Sacking the Sales Staff: Firm Reactions to Extreme Weather and Implications for Policy Design

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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 non-agricultural firms. I combine firm-level data 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. I show that weather shocks reduce firms' labor productivity, and that firms react by scaling back complementary expenditures on items like rented machinery, rented space and sales personnel. This makes firms even less productive. To assess policy implications, I develop a structural model including this mechanism. I combine it with machine learning estimates of the impact of climate change to discipline climate change counterfactuals. Counterfactuals show that these firm reactions make (i) policies benefiting mostly larger firms and (ii) policies improving firm adaptation to climate change especially effective at countering 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. We know relatively little, however, about the effects of weather shocks on non-agricultural firms in these countries. 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 (labor productivity) shocks, that firms react to these shocks by adjusting complementary expenditures on productive capability — expenditures on items like rented machinery, rented space and non-production personnel — and that these reactions are quantitatively important for policy design. My argument proceeds in five steps. First, I assemble a data set combining World Bank Enterprise Surveys across sub-Saharan Africa and South Asia with high-resolution weather data. I test whether weather shocks are predominantly supply or demand shocks. This is a necessary first step for understanding firm reactions, since firms would react to both types of shocks differently. The test I use employs a basic open economy intuition about exporters: They are somewhat insulated from local demand shocks. They are, however, less able to pass on marginal cost increases to their international buyers. Therefore, they are more exposed to supply shocks. I construct a temperature index combining mean temperature, temperature variance, and the number of days with temperatures exceeding 32°C (89.6°F). I regress log sales on this temperature index fully interacted with exporter status, using location fixed effects to isolate random year-to-year weather variation. I find that negative weather shocks have a significantly larger impact on exporters' total sales than on non-exporters' total sales: An 80^{th} percentile weather shock decreases non-exporters' total sales by 3.9 percent, but exporters' total sales by 6.9 percent. For comparison, these effect sizes are similar to the effects of ethnic conflict on Kenyan flower packers' or mobile phone access on Indian fishers' output, for example (Hjort, 2014; Jensen, 2007). The key takeaway is that exporters are more affected by extreme weather. This implies that weather is, on net, a supply shock for these firms, rather than a local demand shock.

Second, I show that firms react to the shock by adjusting spending on *productive capability*, which is complementary with labor productivity, and that this reaction exacerbates the impact of the shock, further reducing the firm's productivity. Productive capability comprises rented or hired equipment, space and non-production personnel. For example, it includes rented machinery, rented office space or a sales team. Productive capability improves overall performance across all markets a firm is active in, either by making labor more productive (providing workers with sufficient equipment or space) or by making it easier to sell the firm's output (e.g., by reducing transaction cost). Productive capability thus lowers the cost of providing the firm's output across all markets the firm serves. Faced with higher temperatures, firms scale back expenditures on productive capability, since these kinds of productivity-enhancing expenditures are complementary to firm productivity. This reaction exacerbates the effect of the weather shock, since it further reduces labor productivity. I provide three key pieces of evidence to show that this reaction is quantitatively important in this context. First, due to the rich survey data I use, I can measure productive capability expenditures in the data. (Specifically, I observe the cost of communications, sales (including sales staff), transportation, and rent for buildings, equipment and land.) I show that firms indeed 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, productive capability reductions mean the firm's overall productivity declines even further. We would then expect sales to decrease even further across all markets the firm is active in. I show that this happens: Exporters not only see a larger reduction in total sales, but also see a larger reduction in domestic sales following weather shocks. Third, a mediation analysis shows that controlling for productive capability removes this differential impact on exporters' domestic sales. This provides strong evidence that productive capability is causing the market linkage. I also run a battery of robustness checks showing that the differential impact on exporters' domestic sales is not due to well-known differences between exporter and non-exporters, such as the sectors they are active in, firm size, or the complexity of their production process.

Third, based on these reduced form results and adapting the basic framework of Hyun and Kim (2022), I develop an international trade model that adds this productive capability adjustment channel to the model of Melitz (2003). I adapt and extend Hyun and Kim (2022) to an international trade setting, include market entry and exit, and estimate the resulting model. The model generates the patterns I observe in the data: In reaction to a negative productivity shock, firms scale back productive capability expenditures. This makes them even less productive and therefore reduces 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. When they exit those markets, they see a discontinuous fall in total sales and productive capability. This, in turn, leads to a discontinuous fall in sales to the domestic market. Adding productive capability 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). I use Zambia as a small open economy, and am able to estimate large parts of the model using reduced form approaches, which reduces the complexity of the estimation considerably without sacrificing key insights from the model. I find that the estimated model matches targeted and non-targeted moments well.

Fourth, I then turn to estimating the causal effect of climate change, based on an array of high-resolution weather projections covering a range of climate change scenarios. I cannot simply extrapolate reduced form estimates using the temperature index to assess the impact of climate change. Those estimates used a parsimonious, simple functional form suited to understanding the impacts of weather shocks. To extrapolate to a different climate, however, I need to correctly estimate the complex relationship between many different weather variables and firm outcomes. I also need the estimator to perform well out of sample, since climate change is inherently something that happens in the future. Finally, I need to capture firm adaptation to climate change in my estimates. I use the causal forest algorithm (Athey, Tibshirani, & Wager, 2019), which is especially well suited to this estimation. An important feature of causal forests is that they perform well even with a large selection of right hand side variables. Causal forests are also optimized for out of sample performance. Finally, I can easily incorporate adaptation to climate change into the estimation by including long-term means and variances of all weather measures. This allows firm reactions to weather shocks to differ based on their climatic environment. I estimate the impact of climate change on firm 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 firm faces an almost eleven percent decrease in sales by the late 2080s. Even under a mild scenario, I find that the average firm's sales would drop by over six percent.

Finally, I combine these projections with the model to demonstrate that productive capability reactions matter for policy effectiveness. I use the causal forest estimates to calibrate a counterfactual baseline scenario under climate change. The calibration shifts firm productivities to match the estimated climate change impact on the average firm. I conduct policy experiments based on this scenario, comparing my model's results to a modified version which shuts down firms' productive capability reactions. I demonstrate two policy implications of productive capability reactions. First, policies mostly benefiting larger firms are especially effective at counteracting the impacts of climate change. A reduction in variable trade costs, which benefits existing exporters, becomes 1.5 times more effective at reducing the impact of climate change. This is because reduced trade cost allows larger firms to hire additional productive capability, combating some of the productivity losses from climate change. The overall welfare gains and gains to large firms come at the expense of smaller producers, however. Second, adaptation to climate change becomes more effective. Adaptation restores some of the productivity losses from climate change. Firms react by increasing productive capability expenditures, further reducing the productivity losses.

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, namely that weather is, on net, a supply rather than a demand shock, and that non-agricultural firms in poor countries react to weather shocks by adjusting their productive capability. 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, 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 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.

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 use a novel approach to estimation using causal forests (Athey et al., 2019). Weather data are very high dimensional, and estimating the impact of climate change is inherently an out of sample exercise. Existing approaches, for example using 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. CFs, on the other hand, are especially well-suited to the problem, since they can easily handle high-dimensional weather data and are optimized for out of sample performance.

The closest paper to mine is Nath (2020), who shows that under climate change, labor is drawn into agriculture, because countries need to grow sufficient food to feed their population. Since climate change especially reduces agricultural productivity, this labor reallocation increases welfare losses. Reduced trade costs allow countries to import more food, which reduces the labor reallocation and decreases damages from climate change. Relative to Nath (2020), I focus on firm-level reactions to extreme weather, rather than aggregate 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. Finally, I use causal forests to estimate the effects of climate change, a method which is especially well-suited to this task. 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 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. Section 3 develops an international trade model. Section 4 estimates the causal impact of climate change on firms. Section 5 presents counterfactual simulations showing how productive capability reactions change the effectiveness of different policy instruments 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, and this guided my selection of data sets. I focus on these two regions for two reasons. First, they 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. At the same time, 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 global poverty reduction efforts over the next century. Second, my main argument is most relevant to countries with relatively small domestic markets compared to world markets — relatively poor countries. Many of these small open economies are located across sub-Saharan Africa and South Asia.

1.1 Firm data: World Bank Enterprise Surveys

For data on firm outcomes and characteristics I use the World Bank Enterprise Surveys (ES).[1] 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 firm data for the last complete fiscal years. All surveys contain weights to make them representative 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 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. The key takeway here is that the Enterprise Surveys have very wide geographic coverage. This is useful for studying the overall implications of climate change,

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

since weather and climate change vary across space.[2]

To match firm and weather data, I require firm locations as lat/lon coordinates and the dates when the last fiscal year began and ended. The exact dates for when that fiscal year started and 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 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 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).[3] 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).[4] 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.

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

[3] More information on CHIRPS is available at https://www.chc.ucsb.edu/data/chirps

[4] More information on BKE is available at https://berkeleyearth.org/data/

1.3 Climate projections: NEX-GDDP-CMIP6

I obtain projections for future weather (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 results of climate model runs that are part of 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 based on different assumptions about greenhouse gas emissions, population 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.[5] Studying results for different SSPs allows me to incorporate deep uncertainty about the broad parameters governning 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 that feature 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 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 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.

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

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, rather than a demand shock. Second, firms react to these shocks by adjusting their spending on productive capability, such as machinery, office space, or a sales team. These stylized facts are 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 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 δ_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. 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 — 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 core trade-off here is that large clusters introduce measurement error due to the averaging of weather variables. 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.

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. 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.

To provide motivating evidence, I use a weather measure x_{jt} that is parsimonious, easy to understand and captures weather over the entire year: an index of three commonly used temperature variables. 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, and each have their own strengths and weaknesses. Combining them into a single index provides a parsimonious combined measures of temperature. To make the index components comparable, I calculate location-specific z-scores for each of the three components x_{jt} as

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

where $\bar{x}_{jt}$ is the average of the variable at firm j's location over the last 20 years and $\sqrt{\widehat{\mathbb{V}}\left(x_{jt}\right)}$ is the corresponding standard deviation.[6] 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 the regressions use. This does not affect significance of any of the estimates, it simply is a first step to making results more interpretable. A one unit increase in the re-scaled index now corresponds to a one standard deviation weather shock.

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 convert the one standard deviation effect sizes into 80$^{\text{th}}$ percentile weather shocks, or 0.320 standard deviations, in the following discussion.

For these estimations, I am interested in the effect of weather over the year on firm outcomes. I do not, here, want to separate the impact of precipitation and temperature, for example. 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.

2.2 Results

This section presents reduced form estimation results.

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. That is consistent identifying assumption that contemporary weather shocks are as good as random.

[6] 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.

2.2.2 Weather is a supply shock

To understand firm reactions, I first need to test 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 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 dominate?

I do this by checking whether exporters see a larger or smaller effect of weather shocks on total sales. 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.[7] Figure 5 shows a 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.

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 exporter interaction 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

[7] 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.

fully capture the complexity of weather data, I do estimate a significant overall effect of weather on firm performance.[8] 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 C.1 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, not reporting their dismal sales, while the least productive exporters do not, leading 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 zero sales indicator actually capture firms reporting lower total sales than the first percentile of total sales.) The table also shows that the results for a regression of exporter status on the temperature index. If anything 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 those, 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 somewhat alleviate the concern of survival bias.

2.2.3 Firms react via spending on productive capability

Since weather is a supply shock, I focus on an obvious reaction to a decline in labor productivity: Scaling back expenditures on productive capability, which are complementary with labor productivity. As I explained in the introduction, productive capability comprises rented or hired equipment, space and 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 percent of exporters' total cost, so they are quantitatively relevant to firms. 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) — it lowers the cost of providing the firm's

[8] 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 difference in the effect for exporters remains highly significant and similar in magnitude, however.

output across all markets the firm serves. Faced with a negative supply shock, firms scale back expenditures on productive capability, since these kinds of productivity-enhancing expenditures are complementary to firm productivity. This exacerbates the impact of the supply shock, since it further reduces labor productivity. A key implication is that firm sales across all markets the firm is active in fall further. 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) are visible in the data, and (iii) productive capability mediates these spillovers.

First, I test whether I see productive capability reactions in the data. Table 5 shows the effect of weather shocks on productive capability expenditures by exporter status. Productive capability expenditures combine the cost of communications, sales (including sales staff), transportation, and rent for buildings, equipment and land, which I can see due to the richness of the Enterprise Surveys data. I see a 1.6 percent decrease in productive capability expenditures for domestically active firms in response to an 80^{th} percentile weather shock, but a significantly larger 5.3 percent decrease for exporters.[9] Because these questions are not included in all rounds of the ES surveys, I only have detailed cost breakdowns for a sub-sample of firms, which is why this analysis uses fewer observations than the preceding results, but this nevertheless provides direct evidence of productive capability reactions when faced with negative weather events — exporters scale back fixed expenditures considerably more than non-exporters in response to negative weather shocks. 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^{th} percentile weather shock. While not a perfect proxy for productivity, this at least suggests that exporters see larger productivity decreases in response to weather shocks. Exporters' larger reduction in productive capability therefore seems to translate into larger productivity declines as well.

Second, a key implication of this reduction in productive capability is that firm productivity falls even further. As a result, sales across all markets the firm is active in should also decline

[9] 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 climate change, they do not adjust owned capital in response to weather shocks. Owned capital also makes firms more productive, but is not driving the immediate responses I focus on in this paper.

even further. I do not have detailed data on which exact markets firms are selling to, but I can differentiate between domestic and international sales. As explained above, because weather shocks are supply shocks, exporters see larger total sales impacts, and therefore also scale back productive capability more. As a result of this larger reduction, exporters see a larger decline in productivity than non-exporters. This suggests the larger total sales reduction exporters experience should spill over, via productive capability adjustments, to their domestic sales — exporters should see larger declines in domestic sales than non-exporters as well. Table 4 shows a regression of 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. That means a key implication of the productive capability adjustment mechanism is borne out in the data.

Finally, 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 signs 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, not at zero log productive capability, which would not be defined.) 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.[10]

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,

[10] 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.

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 another firm characteristic is the 'true' reason for the effects I find, I would expect that once I include that characteristic in the regression, the interaction between exporter status and weather shocks loses significance and/or sees 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 these robustness checks.

First, exporters tend to be large firms, which could be more reliant on short-term hired labor that 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, 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.[11]

I conclude from this that the effect I find is not due to a correlate of being an exporter, but is instead driven by firms reacting to negative supply shocks via 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 seen in Table 5, the spillovers to domestic sales seen in Table 4 and the results of the mediation analysis in Table 6.

[11] 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.

3 Model

This section develops an international trade model which captures the two core reduced form results I highlight in the previous section: the greater impact of productivity shocks on exporters' (i) total and (ii) domestic sales. The model is a variant of Melitz (2003). The core mechanism I add is the key mechanism I discuss in the previous section: firms' ability to hire productive capability, such as machinery, office space, or a sales team. I show that this allows the model to explain the greater impact on exporters' domestic sales. A standard Melitz (2003) model can only explain why productivity shocks have a greater effect on exporters' total sales. It cannot explain why productivity shocks have a greater impact on domestic sales.

3.1 Demand

There are N countries and a mass of goods $\mathcal{G}_n$ is available in each country n. Consumers in n have CES preferences with elasticity of substitution σ, 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 α_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 α_n translates into higher sales in that market at any given price they charge there, either because expenditure is large, or because 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.[12] Instead of linking decisions across markets via demand, I let firms purchase or hire productive capability c_j. This represents factors like machinery, office space, or a sales team. Additional productive capability makes it cheaper to provide goods in all markets. This links choices, including 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.

[12] 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, so I model that channel of adjustment here, rather than quality adjustments.

I assume $f_{ii} = 0$ and $d_{ii} = 1$ for simplicity, because 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 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[13]

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

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 Model reproduces key comparative static

I showed in Section 2 that weather shocks are, on net, negative supply shocks. I further showed that these shocks have a larger impact on exporters' domestic sales than on non-exporters' domestic sales. I now show a comparative static 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 firm's 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

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

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 α_n does not change, because firm j has zero mass. An idiosyncratic shock to only firm j therefore does not affect aggregate demand factors.

The first term in parentheses depends solely on the change in a_j. The second term in parentheses depends on the change in active markets $\mathcal{M}_j$. It represents an indirect effect of the core productivity shock which occurs if lower core productivity leads the firm to exit some markets it was previously active in. For domestic producers, ${\mathcal{M}_j}' = \mathcal{M}_j$, since they will not exit altogether given that $f_{ii} = 0$. For exporters, 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. 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 σ, start-up costs f_n, entry costs f_{ni}, iceberg trade costs d_{ni}, cost parameters b, β and δ, 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 α_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 relies on 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 $\mathcal{M}_j$, I 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. 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 $\mathcal{M}_j^{\text{ub}}$. See Appendix D.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 $\mathcal{M}_j^{\text{lb}}$. See Appendix D.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). Both of these factors speed up computation considerably.

Having found the bounds, I know the optimal set of active markets for all firms with $\mathcal{M}_j^{\text{lb}} = \mathcal{M}_j^{\text{ub}}$. 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 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 firms 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 ensure I have found the firm's true optimal choice.

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 α_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 α_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 $n_i = \left[1 - F_i\left(\underline{a}_i\right)\right] N_i$. To derive the gravity equation, I first calculate the price index for country n as

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

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

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

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 θ, 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 σ 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 σ, 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, β and δ. 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 σ. I make the simplifying assumption that $\beta = \delta$ to ease the computational burden during the structural estimation described below. β and δ 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 δ and β by regressing log home market sales on log total sales, country-year fixed effects (to deal with α_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 as well as fourth-degree polynomials of all continuous variables.

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 σ 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 overall much 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 administrative work equally well.

3.5.2 Small open economy estimation

All remaining parameters — technology shifters T_i, the technology scale parameter θ, 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 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 α_H, taking all other countries' α_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 θ_F is the dispersion parameter for other economies' productivity distributions. Recall that in this model, core and total productivity are identical. I take this parameter from Melitz and Redding (2015) as $\theta_F = 4.25$.[14] 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, because they follow Melitz (2003), trade flows from i to 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 ν_i and ξ_n are exporter and importer fixed effects and $\mathbf{C}_{ni}$ are bilateral variables capturing

[14] The technology scale parameters θ and θ_F capture the dispersion of core productivities, one for Home, the other for all other countries. I take θ_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.

trade cost from n to i. These bilateral trade costs τ_{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 ξ_n. I can then calculate $\mathcal{P}_n$ and therefore α_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 θ, start-up costs f_H, iceberg costs d_{nH} and entry costs f_{nH} — via MSM. The results from the gravity estimation for all other countries are useful here as well, because they make it easier to estimate d_{nH} and f_{nH}. I parameterize iceberg cost d_{nH} as a function of the same variables I include in the gravity equation, distance and the contiguity indicator,

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

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 $f_{HH} = 0$. Parameterizing d_{nH} in this way is an exact analogue to estimating parameters via a gravity equation beforehand and feeding the results into the structural algorithm, as done for example in Antràs et al. (2017).

The parameters T_H, θ, f_H and $\boldsymbol{\gamma}$ are then estimated via MSM. The targeted moments are Home's share of exporters, exports from Home to each other country,[15] 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).

[15] 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.

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 γ and the 75/25 is needed to identify θ. 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 ≈ 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 it, results basically do not differ, implying that trade dynamics among all other countries do not depend crucially on their trade with Zambia.

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 θ means a less dispersed distribution.) That my model finds a larger value makes sense, however. In Melitz (2003), θ governs the dispersion of *total* productivity, whereas in my model, it governs only the dispersion of *core* productivity 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 θ 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. The model matches the data well — the correlation coefficient is 0.68.[16] 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

[16] 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.

is encouraging, since imports depend on the iceberg cost parameters from the MSM estimation and other countries' α_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 to larger purchases of 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 as an input to counterfactual simulations. Those simulations explore the policy implications of productive capability reactions. The counterfactuals conduct policy experiments under a climate change scenario. This climate change scenario is calibrated based on the machine learning estimates I develop in this section. I discuss the counterfactuals and specifics of the calibration in Section 5.

I require a realistic estimate of the impact of climate change on firms. Three key challenges arise in this context. First, weather is a very high-dimensional object. Interactions and higher power effects of various weather variables may be important. I thus need to flexibly estimate how weather affects firm outcomes. Second, estimating the causal impact of climate change is inherently an out of sample exercise, since climate change happens in the future. Third, firms adapt to climate change and my estimation needs to take this into account.

To formalize the problem, I observe firm outcomes y_{jt} and weather data $\mathbf{x}_{jt}$,

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

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_{current}, but $\mathbb{E}_{\text{future}}$ runs across weather from the future climate F_{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_{future}. I do not, however, have data on future outcomes. Therefore, I need to estimate $g(\cdot)$ and plug in future weather projections to estimate $\mathbb{E}_{\text{future}}\left[y_{jt}\right]$.

One solution is to pick a set of weather variables and estimate a relationship using a regression, perhaps including splines or other somewhat flexible functional forms. The choice of weather variables to include is not obvious, however, and gives researchers a lot of leeway. Instead, I use the causal forest (CF) algorithm developed by Athey et al. (2019). CFs are designed to incorporate high-dimensional data and can be tuned to protect against overfitting and to improve out of sample performance. CFs are generally used to estimate heterogeneous treatment effects. I thank Stefan Wager and Erik Sverdrup for pointing out to me that they can also be used to estimate and do inference on unobserved means. Let $D_{jt} = 1$ for data with observed outcomes (the 'treatment' group) and $D_{jt} = 0$ for data without (the 'control' group). 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. CFs 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 just the new outcome itself. I solve this by de-meaning outcomes prior to the estimation. The result is that 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 what the CF estimates, is

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

which is exactly what I need to estimate. (See Appendix D.8 for a derivation.) CFs thus provide a solution to the first two challenges: They are able to incorporate high-dimensional weather data and flexibly relating them to firm outcomes, and they perform well out of sample.

The third challenge, incorporating adaptation, 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.[17] 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 with regards to adaptation of my 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, taking that inherent limitation into account. In this sense, any data-driven estimate of the impact of climate change is a ballpark guess, and it may be off in either direction due uncertainty around technology and other factors determining firms' ability to cope with extreme conditions, such as institutions.

[17] 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). My solution here can take either effect into account.

4.2 Results

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 CF flexibly estimates the response of firm outcomes to all of these weather measures, including their interactions.

I estimate the effects of climate change for the 2086–2090 period. That is, for each SSP, I include projections from all 27 climate models and for each year in the 2086–2090 range and estimate the causal effect on average sales. I choose this period because at that time, differences between the three SSPs are clearly visible in the data.[18] Table 10 shows the estimated average decline in sales under the three different SSPs as well as 90 percent confidence intervals.[19] I consistently estimate negative effects, with larger magnitudes under more extreme climate change scenarios. The impacts range from a 6.6 percent decrease in sales for the average firm under SPP1/2.6 to an 8.3 percent decrease under SSP2/4.5 to a 10.8 percent decrease under SSP5/8.5. The latter two are significant at the ten percent level, while the change under SSP1/2.6 is not (though the confidence interval only barely includes zero). 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.

[18] Appendix A.9 shows results for additional periods.

[19] See Appendix D.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 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.

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 0.108 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 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 29 further shows a comparison between my model and the model of Melitz (2003), estimated in the same way as my model.[20] 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, θ 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

[20] 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.

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 7.9 percent. Shutting down productive capability reactions, I estimate an 11.8 percent welfare decrease. Note that both models are calibrated so that the average firm sees an 0.108 log point decrease in sales between the status quo and the counterfactual — the difference 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 much detail the level differences in welfare changes between the two models, for example the level differences in welfare under the baseline scenario. The 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 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. 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.

There is a further 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 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 attractive than they would have looked without taking those adjustments into account. The same is true if future adaptation becomes harder.

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 4.9 percent decline compared to the status quo. This means lower variable trade costs reduce the impact of climate change by 3.0 percentage points, or 37.6 percent ($\approx 3.0/7.9$) compared to the climate change baseline. Without productive capability reactions, Zambia still sees an 8.9 percent welfare decline under this scenario. This is a 2.9 percentage point or 24.3 percent ($\approx 2.9/11.8$) improvement. Panel B of the same table also summarizes these relative changes, showing what fraction of the baseline welfare gap can be closed using each policy intervention.

Thus, I find that over a third of the welfare impact of iceberg cost reductions, or 35 percent ($\approx (37.6 - 24.3)/37.6$), is due to productive capability responses. Another way to express this is that productive capability reactions make variable trade cost reductions 1.5 times ($\approx 37.6/24.3$) 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, these policies are ones we should put more weight on when considering how poor countries can cope with climate change.

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 6.8 percent decline compared to the status quo. This means adaptation reduces the impact of climate change by 1.1 percentage points, or 13.8 percent ($\approx 1.1/7.9$), compared to the climate change baseline. Without productive capability reactions, Zambia still sees a 10.8 percent welfare decline under this scenario, a 1.0 percentage point or 8.8 percent ($\approx 1.0/11.8$) improvement.

Thus, I find that 36 percent ($\approx (13.8 - 8.8)/13.8$) 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 ($\approx 13.8/8.8$) 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 0.083 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 4.9 percent decline compared to the status quo. This means mitigation reduces the impact of climate change by 3.0 percentage points, or 37.7 percent ($\approx 3.0/8.0$), compared to the climate change baseline. Without productive capability reactions, Zambia still sees a 7.4 percent welfare decline under this scenario, a 4.4 percentage point or 37.4 percent ($\approx 4.4/11.8$) improvement.

Here, the difference due to productive capability reactions is again quite small. The reason is that moving to the new climate change trajectory implies a larger shift up in T_H for the fixed productive capability model. Both models explain the new trajectory by shifting core productivity back up. With productive capability reactions, an upward shift in core productivity is accompanied by firms purchasing more productive capability. This reinforces the upward productivity shift, and the model needs only a smaller shift in core productivity to reach the calibration target shift in sales. Without productive capability reactions, the implied shift is larger. Either way, the relative welfare impact is basically the same.

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. Adaptation policies become more effective when firms increase complementary expenditures. When thinking about mitigation, however, the two models back out *differently sized* shifts in core productivity. For relative welfare changes, these do not matter as much. In both models, firms do better and welfare improves by roughly the same relative magnitude. Thus, productive capability reactions make policies that preserve core productivity more effective, but should not make us reevaluate the importance 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. I further show that firms react to these shocks by adjusting expenditures on productive capability, such as machinery, office space, or a sales team. Productive capability lowers the cost of providing their products across all markets they serve. In response to a negative productivity shock, firms reduce productive capability. This, in turn, makes them less productive across all markets they are active in, reducing sales there as well. I then develop and estimate an international trade model featuring hired productive capability and show that it reproduces these comparative statics. I combine the model with causal forest estimates of the impact of climate change, taking firm adaptation into account. Policy simulations under this climate change scenario show that policies benefiting mostly larger firms become more effective due to productive capability reactions. For example, variable trade cost reductions, which benefit existing exporters, are considerably more effective at mitigating the impact of climate change when I take productive capability responses into account. Policy simulations also show that facilitating firm adaptation to climate change becomes more effective. Firm adaptation reduces the impact of climate on firms' core productivity. Firm reactions — hiring additional productive capability — reinforce this effect.

This is important as we consider what policies both rich and poor countries can adapt so poor countries can better mitigate the impact of climate change. My reduced for results, showing that exporters see a larger negative impact of weather shocks, might have suggested that countries should focus more on domestic production. As counterfactual simulations show, however, this protectionist intuition is wrong. The productive capability reactions I highlight in fact make trade policy more effective than we might have assumed. It is especially well-suited to counteracting the negative productivity effects of climate change and should play a significant role in climate change policy. This is especially true for countries with small domestic markets relative to foreign markets. My results also highlight that as rich countries consider protectionist policies in the wake of Covid (Goldberg & Reed, 2023), they should ensure those policies do not impose unnecessary 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 important as climate change has a direct, negative impact on trade networks, already creating an increased risk for poor countries in the future (Huppertz, 2023).

I show that productive capability reactions make adaptation policy more effective, but do not have a similar implication for mitigation policy. This might suggest that we can do less mitigation now, since future adapation is in fact more effective. I want to stress that there are good reasons to think that prevention is preferable to relying on future adaptation. Trade policy can, in fact, play a key role in reducing the severity of climate change as well (Farrokhi & Lashkaripour, 2021).

Nevertheless, some amount of climate change is already occurring and will continue to occur over the near and medium term. Poor countries will be affected by it. Understanding what policies are especially suited for allowing them to deal with that reality is a crucial task for contemporary social science. A better understanding of firm reactions to extreme weather is an important part of this.

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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^{th} percentile weather shock. Standard errors clustered by firm cluster. Outcomes winsorized at the 95^{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^{th} percentile weather shock. Standard errors clustered by firm cluster. Outcomes winsorized at the 95^{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	-0.036
	[0.753]	[0.722]
Temperature index × Current exporter	-0.117^{***}	-0.048^{**}
	[0.001]	[0.019]
Current exporter	1.233^{***}	0.631^{***}
	[0.000]	[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^{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^{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^{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^{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		
σ	Sales, variable cost	3.016 (0.043)
$\beta\delta$	Sales regression (11)	0.384 (0.016)
Panel B: Structural estimation		
θ	75/25 ratio for domestic sales	7.706
$T_H w_H$	Ratio of Home sales to Foreign sales	0.000
$f_H w_H$	Fraction of exporters	0.002
γ_0		-1.553
γ_{dist}	Export flows	0.605
γ_{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 γ are the intercept γ_0, the coefficient on log distance γ_{dist} and the coefficient on the contiguity indicator γ_{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 for 2086–2090

Scenario	Change in log sales
SSP1/2.6	-0.066 $(-0.131, 0.000)$
SSP2/4.5	-0.083 $(-0.160, -0.006)$
SSP5/8.5	-0.108 $(-0.188, -0.028)$

Note: Standard errors clustered by firm cluster. 90 percent confidence intervals in parentheses.

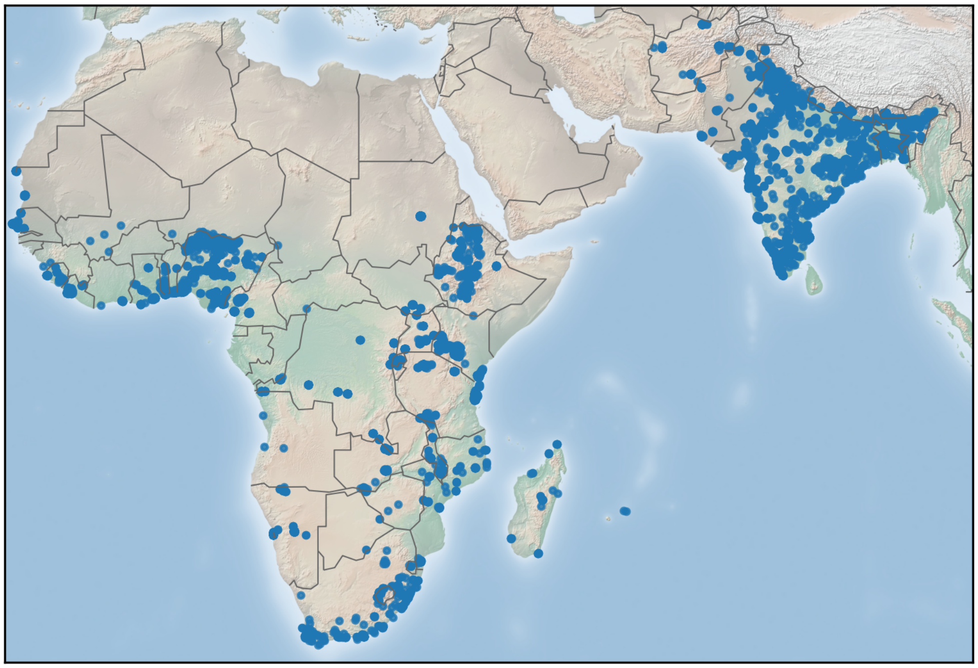
Table 11: Counterfactual change in welfare

Scenario	Full model	Fix c_j
Panel A: Welfare gap compared to status quo		
Climate change baseline	-0.079	-0.118
Iceberg cost reduction	-0.049	-0.089
Entry cost reduction	-0.079	-0.118
Adaptation	-0.068	-0.108
Mitigation	-0.049	-0.074
Panel B: Fraction of welfare gap closed		
Climate change baseline	0.000	0.000
Iceberg cost reduction	0.376	0.243
Entry cost reduction	0.000	0.000
Adaptation	0.138	0.088
Mitigation	0.377	0.374

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.

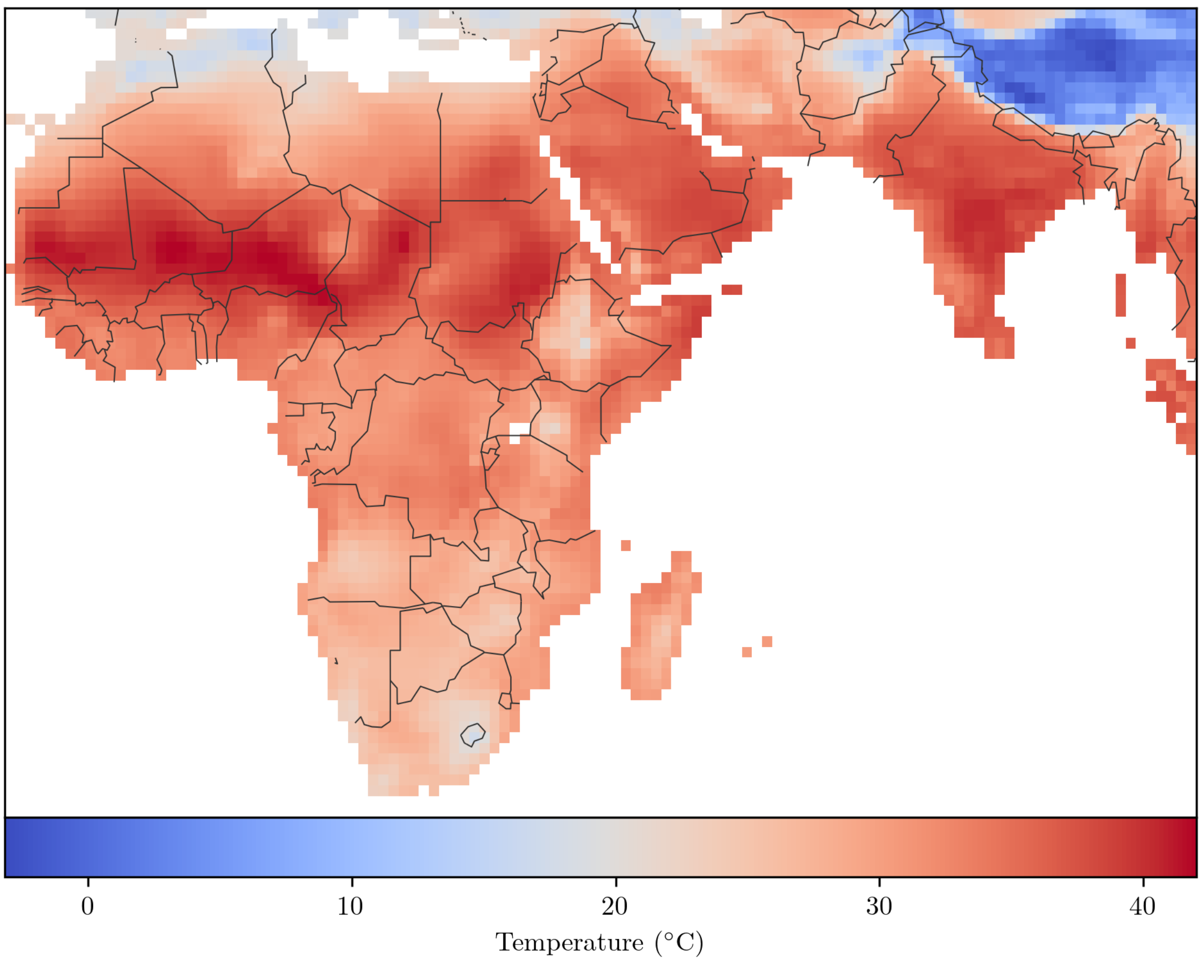
Figures

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



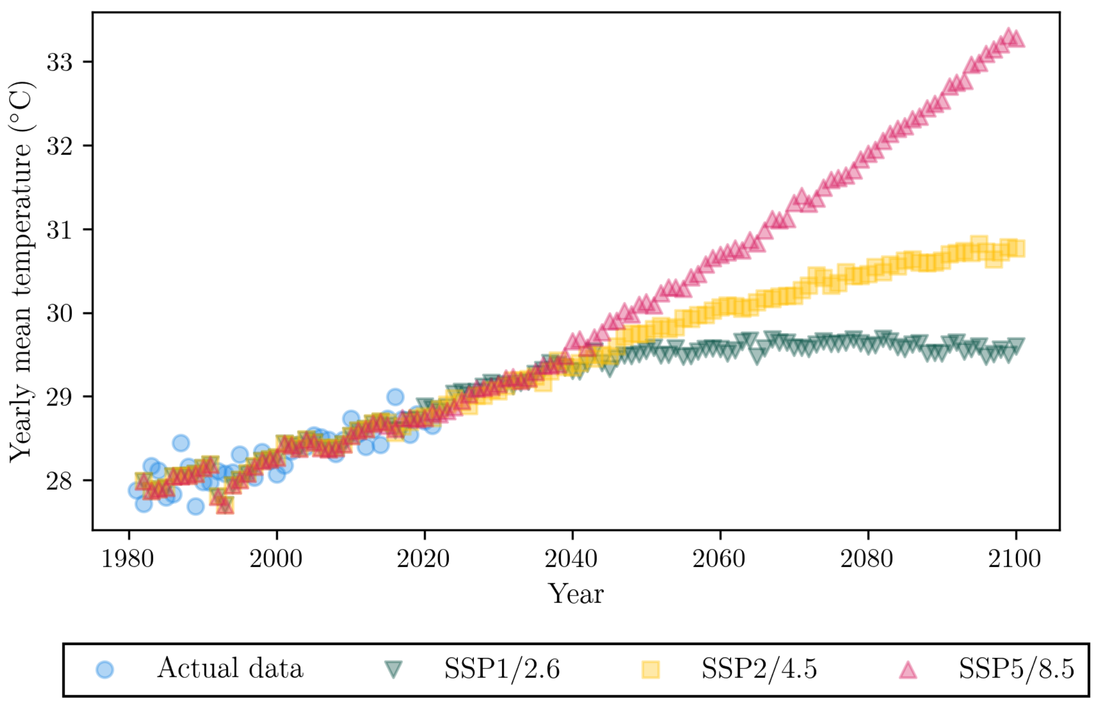
Note: Each dot is either the location of a single firm or the location of a firm cluster. Clusters appear if several firms were recorded as having the same location in the Enterprise Surveys data or if I was able to determine the firms' location via geolocation methods based on the city firms are located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

Figure 2: Maximum temperature on April 24, 1991



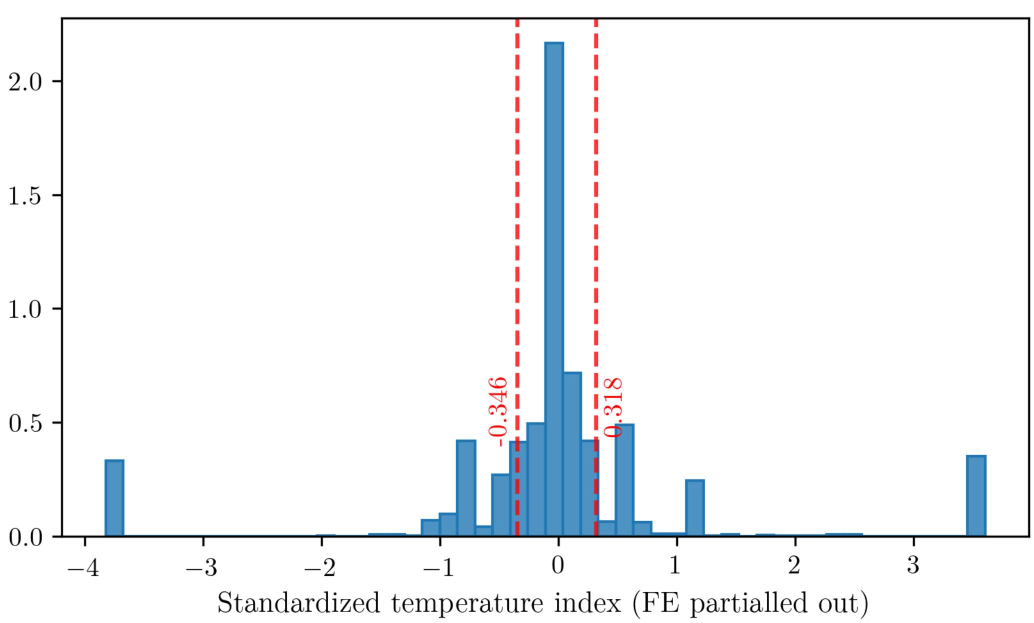
Note: The figure shows temperature from the Berkeley Earth dataset.

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



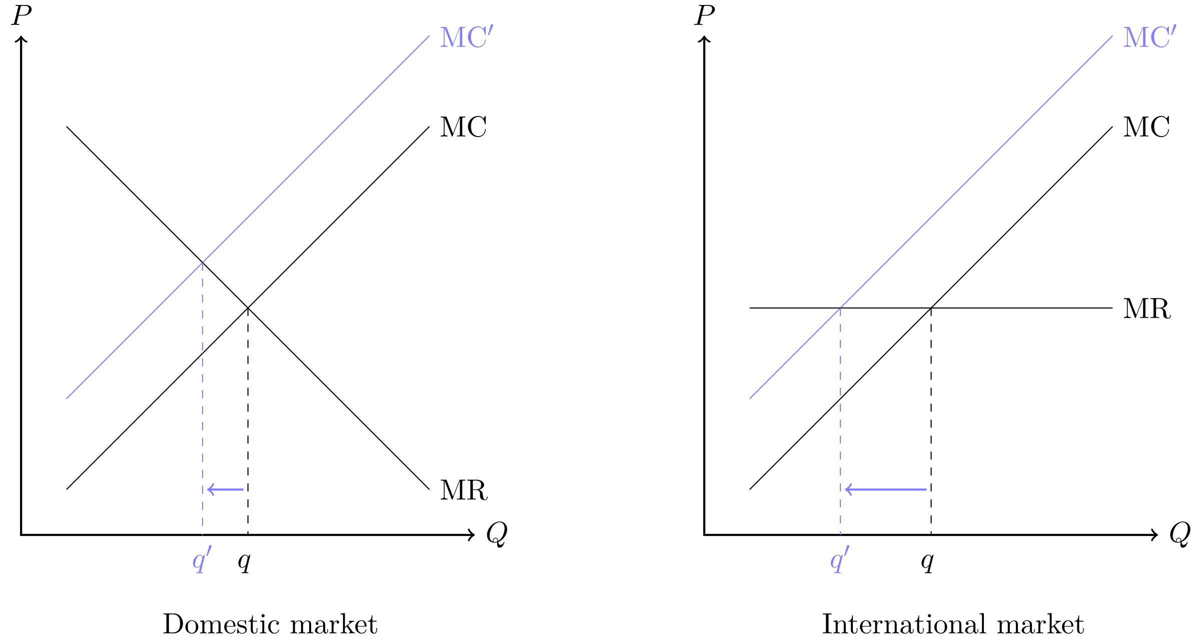
Note: The figure shows yearly averages of daily maximum temperatures. The climate change projections are adjusted for differences in baseline temperature means for each day of the year, as described in Appendix C.

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



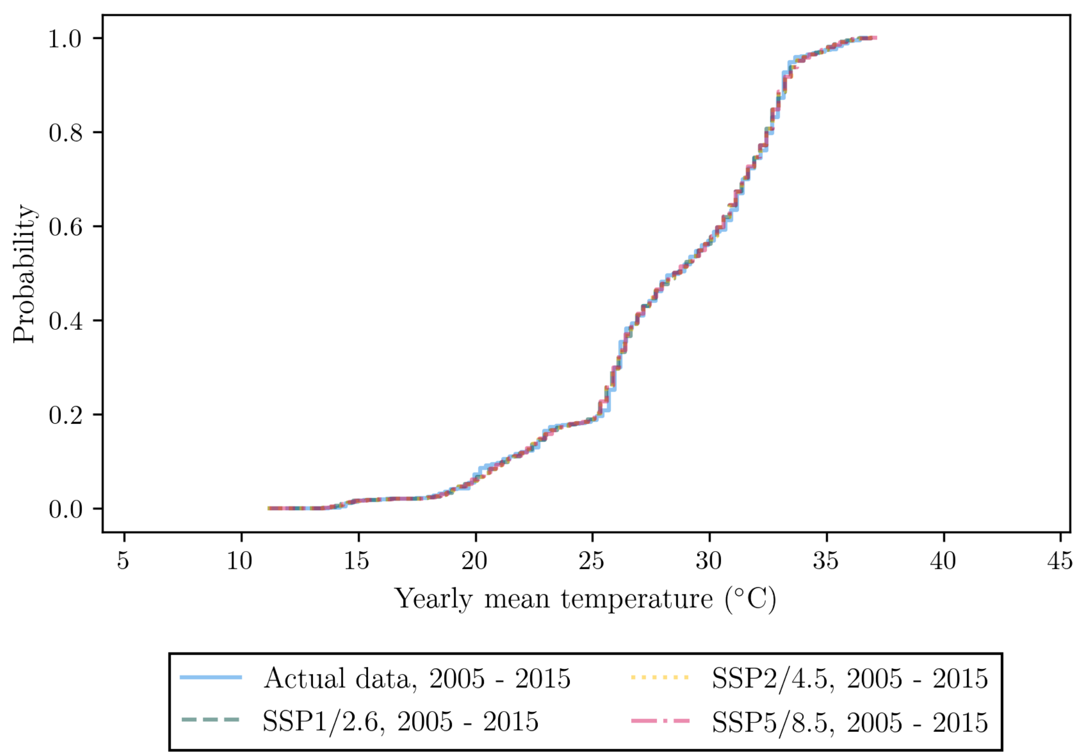
Note: The figure shows the temperature index after partialling out cluster fixed effects. This is the same identifying variation used in the regressions I estimate — the variation remaining in the standardized temperature index after cluster fixed effects are taken into account. Dashed lines indicate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

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



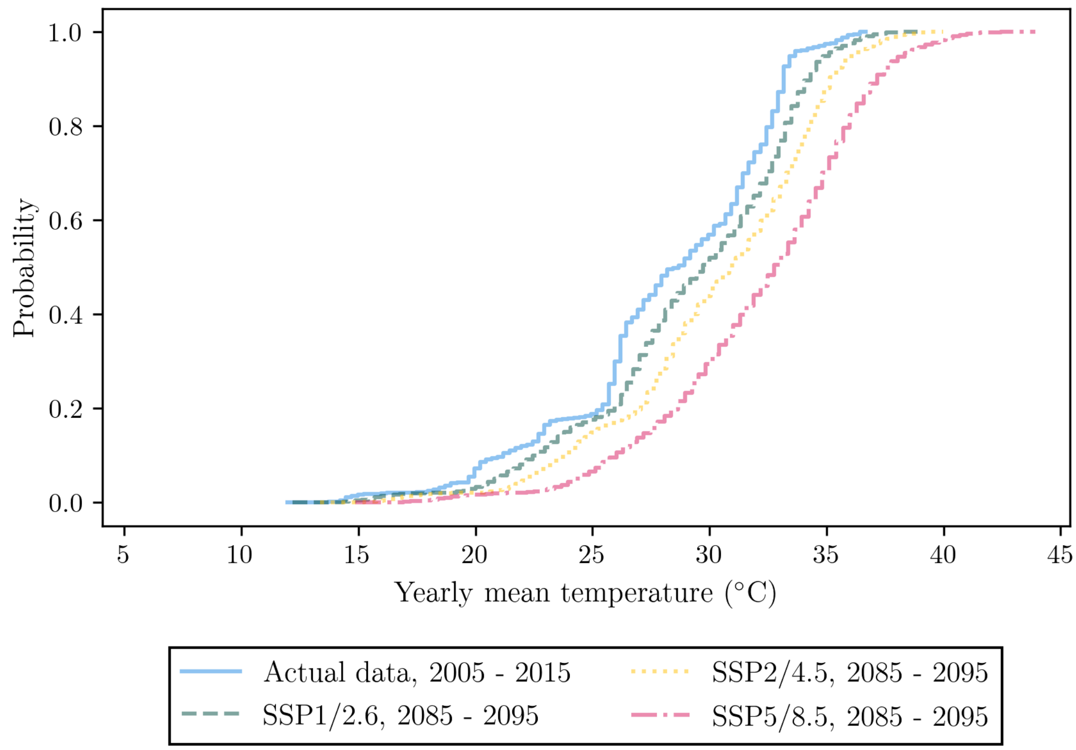
Note: The figure shows a basic open economy intuition for how a supply shock (increase in marginal cost) affects domestic and international sales. MC shows the firm's marginal cost, MR shows its marginal revenue.

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



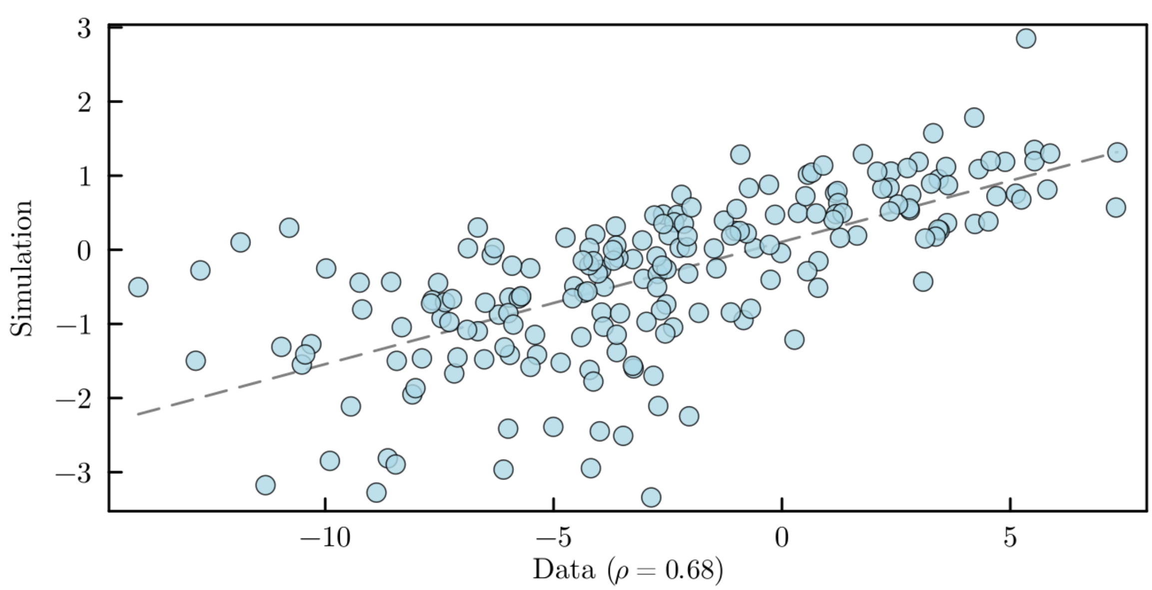
Note: The figure shows the empirical CDF of the yearly average of daily maximum temperatures across firms. The climate change projections are adjusted for differences in baseline temperature means for each day of the year, as described in Appendix C.

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



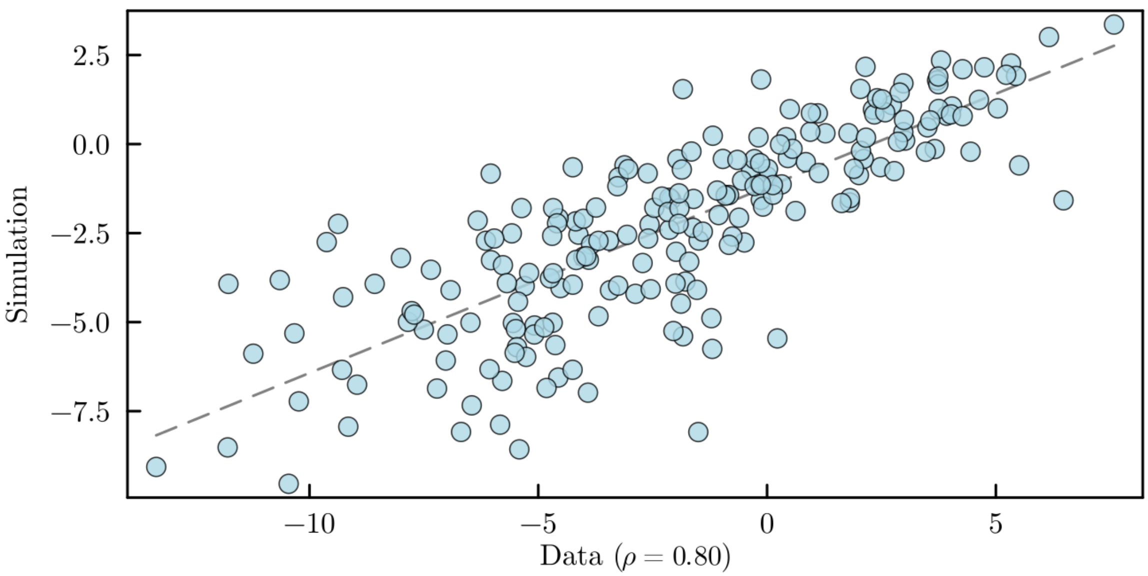
Note: The figure shows the empirical CDF of the yearly average of daily maximum temperatures across firms. The climate change projections are adjusted for differences in baseline temperature means for each day of the year, as described in Appendix C.

Figure 8: Zambian log exports vs. model simulation



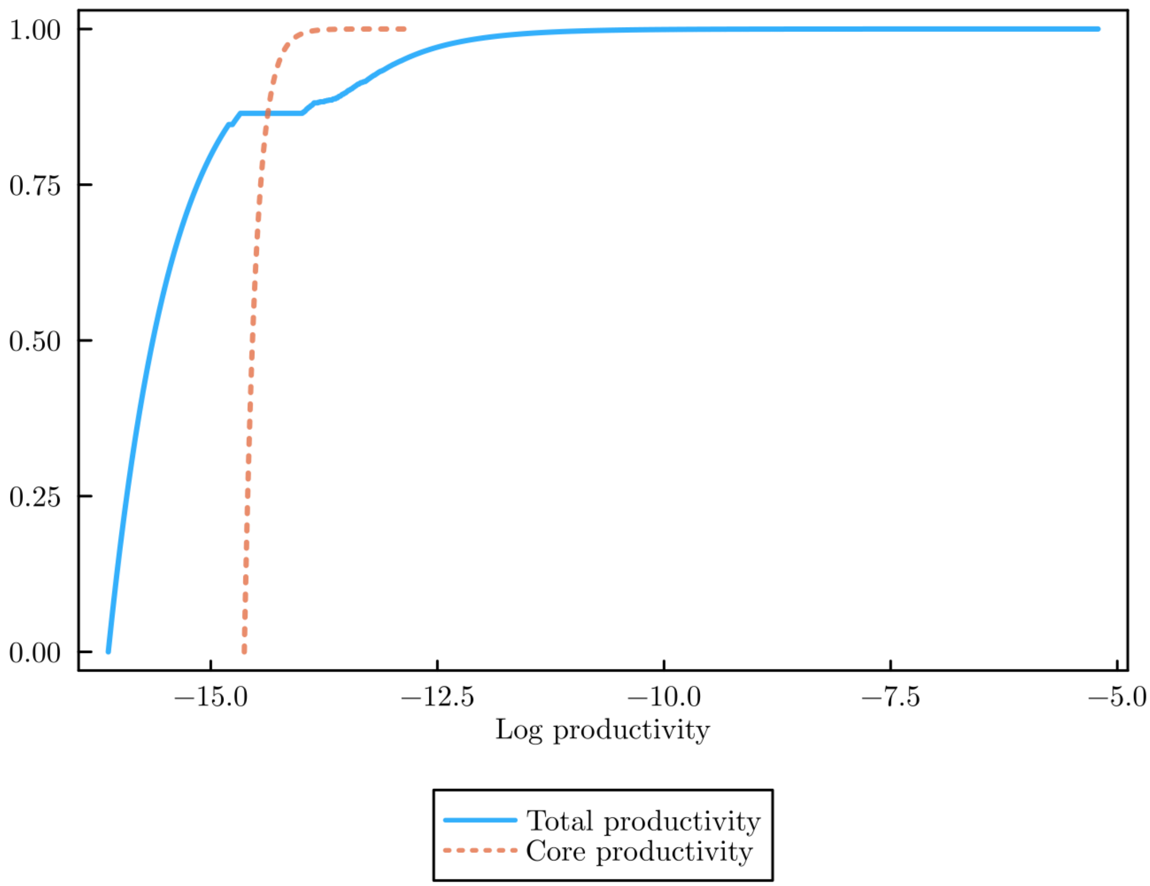
Note: Log exports are a targeted moment, together with the fraction of countries with zero exports.

Figure 9: Zambian log imports vs. model simulation



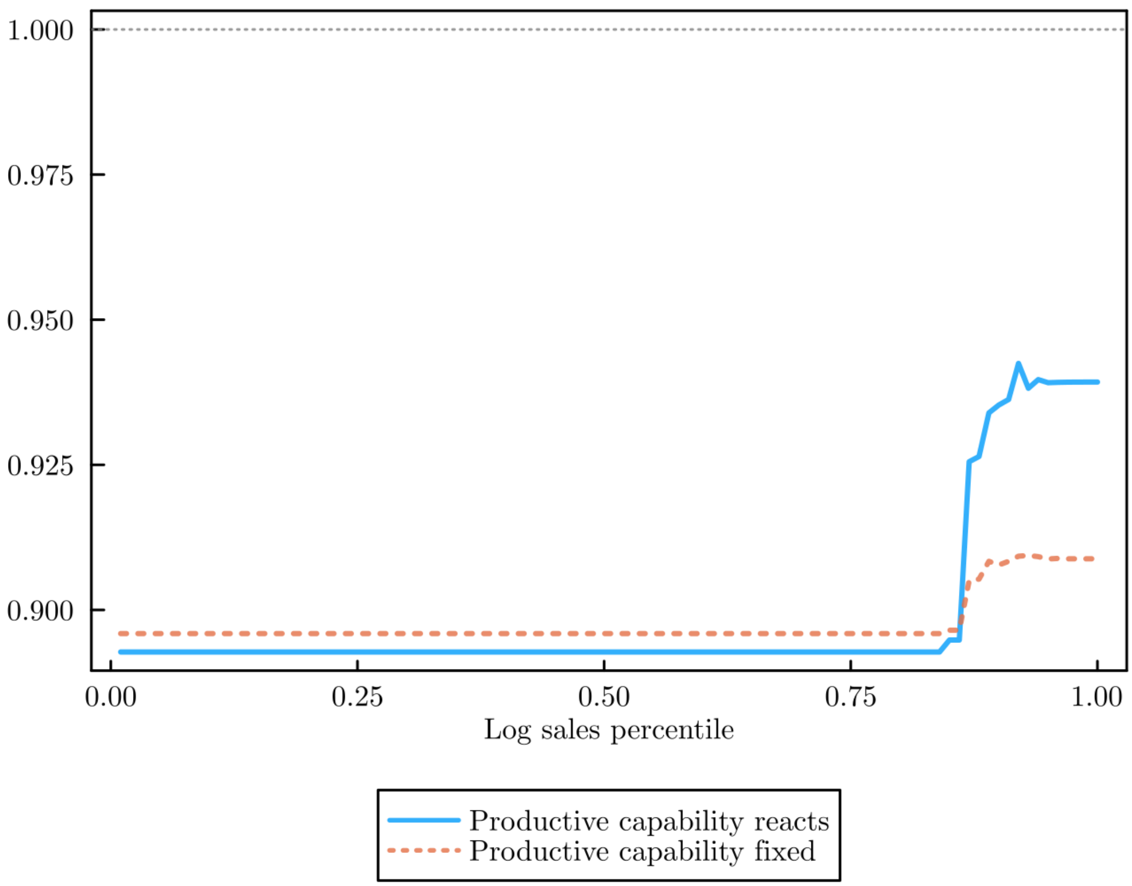
Note: Log imports are an untargeted moment.

Figure 10: Log total productivity compared to log core productivity



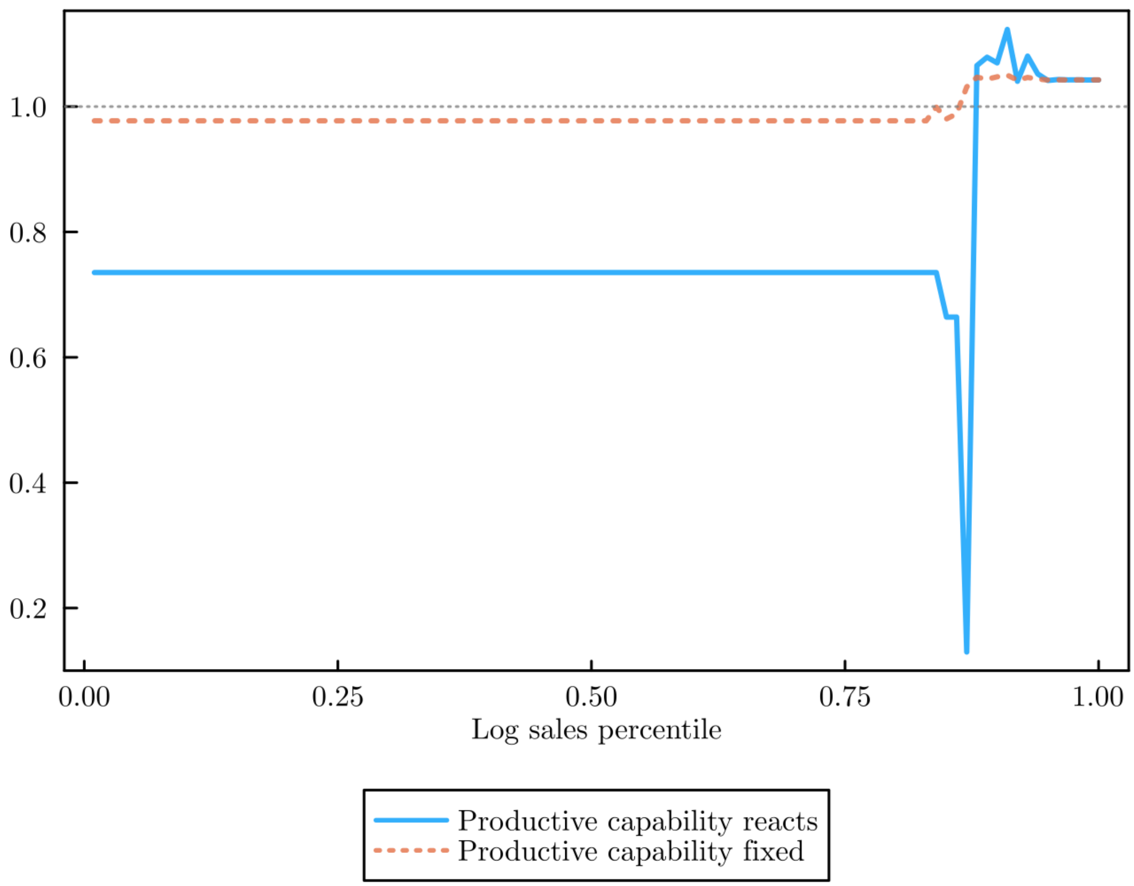
Note: The figure shows log total productivity $a_j c_j^{\delta}$, which depends on core productivity a_j and productive capability c_j. Log core productivity also shown for comparison.

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 [0.405]	-0.036^{*} [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^{th} percentile weather shock. Standard errors clustered by firm cluster. Outcomes winsorized at the 95^{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
	[0.656]
Temperature index × Current exporter	0.035
	[0.464]
Current exporter	1.635***
	[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
	[0.346]
Temperature index × Current exporter	−0.070
	[0.168]
Current exporter	1.039***
	[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^{th} percentile weather shock. Standard errors clustered by firm cluster. Outcomes winsorized at the 95^{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: Sales regression

Variable	Trade flows
Log sales	0.816*** [0.000]
Manager's years of experience	0.037*** [0.000]
Log initial no. of employees	0.333*** [0.000]
Log no. of employees 3 yrs. ago	−0.668*** [0.000]
International certification	0.124*** [0.000]
Had power outage	0.060*** [0.000]
Competes against informal sector	−0.103*** [0.000]
Introduced new product	0.238*** [0.000]
Introduced new process	0.174*** [0.000]
Had RD expenditure	−0.131*** [0.000]
Part of larger firm	0.133*** [0.000]
Formal when founded	0.183*** [0.000]
Applied for grid connection	−0.085*** [0.000]
Applied for water connection	−0.103*** [0.000]
Firm age	0.021*** [0.000]
4^{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		
σ	Sales, variable cost	3.016 (0.043)
Panel B: Structural estimation		
θ	75/25 ratio for domestic sales	4.304
$T_H w_H$	Ratio of Home sales to Foreign sales	0.000
$f_H w_H$	Fraction of exporters	0.768
γ_0		-7.894
γ_{dist}	Export flows	0.421
γ_{contig}		5.876

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 γ are the intercept γ_0, the coefficient on log distance γ_{dist} and the coefficient on the contiguity indicator γ_{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^{th} to the 25^{th} percentile. The other set of targeted moments, log exports, is shown in Figure 13.

A.9 Additional causal forest results

Table 28: Causal forest estimates for 2091–2095

Scenario	Change in log sales
SSP1/2.6	-0.048 $(-0.121, 0.026)$
SSP2/4.5	-0.059 $(-0.133, 0.015)$
SSP5/8.5	-0.101 $(-0.176, -0.026)$

Note: Standard errors clustered by firm cluster. 90 percent confidence intervals in parentheses.

A.10 Additional counterfactual results

Table 29: Counterfactual change in welfare compared to Melitz (2003)

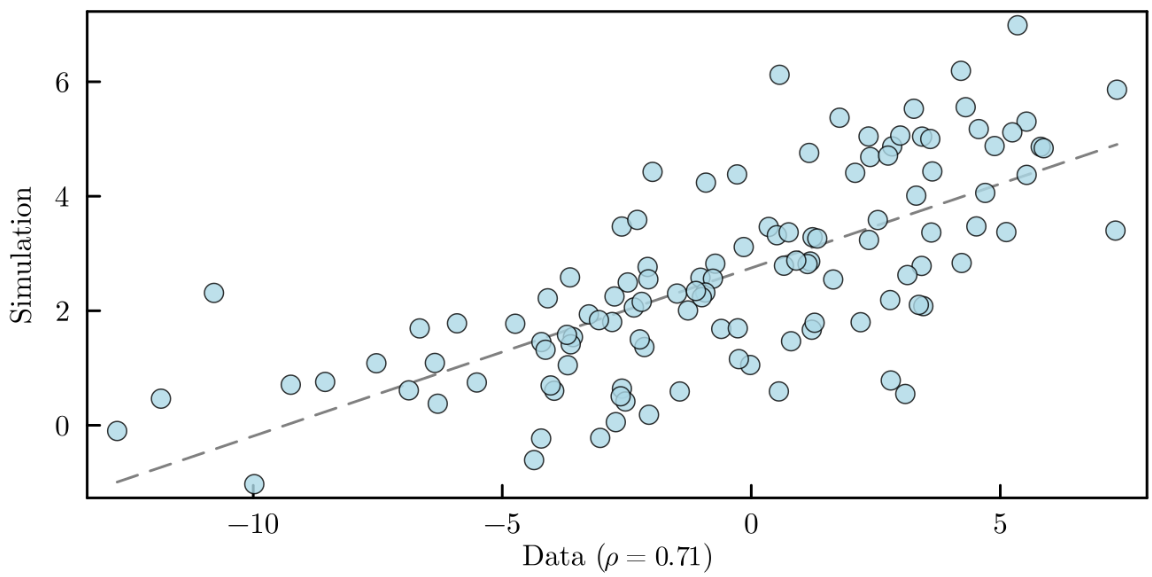
Scenario	Full model	Melitz (2003)
Panel A: Welfare gap compared to status quo		
Climate change baseline	-0.079	-0.127
Iceberg cost reduction	-0.049	-0.118
Entry cost reduction	-0.079	-0.121
Adaptation	-0.068	-0.111
Mitigation	-0.049	-0.080
Panel B: Fraction of welfare gap closed		
Climate change baseline	0.000	0.000
Iceberg cost reduction	0.376	0.071
Entry cost reduction	0.000	0.049
Adaptation	0.138	0.129
Mitigation	0.377	0.372

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

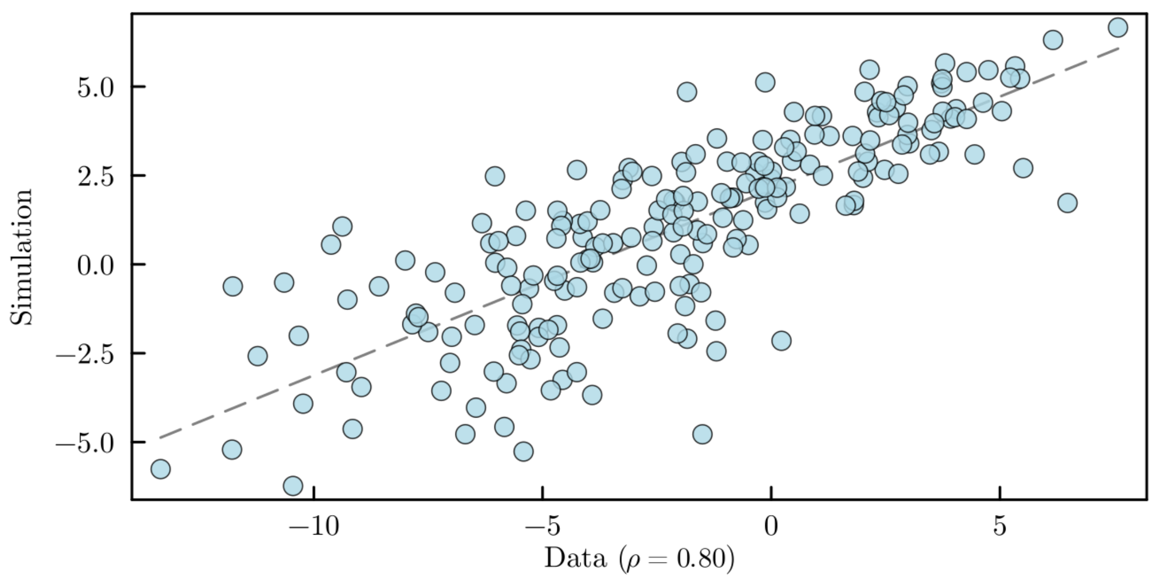
B.1 Moment comparisons for Melitz (2003) estimation

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.

C.1 Possible mechanisms for weather effect on productivity

Before turning to a model that incorporates this reaction, I tie up two loose ends. 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 30 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^{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^{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^{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 30: Indications of productivity impact

Variable	Log sales/employee	Log weekly hours	Outage
Temperature index	−0.074	0.142*	0.065*
	[0.491]	[0.088]	[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 D Proofs and derivations

D.1 Optimal c

The FOC for the optimal distribution network gives

$$\begin{aligned}
0 &= \delta \frac{w_i}{a_j} c_j^{-\delta-1} \left(\sum_{n\in\mathcal{M}_j} d_{ni}\alpha_n p_n(j)^{-\sigma} \right) - b c_j^{\frac{1}{\beta}-1} w_i \\
\Leftrightarrow c_j^{\frac{1}{\beta}+\delta} &= \frac{1}{b}\delta\frac{1}{a_j} \left(\sum_{n\in\mathcal{M}_j} d_{ni}\alpha_n p_n(j)^{-\sigma} \right) \\
\overset{(4)}{\Leftrightarrow} c_j^{\frac{1}{\beta}+\delta} &= \frac{1}{b}\delta(\mu w_i)^{-\sigma} a_j^{\sigma-1} \left(\sum_{n\in\mathcal{M}_j} {d_{ni}}^{1-\sigma}\alpha_n \right) c_j^{\delta\sigma} \qquad (14) \\
\Leftrightarrow c_j &= \left[\frac{1}{b}\delta(\mu w_i)^{-\sigma} a_j^{\sigma-1} \left(\sum_{n\in\mathcal{M}_j} {d_{ni}}^{1-\sigma}\alpha_n \right) \right]^{\frac{\beta}{1-\beta(\sigma-1)\delta}}
\end{aligned}$$

D.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 α_n across all markets the firm is active in. For the same reason as above, choosing a different c_j cannot increase profits.

D.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 α_n across all markets the firm is active in. For the same reason as above, choosing a different c_j cannot increase profits.

D.4 Mass of entrants

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

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

D.5 Price index

The price index of country n is

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

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

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

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,

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

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,

$$= \left(\sum_{i=1}^{N} n_i \int_{\underline{a}_i}^{\infty} \mathbb{1}\left[n \in \mathcal{M}_j\right] p_n(j)^{1-\sigma} \, \mathrm{d}F_i\left(a_j\right) \right)^{\frac{1}{1-\sigma}}$$

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

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,

$$= \mu \left(\sum_{i=1}^{N} n_i (d_{ni} w_i)^{1-\sigma} \int_{\underline{a}_{ni}}^{\infty} \left(a_j c_j^{\delta} \right)^{\sigma-1} \mathrm{d}F_i\left(a_j\right) \right)^{\frac{1}{1-\sigma}} \tag{15}$$

D.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 α_n,

$$\begin{aligned}
&= n_i (\mu d_{ni} w_i)^{1-\sigma} X_n \mathcal{P}_n^{\sigma-1} \int_{\underline{a}_{ni}}^{\infty} \left(a_j c_j^{\delta} \right)^{\sigma-1} \mathrm{d}F_i\left(a_j\right) \\
&\overset{(15)}{=} \frac{n_i (d_{ni} w_i)^{1-\sigma} \int_{\underline{a}_{ni}}^{\infty} \left(a_j c_j^{\delta} \right)^{\sigma-1} \mathrm{d}F_i\left(a_j\right)}{\sum_{k=1}^{N} n_k (d_{nk} w_k)^{1-\sigma} \int_{\underline{a}_{nk}}^{\infty} \left(a_j c_j^{\delta} \right)^{\sigma-1} \mathrm{d}F_k\left(a_j\right)} X_n
\end{aligned}$$

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

From (14), the optimal c can be written as

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

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

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

$$\stackrel{(6)}{=} \left[\frac{1}{b}\frac{\delta}{\mu w_i}\underbrace{\sum_{n\in\mathcal{M}_j} S_n(j)}_{\equiv\mathcal{S}(j)}\right]^{\beta} \tag{16}$$

Plugging (16) into sales to the Home market (6) and remembering that $d_{ii} = 1$ by assumption,

$$S_i(j) = \alpha_i\left(\mu\frac{w_i}{a_j}\left[\frac{1}{b}\frac{\delta}{\mu w_i}\mathcal{S}(j)\right]^{-\beta\delta}\right)^{1-\sigma}$$

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

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

with

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

D.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

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

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

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_{future}, so the first expectation runs across F_{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.

D.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.