Title: Disaster-induced import dynamics: Evidence from South African floods

Author(s): Marina Dodlova, Justyna Jantos, Krisztina Kis-Katos, and Anna Kochanova

Corresponding author: Marina Dodlova

Corresponding author's email address: marina.dodlova@uni-muenster.de

All affiliations: University of Münster, University of Göttingen, Cardiff University

Abstract:

This paper examines the impact of floods on regional import dynamics in South Africa. Natural disasters like floods can disrupt firms' production activities, hindering their participation in import markets. However, firms may increase imports to offset disruptions in their domestic supply networks. Our study explores this adjustment behavior using administrative firm-level and customs transactions data from South Africa. Analyzing a monthly panel of import aggregates and market entries across local municipalities from 2013 to 2021, we find that floods generally deter new firms from entering import markets, yet the disruption to domestic supply chains prompts firms to seek alternative suppliers abroad. Although overall average import values remain unchanged, firms adjust by increasing imports of capital goods. Our results also show stronger import responses from the European Union following supply chain disruptions due to floods. Additionally, firms in manufacturing or mining tend not to respond to flood shocks by adjusting their import levels. Instead, such adjustments are more likely to occur through the trade sector. Such adjustment dynamics would be overlooked when focusing solely on manufacturing firms' data.

Key words: climate change, floods, imports, customs data, South Africa

JEL classification codes: F18, Q51, Q56

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1 Introduction

Climate change is increasing the frequency and severity of natural disasters due to extreme weather events, leading to substantial economic losses (Strömberg 2007; Noy 2009; Felbermayr and Gröschl 2014). However, these natural disasters also prompt a range of adaptive behaviors. Thus, to evaluate the global economic costs of climate change, it is crucial to understand how local economies worldwide adapt to climate-related risks (IPCC 2022). In developing countries, where government capacity is limited, private actors, such as firms, play a crucial role in adaptation processes (Balboni et al. 2023; Greenstone and Jack 2015). Firms may respond to natural disasters by adjusting in several ways: halting or relocating operations, or modifying their use of inputs or technologies. Additionally, decisions about participating in global markets can provide important alternative means of adaptation.

From a theoretical perspective, global market integration presents both opportunities and threats, leading to a trade-off between the ability of global value chains to propagate and absorb idiosyncratic shocks (Baldwin and Freeman 2022). Supply shocks from extreme weather events can limit a country's export capacity (Jones and Olken 2010; El Hadri et al. 2019) and impact foreign markets (Feng et al. 2024). However, global market access may also allow firms to mitigate climate-related risks by diversifying their supply chains, reducing the impact of disruptions to domestic suppliers caused by disasters. This paper focuses on the latter aspect of climate change adaptation, examining how regional import flows respond when South African firms experience flood shocks, either directly affecting their operations or indirectly through domestic supply chains.

South Africa offers an ideal setting for studying the impact of floods on supply chains and firms' import behavior. Floods are the most common natural hazard in the country, accounting for over 30% of all natural disasters since the 1980s. Floods often to destroy infrastructure, productive capital, and output, causing delays in production processes. Equally important from an economic perspective is their impact on input-output networks and the resulting demand for risk diversification. This paper distinguishes between the direct impacts of domestic floods and their indirect impacts through domestic supply chains. Direct flood impacts cause a negative productivity shock, likely restricting the ability of affected firms to participate in import markets in the short term. In contrast, indirect impacts, resulting from disruptions in domestic supply chains, may increase demand for foreign imports.

Our empirical analysis utilizes administrative transaction data from customs offices, which we link with firm-level panel data from corporate income tax and payroll tax records.[1] We examine firm-level international transactions in South Africa from 2013 to 2021, merging data on international market entry and import volumes with information on flood events from the Global Active Archive of Large Flood Events (DFO 2021). Utilizing firm location and employment data from tax records, we can assign treatment at the local municipality (ADM3) level and on a monthly basis. To create a measure of indirect flood exposure, we use South African input-output tables for 50 sectors to construct a synthetic domestic production network for each sector-local municipality pair. This network is weighted by distance and market power, following the approach by Couttenier et al. (2022). We apply a Poisson Pseudo Maximum Likelihood (PPML) model to regress monthly regional import dynamics across South African local municipalities on two cumulative flood indicators: floods occurring directly at firm locations and those impacting the firms' potential domestic input network.

Our results indeed show declines in the number of new importers as a direct consequence of flood events, as well as increases in import market entry due to flood-induced supply-chain shocks. At the same time, we do not observe significant changes in aggregate import values. However, disaggregating

[1] We utilize the SARS-NT/CIT-IRP5/SARS (version 4.0) dataset that has been provided for research use by the SARS and UNU-WIDER.

imports yields a set of further insights. Supply chain shocks lead in particular to increases in imports of capital goods, which are intended for firm use. Moreover, imports are also more likely to respond to shocks in less flood-prone places, where other adjustment mechanisms may be less routinely available. When differentiating among source countries and regions of imports, we observe that floods in the supply chain are relevant for all, but prompt especially strong import adjustments from countries of the European Union (which are a major source of capital products). Finally, we observe substantial adjustment behavior among firms in agriculture and among trading companies, which play an important role in the post-shock adjustments through imports.

In terms of causal identification, while the timing of flood shocks is fully exogenous, their geographic locations are non-random. Floods tend to concentrate in and around South Africa's economic centers, which could lead to an underestimation of their direct effects due to the high concentration of imports in these areas. To check for the sensitivity of our results to non-random locations, we proceed in several steps. Our basic empirical strategy controls for both time and location fixed effects, and distinguishes between the direct and indirect effects of floods. With a long observation period of 108 months, we are less likely to capture spurious single events. Additionally, by controlling for location-specific trends, we can relax the assumption of continuously varying parallel trends across different flood intensities, ensuring our main findings remain stable. Further robustness checks indicate that our results are robust to accounting for flood duration more explicitly. However, they become less stable once we attempt to differentiate flood events based on their intensity. Further analysis of our modeling approach is ongoing.

Our paper contributes to several strands of the literature. Firstly, it is closely related to research on the impact of climate change and natural disasters on trade and global value chains (see Baldwin and Freeman (2022) for a review). This research highlights immediate declines in exports following natural disasters (El Hadri et al. 2019; Tembata and Takeuchi 2019), shifts in global demand to other countries (Freund et al. 2022), and short-term increases in import demand for reconstruction (Gassebner et al. 2010). While most studies in this area focus on country-level adjustments using a global gravity framework, access to firm-level import transaction data enables us to explore regional variations in import dynamics within a country, comparing flood-affected regions to those that are not affected.

Second, our study takes inspiration from the literature on domestic supply chain readjustment processes. Similarly to Balboni et al. (2023), who demonstrate the rearrangement of domestic value chains in response to flood shocks in Pakistan, we differentiate between the direct effect of floods and those that propagate through the domestic supply chain. In the same vein, there is a rapidly expanding body of macroeconomic literature that documents production network rearrangements following disasters (Carvalho et al. 2021; Castro-Vincenzi et al. 2024), and other shocks, such as conflict (Couttenier et al. 2022; Korovkin et al. 2024), and general economic volatility (Kopytov et al. 2024), using structural modelling to asses wider economic impacts. Unlike this second strand of studies, we do not observe firms' domestic transactions, but instead, we measure their international transactions in great detail. This allows us to analyze adjustments in import behavior at the high monthly frequency and to differentiate between specific product categories and source countries. However, it also comes with a limitation, providing only a partial view of firms' economic activities and preventing the integration of domestic and international transactions. Due to these constraints, we adopt a reduced form approach and document lasting changes in regional-level import aggregates in response to flood shocks within the supply network.

Third, our study is connected to the literature examining relocation and spillover processes resulting from disasters in the context of international trade flows. This includes the relocation of trading activities across domestic ports (Hamano and Vermeulen 2020; Friedt 2021), the termination of links to globally exposed suppliers (Pankratz and Schiller 2024), and cross-country spillovers impacting foreign producers through input trade (Boehm et al. 2019). Our analysis differs from these studies as we primarily focus on import market access as a strategy for coping with shocks, rather than on the international propagation of these shocks.

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Finally, our paper contributes to the literature on the trade behavior of South African firms, utilizing customs transaction data (Sequiera 2016; Edwards et al. 2020; Wier 2020; Kilumelume et al. 2021).

The remainder of the paper is structured as follows. Section 2 briefly discusses the conceptual framework. Section 3 introduces data sources and outlines measurement approaches. Section 4 presents the empirical model. Section 5 presents our empirical results, followed by robustness checks in section 6. Section 7 concludes.

2 Conceptual framework

Direct effects of floods on firms. Floods directly affect firms through disruptions in their activities and the subsequent recovery process. In the short run, floods act as a negative productivity shock to the directly impacted firms. In the medium run, the impact depends on the firms' recovery dynamics. The negative productivity shock may persist, be mitigated, or even lead to long-run productivity improvements. Short-term negative effects of natural disasters on firms are well-documented and include the destruction of capital and productive capacities, disruption of workforce productivity, and delays in production processes. Some of these effects may persist, resulting in incomplete recovery (Pan and Qiu 2022). Despite these challenges, firms often rebuild and reinvest in new, potentially higher-quality capital goods. Experimental evidence suggests increased risk-taking after floods (Page et al. 2014), which can lead to more borrowing and stimulate changes in production technology. These changes may result in productivity increases in the medium run (Leiter et al. 2009). Some empirical studies document such productivity gains by firms following floods and other natural disasters (Cole et al. 2019), highlighting the positive impact of financial aid in promoting recovery (Leiter et al. 2009; De Mel et al. 2012).

Indirect effects through the domestic supply chain. In addition to direct effects, floods can also cause negative productivity shocks through their indirect effects, which spread through input-output linkages to other firms both domestically and globally. The concept that shocks propagate through the value chain (Leontief 1936) has gained renewed attention in the recent firm-level literature focused on firms' adjustment behaviors. At the firm level, studies highlight key adjustment strategies, such as relocating and diversifying supplier networks away from disaster affected regions (Balboni et al. 2023; Castro-Vincenzi et al. 2024; Kopytov et al. 2024). The propagation of these shocks can be measured directly using detailed data on firm linkages or indirectly by constructing a synthetic supplier network. This latter approach combines aggregated input-output information with data on the location and market power of sellers for each input product (Bernard et al. 2019; Couttenier et al. 2022).

Floods and imports. The direct and indirect effects of floods can have contrasting implications for firms' participation in import markets. Within the framework of heterogeneous firms (Melitz 2003), flood-induced negative productivity shocks can reduce firms' ability to cover the fix costs of engaging in international trade. Consequently, we expect a decline in import activities in flood affected regions, as firms are less likely to bear the transaction costs associated with importing. These effects may be compounded by a general disruptions to the transportation infrastructure (Osberghaus 2019). Whether these impacts persist in the medium term as firms recover is unclear. The second, indirect, mechanism offers clearer predictions. When floods disrupt supply chains, firms may choose to readjust their supplier networks to mitigate productivity losses. As a result, we expect an increase in imports, as some domestic suppliers might be replaced with international ones.

Heterogeneous effects. When examining import responses to shocks across different types of products and trading partners, certain heterogeneities might be expected. As our focus is primarily on firms' responses to shocks, adjustments are more likely to occur among products commonly used as inputs in firms' production processes. Therefore, we anticipate seeing larger adjustments in imports of raw materials, intermediate goods, and capital goods compared to consumer goods.

Theoretical literature provides further insights regarding product-type specific adjustments. Production network-based models highlight the importance of the complexity of input products, as more complex products are harder to substitute. Therefore, shocks to suppliers of complex products are more likely to propagate through the value chain (Bernard et al. 2019), increasing the need to source them from foreign markets. However, this mechanism may be offset by the higher costs of finding suitable foreign suppliers for complex products. Thus, it is a priori not clear which types of products will see increased imports in response to supply chain shocks. To test these predictions, our empirical analyses will explicitly distinguish between import products based on their complexity.

Finally, a similar argument applies to choosing the country of origin for new suppliers. Generally, finding new foreign trading partners is costly (Antràs 2020), often leading to network effects and path dependencies in choosing partners (Chaney 2014). Consequently, supply chain disruptions may cause larger increases in imports from countries with which there are already stronger trade ties.

3 Data and measurement

3.1 Sample construction and dependent variables

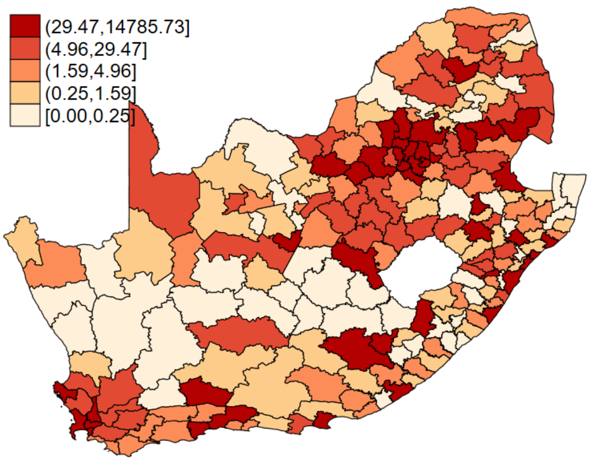
Firm data. Our study uses a combination of firm-level data from customs transactions, corporate income taxes (CIT), and Pay-As-You-Earn payroll taxes (IRP5), provided by the South African Revenue Service (SARS) and the National Treasury (NT). The transaction-level customs dataset contains detailed information on every registered inflow and outflow of goods to and from South Africa, including the date and value of each transaction, Harmonized System (HS) classification code of the traded product, and its country of origin. We use this data to measure the import transaction value, adjusted to 2010 prices. Firms' tax records help us identify relevant transactions and define key variables. We determine each firm's primary sector of operation from the CIT data (Budlender and Ebrahim 2020), and obtain the location of firms' branches from the firm-level aggregates in the IRP5 data (Ebrahim et al. 2021). Additionally, branch-specific employment figures for each firm are generated from employee-level data in the same dataset.

Defining the sample. Due to the availability of geographical data on firms, and for reasons of concordance and data quality, our main empirical analysis is confined to the time period from 2013 to 2021. However, we use data from earlier years for variable constructions where applicable. The customs data includes imports by various legal entities and private individuals. Our focus is solely on imports by corporations, which we refer to as firms throughout the paper. Therefore, we include only import transactions by firms that report both payroll taxes and corporate income taxes (CIT-IRP5). As a result, our dataset excludes private individuals, self-employed persons, and government and nongovernmental organizations. The final dataset captures all trading for-profit businesses, except for the self-employed.

Assigning locations. To link the spatial treatment to importing firms, we need to assign all imports to specific locations. However, location data in customs records is inconsistent and often reports the address of an office, which may not match the firm's headquarters. More importantly, this address does not necessarily represent the location of the firm's production facilities, and does not account for firms that operate in multiple regions. To assign imports to regions more accurately, we utilize employee-level payroll tax data (IRP5), from which we determine each firm's location down to the level of local municipalities (ADM3).

Distributing imports across firm branches. When a firm reports payroll taxes for multiple branches located in different ADM3 regions, we allocate the firm's imports to these regions according to their regional employment shares. These shares are determined based on the number of paid firm employees reported in the payroll tax data for each region (Budlender and Ebrahim 2020). We use the employment shares from 2013, as this is the first year with consistent payroll tax data, making our starting year. For firms that begin their operations after 2013, we use employment shares from the first year they appear in the payroll tax data. By using these fixed (initial) regional employment shares for each firm, we ensure that potential endogenous changes to the workforce distribution, such as those caused by floods, do not impact our calculations of regional imports. Figure 1 illustrates the distribution of import volumes across municipalities over the entire time period. As expected, import activities are heavily concentrated in and around the economic centers, among others, around Johannesburg and the Western Cape.

Figure 1: Average regional import volumes (2013–2021)



Note: The figure shows the spatial distribution of regional aggregates of average yearly import values over the time period 2013–2021, expressed in millions of 2010 South African Rand (ZAR).
Source: authors' compilation based on customs data.

Assigning import market entry to regions. We assign firms' entry into import markets to regions in a similar manner. If we only considered firms operating in a single region, the number of new importers in a given municipality and month would simply be a count of the firms located in the region appearing as importers for the first time in that month. However, since our analysis also includes multi-region firms, the number of market entrants is calculated as a sum of entrants, weighted by the firms' regional employment shares. For example, if a firm originally operates in three regions with its workforce equally distributed across them, when it begins importing, the number of importing firms in each of the three regions increases by $1/3$.

Input-output linkages. To measure input-output linkages, we use the national input-output table from 2010, provided by Statistics South Africa (2014). We identify each firm's main industry using the Standard Industrial Classification (SIC) code from the CIT-IRP5 data. Each firm is then assigned to one of 50 sectors, aligning with the classification in the input-output tables.

Product classifications. We use the 6-digit HS classification to categorize traded products into raw materials, consumer goods, intermediate goods, and capital goods, following defitions by the United Nations Conference on Trade and Development (UNCTAD) in their Special Provision (SoP) classification (WITS n.d.). Raw materials are generally unprocessed, intermediate goods are semi-processed, while consumer and capital goods are fully processed, intended for household consumption and use by firms in productive processes, respectively. Additionally, we differentiate between two levels of product complexity using the continuous Product Complexity Index (PCI) estimated by the Observatory of Economic Complexity for 6-digit HS products (OEC 2022). The PCI measures the relative knowledge intensity of each product (2008–2022) based on international trade data. The index combines information on local production structures with the uniqueness of products on a global scale. Regions producing unique products are assigned a higher economic complexity, while products produced in such regions receive a higher complexity ranking. We calculate the median PCI for each product over the period 2008–2022 to create a single aggregated index. A product is classified as having relatively low complexity if its PCI is below the median across all products, and high complexity if its PCI is above the median.

Final data structure. To build our final analytical sample, we aggregate all variables at the level of local municipalities and months. Our primary variables of interest measure the monthly volume of imports by location. For more detailed analyses, we divide import volumes by product types, source regions, and the sectors of the importing firms.[2] Additionally, from this monthly dataset, we identify the first time a firm imports a product, defining this occurrence as the firm's entry into international markets.[3] When examining import market entry by product type, we identify the first instance when a firm imports a specific type of product. For example, if a firm has previously imported intermediate goods, it will be considered as a new importer of consumer goods the first time it imports consumer goods in our data. Our final dataset is a balanced panel comprising 213 local municipalities, observed over 108 months (9 years).

3.2 Measuring exposure to floods

Flood data. We gather flood information from the Global Archive of Large Flood Events, compiled by the Dartmouth Flood Observatory (DFO 2021). This archive uses sources such as news outlets, governmental records, instrumental data, and remote sensing, and covers all major flood events.[4] From 2013 to 2021, the DFO reports that South Africa experienced a total of 16 major flood events.[5] In our analysis, we aggregate these occurrences on a monthly basis, counting each flood as a single event even if its effects span multiple months.[6] Figure 4 illustrates the geographical spread and frequency of floods based on this criterion. It highlights that municipalities in the eastern part of South Africa were most frequently affected by floods during our study period.

[2] To represent South Africa's main trading partners, we categorize imports into following groups: other African countries, the European Union (EU), the United Kingdom (UK), the United States (USA), China, and the rest of the world (RoW). We treat the EU and the UK separately to account for potential changes due to Brexit.

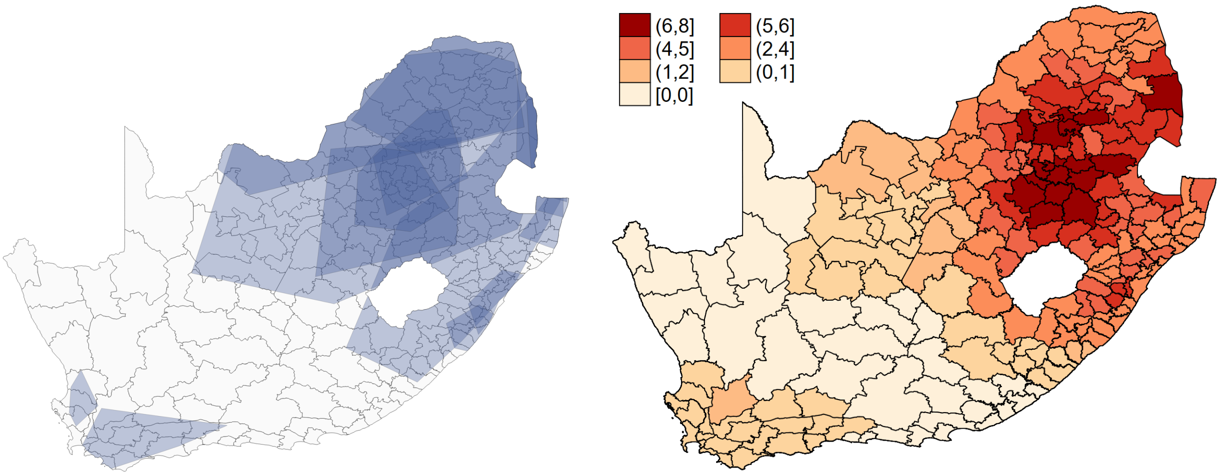
[3] As some firms engage in international trade sporadically, they may have been importers before our observation period began. However, with customs data available from 2009 and our regression sample starting in 2013, we can track firms' trade transactions up to four years prior to our analytical period. Thus, at the start of our sample period, we classify firms as new entrants to international markets only if they have not engaged in importing activities for at least four years.

[4] The DFO categorizes flood events into three classes based on their frequency and severity: Class 1 floods are estimated to occur every 10 to 20 years; Class 1.5 floods are more severe and were initially expected to occur no more than once per century; Class 2 floods are extreme events with an estimated recurrence interval exceeding 100 years.

[5] Out of the 16 reported flood events, 8 were classified as class 1 floods, and 8 as class 1.5 floods. In our main analysis, we do not differentiate floods by their intensity; however, we do treat the two flood intensities separately in our robustness checks.

[6] While 12 floods subside within one month, 2 flood events span two months and 2 further flood events even three months. Thus, alternative robustness checks consider explicitly flood duration in months instead.

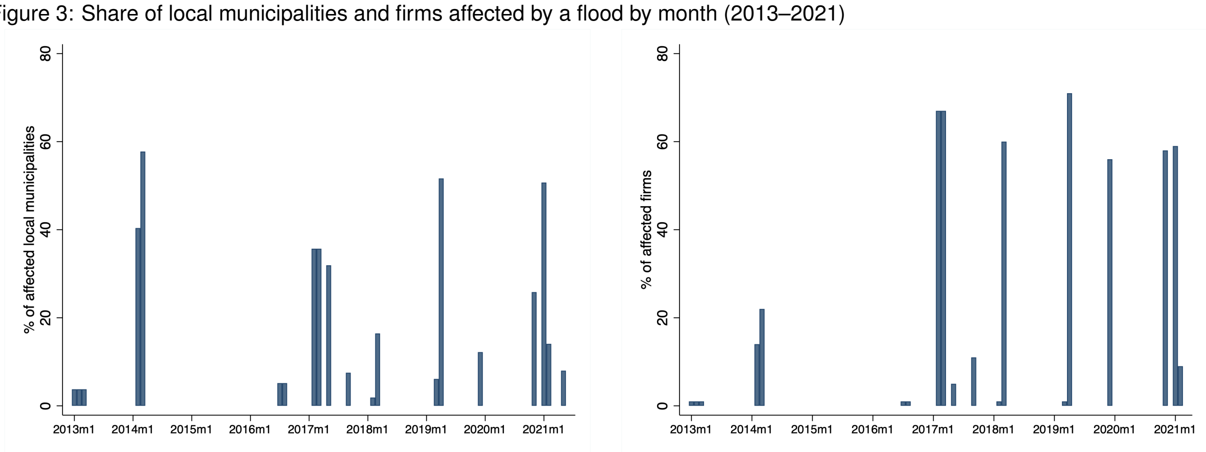
Figure 2: Local exposure to floods from 2013 to 2021



Note: The figure on the left displays 16 flood polygons that occurred between 2013 and 2021 as recorded by the DFO. The figure on the right displays the number of floods that affected each municipality within the same time period.
Source: authors' compilation based on data from the DFO.

Direct flood exposure. Our empirical strategy distinguishes between the direct and indirect effects of floods on firms' participation in foreign markets. The variable *Own floods* captures the direct exposure of firms to floods impacting their operations. This variable represents an absorbing cumulative treatment, indicating the number of floods a municipality has experienced since the start of our observation period in January 2013. Each time the DFO records a significant flood within a municipality's area during a given month, the flood indicator value increases by one. Figure 3 shows the percentage of municipalities and firms directly affected by floods during our sample period. While floods recur, their exact timing is unpredictable and their impact can vary significantly over time. For instance, in 2014 and 2021, up to 60% of municipalities experienced flooding. However, the 2014 flood impacted only about 20% of firms, whereas the 2021 flood affected approximately 60%. Given that economic centers in South Africa are more prone to flooding, the proportion of affected tends to be higher on average than that of affected regions.

Figure 3: Share of local municipalities and firms affected by a flood by month (2013–2021)



Note: The left figure displays the share of municipalities affected by floods by month, whereas the right figure displays the share of importing firms affected by floods by month.
Source: authors' compilation based on DFO and customs data.

Indirect flood exposure. To assess the indirect effects of floods caused by supply chain disruptions, we calculate a second, synthetic measure of flood exposure. This measure records the cumulative intensity of *Floods within the supply chain* over time. Ideally, this would be based on each importing firm's domestic linkages, utilizing comprehensive domestic transaction data, such as detailed value added tax (VAT) transactions, as in the study of Balboni et al. (2023). In the absence of domestic transaction data, a distance-weighted potential supplier network could be constructed using detailed data on each firm's input structure, as outlined in Couttenier et al. (2022). Unfortunately, for South African firms, we do not have access to VAT transaction data or detailed input data from balance sheets. Additionally, CIT data provides output information only at the firm level, without distinguishing between outputs from various regional branches.

To overcome these data limitations, we consider the potential flood exposure of affected firms' domestic value chains in a simplified, regionally aggregated manner. We construct a synthetic regional buyer-supplier network through two steps. First, for a specific buyer sector operating within a region, we estimate a probable network of all seller regions for each of its input products by assigning a weight to each potential seller region. Next, we use national input-output tables to determine the relative importance of each input product for the given buyer sector. Combining the weights that connect buyer and supplier regions with the input-output coefficients that link buyer and supplier sectors, we create a synthetic representation of a potential production network for each region. These weights can then be used to assess how flood shocks in producing regions may propagate to the regions purchasing those products.

Linking buyer and supplier regions. Our measure aligns closely with the method proposed by Couttenier et al. (2022), which is based on the concept of production networks. This concept proposes that firms are more inclined to purchase inputs from geographically nearby firms that possess greater market power (as described by Bernard et al. (2019)). However, rather than constructing a network through firm-product linkages among individual buyers and suppliers, we focus on building a network between pairs of buyer sector-region cells and supplier sector-region cells. Consequently, we define the potential relative strength of buyer-supplier relationships, denoted by ρ_{jik}, between firms located in buyer region i and firms in supplier region j that produce input product k, as follows:

$$\rho_{kji} = \lambda \frac{D_{ji}}{\sum_j D_{ji}} + (1-\lambda) \frac{L_{kj0}}{\sum_j L_{kj0}}, \tag{1}$$

which is a linear combination of two factors: the relative inverse distance between buyers and sellers (measured in kilometers) and the relative market power of each regional seller. The inverse bilateral distance between the buyer region i and the supplier region j, denoted as D_{ji}, is normalized by the sum of distances to all supplier regions. A closer supplier region will receive a larger relative inverse distance value, and hence, a larger bilateral importance weight. For suppliers within the same region where $j = i$, the inverse relative distance is assumed to be 1, the maximum possible value of D. We approximate the market power or relative importance of supplier region j in producing product k based on that region's initial employment in sector k, denoted by L_{kj0}. This figure is normalized by the total employment in that sector across all supplier regions. Consequently, supplier regions with a larger share of employment in a sector will be assigned a grater relative importance within that sector.[7]

The resulting measure of relative importance, ρ_{kji}, is scaled so that the total relative importance of all regions that could potentially supply product k to buyer region i sums up to 1, meaning $\sum_j \rho_{kji} = 1$ for each input product k in a buyer region i. Following Couttenier et al. (2022), we set $\lambda = 0.5$ to assign equal weight to both distance and market power in the formation of buyer-supplier networks.

Linking buyer and supplier sectors. In addition to establishing regional linkages, we also need to measure sectoral linkages. To achieve this, we utilize a national input-output table that describes the overall intensity of buyer-supplier linkages for each domestic buyer-supplier sector pair, h and k. The national input shares, α_{kh}, represent the relative proportion of inputs from sector k among all inputs sold to out-

[7] We use employment data instead of output data for these weights because it allows for more precise allocation of multi-branch firms across regions.

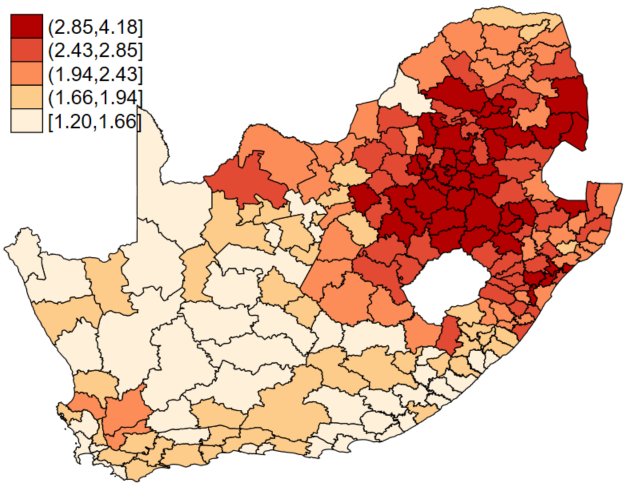
put sector h. To apply these coefficients, we assume that the sectoral input-output structure is relatively stable over time and does not vary significantly across regions.[8]

Measuring the weighted exposure to floods. The supply-chain-based flood exposure, $SC\ Floods_{it}$, represents the cumulative impact of flood events on various buyer sectors $(h = 1, ..., 50)$ operating within a specific region i. This measure is calculated as a weighted sum of all potential flood shocks affecting these sectors through the synthetic production network. This network links the buyer sectors to supplier sectors $(k = 1, ..., 50)$ located across all regions $(j = 1, ..., 213)$. Therefore, the cumulative effects of floods occurring in month t spread through the supply chain in the following manner:

$$SC\ Floods_{it} = \sum_h \frac{L_{hi0}}{L_{i0}} \left(\sum_k \alpha_{kh} \left(\sum_j \rho_{kji}\, OwnFloods_{jt} \right) \right), \tag{2}$$

where $SC\ Floods_{it}$ denotes the cumulative flood exposure through the value chain for buyer region i in month t. This measure is computed as a weighted sum of $OwnFloods_{jt}$, which represents the cumulative direct flood exposure in seller region j during the same month. Initially, floods are aggregated across all seller regions to create an input-product-specific flood exposure measure (inner sum). This aggregation uses the product-specific bilateral importance weights, ρ_{kji}. Next, these input-product specific flood exposure measures are aggregated across all input products k to determine the flood exposure for sector h in region i. The relative importance of each input product is determined by the Leontieff coefficients, α_{kh}. Finally, sector-level exposures through the value chain are combined to form a composite flood exposure measure for region i. This last aggregation uses initial employment weights to determine the relative importance of each output sector in region i's production (outer sum). These weights are calculated by dividing the employment share of sector h in region i in the initial year, L_{hi0}, by the total employment within the same municipality.

Figure 4: Supply chain affectedness from 2013 to 2021



Note: The figure displays the cumulative supply chain affectedness of local municipalities over the period 2013-2021, with higher values indicating greater disruption in domestic trade of local municipalities due to the impact of floods on potential domestic suppliers. The calculation is based on the 2010 Input-Output tables and DFO flood dataset.

Figure 4 displays the spatial variation of floods in the supply chain during our observation period. Compared to figure 3, the supply-chain effects seem to be more dispersed than the actual flood coverage. Finally, Table A1 in the Appendix provides descriptive statistics for the main explanatory and dependent variables used in our analyses.

[8] By using an input-output table from 2010, we ensure that the weights for the relative importance of shocks are not influenced by endogenous adjustments to shocks that may have occurred over time.

4 Empirical framework

Estimation model. Our empirical analysis investigates how variations in firms' aggregate imports are related to spatio-temporal changes in both direct and indirect exposure to flood events. We estimate the long-run adjustment to flood occurrences by using the Poisson Pseudo Maximum Likelihood (PPML) model, expressed as follows:

$$Imports_{it} = \exp\left(\beta_1\, OwnFloods_{it} + \beta_2\, SC\ Floods_{it} + \lambda_i + \theta_t\right) \times \varepsilon_{it}, \tag{3}$$

where $Imports_{it}$ represents an aggregate outcome at the level of local municipality i and month t. This outcome could either be the value of aggregate imports or the number of new entrants into the import market.

As described in section 3.2, the primary explanatory variable, $Own\ Floods_{it}$, represent a cumulative measure of floods for region i and month t, increasing by one with each additional flood event. Similarly, $SC\ Flood_{it}$ quantifies the cumulative exposure to flood events within the same month that propagate through the value chain. For both measures, we assume that the treatment is absorbing, meaning that once a flood occurs, its effects persist over time. This modelling approach is designed to capture long-run adjustments to floods over time, extending beyond the immediate disruption effects experienced during flood events.

In the estimation model, the municipality fixed effects, denoted by λ_i, capture all time-invariant sources of spatial variation. The month fixed effects, θ_t, account for all common temporal dynamics. The error term is represented by ε_{it}, with standard errors clustered at the local municipality level. The coefficients of interest are β_1 and β_2. Coefficient β_1 represents the direct impact of floods on either import volume or the number of new market entrants. Coefficient β_2 measures the indirect effect of floods on imports as they propagate through domestic supply chains.

Model choice. We choose PPML to estimate our models because our dependent variables are natural numbers, which include zero values for region-month pairs where no imports or no import market entry are recorded. A purely logarithmic transformation is not feasible due to these zeros whereas adjusted log-like transformations can lead to misleading effect sizes (Chen and Roth 2024). In contrast, PPML enables us to model the data in its original form, preserving the zeros while effectively handling the non-linearity and heteroskedasticity present in trade data. In exploratory analyses, we also used linear staggered difference-in-differences (DiD) estimators to assess the direct effects of floods on our variables of interest. These results generally supported our primary findings. However, to differentiate between the direct disruption caused by local floods and the indirect effects that propagate through the supply chain, it is essential to simultaneously control for both *OwnFlood* and *SC Flood* variables. Unfortunately, none of the more recent dynamic staggered DiD estimators are able to accommodate two repeated and continuous treatments simultaneously, while estimating a nonlinear model.

Issues of identification. In our setting, the timing of floods is plausibly exogenous but the location of floods is decidedly not, as shown in Figure 4. Flood-prone regions are also closer to South Africa's economic centers, which may put them on inherently different internationalization trends. Because these regions are more economically active, the direct flood coefficient, β_1, could be overestimated if agglomeration benefits drive increased import demand. This is likely to bias a negative own flood coefficient towards zero. Moreover, since our panel data is monthly and spans 108 months, the idiosyncratic timing of new flood events is crucial for identifying the effects of floods. To ensure the robustness of our findings, we perform two sets of checks. First, we control for municipality-specific trends to ensure that our results are not driven by general differences in local development trajectories. Second, we conduct placebo regressions to test whether imports also react to future floods, which would suggest the presence of spurious trends correlated with the spatial distribution of economic activities.

5 Results

Our results presents estimates derived from equation (3) for various regional aggregates of import volumes and firms' import market entry. Table 1 compares the direct and indirect effects of floods on local firms' participation in international trade, highlighting both changes in total imports as well as product-type specific aggregates. Panel A shows the flood-induced changes in the total customs value of imports, measured in constant prices. Panel B indicates coefficient estimates on the number of local firms that begin importing for the first time following a flood.

Table 1: Impact of floods on the aggregate value of imports and market entry

		By product type				By product complexity	
	All products (1)	Raw materials (2)	Intermediate goods (3)	Consumer goods (4)	Capital goods (5)	Low complexity (6)	High complexity (7)
Panel A: Dependent variable: Customs value of imports							
Own floods	-0.029	-0.032	0.025	0.009	-0.029	-0.040	-0.008
	(0.052)	(0.031)	(0.029)	(0.091)	(0.033)	(0.025)	(0.041)
Floods in the supply chain	0.124	3.328***	0.893***	-0.344	0.033	0.120***	0.009
	(0.182)	(0.555)	(0.335)	(0.858)	(0.241)	(0.030)	(0.044)
No. of observations	22,896	20,898	22,642	22,896	22,788	22,894	22,788
No. of clusters	212	201	211	212	211	212	211
Panel B: Dependent variable: Number of new entrants into import markets							
Own floods	-0.085**	0.019	-0.025*	-0.066***	-0.043*	-0.070***	-0.063**
	(0.037)	(0.011)	(0.015)	(0.024)	(0.026)	(0.020)	(0.026)
Floods in the supply chain	0.317**	1.148***	0.447**	0.732***	0.332*	0.191***	0.090***
	(0.142)	(0.235)	(0.176)	(0.190)	(0.193)	(0.036)	(0.030)
No. of observations	21,924	20,683	22,474	22,140	22,356	22,031	21,600
No. of clusters	203	199	209	205	207	204	200
Municipality & month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The models are estimated using Poisson pseudo-maximum likelihood (PPML). The dependent variables in panel A represent the total value of imports by municipality and month. In panel B, dependent variables indicate the number of firms that start importing in a given municipality and month for the first time. In addition to showing aggregated imports, further models differential between raw materials, intermediate, consumer, and capital products. They also categorize inputs based on their complexity. The variable *Own floods* measures the cumulative occurrence of floods within a municipality, while *Floods in the supply chain* measures the cumulative exposure to floods affecting the supply chain since January 2013. Standard errors are clustered at the local municipality level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

When examining the changes in aggregate trade volumes in column 1 of panel A, there is no statistically significant impact of floods on overall import levels. Despite the lack of an aggregate response, panel B shows that the number of new regional entrants into the import markets behaves as anticipated. Specifically, each additional flood reduces the number of new importers by approximately 8.1% (calculated as $\exp(-0.085) - 1$). This outcome highlights the direct disruptions caused by floods: when firms' operations are interrupted, it becomes less likely they can afford the transaction costs required to enter international markets. Conversely, the effects of supply chain disruptions due to floods are as expected. A one standard deviation increase in supply chain flood exposure (equivalent to 0.75), leads to an about 27% rise in the number of new entrants to the import market. This suggests that imports might indeed be used strategically for risk management and diversification when supply chains are compromised.

When we categorize import products into raw materials, intermediate goods, consumer goods, and capital goods, as shown in columns 2 to 5 of Table 1, we observe different aggregate import dynamics across these product categories in panel A. However, there is no notable difference in terms of market entry, as indicated in panel B.[9] Regional imports of consumer and capital goods generally do not respond to flood shocks. In contrast, the imports of raw materials and intermediate goods exhibit statistically significant changes.

When we divide the imported products by their complexity instead in columns 5 and 6, we see a distinct pattern: there is a marked increase in the import value of low complexity products following flood shocks in the supply chain as well as a larger reaction in terms of market entry. Based on theoretical arguments summarized in section 2, high complexity products may become scarcer and more needed after supply shocks, but also harder to substitute. Among South African firms, this latter effect seems to dominate as they adjust to supply chain shocks predominantly by buying low complexity products.

To further illustrate the adjustment mechanisms, Table 2 categorizes South African municipalities based on their vulnerability to floods. The rationale behind this approach is that economic actors learn from past experiences; in regions more prone to disasters, they may be better equipped to handle flood shocks, resulting in less adjustment behavior after disasters. Consequently, we expect more pronounced adjustments after floods in less vulnerable areas. To test this, we define flood vulnerability based on past flood frequency, counting all flood events within each municipality from 1985 to 2012 (DFO 2021). Municipalities experiencing more than four floods during this nearly three-decade period are deemed more vulnerable. Table 2 re-examines the main specifications concerning aggregate imports and import market entry, and distinctions based on product complexity. The results align with our expectations, showing substantially stronger import adjustments among firms in less flood-prone areas. Notably, in these less vulnerable locations, the results regarding high versus low complexity products differ from those seen on aggregate, with larger increases in imports of high complexity goods.

By observing the countries of origin for each import transaction, we can evaluate which trading partners South African firms are more likely to rely on to address flood-induced disruptions in their supply chain. We categorize the total value of imports by major trading partners: all other African countries, the United Kingdom, the United States, European Union countries, China, and all other trading partners, labeled as the rest of the world (RoW). In terms of the absolute volume of imports, the EU was South Africa's dominant trading partner during this time period, supplying items such as vehicles and industrial machinery. The US and the UK played a smaller but still significant role. During the same period, China's importance as a supplier increased sharply, especially in the provision of manufactured goods and machinery. While other African countries were notable exporters of fuel and raw materials, their relative share has been declining over time.

Table 3 presents the import adjustments according to the region of origin of those imports. The number of observations in these regressions is reduced because not all regions import from every trading partner, and the PPML estimator removes excess zeros. Similar to the aggregate results in Table 1, we do not observe consistently statistically significant declines in import values as a direct effect of the floods for most trading partners. Interestingly, direct flood occurrences are even associated with marginally significant increases in imports from other African countries, which may reflect a heightened demand for raw materials. However, imports from the EU, which is the largest trading partner, decline significantly with each additional flood, resulting in an average reduction of 17.6% ($\exp(-0.194) - 1$).

Simultaneously, we observe significant increases in imports across all country regions following floods in the supply chain. The magnitude of this effect varies considerably and aligns with our theoretical expectations. The largest increases are seen in imports from the EU, which indicates that network effects from stronger previous trade relationships facilitate an expansion in imports. Specifically, an increase of 1 in supply chain floods (equivalent to 1.3 times the standard deviation) results in more than

[9] For specific products, we define import market entry to take one when a firm starts importing a product belonging to this category for the first time.

Table 2: Heterogeneous flood effects by past vulnerability to floods

	Less vulnerable			More vulnerable		
	All products (1)	Low complexity (2)	High complexity (3)	All products (4)	Low complexity (5)	High complexity (6)
Panel A: Dependent variable: Customs value of imports						
Own floods	0.006	-0.064**	-0.175***	0.008	0.030	0.064
	(0.035)	(0.032)	(0.045)	(0.063)	(0.034)	(0.042)
Floods in the supply chain	0.293	0.150***	0.488***	0.089	0.063	-0.058
	(0.226)	(0.032)	(0.049)	(0.226)	(0.050)	(0.075)
No. of observations	10,368	10,366	20,734	12,528	12,528	25,056
No. of clusters	96	96	96	116	116	116
Panel B: Dependent variable: Number of new entrants into import markets						
Own floods	-0.076	0.000	0.020	-0.149*	-0.024	-0.045*
	(0.050)	(0.019)	(0.013)	(0.086)	(0.030)	(0.026)
Floods in the supply chain	0.391**	0.135***	0.044**	0.433	0.065	0.055**
	(0.189)	(0.037)	(0.017)	(0.348)	(0.044)	(0.022)
No. of observations	9,936	10,366	20,950	11,988	12,528	25,056
No. of clusters	92	96	97	111	116	116
Municipality & month FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The models are estimated by Poisson pseudo-maximum likelihood (PPML). Dependent variables record the total value of imports by municipality and month in Panel A and the number of firms that start importing in a given municipality and month for the first time in Panel B. The models are estimated for vulnerable and non-vulnerable municipalities separately, where municipalities are defined as vulnerable to floods when the number of past floods in the municipality was higher than 4 (1985–2012). Columns (2) to (3) and (5) to (6) split products by high and low complexity. Standard errors are clustered at the local municipality level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 3: Impact of floods on the aggregate value of imports by country/region of origin

	Africa (1)	US (2)	UK (3)	EU (4)	China (5)	RoW (6)
Own floods	0.132*	-0.069	-0.035	-0.194***	-0.044	-0.041
	(0.080)	(0.086)	(0.079)	(0.050)	(0.029)	(0.060)
Floods in the supply-chain	0.601***	1.012***	1.202**	2.008***	0.601***	1.113***
	(0.189)	(0.336)	(0.484)	(0.484)	(0.088)	(0.218)
Observations	4.124	4.330	3.333	5.779	5.905	5.684
No. of clusters	153	155	131	167	173	169

Note. The models are estimated by Poisson pseudo-maximum likelihood (PPML). Dependent variables record the total value of imports by municipality and month. Models split imports by trading partners and blocks, distinguishing between all other African countries, the US, the UK, members of the EU, China, and the rest of the world (RoW). These categories are exclusive. Standard errors are clustered at the local municipality level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

a six-fold increase from the EU (calculated as $\exp(2.008) - 1 = 6$). In contrast, imports from China or other African countries increase only by about 82%.

Table 4 analyzes the findings based on the sector of the importer firms, rather than the products being imported. In panel A, we classify importers into sectors such as agriculture, mining, manufacturing, trade, and other services. Sin ce many firms do not import directly, we expect that a significant part of the flood-related adjustments is facilitated through companies primarily operating in the trading sector. Table 4 supports this expectation. We observe that trade volumes do not change among mining or manufacturing firms; however, trading companies show substantial and highly significant import reactions. On average, their imported volumes decrease by about 57% after each flood, but when the supply chain flood measure by 1, their imports increase nearly 12-fold. This finding highlights the crucial role that specialized trading companies play in diversifying supply channels. Therefore, firm-level analyses focusing only on manufacturing firms' trading activities in a developing country context might overlook this adjustment channel entirely. Surprisingly, we also see significant adjustments in the import behavior of agricultural firms. Similarly, in panel B, we notice no adjustments among various manufacturing sectors (such as motor vehicles, other heavy, and other light manufacturing), but there is a slight indication that the food sector responds to supply chain shocks by increasing imports. Alongside the large adjustments observed in agricultural firms, these results suggest that farmers not only play a critical role in South Africa's economy but may also be more inclined to engage directly in imports in the aftermath of supply-chain shocks.

Table 4: Impact of floods on the aggregate value of imports by sector of importer

Dependent:	Value of imports by main sector of importer				
Panel A	Agriculture	Mining	Manufacturing	Trade	Other services
	(1)	(2)	(3)	(4)	(5)
Own floods	-0.464***	-0.092	-0.024	-0.452***	-0.140***
	(0.098)	(0.090)	(0.168)	(0.132)	(0.054)
Floods in the supply chain	1.678***	-0.059	0.185	2.559***	0.315
	(0.457)	(0.392)	(0.599)	(0.756)	(0.368)
No. of observations	17,388	11,880	21,708	20,736	22,356
No. of clusters	161	110	201	192	207
Municipality & month FE	Yes	Yes	Yes	Yes	Yes

Dependent:	Value of imports for selected manufacturing sectors			
Panel B	Food	Motor vehicles	Other manufacturing	
			Heavy	Light
	(1)	(2)	(3)	(4)
Own floods	-0.291	-0.341	-0.045	0.003
	(0.185)	(0.282)	(0.178)	(0.136)
Floods in the supply chain	1.299*	1.297	0.211	0.071
	(0.700)	(1.016)	(0.585)	(0.502)
No. of observations	14,040	14,148	13,932	20,952
No. of clusters	130	131	129	194
Municipality & month FE	Yes	Yes	Yes	Yes

Note: The models are estimated by Poisson pseudo-maximum likelihood (PPML). The observations vary at the level of municipalities and months. Dependent variables in Panel A split the total value of imports according to the main sector of production of the importer firms: agriculture, mining, manufacturing, trade, and other services. Panel B further zooms into four subsectors of manufacturing: food, motor vehicles, other heavy manufacturing, and other light manufacturing. Standard errors are clustered at the local municipality level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

6 Robustness checks

To assess the robustness of our results, we aim to evaluate various alternative model specifications, examining the impact of measurement and modeling decisions on our findings. Some of these tests are still in development. The initial set of robustness checks involves altering how we measure floods. In Table 5, we redefine our treatment variable to measure the number of months a region experienced flooding, rather than counting individual flood events. This approach more accurately accounts for flood duration. The results generally align with previous findings. Additionally, Table A2 in the Appendix introduces separate variables for class 1 and class 1.5 floods to determine if the effects of adverse weather events differ based on their intensity. We do not observe a clear pattern indicating a consistent relationship, and the variation across the two flood severity classes seems somewhat arbitrary. This may conceal more complex disparities across different products or geographical areas.

To assess our results are robust against modelling choices, we introduce municipality-specific trends in our regressions, as shown in Table A3 in the Appendix. This adjustment addresses the concern that

Table 5: Robustness: Impact of floods measured in cumulative flood-months on the aggregate value of imports and market entry

	Customs value of imports			New entrants into import markets		
	All products (1)	Low complexity (2)	High complexity (3)	All products (4)	Low complexity (5)	High complexity (6)
Own floods	-0.032	-0.015	0.006	-0.062**	-0.041***	-0.063***
	(0.038)	(0.017)	(0.037)	(0.028)	(0.012)	(0.015)
Floods in the supply chain	0.141	0.073***	-0.008	0.225**	0.118***	0.091***
	(0.126)	(0.018)	(0.039)	(0.111)	(0.021)	(0.020)
No. of observations	22,896	22,894	22,788	21,924	22,894	22,896
No. of clusters	212	212	211	203	212	212
Municipality & month FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The models are estimated by Poisson pseudo-maximum likelihood (PPML). The exposure to floods is measured by the alternative measure of cumulative flood months such that floods that last two or three months are calculated as separate floods. Dependent variables record the total value of imports by municipality and month in Panel A and the number of firms that start importing in a given municipality and month for the first time in Panel B. Further models split by high and low input complexity. Standard errors are clustered at the local municipality level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

cumulative floods might be spuriously related to non-parallel trends resulting from general economic dynamics across municipalities over time. Our findings remain robust with this modification, though we notice some changes, particularly for high complexity products. As this change increases the precision of our results, we intend to adopt the specification with location specific trends as our main approach going forward. Additionally, we incorporate 3-month lags to account for firms' adjustments following a flood event, as shown in Table A4 of the Appendix. The results indicate that import declines following flood events are unlikely to last long. We also intend to conduct further robustness checks by reassigning flood events randomly across time, while maintaining their spatial probability, similar to randomization inference. Finally, to address potential spatial correlation in our data, we are preparing to apply Conley standard errors (Conley 1999) with distance cutoffs of 100 km and 200 km. These analyses are not yet complete.

7 Conclusion

Based on an analysis of municipality-specific customs transactions over 108 months, our study examines how fluctuations in imports respond to cumulative flood events. Our findings indicate that South African firms rely on global markets to deal with flood-related shocks. Generally, while floods directly hinder firms' entry into international markets, disruptions in supply chains can prompt them to diversify their input sources. This is observed with significant variation across product types, markets, and sectors. Although we do not find significant changes in overall import volumes following flood events, the evidence aligns with our theoretical expectations for specific product categories, source regions, and sectors. Notably, we observe significant and sizeable changes in the import behaviors of local trading companies, which may be overlooked in studies focusing on firm responses within the manufacturing sector.

Our results highlight the need to consider for both the direct and indirect impacts of floods when examining adaptation to climate change. They particularly emphasize that access to global market could be crucial for South African firms to adapt successfully to natural disasters. While we have shown that imports can complement domestic reorganization of value chains, whether these adaptation strategies also lead to improved firm productivity remains an area worthy of further investigation.

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A1 Sector classification

The industry classification is based on the HS6 (six-digit) classification of goods and services, which are initially aggregated to match the 50-sector classification found in the South African Input-Output tables. For our analysis, these sectors are further combined into five main industries:

1. *Agriculture:* Includes agriculture, forestry, and fishing.

2. *Mining:* Includes coal and lignite, metal ores, and other mining and quarrying activities.

3. *Manufacturing:* Encompasses a wide range of activities, including food, beverages and tobacco, textiles and spinning, knitted fabrics and fur, leather and luggage, footwear, wood products, paper, publishing and printing, coke oven and petroleum products, basic chemicals and nuclear fuel, other chemicals, rubber, plastic, glass and glass products, non-metallic minerals, furniture, recycling, and other activities not elsewhere classified, basic iron and steel, precious and non-ferrous metals, structural metal products, general and special machinery, electrical machinery, electronic equipment, medical and other appliances, motor vehicles, and coachwork.

4. *Trade:* Comprises activities related to commerce and selling goods.

5. *Othr Services:* Incorporates electricity, gas, and hot water, water distribution, construction, hotels and restaurants, transport, postal and telecommunications services, financial intermediation, insurance and pension funding, auxiliary financial services, real estate activities, machinery rental, research and development, business and computer activities, other communication activities, education, health and social work, and various other services not elsewhere classified.

The manufacturing sector is categorized into four subsectors:

1. *Food:* Includes activities related to food, beverages, and tobacco.

2. *Motor Vehicles:* Encompasses motor vehicles and coachwork.

3. *Other Heavy Manufacturing:* Consists of industries involved in coke oven and petroleum, basic chemicals and nuclear fuel, basic iron and steel, precious and non-ferrous metals, and structural metal products.

4. *Other Light Manufacturing:* Covers spinning and textiles, knitted fabrics and fur, leather and luggage, footwear, wood products, paper, publishing and printing, other chemicals, rubber, plastic, glass and glass products, non-metallic minerals, furniture, recycling, and other activities not elsewhere classified, as well as general and special machinery, electrical machinery, electronic equipment, and medical and other appliances.

A2 Tables

Table A1: Descriptive statistics

	Mean	St. Dev.	Min.	Max.	Mean	St. Dev.	Min.	Max.
Main explanatory variables	Own floods				Floods in the supply chain			
Standard measure (main specifications)	1.38	1.70	0	8	0.80	0.75	0.00	4.18
Accounting for flood duration in months	2.01	2.42	0	11	1.12	0.98	0.00	5.15
Measuring class 1 floods only	0.82	1.17	0	5	0.41	0.36	0.00	1.76
Measuring class 2 floods only	0.58	1.06	0	6	0.40	0.50	0.00	2.87
Main dependent variables	Customs value of imports				No. new entrants in import markets			
All products	214	1 329	0	20 856	0.78	4.60	0	96.89
Raw materials	14	98	0	2 410				
Intermediate goods	12	98	0	3 190	0.14	1.02	0	23.20
Consumer goods	15	130	0	4 730	0.15	1.19	0	36.63
Capital goods	14	129	0	3 150	0.15	1.16	0	29.75
Low complexity products	72	429	0	7 910	0.17	1.22	0	32.40
High complexity products	104	684	0	11 400	0.74	4.31	0	79.85

Note: Summary statistics refer to the values of the independent and main dependent variables used in the analysis. They are based on 108 monthly observations (spanning over 9 years; from 2013 to 2021) across 213 South African local municipalities, resulting in the overall sample size of 23 003 observations. *Own floods* indicate the number of cumulative floods experienced by a local municipality in the same period, while *Floods in the supply chain* measures the indirect impact on an area due to the fact that potential suppliers have been affected by a flood. The latter measure has been calculated by the authors based on the 2010 South African Input-Output tables and DFO flood data, as described in Section 3.2. *Customs value of imports* is expressed in millions of South African Rands (ZAR), adjusted to 2010 values. *No. new entrants in imports markets* indicate the number of firms that start importing in a given municipality and month for the first time. Firms with branches in multiple municipalities are weighted by their location-specific employment shares, ensuring that the sum of all branch weights equals one.

Table A2: Robustness: Distinguishing between floods of different classes

	Customs value of imports			New entrants into import markets		
	All products (1)	Low complexity (2)	High complexity (3)	All products (4)	Low complexity (5)	High complexity (6)
Own floods class 1	-0.035	0.031	0.018	-0.000	-0.121***	-0.152***
	(0.098)	(0.041)	(0.043)	(0.104)	(0.037)	(0.049)
Own floods class 1.5	-0.005	-0.051**	0.044	-0.151*	0.004	-0.029
	(0.088)	(0.024)	(0.060)	(0.085)	(0.031)	(0.043)
Floods class 1 in the supply chain	0.425	0.070	0.120**	-0.191	0.245***	0.209**
	(0.400)	(0.074)	(0.052)	(0.428)	(0.068)	(0.082)
Floods class 1.5 in the supply chain	-0.069	0.116**	-0.118	0.705**	0.072	0.039
	(0.412)	(0.054)	(0.086)	(0.335)	(0.070)	(0.066)
No. of observations	22,896	22,894	22,788	21,924	22,894	22,896
No. of clusters	212	212	211	203	212	212
Municipality & month FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The models are estimated by Poisson pseudo-maximum likelihood (PPML). The models estimate separately the impact of large floods of class 1 and more severe floods of class 1.5. Dependent variables record the total value of imports and the number of firms that start importing by municipality and month. Further models split by high and low input complexity. Standard errors are clustered at the local municipality level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table A3: Robustness: Impact of floods on the aggregate value of imports and market entry including location specific trends

	Customs value of imports			New entrants into import markets		
	All products (1)	Low complexity (2)	High complexity (3)	All products (4)	Low complexity (5)	High complexity (6)
Own floods	-0.025	-0.041	-0.164***	-0.175***	-0.066***	-0.066***
	(0.062)	(0.027)	(0.048)	(0.047)	(0.021)	(0.019)
Floods in the supply-chain	0.030	0.059***	0.335***	0.561***	0.179***	0.071***
	(0.336)	(0.020)	(0.120)	(0.210)	(0.031)	(0.017)
No. of observations	22.896	22.894	45.790	21.924	22.894	46.006
No. of clusters	212	212	212	203	212	213
Municipality & month FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality-specific linear trends	Yes	Yes	Yes	Yes	Yes	Yes

Note: The models are estimated by Poisson pseudo-maximum likelihood (PPML). Dependent variables record the total value of imports and the number of firms that start importing by municipality and month. All models include municipality specific linear trends. Standard errors are clustered at the local municipality level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table A4: Robustness: Impact of floods lagged on the aggregate value of imports and market entry

	Customs value of imports			New entrants into import markets		
	All products (1)	Low complexity (2)	High complexity (3)	All products (4)	Low complexity (5)	High complexity (6)
Own floods	-0.092***	0.008	-0.017	0.026	-0.081	-0.021
	(0.031)	(0.024)	(0.025)	(0.098)	(0.070)	(0.069)
(Lag 1) Own floods	-0.112***	-0.141***	-0.029	-0.139	0.009	-0.063
	(0.030)	(0.036)	(0.026)	(0.115)	(0.092)	(0.107)
(Lag 2) Own floods	0.068	0.002	0.034	-0.210	0.045	-0.072
	(0.045)	(0.035)	(0.048)	(0.146)	(0.097)	(0.073)
(Lag 3) Own floods	0.121***	0.061**	0.010	0.237***	-0.025	0.115**
	(0.041)	(0.031)	(0.034)	(0.091)	(0.067)	(0.046)
Floods in the supply chain	0.269**	0.080***	0.011	0.504	0.225***	0.146***
	(0.112)	(0.019)	(0.016)	(0.410)	(0.039)	(0.037)
(Lag 1) Floods in the supply chain	0.259*	0.041**	-0.015	0.021	-0.062	0.036
	(0.134)	(0.018)	(0.024)	(0.418)	(0.040)	(0.043)
(Lag 2) Floods in the supply chain	-0.048	0.039**	0.018	0.640	0.021	-0.078
	(0.090)	(0.016)	(0.020)	(0.452)	(0.036)	(0.050)
(Lag 3) Floods in the supply chain	-0.401**	0.049**	-0.008	-0.867**	-0.042	-0.052
	(0.156)	(0.021)	(0.019)	(0.387)	(0.053)	(0.040)
No. of observations	22,260	22,258	22,155	21,315	21,419	21,000
No. of clusters	212	212	211	203	204	200
Municipality & month FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The models are estimated by Poisson pseudo-maximum likelihood (PPML). Dependent variables record the total value of imports and the number of firms that start importing by municipality and month. The models include the first and second lags for own floods and for the floods in the supply chain. Standard errors are clustered at the local municipality level and reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.