Bachelor Thesis

Navigating Climate Risks: Assessing Cross-Border Spillovers of African Climate Shocks on European Union through International Trade

Authors:

Luīze Mestere

Anastasija Sergeļa

Supervisor:

Konstantīns Beņkovskis

JEL codes: F18, F64, Q54

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Names of the authors in full: Luīze Mestere, Anastasija Sergeļa

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/Luīze Mestere/ /Anastasija Sergeļa/

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Abstract

With this thesis, our aim is to estimate the spillover effects of climate shocks in Africa on its largest trade partner, the European Union (EU), by examining changes in trade across different product categories. Using EU-Africa monthly trade and disaster data from 1988 to 2022, we apply the difference-in-difference approach, with natural disasters serving as the treatment variable. To examine the medium-term effects, we also include 6 lags to analyse the impact over time. We find negative impacts on both extra-EU imports and exports, which we define as the exchange of goods between the EU member states and African countries. Despite Africa's relatively low share of extra-EU trade flows, disruptions in trade chains due to climate disasters can be concerning for EU member countries whose extra imports from Africa account for a significant proportion of their total extra trade for specific product groups. In terms of specific extra-EU import groups, Foodstuffs and Stone & Glass product imports are significantly negatively affected after a disaster, while changes in Animal and Vegetable products trade are insignificant. Overall, decreased EU exports seem to result from broader export-related factors, such as infrastructure losses and a decrease in purchasing power for affected countries, rather than specific product characteristics. Our analysis highlights a significant disparity in how EU trade flows respond to disaster shocks, with the region of the trade partner having a greater impact than the specific product category. This underscores regional institutions' capacity to address climate risks, thus showcasing the need to close the gap in funding for Africa to increase its climate change resistance.

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We would like to express our gratitude to our supervisor, Konstantīns Beņkoviskis, for guiding us in our research by providing us with useful feedback and suggestions that were of great value throughout our thesis writing process.

1. Introduction

The need for collective action on climate change has never been more pressing. Last year, the Intergovernmental Panel on Climate Change (IPCC) issued its ultimate warning stating that, to avoid the scenario where damage to the Earth results in irreversible climate change, we must take action now. While the glimmer of hope to mitigate the damage caused by the annual increasing greenhouse gas emissions over the past 200 years still exists, the reality remains that we are already immersed in a world where more frequent catastrophic climate events are imposing severe and widespread welfare losses (Harvey, 2023). However, these losses are not distributed equally. Despite the global West being the main contributor to human-induced climate change, the regions that have contributed the least, such as Africa, are already disproportionately affected (IPCC, 2023).

Regardless of the commitments made by developed countries to provide essential funding for Africa to adapt to climate change, the current level of support is inadequate. Presently, Africa is receiving only 12% of the necessary funding required to effectively mitigate the impact of climate change (Savage, 2022). The insufficiency of funding remains a pressing concern and was a central issue discussed at the 27th Conference of the Parties to the United Nations Framework Convention on Climate Change (COP27) (Deutsche Welle, 2022). The policymaker's failure to tackle this issue is concerning, particularly in the context of globalization and international trade. In today's interconnected world, countries without direct risks of climate change disasters can still indirectly bear the impacts of such events unfolding beyond their borders (Jones & Olken, 2010).

Previous research indicates that not all regions will be directly adversely affected by climate change. Some parts of the world are projected to even benefit from higher temperature increases. However, in the case of the world's poorest and most vulnerable regions, the prevailing academic consensus highlights that more extreme climate events are expected to result in primarily negative economic and social consequences. These may include a decrease in GDP and its growth, a decline in exports, productivity, foreign investment, higher mortality rates, and increased political instability (Dell et al. 2008; Faccia et al., 2021). However, despite the unequal distribution of direct climate change risks, climate shock events can lead to negative local effects and negative spillovers to affected countries' main trade partners in the short term as well, owing to the limited substitution between different inputs (Boehm et al., 2019).

While the European Union (EU) serves as Africa's primary trading partner, to the best of our knowledge there is a notable absence of research analysing the sensitivity of international trade between the EU and Africa. This knowledge gap necessitates attention given not only the urgency and expected increase in extreme climate shocks but also the ethical and economic spillovers involved. Therefore, with this work, we bring novelty to previous research by clarifying the climate shock spillover effects from developing countries in a contextual setting. This could provide insights that help develop a better understanding of climate shock transmission via international trade in a contextual setting, effectively raising awareness about the positive externalities of multinational efforts to improve the resilience of climate change-prone regions.

Consequently, to guide our research we formulate our research question as follows: ***How have climate-induced natural disasters in Africa affected trade across various product categories with the EU?***

In this research, we rely on two primary databases. The Emergency Events Database (EM-DAT) supplies information regarding climate shocks in Africa, while trade-related data is extracted from the Eurostat COMEXT database, providing details on exports and imports for EU member countries. Time period that we will cover in this research is from 1988 to 2022.

Since we are examining climate shock spillovers from 54 developing African countries, firm-level data, in this case, could be highly misleading, given that data collection practices in this region may be questionable. Furthermore, since some academics have raised doubts about the accuracy of economic data in developing countries, we choose to use import and export data recorded by EU agencies, similar to the approach taken in the work of Jones & Olken (2010).

For our analysis, we deploy a difference-in-difference model to separate the effect of natural disasters on international trade in the similar way it was done in the works of Boehm et al. (2019), Barrot & Sauvagnat (2016) and Feng et al. (2023). Using the binary variable method, we identify treatment and control groups. The treatment group includes African countries hit by a natural disaster, whereas the control group contains disaster-free African countries. Natural disasters are used as a treatment, the effect of which we aim to quantify. To analyse the medium-term effects on trade, we include lagged values of the binary variable for treatment groups. Additionally, using interaction terms we assess the impact of African regions and product categories on the disaster effect, to see which is the prevailing factor determining effect for disaster-free trade partners.

Utilizing the difference-in-difference approach, we observe a significant negative impact of unexpected climate disasters on both total extra-EU imports and exports. While for imports, we find that underlying product characteristics play a role in determining if respective product imports will decline, from EU export analysis we imply that except for Minerals, the decline in EU exports appears to stem from broader disaster loss-related factors, such as infrastructure losses and reduced purchasing power in affected countries, rather than specific product characteristics. We observe that regional characteristics, such as geography and the political power of the partner country, significantly influence the sensitivity of trade flows to disaster shocks.

The paper is organized as follows: Section 2 covers the literature review on local and spillover effects of climate shocks, as well as literature on the difference-in-difference approach. Section 3 focuses on the description of the data used. It provides a summary of EU-Africa trade to explain which product groups will be analysed in detail and describes climate disaster samples. Section 4 covers the construction of our difference-in-difference regression in combination with lags and fixed effects. Section 5 provides an analysis of the obtained results and describes the robustness checks employed. Section 6 draws on the results obtained in the previous section to discuss the sensitivity of each EU member state to disaster shocks and outlines the future outlook. Section 7 describes the limitations faced in our research, followed by Section 8 where future research opportunities are presented. Lastly, in Section 9, we conclude our findings.

2. Literature review

2.1. The nature of climate-economy relationship

Simultaneously with the IPCC's warnings over the past 30 years about the increasing likelihood of more severe climate events, scholars have sought to quantify the potential consequences of climate change on societies (Jones & Olken, 2010). However, this task is challenging because estimating climate shock effects requires attempting to consider all the mechanisms and channels that might be involved in this highly complex transmission, particularly due to the interconnected nature of these effects (Dell et al., 2009).

As a result of globalization, the world has become more intertwined via international trade chains. This means that, in addition to facing the climate risks associated with their own regions, countries are also exposed to the climate risks of their trade partners. This implies that international trade diversifies climate risk exposure among the countries, making them all more equal in terms of climate risk (Feng et al., 2023). Consequently, it is crucial to proactively anticipate potential risks with the utmost proficiency. Furthermore, this becomes even more critical if, as a society, we are unable to reverse the current trajectory of climate change, which would inevitably result in more frequent and extreme climate shocks.

One side of academic research primarily focuses on the impact of climate change on local communities directly affected. In contrast, another section is dedicated to investigating how these risks propagate to other countries through international trade. Surprisingly, the academic exploration of spillover effects has gained significant traction only over the last decade. Even as recently as 2014, it was considered a scarcely researched field (Pascasio et al., 2014).

2.2. Local effects of climate shocks

Previous research findings on the climate-economy relationship showcase the widespread effects of climate shocks, as it is challenging to identify an area that somehow might not be affected by climate change. A vast number of papers have a natural emphasis on agriculture. Nevertheless, academics have also explored the impact of climate change on aspects such as water access, migration, political stability, mortality, health, investment, crime, and many other factors that inevitably have direct or indirect effects on productivity and economic activity of the country that is directly hit by a climate shock (Dell et al., 2008; Feng et al., 2023; Guiteras, 2009).

Climate shocks, in their most materialistic form, can be observed in terms of output loss due to damaged land, facilities, infrastructure, or disrupted supply chains. As a result, shortages of particular goods can occur, which, according to the law of supply and demand, lead to inflation. The relationship between inflation and climate shocks is currently scarcely explored, but in recent years, this topic has gained more attention from academics. Faccia et al. (2021) explored how increased temperatures impact different measures of inflation. In the time span from 1951-1980 in 48 advanced and emerging economies, increased temperatures in summers led to short-term inflation in food prices and had either no impact or a negative impact in the medium-term. This can be explained by the fact that increased prices exert a negative weight on demand, inevitably driving food prices down. Furthermore, the authors found that this effect is especially prominent for emerging countries. Nevertheless, although inflation eventually goes down, short term increases in inflation as a result of disastrous climate shocks such as hurricanes and floods cannot be taken lightly (Heinen et al., 2019).

Also, to some extent, temperature increases can be considered as supply-side shocks. In brief, elevated temperatures influence weather patterns, subsequently making extreme climate events such as droughts, storms, hurricanes, and heatwaves more frequent. Consequently, increased temperatures can result in direct output losses or indirect losses in terms of productivity that, over the long term, may lead to reduced investment in a particular region. In a comprehensive study, Acevedo et al. (2020) utilized local projection models across more than 180 countries, spanning from 1950 to 2015. The findings reveal that, for a median low-income country, a temperature increase of 1°C in a given year materializes in a 10% decline in investment 7 years later compared to a scenario without such a shock. This evidence is particularly striking considering that low-income countries are already constrained by limited resources for economic development and climate change adaptation.

Due to the complex channels through which climate shocks can propagate, many academics choose to quantify these effects in an aggregate form by analysing changes in economic activity in terms of GDP. A widely recognized paper by Dell et al. (2008) analyses the short-term impact of temperature and precipitation fluctuations on worldwide economic growth from 1950 to 2003. Using panel regression, the authors arrived at extremely relevant conclusions for this thesis, showcasing that the burden of climate change costs will fall on the poorest countries. Firstly, increased temperatures significantly reduce economic output and growth rates in the poorest countries, whereas wealthy countries appear to be somewhat immune to these adverse effects. They found that if a poor country experiences a temperature increase of 1°C, it reduces economic growth in that year by about 1.1 percentage points. Nevertheless, the authors did not find an impact of increased rainfall on economic growth.

It is noticeable that most of the research tends to use weather measures, such as elevated temperature and precipitation, as explanatory variables in their work. However, it's important to note that climate change shocks are not limited to just higher temperatures and increased rainfall. Cevik & Jalles (2023) using local projection model attempted to assess how GDP growth reacts not only to temperature increases but also distinct extreme climate shocks such as droughts and storms. They found that all types of climate shocks have a negative impact on economic growth; however, in the long run, the effect in terms of magnitude and the pattern of response for different climate shocks shows variation.

When addressing poor countries, some academics have questioned the reliability of GDP and suggested that it is better to examine the exports of these countries, as this data is usually recorded by a developed importing country. Nevertheless, even when using export data for poor countries recorded by developed countries, the findings align with those of Dell et al. (2008). Jones & Olken (2010), employing export data, found that increases in temperature have a negative impact on economic activity only for poor countries. Consequently, the evidence regarding the impact of temperature increases on the economic growth of the poorest countries in academia is reasonably robust.

2.3. Spillover effects of climate shocks

Although there is a growing body of literature on the subject, fewer academics have focused on examining how climate shocks or risks propagate through trade and the interconnectedness of input-output linkages. Nowadays, due to globalization, a climate disaster in one part of the world can have a non-negligible effect on the macrofinancial performance of a country thousands of kilometres away.

The concept of input-output linkages has been acknowledged for quite some time. Nearly a century ago, Leontief (1936) outlined that shocks among economies transmit through input-output linkages. Consequently, countries with higher bilateral trade tend to experience more synchronized business cycles (Frankel & Rose, 1998).

However, concerning the transmission of shocks across borders of directly affected countries, it is crucial to consider the substitution between imported products and domestically produced ones.

Boehm et al. (2019) utilized the Tohoku earthquake and tsunami in 2011, the third-largest earthquake in the world over the last century, as an exogenous shock to assess the substitutability of imported inputs from Japan. This natural experiment demonstrated that, in the short run, the substitutability between imported inputs and domestic ones is close to 0. This conclusion arises from the fact that for multinational companies in the U.S. that imported specific inputs from Japan in the aftermath of the climate disaster, output fell almost by 1:1 with the drop in imports. This showcases the role of multinational corporations in shock transmission across borders of the directly affected country. Consequently, it is reasonable to assume that in the short run, trade networks between countries are resilient and do not change significantly as a result of disastrous climate events. However, the situation in the long run has the potential to change. Countries might choose to intentionally decouple from engaging in trade with nations that are prone to suffering from extreme and frequent climate shocks (Feng et al., 2023).

To quantify long-term spillovers, policymakers and large international organizations tend to favor Computable General Equilibrium (CGE) models. In essence, these models are a system of equations that try to account for all possible interconnections within an economy. These models are very intensive in terms of machine computing power and require substantial resources to maintain. Although these models are not considered the most academically robust approach since they have their pitfalls, CGE models play a prominent role in policy-making decisions (Babatunde et al, 2017; Niamir et al, 2020). This strand of literature is beyond the scope of our research since, in this paper, we are mostly focused on short-term effects. Nevertheless, it is worth acknowledging the role that these models play in decision-making processes when it comes to climate change.

When it comes to short term effects, to the best of our knowledge, Feng et al. (2023) are the first ones to provide empirical evidence of the impact of physical climate-induced natural disaster shocks on the macroeconomic situation of main trading partners. Their research highlights that the extent of these spillover effects of climate disaster shocks depends greatly on whether the exogenous climate shock has affected port activities. The authors conducted a comprehensive analysis using data from 151 countries spanning the period from 1970 to 2019. Their findings revealed that direct climate disasters can significantly impact the GDP of the countries directly affected, as well as their main downstream and upstream trading partners. Furthermore, the authors noted that following a climate shock, countries tend to experience a decrease in export volumes and a slight increase in import volumes.

Similar to local effects, when it comes to the impact on imports and exports, temperature increases are the most frequently used explanatory variable among academics. Jones & Olken (2010), through an examination of trade data, offer insights into the impact of increased temperatures on the exports of affected countries across various industries. The authors discovered that temperature increases have a negative impact not only on agricultural exports, as might be expected, but also on manufacturing output. Additionally, Jones & Olken (2010) outline different effects on exports based on the country's development level. Their research indicated that, for poor countries, a temperature increases of 1°C in a given year reduces the growth rate of that country's exports by 2.0 to 5.7 percentage points, with no observable effects for the wealthiest parts of the world. However, the authors speculate that developed countries might still be affected, as their imports from poor countries will decline, leading to inflation for goods imported from countries affected by temperature increases. Pascasio et al. (2014), when analysing Philippine exports and imports, support the Jones & Olken findings about the high sensitivity of agriculture and manufacturing output to temperature increases. However, these authors also find evidence for decreased imports and exports in the Philippines if a trade partner experience increases in temperature, irrespective of the affected country's wealth levels.

In this thesis, our objective is to analyse the propagation of climate shocks through international trade. To underscore the significance of these assessments, we will briefly examine 2 climate shocks and their various spillover effects. This exploration aims to illustrate the need to assess global supply chains within a contextual framework, providing insights into how to mitigate such risks and pre-emptively avoid potential costs before they escalate on a large scale.

(1) Hurricane Maria in 2017 caused a severe landfall in Puerto Rico, resulting in substantial local economic losses equivalent to 225% of Dominica's GDP (WTO, n.d). Beyond its impact on the island's economy, this climate shock posed a significant risk to U.S. pharmaceutical supply chains. Approximately

10% of U.S. pharmaceutical product manufacturing is based in Puerto Rico. The compromised infrastructure and manufacturing facilities in the region led to shortages of pharmaceutical products across the entire U.S. healthcare system. The situation worsened with an unprecedented influenza outbreak peaking at the end of 2017, exerting even greater pressure on the already damaged pharmaceutical supply chain. (Lawrence et al., 2020).

(2) The Russian Heat Wave of 2010 exerted immense pressure on agriculture supply chains. The extreme heat caused wheat yields in the most fertile areas to plummet by 70%. Unfortunately, this heatwave coincided with a similar period of high temperatures in Australia, resulting in even more significant wheat shortages and approximately a 20% increase in global market prices. Furthermore, the situation worsened after Russian authorities announced a ban on wheat exports to prioritize meeting local wheat consumption needs. While it did not directly cause a global food crisis, it sparked panic in the market, leading to a surge in global bread and wheat flour prices worldwide. Moreover, the repercussions extended beyond economic impacts. It is believed that the heatwave contributed to civil unrest in countries such as Egypt and Mozambique (Hunt et al., 2021).

In conclusion, the analysis of climate shocks reveals a profound impact not only on economic aspects but also on social and political dimensions. These effects, whether direct or indirect, underscore the interconnectedness of global supply chains.

2.4. Utilizing difference-in-differences for shock transmission in trade

Our paper analyses the transmission of climate disaster's impact from the directly affected territory to their trade partner, which is not directly damaged by the disaster, using the difference-in-differences approach. This type of econometric analysis we consider to be the most effective to meet the goal of the research comparing to other advanced models considering the amount and quality of available data for the African region.

Difference-in-differences model was first used by Snow (1855) to investigate the source of cholera outbreak. Snow's key investigations involved comparing the cholera incidence among populations served by different water companies. He noted that households consuming water from companies that drew water from sewagecontaminated sections of the Thames River had higher cholera rates than those using cleaner water sources. Since then, the difference-in-differences method has been widely used to analyse the effects of certain interventions by comparing differences between treatment and control group before and after the event. For instance, Hinz & Monastyrenko (2022), use the difference-in-differences method to measure the impact of the self-enforced food import sanctions on consumer prices and welfare in Russia. This study demonstrates the possibility to use trade data for product categories for the difference-in-differences method what, in fact, supports our approach. In the model, the date of introduction of embargo works as a treatment; treatment group are embargoed products, and control group are respectively non-embargoed products. Both treatment group and the shock are identified using binary variables, whose interaction creates the variable in question. The regression includes variables that control for regional, time and product fixed effects. The authors used similar approach to determine if there was a change in imports of embargoed goods from non-sanctioning countries after the sanction policy entered in power.

For the difference-in-differences method, the natural disaster perfectly makes a treatment effect analogous to the imposition of sanctions in Hinz & Monastyrenko (2022). Boehm et al. (2019), whose paper creates a solid base for our research, correspondingly uses the 2011 Tohoku earthquake as a natural experiment and Japanese and American firm-level data to study the transmission of the shock through international trade where treatment group consists of Japanese affiliates in the US and control group are non-Japanese multinationals in the US. The authors also use binary variables to determine the treatment group and the treatment. As a result, the model showed that Japanese affiliates in US which are assumed to actively trade with Japanese companies faced lower production after the earthquake. Consequently, the authors conclude that transmission of shock through trade channels exists in the short run.

Building on that, scientists do not limit their models to only one shock. Barrot & Sauvagnat (2016) use major natural disasters within 30 years in the US to investigate if the impact of idiosyncratic shocks spread from suppliers to customers through production networks, using firm-level data. The authors determine the treatment group with a dummy variable that equals to 1 if a company has at least one supplier located in the county that suffered from a natural catastrophe in the same quarter last year. Findings of the study provide evidence that disruptions in the operation of the supplier negatively affect sale's growth of the company.

Firm-level and county-level data is a frequent choice of researchers who study similar types of problems; however, there is a lack of literature that uses country-level data since in most cases the study is set within one country. Feng et al. (2023) managed to investigate cross-border spillovers of natural disasters' shocks studying countries' international trade data. The researchers follow a matching-and-stacking difference-in-differences method thus they do not use binary variables to identify treatment and control groups. Instead, they use propensity scores to determine for each country that was hit by a disaster the most similar in terms of GDP and population country which was disaster-free during the event window. They proceed with identifying upstream and downstream countries for each country in the treatment and control groups. Feng et al. (2023) argue that trade partners are affected by the disaster through two channels: (1) supply and demand shocks, meaning, the country hit by the disaster exports less to downstream countries, and imports more from upstream countries, (2) trade disruption, which happens often due to damaged infrastructure. However, the authors found that the geographical position of trade partners is not significantly important in the spillover of natural disasters shock in comparison to the exposure to trade with the affected country which in turn plays a huge role in the shock transmission.

Previous literature provides compelling evidence for the effectiveness of using the difference-in-differences approach that we want to undertake.

3. Data

In this research, we rely on two primary databases. The Emergency Events Database (EM-DAT, n.d.) supplies information regarding climate shocks in Africa, while trade-related data is extracted from the Eurostat COMEXT database (Eurostat, n.d.), providing details on exports and imports for EU member countries. The data used in this thesis covers the period from January 1988 to December 2022, as this timeframe is covered by both previously mentioned data sources. The EM-DAT database is a comprehensive open-access database that covers mass disasters globally. It aggregates data from various sources, including UN agencies, non-profit organizations, and the press (EM-DAT, n.d.). After extracting data for 54 African countries for the needed time period, we obtained a database with 2,612 climate disasters. It is important to note that this data base records disaster only if a particular climate shock meets at least one of these criteria: (1) at least 100 people affected; or (2) at least 10 deaths; or (3) a call for international assistance. In our paper, we will analyse 7 types of disasters: storms, droughts, wet and dry mass movements, wildfires, extreme temperatures and infestations. All these types of disasters are linked to climate change and are therefore relevant to our research question. However, floods were excluded from the analysis since, after a detailed data review, they portrayed significant seasonality, thus the floods cannot be viewed as an unexpected shock to trade. Additionally, since our aim is to also explore lagged effects from climate shocks, we created event windows. If there was a disaster 1 or 2 months before in a particular country, the respective disaster was removed from our sample, leaving only the disaster that occurred first.

As a result, our climate related dataset consists of 353 disasters. For each disaster, we have collected information on the month and year when it began and concluded. The initial sample was larger; however, disasters were excluded if the start and end months were not provided.

Since our goal is to explore how different types of EU-African trade product groups react to climate disasters in Africa, we extract import and export data from the Eurostat COMEXT database, aggregated by months. For product classification, we use the Harmonized System (HS) classification. The initial database provides 8-digit product categories; however, due to computer processing power limitations and our aim to discuss more general product groups, we limit ourselves to HS 4-digit product categories. To achieve this, we aggregate HS products from 8 to 4 digits. Additionally, we extract the value of product groups in euros to quantify export and import.

3.1. Trade data

For our regression analysis, we utilize data from the period spanning from 1988 to 2022. However, to gain insight into recent trade volumes and key players, we present export and import statistics for the most recent complete year available at the time of conducting this research.

EU trade flows

	Imports				Exports	
African region	Value, EUR' bln	Share of total imports, %	Value, EUR'bln, excl. HS27	Share of imports, excl. HS27, %	Value, EUR'bln	Share of total exports, %
Northern	118.35	52.89%	46.07	47.48%	87.51	49.56%
Western	37.65	16.83%	11.11	11.45%	42.15	23.87%
Southern	29.75	13.29%	25.45	26.23%	26.51	15.02%
Middle	28.11	12.56%	5.13	5.29%	10.43	5.91%
Eastern	9.91	4.43%	9.27	9.55%	9.95	5.64%

Table 1: *EU imports and exports with Africa in 2022. Created by the authors. (Eurostat, n.d.). Note: 'Excl. HS27' indicates the exclusion of products from the 27th category of the Harmonized System Code, which encompasses mineral fuels, mineral oils, products of their distillation, bituminous substances, and mineral waxes.*

Table 1 showcases the trade statistics between the EU and Africa's regions for 2022. Northern Africa represents the largest portion of EU imports by value, accounting for 53%, followed by Western Africa at 16.8%. The primary commodities imported by the EU are fossil fuels, such as petroleum and coal, with mineral fuels and oils making up 57% of the total EU imports. Given the unique pricing and global significance of mineral fuel trade, we further examine the share of EU imports from African regions, excluding products categorized under the 27th Harmonized System Code (HS) — specifically, "Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes." Upon excluding HS27 category products, Northern Africa remains the leading EU trading partner, though its share drops to 47.5%. Southern Africa emerges as the second major EU partner for products outside the HS27 category (26.2%). Meanwhile, Middle Africa represents the smallest portion of EU imports for non-HS27 goods. Regarding EU exports, the ranking of the largest export destinations mirrors that of EU imports across all product categories.

EU imports

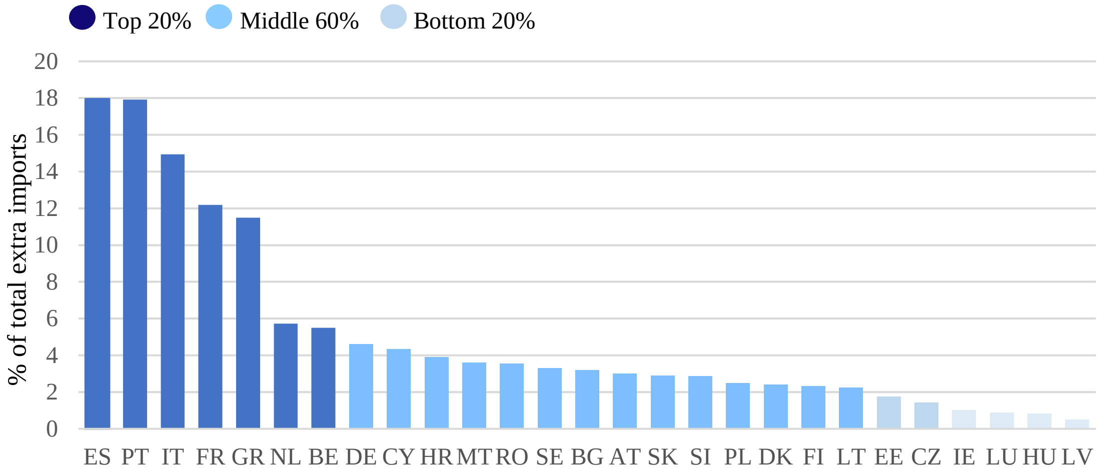


***Figure 1**: EU member states' imports from Africa as a share of each state's total extra-EU imports. Created by the authors. (Eurostat, n.d.).*

Figure 1 illustrates the exposure of EU member states to imports from Africa. We categorize EU countries into three groups: the top 20%, comprising countries with a share of imports from Africa exceeding 5% of total extra-EU imports; the middle 60%, consisting of countries with a share of imports from Africa ranging from 2.26% to 4.61%; and the bottom 20%, representing countries with the lowest exposure to imports from Africa (less than 1.75%). Among EU countries, Spain and Portugal rely most heavily on imports from Africa, with 17.95% and 17.92% of their total EU-extra imports originating from the continent, respectively.

In 2022, Africa accounted for only 7.44% of the total extra-EU imports. Since our goal is to observe the impact of disasters on monthly trade dynamics, we explore how Africa contributes to the EU average total monthly trade of product categories to see what units require the most attention in further analysis. **Table 2** shows the total extra-EU import flows from Africa and how they are distributed across all HS 2-digit product groups as a percentage of the total extra-EU trade. For a detailed breakdown of the HS-2 digit category sub-product groups, please see **Appendix A.**

No.	Product group name	Average monthly EU imports from Africa, EUR'bln	Share of EU-Africa imports from total monthly extra-EU imports, %
1	All products	11.18	7.45%
2	Mineral Products	11.18	15.44%
3	Foodstuffs	0.72	14.35%
4	Vegetable Products	0.96	11.77%
5	Stone & Glass	0.84	11.27%
6	Animal & Animal Products	0.24	7.69%
7	Transportation	0.88	6.15%
8	Metals	0.88	5.55%
9	Textiles	0.63	5.48%
10	Raw hides, skins, leather & furs	0.04	3.31%
11	Plastics/Rubbers	0.26	3.21%
12	Footwear / Headgear	0.08	2.93%
13	Chemicals & Allied Industries	0,66	2.49%
14	Machinery/Electrical	0,98	1.78%
15	Other	0.29	1.51%

Table 2: *Africa's contribution to the average monthly extra-EU import across HS 2-digit product categories. Created by the authors. (Eurostat, n.d.).*

From Table 2, we can conclude that EU-Africa imports are most important for Mineral Products, Foodstuffs, Vegetable Products, Stone & Glass, and Animal & Animal products, collectively accounting for 75% of monthly EU annual imports from Africa. Disruptions in the imports of these product groups potentially pose the greatest risk to the EU in the medium-term.

EU exports

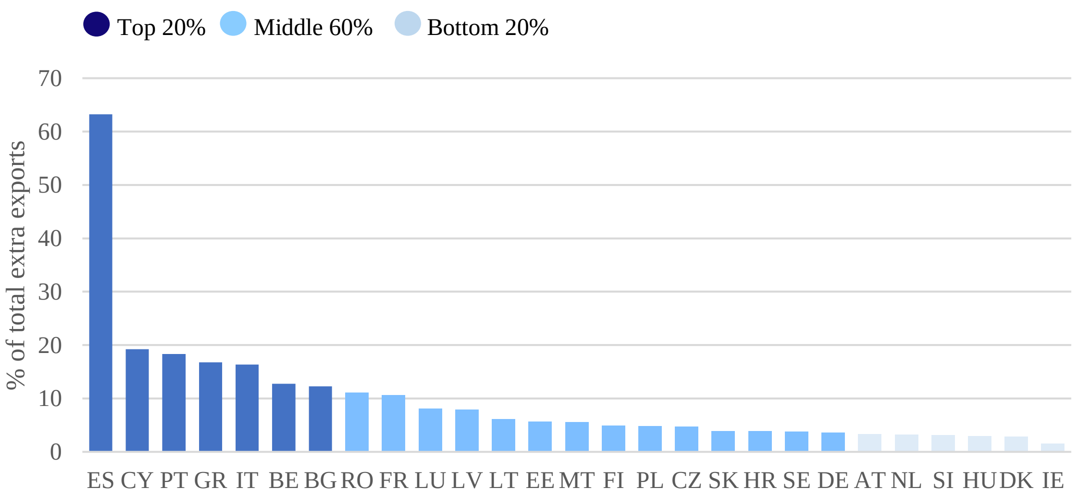


Figure 2: *EU member states' exports from Africa as a share of each state's total extra-EU exports. Created by the authors. (Eurostat, n.d.).*

In a manner similar to Figure 1, we delve into the proportion of extra-EU exports per country that are destined for Africa (Figure 2). In the case of EU exports to Africa, the top 20% comprises countries whose share of African exports exceeds 12.30%, with Spain and Cyprus leading the group at 63.26% and 19.21%, respectively. The middle 60% encompasses countries delivering to Africa between 3.61% and 11.06% of their total extra-EU exports. On the other hand, countries with the lowest reliance on African exports have a share lower than 3.29%, with Ireland having the lowest share at 1.56%.

We report the contribution of EU-Africa exports to total EU monthly exports in Table 3. In case of exports, the largest share can be attributed to Vegetable Products, followed by Mineral Products, Animal & Animal Products, Textiles, and Plastics & Rubbers, which collectively contribute 70% of total EU monthly exports to Africa.

No.	Product group name	Average monthly EU exports from Africa, EUR'bln	Share of EU-Africa exports from total monthly extra-EU exports, %
1	All products	14.71	6.86%
2	Vegetable Products	1.04	21.38%
3	Mineral Products	3.11	19.59%
4	Animal & Animal Products	0.42	10.67%
5	Textiles	0.50	9.01%
6	Plastics/Rubbers	0.65	7.48%
7	Metals	0.85	7.07%
8	Foodstuffs	0.69	6.72%
9	Machinery/Electrical	2.89	5.84%
10	Other	1.13	5.00%
11	Transportation	1.36	4.67%
12	Chemicals & Allied Industries	1.74	4.23%
13	Stone/Glass	0.24	3.45%

Table 3: *Africa's contribution to the average monthly extra-EU exports across HS 2-digit product categories. Created by the authors. (Eurostat, n.d.).*

3.2. Disaster data

To examine the evolution of disaster occurrence trends in Africa over time, Figure 3 displays the fluctuations in the number of recorded disasters. In total 1,578 climate related disasters are recorded. From Figure 3 we observe a growth in the overall number of climate related disasters across the continent. Floods emerged as the most prevalent disaster (1,086), followed by storms (253) and droughts (87). When delving into the trends associated with the most frequent disaster types, it becomes apparent that the occurrence of significant floods, droughts, and storms has been on the rise.

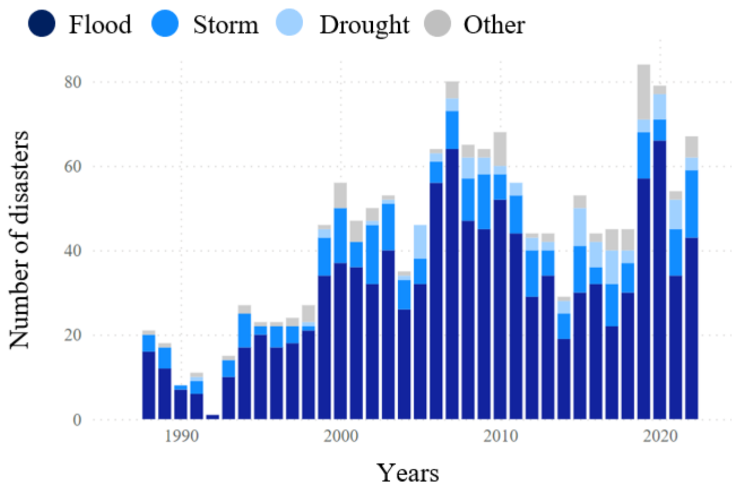


Figure 3: *Disaster trends in Africa from 1988 to 2022. Created by the authors. (EM-DAT, n.d.). Note: In the category 'Others,' all other studied disaster types are summed together.*

Analysing the data geographically uncovers distinct climate disaster patterns over the studied period. Eastern Africa (664) stands out as the region most affected, followed in order by Western (366), Middle (209), Northern (197), and Southern Africa (142). Moreover, our analysis indicates that Eastern Africa experiences the highest occurrences of the 3 most frequent disasters identified previously. In conclusion, despite the varying frequencies of disasters across regions, a consistent theme emerges: the number of disasters in Africa is unequivocally increasing. This is elaborated in **Figure 4**, where the trendline obtained using a linear function supports this observation.

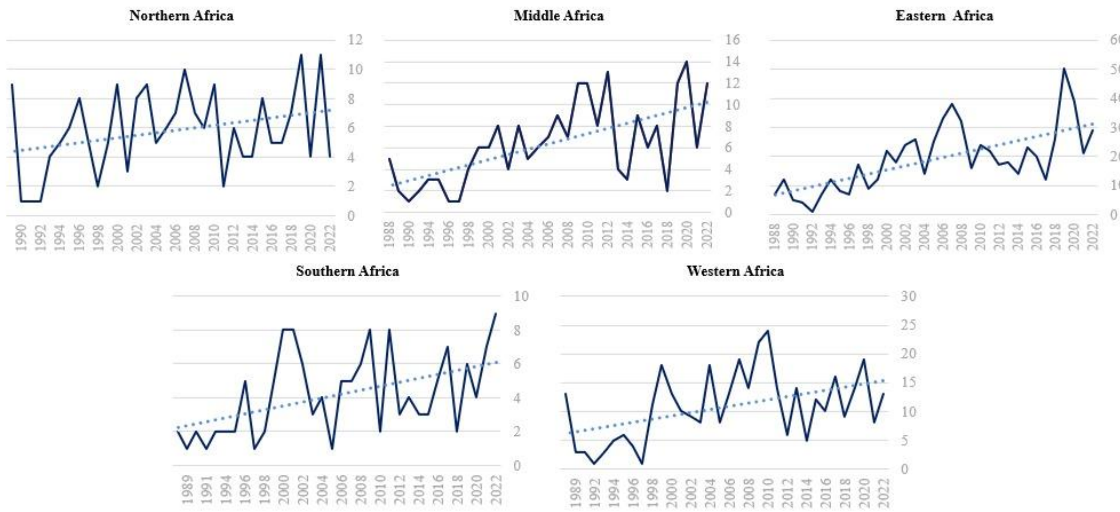


Figure 4: *Disaster trends in African regions from 1988 to 2022. Created by the authors. (EM-DAT, n.d.).*

Since the aim of the thesis is to assess the medium-term effects of exogenous climate shocks, seasonality, and several disasters happening at the same time need to be taken into account. After data analysis, it can be concluded that floods portray high seasonality. Most of the floods took place starting from late winter until the end of spring. Thus, it can be concluded that these disasters were predictable and do not meet the criteria for an exogenous shock needed for difference-in-difference analysis. Therefore, floods are excluded from the sample. Additionally, to isolate disaster effects, we create event windows since there are several instances when there are different or the same disasters taking place in a particular country several months in a row. Therefore, in the analysis, we include only those disasters before which there were a 2-month period without any disasters. Altogether, the exclusion of floods and creation of event windows significantly reduce the sample size to 353, yet it allows for a more explicit capture of the unexpected climate disaster impact on trade. In **Figure 5**, we can see the final cleaned data sample. It consists of 172 storms, 58 droughts, 52 wet mass movements, 28 wildfires, 23 infestations, 16 extreme temperatures, and 4 dry mass movements. Even after data cleaning, the trend of increased climate disasters still persists.

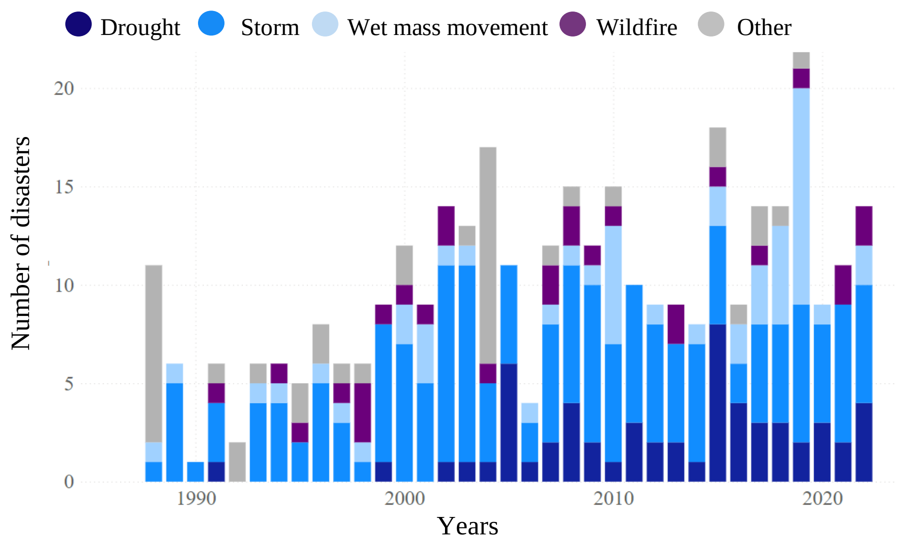


Figure 5: *Cleaned final data set from 1988-2022. Created by the authors. (EM-DAT, n.d.).*

Note: In the category 'Others,' all other studied disaster types are summed together.

4. Methodology

To explore the effect of natural disasters in Africa on trade with the European Union, we rely on difference-in-differences research design due to its appropriateness and effectiveness in terms of the context and available data. This method allows us to separate the effects from a shock by comparing the difference between treatment and control groups before and after the exposure to the shock. Choice of our methodology is supported by the approaches undertaken in the studies of Boehm et al. (2019), Barrot & Sauvagnat (2016) and Feng et al. (2023) that use difference-in-differences model in the similar context.

We begin by running the following OLS regression with fixed effects (1),

$$\ln X_{i,j,p,t} = b_0 + \sum_{L=-1..K}^{n} b_{1L}\, Disaster_{i,t-L} + \lambda_{i,t} + \lambda_{p,t} + \lambda_{j,p} + \lambda_{i,p} + \varepsilon_{i,j,p,t} \quad (1)$$

where we regress natural logarithm of trade flow which is either the European Union country (i) imports or exports of product (p) from/to African country (j) in a month (t). Similar to Boehm et al. (2019) and Barrot & Sauvagnat (2016), we use binary variable $Disaster_{i,t}$ that equals to 1 if imports or exports were coming from/to an African country hit by a disaster. If a disaster lasts longer than 1 month, we only add the binary variable $Disaster_{i,t}$ for the month the disaster starts. To account not only for an immediate effect, but also for the effect that comes into power with a delay, we include lagged values of the $Disaster_{i,t}$, thus we can observe the impact of the disaster that took place up to K months ago (Boehm et al., 2019, Carvalho et al., 2016). Correspondingly, b_{1L} is the coefficient of central interest that will capture the effect of natural disaster in Africa on European imports/exports. We also make a placebo test by including one lead (t+1) of the disaster (see Section 3.2 Disaster Data). We expect the coefficient $b_{1(-1)}$ to be not statistically significant as natural disasters are unexpected shocks to the trade.

Furthermore, in the regression, we also control for various fixed effects. $\lambda_{i,t}$ is the interaction term between the EU country and year fixed effect. This variable accounts for all demand (supply) related macroeconomics factors in the EU countries for the case of EU imports (exports). $\lambda_{p,t}$ is the product category and year fixed effect that captures trends related to the global supply and demand for products. $\lambda_{i,p}$ is the EU country and product category fixed effect. By including it in the regression, we aim to account for the EU's comparative advantage in certain products or industries. The country has a comparative advantage in a certain product category if it can produce it with lower alternative costs compared to other country. The country’s comparative advantage in a certain good negatively affects this good’s imports since it is more convenient to buy it from local suppliers and trade balance for this product category is more likely to be positive. Respectively, we also include fixed effect that captures the effect of comparative advantage of African countries $\leftthreetimes_{j,p}$, which follows the identical logic, meaning, African countries are prone to export products that they have a comparative advantage in. Regression (1) was estimated by the OLS using respective Within Group transformations.

For our analysis, we furthermore conduct additional regressions on trade data for distinct product categories. To achieve this, we differentiate these categories using the two-digit Harmonized System (HS) Codes. Our objective is to explore the sensitivity of African import/export product groups that account for the largest share of total extra-EU trade.

We endeavour to enhance our analysis by investigating potential variations in the immediate impact of disaster shocks on trade volume across geographical regions of African partners and product categories. To achieve this, we employ an Ordinary Least Squares (OLS) regression model Product and Region interaction terms (2):

$$\ln X_{i,j,p,t} = b_0 + b_{1..5} DisasterRegion + b_{6..n} Disaster\mathrm{P}roduct + \lambda_{i,t} + \lambda_{p,t} + \lambda_{j,p} + \lambda_{i,p} + \varepsilon_{i,j,p,t} \qquad (2)$$

In the second model (2), we similarly to the first regression (1) regress natural logarithm of trade volume between EU country (*j*) and African country (*i*) of product category (*p*) in a month (*t*) on several interaction terms. The first set of variables is *Disaster* dummy and *Region* dummy interaction terms. We create 5 binary variables for each geographical region of Africa: North, South, West, East and Middle. They represent the effects of EU trade partners’ membership in the respective regions on trade volume. By interacting *Region* dummies with *Disaster* dummy, we capture the additional effect of the African partner’s location on the impact of disaster. The second set of variables is *Disaster* dummy and *Product* dummy interaction terms. We create binary variables for different product categories. The choice of product categories will depend on the result of the first OLS model (1) performed for distinct product categories. Products that appear to have a significant estimated loss of export or import volumes in case of the disaster will be used for the second (2) regression to understand if the intensity of disaster impact varies between product categories.

The significance of the results will be checked using F-test separately for the sets of *Disaster* and *Region* interaction terms, and *Disaster* and *Product* interaction terms. F-test will prove significance of the varying effects of disasters between different regions and products, if the null hypothesis, which states that the sum of the set of interaction terms' coefficients equals to zero, will be rejected.

5. Analysis

To explore the sensitivity of EU trade product groups originating from Africa, which account for the largest share of total extra-EU trade, we conduct a difference-in-differences analysis. In this analysis, we assign a binary variable *Disaster* a value of 1 in a month when any type of disaster occurs in an African country and 0 if no disaster takes place. To examine the medium-term effects, we also include 6 lags to analyse the impact over time. We chose this timeframe because, during our analysis, we observed that the effect of a disaster mostly disappears within a 7-month period (medium-term). Furthermore, this independent variable *Disaster* is regressed against the logarithmic value of total imports/export for total trade and 5 different product groups (see section 3.1. Trade data) from the respective African country, incorporating fixed effects as outlined in the Methodology section. To strengthen our analysis, we also add one lead value for the binary variable ***Disaster,*** check the significance of our models using the F-test and run 3 robustness checks. Additionally, to provide more context for our findings about EU-Africa trade sensitivity, we calculate expected trade losses in absolute terms for each product group. The figures in this section serves as a summary for explanatory purposes, and the comprehensive regression outputs are available in Appendix B, along with product group categories and their subcategories in Appendix A.

5.1. EU imports

Using the ***Disaster*** variable and its lags, overall, we can observe a negative impact of climate shocks on EU import values over the medium-term. The negative climate shock dynamics on total extra-EU trade with Africa can be observed in Figure 6, where we have showcased the negative climate shock dynamics over a 7-month period. In this figure, we report the coefficient b_{1L}, the coefficient of central interest, together with a 95% confidence band, starting from the leading effect (insignificant in all cases), and then following the immediate and lagged effects. On the vertical axis, we have the coefficient b_{1L} value, and on the horizontal axis, we have the time period in months. The coefficient b_{1L} can be interpreted as the percentage change in trade in a given month when multiplied by 100 (short-term effect). This multiplication needs to be done since our dependent variable is the logarithm of EU import values. However, the overall effect of a disaster over the medium-term is the sum of all short-run effects.

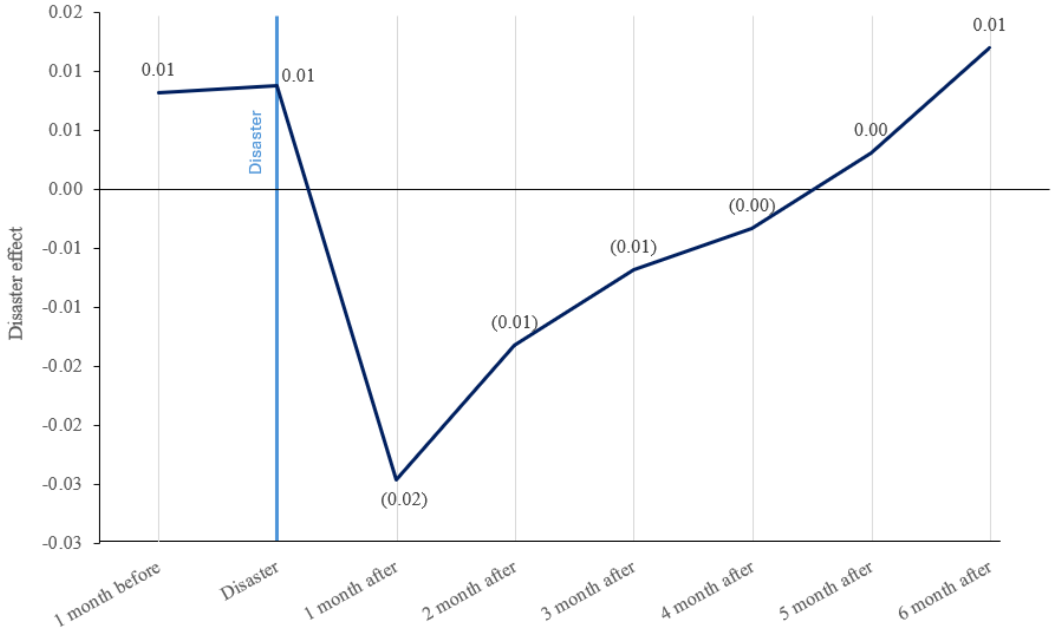
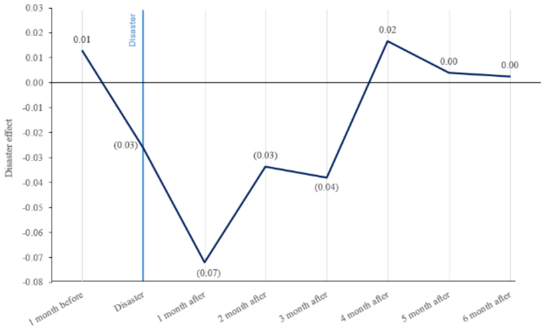


Figure 6: *Dynamics of the disaster effect on EU total imports from Africa in the medium-term (1988-2022). Created by the authors.*

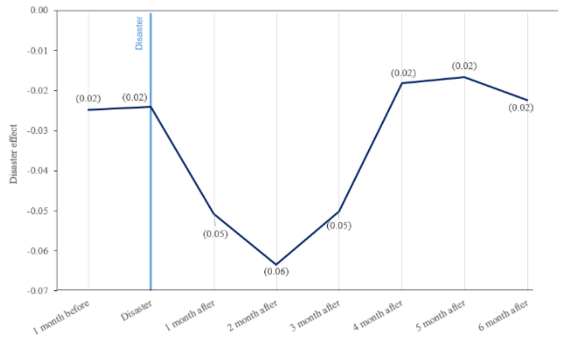
In Figure 6, we can explicitly observe the negative effect of unexpected climate shock on EU import trade. The negative effects start to materialise 1 month after the disaster when the effect is the largest (-2.26%). This could be explained by the fact that the Disaster binary variable is assigned to the start month of the disaster, and the trade shock takes some time to materialize, especially if the disaster occurs in the second part of the month. Another explanation could be the fact that there is some delay in trade registration in EU customs since it takes time to deliver the goods to the EU. Over time the negative effect starts to gradually diminish since value chains start recovering after the hit. Overall, this indicates a persistent yet diminishing effect of climate disasters as economies adjust to the aftermath of a shock by replacing damaged infrastructure and resuming previously disturbed economic activities.

When analysing separately the largest EU import groups coming from African countries, which account for the largest share of total extra-EU imports in Figure 7, more unique climate shock dynamics start to prevail. For Animal & Animal products and Stone & Glass products, the largest impact is observable 1 and 2 months after the disaster starts, which generally mirrors the dynamics previously observed for the total EU imports (Figure 6). Nevertheless, for Foodstuffs, the negative effect dynamics are more persistent. After experiencing a large drop of 7.20% one month after a disaster, the effect starts to gradually diminish. However, 3 months after the disaster begins, the effect starts to increase again, reaching 6.95% 6 months after the disaster. After that, the effect decreases and disappears. On the opposite spectrum, in terms of shock dynamics, we have Vegetables and Minerals, for which a clear shock effect in the figure is not observable, showcasing resistance to unexpected disasters. To understand if these medium-term effects are statistically significant, we move on to addressing the expected value over a 7-month period and testing the significance of this effect.

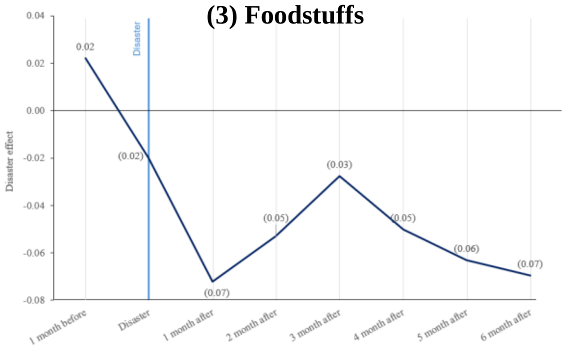
(1) Animal & Animal Products



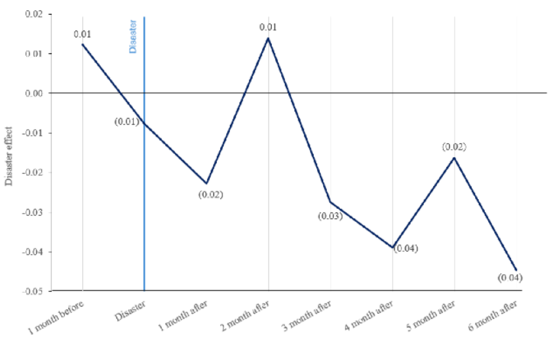
(2) Stone&Glass



(3) Foodstuffs



(4) Minerals



(5) Vegetables

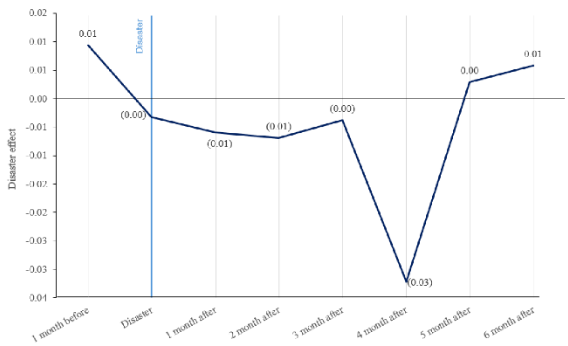


Figure 7: *Dynamics of the disaster effect on the largest EU import categories with Africa in the medium-term (1988-2022). Created by the authors.*

To estimate the expected value change in EU import values, we calculate expected trade changes over 7 months by summing together all obtained coefficients starting from the disaster's start date (D) until the 6th month lagged value (D+6). This sum denotes the overall relative effect of a disaster on the respective trade flow. After that, we use an F-test to assess the statistical significance of the overall medium-term effect of a disaster on the trade flow. This test assesses if the model can explain a significant proportion of the variance of our dependent variable – the logarithm of EU imports. If the null hypothesis, which assumes that the overall medium-term effect is not significant, can be rejected, the obtained results are significant.

In Table 4 we summarise our expected value change calculations together with F-statistics. Additionally, we calculate the total impact in absolute terms on EU imports by using the 2022 average monthly EU import values for the respective product group and multiplying them by (1) 7 to account for the number of months and (2) the obtained expected value change over 7 months after a disaster. The year 2022 was taken as a base since it is the last full available year with trade data reported at the time of writing this thesis.

Product groups	Expected value change over 7 months	F-test	Significance	Total impact in billions of euros
All products	(2.39%)	0.002582	1%	(3.12)
Animal & Animal Products	(14.69%)	0.08	10%	(0.24)
Stone/Glass	(24.54%)	0.0001	0.1%	(1.44)
Foodstuffs	(35.56%)	6.80E-10	0.1%	(1.80)
Mineral Products	(14.36%)	0.1921		(11.24)
Vegetable Products	(4.33%)	0.489		(0.29)

Table 4: *Estimated value of expected climate shock on EU import product groups over a 7-month period. Created by the authors.*

Total EU imports

Taking into account the F-test results, we can conclude that after a disaster, EU imports tend to decline significantly overall (all product groups together). In the medium run, total EU imports are expected to decrease by 2.39% after an unexpected natural disaster. Meanwhile, in absolute terms, it results in a trade decline of €3.12 billion.

Foodstuffs

A staggering result is obtained from the Foodstuffs category, for which the medium-term effect is also statistically significant. We can expect the medium-term climate shock effect to reach double-digit numbers of -35.56% of trade values (equal to €1.8 billion expected losses). By looking also at the disaster shock dynamics in Figure 7 for Foodstuffs we can see that the category is highly sensitive and has a rather high negative effect persistence. This could be explained by factors such as perishability and the need for inputs from other geographic regions to create this category of products, thus resulting in higher economic losses if the supply chains are disrupted.

Stone & Glass

Overall, this product group involves energy-intensive production, and the pronounced decreases in EU imports for Stone & Glass could be attributed to energy disruptions resulting from a disaster. In addition to physically damaged infrastructure after climate shocks in areas that rely on hydroelectric power generation, production may be halted due to insufficient rainfall, leading to electricity shortages with serious economic implications (Trace, 2019). In terms of Stone & Glass, it can be stated that the expected change in EU imports over the medium-term, on average, is a decrease of 24.54% (significant at 0.1% level). In monetary terms, this translates to approximately a €1.44 billion loss in EU import values.

Minerals, Vegetables, Animal & Animal products

According to F-tests, trade for these three product groups in the medium-term does not seem to be significantly affected by climate shocks, as the null hypothesis in the F-test cannot be rejected. For Minerals, this phenomenon could be explained by the large economic stake involved in the trade of minerals. Consequently, during disaster crises, the African-EU mineral trade seems to stay intact. Surprisingly, Vegetable Products also do not seem to possess high sensitivity to disasters. A possible explanation for this resistance to climate shocks could be the fact that producers who grow vegetables are located in regions that are less affected by climate shocks. Alternatively, the second explanation could be that the EU is not the key trade partner to Africa when it comes to vegetables, and therefore, this sensitivity is not captured since we only use Africa-EU trade data. The same reasoning applies to Animal & Animal products, as this agricultural product group also is not significantly affected by disasters in the medium-term.

To obtain a bit more detailed analysis of climate shocks, we conduct subsequent regressions where the general disaster dummy is replaced with specific disaster-type dummies to examine how the negative effects on EU total trade values vary among different disaster scenarios. In this section, we focus on storms and droughts since, after data cleaning, they have more observations to perform the analysis, and their effects have a broader impact on territory, thus having a more pronounced effect on trade rather than having a relatively localized impact.

To confirm the robustness of our results, we alter our regression sample. Although the thorough analysis of disaster data revealed no observed seasonality patterns in the case of droughts, there remains a potential risk of predictability associated with drought occurrences, contradicting the assumptions of the difference-in-difference model. Therefore, we exclude droughts from the disasters dataset to verify the consistency of our results with previous findings. The results of this robustness check (Appendix F) support the previously outlined effects, indicating no evidence of drought predictability.

We additionally check the validity of our results by aggregating the EU import data from 4-digit HS product codes to 2-digit HS codes. This robustness test reduces noise in the data caused by fluctuations at a more detailed level. The aggregation also allows to test the sensitivity of the results to the level of data granularity. The test results shown in Appendix F, Table 1 are consistent with previous findings suggesting that the conclusions are not dependent on the specific level of product categorization used.
To strengthen the robustness of the regression analysis, we also create a subsample that excludes import of products whose share in the total extra-EU import is lower than 3% since imports of goods with low values may be subject to greater measurement error or volatility compared to higher-value imports, which represent more substantial trade flows and may have a greater impact on overall trade dynamics. Appendix F, Table 1 confirms the robustness of the regressions used in the main analysis.

5.2. EU exports

In order to understand the effect of climate disasters on EU exports, we follow the same approach as was previously performed for EU imports. Using regression with one starting lead, the coefficient of the central interest and six lags, we estimate the strength and length of the disaster's impact on the dynamics of trade. The complete regression output is available in Appendix C.

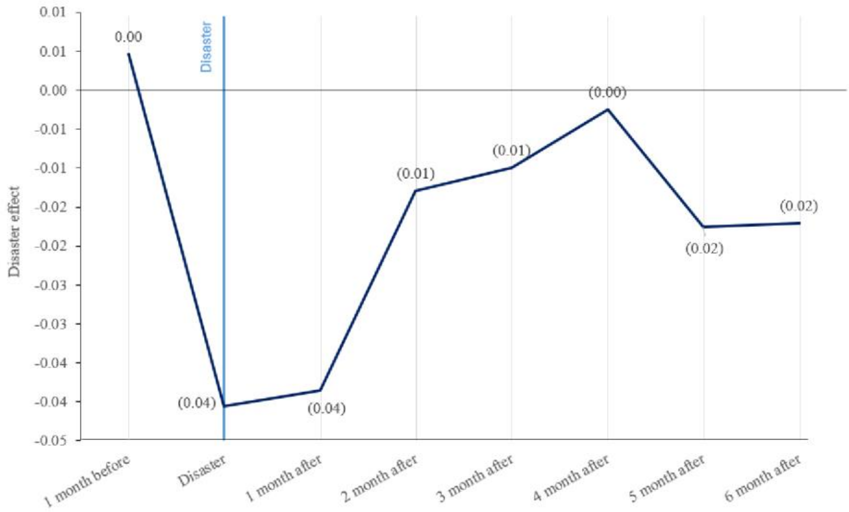
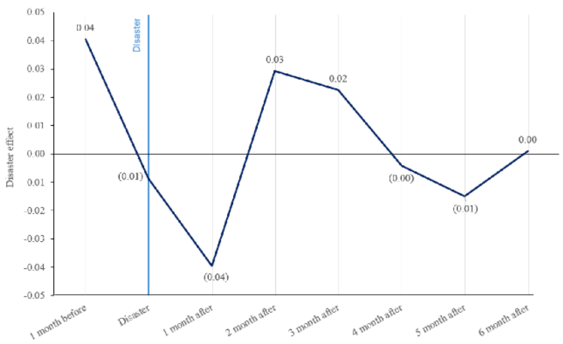


Figure 8: *Dynamics of the disaster effect on EU total exports to Africa in the medium-term (1988-2022). Created by the authors.*

Figure 8 visually demonstrates the change in EU export dynamics after the climate shock. The negative effect is already observed during the first month of the disaster with the exports decreasing by 4.05%. The impact remains strong one month after the disaster shock destroying the value of exports by an additional 3.86%. The dynamics of EU exports following a climate disaster differ from the import dynamics mentioned earlier. In contrast to EU imports, exports exhibit greater sensitivity and respond more rapidly to the shock. This phenomenon may be attributed to damaged infrastructure, which disrupts supply chains. Delivery of goods could be delayed when partners are aware of disasters occurring in their counterpart countries, which is especially relevant in the recent years due to faster information transmission speeds. In response to disaster news, EU suppliers of African imports can invoke the Force Majeure clause commonly included in supplier-consumer agreements. This clause releases the supplier from the obligation of delivering goods in the event of unforeseen extreme circumstances, which will decrease the export flow in the first period of the disaster. In the subsequent months, the adverse effect is notably diminished. Nevertheless, the impact remains persistent in the fifth and sixth months following the disaster, resulting in a decrease in EU exports by 1.76% and 1.71% respectively. The prolonged aftershock effect of the disaster could be attributed to the increased incentive for savings among the African population caused by financially stressful conditions resulting from unforeseen damages (Berg & Burger, 2008).

We take a closer look into EU export dynamics by looking at the trade of product groups that take the largest share of total extra-EU exports in Figure 9. Similar pattern is observed in the trade of Mineral products, Animal & Animal products, Textiles and Plastics & Rubbers. The export of those product categories experiences a strong decline in the month when disaster occurred or a month after the shock. Similarly to the regression results for all product categories, the shock diminishes in the following months. However, a strong aftershock is observed five months after the disaster. This might result from disrupted supply chains, leading to delays or interruptions in the production and distribution of goods. If the EU relies heavily on inputs from Africa for its exports, any disruption in African production due to a climate disaster could directly impact EU exports and lead to the presented aftershock impact. On the other hand, the dynamics of EU vegetable exports differ, with the most pronounced negative impact of 5.75% occurring three months after the disaster. This can be attributed to supply chains being less sensitive to disruptions, which respond to shocks with a delay due to reduced consumer purchasing power and the adjustment or cancellation of delivery orders, processes that do not happen immediately. EU exports of Vegetables and Textiles have a negative coefficient for the leading month, potentially attributed to discrepancies in disaster registration dates. The accuracy of these dates could be called into question due to the challenges of determining when disasters without explicit triggers, such as droughts, begin.

(1) Minerals



(2) Animals & Animal products

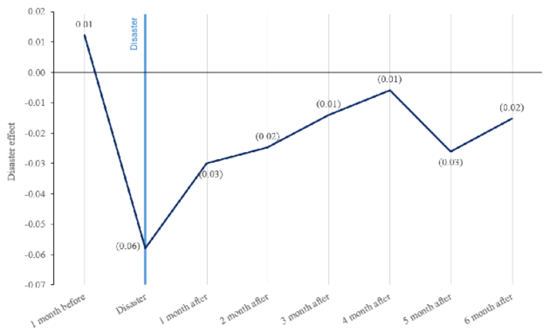
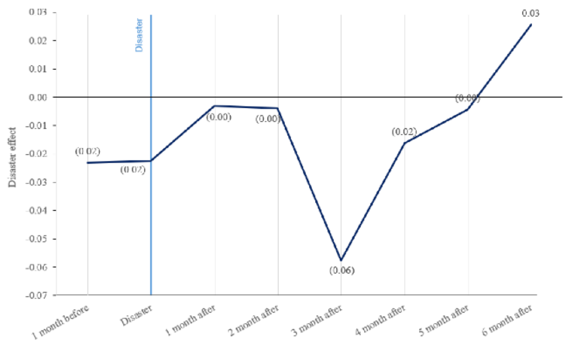
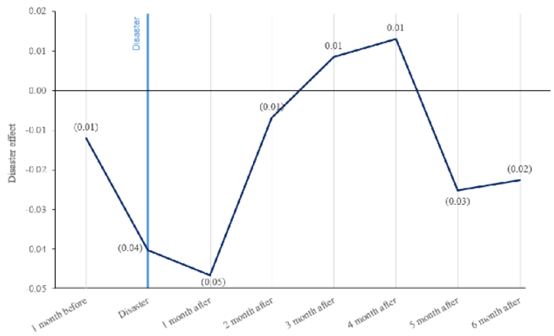


Figure 9(A): *Dynamics of the disaster effect on the largest EU export categories with Africa in the medium-term (1988-2022). Created by the authors.*

(3) Vegetables



(4) Textiles



(5) Plastics & Rubbers

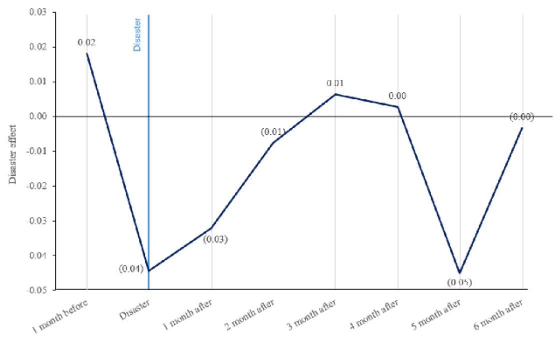


Figure 9(B): *Dynamics of the disaster effect on the largest EU export categories with Africa in the medium-term (1988-2022). Created by the authors.*

We proceed by examining the expected value over a seven-month period and testing the significance of this impact. Table 5 includes calculated expected value changes and F-statistics, taking EU export values from 2022.

Total EU exports

The F-test yields evidence that the overall decline in EU exports across all product categories is statistically significant. In the medium term, the total value of EU exports is estimated to shrink by 13.92% in response to a climate disaster, equivalent to €14.33 billion in absolute terms using 2022 trade relationships among partner countries.

Product groups	Expected value	F-test	Significance	Total impact in billions of euros
All products	-13,92%	2,20E-16	0.1%	-14,33
Vegetable Products	-13,29%	0.00103	1%	-0,96
Mineral Products	-13,29%	0.7116		-2,89
Animal & Animal Products	-17,33%	0,004014	1%	-0,52
Textiles	-12,00%	2,91E-06	0.1%	-0,42
Plastics/Rubbers	-14,17%	0.001635	1%	-0,65

Table 5: *Estimated value of expected climate shock on EU export product groups over a 7-month period. Created by the authors.*

Animal Products, Vegetables, Textile, Plastic & Rubbers

Four out of the five largest product categories in terms of EU exports demonstrate significantly negative effects in the aftermath of a climate shock. Animal products, vegetables, textiles, and plastics & rubbers are particularly affected.

Animal product exports are notably vulnerable, showing a substantial 17.33% decrease, equating to a loss of €0.52 billion. Meanwhile, vegetable exports decline by 13.29%, equivalent to the estimated loss of €0.96 billion. Textile exports are also affected, experiencing a 12% decrease, amounting to an estimated €0.42 billion loss. Additionally, plastics & rubbers suffer a significant 14.17% decline, resulting in a €0.65 billion expected loss in export values.

Mineral products

The observed negative significance for all analyzed product groups, except for Mineral Products, leads us to infer that the losses are predominantly attributed to broader export-related factors rather than specific product characteristics. The reasoning behind decreasing EU exports could be infrastructural damages that interrupt the delivery of goods and diminishing consumer and capital expenditure that might be caused by the loss of income generating assets and tendency to increase savings to repair potential damages (Berg & Burger, 2008).

Mineral products emerge as the sole category relatively unscathed by the disaster, underscoring the distinctiveness of this product category characterized by its inelastic demand and strong correlation with energy market prices. These attributes render it less sensitivity to external factors such as disasters.

Similar to the analysis conducted for EU imports, we undertake an identical set of robustness checks. To ensure the reliability of our findings, we first remove droughts from the disaster sample, secondly, aggregate export data from 4 to 2-HS codes, and finally, exclude from the export dataset those product categories with the share lower than 3% in the total extra-EU export. The results of the robustness checks supporting the validity of our finding are presented in Appendix F, Table 2.

5.3. Regional & product factors

To discern whether trade flows are more vulnerable to disasters due to the region where the trade partner is located or the specific product category being traded, we construct a regression model incorporating interaction terms between the *Disaster* binary variable and specific regions, as well as between the *Disaster* dummy variable and the most affected product category. For the *Disaster* and *Region* interaction terms, we create 5 binary variables (North Africa, South Africa, West Africa, East Africa and Middle Africa), which equal to 1 if partner country is located in the particular region. For the *Disaster* and *Product* interaction terms, we add binary variables for product groups that had a statistically significant estimated loss in the previous regressions (Table 4 and Table 5). Interaction terms demonstrate how the effect of the disaster on the trade volume changes depending on the value of a third variable. The significance of those interaction terms is then compared using F-test to determine which factor exerts a stronger influence. Complete regression output can be accessed in Appendix D.

EU imports

For the purpose of studying the significance of the regional and product factor for EU imports' vulnerability to disasters, in addition to 5 African regions, three product categories, Animal & Animal products, Foodstuffs and Stone & Glass, are chosen since they were proven to have significant impact in the previously performed analysis (Table 4). We then regress interaction terms on the logarithm of EU imports to capture the combined effect of the disaster and region or product. Table 6 summarizes the results of the regression. To check the significance of the results, we perform two F-tests for the interaction terms of regions with *Disaster* dummy and products with *Disaster* dummy separately. The F-test proves if the sum of interaction term effects is equal to 0. The results of the test (Table 6) demonstrate that only the combined effect of *Region* dummy with *Disaster* dummy is significant. Therefore, the location of partnering country is more vital in understanding the strength of the disaster impact. We observe that EU imports coming from countries in Middle and Northern Africa experience a stronger impact having negative 6.90% and 2.75% effects respectively in addition to the sole disaster effect. In contrast, partners located in Southern Africa have by 4.15% less pronounced disaster effect.

Interaction terms	Expected value	Significance
Disaster:North	(2.75%)	0.1%
Disaster:South	4.15%	0.1%
Disaster:West	(1.53%)	
Disaster:East	0.76%	
Disaster:Middle	(6.90%)	0.1%
Disaster:Animal	(1.61%)	
Disaster:Foodstuffs	(0.71%)	
Disaster:Stone	(2.56%)	
F-test (Region effects):	0.008401 **	
F-test (Product effects):	0.1138	

Table 6: *Impact of regions and product categories on disaster effect on EU imports. ***, **, *, and . denote statistical significance at 0-0.1%, 0.1-1%, 1-5%, and 5-10% levels, respectively. Created by the authors.*

EU exports

Following the same procedure for EU exports, we create Region and Disaster interaction terms. However, in terms of product categories, the set of binary variables correspond to the results of significance tests in Table 5, performed for the product categories with the biggest share in the overall extra-EU export. Therefore, for the regression four product categories are chosen: Animal & Animal products, Vegetable products, Textiles and Plastics & Rubbers. We interact them with the *Disaster* dummy to capture the combined effect of two variables on the logarithm of EU exports' value. Using F-test, we see if we can reject the hypothesis of interaction terms having no significant impact on the logarithm of the value of EU exports. The results (Table 7) offer compelling evidence that, consistent with the regression findings for EU imports, the location of the trade partner significantly influences the impact of disaster shocks on export volumes. Based on the regression output (Table 7), EU trade with African partners situated in the Northern and Eastern regions experience notably worse negative effects from disasters on exports, with impacts of negative 4.23% and 4.42% respectively. Conversely, damage to EU exports is expected to be 1.45% less severe when exporting to countries located in Western Africa, respectively.

Interaction terms	Expected value	Significance
Disaster:North	(4.23%)	0.1%
Disaster:South	0.32%	
Disaster:West	1.44%	1%
Disaster:East	(4.42%)	0.1%
Disaster:Middle	1.39%	
Disaster:Animal	(1.26%)	
Disaster:Vegetables	(0.54%)	
Disaster:Textiles	(0.30%)	
Disaster:Plastics	(0.83%)	
F-test (Region effects):	5.772e-05 ***	
F-test (Product effects):	0.6371	

Table 7: *Impact of regions and product categories on disaster effect on EU exports. ***, **, *, and . denote statistical significance at 0-0.1%, 0.1-1%, 1-5%, and 5-10% levels, respectively Created by the authors.*

The regression analysis underscores a noticeable trend: disaster shocks in Northern, Eastern, and Middle African regions tend to result in greater reductions in trade volumes compared to Southern and Western Africa. Trade with partners in the latter regions exhibit better resilience to disasters. The significant difference in the sensitivities to the disasters could be attributed to several factors. First, due to its geographical specifics certain regions are prone to more severe and frequent disasters, and; therefore, face bigger losses due to disaster shocks. As previously highlighted in the Disaster Data Analysis section, Eastern Africa suffered the biggest number of disasters, which corresponds the additional negative contribution to the overall impact of the disaster. Conversely, Western Africa, while experiencing a high frequency of disasters, exhibits a lesser overall effect on trade in the event of disaster shocks. This could potentially be explained by the intensity of the disasters or lack of disasters' direct connection to production. However, this aspect necessitates further investigation as data on the magnitude of disaster damage remains limited at present, highlighting a potential area for future research. Moreover, one more specific country characteristic to keep in mind is the proportion of disaster intensity and frequency to the size of the country (Cuaresma et al., 2008). In addition to geographical factors, the resistance of trade volumes also depends on the political factor such as power of institutions of partnering countries, and their ability to mitigate climate shocks and quickly react to them (Dallmann, 2019). Therefore, region characteristics and overall economic and political background determine the vulnerability of trade flows to the disaster shocks.

6. Discussion

We present evidence that unexpected climate shocks in Africa significantly impact both EU imports and exports with African countries in the medium term. However, the extent of this impact varies significantly among the top 5 product groups, which account for the largest monthly share in EU-Africa trade flows against total extra-EU imports/exports. Additionally, we demonstrate that African countries that are EU trade partners hold great importance, as their responsiveness to climate shocks depends on local disaster strength as well as the quality of institutions. Thus, the negative spillovers experienced by EU member states will depend not only on the types of goods these countries trade with but also on the countries with which they engage in trade relationships.

Although trade partners can change in the long run, there is limited power to substitute them in the short term (Boehm et al., 2019). To highlight the variance of current risk exposure for each EU member state, we present an EU member state heatmap using the 2022 trade data. The following figures are created by computing the proportion of extra-EU trade with Africa against the total extra-EU trade of each respective country. We perform this analysis for product categories that we concluded to be significantly negatively affected in the analysis section for EU imports/exports. After obtaining these proportions, they are compared to those of other EU member countries using 80% and 20% percentiles and categorized using color coding. Although, as proven previously, negative spillover experienced by disaster-affected countries' main trade partners will depend on which country in Africa the trade is conducted with, for risk assessment purposes, we argue that it is reasonable to assume that countries with the largest proportion of extra-EU trade with Africa against total extra-EU trade for a particular product category can be classified as having the highest exposure to negative changes in trade flows stemming from two sources: Firstly, disaster-hit countries' trade partners have limited imported input substitutability in the medium term. Secondly, unaffected countries' GDP might decrease in the medium-term because of the decrease in extra-EU exports to climate-hit countries. In this section, Figures 10 and 11 are created for illustrative purposes, but detailed tables with exact extra-EU trade proportions for each member state can be found in Appendix E.

EU imports

Considering the Stone & Glass product group, the top 20% of the data points rank above 13.57% of extra-EU imports from Africa from the total respective countries' extra-EU imports. Belgium (24.54%), Denmark (12.62%), and Ireland (11.00%) rank as the top 3 countries currently facing the largest risk exposure to negative spillovers from disasters (Figure 10). In the case of Foodstuffs, 80% of the EU member states fall below a 7.63% share of extra-EU imports from Africa. In this category, again, Belgium ranks at the top with a notable 31.51%, followed by Estonia with a 25.09% share, and the Netherlands with a 21.37% share.

Based on the observed vulnerability in these two groups, Belgium, Estonia, and Portugal emerge as the countries facing the highest risk of experiencing extra-EU import losses. This could potentially impair their economic activities due to input loss in the Foodstuff and Stone & Glass sectors.

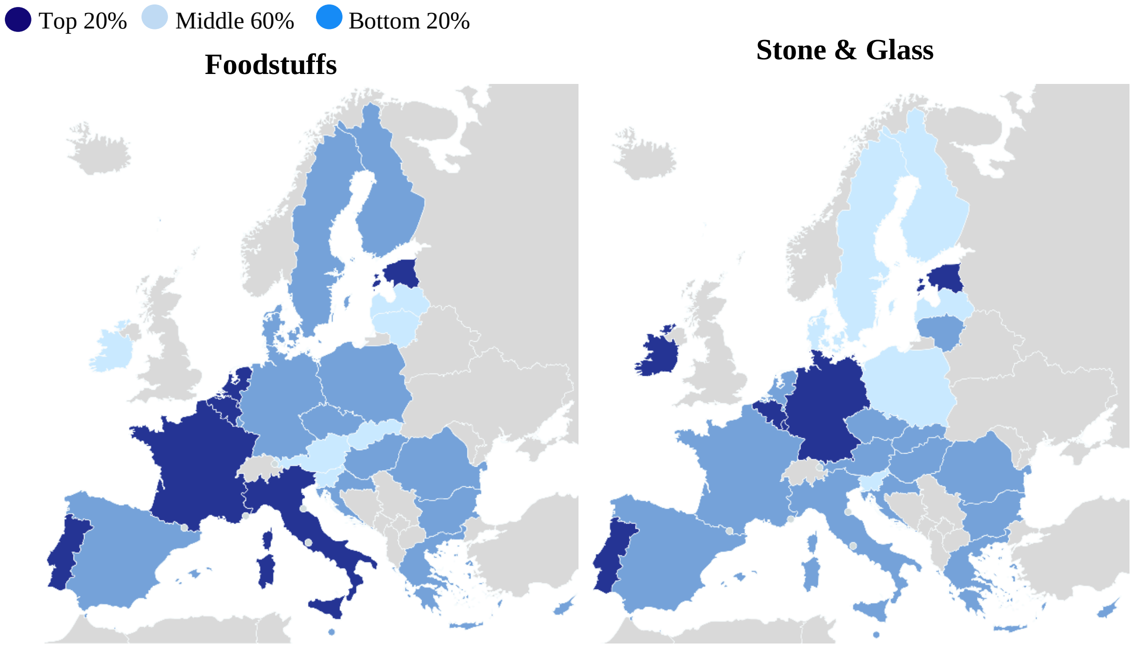


Figure 10: *Risk exposure to disasters in Foodstuffs and Stone & Glass extra-EU trade for EU member states. Created by the authors.*

EU exports

When considering extra-EU exports among EU member states (Figure 11), France stands out as it is considered at the highest risk among 3 out of 4 product categories, ranking in the top 20th percentile in Animal & Animal products (18.08%), Textile (12.74%), and Vegetables (43.64%) categories. By looking at the Vegetable category separately, Africa seems to be one of the largest trade destinations in this extra-EU export category for several EU member states since the 80th percentile of all 27 data points is located at 37.01%. The top 3 countries with the largest share of Vegetable extra-EU exports to Africa are Latvia, Lithuania, and Bulgaria, with impressive percentages of 56.36%, 49.50%, and 43.84% respectively, thus indicating the highest risk exposure for Vegetable product export loss. Additionally, exports of Plastics & Rubber to Africa for several countries account for the largest share of total extra-EU export trade flow for this product category. In this category, the 80th percentile stands at 14.29%. The top 3 countries are Malta with a staggering 54.70%, Belgium with 45.22%, and Greece with 24.60%. Exposure for Animal & Animal products and Textiles is relatively lower compared to the first two analyzed groups, as the top 20th percentile of the data points in these categories is no higher than roughly 10%.

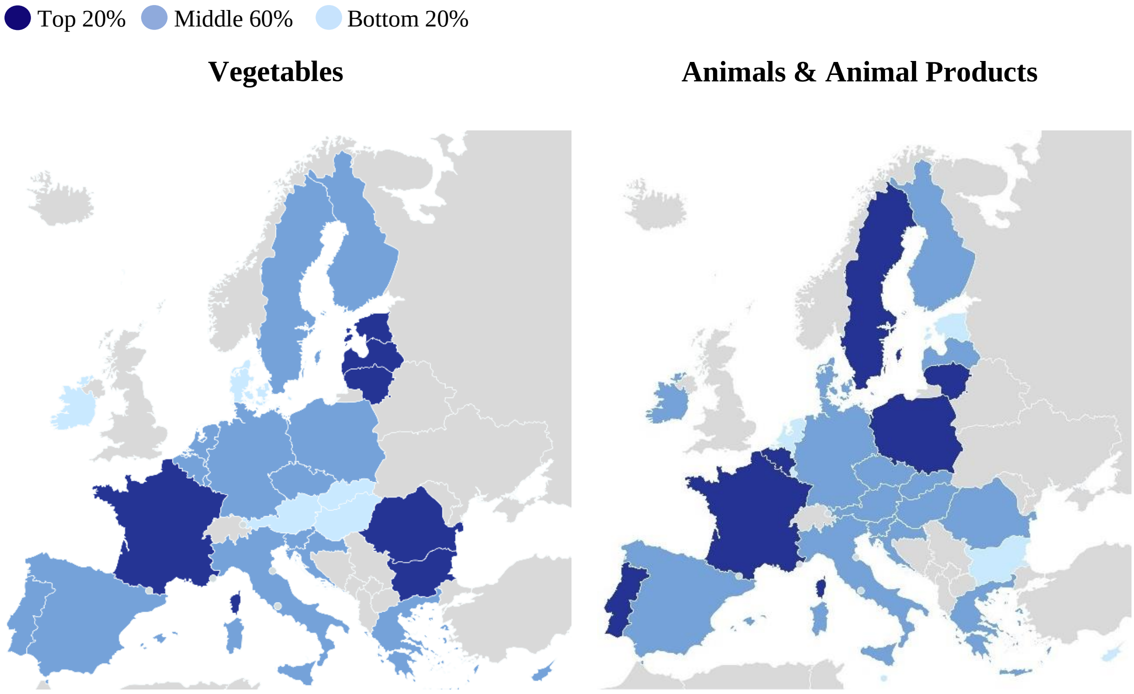


Figure 11(A): *Sensitivity to disasters for total extra-EU exports from Africa for EU member states. Created by the authors.*

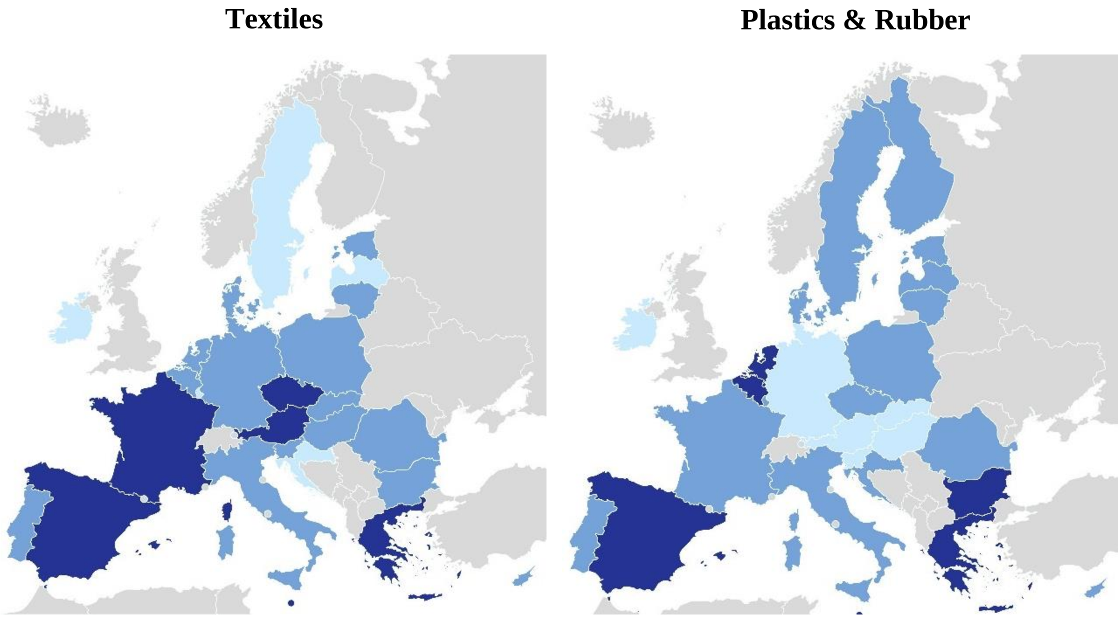


Figure 11(B): *Sensitivity to disasters for total extra-EU exports from Africa for EU member states. Created by the authors.*

Considering the current sensitivity of the EU-Africa trade relationship, it would be reasonable to assume that some of the EU trade partners might decide to unwind their trade relationship with Africa if they could substitute African trade partners with ones less prone to suffering from climate hits, especially taking into account projected increases in climate shock frequency and severity across all African regions (IPCC, n.d.). This could reduce uncertainty and possibly trade costs in the long run. Nevertheless, such outcomes might have serious economic implications for Africa's development.

Taking into account the already existent landscape in Africa of fragile and conflict-affected states, climate shocks widen the gap between Africa and developed countries. After experiencing a climate disaster, governments have to deal with damages such as infrastructure with already limited funds. Consequently, financially distressed governments, instead of investing in more robust infrastructure, try to salvage what is left of the damaged infrastructure. This creates a vicious cycle of repeated climate disasters that limit economic development since African countries need to deal with disaster damages instead of compensating for already substantial deficits. What is even more concerning is that by replacing Africa as a trade partner, this vicious cycle is fuelled to spin even quicker due to export revenues that could enable employment and reduce unemployment in the long run (GCA, 2021).

This showcases the positive externalities involved in collective climate resistance building in the long run, as it makes African countries less reliant on international aid by enabling them to grow their economies, whose current growth prospects are limited because of the climate-induced climate change to which it has contributed the least.

7. Limitations

Our research encounters several limitations, with one of the primary ones being associated with disaster data. In the EM-DAT database, only 10% of all eligible disasters for our research, after data collection and clearance, contained information about disaster damages. This lack of data on disaster damages hampers our ability to measure the severity of disasters accurately. Understanding the extent of damages could help us determine the impact on trade volumes more precisely because not all disasters disrupt supply chains and infrastructure equally.

The precision of our analysis was hindered by a lack of information regarding the methodology used to determine the start and finish of the disaster. This aspect is particularly crucial for disasters lacking clear, easily identifiable triggers. Take droughts, for instance, which often evolve gradually without distinct onset points. Consequently, identifying precisely when economic disruptions occur as a result of drought becomes a challenging endeavor.

Additionally, the simultaneous occurrence of multiple disasters presents another challenge. To address this issue, we implemented event windows, merging overlapping disasters to distinguish the beginning of the disaster period. Nevertheless, this approach resulted in the loss of numerous disaster observations, particularly those with shorter durations that frequently coincide with more prolonged disaster periods, such as storms occurring during droughts, which limited us from the studying the effect of different disaster types.

When dealing with trade data, it is important to note that not all HS 4-digit categories are traded every month. This means that if a disaster happens in a particular month, but a certain product group is not traded during that time, we might miss capturing the initial shock, even though it could have influenced the trade flows of specific product groups. Consequently, the impact on less frequently traded product groups might be underestimated in our analysis. Furthermore, our analysis solely examines the impact on trade volumes between Europe and Africa. Yet, if a specific African region engages in more trade with other continents, we may not capture potential losses in those trade directions.

Furthermore, because we rely on data provided by the European Union, the period of export and import sent and received respectively is documented when the traded product passes through EU customs. Consequently, the trade period recorded may not align with the actual timing of orders placed or deliveries made, as it does not consider the time of delivery. As a result, shocks in trade might be observed with delays, potentially introducing inaccuracies in the examination of the effects of disasters on the trade. This limitation could lead to an underestimation or overestimation of the impact of disasters on trade dynamics, as the recorded data may not accurately capture the immediate consequences of these events on trade flows.

8. Future research

To expand upon our current findings in the topic of natural disaster spillover effects, there are several recommendations that could be undertaken for future research.

The analysis could be extended by studying the cross-border spillover effects of natural disasters. This extension would explore whether there's an impact on trade volume if a neighboring country of the trading partner experiences a disaster. Given that supply chains often rely on infrastructure across borders, exploring this aspect could provide valuable insights into the interconnected nature of trade dynamics. Furthermore, utilizing trade data categorized by mode of transport would offer insights into how different transportation methods contribute to the transmission of disaster shocks on trade volumes.

For a deeper comprehension of the behaviours of exporting and importing firms between the EU and Africa, it would be beneficial to leverage firm-level data, which was not covered in this stud due to data quality issues. Parameters such as inventory days could unveil shifts in production and inventory management strategies in response to disasters. Such insights are crucial as they shed light on the ability of firms to maintain trade flows with the EU during disaster shocks.

Finally, to enhance the accuracy of our findings, it may be advantageous to transition from monthly to annual data. This shift would help mitigate potential noise inherent in monthly data and provide a clearer overview of trends over longer timeframes. Additionally, future research could develop an index to evaluate the severity and frequency of disasters within a given year, allowing for a more comprehensive assessment of disasters' annual impact on trade volumes.

9. Conclusions

In this thesis, our embarked to analyse the impact of unexpected climate disasters in Africa on trade with the EU across various product categories. Our objective was to provide insights into the spillover effects from climate shock affected countries to its main trade partners through trade links, highlighting the positive externalities of multinational efforts to increase resilience in climate change-prone regions. To achieve this, we utilized EU-Africa monthly trade data and disaster data from Africa spanning from 1988 to 2022. Our chosen research method was the difference-in-difference approach. To account not only for the immediate effect, we used 6 lags to estimate the medium-term expected trade flow change. This analysis was performed for total trade flows and the five largest HS-2 digit product groups, which constitute the largest percentage of the total extra-EU trade within their respective HS product group.

In terms of total extra-EU imports to Africa, we found that over the medium term, EU imports following an unexpected climate disaster are anticipated to decrease by 2.39%, amounting to an estimated loss of €3.12 billion. Although this is less than 1% of the total extra-EU trade in 2022, this loss can be of great value for countries whose extra-EU imports from Africa account for a significant proportion of their total extra-EU trade for specific product groups. This is due to the limited substitution between imported goods and domestic ones.

We discovered a significant effect for two explored product groups that pose the highest import substitution risk to the EU. Over the medium term, Foodstuffs are expected to decrease by 35.56% in the aftermath of a climate shock, which in absolute terms can be estimated to reach €1.80 billion. Meanwhile, Stone & Glass exports are anticipated to drop by 24.54%, resulting in estimated losses of €1.44 billion. We did not find evidence for sensitivity in Animal & Animal Products, Vegetables, and Minerals. The resistance observed in agricultural products could be due to the location of agricultural producers in regions less affected by climate shocks or because the EU is not the primary trade partner for Africa when it comes to agricultural products.

EU exports are found to react more pronouncedly to disasters in relative terms than EU imports. In the medium term, we found that EU exports followed a 13.92% decline, resulting in an estimated loss amounting to €14.33 billion after a disaster. By analysing Vegetables, Minerals, Animal & Animal Products, Textiles, and Plastics & Rubbers, only Minerals showcased resistance to trade decline associated with unexpected climate shocks. Considering the unique nature of mineral products, as also observed in EU import analysis, we can imply that the decrease in exports is attributed to broader export-related factors rather than specific product characteristics. This loss for EU export volumes is expected to mostly arise from infrastructural damages that disrupt supply chains and decreased consumer purchasing power caused by unexpected financial losses.

The research findings reveal a significant difference in how EU trade flows are affected by disaster shocks, with the location of the trade partner having a greater impact than the specific product category being traded. The analysis indicates that EU imports from Middle, Eastern and Northern Africa experience more pronounced negative effects from disasters compared to Southern and Western Africa, emphasizing the importance of regional factors such as geographical characteristics and institutional capability to mitigate climate risks in understanding the sensitivity of trade flows to disaster shocks.

We believe our thesis introduces novelty to existing academic research by examining climate shock spillover effects from developing countries to developed ones within a contextual framework. Despite the EU being Africa's largest trade partner, there is a noticeable absence of research addressing this gap, which we aimed to address. Additionally, our work contributes to the literature by exploring the medium-term effects of climate shocks using specific disaster types, rather than focusing solely on temperature or precipitation increases, as seen in the majority of the previous research. While temperature and precipitation data provide valuable insights into long-term effects, they may underestimate the immediate shocks following a disaster in the medium-term.

Overall, climate shocks exacerbate existing challenges faced by fragile and conflict-affected African states, widening the development gap between Africa and developed countries. The risk of possible decoupling of Africa as a trade partner can have serious negative economic effects, accelerating the vicious cycle of climate shocks that divert funds from infrastructure investment to disaster recovery, thereby limiting the growth prospects of developing countries. Fostering multinational collaboration in infrastructure climate resilience is crucial. It can stimulate African economic growth, reduce reliance on economic aid in the long term, and benefit its main trade partners by making international trade chains more robust to unexpected climate shocks.

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Acknowledgement

The AI was used to check the spelling, sentence structure and grammar of the text.

Appendices

Appendix A: HS-2 product group categories' definitions

01-05 Animal & animal products
01 Live animals; **02** Meat and edible meat offal; **03** Fish and crustaceans, molluscs and other aquatic invertebrates; **04** Dairy produce, birds' eggs, natural honey, edible products of animal origin, not elsewhere specified or included; **05** Products of animal origin, not elsewhere specified or included
06-15 Vegetable products
06 Live trees and other plants; bulbs, roots and the like, cut flowers and ornamental foliage; **07** Edible vegetables and certain roots and tubers; **08** Edible fruit and nuts; peel of citrus fruits or melons **09** Coffee, tea, mate and spices; **10** Cereals; **11** Products of the milling industry; malt; starches; inulin ; wheat gluten; **12** Oil seeds and oleaginous fruits; miscellaneous grains, seeds and fruit; industrial or medicinal plants; straw and fodder; **13** Lac; gums, resins and other vegetable saps and extracts; **14** Vegetable plaiting materials; vegetable products not elsewhere specified or included; **15** Animal or vegetable fats and oils and their cleavage products; prepared edible fats; animal or vegetable waxes
16-24 Foodstuffs
16 Preparations of meat, of fish or of crustaceans, molluscs or other aquatic invertebrates; **17** Sugars and sugar confectionery; **18** Cocoa and cocoa preparations; **19** Preparations of cereals, flour, starch or milk; pastrycooks' products; **20** Preparations of vegetables, fruit, nuts or other parts of plants **21** Miscellaneous edible preparations; **22** Beverages, spirits and vinegar; **23** Residues and waste from the food industries; prepared animal fodder; **24** Tobacco and manufactured tobacco substitutes
25-27 Mineral products
25 Salt; sulphur; earths and stone ; plastering materials, lime and cement; **26** Ores, slag and ash; **27** Mineral fuels, mineral oils and products of their distillation ; bituminous substances; mineral waxes
28-38 Chemicals & allied industries
28 Inorganic chemicals; organic or inorganic compounds of precious metals, of rare-earth metals, of radioactive elements or of isotopes; **29** Organic chemicals 30 Pharmaceutical products; **31** Fertilisers; **32** Tanning or dyeing extracts; tannins and their derivatives; dyes, pigments and other colouring matter; paints and varnishes; putty and other mastics; inks; **33** Essential oils and resinoids; perfumery, cosmetic or toilet preparations; **34** Soap, organic surface-active agents, washing preparations, lubricating preparations, artificial waxes, prepared waxes, polishing or scouring preparations, candles and similar articles, modelling pastes, 'dental waxes' and dental preparations with a basis of plaster; **35** Albuminoidal substances; modified starches; glues; enzymes; **36** Explosives; pyrotechnic products; matches; pyrophoric alloys; certain combustible preparations; **37** Photographic or cinematographic goods; **38** Miscellaneous chemical products
39-40 Plastics/ rubbers
39 Plastics and articles thereof; **40** Rubber and articles thereof

41-43 Raw hides, skins, leather & furs
41 Raw hides and skins (other than furskins) and leather; **42** Articles of leather; saddlery and harness; travel goods, handbags and similar containers; articles of animal gut (other than silkworm gut); **43** Furskins and artificial fur; manufactures thereof
44-49 Wood & wood products
44 Wood and articles of wood ; wood charcoal; **45** Cork and articles of cork; **46** Manufactures of straw, of esparto or of other plaiting materials; basketware and wickerwork; **47** Pulp of Wood or of other fibrous cellulosic material; waste and scrap of paper or paperboard; **48** Paper and paperboard ; articles of paper pulp, of paper or of paperboard; **49** Printed books, newspapers, pictures and other products of the printing industry; manuscripts, typescripts and plans
50-63 Textiles
50 Silk; **51** Wool, fine or Coarse animal hair; horsehair yarn and woven fabric; **52** Cotton; **53** Other vegetable textile fibres; paper yarn and woven fabrics of paper yarn; **54** Man-made filaments**; 55** Man-made staple fibres; **56** Wadding, felt and nonwovens; special yarns; twine, cordage, ropes and cables and articles thereof; **57** Carpets and other textile floor coverings 58 Special woven fabrics; tufted textile fabrics; lace ; tapestries; trimmings; embroidery; **59** Impregnated, coated, covered or laminated textile fabrics; textile articles of a kind suitable for industrial use; **60** Knitted or crocheted fabrics**; 61** Articles of apparel and clothing accessories, knitted or crocheted; **62** Articles of apparel and clothing accessories, not knitted or crocheted 63 Other made-up textile articles; sets; worn clothing and worn textile articles; rags
64-67 Footwear / Headgear
64 Footwear, gaiters and the like; parts of such articles; **65** Headgear and parts thereof; **66** Umbrellas, sun umbrellas, walking-sticks, seat sticks, whips, riding-crops and parts thereof; **67** Prepared feathers and down and articles made of feathers or of down; artificial flowers; articles of human hair
68-71 Stone / Glass
68 Articles of stone, plaster, cement, asbestos, mica or similar materials; **69** Ceramic products; **70** Glass and glassware; **71** Natural or cultured pearls, precious or semi-precious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin
72-83 Metals
72 Iron and steel; **73** Articles of iron or steel; **74** Copper and articles thereof **75** Nickel and articles thereof; **76** Aluminium and articles thereof; **77** (Reserved for possible future use in the harmonized system); **78** Lead and articles thereof; **79** Zinc and articles thereof; **80** Tin and articles thereof; **81** Other base metals; cermets; articles thereof; **82** Tools, implements, cutlery, spoons and forks, of base metal ; parts thereof of base metal; **83** Miscellaneous articles of base metal
84-85 Machinery / Electrical

84 Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof; **85** Electrical machinery and equipment and parts thereof; sound recorders and reproducers, television image and sound recorders and reproducers, and parts and accessories of such articles
86-89 Transportation
86 Railway or tramway locomotives, rolling-stock and parts thereof; railway or tramway track fixtures and parts thereof; mechanical (including electromechanical) traffic signalling equipment of all kinds; **87** Vehicles other than railway or tramway rollingstock, and parts and accessories thereof; **88** Aircraft, spacecraft, and parts thereof; **89** Ships, boats and floating structures
90-97 Miscellaneous
90 Optical, photographic, cinematographic, measuring, checking, precision, medical or surgical instruments and apparatus; parts and accessories thereof; **91** Clocks and watches and parts thereof; **92** Musical instruments; parts and accessories of such articles; **93** Arms and ammunition; parts and accessories thereof; **94** Furniture; bedding, mattresses, mattress supports, cushions and similar stuffed furnishings; lamps and lighting fittings, not elsewhere specified or included; illuminated signs, illuminated name-plates and the like; prefabricated buildings; **95** Toys, games, and sports requisites; parts and accessories thereof; **96** Miscellaneous manufactured articles

Table 1: *HS-2 product group categories. Created by the authors. (WCO, 2022).*

Appendix B: Impact of the disaster shock on the value of EU imports from Africa in the midterm (OLS regressions with fixed effects)

	Dependent variable: log(EU import values)			
Product sample:	All products	Animal	Foodstuffs	Vegetables
1 month before	0.0082 (0.0050)	0.0127 (0.0234)	0.0220 (0.0207)	0.0094 (0.0149)
Disaster	0.0088 . (0.0050)	-0.0260 (0.0239)	-0.0200 (0.02089)	-0.0032 (0.0151)
1 month after	-0.0246*** (0.0050)	-0.0721** (0.0238)	-0.0720*** (0.0209)	-0.0059 (0.0150)
2 months after	-0.0132** (0.0050)	-0.0337 (0.0235)	-0.0531* (0.0208)	-0.0069 (0.0150)
3 months after	-0.0068 (0.0049)	-0.0381 (0.0235)	-0.0277 (0.0205)	-0.0038 (0.0149)
4 months after	-0.0033 (0.0049)	0.0167 (0.0234)	-0.0502* (0.0206)	-0.0322* (0.0149)
5 months after	0.0031 (0.0050)	0.0039 (0.0237)	-0.0631** (0.0206)	0.0029 (0.0149)
6 months after	0.0120* (0.0049)	0.0025 (0.0237)	-0.0696*** (0.0206)	0.0058 (0.0150)
Observations	5142481	187466	328968	638908
R2	0.6453	0.6483	0.7014	0.5974
Adjusted R2	0.6375	0.6409	0.6958	0.5912
F Statistic	83.05***	87.99***	125.5***	96.25***

*Table 1: The table shows the results of the regressions with natural logarithm of the value of EU imports to Africa for 4 different samples of import data. ***, **, *, and . denote statistical significance at 0-0.1%, 0.1-1%, 1-5%, and 5-10% levels, respectively. Source: Created by the authors. Information: The regression analyses were conducted in RStudio by the authors.*

	Dependent variable: log(EU import values)	
Product sample:	Minerals	Stone & Glass
1 month before	0.0122 (0.0292)	-0.0248 (0.0210)
Disaster	-0.0076 (0.0295)	-0.0241 (0.0213)
1 month after	-0.0228 (0.0294)	-0.0508* (0.0215)
2 months after	0.0139 (0.0296)	-0.0634** (0.0214)
3 months after	-0.0274 (0.0292)	-0.0501* (0.0209)
4 months after	-0.0389 (0.0295)	-0.0182 (0.0209)
5 months after	-0.0162 (0.0294)	-0.0166 (0.0209)
6 months after	-0.0446 (0.0292)	-0.0223 (0.0208)
Observations	157762	235172
R2	0.7649	0.6693
Adjusted R2	0.7563	0.6599
F Statistic	89.39***	71.27***

*Table 2: The table shows the results of the regressions with natural logarithm of the value of EU imports from Africa for 2 different samples of import data. ***, **, *, and . denote statistical significance at 0-0.1%, 0.1-1%, 1-5%, and 5-10% levels, respectively. Source: Created by the authors. Information: The regression analyses were conducted in RStudio by the authors.*

Appendix C: Impact of the disaster shock on the value of EU exports to Africa in the midterm (OLS regressions with fixed effects)

	Dependent variable: log(EU export values)			
Product sample:	All products	Animal	Minerals	Vegetables
1 month before	0.0047 (0.0027)	0.0122 (0.0179)	0.0405 . (0.0225)	-0.0231 (0.0150)
Disaster	-0.0405*** (0.0027)	-0.0578** (0.0180)	-0.0087 (0.0227)	-0.0224 (0.0151)
1 month after	-0.0386*** (0.0027)	-0.0299 . (0.0180)	-0.0396 . (0.0224)	-0.0030 (0.0151)
2 months after	-0.0129*** (0.0027)	-0.0247 (0.0179)	0.029257 (0.0226)	-0.0038 (0.0149)
3 months after	-0.0099*** (0.0027)	-0.0140 (0.0177)	0.022600 (0.0225)	-0.0576*** (0.0148)
4 months after	-0.0025 (0.0027)	-0.0058 (0.0178)	-0.004074 (0.0225)	-0.0162 (0.0150)
5 months after	-0.0176*** (0.0027)	-0.0260 (0.0178)	-0.014869 (0.0226)	-0.0043 (0.0152)
6 months after	-0.0171*** (0.0027)	-0.0151 (0.0178)	0.0011 (0.0226)	-0.0257 . (0.0150)
Observations	23963671	505129	390101	757014
R2	0.4787	0.575	0.513	0.5986
Adjusted R2	0.4756	0.5706	0.5046	0.5926
F Statistic	154.7***	130.8***	60.89***	99.74***

*Table 1: The table shows the results of the regressions with natural logarithm of the value of EU exports to Africa for 4 different samples of export data. ***, **, *, and . denote statistical significance at 0-0.1%, 0.1-1%, 1-5%, and 5-10% levels, respectively. Source: Created by the authors. Information: The regression analyses were conducted in RStudio by the authors.*

	Dependent variable: log(EU export values)	
Product sample:	Plastics & Rubbers	Textiles
1 month before	0.0181 (0.0107)	-0.0120 (0.0089)
Disaster	-0.0444*** (0.0108)	-0.0402*** (0.0089)
1 month after	-0.0322** (0.0107)	-0.0466*** (0.0090)
2 months after	-0.0076 (0.0168)	-0.0069 (0.0089)
3 months after	0.0063 (0.0107)	0.0085 (0.0088)
4 months after	0.0027 (0.0107)	0.0130 (0.0089)
5 months after	-0.0451*** (0.0108)	-0.0252** (0.0090)
6 months after	-0.0033 (0.0107)	-0.0226* (0.008940)
Observations	1598775	1858182
R2	0.464	0.5097
Adjusted R2	0.4621	0.5051
F Statistic	238.2***	109.9***

*Table 2: The table shows the results of the regressions with natural logarithm of the value of EU exports to Africa for 2 different samples of export data. ***, **, *, and . denote statistical significance at 0-0.1%, 0.1-1%, 1-5%, and 5-10% levels, respectively. Source: Created by the authors. Information: The regression analyses were conducted in RStudio by the authors.*

Appendix D: Impact of regions and product categories on disaster effects (OLS regressions with interaction terms and fixed effects)

	Dependent variable: log(EU import values)
Product sample:	All products
D:North	-0.0275*** (0.0062)
D: South	0.0415*** (0.0063)
D:West	-0.0153 (0.0096)
D:East	0.0075 (0.0088)
D:Middle	-0.0690*** (0.0166)
D:Animal	-0.0161 (0.0194)
D:Foodstuffs	-0.0071 (0.0144)
D:Stone	-0.0256 (0.0167)
Observations	5142481
R2	0.6453
Adjusted R2	0.6375
F Statistic	83.05***

*Table 1: The table shows the results of the regressions with natural logarithm of the value of EU imports Africa for the full sample of import data. ***, **, *, and . denote statistical significance at 0-0.1%, 0.1-1%, 1-5%, and 5-10% levels, respectively. Source: Created by the authors. Information: The regression analyses were conducted in RStudio by the authors.*

	Dependent variable: log(EU export values)
Product sample:	All products
D:North	-0.0423*** (0.0047)
D: South	0.0032 (0.0065)
D:West	0.0145** (0.0045)
D:East	-0.0442*** (0.0054)
D:Middle	0.0139 (0.0167)
D:Animal	-0.0126 (0.0167)
D:Vegetables	-0.0054 (0.0132)
D:Textiles	-0.0030 (0.0089)
D:Plastic	-0.0083 (0.0093)
Observations	23963671
R2	0.5029
Adjusted R2	0.4989
F Statistic	125.7***

*Table 2: The table shows the results of the regressions with natural logarithm of the value of EU exports to Africa for the full sample of export data. ***, **, *, and . denote statistical significance at 0-0.1%, 0.1-1%, 1-5%, and 5-10% levels, respectively. Source: Created by the authors. Information: The regression analyses were conducted in RStudio by the authors.*

Appendix E: Proportion of EU member states' extra-EU trade with Africa of total EU member states' extra-EU trade

Country code	Stone & Glass	Fooodstuffs	All products
AT	1.60%	0.99%	3.01%
BE	24.54%	31.51%	5.50%
BG	1.75%	12.13%	3.21%
CY	4.34%	7.90%	4.33%
CZ	5.10%	3.81%	1.43%
DE	12.62%	11.83%	4.61%
DK	0.44%	4.84%	2.41%
EE	9.29%	25.09%	1.75%
ES	6.23%	13.49%	17.95%
FI	0.31%	3.91%	2.34%
FR	3.47%	20.99%	12.18%
GR	3.20%	9.36%	11.50%
HR	1.69%	3.62%	3.90%
HU	2.12%	6.05%	0.83%
IE	11.00%	1.93%	1.02%
IT	7.47%	13.60%	14.94%
LT	2.46%	1.95%	2,26%
LU	7.67%	6.33%	0.89%
LV	0.40%	0.37%	0.50%
MT	5.77%	3.96%	3.59%
NL	2.14%	21.37%	5.72%
PL	1.31%	6.14%	2.48%
PT	9.83%	16.56%	17.92%
RO	5.02%	5.65%	3.56%
SE	0.66%	4.86%	3.32%
SI	0.94%	0.25%	2.88%
SK	2.89%	3.24%	2.89%
60^{th} percentile	7.63%	13.58%	5.67%
20^{th} percentile	1.37%	3.32%	1.85%

Table 1: Percentage of EU member states' extra-EU imports from Africa as a share of total EU member countries' extra-EU trade. Source: Created by the authors.

Country code	Animal	Plastics & Rubbers	Textile	Vegetables	All products
AT	6.70%	0.14%	18.70%	0.71%	3.29%
BE	20.19%	45.22%	9.81%	13.34%	12.73%
BG	0.50%	14.59%	6.02%	43.84%	12.30%
CY	0.74%	13.11%	2.65%	18.72%	19.21%
CZ	1.91%	2.37%	11.40%	3.43%	4.74%
DE	9.49%	1.33%	5.20%	16.75%	3.61%
DK	1.84%	2.35%	2.95%	2.18%	2.86%
EE	0.73%	11.91%	2.09%	39.56%	5.68%
ES	8.71%	21.21%	22.0%	11.73%	63.26%
FI	2.26%	1.52%	1.44%	16.02%	4.89%
FR	18.08%	7.06%	13.74%	43.64%	10.66%
GR	2.20%	24.60%	13.04%	11.20%	16.80%
HR	7.08%	2.29%	0.27%	5.37%	3.86%
HU	2.58%	0.54%	9.36%	2.16%	2.91%
IE	8.08%	0.16%	1.71%	0.62%	1.56%
IT	4.95%	2.,67%	5.54%	10.11%	16.36%
LT	1.57%	5.66%	3.10%	49.30%	6.17%
LU	0.00%	4.85%	0.81%	10.50%	8.07%
LV	5.34%	2.40%	2.06%	56.36%	7.93%
MT	0.63%	54.70%	16.85%	0.03%	5.54%
NL	0.15%	24.52%	6.64%	8.97%	3.24%
PL	16.46%	4.60%	4.62%	26.81%	4.79%
PT	19.50%	5.70%	10.36%	25.90%	18.36%
RO	2.53%	7.25%	2.59%	40.77%	11.06%
SE	12.42%	3.58%	0.36%	7.13%	3.76%
SI	3.26%	0.23%	4.44%	2.47%	3.18%
SK	2.82%	0.12%	4.38%	0.20%	3.89%
60th percentile	11.16%	14.29%	11.19%	37.01%	12.64%
20th percentile	9.61%	1.37%	2.07%	2.24%	3.35%

Table 2: Percentage of EU member states' extra-EU imports from Africa as a share of total EU member countries' extra-EU trade. Source: Created by the authors.

Appendix F: Robustness tests for OLS regressions with midterm effects

	Dependent variable: log(EU import values)		
Product sample:	HS code aggregated to 2 digits	Excluding droughts	Excluding product groups with low share of total extra-EU import
1 month before	-0.0003 (0.0060)	0.0145 (0.2250)	0.0066 (0.0059)
Disaster	0.0102 . (0.0060)	0.0050 (0.0050)	0.0070 (0.0059)
1 month after	-0.0156* (0.0061)	-0.0243*** (0.0050)	-0.0276*** (0.0060)
2 months after	-0.0087* (0.0061)	-0.0114* (0.0050)	-0.0172** (0.0059)
3 months after	-0.0079 (0.0060)	-0.0068 (0.0050)	-0.0087 (0.0059)
4 months after	-0.0035 (0.0060)	-0.0037 (0.0050)	-0.0054 (0.0059)
5 months after	0.0028 (0.0060)	-0.0015 (0.0050)	-0.0009 (0.0059)
6 months after	0.0116 . (0.0060)	0.0030 (0.0050)	0.0101. (0.0059)
Observations	2590802	5142473	3649728
R2	0.4526	0.6453	0.6717
Adjusted R2	0.4513	0.6375	0.665
F Statistic	368.4***	83.05***	99.72***

*Table 1: The table shows the results of the regressions with natural logarithm of the value of EU imports to Africa. ***, **, *, and . denote statistical significance at 0-0.1%, 0.1-1%, 1-5%, and 5-10% levels, respectively. Source: Created by the authors. Information: The regression analyses were conducted in RStudio by the authors.*

Product sample:	Dependent variable: log(EU export values) HS code aggregated to 2 digits	Excluding droughts	Excluding product groups with low share of total extra-EU export
1 month before	0.0071 (0.0031)	0.0047 (0.0027)	0.0028 (0.0027)
Disaster	-0.0305*** (0.0031)	-0.0405*** (0.0027)	-0.0359*** (0.0027)
1 month after	-0.0314*** (0.0031)	-0.0386*** (0.0027)	-0.0386*** (0.0027)
2 months after	-0.0086** (0.0031)	-0.0129*** (0.0027)	-0.01507*** (0.0027)
3 months after	-0.0111*** (0.0031)	-0.0099*** (0.0027)	-0.0129*** (0.0027)
4 months after	-0.0059 (0.0031)	-0.0025 (0.0027)	-0.0034 (0.0027)
5 months after	-0.0098** (0.0031)	-0.0176*** (0.0027)	-0.0132*** (0.0027)
6 months after	-0.0072* (0.0031)	-0.017052*** (0.0027)	-0.0099*** (0.0027)
Observations	7078569	23963663	23515407
R2	0.2807	0.4787	0.4771
Adjusted R2	0.2804	0.4756	0.474
F Statistic	785.1***	154.7***	155.8***

*Table 2: The table shows the results of the regressions with natural logarithm of the value of EU exports to Africa. ***, **, *, and . denote statistical significance at 0-0.1%, 0.1-1%, 1-5%, and 5-10% levels, respectively. Source: Created by the authors. Information: The regression analyses were conducted in RStudio by the authors.*