserved variation at different levels, e.g. the establishment of new transport routes, or the enforcement of trade agreements. Subsequently, we use the regression results to estimate the size and spatial distribution of global equilibrium costs of extreme temperature events, and project these costs under a climate change scenario for the period 2020-2039.

We find significant negative contemporaneous effects of high absolute temperatures and extreme temperature deviations in the exporting country on exports. Importantly, our data set contains an aggregate measure of all traded goods from all economic sectors. One may expect stronger effects for some traded goods than for others. Still, we find an average trade decline of 3.4 percent in months of absolutely high temperature (monthly average temperature at least 30 °C), compared to a month with a temperature below this threshold. We then examine if specific characteristics of the exporting country govern the effect size and find that export flows which are characterized by high labour intensity in their underlying production processes suffer most from high temperatures. In contrast, agricultural production shares, sector shares of export flows (without considering labour intensities), the overall economic development in terms of GDP, and climate change vulnerability are not statistically relevant for shaping the contemporaneous temperature effects on exports.

Equipped with the estimates from the partial-equilibrium Gravity equation that — up to one free parameter — fully specify our general equilibrium model, we then compute the equilibrium adjustments caused by these temperature shocks and simulate counterfactuals assuming that a specific weather event did not occur. This equilibrium adjustment reduces the costs of a heat event by about 20 percent relative to a situation without substitution and the respective price adjustments. This indicates that general equilibrium adjustments on global markets are an important lever to reduce aggregate costs of temperature shocks. Using bootstrapped estimates from a large number of simulations, we find that the mean temperature shock from the set of events where the monthly average temperature was above 30 °C has average costs of 360 million USD in terms of reduced global imports. Almost two thirds of this price tag appear in countries that have not been directly exposed to the high temperature event but rather face losses from less available imports. We compute these costs over a wide trade elasticity parameter range and find that they remain statistically different from zero across the whole range.

We finally use our model to examine the consequences of climate projections for the coming twenty years and find increasing costs from high temperature events, in particular in India and South East Asian countries. In total, the expected additional temperature shocks lead to a reduction of annual global trade by 735 million USD between 2020 and 2039 relative to today.

These findings show that for a comprehensive cost assessment of temperature shocks, but also for impacts from other hazards and climate impacts in general, the international and spatial spillover dimension must be included. However, by the same token, it should also be made clear that a protectionism-oriented trade policy is the wrong response to this challenge. As our analysis shows, it is actually the trade system with its substitution opportunities that reduces global trade costs of these events.

This study highlights the link between the economic costs of weather shocks and international trade. However, several open questions remain, which deserve to be examined in greater detail in future research. In particular, a clearer understanding of the exact mechanisms how weather shocks affect international trade and subsequently welfare would be important to design adequate policy responses.

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A Appendix - For Online Publication

A.1 Derive Gravity System of Equation

Fally (2015) showed that a complete system of equations that composes our Gravity model developed in section 2 can be consistently retrieved from the Gravity equation (10) if estimated with fixed effects and Poisson pseudo maximum likelihood (PPML). In the following we derive this system of equation.

Total exports of i in year t are $X_{it} = \sum_j \sum_m X_{ijtm}$. Total expenditures of j in t are $E_{j,t} = \sum_i \sum_m X_{ijtm}$. Fally (2015) demonstrated that there exists a unique pair of variables P_{jt} and Π_{it} with $P_{Rt} = 1$ such that the predicted trade $\hat{X}_{ijtm}$ is consistent with our structural Gravity model.

Starting from our equation (10):

$$\hat{X}_{ijtm} = exp[\pi_{it} + \delta_{im} + \xi_{jt} + \psi_{jm} + \mu_{ijt} + \rho\, \mathbb{1}_{itm}(D_{itm})]. \tag{A.1}$$

Thus,

$$\sum_j \sum_m exp[\pi_{it} + \delta_{im} + \xi_{jt} + \psi_{jm} + \mu_{ijt} + \rho\, \mathbb{1}_{itm}(D_{itm})] = \hat{X}_{it}, \tag{A.2a}$$

$$\sum_i \sum_m exp[\pi_{it} + \delta_{im} + \xi_{jt} + \psi_{jm} + \mu_{ijt} + \rho\, \mathbb{1}_{itm}(D_{itm})] = \hat{E}_{jt}, \tag{A.2b}$$

or equivalently,

$$\sum_j \sum_m exp[\xi_{jt} + \psi_{jm} + \mu_{ijt}]E_{Rt} = \sum_m exp[-\pi_{it} - \delta_{im} - \rho\, \mathbb{1}_{itm}(D_{itm})]E_{Rt}\hat{X}_{it} \tag{A.3a}$$

$$\sum_m \sum_i exp[\pi_{it} + \delta_{im} + \rho\, \mathbb{1}_{itm}(D_{itm}) + \mu_{ijt}]E_{Rt}^{-1} = \sum_m exp[-\xi_{jt} - \psi_{jm}]E_{Rt}^{-1}\hat{E}_{jt}. \tag{A.3b}$$

Note that by normalization $\sum_m exp[\psi_{j,m}] = \sum_m exp[\delta_{i,m}] = 0.$. We therefore can define

$$P_{jt}^{1-\sigma} \equiv \frac{E_{jt}}{E_{Rt}} exp[-\chi_{jt}] \tag{A.4a}$$

$$\Pi_{it}^{1-\sigma} \equiv E_{Rt}X_{it}exp[-\pi_{it}]. \tag{A.4b}$$

In addition, we know that $exp[\mu_{ijt}] = \tau_{ijt}^{1-\sigma}$. Finally,

$$\sum_j \left(\frac{\tau_{ijt}}{P_{jt}}\right)^{1-\sigma} E_{jt} = \Pi_{it}^{1-\sigma} \sum_m exp[\rho\, \mathbb{1}_{itm}(D_{itm}] \tag{A.5a}$$

$$\sum_i \left(\frac{\tau_{ijt}}{\Pi_{it}}\right)^{1-\sigma} X_{it} \sum_m exp[\rho\, \mathbb{1}_{itm}(D_{itm}] = P_{jt}^{1-\sigma} \tag{A.5b}$$

A.2 Descriptive statistics

In Table A.1, we present the descriptive statistics of key variables at the country-pair-month-level (exports X_{ijtm}), at the country-pair-year-level (labour intensities of exports $labourint_{ijt}$) at the country-month-level (temperature variables), and at the country-year-level ($agri_{it}$, sector shares of exports, $ndgain_{it}$ and gdp_{it}). In the estimation routine observations which are either singletons or separated by a fixed effect are automatically dropped, which reduces the estimation samples by approximately 15 percent. The descriptive statistics presented in Table A.1 however, are based on all observations with non-missing data for the relevant variables.

In Figure A.1, we present the overall value of exports (in current USD, hence not adjusted for inflation) and the number of exporting countries in the data set over time. Comparing the two sub-graphs, one can detect two spikes in the number of exporters which do not translate in increases of export values (in 1981 and 2000). The first spike is because the raw data started to report explicitly on zero exports in 1981. From 2000 onward, additional country pair-months could safely coded as zero exports, as mentioned above. Both inclusions result in higher number of countries in the data set, but no increases in the trade value.

Figure A.2 plots the distribution of temperature events over calendar months, separated for D_{itm}^{t30} and D_{itm}^{p99}, based on all available observations of the temperature data set. Both events concentrate in the summer months of the Northern hemisphere, while there are also abnormally hot months (D_{itm}^{p99} events) in summer months of the Southern hemisphere (these events occurred e.g. in Australia, Argentina, and island states in the Pacific).

Table A.1: Descriptive statistics of key variables

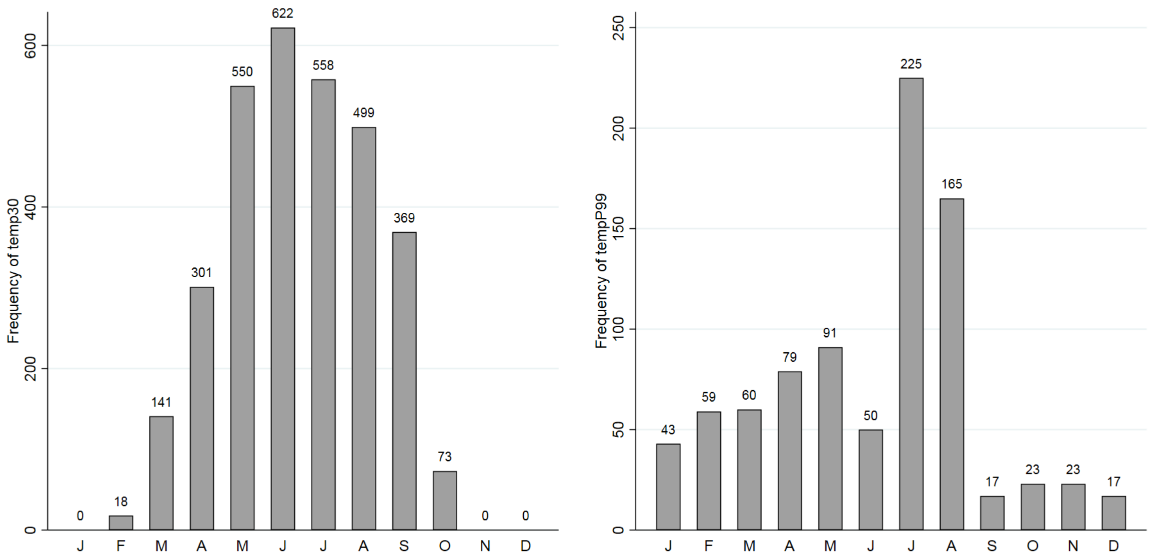
Variable	Description	Mean	Std. dev.	Min.	Max.	Obs.
X_{ijtm}	Export value from exporter *i* to importer *j*, FOB, in million current USD	48.3	444.3	0.0	39,200.6	4,475,726
$temp_{itm}$	Mean temperature in °C , average of country area	16.5	10.5	-32.0	37.5	49,597
D^{t30}_{itm}	Mean temperature at least 30°C	0.015	0.121	0.0	1.0	49,597
D^{p99}_{itm}	Mean temperature in country-specific top percentile	0.013	0.111	0.0	1.0	49,597
$labourint_{ijt}$	Labour intensity of X_{ijt} as share of labour input of total inputs	0.15	0.08	0.00	0.93	52,571
gdp_{it}	GDP per capita in current USD	9,834	15,283	49	119,225	4,046
$ndgain_{it}$	ND-GAIN index of climate vulnerability and readiness	52.8	11.3	29.4	76.1	2,057
$agri_{it}$	Percentage of agriculture, forestry, hunting, and fishing in GDP	13.0	12.4	0.0	79.0	3,306
$prFood_{ijt}$	Percentage of food and live animals in total trade flows	17.8	24.5	0.0	100.0	230,006
$prBevTob_{ijt}$	Percentage of beverages and tobacco in total trade flows	2.5	8.5	0.0	100.0	230,006
$prCrude_{ijt}$	Percentage of crude materials, inedible, except fuels in total trade flows	8.5	17.4	0.0	100.0	230,006
$prFuels_{ijt}$	Percentage of mineral fuels, lubricants and related materials in total trade flows	3.9	12.4	0.0	100.0	230,006
$prOils_{ijt}$	Percentage of animal and vegetable oils and fats in total trade flows	1.3	6.2	0.0	100.0	230,006
$prChemic_{ijt}$	Percentage of chemicals in total trade flows	11.9	15.6	0.0	100.0	230,006
$prManuf_{ijt}$	Percentage of manufactured goods classified chiefly by material in total trade flows	17.8	18.3	0.0	100.0	230,006
$prMachin_{ijt}$	Percentage of machinery and transport equipment in total trade flows	24.2	22.6	0.0	100.0	230,006
$prMiscMan_{ijt}$	Percentage of miscellaneous manufactured articles in total trade flows	10.7	14.7	0.0	100.0	230,006

Based on data of 155 countries, 20,209 country pairs, and 684 months. Descriptive statistics are calculated at the country-pair-month-level (trade volume X), at the country-pair-year-level ($labourint$ and trade product shares pr), at the country-month-level ($temp$), and at the country-year-level ($agri$, $ndgain$ and gdp). The trade sector shares are running means of the preceding four years. Subscripts refer to exporter (i), importer (j), year (t), and calendar month (m). For reasons of brevity, country-specific statistics are only reported for exporters.

Figure A.1: Value of exports and number of exporting countries over time

Based on all available data on exports (unbalanced panel of 215 countries, 1960-2016).

Figure A.2: Frequency of temperature events over calendar months

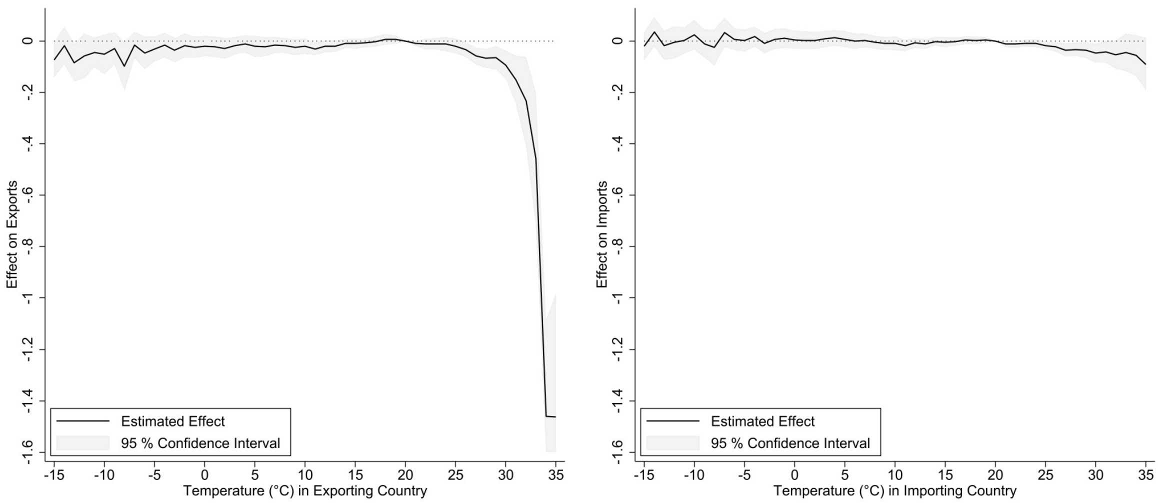


Based on all available data on temperature (unbalanced panel of 197 countries, 1960-2016).

A.3 Further temperature specifications and analyses

In this section, we present alternative and complementary estimations of the temperature effects on exports. First, in Figure A.3 we replicate the results illustrated in Figure 2, but present also large negative effects, which were omitted in the main text for reasons of clarity. Figure A.4 aggregates the single °C bins to 5 °C bins. Both graphs confirm the substantial drop of exports in months with very warm average temperature levels.

Figure A.3: Contemporaneous effects of temperature on exports in 1°C steps, unrestricted plot

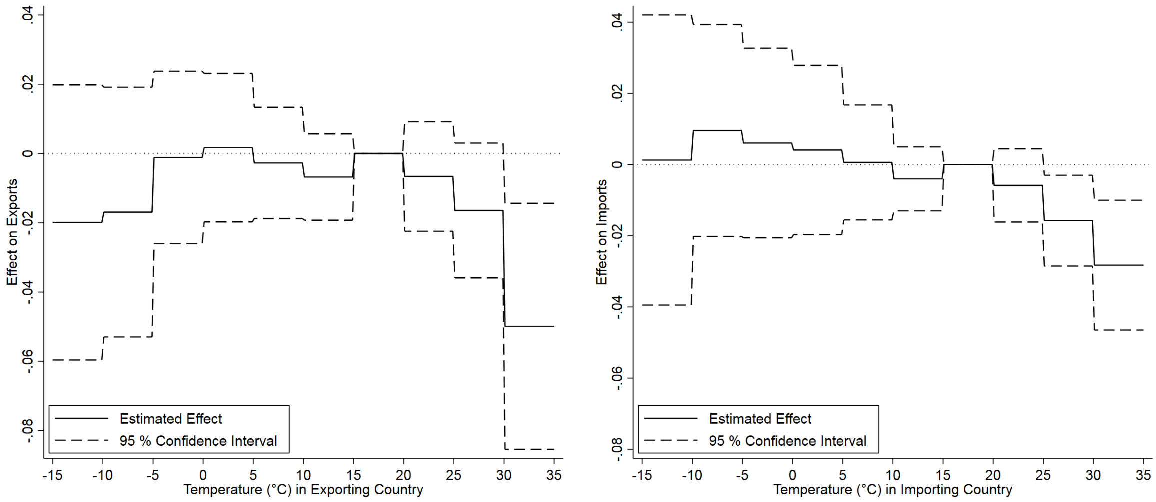


Estimated coefficients for each °C in the exporting country (left panel) and the importing country (right panel) and their 95 percent confidence intervals, using 20 °C as the baseline category. Based on a PPML regression with fixed effects at the country-pair-year-level, exporter-calendar month-level, and importer-calendar month-level (N=3,821,155).

We test for a linear and a quadratic effect of temperature in Table A.2. Model 1 includes absolute monthly average temperatures in the exporting country ($temp_{itm}$) and in the importing country ($temp_{jtm}$). Using our high dimensional fixed effects structure with country-pair-year, importer- and exporter-calendar month- effects we do not find a significant linear effect of the absolute average monthly temperature on trade. In contrast, the quadratic specification yields significant coefficients for exporters, confirming our previous finding of non-linear effects of high temperature on exports.

Moreover, in Models 3 to 6 in Table A.2 we assess whether the estimated effects are observed due to effects on the extensive or the intensive margin of bilateral trade. For Model 3 and 4, we construct a binary variable *tradeext* which takes the value of one if the country-pair has a positive trade value and zero if the trade value equals zero. Due to missing observations about zero trade flows before 2000, *tradeext* is only observable for the years from 2000 to 2016. In this time span, about 79.4 percent of the observations had a positive trade flow. Instead of using

Figure A.4: Contemporaneous effects of temperature on exports in 5 °C bins



Estimated coefficients for temperature bins in the exporting country (left panel) and the importing country (right panel) and their 95 percent confidence intervals, using 15-20 °C as the baseline category. Based on a PPML regression with fixed effects at the country-pair-year-level, exporter-calendar month-level, and importer-calendar month-level (N=3,821,155).

the PPML estimator, we rely on the linear high dimensional fixed effects estimator `reghdfe` to estimate a simple linear probability model. Model 5 and 6, in contrast, depict the results of estimations covering only positive exports. The results broadly suggest that the effect is on the intensive margin, as there is no significant effect on the binary variable indicating positive trade (Models 3 and 4), but a substantial effect on the trade value in the sub-sample of positive exports (Models 5 and 6). Note that the number of observations in the Models 3 to 6 is lower than in the Models 1 and 2, since we can only safely identify zero trade flows since the year 2000.

Figure A.5 illustrates the lagged impacts of a temperature shock at the importer's location, estimated as covariates in the context of assessing lagged impacts on exports (presented in Figure 3). The estimated coefficients are not statistically different from zero throughout the first year after the temperature shock.

In Figure A.6, we depict the cumulative effects of D^{t30}_{itm} during twelve months after the temperature shock. The estimation confirms the negative effect on exports in the first months after the temperature shock, and shows that these export values are not recovered in subsequent periods. There is no significant impact on imports.

Table A.2: Linear and quadratic temperature effects on exports, estimates of the extensive and intensive margin

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
$temp_{itm}$	0.0013	0.0022*				
	(0.0010)	(0.0011)				
$temp^2_{itm}$		-0.0001**				
		(0.0000)				
D^{t30}_{itm}			0.0017		-0.0398***	
			(0.0035)		(0.0125)	
D^{p99}_{itm}				0.0009		-0.0235***
				(0.0013)		(0.0090)
$temp_{jtm}$	-0.0005	-0.0002				
	(0.0008)	(0.0009)				
$temp^2_{jtm}$		-0.0000				
		(0.0000)				
D^{t30}_{jtm}			0.0024		-0.0239***	
			(0.0016)		(0.0073)	
D^{p99}_{jtm}				-0.0020**		-0.0194**
				(0.0009)		(0.0086)
Observations	3821155	3821155	2698697	2698697	1725813	1725813

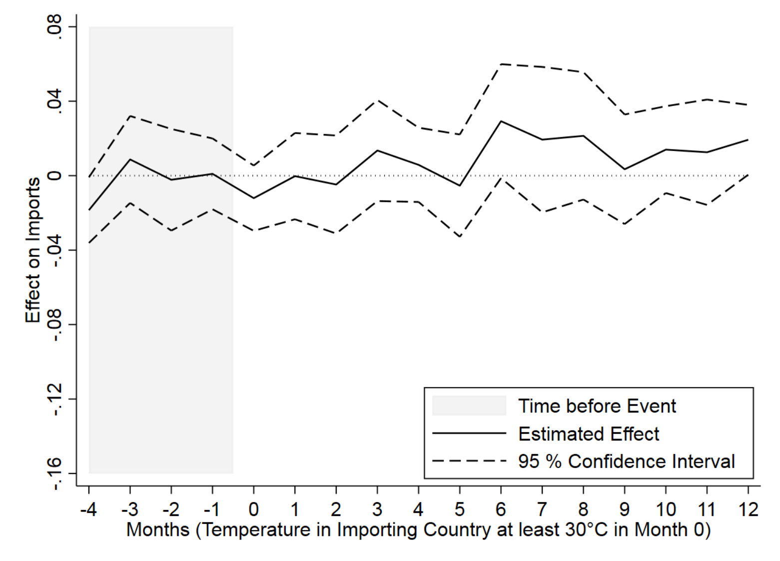
Model 1 and 2: PPML estimations of bilateral exports in current USD, including zero exports. Model 3 and 4: Linear probability estimations of a binary variable indicating the existence of positive exports (extensive margin). Model 5 and 6: PPML estimations of bilateral exports in current USD, excluding zero exports (intensive margin). All regressions are with fixed effects at the country-pair-year-level, exporter-calendar month-level, and importer-calendar month-level. * $p < .1$ ** $p < .05$ *** $p < .01$.

Regarding relatively warm temperature events (D^{p99}_{itm}), we depict the lagged and cumulative effects on exports in Figures A.7 and A.8, respectively. As for the case of absolute hot temperatures, the effect is concentrated on exporters, and short-lived. However, in contrast to the D^{t30}_{itm}-specification, the effect is not aggravating in the first few months but there is a slight tendency towards catching-up, such that the cumulative effect within one year after the event is statistically equal to zero.

In Figure A.9, we replicate the interaction analysis for the potential labour intensity channel for temperature events in the top percentile (D^{p99}_{itm}). In this specification, the effect is not significant which may be rationalized by the insights of prior studies that absolute temperature levels are more important for effects on labour capacity.

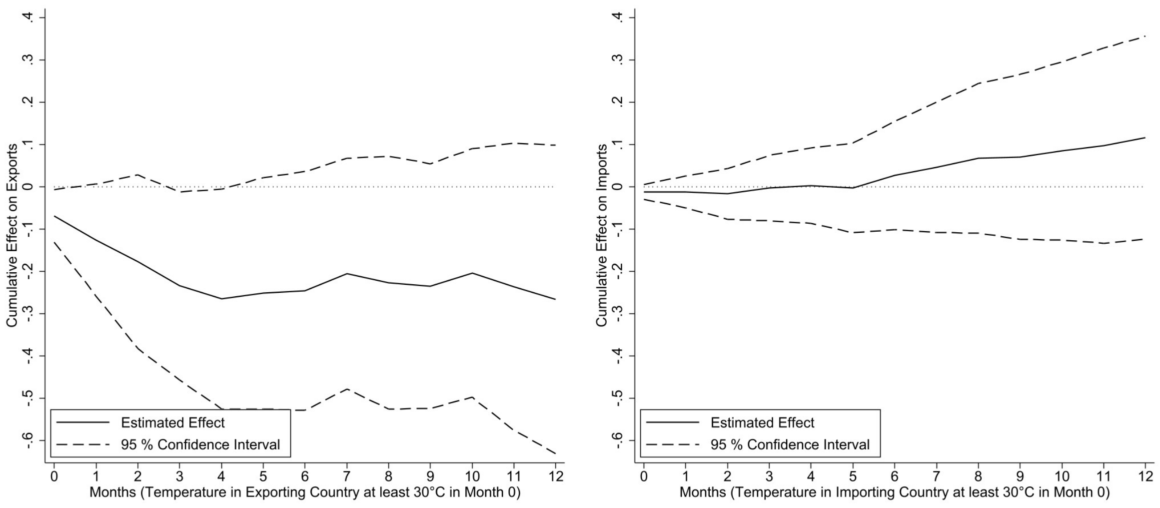
Figures A.10 and A.11 summarize the estimates of various interaction effects. Most of the

Figure A.5: Lagged impact on imports of an average monthly temperature of at least 30 °C



Estimated effects on imports of a hot month on exports, including 95-percent confidence intervals. The effects are relative to a month with a temperature below 30 °C. The model is estimated with PPML and include temperature at the exporter location, country-pair-year, exporter-calendar month, and importer-calendar month fixed effects. Standard errors are multi-way-clustered at exporter, importer and time step-level.

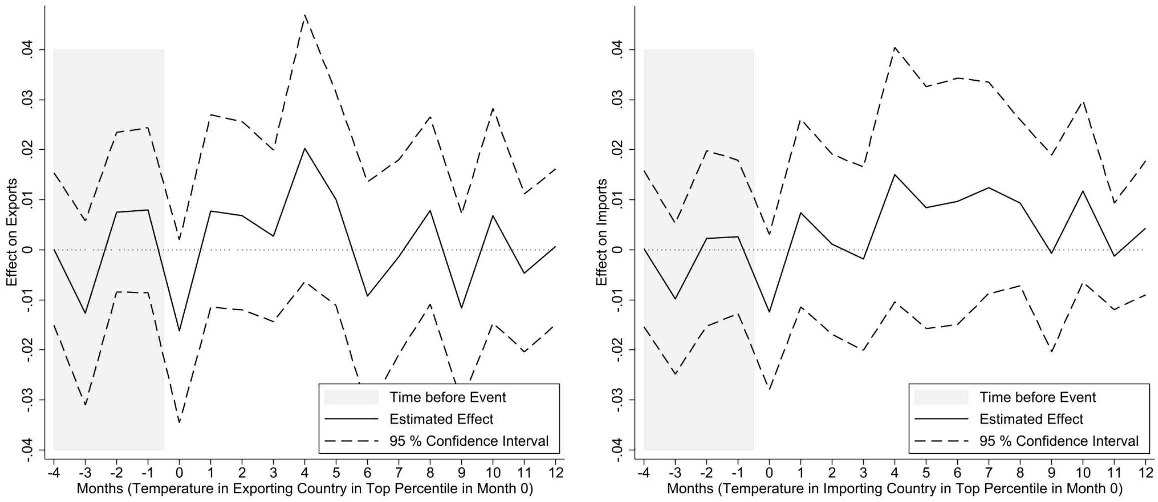
Figure A.6: Cumulative effects of an average monthly temperature of at least 30 °C



Estimated cumulative effects of a hot month on exports (left panel) and imports (right panel), including 95-percent confidence intervals. The effects are relative to a month with a temperature below 30 °C. The model is estimated with PPML and include country-pair-year, exporter-calendar month, and importer-calendar month fixed effects.

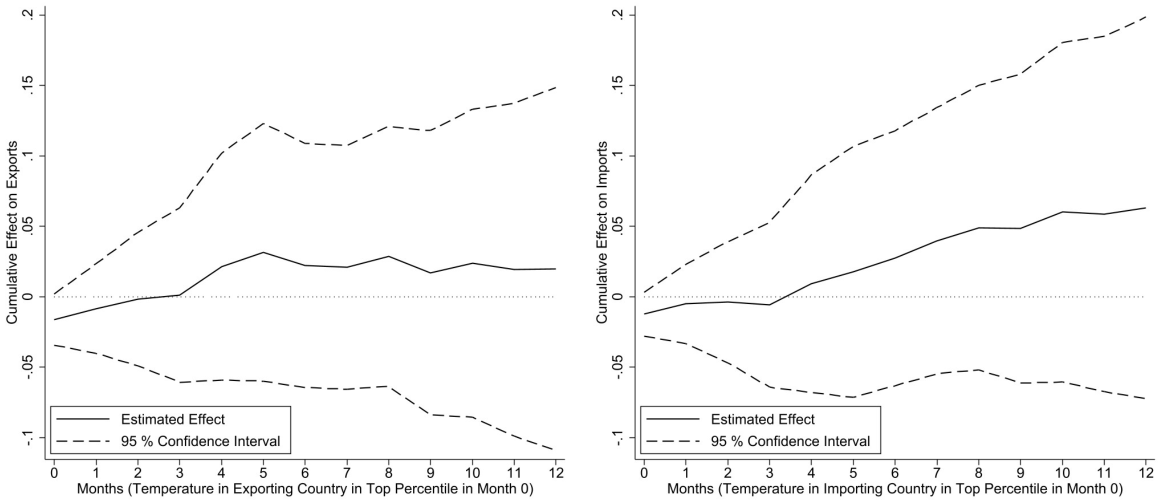
analyzed potential heterogeneity variables show no significant impact on the estimated effects of D^{t30}_{itm} or D^{p99}_{itm}.

Figure A.7: Lagged effects of an average monthly temperature in the top percentile



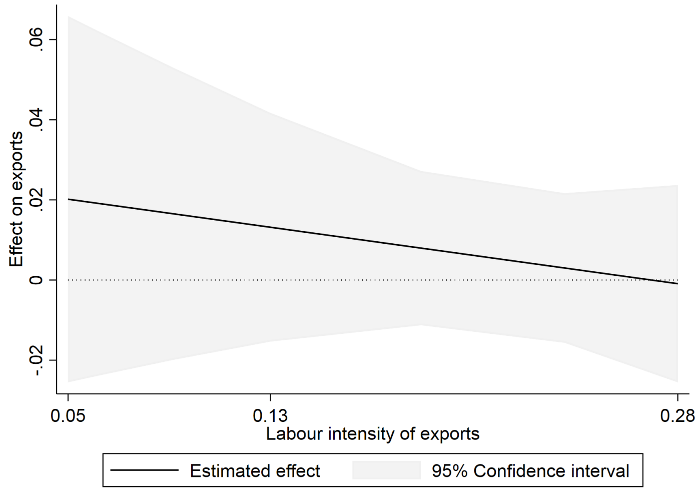
Estimated effects of a hot month on exports (left panel) and imports (right panel), including 95-percent confidence intervals. The effects are relative to a month with non-extreme temperature. The model is estimated using PPML and include country-pair-year, exporter-calendar month, and importer-calendar month fixed effects. Standard errors are multi-way-clustered at exporter, importer and time step-level.

Figure A.8: Cumulative effects of an average monthly temperature in the top percentile



Estimated cumulative effects of a hot month on exports (left panel) and imports (right panel), including 95-percent confidence intervals. The effects are relative to a month with non-extreme temperature. The model is estimated with PPML and include country-pair-year, exporter-calendar month, and importer-calendar month fixed effects. Standard errors are multi-way-clustered at exporter, importer and time step-level.

Figure A.9: Estimated effect of an average monthly temperature in the top percentile on exports for different levels of labour intensity



Estimated contemporaneous effects of D^{p99}_{itm} on exports for given levels of labour intensity, including 95-percent confidence intervals. The effects are relative to a month with non-extreme temperature. The model is estimated with PPML and includes country-pair-year, exporter- and importer-calendar month fixed effects. Labelled values at the x-axis are the 5th, 50th, and 95th percentile of $labourint_{ijt}$.

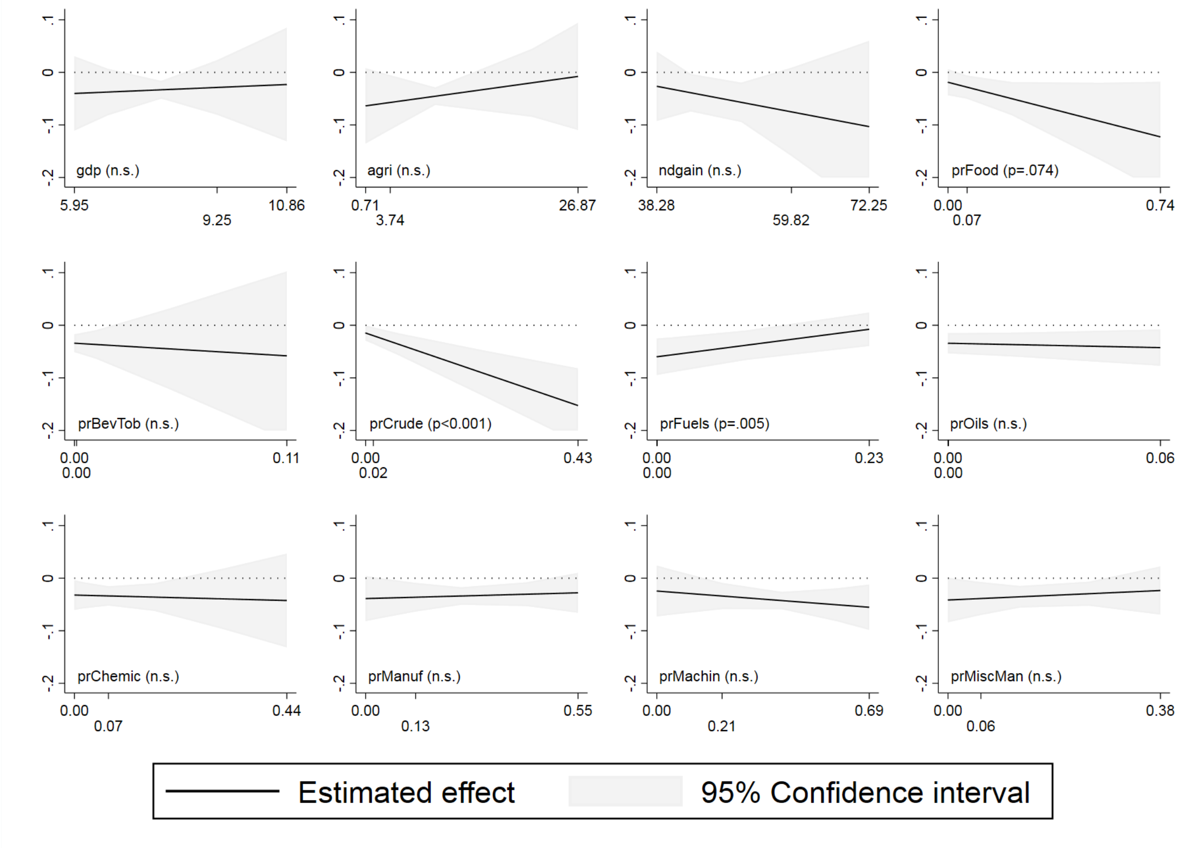
A.4 Effects of precipitation and storms

As for the case of temperature, our main source of historical precipitation data is CCKP (World Bank, 2022a). As for the case of temperature, the values are monthly means aggregated at the country level. In Table A.3, we present the descriptive statistics of the additional weather variables used in this and the subsequent section.

For effects of storms, we use data on the maximum wind speed at the country-month level from the ifo GAME data set (Felbermayr and Gröschl, 2014), which is based on two primary data sources: First, it uses the International Best Track Archive for Climate Stewardship (IBTrACS) which is provided by the National Climatic Data Center of the National Oceanic and Atmospheric Administration (NOAA) and contains data of individual hurricane events. Second, in order to capture tornadoes, summer and winter storms not included in IBTrACS, the hurricane data is matched to daily data of the Global Surface Summary of Day (GSOD) data (version 7) on maximum wind speed and wind gust from over 9,000 weather stations worldwide. Wind data from ifo GAME is available at the country-month level for the period 1979-2010.

In Table A.4 we study the effect of different models estimating the precipitation impacts on

Figure A.10: Estimated effects of an average monthly temperature of at least 30 °C for various heterogeneity variables



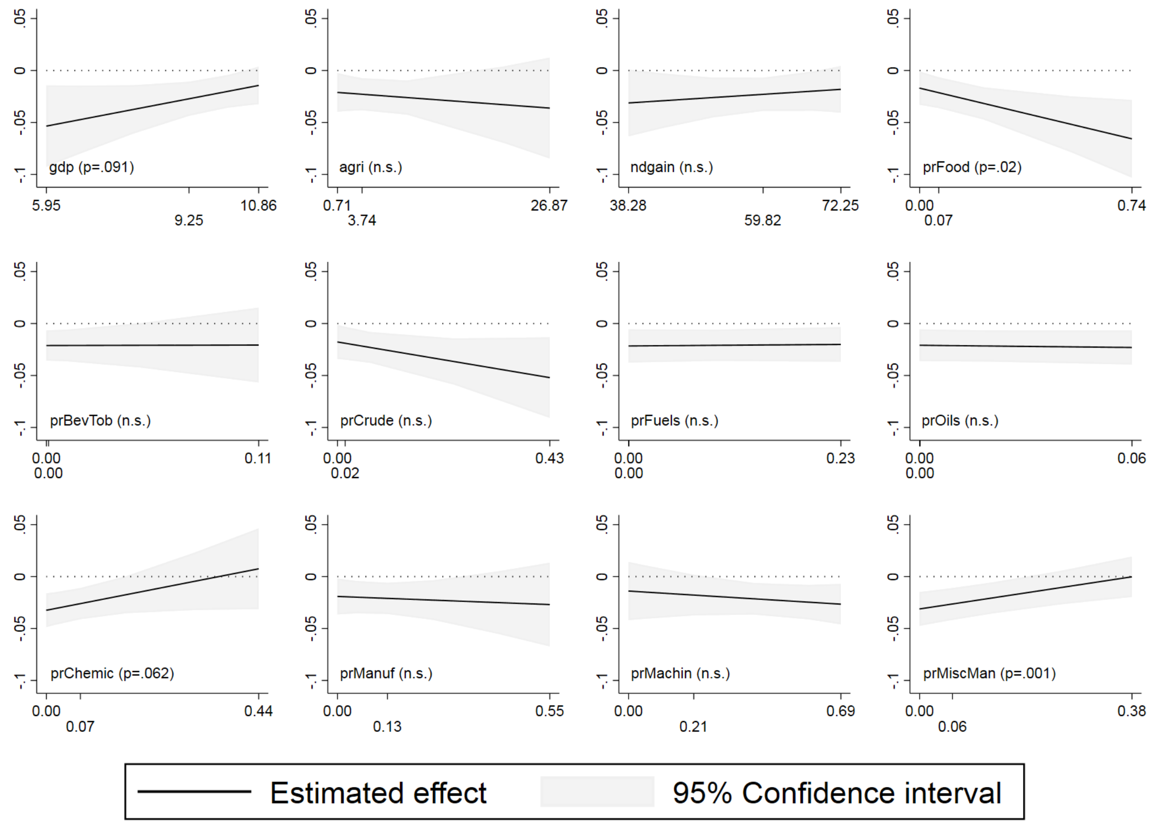
Estimated contemporaneous effects of D^{t30}_{itm} on exports for given levels of various heterogeneity variables, including 95-percent confidence intervals. The effects are relative to a month with a temperature below 30 °C. The model is estimated with PPML and includes country-pair-year, exporter- and importer-calendar month fixed effects. Standard errors are multi-way-clustered at exporter, importer and time step-level. Labelled values at the x-axes are the 5^{th}, 50^{th}, and 95^{th} percentiles of the heterogeneity variables. The reported p-values refer to the significance of the interaction term (n.s.: $p \geq 0.1$).

exports. In more detail, we examine the linear and quadratic effects of absolute precipitation, and effects of extremely dry (*precP*1) and wet months (*precP*99). We do not find significant effects of precipitation in any of the specifications.

Table A.5 shows the results of similar estimations of wind speed impacts on exports. There are neither effects in the linear and quadratic specifications, nor do months with country-specific high wind speeds show an effect on exports.

However, using country-specific distributions may not be the appropriate strategy for identifying non-linear effects of storms, since the occurrence of harmful wind speeds is not equally distributed on countries (as the variable *combiP*99), but is mainly an issue in tropical cyclone-

Figure A.11: Estimated effects of an average monthly temperature in the top percentile for various heterogeneity variables



Estimated contemporaneous effects of D_{itm}^{p99} on exports for given levels of various heterogeneity variables, including 95-percent confidence intervals. The effects are relative to a month with non-extreme temperature. The model is estimated with PPML and includes country-pair-year, exporter- and importer-calendar month fixed effects. Standard errors are multi-way-clustered at exporter, importer and time step-level. Labelled values at the x-axes are the 5^{th}, 50^{th}, and 95^{th} percentiles of the heterogeneity variables. The reported p-values refer to the significance of the interaction term (n.s.: $p \geq 0.1$).

exposed locations. Therefore, we use a similar strategy as for temperature bins (Figure A.4), and estimate effects of absolute wind speed bins in Figure A.12, using the bin with the largest number of observations (40-45 knots) as the baseline category. The results suggest that for wind speeds above 140 knots, exports decrease substantially in the month of the weather event, while imports remain largely unaffected. These potential short-term and non-linear effects of intense storms on exports are beyond the scope of this analysis, and may be a promising avenue for further research.

Table A.3: Descriptive statistics of additional weather variables

Variable	Description	Mean	Std. dev.	Minimum	Maximum	Obs.
$prec_{itm}$	Mean precipitation in mm, average of country area	94.67	93.57	0.00	1,063.69	49,597
$precP1_{itm}$	Mean precipitation in lowest country-specific percentile	0.015	0.121	0.00	1.00	49,597
$precP99_{itm}$	Mean precipitation in country-specific top percentile	0.010	0.099	0.00	1.00	49,597
$wind_{itm}$	Maximum wind speed in knots	48.58	19.12	0.00	165.00	26,559
$windP99_{itm}$	Maximum wind speed in country-specific top percentile	0.007	0.082	0.00	1.00	26,559

Descriptive statistics are calculated at the country-month-level. For reasons of brevity, country-specific statistics are only reported for exporters.

Table A.4: Contemporaneous precipitation effects on exports

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
$prec_i$	-0.0000	-0.0000		
	(0.0000)	(0.0001)		
$prec_i^2$		-0.0000		
		(0.0000)		
$precP1_i$			0.0026	
			(0.0190)	
$precP99_i$				0.0019
				(0.0080)
Observations	3821155	3821155	3821155	3821155

All models are estimated using PPML and include country-pair-year, exporter-calendar month, and importer-calendar month fixed effects. In all estimates we control for weather effects in the importing country.

A.5 Additional information on counterfactual simulations

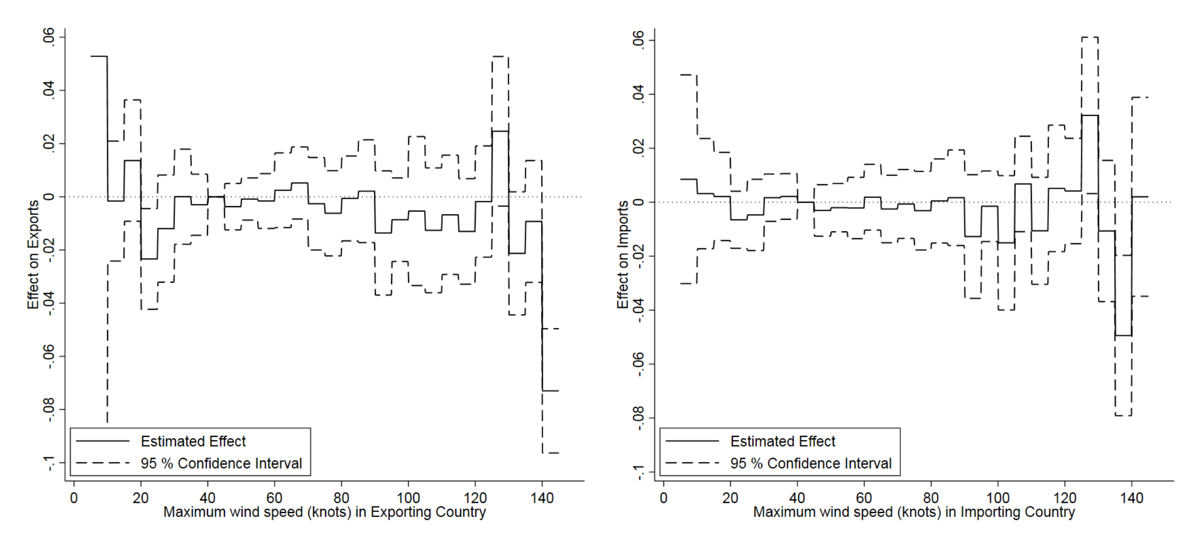
Table A.6 presents the list of countries included in the simulation analysis.

Table A.5: Contemporaneous wind speed effects on exports

	(1) Model 1	(2) Model 2	(3) Model 3
$wind_i$	-0.0001	0.0003	
	(0.0001)	(0.0005)	
$wind_i^2$		-0.0000	
		(0.0000)	
$windP99_i$			0.0003
			(0.0085)
Observations	2155697	2155697	2155697

All models are estimated using PPML and include country-pair-year, exporter-calendar month, and importer-calendar month fixed effects. In all estimates we control for weather effects in the importing country.

Figure A.12: Contemporaneous effects of maximum wind speed on exports in 5 knots bins



Estimated coefficients for wind speed bins in the exporting country (left panel) and the importing country (right panel) and their 95 percent confidence intervals, using 40-45 knots as the baseline category. Based on a PPML regression with fixed effects at the country-pair-year-level, exporter-calendar month-level, and importer-calendar month-level (N=2,153,305). Standard errors are clustered at exporter, importer and time step-level.

Table A.6: List of countries in used in simulations

Argentina	Australia	Austria	Belgium	Bangladesh	Brazil
Canada	Switzerland	China	Colombia	Czechia	Germany
Denmark	Algeria	Spain	France	Great Britain	Hungary
Indonesia	India	Ireland	Iraq	Italy	Japan
South Korea	Mexico	Malaysia	Netherlands	Norway	New Zealand
Oman	Philippines	Poland	Russia	Saudi Arabia	Singapore
Sweden	Thailand	Turkey	United States	Venezuela	Viet Nam
South Africa					

List of countries used in counterfactual simulations. Trade between these countries covers 90 percent of the trade volume over the sample period.

Table A.7: Change in annual import expenditure under climate projection CIMP5 RCP 4.5 for mean 2020-2039

Country	Mean	95% Conf. Interval		Country	Mean	95% Conf. Interval	
AUS	0.0092	0.0063	0.0121	AUT	0.0067	0.0040	0.0094
BEL	0.0075	0.0047	0.0103	BGD	0.0076	0.0047	0.0104
BRA	0.0076	0.0048	0.0104	CAN	0.0073	0.0044	0.0102
CHE	0.0102	0.0071	0.0132	CHN	0.0081	0.0052	0.0111
COL	0.0076	0.0048	0.0105	CZE	0.0067	0.0039	0.0094
DEU	0.0068	0.0041	0.0096	DNK	0.0067	0.0039	0.0095
ESP	0.0066	0.0039	0.0094	FRA	0.0068	0.0041	0.0096
GBR	0.0070	0.0042	0.0097	HUN	0.0067	0.0039	0.0094
IDN	0.0107	0.0075	0.0138	IND	0.1879	0.1756	0.2001
IRL	0.0067	0.0039	0.0094	ITA	0.0065	0.0038	0.0092
JPN	0.0071	0.0044	0.0099	KOR	0.0079	0.0051	0.0107
MEX	0.0068	0.0039	0.0097	MYS	0.0088	0.0059	0.0118
NLD	0.0067	0.0039	0.0094	NOR	0.0066	0.0038	0.0094
NZL	0.0072	0.0044	0.0100	PHL	0.0073	0.0045	0.0101
POL	0.0066	0.0038	0.0094	RUS	0.0077	0.0049	0.0105
SGP	0.0086	0.0057	0.0115	SWE	0.0070	0.0042	0.0098
THA	0.0081	0.0054	0.0109	TUR	0.0058	0.0032	0.0085
USA	0.0075	0.0047	0.0104	ZAF	0.0102	0.0072	0.0133

Relative to historic mean of 1980-1999 for estimated world economy in 2015. Mean and 95%-confidence intervals are bootstrapped.

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