# Sacking the sales staff: Weather as a labor productivity shock, complementary input adjustments, and climate change policy

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**Abstract**

Climate change and extreme weather events are a global problem but especially affect poor countries. The effect on agriculture is well studied, but we know less about how non-agricultural firms cope with weather shocks and climate change. I combine firm-level information from sub-Saharan Africa and South Asia with high-resolution weather data to study how non-agricultural firms in poor countries react to weather shocks in the short run. I show that weather shocks primarily affect these firms by reducing their labor productivity and that firms react by scaling back expenditures on complementary inputs like rented machinery, rented space and non-production personnel. This further reduces effective labor productivity. To assess the general equilibrium and policy implications, I develop and estimate a structural model featuring these input adjustments. I combine the model with machine learning estimates of the impact of climate change to discipline climate change counterfactuals. I show that taking complementary input adjustments into account makes (i) policies benefiting larger firms and (ii) policies allowing firms to adapt to climate change more effective at reducing welfare losses from climate change.

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Climate change and extreme weather events are a global problem but especially affect poor countries. There is an extensive literature on the effects of extreme weather on agricultural production in poor countries, but we know relatively little about the effects of weather shocks on non-agricultural firms. We *do* know that weather affects non-agricultural firms, with extreme temperatures decreasing their sales. We further know that this effect can operate both through a demand channel, by reducing local demand, and through a supply channel, by decreasing firm productivity (Adhvaryu, Kala, & Nyshadham, 2019; Costinot, Donaldson, & Smith, 2016; Nath, 2020; Santangelo, 2019; Somanathan, Somanathan, Sudarshan, & Tewari, 2021; Zhang, Dêschenes, Meng, & Zhang, 2018). We do not yet, however, have a good understanding of firm reactions to these shocks (Goicoechea & Lang, 2023). Understanding firm reactions, and how we can leverage these reactions in policy design, could significantly improve our ability to help poor countries cope with the impact of climate change.

I show that weather shocks are predominantly supply, i.e., labor productivity, shocks. I then show that firms react to these shocks by adjusting expenditures on complementary inputs, such as rented machinery, rented space and non-production personnel. These input adjustments further reduce firms' effective labor productivity. Finally, I show that these adjustments are quantitatively important for general equilibrium counterfactuals and policy design.

I assemble a data set combining World Bank Enterprise Surveys across sub-Saharan Africa and South Asia with high-resolution weather data. My argument then proceeds in five steps. First, I test whether weather shocks are predominantly supply or demand shocks for these firms — we have micro evidence that they *can* be both, but we do not know which channel is quantitatively more important. This is interesting in its own right, and also a necessary first step for understanding firm reactions, since firms would react differently to either type of shock. The test I use employs a basic open economy intuition about exporters: They are somewhat insulated from local demand shocks, but are less able to pass on marginal cost increases to their international buyers. They are, therefore, more exposed to supply shocks. To measure weather shocks, I construct a temperature index combining mean temperature, temperature variance, and the number of days with temperatures exceeding 32°C (89.6°F), which provides a parsimonious measure of heat stress. I regress log sales during a given fiscal year on the temperature index during that fiscal year and test whether the impact of heat stress on sales differs by exporter status. For identification, I include location fixed effects to isolate random year-to-year weather variation. I find that hotter years have a significantly larger negative impact on exporters' total sales than on non-exporters' total sales: An 80$^{\text{th}}$ percentile weather shock decreases non-exporters' total sales by 3.9 percent, but exporters' total sales by 6.9 percent.[1] I thus find that exporters are more affected by extreme weather, implying that weather is, on net, a supply shock for these firms (rather than a local demand shock).

Second, in the main reduced form result of the paper, I show that firms react to these shocks by adjusting expenditures on inputs complementary with production labor, such as rented machinery, rented space and non-production personnel. Importantly, I then show that these adjustments further reduce effective labor productivity, which exacerbates the impact of the shock on productivity. As a catch-all piece of jargon I introduce for ease of exposition, I will call these inputs *productive capability*. The common feature of these inputs is that they make it cheaper for a firm to provide its output in all markets it is active in, either by making its labor more productive (e.g., by providing workers with sufficient equipment — rented machinery — or space — rented office space) or by making it easier to sell the firm's output (e.g., by reducing transaction cost, as is done by sales staff, a key component of non-production personnel). Because it reduces the cost of providing a firm's output across all markets the firm serves, productive capability is complementary with the firm's labor productivity — when a negative productivity shock causes production lines to produce less output, sales staff have less output to sell, and are themselves less valuable to the firm. Faced with higher temperatures, firms therefore scale back expenditures on productive capability. This is rational from the firm's perspective, but has the effect of further reducing labor productivity. I provide three key pieces of reduced form evidence for this adjustment mechanism. First, due to the rich survey data I use, I can measure productive capability expenditures in the data.[2] I show that firms adjust productive capability in reaction to weather shocks: In response to an 80$^{\text{th}}$ percentile weather shock, domestic producers reduce their expenditure on productive capability by 2.9 percent, while exporters reduce their expenditure by 6.7 percent. Second, a key implication of this adjustment is that firms' productivity should be reduced, and more so for firms that make larger adjustments. I show that this is the case: Exporters not only see a larger reduction in *total sales* as a result of weather shocks, but also a larger reduction in *domestic sales*. Crucially, I show that this is driven by adjustments in productive capability: A mediation analysis controlling for productive capability removes this differential impact on domestic sales.[3]

[1] For comparison, these effect sizes are similar to other supply shocks found in comparable contexts, such as the effects of ethnic conflict on Kenyan flower packers' or mobile phone access on Indian fishers' output, for example (Hjort, 2014; Jensen, 2007).

[2] Specifically, I observe the cost of communications, sales (including sales staff), transportation, and rent for buildings, equipment and land.

[3] I also run a battery of robustness checks showing that the differential impact on domestic sales is not driven by obvious differences between exporters and non-exporters, such as the sectors they are active in, firm size, or the

Third, I develop an international trade model that adds this productive capability adjustment channel to the model of Melitz (2003). To do this, I adapt and extend the domestic multi-market model of Hyun and Kim (2022) to an international trade setting, include market entry and exit, and estimate the resulting model. The model generates the reduced form patterns I discuss above: In reaction to a negative productivity shock, firms scale back productive capability expenditures. This is a rational, profit maximizing reaction, but does have the effect of further reducing their productivity, and therefore further reducing their sales across all markets they are active in. The effect is larger for exporters, because exporters may no longer find it profitable to trade with some of their export destinations following the productivity shock. When they exit those markets, they see a discontinuous fall in total sales, mirroring the reduced form differential impact on total sales discussed above. Exporters then also discontinuously reduce their productive capability, which leads to a discontinuous fall in sales in all markets they are active in, including the domestic market (again mirroring my reduced form results). Adding this productive capability channel makes the model computationally more challenging, since firms' decisions to enter various markets are no longer independent: If a firm enters a new market, the additional demand it can now reach makes it worthwhile to hire additional productive capability, which in turn can make it profitable to enter additional markets. I develop a novel algorithm for solving this high-dimensional combinatorial problem in my setting. While the model remains computationally more burdensome than a standard Melitz (2003) model, I show that it can be readily estimated using novel small open economy methods (Bartelme, Lan, & Levchenko, 2023; Demidova, Naito, & Rodríguez-Clare, 2022). These make it possible to estimate large parts of the model using reduced form approaches, which reduces the complexity of the structural estimation considerably without sacrificing key insights from the model. I use Zambia as a small open economy, which is a good candidate for estimation due to its extensive data coverage in the Enterprise Surveys, nearly balanced trade, and (globally speaking) small size. I find that the estimated model matches targeted and non-targeted moments well.

Fourth, in order to be able to construct climate change counterfactuals for this model, I develop an estimate of the impact of climate change on the firms in my sample.[4] As an empirical basis for this, I collect high-resolution weather projections from NASA NEX covering a range of climate change scenarios. To estimate the causal impact of going from the current climate to these projected climates, I cannot simply extrapolate my reduced form estimates, however — those estimates rely

complexity of their production processes.

[4] Here, climate should be thought of as the distribution of weather.

on a parsimonious, simple functional form well-suited to understanding the marginal impacts of weather shocks within a given climate. To extrapolate to an entirely different climate, I instead need an estimator that solves three challenges: First, I need to capture the complexity of that climate via a large array of different weather variables, and I need to then estimate the complex relationship between those variables and firm outcomes in a way that allows for *correct inference* on the resulting estimates. Second, I need the estimator to perform well out of sample, since *future* climate change is inherently something that happens out of sample. Finally, I need to capture firm adaptation to climate change. I show how the causal forest algorithm (Athey, Tibshirani, & Wager, 2019) can be used to solve these three problems: It performs well and provides (using a few simple data manipulations) reliable inference even with a large selection of explanatory variables, can be optimized for out of sample performance, and can easily incorporate adaptation to climate change by including long-term means and variances of all weather variables. Because estimating the impact of moving to a new climate is a problem of general interest in climate change economics, showing how this estimator can be adapted to solving this problem is a result of interest in its own right. For the purposes of this paper, however, I then estimate the impact of climate change on Zambian firms' sales under three different climate change scenarios, using predictions from 27 different climate models for each scenario. Under a severe climate change scenario, I estimate that the average Zambian firm faces an almost 19 percent decrease in sales by the 2080s. Even under a mild scenario, I find that the average Zambian firm's sales would drop by almost nine percent.

Finally, I combine these estimates with the model to construct climate change counterfactuals and demonstrate that productive capability reactions matter for general equilibrium results and policy effectiveness. I first calibrate a counterfactual baseline scenario under a severe climate change pathway. The calibration shifts the firm productivity distribution to match the estimated impact of climate change on the average firm. I then conduct policy experiments under this baseline, comparing my full model's results to a modified version which shuts down firms' productive capability adjustments. I demonstrate two key policy implications of productive capability adjustments. First, motivated by the development economics literature on targeting interventions along the firm size distribution, I show that productive capability adjustments make policies which especially benefit larger firms more effective at counteracting the impacts of climate change. Specifically, a reduction in variable trade costs, which especially helps large exporters, becomes 1.6 times more effective at reducing the impact of climate change, compared to the model without productive capability adjustments. This is because reduced trade costs allow these larger firms especially to hire additional productive capability, increasing their productivity. Second, I show that adaptation to climate change becomes more effective at counteracting the impact of climate change. Allowing firms to adapt to the climate change counterfactual — by recovering some of the productivity losses from climate change — causes firms to increase their productive capability, further increasing their productivity. A model without productive capability misses this endogenous productivity reaction.

I contribute to the literature on the impact of climate change on poor countries, especially its impact on firms and trade (e.g., Castro-Vincenzi, 2024; Conte, 2022; Costinot et al., 2016; Nath, 2020; Santangelo, 2019; Somanathan et al., 2021; Zhang et al., 2018); see Goicoechea and Lang (2023) for a recent summary. I add two important stylized facts to this literature: First, weather is, on net, a supply (rather than a demand) shock. Second, non-agricultural firms (in poor countries) react to weather shocks by adjusting expenditures on productive capability — complementary inputs such as rented machinery, rented space and non-production personnel. I build and estimate a trade model incorporating this mechanism. While existing studies often focus on shifting patterns of comparative advantage and differences across sectors (i.e., Ricardian effects), or on relatively sophisticated multinationals, I focus on a very general adjustment mechanism at the firm level. Finally, I demonstrate that productive capability reactions make (i) policies benefiting larger firms and (ii) policies allowing firms to adapt to climate change especially effective at counteracting the negative impacts of climate change.

I further contribute to the broader literature on estimating the effects of weather shocks and climate change (e.g., Auffhammer, Hsiang, Schlenker, & Sobel, 2013; Burke & Emerick, 2016; Burke, Hsiang, & Miguel, 2015; Burke & Tanutama, 2019; Carleton & Hsiang, 2016; Carleton et al., 2022; Castro-Vincenzi, 2024; Dell, Jones, & Olken, 2012; Deschênes & Greenstone, 2007, 2011; Lin, Schmid, & Weisbach, 2019; Nath, 2020; Ortiz-Bobea, 2021; Somanathan et al., 2021; Zhang et al., 2018). Here, I demonstrate how causal forests (Athey et al., 2019) can be used to solve a very general problem in this literature, namely, the problem of estimating (and doing inference on) the causal impact of moving from one climate to another climate. A key problem causal forests solve is dimensionality: Weather data are very high dimensional. Existing approaches, for example linear regression, often require researchers to pick only a few weather measures in their analysis to keep the estimation feasible, or to achieve reasonable out of sample performance. Causal forests, on the other hand, can easily handle high-dimensional weather data, are optimized for out of sample performance, and provide correct inference using only a few basic data manipulations I highlight in the paper.

The closest paper to mine is Nath (2020), who shows that climate change causes labor to be drawn into agriculture, because countries need to grow sufficient food to feed their population. Since climate change especially reduces agricultural productivity, however, this labor reallocation increases welfare losses. Reduced trade costs allow countries to import more food, which reduces this inefficient labor reallocation and decreases damages from climate change. Relative to Nath (2020), I focus on firm-level reactions to extreme weather, rather than aggregate Ricardian reallocations across sectors. Accordingly, I use a model of firm-based trade to study the impacts of climate change, instead of a Ricardian model driven by comparative advantage. Further, the mechanism I study is driven by supply-side features of how firms produce goods, and accordingly, how they can react to weather shocks. Nath (2020) is driven by demand-side features, namely non-homothetic preferences and the need for food. Another related paper is Castro-Vincenzi (2024), who shows that climate risk leads car producers to open smaller factories with spare capacity, leading to less efficient production and higher consumer prices. The mechanism I study is relevant even for single-establishment firms and across sectors, complementing this existing evidence on the importance of location and capacity choice for multinationals.

The rest of the paper is organized as follows: Section 1 describes the data I use. Section 2 presents reduced form evidence on weather shocks as supply shocks and productive capability adjustments. Section 3 develops the international trade model I use. Section 4 estimates the causal impact of climate change on firms using causal forests. Section 5 combines the model and those estimates, and presents counterfactual simulations showing how productive capability reactions change the effectiveness of different policies under climate change. Section 6 summarizes my main findings and concludes.

# 1 Data

This section describes the different data sets I use throughout the paper. My analyses focus on non-agricultural firms across sub-Saharan Africa and South Asia, which guided the selection of data sets. I focus on these two regions because they (i) contain the countries on Earth with the highest fraction of people living in absolute poverty and the largest number of people living in absolute poverty, and (ii) climate change stands to be especially damaging to these regions (Costinot et al., 2016). Understanding how economies across these regions can cope with climate change is therefore especially important for reducing the negative impacts of climate change, and for global poverty reduction efforts over the next century.

### 1.1 Firm data: World Bank Enterprise Surveys

For data on firm outcomes and characteristics I use the World Bank Enterprise Surveys (ES).[5] Specifically, I use the harmonized data set provided by the World Bank, comprised of surveys between 2006 and 2020. The Enterprise Surveys data include formal companies with at least five employees in the manufacturing and service sectors. The surveys contain data for firms' last complete fiscal year. All surveys contain weights to get representative samples of each country-year's non-agricultural firms, and all estimations and summary statistics in this paper use those weights.

Table 1 shows basic summary statistics for ES firms across sub-Saharan Africa and South Asia. There is a lot of heterogeneity, with firm sizes ranging from six employees at the $25^{\text{th}}$ percentile to 22 at the $75^{\text{th}}$ percentile. There is also a noticeable right tail of large firms, with the average number of employees, 23, exceeding even the $75^{\text{th}}$ percentile. (This is despite winsorizing the data at the $95^{\text{th}}$ percentile to ensure means are not overly skewed by the largest firms.) The sales distribution is similarly skewed, with median sales of ≈USD 100,000, but average sales of ≈USD 800,000. 12 percent of firms are exporters and 31 percent are in manufacturing. The overall takeaway is that I observe a wide range of firms, including some very large firms, offering a representative overview of non-agricultural formal sector economic activity. Figure 1 shows the locations of all firms across sub-Saharan Africa and South Asia, highlighting that the Enterprise Surveys have very wide geographic coverage. This is useful for studying the overall implications of climate change, since weather and climate change vary across space.[6]

To match firm and weather data, I require (i) firm locations as latitude/longitude coordinates and (ii) the end date for the last fiscal year (since firm data cover that last fiscal year). The exact dates for when the last fiscal year started and/or ended are sometimes missing, but I obtained meta data from the World Bank that allow me to fill in missing fiscal year dates. I also obtained location data from the Enterprise Surveys unit in the World Bank. For firms that lack location data, I use information on the city, state and country the firm is located in to geocode the firm's location, using three different web services (OpenStreetMap, GeoNames and Google Maps) accessible via `Python`. This fails for some location names which cannot be retrieved by any of the location services. Overall, 52 percent of my sample has non-missing location data. Of these, 86 percent have near-exact

[5] More information on the Enterprise Surveys data is available at https://www.enterprisesurveys.org/

[6] Appendix Table 12 shows the number of firms observed by country, as well as the number of firms with non-missing real sales data and non-missing location information.

location data provided by the World Bank, and the remainder have location data found via web search.

### 1.2 Weather data: CHIRPS and Berkeley Earth

The weather variables used in most previous studies of the impact of weather shocks or climate change are measures of temperature and precipitation (Carleton & Hsiang, 2016). I, too, use data on both temperature and precipitation, as needed for any given analysis. I obtain precipitation data from the Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) data set (Funk et al., 2015).[7] CHIRPS is a global, daily, high spatial resolution (0.05° grid) precipitation data set going back to 1981. I obtain daily maximum temperature data from the Berkeley Earth (BKE) data set (Rohde et al., 2013).[8] These data are at a somewhat lower spatial resolution (1° grid) but cover recent years, which is important since my most recent data points come from 2020. Figure 2 shows daily maximum temperature on April 24, 1991, to illustrate the resolution of the temperature data. Precipitation data, as discussed above, are at an even higher resolution.

The firm locations provided by the World Bank are slightly randomly offset from the actual firm location to preserve data confidentiality. It therefore happens in some cases that firm locations are over the water, where CHIRPS and BKE do not cover them. For these cases, I use weather data for the closest firm that does not have this problem to interpolate the missing data.

### 1.3 Climate projections: NEX-GDDP-CMIP6

I obtain projections for future weather (that is, weather drawn from a changed climate) from the NEX-GDDP-CMIP6 data set (Thrasher, Wang, Michaelis, Melton, Lee, & Nemani, 2022; Thrasher, Wang, Michaelis, & Nemani, 2021). These are the results of the climate model runs that are part of the Coupled Model Intercomparison Project Phase 6 (CMIP6), downscaled to a higher resolution and bias corrected by the NASA Center for Climate Simulation. The data contain daily projections for temperature and precipitation, though I do not need them to accurately project temperature on any given day; I just need them to produce reasonable projections of expected weather patterns in future years.

I use projections for three different climate change scenarios; these scenarios are called Shared Socioeconomic Pathways (SSPs). Each SSP describes a different path for future climate change

[7] More information on CHIRPS is available at https://www.chc.ucsb.edu/data/chirps
[8] More information on BKE is available at https://berkeleyearth.org/data/

based on different assumptions about greenhouse gas emissions, population growth and international cooperation. The three different scenarios I consider, which are the most commonly used SSPs, are SSP1/2.6, which is a very optimistic scenario featuring climate change mitigation and sustainable development, SSP2/4.5, which is a middle of the road scenario featuring some mitigation, and SSP5/8.5, which features the most rapid climatic change.[9] Studying results for different SSPs allows me to incorporate deep uncertainty about the broad parameters governing the future path of climate change.

Beyond this deep uncertainty, the NEX-GDDP-CMIP6 data contain results for 27 different climate models for each SSP, featuring temperature and precipitation variables comparable to those from CHIRPS and BKE. These 27 different models reflect uncertainty about modeling climate even for a given broad climate trajectory. I combine all of these different models for a given SSP when projecting the causal impact of climate change in Section 4. My results therefore incorporate modeling uncertainty about future weather as well. See Appendix C for more detail on data processing for the weather projections.

Figure 3 shows the trajectory of yearly average daily maximum temperature in the actual data and across SSPs (taking the average across all models within each SSP). Starting in 2040, the differences between the three scenarios become apparent, with temperature rising fastest in SSP5/8.5, and plateauing (in fact slightly decreasing towards the end of the century) in SSP1/2.6.

### 1.4 Trade data

For international trade flows, I use the International Trade and Production Database for Estimation (ITPD-E). ITPD-E covers inter- and intranational trade across all sectors of the economy. It is designed to be used for the estimation of international trade models, especially gravity frameworks (Borchert, Larch, Shikher, & Yotov, 2021). ITPD-E is especially useful for me since it covers a broad range of countries, specifically across sub-Saharan Africa and South Asia, which other comparable databases do not always contain.

## 2 Motivating reduced-form evidence

This section documents two new stylized facts. First, weather shocks are primarily a supply shock (affecting firms' labor productivity), rather than a demand shock. Second, firms react to these

[9] See O'Neill et al. (2017) and Riahi et al. (2017) for more detail on the SSPs.

shocks by adjusting *productive capability* (complementary inputs such as rented machinery, rented space, or non-production personnel). These stylized facts are interesting in their own right, since they shed light on how firms cope with adverse weather shocks. They are also the key motivation for my modeling choices in Section 3.

### 2.1 Identification

I estimate regressions of the form

$$y_{jt} = \beta_1 x_{jt} + \gamma_{n(j)} + \delta_t + \varepsilon_{jt}$$

where $y_{jt}$ is an outcome for firm $j$ at location $n(j)$ at time $t$, measured over the preceding fiscal year, and $x_{jt}$ is a measure of weather at the firm's location over the preceding fiscal year. I include location fixed effects $\gamma_{n(j)}$ for identification, as explained below, and year fixed effects $\delta_t$ purely to gain precision in my estimates. To explore heterogeneity, I interact weather with firm characteristics $\mathbf{z}_{jt}$,

$$y_{jt} = \beta_1 x_{jt} + x_{jt}\mathbf{z}'_{jt}\boldsymbol{\beta}_2 + \mathbf{z}'_{jt}\boldsymbol{\beta}_3 + \gamma_{n(j)} + \delta_t + \varepsilon_{jt}$$

The key challenge to identification is that more or less productive firms could be more likely to be located in places with specific climates, such as hotter or colder places (e.g., Burke & Emerick, 2016). To overcome this threat, firm or location fixed effects can be used. These isolate random year-to-year variation in weather variables. I do not have panel data on firms, so I group firms into clusters based on geographic proximity (see below). I then average weather variables within each cluster-fiscal year combination. Conditional on cluster fixed effects, there is now no correlation between unobserved firm characteristics and weather shocks, because all firms in the same cluster at the same time receive the same weather shock.

An additional econometric challenge is correlation of errors across space, an issue raised for the historical persistence literature in Kelly (2020). Fortunately, I use variation over time rather than just cross-sectional variation across space. By choosing an appropriate clustering distance, I can ensure that errors are correlated within, but not across clusters. As a result, clustered errors are sufficient for correct inference.

I group firms into clusters using the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm, which I implement using the `Python` package `scikit-learn` (Pedregosa et al., 2011). This algorithm takes a distance parameter to determine core groups of firms that are located close to each other, and in a second step adds periphery firms to a cluster if they are close enough to a set of core firms. The key trade-off here is that large clusters introduce measurement error due to the averaging of weather variables over a larger group of firms. Small clusters, on the other hand, leave more firms out of any cluster altogether because they are not close enough to any other firms, dropping them from the analysis and reducing the sample size.

My preferred clustering distance is ten kilometers, since the fraction of firms included in any cluster plateaus at this distance, while the distance is still relatively small. Therefore, the measurement error induced by clustering at this distance should likewise be small. I also cannot reject the null that errors at this clustering distance are uncorrelated across clusters, alleviating concerns around spatial correlation of errors.[10]

To provide motivating evidence, the weather measure I use is a parsimonious indicator of adverse weather — an index of three variables, each of which is commonly used to measure temperature shocks or stress. The index combines (i) average temperature over the year, (ii) variance of temperature over the year and (iii) the number of days with temperatures exceeding 32°C (89.6°F). These are three different measures of how hot a year is or how much temperature varies over the year, and each has its strengths and weaknesses. Combining them into a single index provides a parsimonious combined measures of heat stress and general adverse weather conditions. To make the index components comparable, I calculate location-specific $z$-scores for each of the three components $d_{jt}$ as

$$\tilde{d}_{jt} = \frac{d_{jt} - \bar{d}_{jt}}{\sqrt{\widehat{\mathbb{V}}\left(d_{jt}\right)}}$$

where $\bar{d}_{jt}$ is the average of the variable at firm $j$'s location over the last 20 years and $\sqrt{\widehat{\mathbb{V}}\left(d_{jt}\right)}$ is the corresponding standard deviation.[11] The index is then just the average of the three $z$-scores.

To make the effect size more interpretable, I scale the index by its standard deviation across locations after partialling out cluster fixed effects. I use the standard deviation after removing fixed effects since that is the identifying variation my regressions use. Note that this of course does not affect significance of any of the estimates. It is simply a first step towards making the results easy

[10] See Appendix Table 13 for a formal test of error correlation at various clustering distances, as well as the fraction of firms with non-missing location information included in any cluster.

[11] Another advantage of the location-specific de-meaning is that, since my estimations include cluster fixed effects, I now effectively use deviations of location-specific shocks from a linear growth trend to identify the effects of weather shocks on firms, rather than relying purely on the randomness of weather shocks.

to interpret.

Figure 4 shows a histogram of the resulting standardized index after partialling out fixed effects. The figure also indicates the $20^{\text{th}}$ and $80^{\text{th}}$ percentiles of the variable. A one standard deviation weather shock in either direction is quite large — most shocks are smaller in absolute magnitude than this. To give a sense of scale, I therefore convert the one standard deviation effect sizes into $80^{\text{th}}$ percentile weather shocks, or 0.320 standard deviations, in the following discussion.

Note that, for these estimations, I am interested in the effect of *weather* over the year on firm outcomes. I do not want or need to separate out the impact of different components of weather (e.g., precipitation and temperature). A higher temperature index serves as an indicator of generally unfavorable weather conditions. For this reason, I do not control for other weather variables in these estimations.

Note also that I want a simple, parsimonious measure of what happens when weather conditions are unfavorable. Using a simple index means that I obtain simple to interpret regression results, which are a good indication of the first order impact of weather shocks. Later in the paper, when I turn to estimating the impact of climate change, I of course can no longer use this first order approximation, and need to take the complexity of climate more seriously. Accordingly, I use a different estimation approach once I turn to climate change in Section 4.

### 2.2 Results

This section presents reduced form estimation results. After briefly discussing the overall effect of weather on firms' sales, the section presents evidence for weather being primarily a supply (labor productivity) shock. It then shows that firms react to this shock by adjusting expenditures on productive capability.

#### 2.2.1 Overall effect of weather on firms

Table 2 shows the effect of weather on firms' log total sales. An $80^{\text{th}}$ percentile weather shock leads to a 7.1 percent decline in total sales. This is statistically different from zero at the ten percent level, and an economically meaningful impact. Appendix Table 14 contains a version of this regression including a one year lead of the temperature index. Results show that the lead does not have a significant effect on contemporary outcomes. This suggests that firms do not perfectly anticipate future weather shocks. This pattern is consistent with the core identifying assumption — contemporary weather shocks are as good as random.

### 2.2.2 Weather is a supply shock

To understand how firms react to weather shocks, I first need to know whether weather is, on net, a demand or supply shock. This is required since firm reactions to either kind of shock could differ markedly. We know that weather shocks affect local demand (Santangelo, 2019), but we also have evidence that they have a supply-side effect, since they affect firms' marginal cost (Nath, 2020; Somanathan et al., 2021; Zhang et al., 2018). The question I want to answer is, does one of the two channels — the demand or supply side impact of weather shocks — dominate?

If I had detailed price data, I could use these to test this. I do not, however, have those data. Instead, I rely on a basic open economy intuition: If weather is predominantly a demand shock, then exporters should be less affected by it, since they have access to a foreign source of demand that is insulated from the local shock. If weather is predominantly a supply shock, on the other hand, they should see a larger effect. This is because in the domestic market, firms can pass on some of the marginal cost increase to local consumers. Internationally, however, it is harder to pass on cost increases. This could be, for example, because competition is tougher.[12] Figure 5 shows a simple graphical version of this intuition. It shows the marginal cost and domestic and international marginal revenue curves faced by a firm in a small open economy. Marginal cost is identical across markets. While the firm has some market power domestically, it takes world prices as given. Therefore, the domestic marginal revenue curve slopes down, but the international marginal revenue curve is flat. An increase in marginal cost then leads to a larger response for international than for domestic sales. This is because domestically, the firm can pass on part of the marginal cost increase via prices, but internationally it cannot, and has to react via quantities. Exporters therefore see a larger relative reduction in total sales in response to a supply shock.

Accordingly, I test whether weather shocks are primarily a demand or supply side issue by testing whether exporters see a larger or smaller effect of weather shocks on total sales. Table 3 shows that purely domestic firms see a 4.0 percent decline in total sales in response to an 80$^{\text{th}}$ percentile weather shock, while currently exporting firms see a 7.0 percent decrease, with the difference significant at the one percent level. Appendix A.5 shows that this significant exporter

[12] One might think that in a monopolistic competition model such as Melitz (2003), pass-through is the same in all markets. Even in that model, however, exporters will respond to a negative productivity shock by reducing total sales more than non-exporters. This is because of fixed costs of accessing different markets. As long as some of those costs need to be paid every period, an exporter that receives a negative productivity shock will not find it worthwhile to keep selling to all of the markets is was previously active in. When the exporter chooses to leave markets in response, this leads to a discontinuous fall in sales. Non-exporters do not see this effect, unless their productivity shock is so extreme that they leave the domestic market entirely.

interaction term is not sensitive to using alternative ways of measuring exporter status (for example, using past exporter status instead of current exporter status). The estimate of the base effect for domestic producers is somewhat noisy, but as Section 4 shows, using estimation methods that can fully capture the complexity of weather data, I do estimate a significant overall effect of weather on firm performance.[13] The key takeaway is that the supply effect of weather shocks outweighs their demand effect. I do not take a stance on the exact channel through which weather affects firm productivity, but Appendix D lays out several well-documented channels as well as supporting evidence from my data.

One concern here is survival bias: It could be that the least productive domestic firms shut down and disappear from the data, thus not reporting their reduced sales, while the least productive exporters do not have to shut down, and thus report their reduced sales. This would lead to larger observed impacts on exporters. I cannot observe exit directly, though I can see firms reporting extremely low, even zero sales. (This is not the same as shutting down, but it is the best proxy I have.) To do my best to address this issue, Appendix Table 15 shows a regression of a 'zero sales' indicator on the temperature index, showing no significant effect. (Since I only observe six instances of literally zero sales in the data, the indicator actually captures firms reporting total sales below the first percentile of total sales.) The table also shows results for a regression of exporter status on the temperature index. If survival bias were a concern, I should see a higher fraction of exporters as a result of negative weather shocks. If anything, though, I find somewhat fewer firms being exporters as a result of extreme weather. (This second result is not robust to excluding the year fixed effects, however — without the fixed effects, there is no significant effect.) Either way, the fraction of exporters certainly does not increase, suggesting that domestic firms do not differentially exit in large numbers. Both of these results help to alleviate the concern of survival bias.

#### 2.2.3 Firms adjust spending on productive capability in response

Since weather is a supply shock, I focus on an obvious reaction to a decline in labor productivity: Scaling back expenditures on productive capability, because it is complementary with labor productivity. As I explained in the introduction, productive capability comprises rented machinery, rented space or non-production personnel. For example, it includes rented machinery, rented office space, or a sales team. These kinds of expenditures make up about 8.5 percent of non-exporters' and 10.9

[13] To highlight that year fixed effects are present purely to increase precision, and do not affect point estimates much, Appendix Table 16 shows an estimation without year fixed effects. Results for the effect on non-exporters are much less precise. The exporter interaction term remains highly significant and similar in magnitude, however.

percent of exporters' total cost, so they are quantitatively relevant to firms. Since they are rented or hired, rather than owned, they could in principal be adjusted in the short run, as a reaction to supply shocks.

Productive capability improves overall performance across all markets a firm is active in, by increasing labor productivity (through providing workers with sufficient equipment or space) or by making it easier to sell the firm's output (e.g., by reducing transaction cost). Put differently, productive capability lowers the cost of providing the firm's output across all markets the firm is active in. Faced with a negative supply shock, firms scale back expenditures on productive capability, since these kinds of productivity-enhancing inputs are complementary to firm productivity. (That is, when workers on the production line have a difficult time producing goods, members of the sales team, for example, are also less valuable to the firm — they have fewer goods to sell.) This adjustment is rational from the firm's perspective, but it further reduces labor productivity. In that sense, it exacerbates (goes in the same direction as) the impact of the supply shock. A key implication is that sales across all markets the firm is active in fall even further as a result of this input adjustment, compared to how much they would fall as a result of a negative supply shock alone. I now present reduced form evidence showing that (i) this productive capability reaction is visible in the data, (ii) spillovers to sales across all markets (a core implication of this reaction, as I just explained) are visible in the data, and (iii) productive capability adjustments mediate (i.e., explain) these spillovers.

First, I check for productive capability reactions in the data — due to the richness of the Enterprise Surveys data, I can observe these adjustments directly. Specifically, I measure productive capability expenditures by adding up the cost of communications, sales (including sales staff), transportation, and rent for buildings, equipment and land. Table 5 shows the effect of weather shocks on productive capability expenditures by exporter status. I see a 1.6 percent decrease in productive capability expenditures for domestically active firms in response to an $80^{\text{th}}$ percentile weather shock, but a significantly larger 5.3 percent decrease for exporters. This is consistent with the previous results that exporters reduce their overall sales more in the face of these supply shocks than non-exporters — accordingly, to exporters, these complementary inputs become even less valuable than to non-exporters.[14]

[14] A potential worry could be that weather shocks lead firms to report a lower valuation of their productive capability, even though they have not reduced its physical quantity. Appendix Table 21 shows, however, that weather has no effect on firms' valuation of their stock of machinery, where I should see that same effect at play if it mattered. This suggests the productive capability effect I find is due to a reduction in its quantity, rather than just due to a change in reported valuation. This also shows that, though firms might adjust capital they *own* in response to

Because questions on firms' detailed cost breakdowns required to measure productive capability are not included in all rounds of the Enterprise surveys, this analysis has to rely on a sub-sample of firms. Nevertheless, it provides direct evidence of productive capability adjustments in the face of negative weather shocks. Furthermore, the results are consistent with the supply shock intuition I find above — exporters scale back these complementary inputs considerably more than non-exporters in response to negative weather shocks.

A key implication of productive capability being complementary with labor productivity is that this reduction in productive capability should feed through into a decline in productivity. I cannot measure productivity directly, but I can use sales per employee as a proxy for productivity. The second column of Table 5 shows that sales per employee see a significantly larger relative decline for exporters compared to non-exporters. I estimate a 2.7 vs. 1.1 percent decline in response to an 80$^{\text{th}}$ percentile weather shock. While not a perfect proxy for productivity, this at least provides suggestive evidence that exporters see larger productivity decreases in response to weather shocks. Exporters' larger reductions in productive capability therefore indeed seem to translate into larger productivity declines as well.

Second, as explained above, adjustments in productive capability should lead to spillovers on sales across all markets firms are active in. I do not have detailed data on which exact markets firms are selling to, but I *can* differentiate between domestic and international sales. Why is this distinction useful? Weather shocks being supply shocks explains why exporter should see larger declines in *total* sales due to weather shocks: they cannot easily pass these shocks on to their international customers via prices, and instead have to react via quantities. Accordingly, exporters also scale back productive capability more, which then causes a larger decline in productivity for exporters compared to non-exporters as well. This should create a spillover effect and lead to a larger decline in *domestic* sales as well — exporters should see larger declines in domestic sales than non-exporters, due to their productive capability adjustments. Table 4 shows a regression of purely domestic sales on weather shocks by exporter status. Indeed, exporters' domestic sales also see a larger decline in response to negative weather shocks. Non-exporters see a 6.0 percent decline in domestic sales in response to an 80$^{\text{th}}$ percentile weather shock, but exporters see an 8.2 percent decrease. I thus find that this key implication of productive capability adjustments — spillovers to sales in all markets — is present in the data as well.

*climate change*, i.e., in the longer term, they do not adjust owned capital in response to *weather shocks*, i.e., in the short run. Owned capital adjustments are thus not driving the results I find in this paper.

Finally, I do my best to check whether this spillover to domestic sales is indeed *caused by* exporters adjusting their productive capability more. Table 6 shows a mediation analysis which adds log productive capability expenditures, fully interacted with exporter status and the temperature index, to the domestic sales regression from Table 4. The interaction between exporter status and the temperature index flips sign and is longer statistically significantly different from zero, even at the ten percent level. (I de-mean log productive capability expenditures, so all coefficients shown are evaluated at mean log productive capability.) Since mediation analyses like this one add clearly endogenous regressors, I am careful in over-interpreting these results. Nevertheless, this strongly suggests that it is *because* of their productive capability cutbacks that exporters see a larger decline in domestic sales in response to weather shocks.[15]

### 2.3 Alternative explanations for differential impact on exporters' sales

Of course, exporters are different from other firms in many ways; Table 7 shows a comparison of exporting and non-exporting firms' characteristics. Exporters have higher averages sales (≈USD 1,800,000 compared to ≈USD 660,000 for non-exporters), more employees (≈44 compared to ≈20), are more likely to be in manufacturing (47 percent of exporters are in manufacturing, compared to 28 percent of non-exporters), are more likely to use international quality certifications (28 percent compared to 10 percent) and have more experienced managers (≈15 years of experience compared to ≈13).

It could be that these differences simply make exporters more susceptible to weather shocks, explaining the larger impact on sales seen in Table 3. To address this concern, I run an extensive battery of robustness checks that regress log total sales on the temperature index interacted with exporter status and additionally interacted with other firm characteristics, plus base effects for those characteristics. If it were the case that differences in another firm characteristic are the true underlying cause of the differential impacts I find, I would expect that once I include that characteristic in the regression, the interaction between exporter status and weather shocks should lose significance and/or see a drastically smaller point estimate. I find that neither happens for any of the three alternative hypotheses I describe in the rest of this section. Appendix Table 23 summarizes all related robustness checks.

First, exporters tend to be large firms, which could be more reliant on short-term hired labor that

[15] Table 22 shows the domestic sales regression using only firms with non-missing log productive capability data. The pattern of coefficients remains unchanged, though the estimates are noisier. Clearly, the mediation analysis changes the exporter coefficient substantially even when compared to results only for this sub-sample of firms.

can get drawn into agriculture when negative weather shocks hit (Santangelo, 2019); accordingly, I check whether the initial number of employees or the number of employees three years ago can explain the exporter effect. Second, since exporters are more likely to be in large-scale manufacturing, where temperature control can be a problem (Adhvaryu et al., 2019), I control for two- and four-digit ISIC sectors, fully interacted with weather shocks. This also addresses concerns around an effect through input prices — if it were true that exporters simply use a different import structure due to the sector they are active in, I would expect firms in similar sectors to face the same issue. Third, exporters could potentially be using more complex production processes (Costinot, 2009), so I control for measures of complexity: whether a firm has an international quality certification, the firm's ownership structure, and the manager's years of experience. None of these alternative hypotheses alone can explain the different effects for exporters, and I find that weather has a differential impact on exporters even when including them all in the regression at once.[16]

I conclude from this that the effects I find are not due to a correlate of being an exporter, but are instead driven by weather being a supply shock and firms reacting to negative supply shocks by adjusting complementary inputs, i.e., by adjusting productive capability. As I show in Section 3, a simple extension of Melitz (2003) allowing firms to hire productive capability immediately yields the reduced form comparative statics I highlighted. This provides a parsimonious explanation of the patterns I see in the data, including the greater decrease in productive capability for exporters seen in Table 5, the spillovers to domestic sales seen in Table 4 and the results of the mediation analysis in Table 6.

# 3 Model

This section develops an international trade model which captures the core reduced form results from the previous section: (i) the greater impact of productivity shocks on exporters' total sales, (ii) the resulting adjustment in productive capability being larger for exporters, and (iii) this adjustment causing a differential impact on domestic sales. The model is a variant of Melitz (2003). The core mechanism I add is exactly the key mechanism I discuss in the previous section: firms' ability to hire productive capability, such as rented machinery, rented office space, or non-production personnel.

[16] A final concern would be differential measurement error for exporters and non-exporters. To rule out this possibility, I estimate the main regression using only data on firms coming directly from the firms' books. Appendix Table 17 shows the results. Due to the greatly reduced sample size, point estimates become noisier but remain very similar to my main results. If the main results were driven by differential measurement error, I would expect the point estimate for the exporter differential to be close to zero. As it stands, I could not reject that the estimate using numbers only from books is the same as the point estimate I find using my main estimation sample.

I show that this allows the model to explain the greater impact of productivity shocks on both exporters' total and domestic sales, while the standard Melitz (2003) model can only explain the greater impact on exporters' total sales.

### 3.1 Demand

There are $N$ countries. A mass of goods $\mathcal{G}_n$ is available in country $n$. Consumers in $n$ have CES preferences with elasticity of substitution $\sigma$, a budget of $X_n$, and solve

$$\max_{\{q_n(j)\}} \left( \int_{\mathcal{G}_n} q_n(j)^{\frac{\sigma-1}{\sigma}} \, \mathrm{d}j \right)^{\frac{\sigma}{\sigma-1}} \text{ s.t. } X_n = \int_{\mathcal{G}_n} q_n(j) p_n(j) \, \mathrm{d}j \tag{1}$$

This yields quantity demanded as

$$q_n(j) = \underbrace{X_n \mathcal{P}_n^{\sigma-1}}_{\equiv \alpha_n} p_n(j)^{-\sigma} = \alpha_n p_n(j)^{-\sigma} \tag{2}$$

where

$$\mathcal{P}_n \equiv \left( \int_{\mathcal{G}_n} p_n(j)^{1-\sigma} \, \mathrm{d}j \right)^{\frac{1}{1-\sigma}}$$

is the optimal price index in $n$. I introduce the shorthand $\alpha_n$ to denote demand factors. These depend on total expenditures and the price index in country $n$. From the perspective of firms selling in market $n$, a higher $\alpha_n$ translates into higher sales in that market at any given price they charge there, either because total expenditure in $n$ is large, or because other products in $n$ tend to be expensive, lowering the firm's relative price.

### 3.2 Supply

Firms are located in their home country $i$ and export to other countries $n$. Each country has an infinite mass of potential entrants. Firm $j$, producing the proprietary variety $j$, is characterized by its *core productivity* $a_j \sim F_i$, drawn from a country specific distribution. I adapt the framework of Hyun and Kim (2022), which is an extension of Melitz (2003). They allow firms to choose a common quality level (a demand shifter) across all markets they are active in.[17] Instead of linking decisions

[17] Using their model as-is and focusing on quality choices could explain the differential impact I see on exporters. I cannot, however, observe quality in the data, while I can measure productive capability. My reduced form results suggest productive capability explains the differential exporter effect, which suggests these are first order responsible for the patterns I observe in the data. Accordingly, I model that channel of adjustment here, rather than quality

across markets via demand, however, I let firms hire productive capability $c_j$. (As a simplifying assumption, I assume productive capability is hired labor, though it represents factors like rented machinery, rented office space, or non-production personnel.) Additional productive capability makes it cheaper to provide goods in all markets. This links firm choices, including market entry decisions, across markets. The cost of acquiring $c_j$ is $b\beta c_j^{\frac{1}{\beta}}$ and measured in units of labor in $i$. Firm $j$, active in a set of markets (countries) $\mathcal{M}_j$, has *total productivity* $a_j c_j^{\delta}$ and incurs variable cost

$$v\left(\{q_n(j)\}\right) = \sum_{n \in \mathcal{M}_j} d_{ni} q_n(j) \frac{w_i}{a_j c_j^{\delta}}$$

which also includes an iceberg trade cost $d_{ni}$ and the wage $w_i$. Note that Hyun and Kim (2022) focus on domestic firms, so their model does not feature an iceberg cost. The firm's profit maximization problem is

$$\begin{aligned} &\max_{\{p_n(j), q_n(j)\}, c_j, \mathcal{M}_j} \left[\sum_{n \in \mathcal{M}_j} p_n(j) q_n(j) - d_{ni} q_n(j) \frac{w_i}{a_j c_j^{\delta}} - f_{ni} w_i\right] - b\beta c_j^{\frac{1}{\beta}} w_i - f_i w_i \\ \overset{(2)}{\Leftrightarrow} &\max_{\{p_n(j)\}, c_j, \mathcal{M}_j} \left[\sum_{n \in \mathcal{M}_j} \alpha_n p_n(j)^{1-\sigma} - d_{ni} \alpha_n p_n(j)^{-\sigma} \frac{w_i}{a_j c_j^{\delta}} - f_{ni} w_i\right] - b\beta c_j^{\frac{1}{\beta}} w_i - f_i w_i \end{aligned} \tag{3}$$

plugging in for consumers' optimal quantity choices to simplify the problem. Unlike Hyun and Kim (2022) I explicitly consider market entry and exit, so I include a fixed cost $f_{ni}$, measured in units of labor, for operating in each market, as in Melitz (2003). These fixed costs are costs that need to be paid every period in order to retain market access, so they include things like maintaining an export license, maintaining relationships with buyers, and maintaining any certifications required by the destination country. I do not explicitly model dynamics because that would make the model intractable without gaining much insight — productive capability is hired rather than owned, so related decisions are not linked across periods.

I assume no entry or iceberg cost for the domestic market ($f_{ii} = 0$ and $d_{ii} = 1$) for simplicity — it makes the model computationally easier to solve. I further include a fixed start-up cost $f_i$, also measured in units of labor, which entrants have to pay once to discover their core productivity $a_j$, again as in Melitz (2003). For a given $c_j$, optimal prices $p_n(j)$, quantities $q_n(j)$ and sales $S_n(j)$ for

adjustments.

firm $j$ in market $n$, as well as profits across all markets $\pi(j)$, follow from first order conditions as

$$p_n(j) = \underbrace{\frac{\sigma}{\sigma - 1}}_{\equiv \mu} d_{ni} \frac{w_i}{a_j c_j^{\delta}} \tag{4}$$

$$q_n(j) = \alpha_n \left( \mu d_{ni} \frac{w_i}{a_j c_j^{\delta}} \right)^{-\sigma} \tag{5}$$

$$S_n(j) = \alpha_n \left( \mu d_{ni} \frac{w_i}{a_j c_j^{\delta}} \right)^{1-\sigma} \tag{6}$$

After solving for prices and quantities, the FOC for the optimal productive capability choice gives[18]

$$c_j = \left[ \frac{1}{b} \delta (\mu w_i)^{-\sigma} a_j^{\sigma-1} \left( \sum_{n \in \mathcal{M}_j} {d_{ni}}^{1-\sigma} \alpha_n \right) \right]^{\frac{\beta}{1-\beta(\sigma-1)\delta}} \tag{7}$$

Analogous to Hyun and Kim (2022), the parameter restrictions to ensure an interior solution are $\sigma > 1$, which is a standard CES assumption and ensures that goods are substitutes, $\delta > 0$, which ensures that additional productive capability decreases marginal cost, and $\beta (\sigma - 1) \delta < 1$, which ensures that the optimal $c_j$ is finite, because the increase in the cost of acquiring productive capability outpaces the decrease in marginal cost. As I discuss in Section 3.5, I find that these restrictions are fulfilled in the data.

### 3.3 Productive capability enables reproducing domestic sales result

Recall from Section 2 that weather shocks are, primarily, supply shocks, and thus have a larger impact on exporters' total sales, compared to non-exporters. Due to productive capability adjustments, this spills over into a larger impact on exporters' *domestic* sales as well. I now show that my model yields comparative statics matching these reduced form results.

Let firm $j$ in country $i$ experience a shock shifting its core productivity to $a_j' < a_j$. This shock affects only firm $j$, leaving all others firms' productivities unchanged. Then, compare what firm $j$ would have done prior to the shock to what it does when faced with the shock. Let ${\mathcal{M}_j}' \subseteq \mathcal{M}_j$ denote the set of markets the firm is active in after the shock. Using primes to denote post-shock

[18] Detailed derivations for this and all following results can be found in Appendix E.

variables, the relative decline in *domestic* sales is

$$\frac{S_i(j)'}{S_i(j)} \overset{(6)}{=} \left(\frac{a_j' {c_j'}^{\delta}}{a_j c_j^{\delta}}\right)^{\sigma-1} \overset{(7)}{=} \left[\left(\frac{a_j'}{a_j}\right)\left(\frac{\sum_{n\in\mathcal{M}_j{}'} {d_{ni}}^{1-\sigma}\alpha_n}{\sum_{n\in\mathcal{M}_j} {d_{ni}}^{1-\sigma}\alpha_n}\right)^{\beta\delta}\right]^{\frac{\sigma-1}{1-\beta(\sigma-1)\delta}}$$

Note that the parameter restrictions ensure the outermost exponent is positive. Note also that none of the $\alpha_n$ change as a result of the shock to firm $j$, because firm $j$ has zero mass. An idiosyncratic shock to only firm $j$ therefore does not affect aggregate demand factors in market $n$.

The first term in parentheses depends solely on the change in core productivity $a_j$, and is less than one by assumption. For a given relative reduction in productivity $a_j'/a_j$, both an exporter and a purely domestic firm would see the same impact on domestic sales from this term. The second term in parentheses, however, depends on the change in active markets $\mathcal{M}_j$, and is present only because the firm's optimal productive capability depends on the set of active markets. This term thus represents an indirect effect of the core productivity shock which operates through productive capability adjustments: If lower core productivity leads the firm to exit some markets it was previously active in, it will scale back productive capability, which will further reduce its total productivity, and hence reduce its domestic sales. For purely domestic producers, $\mathcal{M}_j{}' = \mathcal{M}_j$, since they will not exit altogether given that $f_{ii} = 0$, and the second term is equal to one. For exporters, though, their profit in some markets may now be below the fixed cost of entry for the period $f_{ni}$, leading them to exit the market. That means $\mathcal{M}_j{}' \subset \mathcal{M}_j$, so the second term in parentheses is smaller than one, exacerbating the effect of the shock and leading to a larger relative decline in domestic sales. (The firm will similarly see a larger relative decline in total sales.)

This model therefore generates the comparative statics I observe in the data. The standard Melitz (2003) model, in contrast, generates only the comparative static for total sales. Recall that in that model, total and core productivity are identical — there is no productive capability. When an exporter leaves a market following a productivity shock, they see a discontinuous drop in *total* sales. This leads to a larger relative decline in *total* sales for the exporter compared to a non-exporter. For *domestic* sales, however, exporters and non-exporters see the exact same relative decline, as long as they face the same relative productivity shock $a_j'/a_j$. This is because the productivity shock only has a direct effect on domestic sales. There is no additional indirect effect via productive capability adjustments.

## 3.4 Equilibrium

I now provide a definition of an equilibrium for this model. I then show how to find an equilibrium. Some of the formal statements of equilibrium conditions follow in the section below, after the equilibrium definition.

**Definition 1** *For a given a CES elasticity $\sigma$, start-up costs $f_n$, entry costs $f_{ni}$, iceberg trade costs $d_{ni}$, cost parameters $b$, $\beta$ and $\delta$, and core productivity distributions $F_i$, an equilibrium for this model is a set of prices $p_n(j)$, quantities $q_n(j)$, productive capabilities $c_j$, active markets $\mathcal{M}_j$, masses of entrants $N_n$ and active firms $n_n$, incomes $X_n$ and wages $w_n$ such that, for all firms $j$ and all countries $n$,*

- *Consumers are maximizing utility* (1)
- *Firms are maximizing profits* (3)
- *Expected profits prior to entry are zero in all countries* (8)
- *Labor supply $L_n$ equals labor demand in all countries* (9)
- *Income equals expenditure in all countries, i.e. trade is balanced* (10)

### 3.4.1 Optimal choice of active markets

The first step in finding the equilibrium is determining active markets $\mathcal{M}_j$ for each firm, for a given set of demand factors $\alpha_n$. This is a high-dimensional combinatorial problem. Antràs, Fort, and Tintelnot (2017) confront a similar problem when modeling input sourcing and use the algorithm developed by Jia (2008). This works by first finding an upper bound on $\mathcal{M}_j$ by assuming the firm is active in all $N$ markets and determining whether leaving an individual market $n$ would increase firm profits. If so, as Jia (2008) shows, $n$ cannot be part of the optimal set of markets. A similar procedure yields a lower bound, starting from the firm being active in no markets at all and checking where entry increases profits. To find the optimal $\mathcal{M}_j$, one would then calculate profits across all combinations of markets between the bounds (all combinations of the markets which are present in both the lower and upper bound).

In my setting, I can use a more computationally efficient algorithm for finding upper and lower bounds, however. To find an upper bound, start by assuming the firm is active in all markets, and set that as the initial $\mathcal{M}'_j$. Then,

1. Calculate $c_j$ if the firm were active in $\mathcal{M}'_j$ and calculate variable profits in each market, that is, sales in each market minus variable cost and the entry cost $f_{ni}$ (ignoring the cost of $c_j$)

2. Drop all markets where the firm would be earning negative variable profits from $\mathcal{M}'_j$, and use those where it makes weakly positive profits as the new $\mathcal{M}'_j$

Iterate until the firm makes weakly positive variable profits in all markets in $\mathcal{M}'_j$. This gives the upper bound $\mathcal{M}^{\text{ub}}_j$. See Appendix E.3 for a proof that this is an upper bound.

To find a lower bound, start by assuming the firm is active only at Home, and set that as the initial $\mathcal{M}'_j$. (Since I assume $f_{ii} = 0$, firms will always be active in the Home market.) Then,

1. Calculate $c_j$ if the firm were active in $\mathcal{M}'_j$ and calculate variable profits in each market, that is, sales in each market minus variable cost and the entry cost $f_{ni}$ (ignoring the cost of $c_j$)

2. Add all markets where the firm would be earning positive variable profits to $\mathcal{M}'_j$, and use these plus the markets in $\mathcal{M}'_j$ as the new $\mathcal{M}'_j$

Iterate until the firm cannot enter additional markets where it would make weakly positive variable profits when $c_j$ is chosen optimally under $\mathcal{M}'_j$. This gives the lower bound $\mathcal{M}^{\text{lb}}_j$. See Appendix E.2 for a proof that this is a lower bound.

In simulations, I find both bounds in many fewer steps than I can find the bounds from Jia (2008). This is largely because finding the bounds from Jia (2008) always requires as many steps as there are markets, whereas my bounding algorithms can often exclude or include multiple markets in one step. I also find that my bounds are usually tighter than those from Jia (2008) for my setting. Both of these factors speed up computation considerably.

Having found the bounds, I know the optimal set of active markets for all firms with $\mathcal{M}^{\text{lb}}_j = \mathcal{M}^{\text{ub}}_j$. In practice, I find this is the case for the majority of firms. For firms where the bounds do not coincide, I could check all possible combinations of markets in between the two bounds. Unfortunately, unlike Antràs et al. (2017), I find that the cardinality of that difference can be large. Though most firms only need to decide between a few markets, some have over 100 different markets (on the order of $10^{30}$ combinations) to choose from. Therefore, I cannot feasibly solve the optimal market entry problem by checking profit across all combinations of markets between the bounds.

Instead of searching over sets of active markets $\mathcal{M}_j$ and determining the optimal profit for each set, I invert the problem. I search across $c_j$ (productive capability) to find optimal profits across possible choices of productive capability. Determining $\mathcal{M}_j$ for a given $c_j$ is easy, since with a known total productivity, market entry decisions just boil down to Melitz (2003): Firms enter markets in which they make a variable profit (markets where sales exceed variable cost plus the entry cost). The lower and upper bounds for markets the firm could be active in, $\mathcal{M}_j^{\text{lb}}$ and $\mathcal{M}_j^{\text{ub}}$, also yield lower and upper bounds on $c_j$, since as firms increase $c_j$, they only ever enter additional markets; they do not exit markets they are already active in. (Leaving a market the firm is making positive variable profit in cannot increase its total profit for a given $c_j$.) The $c_j$ the firm would optimally choose if it were active in $\mathcal{M}_j^{\text{lb}}$ thus is a lower bound on the optimal $c_j$, and similarly the optimal $c_j$ at $\mathcal{M}_j^{\text{ub}}$ yields an upper bound. I then simply conduct a grid search between those two bounds. Once I have found the $c_j$ that maximizes profits, I get the associated set of activate markets $\mathcal{M}_j$ and re-calculate the optimal $c_j$ for that set of markets, to further increase precision on the firm's true optimal choice of $c_j$.

The core feature of my model that enables me to use more efficient bounds and a more efficient algorithm for optimization between bounds is that the link between entering or exiting different markets is due to an optimal firm decision on $c_j$. This creates a way of sorting all markets along a scalar dimension, $c_j$, and do a grid search along that dimension.

### 3.4.2 Remaining equilibrium objects

To determine $\alpha_n$, I turn to the free entry condition for country $i$. It states that expected profits before paying the fixed start-up cost $f_i$, required to discover core productivity, should be zero. Let $\underline{a}_i$ denote the least productive firm that finds it profitable to operate in country $i$ (instead of shutting down after discovering $a_j$), then the free entry condition is

$$f_i w_i = \int_{\underline{a}_i}^{\infty} \frac{1}{\sigma}\left(\mu \frac{w_i}{a_j {c_j}^{\delta}}\right)^{1-\sigma}\left(\sum_{n\in\mathcal{M}_j} d_{ni}^{1-\sigma}\alpha_n\right) - \left(\sum_{n\in\mathcal{M}_j} f_{ni}\right) w_i - b\beta c_j^{\frac{1}{\beta}} w_i \; \mathrm{d}F_i\left(a_j\right) \tag{8}$$

The integral cannot be solved analytically because it depends on the sets of active markets $\mathcal{M}_j$ (directly but also, non-linearly, through $c_j$). These sets are a function of $a_j$ and (being sets) do not have an easily computable antiderivative. This condition nevertheless pins down the equilibrium $\alpha_n$ terms, given wages and sets of active markets.

The full employment condition for country $i$ yields the mass of entrants

$$N_i = \frac{\mu^{\sigma-1} w_i^{\sigma} L_i}{\int_{\underline{a}_i}^{\infty}\left(a_j c_j^{\delta}\right)^{\sigma-1} \sum_{n\in\mathcal{M}_j} d_{ni}^{1-\sigma}\alpha_n \; \mathrm{d}F_i\left(a_j\right)} \tag{9}$$

which can be used to find the mass of active firms $n_i = [1 - F_i(\underline{a}_i)] N_i$. To derive the gravity equation, I first calculate the price index for country $n$ as

$$\mathcal{P}_n = \mu \left( \sum_{i=1}^{N} n_i (d_{ni} w_i)^{1-\sigma} \int_{\underline{a}_{ni}}^{\infty} \left( a_j c_j^{\delta} \right)^{\sigma - 1} \mathrm{d}F_i(a_j) \right)^{\frac{1}{1-\sigma}}$$

Plugging this into aggregate trade flows from $i$ to $n$ leads to the gravity equation

$$X_{ni} = \frac{n_i (d_{ni} w_i)^{1-\sigma} \int_{\underline{a}_{ni}}^{\infty} \left( a_j c_j^{\delta} \right)^{\sigma-1} \mathrm{d}F_i(a_j)}{\sum_{k=1}^{N} n_k (d_{nk} w_k)^{1-\sigma} \int_{\underline{a}_{nk}}^{\infty} \left( a_j c_j^{\delta} \right)^{\sigma-1} \mathrm{d}F_k(a_j)} X_n \tag{10}$$

where $\underline{a}_{ni}$ is the least productive firm from $i$ selling in $n$. This looks similar to the typical gravity structure, but the integrals of total productivity across producers selling from $i$ to $n$ again cannot be solved analytically. The gravity equation nevertheless pins down wages, closing the model with world GDP as the numeraire.

## 3.5 Estimation

### 3.5.1 Reduced form

I follow the common practice of assuming that core productivities come from a Pareto distribution with shape parameter $\theta$, shifted by a country-specific scale parameter $T_i^{\frac{1}{\theta}}$, where $T_i$ captures differences in technology across countries. I simulate firm productivities using draws $u_j$ from a uniform distribution on $(0, 1]$, since

$$u_j = T_i a_j^{-\theta}$$

is uniformly distributed and can be used to back out $a_j$ given the dispersion parameter and technology shifters (Eaton, Kortum, & Kramarz, 2011).

Following Eaton et al. (2011), I estimate $\sigma$ based on the ratio of firms' sales to their variable costs. Variable costs include the cost of labor, raw materials, fuel, water, electricity, goods for resale, and other costs of production. I first calculate the mark-up for each firm and then use the average across firms to calibrate $\sigma$, which yields $\hat{\sigma} = 3.016$ with a standard error of 0.043. Table 8 shows estimates for all parameters of the structural model.

Next, I turn to the parameters governing firms' optimal productive capability, $\beta$ and $\delta$. Log sales in firm $j$'s home market $i$ can be written as

$$\log\left(S_i(j)\right) = I + \log\left(\alpha_i\right) + (\sigma - 1)\log\left(a_j\right) - (\sigma + \beta\delta - 1)\log\left(w_i\right) + (\sigma - 1)\,\beta\delta\log\left(\mathcal{S}(j)\right) \tag{11}$$

with $I$ a constant. This shows that the elasticity of home market sales with respect to total sales identifies $\beta\delta$ for a known $\sigma$. I make the simplifying assumption that $\beta = \delta$ to ease the computational burden during the structural estimation described below. $\beta$ and $\delta$ both discipline firms' choices of productive capability $c_j$, and in simulations, equilibrium wages and welfare depend only on the product of both parameters.

I can then directly estimate $\delta$ and $\beta$ by regressing log home market sales on log total sales, country-year fixed effects (to deal with $\alpha_i$ and $w_i$) and proxies for core productivity $a_j$. I proxy for core productivity using country-sector-year fixed effects (obviating the need for country-year fixed effects), the manager's years of experience, log initial number of employees, log number of employees three years ago, whether the firm uses an international quality certification, whether the firm experienced power outages, whether the firm competes against the informal sector, whether the firms introduced a new product or service during the last three years, whether the firm introduced a new process during the last three years, whether the firm had any R&D expenditures, whether the firm is part of a larger firm, whether the firm was formal when it was founded, whether the firm applied for an electricity connection over the last three years, whether the firm applied for a water connection over the last three years, the firm age, and legal status indicators. To allow for more flexibility in the estimation, I add all pairwise interactions between these productivity proxies, as well as adding fourth-degree polynomials of each continuous variable.

I estimate (11) using only data on exporters, since purely domestically active firms mechanically yield an elasticity of one (their home sales and total sales are identical); see Appendix Table 24 for a summary of the results. Since the estimate for $\beta\delta$ depends on $\hat{\sigma}$, I obtain its standard error via a pairs bootstrap, estimating $\sigma$ and $\beta\delta$ for 999 bootstrap samples. I find $\widehat{\delta\beta} = 0.388$ with a standard error of 0.016, which results in $\hat{\delta} = \hat{\beta} \approx 0.623$. Regardless of the assumption that $\beta = \delta$, these parameter estimates satisfy the crucial restriction that $\beta(\sigma - 1)\delta < 1$, ensuring an internal solution for firms' productive capability $c_j$.

Finally, I need to fix the productive capability cost shifter $b$. This is not separately identified from the technology shifters $T_i$, because making productive capability cheaper has the same effect as shifting core productivity. I assume that $b = 1$ to resolve this set identification problem. The interpretation of this assumption is simply that workers can do production work and non-production (e.g., administrative) work equally well.

### 3.5.2 Small open economy estimation

All remaining parameters — technology shifters $T_i$, the technology scale parameter $\theta$, start-up costs $f_i$, iceberg costs $d_{ni}$ and entry costs $f_{ni}$ — need to be estimated via the method of simulated moments (MSM). Estimating the model for the entire set of economies I have in my data is computationally infeasible, however. Finding a single equilibrium of the model for many countries and with a large number of simulated firms per country takes considerable time even with my efficient algorithm for finding active markets.

Instead, I estimate the model for a small open economy Home ($H$), building on the theoretical work by Demidova et al. (2022) and the estimation strategy in Bartelme et al. (2023). Specifically, I solve (8) only for the Home price index $\alpha_H$, taking all other countries' $\alpha_n$ as given. I take the labor force size $L_H$ from the World Development Indicators (World Bank, 2023).

I can estimate $\alpha_n \equiv X_n \mathcal{P}_n^{\sigma-1}$ for all other countries outside of the MSM estimation. To do that, I run a gravity estimation using ITPD-E data on all countries but Home, similar to Bartelme et al. (2023). I model all other countries' economies as following the model in Melitz (2003), which means their price indices are

$$\mathcal{P}_n = \frac{\sigma}{\sigma-1}\left(\frac{\theta_F}{\theta_F-\sigma+1}\right)^{-\frac{1}{\theta_F}}\left(\frac{\sigma}{X_n}\right)^{\frac{\theta_F-\sigma+1}{\theta_F(\sigma-1)}}\left(\sum_{i=1}^{N} T_i n_i (d_{ni} w_i)^{-\theta_F} (f_{ni} w_i)^{\frac{\theta_F-\sigma+1}{1-\sigma}}\right)^{-\frac{1}{\theta_F}}$$

where $\theta_F$ is the dispersion parameter for other economies' productivity distributions — recall that in the Melitz (2003) model, core and total productivity are identical. I take this parameter from Melitz and Redding (2015) as $\theta_F = 4.25$.[19] Everything else in this expression is either data or a parameter I can estimate via the reduced form approaches above, while the final term in parentheses can be recovered from a gravity estimation. Specifically, under Melitz (2003), trade flows from $i$ to

[19] The technology scale parameters $\theta$ and $\theta_F$ capture the dispersion of core productivities, one for Home, the other for all other countries. I take $\theta_F$ from the literature since good estimates of this parameter exist, but allow $\theta \neq \theta_F$ because those existing estimates are for the dispersion in total productivity when $a_j$ completely captures firm productivity, that is, when core and total productivity are identical. In my model, total firm productivity is $a_J c_j^\delta$, which has a different distribution than core productivity $a_j$ by itself. I therefore allow for a different dispersion of core productivity.

$n$ for all other countries are

$$X_{ni} = \frac{T_i n_i (d_{ni} w_i)^{-\theta_F} (f_{ni} w_i)^{\frac{\theta_F - \sigma + 1}{1-\sigma}}}{\sum_{l=1}^{N} T_l n_l (d_{nl} w_l)^{-\theta_F} (f_{nl} w_l)^{\frac{\theta_F - \sigma + 1}{1-\sigma}}} X_n \tag{12}$$

I estimate this as

$$\mathbb{E}\left[\frac{X_{ni}}{X_n}\right] = \exp\left\{\nu_i + \xi_n + \mathbf{C}'_{ni}\boldsymbol{\beta}\right\}$$

where $\nu_i$ and $\xi_n$ are exporter and importer fixed effects and $\mathbf{C}_{ni}$ are bilateral variables capturing trade cost from $n$ to $i$. These bilateral trade costs $\tau_{ni}$ combine iceberg costs and entry costs

$$\tau_{ni} \equiv d_{ni}^{-\theta_F} f_{ni}^{\frac{\theta_F - \sigma + 1}{1-\sigma}} \tag{13}$$

Following Bartelme et al. (2023), I use distance and an indicator for contiguity to approximate this bilateral term. I estimate this gravity equation using pseudo-Poisson maximum likelihood estimation to deal with zero trade shares (Santos Silva & Tenreyro, 2006), based on data for all countries except Home (Bartelme et al., 2023). To minimize measurement error in the trade data, I calculate average real flows across all years from 2000 to 2019 and use these in the estimation. Appendix Table 25 shows the estimation results. I recover $\sum_{i=1}^{N} T_i n_i (d_{ni} w_i)^{-\theta_F} (f_{ni} w_i)^{\frac{\theta_F - \sigma + 1}{1-\sigma}}$ from the importer fixed effect $\xi_n$. I can then calculate $\mathcal{P}_n$ and therefore $\alpha_n$ for all countries except Home.

### 3.5.3 Method of simulated moments

I estimate the remaining parameters for Home — its technology shifter $T_H$, the technology scale parameter $\theta$, start-up costs $f_H$, and iceberg costs $d_{nH}$ and entry costs $f_{nH}$ between Home and all other countries $n$ — via MSM. For computational efficiency, I parameterize iceberg cost $d_{nH}$ as a function of the same variables I include in the gravity equation, distance and the contiguity indicator, as

$$d_{nH} = 1 + \exp\left\{\mathbf{X}_{nH}\boldsymbol{\gamma}\right\}$$

where $\mathbf{X}_{nH}$ also contains a constant term. For a guess of $\boldsymbol{\gamma}$, I can then recover $f_{nH}$ from (13). (I maintain the assumptions that $d_{HH} = 1$ and $f_{HH} = 0$.) Note that parameterizing $d_{nH}$ in this way is analogue to obtaining reduced from estimates of trade cost parameters from a gravity estimation and feeding the results into the structural algorithm, as done for example in Antràs et al. (2017).

The parameters $T_H$, $\theta$, $f_H$ and $\gamma$ are then estimated via MSM. The targeted moments are Home's share of exporters, exports from Home to each other country,[20] the ratio of Home's trade with itself to its total exports, and the ratio of the 75$^{\text{th}}$ to the 25$^{\text{th}}$ percentile of domestic sales (75/25 ratio). In simulated data, these moments are sufficient to identify all model parameters. To minimize measurement error in the trade data, I again use average real flows across all years from 2000 to 2019 (the most recent year in the data), as I did when estimating (12).

While all parameters are identified by all moments, the share of exporters and ratio of Home's trade with itself to total exports are especially helpful for identifying $f_H$ and $T_H$, the export flows are especially useful for identifying $\gamma$ and the 75/25 is needed to identify $\theta$. Table 8 also shows which variation in the data is especially important for identifying which parameters. I simulate the model using one million firms.

### 3.6 Estimation results

I implement the estimation in `Julia`, using `BlackBoxOptim` to find an initial set of estimates and refining those with the Nelder-Mead Subplex implementation from `NLopt`, an improved version of the standard Nelder-Mead algorithm (Bezanson, Edelman, Karpinski, & Shah, 2017; Feldt, 2023; Johnson, 2023; Rowan, 1990). I estimate the model using Zambia as the small open economy, Home, because I have three rounds worth of Enterprise Surveys data (2007, 2013 and 2019) and because it could reasonably be described as a small open economy. It has a ratio of total exports to total domestic trade (trade with itself) of $\approx 58$ percent, so trade makes up a large fraction of its economy, and it exhibits roughly balanced trade: Its trade imbalance (exports minus imports) as a fraction of its total trade (exports plus imports) is only six percent. Finally, when I estimate a gravity model with and without including Zambia, results basically do not differ, highlighting that trade with Zambia is small relative to global trade.

Table 8 shows the parameter estimates. I estimate a core productivity dispersion parameter $\theta = 7.706$, which is somewhat higher than, for example, the preferred estimate for the standard Melitz (2003) of 4.25 from Melitz and Redding (2015). (A higher $\theta$ means a less dispersed distribution.) That my model finds a larger value makes sense, however. In Melitz (2003), $\theta$ governs the dispersion of *total* productivity, whereas in my model, it governs only the dispersion of *core* productivity

[20] In order not to overweight a few large export destinations, I take the log of exports and add the fraction of countries Home does not export to as an additional moment.

$a_j$, whereas total productivity $a_j c_j^\delta$ also depends on productive capability $c_j$. In my model, firms' productive capability choices multiply core productivity and lead to additional dispersion in total productivity, so $\theta$ no longer captures the full dispersion of total productivity.

The model fits targeted moments well. Figure 8 shows a comparison of Zambian log exports and model results, where I obtain a relatively high correlation coefficient of 0.68.[21] In addition, Figure 9 shows Zambian log imports, which are not a targeted moment in the MSM estimation, compared to the model simulation. The correlation here is even stronger, at 0.80. This is encouraging, since imports depend on the iceberg cost parameters from the MSM estimation and other countries' $\alpha_n$, which I estimate outside the model. That imports are well approximated suggests that the theoretical model captures key relationships in the data, that the estimates of that model reproduce those relationships for untargeted data moments, and that the MSM estimation and estimations outside the model combine well. Comparisons of the data and estimated values for the other three targeted moments are shown in Table 9. The model produces a share of exporters of 15.7 percent, which is almost identical to the share of 15.2 percent in the data, a ratio of own trade to total exports of 1.818, which is also essentially identical to the data moment of 1.819, and a 75/25 ratio for domestic sales of 4.788, which is similar to the data moment of 3.596.

An important difference between my model and a standard Melitz (2003) model is that my model generates a notably different distribution of total productivity, $a_j c_j^\delta$. In Melitz (2003), total productivity is drawn from a Pareto distribution and follows that exactly. In my model, total productivity depends both on core productivity $a_j$ and productive capability $c_j$. Figure 10 shows the CDF of log core productivity and log total productivity. Log core productivity follows a Pareto distribution. Log total productivity, however, is much more dispersed. It also exhibits jumps at places where firms' core productivity allows them to access export destinations, leading firms to hire a chunk of additional productive capability.

# 4 Estimating the impact of climate change

## 4.1 Setup

This section uses a machine learning approach to estimate the impact of climate change on firm sales. I need this to be able to calibrate counterfactual simulations, which I use below to explore

[21] Because I parameterize $d_{nH}$ as a linear function of bilateral variables, the model cannot perfectly match each trade flow to every destination. To do that, I would need to estimate $d_{nH}$ separately for every destination, which would add over 100 parameters to the model and greatly slow down estimation.

the policy implications of productive capability adjustments. The counterfactuals conduct policy experiments under a climate change scenario, in which firms face reduced productivity (a worse productivity distribution to draw from) due to climate change. Calibrating this climate change scenario thus requires an estimate of how bad climate change is — how much should I reduce firm productivity in this scenario? The machine learning estimates I develop in this section are crucial for that calibration. I discuss the counterfactuals and specifics of the calibration in detail in Section 5.

To calibrate a counterfactual climate change scenario, I require a realistic estimate of the impact of climate change on firms. Estimating the impact of *climate change* based on *weather data* is hard, especially because my survey data do not cover the kind of time horizon over which climate change itself becomes clearly visible. (A not uncommon problem in the economics of climate change, given that economic data, especially in developing country contexts, often do not go back many decades.) As a result, I need to use variation in weather to make inferences about the impact of changes in climate (that is, changes in the distribution of weather). In practice, I need to estimate how firm outcomes would change if firms had to cope with a new set of weather observations derived from climate change projections.[22]

To formalize the problem of estimating the impact of future climate change on firm outcomes based on current weather data, I observe firm outcomes $y_{jt}$ and weather data $\mathbf{x}_{jt}$,

$$y_{jt} = g\left(\mathbf{x}_{jt}\right) + \varepsilon_{jt} \tag{14}$$

Current weather data are drawn from the current climate, $\mathbf{x}_{jt} \sim F_{\text{current}}$. I want to estimate

$$\mathbb{E}_{\text{future}}\left[y_{jt}\right] - \mathbb{E}_{\text{current}}\left[y_{jt}\right]$$

where $\mathbb{E}_{\text{current}}$ runs across weather from the current climate $F_{\text{current}}$, but $\mathbb{E}_{\text{future}}$ runs across weather from the future climate $F_{\text{future}}$. That is, I want to estimate the change in the expected firm outcome resulting from a shift to the future climate. From the NASA NEX climate projections, I have a sample of weather data from $F_{\text{future}}$. I do not, however, have data on future outcomes. Therefore, I need to estimate $g(\cdot)$ and take an average over future weather projections to estimate $\mathbb{E}_{\text{future}}\left[y_{jt}\right]$. This is a fairly common problem in the economics of climate change, and the solution I develop here should be of general interest to researchers in that field.

[22] Note that this is markedly different to the reduced form estimations I used in Section 2, where I was simply interested in capturing the first order impact of weather *shocks*, that is, weather variation within a given climate.

The core challenge here is that $g(\cdot)$ could be a complicated function, since interactions between the different weather variables in $\mathbf{x}_{jt}$ as well as higher order powers of those variables could matter for firm outcomes. I thus need an estimator that can flexibly estimate this function, yet provide reliable inference on the mean shift I am interested in. Another potential problem is that this is inherently an out of sample exercise, and one would accordingly want an estimation procedure to perform well out of sample.

One solution would be to pick a relatively small set of weather variables and estimate this relationship using OLS, perhaps including splines or other somewhat flexible functional forms. (Selecting weather variables is necessary for OLS to work well in finite samples.) The choice of weather variables to include is not obvious, however, and gives researchers a lot of leeway. Furthermore, OLS is not optimized for out of sample performance.

Instead, I use the causal forest algorithm developed by Athey et al. (2019). Causal forests are designed to incorporate high-dimensional data and can be tuned to protect against overfitting and to improve out of sample performance. Causal forests are most often used to estimate heterogeneous treatment effects, e.g., in the context of randomized controlled trials; I thank Stefan Wager and Erik Sverdrup for suggesting to me that they could also be used to estimate and do inference on unobserved means. All that is required to do this is a simple data manipulation. Let $D_{jt} = 1$ for data with observed outcomes (the 'treatment' group) and $D_{jt} = 0$ for data without (the 'control' group — in my case, the NASA NEX weather projections). Keep $y_{jt}(1) = y_{jt}$ for observed data and set $y_{jt}(0) = 0$ for unobserved outcomes. Then, the conditional average treatment effect for the control group is

$$\mathbb{E}\left[y_{jt}(1) - y_{jt}(0)|D_{jt} = 0\right] = \mathbb{E}\left[y_{jt} - 0|D_{jt} = 0\right] = \mathbb{E}\left[y_{jt}|D_{jt} = 0\right]$$

which is the expected outcome among observations with unobserved outcomes; since I set $D_{jt} = 0$ for weather projections from NASA NEX, this is equal to $\mathbb{E}_{\text{future}}\left[y_{jt}\right]$. Causal forests provide efficient cluster-robust confidence intervals for this expected outcome and can easily be estimated using the `grf` package in `R` (Tibshirani et al., 2023).

The final remaining problem is that I want to do inference on the *shift* in expected outcome resulting from climate change, not on the new expected outcome itself. I solve this by de-meaning outcomes prior to the estimation. As a result, the quantity the causal forest estimates becomes the expectation of the de-meaned outcome $y_{jt} - \bar{y}$ among the set of observations with future weather data ($D_{jt} = 0$), which is

$$\mathbb{E}\left[y_{jt} - \bar{y} | D_{jt} = 0\right] = \mathbb{E}_{\text{future}}\left[y_{jt}\right] - \mathbb{E}_{\text{current}}\left[y_{jt}\right]$$

This, however, is exactly the quantity I want to estimate. (See Appendix E.8 for a derivation.) Causal forests thus provide an attractive solution to the problem of estimating the impact of climate change on expected outcomes: They are able to incorporate high-dimensional weather data and flexibly relate them to firm outcomes while still providing reliable inference, and they perform well out of sample.

### 4.2 Firm adaptation to climate change

It is reasonable to assume that as the climate changes, firms try to adapt to the changing climate. This can be addressed by including long-term moments of weather in the estimation. Adaptation means reacting differently to an identical weather shock depending on the climatic environment. For example, a firm that is used to an average yearly temperature of 28°C may be severely affected by a year that averages 30°C. If over time, the average temperature rises to 30°C, the same firm may adapt to the changed climatic environment, for example by installing climate control measures (Adhvaryu et al., 2019). It may then be less affected by a 30°C year.[23] To capture this, I include longer-term moments of contemporary weather variables in the estimation, akin to Carleton et al. (2022). Specifically, I include the mean and variance over the preceding 20 years for each weather measure I use in the estimation.

The key shortcoming of this and any data-driven approach to the question of adaptation is that I cannot capture how future adaptation differs from past adaptation. If firms become better able to adapt to more extreme climates than they have been in the past, any data-driven approach will underestimate the benefits of adaptation. If, on the other hand, climate change leads to a harsher business environment, for example by degrading local institutions, firms may become less able to adapt to a changing climate. In that case, any data-driven approach to adaptation will overstate its benefits. I am aiming to provide the best estimate of the impact of climate change I can, but I am conscious of this inherent limitation. Any data-driven estimate of the impact of climate change is, ultimately, a relatively ballpark guess, and may be off in either direction due to uncertainty around

[23] It is also conceivable that rising average temperatures could make firms more vulnerable to weather shocks, for example if they negatively affect local labor markets (Santangelo, 2019) or due to impacts on the political and social environment firms operate in. My solution here can take either effect into account.

future technology and other factors determining firms' ability to cope with extreme conditions, such as institutions.

### 4.3 Results

To capture the complexity of weather, I explicitly use both temperature and precipitation data for this estimation. Of course, there are several different ways to summarize these over the course of a given fiscal year, and I try to be parsimonious by including a large selection of such measures in the estimation. Specifically, the weather measures I use include yearly averages, yearly averages of daily values raised to the second, third, fourth, fifth and sixth power (that is, the second to sixth non-centered moments of each variable), as used in Carleton et al. (2022), the corresponding centered moments, and counts for days in specific intervals and above certain thresholds. As I described above, I also include long-term means and variances to capture adaptation. I partial out cluster fixed effects from all variables, including the outcome, before conducting the estimation. The causal forest then flexibly estimates the response of firm outcomes to all of these weather measures, including their interactions and higher order powers.

I focus on estimating the causal impact of climate change for Zambia. This matches the fact that the structural estimation in Section 3 focuses on Zambia as a small open economy. To do this, I estimate the relationship between weather and firm outcomes (14) on data for the whole Enterprise Surveys sample, since causal forests perform better with a larger estimation sample, but I then estimate the causal impact of climate change only for Zambian firms. That is, I obtain an estimate of $g(\cdot)$ based on data for all firms, but I then estimate the change in outcomes $\mathbb{E}_{\text{future}}[y_{jt}] - \mathbb{E}_{\text{current}}[y_{jt}]$ only for Zambian firms.

Finally, I need to choose a reference period — a time at which I assess the impact of climate change (i.e., when is 'future' above). I estimate the effects of climate change for the 2080s (2080–2089). That is, for each SSP, I include projections from all 27 climate models and for each year in the 2080s and estimate the causal effect on average sales. I choose this period because at that time, differences in temperature between the three SSPs are clearly visible in the climate projections, as already seen in Figure 3.

Table 10 shows the estimated average decline in sales under the three different SSPs as well as 90 percent confidence intervals.[24] I consistently estimate negative effects, with larger magnitudes

[24] See Appendix E.9 for a derivation highlighting that, because I use log sales as an outcome, the causal forest estimates can be interpreted as the expected percent change in sales, rather than the percent change in expected sales. That is, the causal forest estimates an average of the percent decline in sales faced by each firm, rather than

under more extreme climate change scenarios. The impacts range from a 7.8 percent decrease in sales for the average Zambian firm under SPP1/2.6 to an 8.7 percent decrease under SSP2/4.5 to an 18.7 percent decrease under SSP5/8.5. All three are significant at the ten percent level. I want to highlight again that the confidence intervals I present incorporate two sources of uncertainty. First, they of course reflect uncertainty in fitting the model (statistical uncertainty). Second, since I combine data for many different model projections of future weather under each scenario, the intervals are also affected by scientific uncertainty regarding the path of future weather. Both contribute to the relatively wide confidence intervals around my estimates.

# 5 Counterfactuals

This section combines the model estimates from Section 3 with the estimated impacts of climate change from Section 4. I conduct counterfactual simulations to show that productive capability reactions matter for climate change policy. Specifically, I show that that productive capability reactions make (i) policies benefiting mostly larger firms and (ii) policies allowing firms to adapt to climate change especially effective at countering the negative impacts of climate change, compared to a model that ignores these reactions.

## 5.1 Calibrating climate change baseline scenario

I first calibrate a counterfactual that changes the technology parameter $T_H$ to match the estimated impact of climate change under SPP5/8.5 from Section 4. That is, I calibrate $T_H$ so the average firm experiences a real sales decline of 0.187 log points. The rationale for setting the counterfactual up this way is that, since weather shocks are primarily supply shocks, climate change is modeled as shifting the core productivity distribution. My counterfactual therefore finds the shift in the distribution of core productivity $a_j$ which would lead to the estimated impact on firms' real sales. I call this the *climate change baseline* counterfactual. I can then conduct policy experiments under this climate change scenario and calculate welfare impacts.

To estimate the impact of productive capability reactions on the welfare impact of different policies, I compare results for my model to a modified version of my model in which I shut down

estimating the percent decline in expected sales under climate change. Those two quantities coincide only if all firms see the same percentage sales decline under climate change. If, for example, there were equally many small and large firms in the economy, and small firms saw a 15 percent decline in sales while large firms saw a five percent decline in sales, the expected decline in sales would be ten percent. The change in expected sales, however, would be smaller, because larger firms see only a five percent decline in sales, so the percent change in expected sales would be closer to five percent.

these reactions. That is, I fix the distribution of productive capability $c_j$ at the status quo and do not allow it to adjust when moving to counterfactuals. I calibrate the climate change baseline scenario for this modified model in the same way, finding the shift in $T_H$ that leads to sales losses matching the estimated impact of climate change.

Appendix Table 28 further shows a comparison between my model and the model of Melitz (2003), estimated in the same way as my model.[25] I find that the Melitz (2003) model has difficulty fitting the Zambian data as well as my model, especially with accounting for the observed dispersion of firm sales. This is because the Melitz (2003) model has to fulfill the parameter restriction $\theta > \sigma - 1$. Since in this model, $\theta$ governs the dispersion in total productivity, this puts a lower bound on that dispersion. I also find that the comparison between my model and Melitz (2003) only exacerbates the results I present here — where I find that productive capability reactions make a policy more beneficial, the comparison with Melitz (2003) makes the difference even larger. Thus, to be conservative in what I consider my main results, I present comparisons between my model with and without productive capability reactions, rather than to Melitz (2003).

### 5.2 Welfare impacts under climate change baseline

I first calculate the change in welfare resulting from moving to the climate change baseline scenario for each model. This welfare change can also be thought of as the change in real GDP, using the consumer price index to convert nominal to real GDP. As the first row of Panel A in Table 11 shows, I find that with productive capability reactions, welfare declines by 13.2 percent. Shutting down productive capability reactions, I estimate a 19.5 percent welfare decrease. Note that both models are calibrated so that the average firm sees an 0.187 log point decrease in sales between the status quo and the counterfactual. The difference in welfare change is entirely due to productive capability reactions and their effects on the *distribution* of firm sales. Note also that I keep the rest of the world at its status quo production levels, since I want to study the implications for policy effectiveness in Zambia. All welfare level results, for example the impact of climate change on welfare in this baseline scenario, are therefore upper bounds. If I also allowed climate change to affect the rest of the world, Zambia would do worse as well.

In the following discussion, I focus heavily on how much of the welfare gap between the status quo and the climate change baseline different policy interventions can close. I do not discuss in as

[25] For more details on the estimated Melitz (2003) model, Appendix Table 26 shows parameter estimates, Appendix Table 27 shows moment comparisons, and Appendix Figures 13 and 14 further show comparisons for log exports and imports.

much detail the level differences in welfare changes between the two models, for example the level differences in welfare under the baseline scenario. I do so for two reasons. The first reason is that I mostly care about which policies are most effective at *counteracting* the effects of climate change. That is a question about welfare *changes* between the climate change baseline scenario and different policy experiments departing from that baseline scenario. It is a question about how much — what fraction — of the welfare loss under the baseline scenario can be recovered using different policies. To briefly highlight why the level results are different, however, Figure 11 shows how each percentile of log real sales shifts when moving from the status quo to the climate change baseline, with and without productive capability reactions. The figure shows the ratio of the new to the old percentile. The first takeaway is that climate change is bad for all firms: All percentiles are shifted down in both cases. With productive capability reactions, however, smaller firms reduce their productive capability more than larger firms. Therefore, larger firms manage to retain more of their status quo sales. On the flip side, smaller firms see a larger decline in sales. Overall, this allows Zambian firms to remain more productive and retain a better connection to export destinations, which leads to a smaller welfare decline. The cost is that smaller firms are more severely affected.

The second reason to focus on changes in welfare compared to the climate change baseline rather than welfare levels. As I explain in Section 4, my estimates of the impact of climate change cannot account for future improvements or decreases in firms' ability to adapt to climate change. There is, therefore, inherent uncertainty about the exact *level* of welfare impacts. There is no such uncertainty around which policies become *more effective* at counteracting climate change damages, however. Certain policies, as I discuss below, become more effective at reducing losses from climate change, and they will be more effective at reducing those losses regardless of the exact level of welfare decrease we face in the baseline climate change scenario. If firms have an easier time to adapt to future climate change, for example due to technological innovation, welfare losses will be smaller. If we want to reduce those losses, however, it will still be true that taking productive capability adjustments into account makes certain policies more effective doing that. Those policies thus become more attractive than they would have looked without taking productive capability adjustments into account. (The same is true if future adaptation becomes harder, and welfare losses in the baseline scenario become larger.)

## 5.3 Policy experiments under climate change baseline

I now turn to policy experiments under the climate change baseline. I focus on two sets of policy experiments. For each of these, I compare welfare implications with and without productive capability adjustments. The first set of experiments considers the impact of a policy benefiting larger firms compared to a policy targeted at mid-sized firms. The second set considers adaptation to climate change and mitigation of climate change itself.

### 5.3.1 Policies benefiting mostly large vs. mid-sized firms

The first set of policy experiments compares the effect of reducing iceberg trade costs to the effect of reducing entry costs to foreign markets. Iceberg cost reductions benefit existing exporters, allowing them to expand sales to foreign markets. Entry cost reductions mostly help marginal entrants. Marginal entrants are firms with a core productivity which is almost high enough to make exporting profitable. When entry costs are reduced, these firms can profitably start exporting. They are therefore the main beneficiaries of entry cost reductions. These firms are smaller than existing exporters, but larger than many other non-exporters. I therefore call these marginal entrants mid-sized firms.

I consider a reduction in iceberg trade cost from Home to all other countries, $d_{nH}$, by 10 percent across the board. (This is an asymmetric reduction — I keep trade costs from all other countries to Home, $d_{Hn}$, fixed.) The results are presented in row two of panel A in Table 11. Compared to current welfare, when productive capability is allowed to react, Zambia now experiences only a 10.4 percent decline compared to the status quo. This means lower variable trade costs reduce the impact of climate change by 2.8 percentage points, or 21.4 percent ($\approx 2.8/13.2$) compared to the climate change baseline. Without productive capability reactions, Zambia still sees a 16.8 percent welfare decline under this scenario. This is a 2.7 percentage point or 13.7 percent ($\approx 2.7/19.5$) improvement. Panel B of the same table summarizes these relative changes, showing what fraction of the baseline welfare gap can be closed using each policy intervention.

Thus, I find that a little over a third of the welfare impact of iceberg cost reductions, or 36 percent ($\approx [21.4 - 13.7]/21.2$), is due to productive capability responses. Another way to express this is that productive capability reactions make variable trade cost reductions 1.6 times ($\approx 21.4/13.7$) more effective. A key reason for this is that variable trade cost reductions allow very productive firms, which are already exporting, to increase their productive capability. This may hurt smaller firms, which may not be able to retain some of their productive capability, but increases efficiency overall. Figure 12 shows the change in the distribution of real sales when moving from the climate change baseline scenario to the iceberg cost reduction policy experiment. With and without productive capability reactions, smaller firms lose sales while larger firms increase sales. This is because trade cost reductions benefit existing exporters, who hire additional production labor to expand their operations. This puts upwards pressure on wages, which leads to sales losses for smaller firms. Productive capability reactions exacerbate this, leading small firms to lose additional sales because they cannot afford to retain their productive capability, while larger firms purchase additional productive capability and become more efficient. Since large firms have considerably higher sales than smaller firms, the overall impact is positive for the Zambian economy.

The second policy change is a reduction in entry cost $f_{nH}$ by 10 percent across the board. The results are presented in row three of Panels A and B in Table 11. Here, both with and without productive capability reactions, the effects are negligible. They are still larger with productive capability reactions, but the difference is quite small. The reason for the overall lower impact is that most of the benefit from entry cost reductions goes to relatively less productive firms — marginal entrants which were not productive enough to reach export destinations before. Variable trade cost reductions, on the other hand, benefit already exporting firms, leading to the dynamics discussed above. This also explains why there is less of a difference in effectiveness with and without productive capability reactions.

The takeaway from this first set of policy experiments is that productive capability reactions matter a lot more for policies benefiting mostly larger firms. Those policies become notably more effective at reducing the welfare impact of climate change. Therefore, once we take productive capability reactions seriously, these policies are ones we should put more weight on when considering how poor countries can cope with climate change. Large firms matter more than we might have thought in this context.

#### 5.3.2 Adaptation vs. mitigation

The second set of experiments compares increased firm adaptation to climate change with mitigating climate change itself. The adaptation experiments shifts the climate change baseline $T_H$ up by ten percent. This simulates firms becoming more productive in a climate change scenario. This could be due to improved, cheaper technology allowing firms to adapt, or due to government infrastructure investments, for example in reliable water supply infrastructure in the faced of increased risks of drought (Islam & Hyland, 2019).

The results are presented in row four of Panels A and B in Table 11. Compared to current welfare, when productive capability is allowed to react, Zambia now experiences only a 12.2 percent decline compared to the status quo. This means adaptation reduces the impact of climate change by 1.0 percentage point, or 7.7 percent ($\approx 1.0/13.2$), compared to the climate change baseline. Without productive capability reactions, Zambia still sees an 18.6 percent welfare decline under this scenario, an 0.9 percentage point or 4.9 percent ($\approx 0.9/19.5$) improvement.

Thus, I find that 36 percent ($\approx [7.7 - 4.9]/7.7$) of the welfare impact of adaptation to climate change is due to productive capability responses. Another way to express this is that productive capability reactions make adaptation 1.6 times ($\approx 7.7/4.9$) more effective. The reason is straightforward: When firms become more productive due to improved adaptation, they react by additionally hiring productive capability. This reinforces the productivity gains from adaptation. A model which treats productive capability as fixed ignores this second order impact.

The mitigation scenario instead calibrates a new $T_H$ matching the estimated impact of climate change under the SSP2/4.5 scenario. That is, the average firm under this scenario sees an 0.087 log point decline in sales. This simulates achieving enough mitigation now to end up on a more favorable climate change trajectory in the future.

The results are presented in row five of Panels A and B in Table 11. Compared to current welfare, when productive capability is allowed to react, Zambia now experiences only a 6.4 percent decline compared to the status quo. This means mitigation reduces the impact of climate change by 6.8 percentage points, or 51.5 percent ($\approx 6.8/13.2$), compared to the climate change baseline. Without productive capability reactions, Zambia still sees a 9.6 percent welfare decline under this scenario, a 9.9 percentage point or 50.7 percent ($\approx 9.6/19.5$) improvement.

Here, the difference due to productive capability reactions is again quite small — around two percent ($\approx [51.5 - 50.7]/51.5$) of the welfare impact of mitigation of climate change is due to productive capability responses, or expressed another way, those responses make mitigation 1.02 times ($\approx 51.5/50.7$) more effective.

It may seem counterintuitive that productive capability reactions make adaptation so much more effective at combating welfare losses from climate change, but barely affect mitigation. The reason for this difference is that under the adaptation scenario, both models shift core productivity up by the *same* factor. Under mitigation, however, both models shift core productivity very differently: Instead of the severe SSP5/8.5 scenario with an 0.187 log point loss in sales for the average Zambian firm, both models are now calibrated to the less severe SSP2/4.5 scenario with an 0.087 log point loss in sales. To achieve this lower loss in sales, both models shift core productivity back up, by shifting $T_H$ up. With productive capability reactions, an upward shift in core productivity is accompanied by firms purchasing more productive capability. This reinforces the upward core productivity shift, leads to a larger total productivity shift, and the model calibration needs only a small shift in core productivity to reach the targeted change in sales. Without productive capability reactions, on the other hand, the entire shift in sales has to come from shifting core productivity. The calibration for the model with fixed productive capability thus shifts $T_H$ up more. This difference in shift size explains why the relative welfare impact of mitigation is similar with and without productive capability reactions.

The takeaway here is that a *given* shift in core productivity leads to a larger welfare impact when firms react via productive capability. Adaptation means reducing the impact of climate change on core productivity by a given factor. Adaptation policies become more effective when firms increase complementary expenditures in response to them, generating positive feedback for these policies. When thinking about mitigation, however, the two models back out *differently sized* shifts in core productivity. Those lead to similar relative welfare impacts. Thus, productive capability reactions do not change the effectiveness of mitigating climate change.

# 6 Conclusion

In this paper, I show that weather shocks are, predominantly, supply shocks rather than demand shocks for non-agricultural firms in poor countries. In the main reduced form result of the paper, I further show that firms react to these shocks by adjusting expenditures on complementary inputs, such as rented machinery, rented space, and non-production personnel. This is a rational reactions, but further reduces firms' effective productivity. I then develop and estimate an international trade model featuring these input adjustments, and show that the model reproduces my reduced form results. To calibrate climate change counterfactuals for the model, I need an estimate of the impact of climate change on firm outcomes. I argue that causal forests are especially well suited to this problem, and show how they can be adapted to solving it. I then construct climate change counterfactuals based on these estimates. Policy simulations under this climate change scenario show two key policy implications. First, policies benefiting larger firms become more effective at counteracting the negative impacts of climate change. This is because large firms are especially well placed to hire complementary inputs in response to such policies, leading to an endogenous increase in large firms' productivity. Second, facilitating firm adaptation to climate change also becomes more effective at reducing welfare losses from climate change. This is because adaptation allows firms to recover some of the productivity losses from climate change; in reaction, firms hire additional complementary inputs, leading to further productivity gains.

My results are important as we consider what policies both rich and poor countries can adapt to help poor countries mitigate the impact of climate change. Some of these may be counterintuitive looking only at reduced form results. I show, for example, that exporters see a larger negative impact of weather shocks. This might have suggested that countries should focus more on domestic production. As counterfactual simulations show, however, this protectionist intuition is wrong once we take general equilibrium forces into account. The input adjustments I highlight in fact make trade policy, which tends to especially benefit larger firms, more effective at combating the impact of climate change than we might have assumed. This is especially true for countries with small domestic markets. My results also highlight that as rich countries consider protectionist policies in the wake of the Covid-19 pandemic (Goldberg & Reed, 2023), they should ensure those policies do not impose outsized collateral damage on poor countries. Ill-targeted, such policies could in fact greatly reduce poor countries' ability to deal with climate change. This is especially concerning given that climate change itself has a negative impact on trade networks (Huppertz, 2024).

Another point of caution concerns adaptation compared to mitigation. In this paper, I show that input adjustments make adaptation policy more effective at counteracting the negative impacts of climate change. I do not find a similar result for mitigation policy. This is, first and foremost, an encouraging result — it means that we are better positioned than we might have hoped to cope with future climate change. This result might also suggest that we can do less mitigation now, since future adapation is in fact more effective. I want to stress, however, that there are good reasons to think that prevention is preferable to relying on future adaptation. Across the counterfactuals I explore, I find that, even compared to sizable trade cost reductions, climate change mitigation leads to *by far* the largest reductions in welfare losses from climate change. It is a very effective tool in reducing future welfare losses from climate change. Of course, trade policy itself can also play a key role in climate change mitigation (Farrokhi & Lashkaripour, 2021).

Ultimately, climate change is already occurring and will continue to occur; mitigation efforts may prevent some of it, but they will not prevent all of it. Poor countries will be severely affected by climate change. Understanding what policies are especially suited for allowing these countries to cope with it is a crucial task for contemporary social science. A better understanding of firm reactions to extreme weather is an important part of this, and this paper takes a first step in that direction.

## References


Adhvaryu, A., Kala, N., & Nyshadham, A. (2019). The light and the heat: Productivity co-benefits of energy-saving technology. *The Review of Economic Studies*, 1–36. https://doi.org/10.1162/rest_a_00886

Antràs, P., Fort, T. C., & Tintelnot, F. (2017). The margins of global sourcing: Theory and evidence from US firms. *American Economic Review*, *107*(9), 2514–2564. https://doi.org/10.1257/aer.20141685

Athey, S., Tibshirani, J., & Wager, S. (2019). Generalized random forests. *Annals of Statistics*, *47*(2), 1148–1178. https://doi.org/10.1214/18-AOS1709

Auffhammer, M., Hsiang, S. M., Schlenker, W., & Sobel, A. (2013). Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy*, *7*(2), 181–198. https://doi.org/10.1093/reep/ret016

Bartelme, D., Lan, T., & Levchenko, A. A. (2023). *Specialization, market access and real income*. Working paper. https://alevchenko.com/Bartelme_Lan_Levchenko.pdf

Bezanson, J., Edelman, A., Karpinski, S., & Shah, V. B. (2017). Julia: A fresh approach to numerical computing. *SIAM review*, *59*(1), 65–98. https://doi.org/10.1137/141000671

Borchert, I., Larch, M., Shikher, S., & Yotov, Y. V. (2021). The international trade and production database for estimation (ITPD-E). *International Economics*, *166*, 140–166. https://doi.org/10.1016/j.inteco.2020.08.001

Burke, M., & Emerick, K. (2016). Adaptation to climate change: Evidence from US agriculture. *American Economic Journal: Economic Policy*, *8*(3), 106–40. https://doi.org/10.1257/pol.20130025

Burke, M., Hsiang, S., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, *527*, 235–239. https://doi.org/10.1038/nature15725

Burke, M., & Tanutama, V. (2019). *Climatic constraints on aggregate economic output*. NBER working paper 25779. https://www.nber.org/papers/w25779

Carleton, T. A., & Hsiang, S. M. (2016). Social and economic impacts of climate. *Science*, *353*(6304). https://doi.org/10.1126/science.aad9837

Carleton, T. A., Jina, A., Delgado, M., Greenstone, M., Houser, T., Hsiang, S., Hultgren, A., Kopp, R. E., McCusker, K. E., Nath, I., Rising, J., Rode, A., Seo, H. K., Viaene, A., Yuan, J., & Zhang, A. T. (2022). Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits. *The Quarterly Journal of Economics*, *137*(4), 2037–2105. https://doi.org/10.1093/qje/qjac020

Castro-Vincenzi, J. (2024). *Climate hazards and resilience in the global car industry*. Working paper. https://static1.squarespace.com/static/5fbd5c064c271a353f8a9840/t/65bc0e00d191801b89d03bb2/1706823170656/castrovincenzi_jmp.pdf

Conte, B. (2022). *Climate change and migration: The case of Africa*. CESifo Working Paper No. 9948. https://www.cesifo.org/en/publications/2022/working-paper/climate-change-and-migration-case-africa

Costinot, A. (2009). On the origins of comparative advantage. *Journal of International Economics*, *77*(2), 255–264. https://doi.org/10.1016/j.jinteco.2009.01.007

Costinot, A., Donaldson, D., & Smith, C. (2016). Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world. *Journal of Political Economy*, *124*(1), 205–248. https://doi.org/10.1086/684719

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, *4*(3), 66–95. https://doi.org/10.1257/mac.4.3.66

Demidova, S., Naito, T., & Rodríguez-Clare, A. (2022). *The small open economy in a generalized gravity model*. NBER Working Paper 30394. https://www.nber.org/papers/w30394

Deschênes, O., & Greenstone, M. (2007). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *American Economic Review*, *97*(1), 354–385. https://doi.org/10.1257/aer.97.1.354

Deschênes, O., & Greenstone, M. (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics*, *3*(4), 152–185. https://doi.org/10.1257/app.3.4.152

Eaton, J., Kortum, S., & Kramarz, F. (2011). An anatomy of international trade: Evidence from french firms. *Econometrica*, *79*(5), 1453–1498. https://doi.org/https://doi.org/10.3982/ECTA8318

Farrokhi, F., & Lashkaripour, A. (2021). Can trade policy mitigate climate change? https://alashkar.pages.iu.edu/FL2021_Climate_Policy.pdf

Feldt, R. (2023). *Blackboxoptim* (Version 0.6.2). https://github.com/robertfeldt/BlackBoxOptim.jl

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations — A new environmental record for monitoring extremes. *Scientific Data*, *2*(150066). https://doi.org/10.1038/sdata.2015.66

Goicoechea, A., & Lang, M. (2023). *Firms and climate change in low- and middle-income countries*. World Bank Policy Research Working Paper 10644. https://documents1.worldbank.org/curated/en/099520212132322680/pdf/IDU0547ba0d4074fe049c10b8d90e70009f655c3.pdf

Goldberg, P. K., & Reed, T. (2023). *Is the global economy deglobalizing? and if so, why? and what is next?* NBER Working Paper 31115. http://www.nber.org/papers/w31115

Hardy, M., & McCasland, J. (2019). Lights off, lights on: The effects of electricity shortages on small firms. *The World Bank Economic Review*, *35*(1), 19–33. https://doi.org/10.1093/wber/lhz028

Hjort, J. (2014). Ethnic divisions and production in firms. *The Quarterly Journal of Economics*, *129*(4), 1899–1946. https://doi.org/10.1093/qje/qju028

Huppertz, M. (2024). *Climate change increases bilateral trade cost*. Working paper. https://maxhuppertz.github.io/files/trade_network_changes.pdf

Hyun, J., & Kim, R. (2022). *Spillovers through multimarket firms: The uniform product replacement channel*. Working paper. https://www.dropbox.com/s/jly2dztl0nmu58w/draft.pdf

Islam, A., & Hyland, M. (2019). The drivers and impacts of water infrastructure reliability — a global analysis of manufacturing firms. *Ecological Economics*, *163*, 143–157. https://doi.org/https://doi.org/10.1016/j.ecolecon.2019.04.024

Jensen, R. (2007). The digital provide: Information (technology), market performance, and welfare in the South Indian fisheries sector. *The Quarterly Journal of Economics*, *122*(3), 879–924. https://doi.org/10.1162/qjec.122.3.879

Jia, P. (2008). Whan happens when Wal-Mart comes to town: An empirical analysis of the discount retailing industry. *Econometrica*, *76*(6), 1263–1316. https://doi.org/10.3982/ECTA6649

Johnson, S. G. (2023). *The NLopt nonlinear-optimization package* (Version 2.7.1). https://github.com/stevengj/nlopt

Kelly, M. (2020). *Understanding persistence*. CEPR Press Discussion Paper No. 15246. https://cepr.org/publications/dp15246

Lin, C., Schmid, T., & Weisbach, M. S. (2019). *Climate change, operating flexibility and corporate investment decisions*. NBER Working Paper 26441. https://www.nber.org/papers/w26441

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, *71*(6), 1695–1725. https://doi.org/10.1111/1468-0262.00467

Melitz, M. J., & Redding, S. J. (2015). New trade models, new welfare implications. *American Economic Review*, *105*(3), 1105–1146. https://doi.org/10.1257/aer.20130351

Nath, I. B. (2020). *The food problem and the aggregate productivity consequences of climate change*. NBER Working Paper 27297. https://www.nber.org/papers/w27297

O'Neill, B. C., Kriegler, E., Ebi, K. L., Kemp-Benedict, E., Riahi, K., Rothman, D. S., van Ruijven, B. J., van Vuuren, D. P., Birkmann, J., Kok, K., Levy, M., & Solecki, W. (2017). The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Global Environmental Change*, *42*, 169–180. https://doi.org/https://doi.org/10.1016/j.gloenvcha.2015.01.004

Ortiz-Bobea, A. (2021). Chapter 76 - the empirical analysis of climate change impacts and adaptation in agriculture. In C. B. Barrett & D. R. Just (Eds.), *Handbook of agricultural economics* (pp. 3981–4073). Elsevier. https://doi.org/10.1016/bs.hesagr.2021.10.002

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, *12*, 2825–2830. https://jmlr.csail.mit.edu/papers/v12/pedregosa11a.html

Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J. C., KC, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., … Tavoni, M. (2017). The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change*, *42*, 153–168. https://doi.org/https://doi.org/10.1016/j.gloenvcha.2016.05.009

Rohde, R., Muller, R. A., Jacobsen, R., Muller, E., Perlmutter, S., Rosenfeld, A., Wurtele, J., Groom, D., & Wickham, C. (2013). A new estimate of the average earth surface land temperature spanning 1753 to 2011. *Geoinformatics & Geostatistics: An Overview*, *1*(1). https://doi.org/10.4172/2327-4581.1000101

Rowan, T. H. (1990). *Functional stability analysis of numerical algorithms* (Doctoral dissertation). Department of Computer Science, University of Texas at Austin. Austin, TX.

Santangelo, G. (2019). *Firms and farms: The local effects of farm income on firms' demand*. Working paper. https://gabriellasantangelo.files.wordpress.com/2019/03/gabriella_santangelo_-_jmp_-_latest.pdf

Santos Silva, J. M. C., & Tenreyro, S. (2006). The log of gravity. *The Review of Economics and Statistics*, *88*(4), 641–658. https://doi.org/10.1162/rest.88.4.641

Somanathan, E., Somanathan, R., Sudarshan, A., & Tewari, M. (2021). The impact of temperature on productivity and labor supply: Evidence from indian manufacturing. *Journal of Political Economy*, *129*(6), 1797–1827. https://doi.org/10.1086/713733

Thrasher, B., Wang, W., Michaelis, A., Melton, F., Lee, T., & Nemani, R. (2022). NASA global daily downscaled projections, CMIP6. *Scientific Data*, *9*(262 (2022)). https://doi.org/10.1038/s41597-022-01393-4

Thrasher, B., Wang, W., Michaelis, A., & Nemani, R. (2021). *NEX-GDDP-CMIP6*. NASA Center for Climate Simulation. https://doi.org/10.7917/OFSG3345

Tibshirani, J., Athey, S., Friedberg, R., Hadad, V., Hirshberg, D., Miner, L., Sverdrup, E., Wager, S., & Wright, M. (2023). *grf* (Version 2.2.1). https://grf-labs.github.io/grf/index.html

World Bank. (2023). *World development indicators*. The World Bank Group. https://datatopics.worldbank.org/world-development-indicators/

Zhang, P., Dêschenes, O., Meng, K., & Zhang, J. (2018). Temperature effects on productivity and factor reallocation: Evidence from half a million Chinese manufacturing plants. *Journal of Environmental Economics and Management*, *88*, 1–17. https://doi.org/10.1016/j.jeem.2017.11.001

# Tables

Table 1: Firm summary statistics

| Variable | Count | Mean | P25 | Median | P75 |
|---|---|---|---|---|---|
| Sales (real 2009 USD) | 40,027 | 807,990.85 | 27,548.70 | 104,589.13 | 495,465.96 |
| Number of employees | 49,514 | 23.03 | 6.00 | 10.00 | 22.00 |
| Initial number of employees | 41,212 | 11.59 | 4.00 | 6.00 | 12.00 |
| Exporter | 48,962 | 0.12 | 0.00 | 0.00 | 0.00 |
| Manufacturing | 49,919 | 0.31 | 0.00 | 0.00 | 1.00 |
| Internat. quality cert. | 48,347 | 0.13 | 0.00 | 0.00 | 0.00 |
| Manager experience (years) | 49,080 | 13.73 | 7.00 | 12.00 | 20.00 |
| Yearly mean temperature (°C) | 28,699 | 29.54 | 26.62 | 30.29 | 33.15 |
| Yearly total precipitation (1,000 mm) | 28,699 | 0.99 | 0.57 | 0.92 | 1.28 |

*Note*: Outcomes winsorized at the $95^{\text{th}}$ percentile. The lower observation counts for weather variables stem from the fact that I can only match firm and weather data for firms that have non-missing location information. I use the ES survey weights to ensure representativeness.

Table 2: Effect of weather shocks on sales

| Variable | Log sales |
|---|---|
| Temperature index | $-0.223^{*}$ |
| | [0.091] |
| Year FE | Yes |
| Cluster FE | Yes |
| Clusters | 587 |
| Observations | 18,273 |

*Note*: *Temperature index* is an index combining mean temperature, temperature variance and the number of days with temperatures exceeding 32°C (89.6°F). The index is an average of location-specific $z$-scores for each variable (using the 20-year mean and standard deviation of reach variable). An 0.320 increase in the index is an $80^{\text{th}}$ percentile weather shock. Standard errors clustered by firm cluster. Outcomes winsorized at the $95^{\text{th}}$ percentile for each survey round. $p$-values in brackets. I use the ES survey weights to ensure representativeness.

Table 3: Effect of weather shocks by exporter status

| Variable | Log sales |
|---|---|
| Temperature index | $-0.125$ [0.296] |
| Temperature index × Current exporter | $-0.094^{***}$ [0.006] |
| Current exporter | $1.603^{***}$ [0.000] |
| Year FE | Yes |
| Cluster FE | Yes |
| Clusters | 586 |
| Observations | 17,975 |

*Note*: *Current exporters* are firms that export in the current fiscal year. *Temperature index* is an index combining mean temperature, temperature variance and the number of days with temperatures exceeding 32°C (89.6°F). The index is an average of location-specific $z$-scores for each variable (using the 20-year mean and standard deviation of reach variable). An 0.320 increase in the index is an 80$^{\text{th}}$ percentile weather shock. Standard errors clustered by firm cluster. Outcomes winsorized at the 95$^{\text{th}}$ percentile for each survey round. $p$-values in brackets. I use the ES survey weights to ensure representativeness.

Table 4: Effect of weather shocks on domestic sales

| Variable | Log domestic sales |
|---|---|
| Temperature index | $-0.186$ [0.118] |
| Temperature index × Current exporter | $-0.071^{**}$ [0.013] |
| Current exporter | $0.886^{***}$ [0.000] |
| Year FE | Yes |
| Cluster FE | Yes |
| Clusters | 584 |
| Observations | 17,250 |

*Note*: *Temperature index* is an index combining mean temperature, temperature variance and the number of days with temperatures exceeding 32°C (89.6°F). The index is an average of location-specific $z$-scores for each variable (using the 20-year mean and standard deviation of reach variable). An 0.320 increase in the index is an 80$^{\text{th}}$ percentile weather shock. Standard errors clustered by firm cluster. Outcomes winsorized at the 95$^{\text{th}}$ percentile for each survey round. $p$-values in brackets. I use the ES survey weights to ensure representativeness.

Table 5: Effect of weather shocks on productive capability and sales per employee

| Variable | Log productive capability | Log sales/employee |
|---|---|---|
| Temperature index | $-0.049$ [0.753] | $-0.036$ [0.722] |
| Temperature index × Current exporter | $-0.117^{***}$ [0.001] | $-0.048^{**}$ [0.019] |
| Current exporter | $1.233^{***}$ [0.000] | $0.631^{***}$ [0.000] |
| Year FE | Yes | Yes |
| Cluster FE | Yes | Yes |
| Clusters | 377 | 586 |
| Observations | 8,003 | 17,870 |

*Note*: *Temperature index* is an index combining mean temperature, temperature variance and the number of days with temperatures exceeding 32°C (89.6°F). The index is an average of location-specific $z$-scores for each variable (using the 20-year mean and standard deviation of reach variable). An 0.320 increase in the index is an $80^{\text{th}}$ percentile weather shock. Productive capability expenditures combine the cost of communications, sales (including sales staff), transportation, and rent for buildings, equipment and land. Standard errors clustered by firm cluster. Outcomes winsorized at the $95^{\text{th}}$ percentile for each survey round. $p$-values in brackets. I use the ES survey weights to ensure representativeness.

Table 6: Effect of weather shocks on domestic sales, mediation via productive capability

| Variable | Log domestic sales |
|---|---|
| Temperature index | $-0.182$ [0.139] |
| Temperature index × Current exporter | 0.041 [0.438] |
| Current exporter | 0.179 [0.112] |
| Log productive capability controls | Yes |
| Year FE | Yes |
| Cluster FE | Yes |
| Clusters | 375 |
| Observations | 7,447 |

*Note*: *Temperature index* is an index combining mean temperature, temperature variance and the number of days with temperatures exceeding 32°C (89.6°F). The index is an average of location-specific $z$-scores for each variable (using the 20-year mean and standard deviation of reach variable). An 0.320 increase in the index is an $80^{\text{th}}$ percentile weather shock. *Log productive capability controls* comprises log productive capability expenditures fully interacted with exporter status and the temperature index. I do not show the coefficients on these endogenous regressors. *(DM)* indicates the variable is de-meaned to center interaction terms. Productive capability expenditures combine the cost of communications, sales (including sales staff), transportation, and rent for buildings, equipment and land. Standard errors clustered by firm cluster. Outcomes winsorized at the $95^{\text{th}}$ percentile for each survey round. $p$-values in brackets. I use the ES survey weights to ensure representativeness.

Table 7: Exporters compared to non-exporters

| Variable | Mean non-exporter | Mean exporter | $p$-value |
|---|---|---|---|
| Sales (real 2009 USD) | 657,600.35 | 1,772,946.67 | 0.000*** |
| Number of employees | 19.82 | 43.67 | 0.000*** |
| Initial number of employees | 10.49 | 18.82 | 0.000*** |
| Manufacturing | 0.28 | 0.47 | 0.000*** |
| Internat. quality cert. | 0.10 | 0.28 | 0.000*** |
| Manager experience (years) | 13.47 | 15.32 | 0.002*** |
| Yearly mean temperature (°C) | 29.53 | 29.65 | 0.467 |
| Yearly total precipitation (1,000 mm) | 0.99 | 0.98 | 0.476 |

*Note*: $p$-values are for the null that the difference between exporters and non-exporters is zero. The underlying standard errors are robust to heteroskedasticity.

Table 8: Parameter estimates for structural model

| Parameter | Source/identifying variation | Estimate |
|---|---|---|
| *Panel A: Reduced form and data* | | |
| $\sigma$ | Sales, variable cost | 3.016 (0.043) |
| $\beta\delta$ | Total on domestic sales regression (11) | 0.384 (0.016) |
| *Panel B: Structural estimation* | | |
| $\theta$ | 75/25 ratio for domestic sales | 7.687 |
| $T_H w_H$ | Ratio of Home sales to Foreign sales | 0.000 |
| $f_H w_H$ | Fraction of exporters | 0.008 |
| $\gamma_0$ | | -1.564 |
| $\gamma_{\text{dist}}$ | Export flows | 0.605 |
| $\gamma_{\text{contig}}$ | | 0.402 |

*Note*: Standard errors in parentheses where available. I present the minimum core productivity $T_H$ and start-up cost $f_H$ times the estimated Home wage $w_H$ to convert them into an easier to interpret unit, millions of USD, rather than presenting them in units of labor. The three components of $\gamma$ are the intercept $\gamma_0$, the coefficient on log distance $\gamma_{\text{dist}}$ and the coefficient on the contiguity indicator $\gamma_{\text{contig}}$.

Table 9: Moment comparisons for structural model

| Moment | Data | Model |
|---|---|---|
| Fraction exporting | 0.152 | 0.153 |
| Ratio own trade/total exports | 1.819 | 1.504 |
| 75/25 domestic sales ratio | 3.596 | 4.806 |

*Note*: *75/25 ratio* is the ratio of the $75^{\text{th}}$ to the $25^{\text{th}}$ percentile. The other set of targeted moments, log exports, is shown in Figure 8.

Table 10: Causal forest estimates of the impact of 2080s climate change on Zambian firms

| Scenario | Change in log sales |
|---|---|
| SSP1/2.6 | $-0.078$<br>$(-0.127, -0.028)$ |
| SSP2/4.5 | $-0.087$<br>$(-0.131, -0.042)$ |
| SSP5/8.5 | $-0.187$<br>$(-0.271, -0.102)$ |

*Note*: Each row presents the average firm's loss in sales under the 2080s climate change trajectory for a given SSP. Standard errors clustered by firm cluster. 90 percent confidence intervals in parentheses.

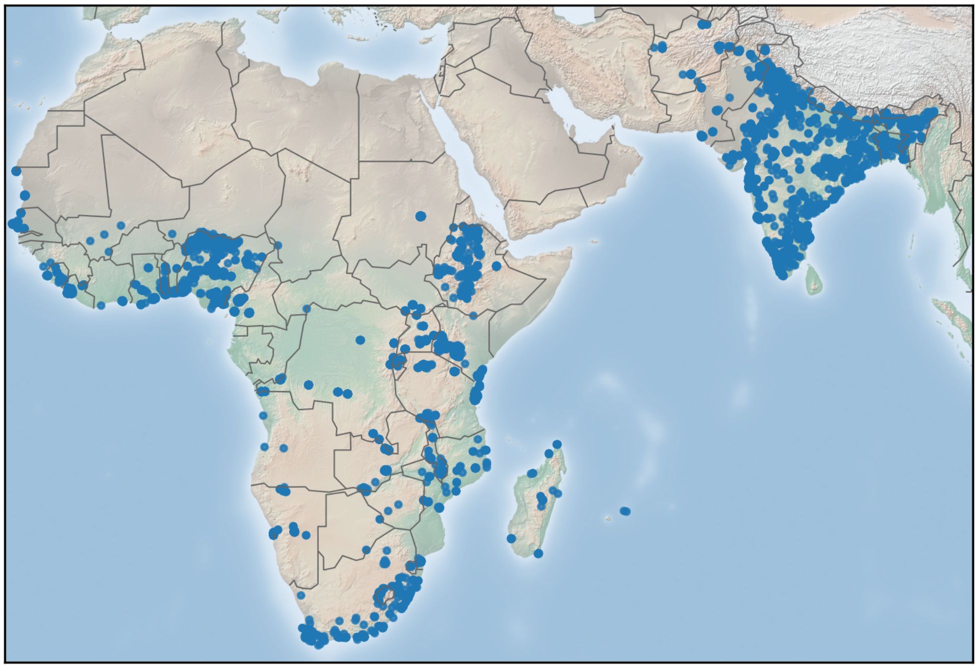
Table 11: Counterfactual change in welfare

| Scenario | Full model | Fix $c_j$ |
|---|---|---|
| *Panel A: Welfare gap compared to status quo* | | |
| Climate change baseline | -0.132 | -0.195 |
| Iceberg cost reduction | -0.104 | -0.168 |
| Entry cost reduction | -0.132 | -0.195 |
| Adaptation | -0.122 | -0.186 |
| Mitigation | -0.064 | -0.096 |
| *Panel B: Fraction of welfare gap closed* | | |
| Climate change baseline | 0.000 | 0.000 |
| Iceberg cost reduction | 0.214 | 0.137 |
| Entry cost reduction | 0.000 | 0.000 |
| Adaptation | 0.077 | 0.049 |
| Mitigation | 0.515 | 0.507 |

*Note*: Each column presents results for a different model. *Full model* shows results for my full model and *Fix* $c_j$ shows results for my model with productive capability reactions shut down (fixing the distribution of productive capability at the status quo). In panel A, each row presents the relative change in welfare under a different counterfactual scenario compared to the status quo. For example, a value of -0.1 means a ten percent decrease in welfare. These welfare changes are also changes in real GDP, using the optimal consumer price index to convert nominal to real values. In panel B, each row presents what fraction of the welfare gap under the *climate change baseline* scenario a given policy intervention manages to close. For example, a value of 0.1 means that ten percent of the baseline welfare gap has been closed. *Climate change baseline* uses the technology parameter $T_H$ to match the estimated impact of climate change on the Zambian economy. Starting from that scenario, *iceberg cost reduction* reduces variable trade costs from Zambia to all other markets by ten percent, while *entry cost reduction* reduces entry cost for Zambian firms to all other markets by ten percent. *Adaptation* shifts the technology parameter $T_H$ up by ten percent, whereas *mitigation* calibrates a new counterfactual scenario matching the climate change impact under SSP2/4.5.

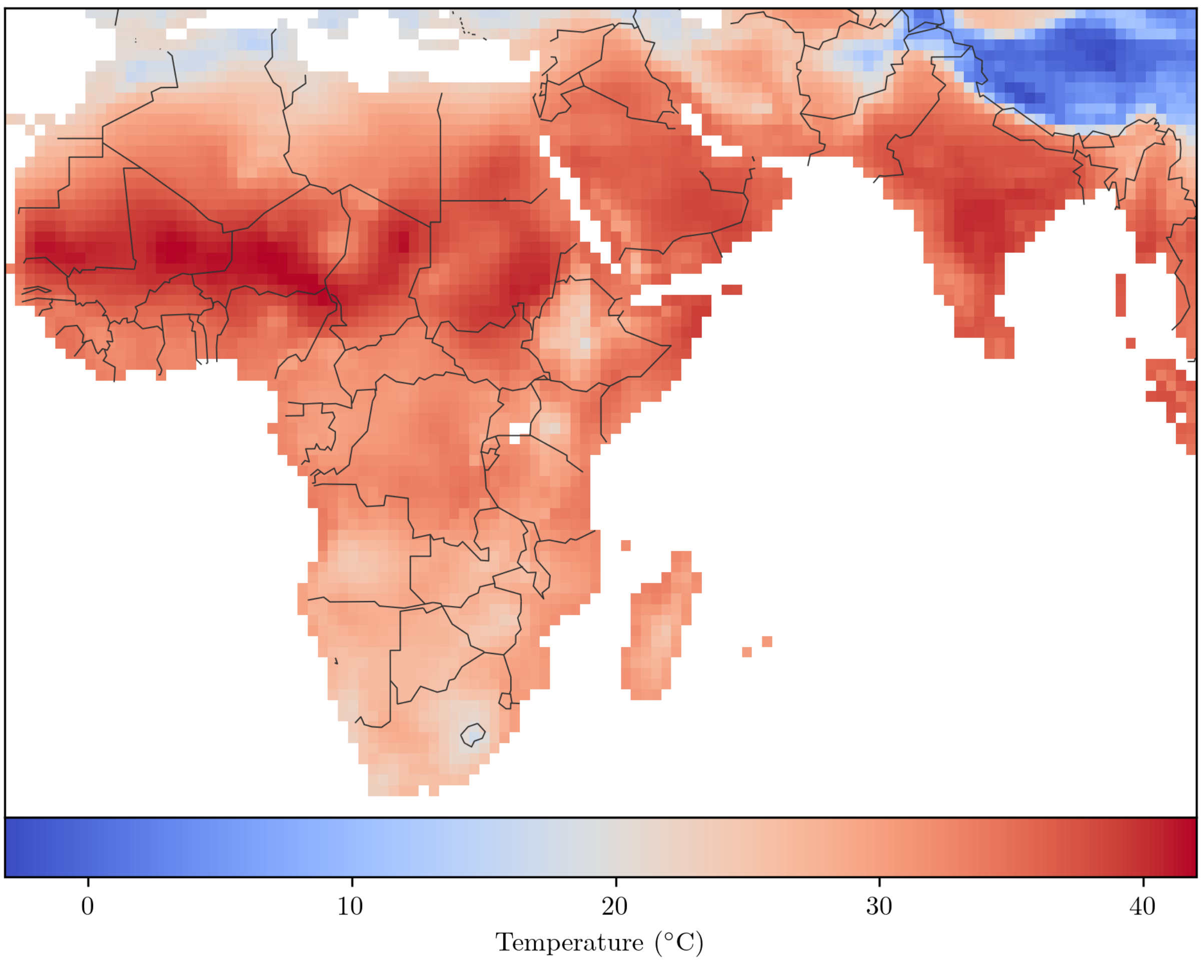
# Figures

Figure 1: Locations of firms and firm clusters across Africa and South Asia



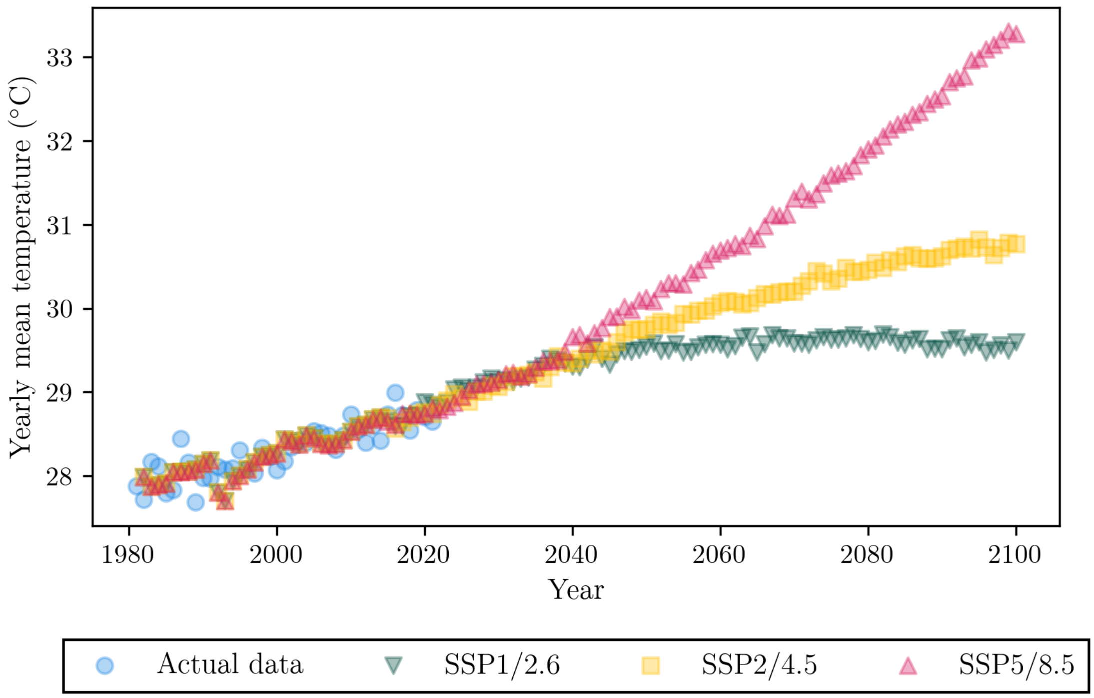
*Note*: Each dot is either the location of a single firm or the location of a firm cluster. Clusters appear if several firms were recorded as having the same location in the Enterprise Surveys data or if I was able to determine the firms' location via geolocation methods based on the city firms are located in.

Figure 2: Maximum temperature on April 24, 1991



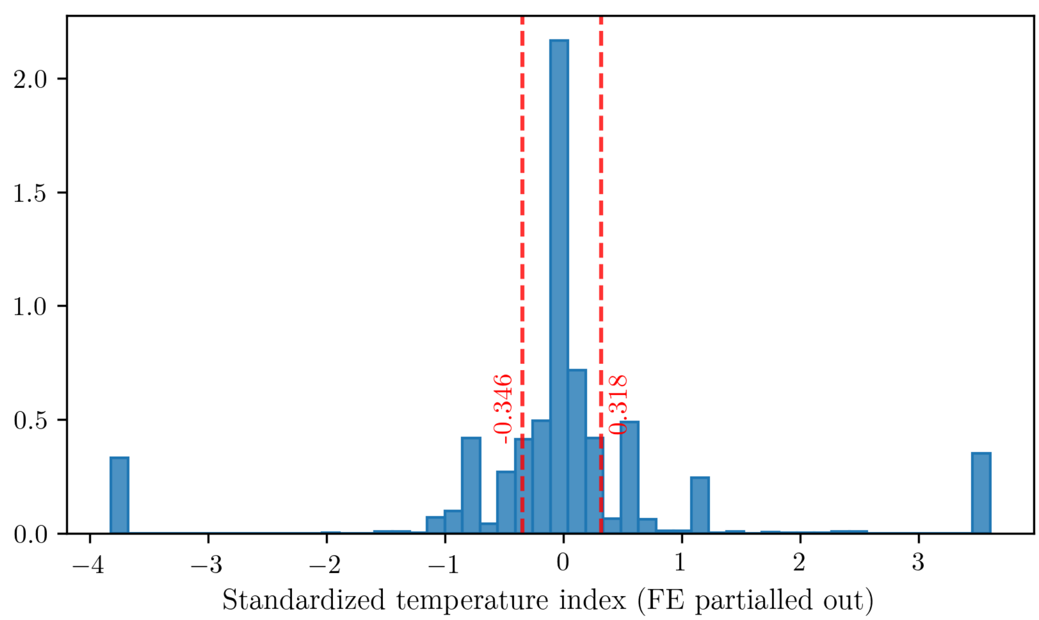

*Note*: The figure shows temperature from the Berkeley Earth dataset.

Figure 3: Yearly average daily maximum temperature across climate change scenarios



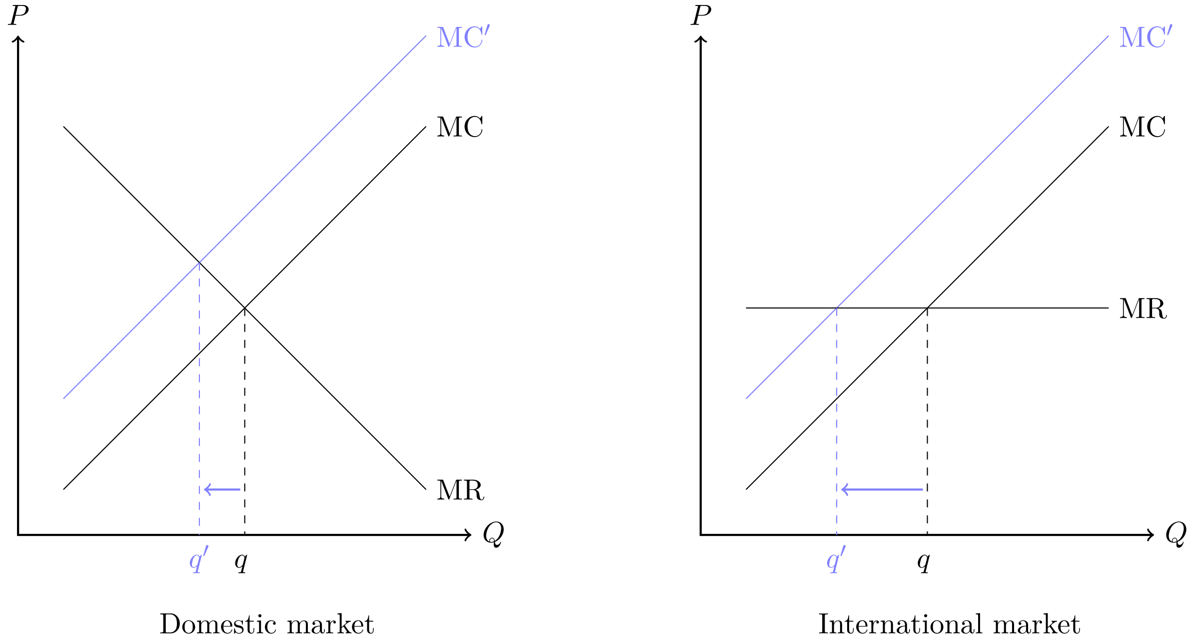

*Note*: The figure shows yearly averages of daily maximum temperatures. The climate change projections are adjusted for differences in baseline temperature means for each day of the year, as described in Appendix C.

Figure 4: Histogram of temperature index after partialling out cluster FE



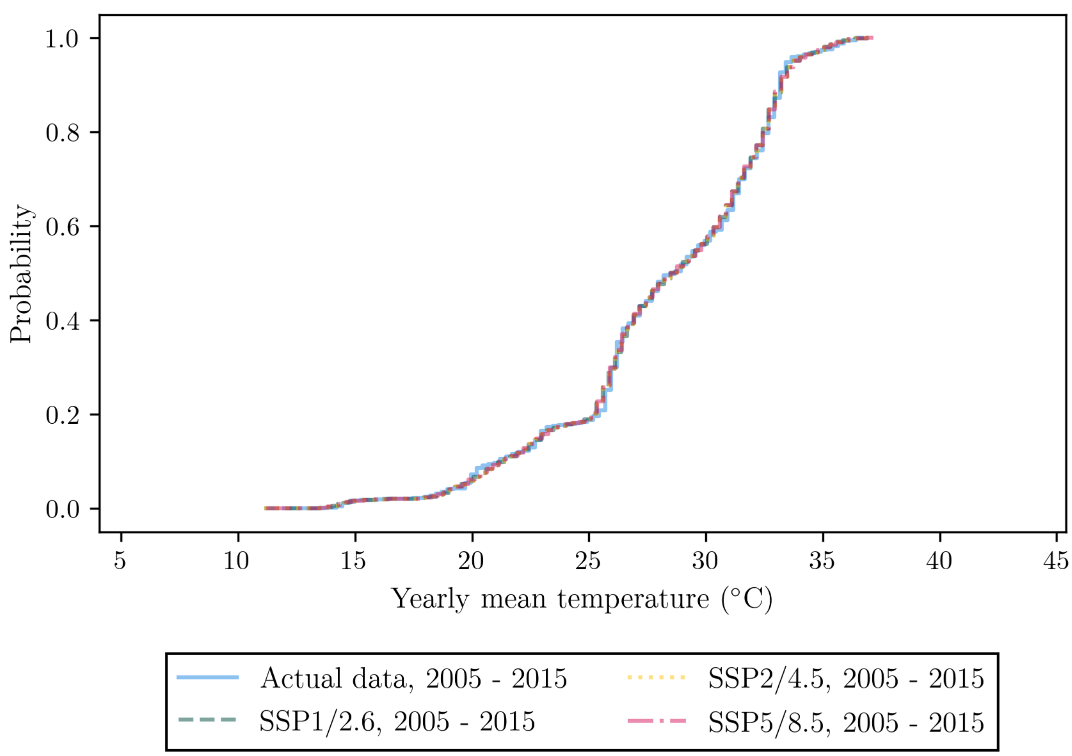

*Note*: The figure shows the temperature index after partialling out cluster fixed effects. This is the same identifying variation used in the regressions I estimate — the variation remaining in the standardized temperature index after cluster fixed effects are taken into account. Dashed lines indicate the 20th and 80th percentile. Observations without variation after partialling out FE not shown.

Figure 5: Graphical intuition for effect of supply shock on sales



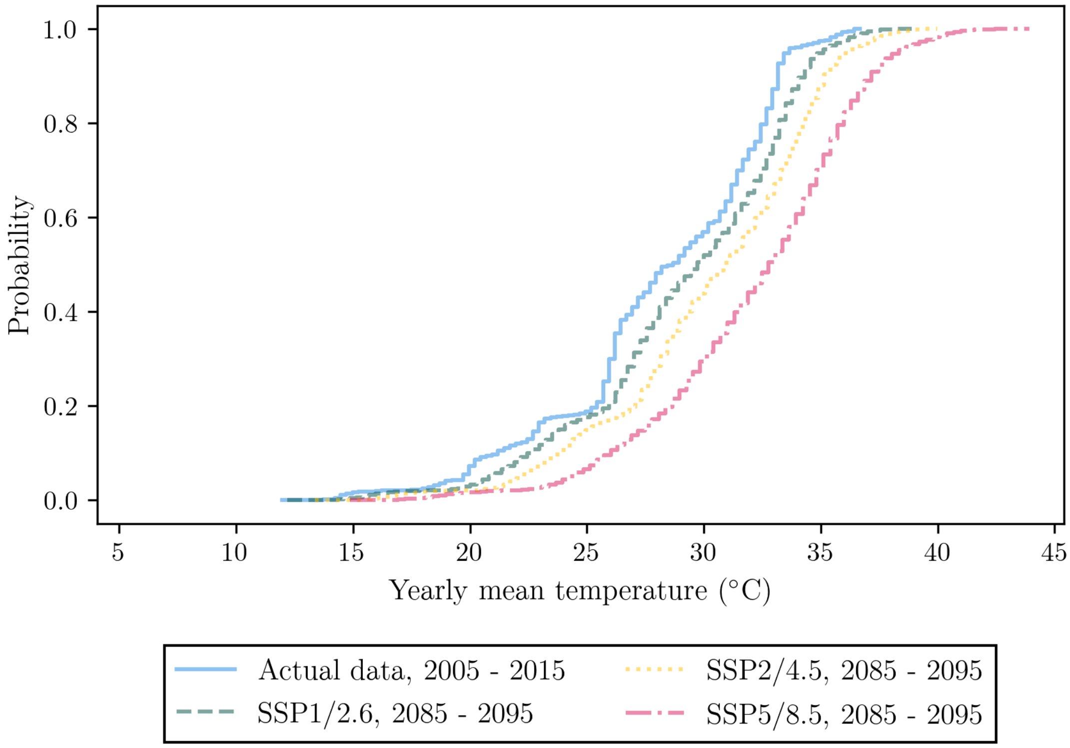

*Note*: The figure shows a basic open economy intuition for how a supply shock (increase in marginal cost) affects domestic and international sales. MC shows the firm's marginal cost, MR shows its marginal revenue.

Figure 6: Distribution of yearly average daily maximum temperature, 2005–2015, for actual data and climate change projections



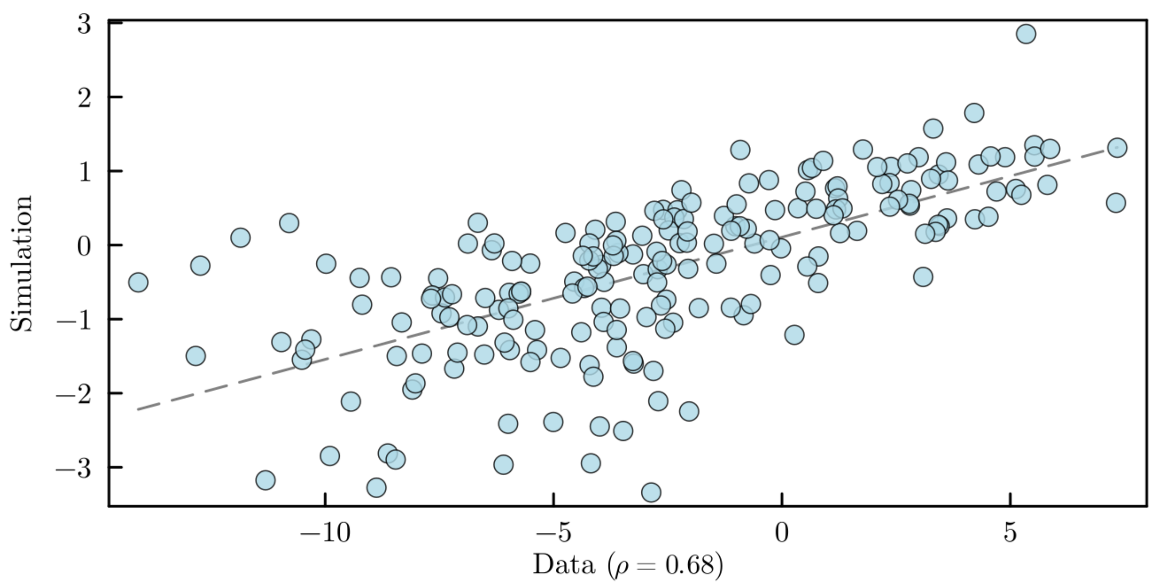

*Note*: The figure shows the empirical CDF of the yearly average of daily maximum temperatures across firms. The climate change projections are adjusted for differences in baseline temperature means for each day of the year, as described in Appendix C.

Figure 7: Distribution of yearly average daily maximum temperature, 2005–2015 for actual data and 2085–2095 for climate change projections



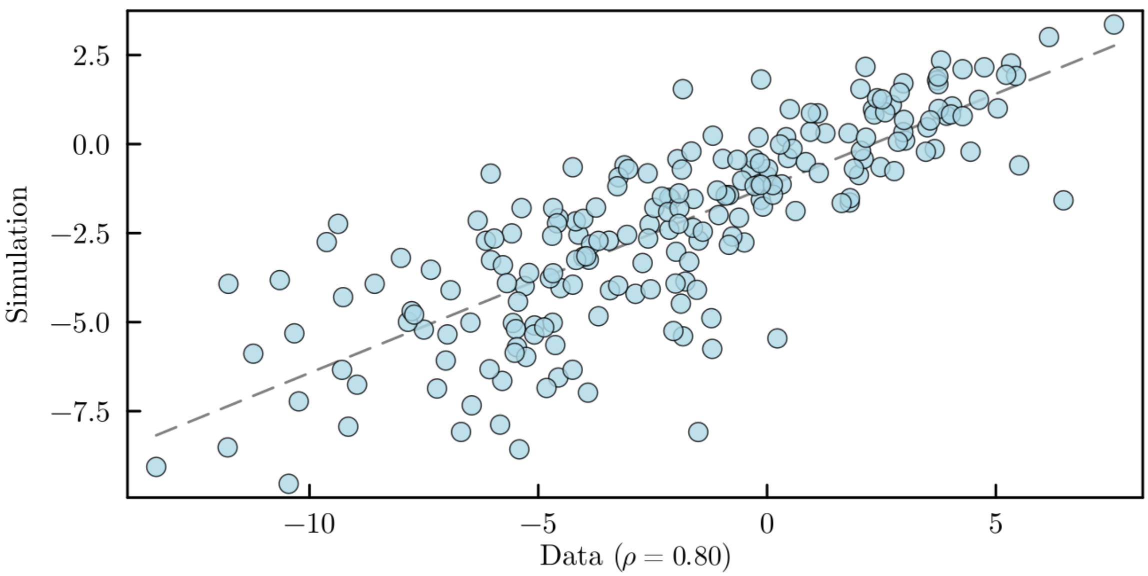

*Note*: The figure shows the empirical CDF of the yearly average of daily maximum temperatures across firms. The climate change projections are adjusted for differences in baseline temperature means for each day of the year, as described in Appendix C.

Figure 8: Zambian log exports vs. model simulation



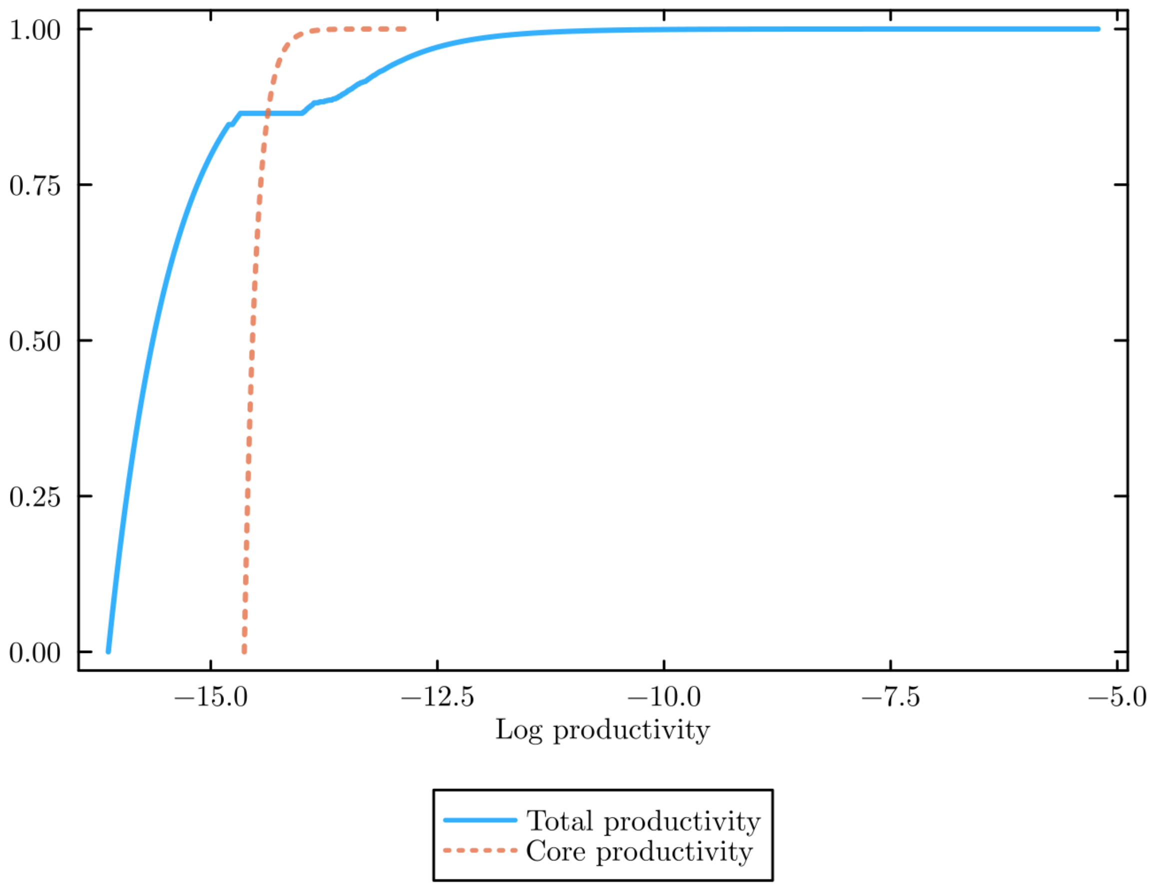

*Note*: Log exports are a targeted moment, together with the fraction of countries with zero exports.

Figure 9: Zambian log imports vs. model simulation



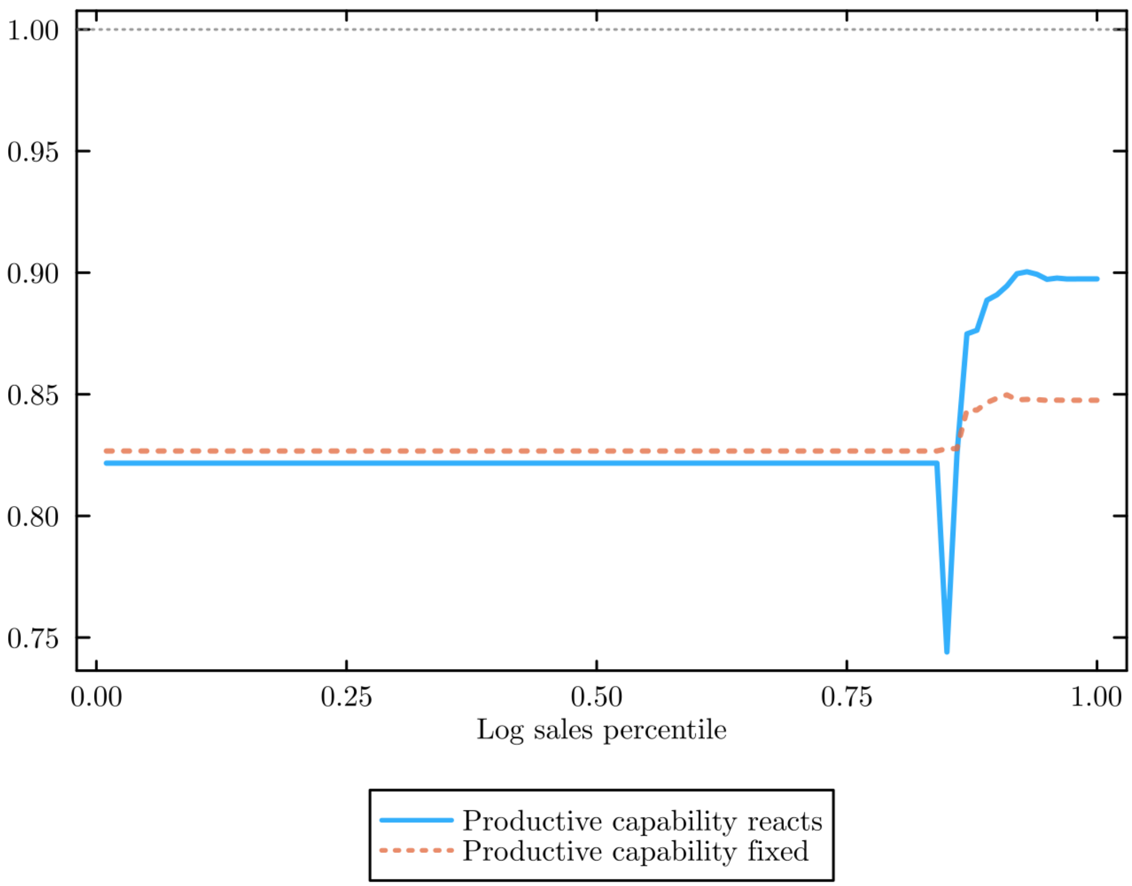

*Note*: Log imports are an untargeted moment.

Figure 10: Log total productivity compared to log core productivity



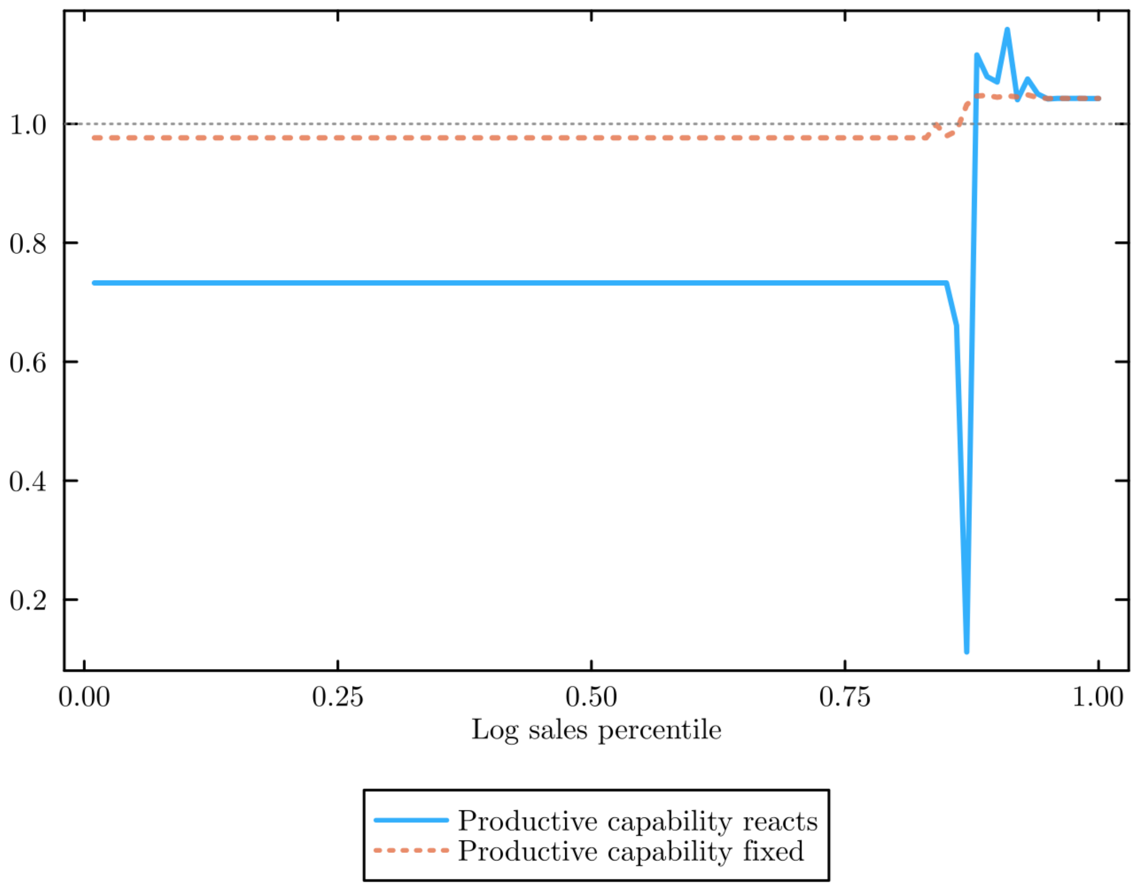

*Note*: The figure shows log total productivity $a_j c_j^{\delta}$, which depends on core productivity $a_j$ and productive capability $c_j$. Log core productivity also shown for comparison.

Figure 11: Change in log real sales under climate change baseline scenario




*Note*: The figure shows the change in real sales at each percentile of the real sales distribution. I calculate the ratio of each percentile in the climate change baseline scenario to the same percentile in the status quo. Values less than one thus indicate that the percentile shifts to the left. The grey dotted line at 1.0 indicates no change.

Figure 12: Change in log real sales with iceberg cost reduction




*Note*: The figure shows the change in real sales at each percentile of the real sales distribution. I calculate the ratio of each percentile in the iceberg trade cost reduction scenario to the same percentile in the climate change baseline scenario. Values less than one thus indicate that the percentile shifts to the left. The grey dotted line at 1.0 indicates no change.

# Appendix A Additional tables

## A.1 Additional descriptive statistics

Table 12: Number of observations by country

| Country | Total | Non-missing sales | Non-missing location |
|---|---|---|---|
| India | 8,808 | 8,505 | 4,540 |
| Nigeria | 4,234 | 3,759 | 2,655 |
| Bangladesh | 2,859 | 1,352 | 2,157 |
| Kenya | 2,359 | 2,172 | 1,967 |
| Pakistan | 2,027 | 564 | 1,083 |
| South Africa | 2,022 | 2,003 | 1,272 |
| Zambia | 1,747 | 1,643 | 1,739 |
| Ethiopia | 1,455 | 1,265 | 1,348 |
| Uganda | 1,225 | 1,016 | 986 |
| Tanzania | 1,185 | 912 | 901 |
| Congo, Dem. Rep. | 1,176 | 1,030 | 403 |
| Ghana | 1,161 | 1,013 | 467 |
| Zimbabwe | 1,153 | 570 | 449 |
| Senegal | 1,061 | 922 | 809 |
| Mozambique | 993 | 993 | 479 |
| Mali | 977 | 849 | 953 |
| Madagascar | 899 | 721 | 591 |
| Afghanistan | 890 | 552 | 350 |
| Namibia | 872 | 652 | 446 |
| Nepal | 833 | 820 | 360 |
| Rwanda | 802 | 569 | 354 |
| Cote d'Ivoire | 763 | 700 | 413 |
| Angola | 756 | 739 | 529 |
| South Sudan | 669 | 620 | 181 |
| Cameroon | 640 | 627 | 314 |
| Malawi | 622 | 331 | 368 |
| Sudan | 605 | 227 | 605 |
| Sri Lanka | 578 | 532 | 0 |
| Botswana | 576 | 546 | 290 |
| Bhutan | 486 | 241 | 250 |
| Eswatini | 445 | 431 | 439 |
| Burundi | 415 | 411 | 0 |
| Mauritius | 389 | 376 | 28 |
| Guinea | 369 | 303 | 35 |
| Mauritania | 369 | 334 | 157 |
| Burkina Faso | 345 | 333 | 0 |
| Gambia, The | 315 | 313 | 0 |
| Chad | 291 | 143 | 147 |
| Lesotho | 289 | 143 | 285 |
| Sierra Leone | 287 | 143 | 143 |
| Niger | 285 | 108 | 145 |
| Liberia | 281 | 133 | 133 |
| Togo | 267 | 126 | 134 |
| Benin | 255 | 132 | 136 |
| Eritrea | 178 | 0 | 0 |
| Guinea-Bissau | 155 | 153 | 0 |
| Cabo Verde | 152 | 0 | 0 |
| Central African Republic | 145 | 0 | 139 |
| Gabon | 134 | 0 | 0 |
| Congo, Rep. | 120 | 0 | 0 |

*Note*: *Total* shows the total number of firms in the sample for each country. *Non-missing sales* shows the number of firms with non-missing real total sales data. *Non-missing location* shows the number of firms with non-missing location data.

## A.2 Clustering distance choice

Table 13: Moran test for spatial correlation

| Clustering distance | $p$-value | Adjusted $p$-value | Fraction included |
|---:|---|---|---|
| 0.25 km | 0.116 | 1.000 | 0.211 |
| 0.5 km | 0.686 | 1.000 | 0.415 |
| 1.0 km | 0.535 | 1.000 | 0.627 |
| 2.5 km | 0.147 | 1.000 | 0.767 |
| 5.0 km | 0.582 | 1.000 | 0.782 |
| 10.0 km | 0.130 | 1.000 | 0.798 |
| 15.0 km | 0.161 | 1.000 | 0.801 |
| 20.0 km | 0.422 | 1.000 | 0.803 |
| 25.0 km | 0.440 | 1.000 | 0.814 |
| 50.0 km | 0.678 | 1.000 | 0.827 |
| 100.0 km | 0.605 | 1.000 | 0.832 |
| 200.0 km | 0.757 | 1.000 | 0.847 |
| 500.0 km | 0.500 | 1.000 | 0.979 |

*Note*: The Moran test is for the null that errors from a regression of log sales on a temperature index are not correlated across clusters. The index combines mean temperature, temperature variance and the number of days with temperatures exceeding 32°C (89.6°F). The index is an average of location-specific $z$-scores for each variable (using the 20-year mean and standard deviation of reach variable). Standard errors clustered by firm cluster. *Adjusted p-values* are adjusted for multiple hypothesis testing using the Holm-Bonferroni correction. *Fraction included* is the fraction of firms with non-missing location information which are included in any cluster.

## A.3 Specification and survival robustness checks

Table 14: Effect of weather shocks on sales including lead of temperature index

| Variable | Log sales |
|---|---|
| Temperature index | $-0.220^{*}$ |
| | [0.080] |
| Temperature index lead | $-0.037$ |
| | [0.790] |
| Year FE | Yes |
| Cluster FE | Yes |
| Clusters | 587 |
| Observations | 18,273 |

*Note*: *Temperature index* is an index combining mean temperature, temperature variance and the number of days with temperatures exceeding 32°C (89.6°F). The index is an average of location-specific $z$-scores for each variable (using the 20-year mean and standard deviation of reach variable). An 0.320 increase in the index is an 80$^{\text{th}}$ percentile weather shock. *Temperature index lead* is the same index for the next year, i.e., a one-year lead of the index. Standard errors clustered by firm cluster. Outcomes winsorized at the 95$^{\text{th}}$ percentile for each survey round. $p$-values in brackets. I use the ES survey weights to ensure representativeness.

Table 15: Checks for survival bias

| Variable | Zero sales | Current exporter |
|---|---|---|
| Temperature index | $-0.004$ | $-0.036^{*}$ |
| | [0.405] | [0.085] |
| Year FE | Yes | Yes |
| Cluster FE | Yes | Yes |
| Clusters | 595 | 592 |
| Observations | 22,458 | 21,810 |

*Note*: *Zero sales* is an indicator for firms reporting sales below the first percentile of sales. (I do not use literally zero sales because I have only six such observations.) *Current exporters* are firms that export in the current fiscal year. *Temperature index* is an index combining mean temperature, temperature variance and the number of days with temperatures exceeding 32°C (89.6°F). The index is an average of location-specific $z$-scores for each variable (using the 20-year mean and standard deviation of reach variable). An 0.320 increase in the index is an 80$^{\text{th}}$ percentile weather shock. $p$-values in brackets. I use the ES survey weights to ensure representativeness.

## A.4 Alternative specifications for exporter effect

Table 16: Effect of weather shocks by exporter status, no year FE

| Variable | Log sales |
|---|---|
| Temperature index | $-0.004$ [0.938] |
| Temperature index × Current exporter | $-0.094^{***}$ [0.006] |
| Current exporter | $1.630^{***}$ [0.000] |
| Cluster FE | Yes |
| Clusters | 586 |
| Observations | 17,975 |

*Note*: *Current exporters* are firms that export in the current fiscal year. *Temperature index* is an index combining mean temperature, temperature variance and the number of days with temperatures exceeding 32°C (89.6°F). The index is an average of location-specific $z$-scores for each variable (using the 20-year mean and standard deviation of reach variable). An 0.320 increase in the index is an 80$^{\text{th}}$ percentile weather shock. Standard errors clustered by firm cluster. Outcomes winsorized at the 95$^{\text{th}}$ percentile for each survey round. $p$-values in brackets. I use the ES survey weights to ensure representativeness.

Table 17: Effect of weather shocks by exporter status, most reliable numbers only

| Variable | Log sales |
|---|---|
| Temperature index | $-0.120$ [0.307] |
| Temperature index × Current exporter | $-0.069$ [0.216] |
| Current exporter | $1.473^{***}$ [0.000] |
| Year FE | Yes |
| Cluster FE | Yes |
| Clusters | 429 |
| Observations | 6,161 |

*Note*: This estimation uses only data that came directly from firm records, as opposed to being estimates, for example. *Current exporters* are firms that export in the current fiscal year. *Temperature index* is an index combining mean temperature, temperature variance and the number of days with temperatures exceeding 32°C (89.6°F). The index is an average of location-specific $z$-scores for each variable (using the 20-year mean and standard deviation of reach variable). An 0.320 increase in the index is an 80$^{\text{th}}$ percentile weather shock. Standard errors clustered by firm cluster. Outcomes winsorized at the 95$^{\text{th}}$ percentile for each survey round. $p$-values in brackets. I use the ES survey weights to ensure representativeness.

## A.5 Alternative indicators for exporter status

Table 18: Exporter effect using past exporter status

| Variable | Log sales |
|---|---|
| Temperature index | 0.119 |
| | [0.358] |
| Temperature index × Past exporter | $-0.074^{**}$ |
| | [0.036] |
| Past exporter | $1.208^{***}$ |
| | [0.000] |
| Year FE | Yes |
| Cluster FE | Yes |
| Clusters | 587 |
| Observations | 18,273 |

*Note*: *Past exporter* is an indicator for firms reporting a past year as their first year of exporting. *Temperature index* is an index combining mean temperature, temperature variance and the number of days with temperatures exceeding 32°C (89.6°F). The index is an average of location-specific $z$-scores for each variable (using the 20-year mean and standard deviation of reach variable). An 0.320 increase in the index is an 80$^{\text{th}}$ percentile weather shock. Standard errors clustered by firm cluster. Outcomes winsorized at the 95$^{\text{th}}$ percentile for each survey round. $p$-values in brackets. I use the ES survey weights to ensure representativeness.

Table 19: Exporter effect using ever exporter status

| Variable | Log sales |
|---|---|
| Temperature index | 0.141 |
| | [0.269] |
| Temperature index × Ever exporter | $-0.079^{**}$ |
| | [0.022] |
| Ever exporter | $1.384^{***}$ |
| | [0.000] |
| Year FE | Yes |
| Cluster FE | Yes |
| Clusters | 586 |
| Observations | 17,975 |

*Note*: *Ever exporter* is an indicator for firms which exported in the past and/or report international sales this year. *Temperature index* is an index combining mean temperature, temperature variance and the number of days with temperatures exceeding 32°C (89.6°F). The index is an average of location-specific $z$-scores for each variable (using the 20-year mean and standard deviation of reach variable). An 0.320 increase in the index is an 80$^{\text{th}}$ percentile weather shock. Standard errors clustered by firm cluster. Outcomes winsorized at the 95$^{\text{th}}$ percentile for each survey round. $p$-values in brackets. I use the ES survey weights to ensure representativeness.

Table 20: Effect on continuing, discontinuing, and first-time exporters

| Variable | Log sales |
|---|---|
| Temperature index | $-0.143$ [0.178] |
| Temperature index × Continuing exporter | $-0.097^{***}$ [0.005] |
| Temperature index × Discontinuing exporter | $-1.451^{***}$ [0.002] |
| Temperature index × First-time exporter | 0.092 [0.573] |
| Year FE | Yes |
| Exporter status FE | Yes |
| Cluster FE | Yes |
| Clusters | 586 |
| Observations | 17,975 |

*Note*: *Continuing exporters* are firms that exported in the past and do so in the observed year. *Discontinuing past exporters* are firms that exported in the past and are not doing so in the observed year. *First-time exporters* did not export in the past, but are doing so now. *Temperature index* is an index combining mean temperature, temperature variance and the number of days with temperatures exceeding 32°C (89.6°F). The index is an average of location-specific $z$-scores for each variable (using the 20-year mean and standard deviation of reach variable). An 0.320 increase in the index is an 80$^{\text{th}}$ percentile weather shock. Standard errors clustered by firm cluster. Outcomes winsorized at the 95$^{\text{th}}$ percentile for each survey round. $p$-values in brackets. I use the ES survey weights to ensure representativeness.

## A.6 Additional regressions

Table 21: Effect of weather shocks on cost of repurchasing machinery

| Variable | Log value of re-purchasing machinery |
|---|---|
| Temperature index | 0.121<br>[0.656] |
| Temperature index × Current exporter | 0.035<br>[0.464] |
| Current exporter | 1.635***<br>[0.000] |
| Year FE | Yes |
| Cluster FE | Yes |
| Clusters | 412 |
| Observations | 6,858 |

*Note*: *Temperature index* is an index combining mean temperature, temperature variance and the number of days with temperatures exceeding 32°C (89.6°F). The index is an average of location-specific $z$-scores for each variable (using the 20-year mean and standard deviation of reach variable). An 0.320 increase in the index is an 80$^{\text{th}}$ percentile weather shock. Outcomes winsorized at the 95$^{\text{th}}$ percentile for each survey round. $p$-values in brackets. I use the ES survey weights to ensure representativeness.

Table 22: Effect of weather shocks on domestic sales among firms with non-missing data for log productive capability

| Variable | Log domestic sales |
|---|---|
| Temperature index | −0.157<br>[0.346] |
| Temperature index × Current exporter | −0.070<br>[0.168] |
| Current exporter | 1.039***<br>[0.000] |
| Year FE | Yes |
| Cluster FE | Yes |
| Clusters | 375 |
| Observations | 7,447 |

*Note*: This estimation uses only firms with non-missing observations for log productive capability. *Temperature index* is an index combining mean temperature, temperature variance and the number of days with temperatures exceeding 32°C (89.6°F). The index is an average of location-specific $z$-scores for each variable (using the 20-year mean and standard deviation of reach variable). An 0.320 increase in the index is an 80$^{\text{th}}$ percentile weather shock. Standard errors clustered by firm cluster. Outcomes winsorized at the 95$^{\text{th}}$ percentile for each survey round. $p$-values in brackets. I use the ES survey weights to ensure representativeness.

Table 23: Checks for alternative explanations

| Variable | Log sales | Log sales | Log sales | Log sales | Log sales | Log sales | Log sales | Log sales |
|---|---|---|---|---|---|---|---|---|
| Temperature index | −0.269** [0.023] | −0.049 [0.671] | −0.113 [0.240] | −0.077 [0.378] | −0.105 [0.303] | −0.050 [0.611] | −0.101 [0.357] | 0.064 [0.312] |
| Temperature index × Current exporter | −0.088*** [0.006] | −0.063** [0.025] | −0.089** [0.015] | −0.101*** [0.000] | −0.079** [0.014] | −0.099*** [0.000] | −0.098*** [0.003] | −0.049*** [0.002] |
| Temperature index × Initial no. of employees > median | −0.017 [0.516] | | | | | | | −0.014 [0.444] |
| Initial no. of employees > median | 1.208*** [0.000] | | | | | | | 0.434*** [0.000] |
| Temperature index × No. of employees 3 yrs. ago > median | | −0.036 [0.146] | | | | | | −0.042* [0.094] |
| No. of employees 3 yrs. ago > median | | 1.772*** [0.000] | | | | | | 1.321*** [0.000] |
| Temperature index × International certification | | | | | −0.026 [0.646] | | | 0.008 [0.789] |
| International certification | | | | | 1.251*** [0.000] | | | 0.597*** [0.000] |
| Temperature index × Manager's years of experience > median | | | | | | | −0.060*** [0.000] | −0.014 [0.394] |
| Manager's years of experience > median | | | | | | | 0.563*** [0.000] | 0.241*** [0.000] |
| ISIC2 FE | | | Yes | | | | | |
| ISIC2 FE × weather variables | | | Yes | | | | | |
| ISIC4 FE | | | | Yes | | | | Yes |
| ISIC4 FE × weather variables | | | | Yes | | | | Yes |
| Legal status FE | | | | | | Yes | | Yes |
| Legal status FE × weather variables | | | | | | Yes | | Yes |
| Current exporter | 1.277*** [0.000] | 1.050*** [0.000] | 1.494*** [0.000] | 1.419*** [0.000] | 1.365*** [0.000] | 1.286*** [0.000] | 1.568*** [0.000] | 0.733*** [0.000] |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Clusters | 584 | 582 | 584 | 583 | 586 | 586 | 586 | 573 |
| Observations | 16,169 | 16,554 | 16,446 | 16,221 | 17,537 | 17,903 | 17,774 | 13,417 |

*Note*: *ISIC2 FE* and *ISIC4 FE* are indicators for two-digit and four-digit ISIC sectors, respectively. *International certification* is an indicator for firms reporting that they have an international quality certification. *Legal status FE* are indicators for the legal status of the firm. The omitted status are sole proprietorships. *Temperature index* is an index combining mean temperature, temperature variance and the number of days with temperatures exceeding 32°C (89.6°F). The index is an average of location-specific $z$-scores for each variable (using the 20-year mean and standard deviation of reach variable). An 0.320 increase in the index is an 80$^{\text{th}}$ percentile weather shock. Standard errors clustered by firm cluster. Outcomes winsorized at the 95$^{\text{th}}$ percentile for each survey round. $p$-values in brackets. I use the ES survey weights to ensure representativeness.

## A.7 Reduced form parameter estimation for structural model

Table 24: Total on domestic sales regression

| Variable | Trade flows |
|---|---|
| Log sales | 0.816*** <br> [0.000] |
| Manager's years of experience | 0.037*** <br> [0.000] |
| Log initial no. of employees | 0.333*** <br> [0.000] |
| Log no. of employees 3 yrs. ago | −0.668*** <br> [0.000] |
| International certification | 0.124*** <br> [0.000] |
| Had power outage | 0.060*** <br> [0.000] |
| Competes against informal sector | −0.103*** <br> [0.000] |
| Introduced new product | 0.238*** <br> [0.000] |
| Introduced new process | 0.174*** <br> [0.000] |
| Had RD expenditure | −0.131*** <br> [0.000] |
| Part of larger firm | 0.133*** <br> [0.000] |
| Formal when founded | 0.183*** <br> [0.000] |
| Applied for grid connection | −0.085*** <br> [0.000] |
| Applied for water connection | −0.103*** <br> [0.000] |
| Firm age | 0.021*** <br> [0.000] |
| $4^{\text{th}}$ degree polynomials | Yes |
| Pairwise interactions | Yes |
| Country-sector (ISIC4)-year FE | Yes |
| Observations | 4,160 |

*Note*: *Fourth degree polynomials* are included for all continuous variables besides log sales. *Pairwise interactions* include only level variables, not variables raised to a power as part of the polynomials. $p$-values in brackets. I use the ES survey weights to ensure representativeness. The underlying standard errors are robust to heteroskedasticity.

Table 25: Gravity estimation results

| Variable | Trade flows |
|---|---|
| Log distance | $-1.167^{***}$ |
| | [0.000] |
| Contiguous | $0.661^{***}$ |
| | [0.000] |
| Importer FE | Yes |
| Exporter FE | Yes |

*Note*: Estimated using pseudo-Poisson maximum likelihood estimation to deal with zero trade shares (Santos Silva & Tenreyro, 2006). The coefficient on log distance therefore represents an elasticity. Based on data for all countries except Zambia (Bartelme, Lan, & Levchenko, 2023). $p$-values in brackets. I use the ES survey weights to ensure representativeness. The underlying standard errors are robust to heteroskedasticity.

## A.8 Results for Melitz (2003) estimation

Table 26: Parameter estimates for Melitz (2003)

| Parameter | Source/identifying variation | Estimate |
|---|---|---|
| *Panel A: Reduced form and data* | | |
| $\sigma$ | Sales, variable cost | 3.016 (0.043) |
| *Panel B: Structural estimation* | | |
| $\theta$ | 75/25 ratio for domestic sales | 5.557 |
| $T_H w_H$ | Ratio of Home sales to Foreign sales | 0.000 |
| $f_H w_H$ | Fraction of exporters | 0.196 |
| $\gamma_0$ | | 7.719 |
| $\gamma_{\text{dist}}$ | Export flows | -9.796 |
| $\gamma_{\text{contig}}$ | | 6.284 |

*Note*: Standard errors in parentheses where available. I present the minimum productivity $T_H$ and start-up cost $f_H$ times the estimated Home wage $w_H$ to convert them into an easier to interpret unit, millions of USD, rather than presenting them in units of labor. The three components of $\gamma$ are the intercept $\gamma_0$, the coefficient on log distance $\gamma_{\text{dist}}$ and the coefficient on the contiguity indicator $\gamma_{\text{contig}}$.

Table 27: Moment comparisons for structural estimation of Melitz (2003)

| Moment | Data | Model |
|---|---|---|
| Fraction exporting | 0.152 | 0.148 |
| Ratio own trade/total exports | 1.819 | 1.805 |
| 75/25 domestic sales ratio | 3.596 | 1.569 |

*Note*: *75/25 ratio* is the ratio of the $75^{\text{th}}$ to the $25^{\text{th}}$ percentile. The other set of targeted moments, log exports, is shown in Figure 13.

## A.9 Additional counterfactual results

Table 28: Counterfactual change in welfare compared to Melitz (2003)

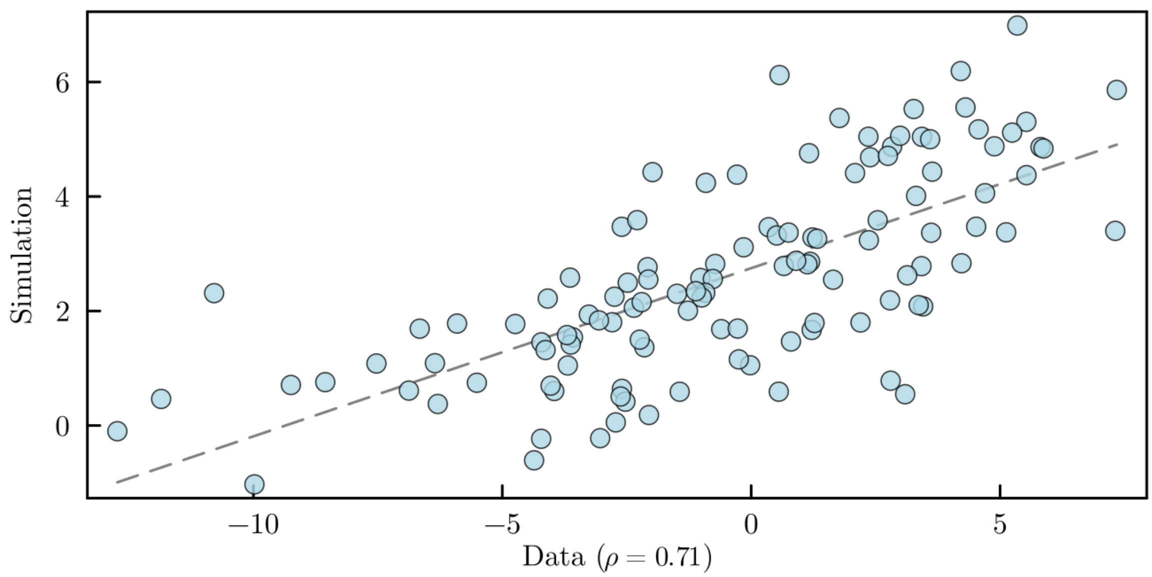
| Scenario | Full model | Melitz (2003) |
|---|---|---|
| *Panel A: Welfare gap compared to status quo* | | |
| Climate change baseline | -0.132 | -0.205 |
| Iceberg cost reduction | -0.104 | -0.205 |
| Entry cost reduction | -0.132 | -0.199 |
| Adaptation | -0.122 | -0.192 |
| Mitigation | -0.064 | -0.102 |
| *Panel B: Fraction of welfare gap closed* | | |
| Climate change baseline | 0.000 | 0.000 |
| Iceberg cost reduction | 0.214 | 0.000 |
| Entry cost reduction | 0.000 | 0.029 |
| Adaptation | 0.077 | 0.064 |
| Mitigation | 0.515 | 0.505 |

*Note*: Each column presents results for a different model. *Full model* shows results for my full model and *Melitz (2003)* shows results for the model of Melitz (2003). In panel A, each row presents the relative change in welfare under a different counterfactual scenario compared to the status quo. For example, a value of -0.1 means a ten percent decrease in welfare. These welfare changes are also changes in real GDP, using the optimal consumer price index to convert nominal to real values. In panel B, each row presents what fraction of the welfare gap under the *climate change baseline* scenario a given policy intervention manages to close. For example, a value of 0.1 means that ten percent of the baseline welfare gap has been closed. *Climate change baseline* uses the technology parameter $T_H$ to match the estimated impact of climate change on the Zambian economy. Starting from that scenario, *iceberg cost reduction* reduces variable trade costs from Zambia to all other markets by ten percent, while *entry cost reduction* reduces entry cost for Zambian firms to all other markets by ten percent. *Adaptation* shifts the technology parameter $T_H$ up by ten percent, whereas *mitigation* calibrates a new counterfactual scenario matching the climate change impact under SSP2/4.5.

# Appendix B Additional figures

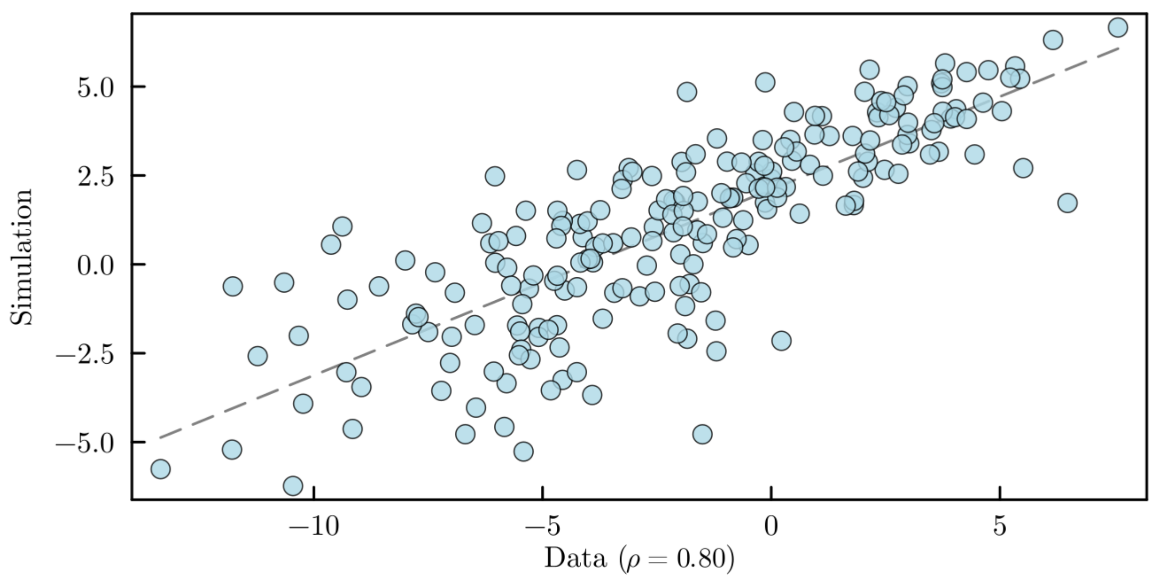
## B.1 Moment comparisons for Melitz (2003) estimation

Figure 13: Zambian log exports vs. model simulation from Melitz (2003) estimation




*Note*: Log exports are a targeted moment, together with the fraction of countries with zero exports.

Figure 14: Zambian log imports vs. model simulation from Melitz (2003) estimation




*Note*: Log imports are an untargeted moment.

# Appendix C Climate data processing

For firms that, due to their offset locations, ended up with interpolated data from CHIRPS or BKE, I also interpolate projection data in the same way to ensure that observed changes in weather are due to differences in weather over time at the same location, rather than weather data and projections coming from different locations. Since I combine weather data (CHIRPS and BKE) with the NEX-GDDP-CMIP6 projections, I need to take care to remove underlying differences in average weather at baseline, to isolate the effect of changes in weather patterns over time (Auffhammer et al., 2013). To this end, I also download historical runs of each model for the period from 1980–2014. This gives me an overlapping period of 34 years to assess existing biases across models and correct for them. For both temperature and precipitation, I calculate the average value for each day of the year (e.g., January 1) across this overlapping period and subtract the difference from projection data, as recommended by Auffhammer et al. (2013). For one of the climate models, TaiESM1, temperature jumps significantly between the historical run and climate change projection, making it impossible to adjust for bias and making me question the validity of the projection. I thus exclude the TaiESM1 projections for both temperature and precipitation from my analyses. No other model has this issue.

# Appendix D Possible mechanisms for weather effect on productivity

My results show an effect of weather on output, which I interpret as evidence of a net productivity reduction because of the differential impact on exporters. This begs the question, through what mechanism does weather affect firm productivity? I will not be able to determine a single channel through which this happens, and I think it is reasonable to assume that multiple channels are important here. There is a large literature on productivity effect of weather in different contexts, highlighting multiple ways in which weather can decrease productivity.

For example, Adhvaryu et al. (2019) find direct evidence for lower worker productivity on assembly lines during hot days, exacerbated by heat-generating lighting, Somanathan et al. (2021) find lower worker productivity in Indian manufacturing firms on hot days, and Zhang et al. (2018) find reduced total factor productivity in Chinese manufacturing during hotter years. In their wide-ranging literature summary, Carleton and Hsiang (2016) note negative impacts of temperature on labor supply, which are also found to be important in Somanathan et al. (2021) and Santangelo (2019). If workers supply less labor at each wage level, for example because they need to work on their own subsistence farms, that has an effect similar to lower worker productivity — to produce a given quantity, the firm needs to incur higher labor cost. These arguments may pertain more to employees in lower skilled jobs, but as Carleton and Hsiang (2016) note, previous research also finds that extreme temperatures reduce cognitive performance, e.g., lowering math test scores. With imperfect climate control, even workers in an office setting would face lower productivity due to extreme heat. Through this cognitive performance channel, temperature can reduce worker productivity even for firms in the service sector, for example. Ultimately, working in extreme heat makes it hard for anyone to perform their best, is at best unpleasant and at worst outright dangerous.

Table 29 shows evidence that several of these channels are present in my data, albeit the estimates are all somewhat noisy. For example, I see sales per employee declining by 2.4 percent following an $80^{\text{th}}$ percentile weather shock, which is a direct indication that labor productivity is reduced. I also see firms' total operating hours increasing by 4.3 percent in response to a $80^{\text{th}}$ percentile weather shock. Since firms' sales are falling, this suggests lower output per hour, as for example found by Adhvaryu et al. (2019). I further find that hotter years lead to more power outages, with an $80^{\text{th}}$ percentile weather shock increasing the likelihood of an outage by 1.7 percentage points (again, the estimate is somewhat noisy). Outages can directly decrease firm productivity (Hardy & McCasland, 2019).

Table 29: Indications of productivity impact

| Variable | Log sales/employee | Log weekly hours | Outage |
|---|---|---|---|
| Temperature index | $-0.074$ [0.491] | $0.142^{*}$ [0.088] | $0.065^{*}$ [0.075] |
| Year FE | Yes | Yes | Yes |
| Cluster FE | Yes | Yes | Yes |
| Clusters | 587 | 522 | 595 |
| Observations | 18,133 | 11,837 | 22,327 |

*Note*: *Temperature index* is an index combining mean temperature, temperature variance and the number of days with temperatures exceeding 32°C (89.6°F). The index is an average of location-specific $z$-scores for each variable (using the 20-year mean and standard deviation of reach variable). An 0.320 increase in the index is an $80^{\text{th}}$ percentile weather shock. Each column shows results for a different outcome. *Log weekly hours* is the log of the firm's total operating hours per week. *Log female employment* is the log of the firm's number of female employees. *Outage* is an indicator for whether the firm experienced power outages. Outcomes winsorized at the $95^{\text{th}}$ percentile, except indicators. $p$-values in brackets. I use the ES survey weights to ensure representativeness.

# Appendix E Proofs and derivations

## E.1 Optimal $c$

The FOC for the optimal distribution network gives

$$
\begin{aligned}
0 &= \delta \frac{w_i}{a_j} c_j^{-\delta-1} \left( \sum_{n \in \mathcal{M}_j} d_{ni} \alpha_n p_n(j)^{-\sigma} \right) - b c_j^{\frac{1}{\beta}-1} w_i \\
\Leftrightarrow c_j^{\frac{1}{\beta}+\delta} &= \frac{1}{b} \delta \frac{1}{a_j} \left( \sum_{n \in \mathcal{M}_j} d_{ni} \alpha_n p_n(j)^{-\sigma} \right) \\
\overset{(4)}{\Leftrightarrow} c_j^{\frac{1}{\beta}+\delta} &= \frac{1}{b} \delta (\mu w_i)^{-\sigma} a_j^{\sigma-1} \left( \sum_{n \in \mathcal{M}_j} {d_{ni}}^{1-\sigma} \alpha_n \right) c_j^{\delta\sigma} \qquad (15) \\
\Leftrightarrow c_j &= \left[ \frac{1}{b} \delta (\mu w_i)^{-\sigma} a_j^{\sigma-1} \left( \sum_{n \in \mathcal{M}_j} {d_{ni}}^{1-\sigma} \alpha_n \right) \right]^{\frac{\beta}{1-\beta(\sigma-1)\delta}}
\end{aligned}
$$

## E.2 Proof that $\mathcal{M}_j^{\text{lb}}$ is a lower bound

I need to show that there is no set of markets $\mathcal{M}_j^{\text{cand}}$ included in $\mathcal{M}_j^{\text{lb}}$ such that exiting these markets would increase firm profits. I first show that there is no single market included in the lower bound that the firm could profitably exit, and then show that this also implies there is no set of markets included in the lower bound that the firm could profitably exit.

Suppose firm $j$ is active in markets $\mathcal{M}_j \supseteq \mathcal{M}_j^{\text{lb}}$ with $c_j$ optimally chosen and considers whether exiting a market $n \in \mathcal{M}_j^{\text{lb}}$ could increase its profit. Let $\widetilde{\mathcal{M}}_j = \mathcal{M}_j \setminus \{n\}$ and let $\tilde{c}_j$ be the corresponding optimal productive capability. Since $c_j$ is increasing in $|\mathcal{M}_j|$, I know that $\tilde{c}_j < c_j$. I also know that at the iteration of the algorithm during which $n$ was added to $\mathcal{M}_j^{\text{lb}}$ the firm was active in a set of markets $\mathcal{M}'_j$ not including $n$ and would have made a variable profit in $n$ at the optimal $c'_j$. Since the algorithm only ever adds markets at each iteration and $\mathcal{M}_j \supseteq \mathcal{M}_j^{\text{lb}}$ I know that every market in $\mathcal{M}'_j$ must also be in $\widetilde{\mathcal{M}}_j = \mathcal{M}_j \setminus \{n\}$. I therefore have $\mathcal{M}'_j \subseteq \widetilde{\mathcal{M}}_j$ which implies $c'_j \leq \tilde{c}_j$. That is, the firm made a variable profit in $n$ at some $c'_j \leq \tilde{c}_j < c_j$. Therefore, it will certainly make a variable profit in $n$ at $c_j$ or $\tilde{c}_j$, and variable losses incurred in $n$ cannot be the reason to exit it (since there are none). Exiting $n$ could still increase the firm's total profit because at $\widetilde{\mathcal{M}}_j$, the fact that $\tilde{c}_j < c_j$ decreases its cost of acquiring productive capability. But there is nothing stopping the firm from choosing $\tilde{c}_j$ at $\mathcal{M}_j$ while still incurring a variable profit in $n$. Since at $\mathcal{M}_j$, the firm instead optimally chooses $c_j$, deviating to $\tilde{c}_j$ cannot increase profits. Therefore, the firm would never want to exit any market $n \in \mathcal{M}_j^{\text{lb}}$.

This argument extends to exiting a set of markets $\mathcal{M}_j^{\text{cand}}$ that the algorithm included in $\mathcal{M}_j^{\text{lb}}$, because $c_j$ depends only on the total effective demand of all markets in $\mathcal{M}_j^{\text{cand}}$ (not on their indices, for example). The firm would make a profit in any market $n \in \mathcal{M}^{\text{cand}}$, so direct losses cannot be the reason to exit. For the firm's choice of $c_j$, exiting several markets at once is just like exiting one large market, because $c_j$ depends only on the sum of $\alpha_n$ across all markets the firm is active in. For the same reason as above, choosing a different $c_j$ cannot increase profits.

### E.3 Proof that $\mathcal{M}_j^{\text{ub}}$ is an upper bound

I need to show that there is no set of markets $\mathcal{M}_j^{\text{cand}}$ excluded from $\mathcal{M}_j^{\text{ub}}$ such that entering these markets would increase firm profits. I first show that there is no single market excluded from the upper bound that the firm could profitably enter, and then show that this also implies there is no set of markets excluded from the upper bound that the firm could profitably enter.

Suppose firm $j$ is active in markets $\mathcal{M}_j \subseteq \mathcal{M}_j^{\text{ub}}$ with $c_j$ optimally chosen and considers whether entering a market $n \notin \mathcal{M}_j^{\text{ub}}$ could increase its profit. Let $\widetilde{\mathcal{M}}_j = \mathcal{M}_j \cup \{n\}$ and let $\tilde{c}_j$ be the corresponding optimal productive capability. Since $c_j$ is increasing in $|\mathcal{M}_j|$, I know that $\tilde{c}_j > c_j$. I also know that at the iteration of the algorithm during which $n$ was dropped from $\mathcal{M}_j^{\text{ub}}$ the firm was active in a set of markets $\mathcal{M}'_j$ including $n$ and did not make a variable profit in $n$ at the optimal $c'_j$. Since the algorithm only ever drops markets at each iteration and $\mathcal{M}_j \subseteq \mathcal{M}_j^{\text{ub}}$, I know that every market in $\widetilde{\mathcal{M}}_j = \mathcal{M}_j \cup \{n\}$ must also be in $\mathcal{M}'_j$. I therefore have $\mathcal{M}'_j \supseteq \widetilde{\mathcal{M}}_j$ which implies $c'_j \geq \tilde{c}_j$. That is, the firm made a variable loss in $n$ at some $c'_j \geq \tilde{c}_j > c_j$. Therefore, it will certainly make a variable loss in $n$ at $c_j$ or $\tilde{c}_j$ and variable profits made in $n$ cannot be the reason to enter it (since there are none). Entering $n$ could still increase the firm's total profit because at $\widetilde{\mathcal{M}}_j$, the fact that $\tilde{c}_j > c_j$ increases its profit in other markets. But there is nothing stopping the firm from choosing $\tilde{c}_j$ at $\mathcal{M}_j$ without incurring a variable loss in $n$. Since at $\mathcal{M}_j$, the firm instead optimally chooses $c_j$, deviating to $\tilde{c}_j$ cannot increase total profits. Therefore, the firm would never want to enter any market $n \notin \mathcal{M}_j^{\text{ub}}$.

This argument extends to entering a set of markets $\mathcal{M}_j^{\text{cand}}$ that the algorithm excluded from $\mathcal{M}_j^{\text{ub}}$, because $c_j$ depends only on the total effective demand of all markets in $\mathcal{M}_j^{\text{cand}}$ (not on their indices, for example). The firm would make a variable loss in any market $n \in \mathcal{M}^{\text{cand}}$, so variable profits cannot be the reason to enter. For the firm's choice of $c_j$, entering several markets at once is just like entering one large market, because $c_j$ depends only on the sum of $\alpha_n$ across all markets the firm is active in. For the same reason as above, choosing a different $c_j$ cannot increase profits.

### E.4 Mass of entrants

Letting $\Omega_i$ denote the set of entrants in $i$, so $N_i = |\Omega_i|$, country $i$'s full employment condition is that

$$\begin{aligned}
L_i &= \int_{\Omega_i} \mathbb{1}\left[a_j \geq \underline{a}_i\right] \left\{ \left[ \sum_{n \in \mathcal{M}_j} d_{ni} q_n(j) \frac{1}{a_j c_j^{\delta}} + f_{ni} \right] + b\beta c_j^{\frac{1}{\beta}} \right\} + f_i \text{ d}j \\
&= N_i \left( \int_{\underline{a}_i}^{\infty} \left[ \sum_{n \in \mathcal{M}_j} d_{ni} q_n(j) \frac{1}{a_j c_j^{\delta}} + f_{ni} \right] + b\beta c_j^{\frac{1}{\beta}} \text{ d}F_i\left(a_j\right) + f_i \right) \\
\Leftrightarrow w_i L_i &= N_i \left( \int_{\underline{a}_i}^{\infty} \left[ \sum_{n \in \mathcal{M}_j} d_{ni} q_n(j) \frac{w_i}{a_j c_j^{\delta}} + f_{ni} w_i \right] + b\beta c_j^{\frac{1}{\beta}} w_i \text{ d}F_i\left(a_j\right) + f_i w_i \right) \\
&\overset{(5)}{=} N_i \left( \int_{\underline{a}_i}^{\infty} \left[ \sum_{n \in \mathcal{M}_j} \mu^{-\sigma} \left( d_{ni} \frac{w_i}{a_j c_j^{\delta}} \right)^{1-\sigma} \alpha_n + f_{ni} w_i \right] + b\beta c_j^{\frac{1}{\beta}} w_i \text{ d}F_i\left(a_j\right) + f_i w_i \right) \\
&\overset{(8)}{=} N_i \int_{\underline{a}_i}^{\infty} \sum_{n \in \mathcal{M}_j} \left( \frac{1}{\mu} + \frac{1}{\sigma} \right) \left( \mu d_{ni} \frac{w_i}{a_j c_j^{\delta}} \right)^{1-\sigma} \alpha_n \text{ d}F_i\left(a_j\right) \\
\Leftrightarrow N_i &= \frac{\mu^{\sigma-1} w_i^{\sigma} L_i}{\int_{\underline{a}_i}^{\infty} \left(a_j c_j^{\delta}\right)^{\sigma-1} \sum_{n \in \mathcal{M}_j} d_{ni}^{1-\sigma} \alpha_n \text{ d}F_i\left(a_j\right)}
\end{aligned}$$

### E.5 Price index

The price index of country $n$ is

$$\mathcal{P}_n = \left( \int_{\mathcal{G}_n} p_n(j)^{1-\sigma} \text{ d}j \right)^{\frac{1}{1-\sigma}}$$

Letting $\mathcal{E}_{ni}$ denote the set of goods produced in $i$ and exported to $n$,

$$= \left( \sum_{i=1}^{N} \int_{\mathcal{E}_{ni}} p_n(j)^{1-\sigma} \text{ d}j \right)^{\frac{1}{1-\sigma}}$$

Dealing with $\mathcal{E}_{ni}$ directly is cumbersome, because it involves conditional probabilities. Instead, let $\mathcal{O}_i$ denote the set of goods produced in $i$, regardless of where they're shipped to. Then,

$$= \left( \sum_{i=1}^{N} \int_{\mathcal{O}_i} \mathbb{1}\left[j \in \mathcal{E}_{ni}\right] p_n(j)^{1-\sigma} \text{ d}j \right)^{\frac{1}{1-\sigma}}$$

which, using that $j \in \mathcal{E}_{ni} \Leftrightarrow n \in \mathcal{M}_j$, switching to integrating over the CDF of productivities and remembering that there is a mass $n_i$ of firms active in country $i$,

$$
\begin{aligned}
&= \left( \sum_{i=1}^{N} n_i \int_{\underline{a}_i}^{\infty} \mathbb{1}\left[n \in \mathcal{M}_j\right] p_n(j)^{1-\sigma} \, \mathrm{d}F_i\left(a_j\right) \right)^{\frac{1}{1-\sigma}} \\
&\overset{(4)}{=} \left( \sum_{i=1}^{N} n_i \int_{\underline{a}_i}^{\infty} \mathbb{1}\left[n \in \mathcal{M}_j\right] \left( \mu d_{ni} \frac{w_i}{a_j c_j^{\delta}} \right)^{1-\sigma} \mathrm{d}F_i\left(a_j\right) \right)^{\frac{1}{1-\sigma}}
\end{aligned}
$$

Since there will also be a cutoff $\underline{a}_{ni}$ such that all firms in $i$ with $a_j \geq \underline{a}_{ni}$ will sell in $n$, and all other firms in $i$ will not,

$$
= \mu \left( \sum_{i=1}^{N} n_i (d_{ni} w_i)^{1-\sigma} \int_{\underline{a}_{ni}}^{\infty} \left( a_j c_j^{\delta} \right)^{\sigma-1} \mathrm{d}F_i\left(a_j\right) \right)^{\frac{1}{1-\sigma}} \tag{16}
$$

### E.6 Gravity equation

Sales from firms in $i$ to $n$ are

$$
\begin{aligned}
X_{ni} &= \int_{\mathcal{E}_{ni}} S_n(j) \, \mathrm{d}j \\
&= n_i \int_{\underline{a}_{ni}}^{\infty} S_n(j) \, \mathrm{d}F_i\left(a_j\right) \\
&\overset{(6)}{=} n_i \int_{\underline{a}_{ni}}^{\infty} \alpha_n \left( \mu d_{ni} \frac{w_i}{a_j c_j^{\delta}} \right)^{1-\sigma} \mathrm{d}F_i\left(a_j\right) \\
&= n_i (\mu d_{ni} w_i)^{1-\sigma} \alpha_n \int_{\underline{a}_{ni}}^{\infty} \left( a_j c_j^{\delta} \right)^{\sigma-1} \mathrm{d}F_i\left(a_j\right)
\end{aligned}
$$

which, by definition of $\alpha_n$,

$$
\begin{aligned}
&= n_i (\mu d_{ni} w_i)^{1-\sigma} X_n \mathcal{P}_n^{\sigma-1} \int_{\underline{a}_{ni}}^{\infty} \left( a_j c_j^{\delta} \right)^{\sigma-1} \mathrm{d}F_i\left(a_j\right) \\
&\overset{(16)}{=} \frac{n_i (d_{ni} w_i)^{1-\sigma} \int_{\underline{a}_{ni}}^{\infty} \left( a_j c_j^{\delta} \right)^{\sigma-1} \mathrm{d}F_i\left(a_j\right)}{\sum_{k=1}^{N} n_k (d_{nk} w_k)^{1-\sigma} \int_{\underline{a}_{nk}}^{\infty} \left( a_j c_j^{\delta} \right)^{\sigma-1} \mathrm{d}F_k\left(a_j\right)} X_n
\end{aligned}
$$

### E.7 Home sales as a log-linear function of total sales

From (15), the optimal $c$ can be written as

$$
c_j^{\frac{1}{\beta}+\delta} = \frac{1}{b} \delta (\mu w_i)^{-\sigma} a_j^{\sigma-1} \left( \sum_{n \in \mathcal{M}_j} d_{ni}{}^{1-\sigma} \alpha_n \right) c_j^{\delta\sigma}
$$

$$
\begin{aligned}
&\Leftrightarrow c_j^{\frac{1}{\beta}} = \frac{1}{b}\delta(\mu w_i)^{-\sigma} a_j^{\sigma-1}\left(\sum_{n\in\mathcal{M}_j} d_{ni}{}^{1-\sigma}\alpha_n\right) c_j^{\delta(\sigma-1)} \\
&\Leftrightarrow c_j = \left[\frac{1}{b}\frac{\delta}{\mu w_i}\left(\mu\frac{w_i}{a_j c_j^{\delta}}\right)^{1-\sigma}\sum_{n\in\mathcal{M}_j} d_{ni}{}^{1-\sigma}\alpha_n\right]^{\beta} \\
&\overset{(6)}{=} \left[\frac{1}{b}\frac{\delta}{\mu w_i}\underbrace{\sum_{n\in\mathcal{M}_j} S_n(j)}_{\equiv\mathcal{S}(j)}\right]^{\beta}
\end{aligned} \tag{17}
$$

Plugging (17) into sales to the Home market (6) and remembering that $d_{ii} = 1$ by assumption,

$$
\begin{aligned}
&S_i(j) = \alpha_i\left(\mu\frac{w_i}{a_j}\left[\frac{1}{b}\frac{\delta}{\mu w_i}\mathcal{S}(j)\right]^{-\beta\delta}\right)^{1-\sigma} \\
&\Leftrightarrow \log\left(S_i(j)\right) = \log\left(\alpha_i\right) + (\sigma-1)\left[\log\left(\frac{1}{\mu}\frac{a_j}{w_i}\right) + \beta\delta\log\left(\frac{1}{b}\frac{\delta}{\mu w_i}\mathcal{S}(j)\right)\right] \\
&\Leftrightarrow \log\left(S_i(j)\right) = I + \log\left(\alpha_i\right) + (\sigma-1)\log\left(a_j\right) - (\sigma+\beta\delta-1)\log\left(w_i\right) + (\sigma-1)\,\beta\delta\log\left(\mathcal{S}(j)\right)
\end{aligned}
$$

with

$$
I \equiv (\sigma-1)\left[\log\left(\frac{1}{\mu}\right) + \beta\delta\log\left(\frac{1}{b}\frac{\delta}{\mu}\right)\right]
$$

## E.8 Causal forest estimates the desired quantity

The expectation of the de-meaned outcome, $y_{jt} - \bar{y}$, among the set of observations with future weather data ($D_{jt} = 0$), is

$$
\begin{aligned}
&\mathbb{E}\left[y_{jt} - \bar{y} | D_{jt} = 0\right] \\
&= \mathbb{E}\left[y_{jt} | D_{jt} = 0\right] - \mathbb{E}\left[\bar{y} | D_{jt} = 0\right]
\end{aligned}
$$

The average outcome $\bar{y}$ is calculated using currently observed firm outcomes (observations with $D_{jt} = 1$). Therefore, its expectation across observations with unobserved outcomes is the same as its expectation across observations with observed outcomes,

$$
= \mathbb{E}\left[y_{jt} | D_{jt} = 0\right] - \mathbb{E}\left[\bar{y} | D_{jt} = 1\right]
$$

Since $\bar{y}$ is simply the current average outcome,

$$= \mathbb{E}\left[y_{jt} | D_{jt} = 0\right] - \mathbb{E}_{\text{current}}\left[y_{jt}\right]$$

Observations with $D_{jt} = 0$ have weather variables drawn from the future climate $F_{\text{future}}$, so the first expectation runs across $F_{\text{future}}$,

$$= \mathbb{E}_{\text{future}}\left[y_{jt}\right] - \mathbb{E}_{\text{current}}\left[y_{jt}\right]$$

which is the quantity I want to estimate.

## E.9 Interpreting causal forest results with log outcomes

Letting $\mathcal{O}$ denote the universe of firms in poor countries, $f_f$ the measure of future firms, $f_c$ the measure of current firms, $y_j^f$ firm $j$'s future outcome and $y_j^c$ firm $j$'s current outcome, the causal forest estimand becomes (see below for a note on $j$ vs. $jt$ indexing)

$$\begin{aligned}
&\mathbb{E}_{\text{future}}\left[y_j\right] - \mathbb{E}_{\text{current}}\left[y_j\right] \\
&= \int_{j \in \mathcal{O}} y_j^f f_f(j) \, \mathrm{d}j - \int_{j \in \mathcal{O}} y_j^c f_c(j) \, \mathrm{d}j
\end{aligned}$$

Now, since the sets of firms in the current and future periods are identical, the measure of firms does not change, $f_f = f_c = f$, so

$$= \int_{j \in \mathcal{O}} \left(y_j^f - y_j^c\right) f(j) \, \mathrm{d}j$$

Plugging in the outcome used in the estimation, log sales, $y_i^t = \log\left(s_i^p\right), p \in \{c, f\}$,

$$\begin{aligned}
&= \int_{j \in \mathcal{O}} \left(\log\left(s_j^f\right) - \log\left(s_j^c\right)\right) f(j) \, \mathrm{d}j \\
&= \int_{j \in \mathcal{O}} \log\left(\frac{s_j^f}{s_j^c}\right) f(j) \, \mathrm{d}j \\
&= \mathbb{E}\left[\log\left(\frac{s_j^f}{s_j^c}\right)\right]
\end{aligned}$$

which is the average log change in sales, or in other words, the average firm's decline in sales. Note that I abstract from the time dimension within the current and future periods here and move to $j$

instead of $jt$ indexing. This is purely for simplicity of the presentation. In practice, each firm $j$ I observe in the sample has many future potential realizations $y_{jt}^f$ across future periods $t$. Explicitly including this time dimension and moving to $jt$ indexing just introduces a second inner layer of averaging, such that the causal forest estimates

$$\mathbb{E}\left[\mathbb{E}\left[\log\left(\frac{s_j^f}{s_j^c}\right)\middle| j\right]\right] = \mathbb{E}\left[\log\left(\frac{s_j^f}{s_j^c}\right)\right]$$

where the inner conditional expectation runs over future periods $t$ for firm $j$, while the outer expectation runs across firms $j$.