Stormy Seas: Unpacking the Trade Effects of Disruptions in the Container Ship Network

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Abstract

This paper investigates how much bilateral trade is affected by temporary disruptions of shipping networks caused by storms. Specifically, we examine how much trade is directed to other shipping routes or does not take place at all. We unpack the aggregate impact of oceanic cyclones by examining transportation volume and freight rates by a major container ship company. In event-studies nested in a gravity-style equation, we find that a cyclone reduces trade by 2% between countries across all modes of transport, while this effect doubles for affected port-pairs. After a storm, shipping firms increase freight rates on affected routes amplifying the trading impact. Neighboring port pairs step in as substitutes for industrially relevant goods such as machinery, electrical and intermediate materials. Data on geo-located ship voyages show that following a storm, ships travel at slower speed incurring delay by up to 30 hours depending on the shipping company.

JEL-classification: F14, F18, Q54, R40

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1 Introduction

Extreme weather events such as tropical cyclones pose a threat to economic production and international trade. Over 35 tropical cyclones rage across oceans and coastal areas every year. At the same time, container ships are the engine of global trade as they transport approximately 46% of all international trade by value across all transportation modes and ship types[1]. Instances like attacks on container ships by the Huthi rebel groups, the blockade of the Suez Canal as well as port closures in China due to Coronavirus outbreaks have illustrated the importance of the shipping network for supply chains and delivery of consumer goods. Therefore, we ask how much do temporary disruptions caused by storm storms affect bilateral trade? Specifically, we examine how much trade is re-directed towards other routes, creating winners and losers on the part of ports and shipping companies? Trade could be also re-directed towards other means of transport like air cargo instead of container ship.

In our analysis, we *unpack* the aggregate bilateral short-term trade effects of storms in a disaggregated analysis at global scale[2]. Unlike prior studies which exclusively studied storms that hit land, we examine storms *at sea* that cross trading routes. Going from monthly country-pair trade statistics to port-pair transactions data, we study the impact on traded quantities but also on transportation costs as charged by one of the largest shipping companies worldwide. For this, we nest an event-study in a gravity-style PPML regression of trade, controlling for trade seasonality and trade trajectories. With the onset of a tropical cyclone, we find a reduction in trade between affected port-pairs, accompanied by an increase in freight prices, potentially prolonging the trade decline. Regarding substitution of trade towards neighboring routes that were not directly affected by the storm, we find that strategically important intermediate goods like machinery, electrical or minerals are re-directed to these alternative routes. However, for final consumer goods, neighboring routes rather amplify the initial shock rather than mitigate it. Moreover, to examine channels behind the aggregate results, we leverage the movement profiles of

[1] Value calculated from seaborn trade accounting for 70% of global trade (UNCTAD, 2019) and from container ships carrying 66% of seaborn trade by value (Notteboom et al., 2022)

[2] Since the frequency of tropical cyclones has not changed systematically over the past decades, this work focuses on the short term disruptions of trade along pre-existing routes and not on long term adjustments of trade or the transportation industry.

all container ships globally. This allows us to document the heterogeneous behavior of cargo vessels at sea like speed, effective distance traveled, resulting in different extent of delays for different shipping operators.

Our study has important implications for our assessment of the costs of climate change. We find that the actors of global trade deal differently in the short-run with the hazards posed by tropical cyclones. As climatic changes heat up the oceans, especially severe tropical cyclones are projected to become more severe (IPCC, 2019) in the upcoming decades. Trading operators need to think about how the costs for shipping companies, but also the repercussions for producers and consumers who rely on smooth functioning of global supply chains can be kept at a minimum.

2 Related Literature

First, we apply the gravity model of trade at the port-pair level to the treatment effect of tropical cyclones on trade. The paper, therefore, relates to the strand of literature that concerns the effect of natural disasters on trade. Country-level studies such as Gassebner et al. (2010) or Felbermayr et al. (2020) find that that exports decline. Typically, the impact is stronger, the less developed the country. Regarding imports, the impact is milder (Felbermayr et al., 2020). In the analysis by Gassebner et al. (2010), the effect on imports is negative for autocratic countries and even positive for democracies. While Gassebner et al. (2010) point towards strong political institutions being able to dampen the impact, Felbermayr et al. (2020) stress the role of borrowing for smoothing short-run fluctuations. However, country-level studies treat the country as a "black box". It remains unclear to what extent the effect is transmitted via industrial production, the agricultural sector or the transportation sector. Some more recent studies examine these channels more closely: For instance, Costinot et al. (2016) and Gröschl et al. (2020) evaluate the impact of extreme weather on the agricultural sector. Specifically, Gröschl et al. (2020) show that high connectedness of a region leads to higher relocation of economic activity in the event of a disaster. Besedeš and Murshid (2019) focus on air traffic as a mode of transport in their examination of a volcano eruption's effects on trade. To the best of the authors' knowledge, this is the first work to study the economic impact of storms at sea at the global level and the impact of disasters on the worldwide maritime transport industry.

Moreover, we complement the case studies on natural disasters and trade and extend to a global analysis while sticking to the micro-level perspective that makes the case studies so appealing. Elliott et al. (2019) use firm-level data from manufacturing plants in China. They find that tropical cyclones cause reductions in sales which are worth 2.3 billion USD annually, corresponding to 1% of turnover. Sales are reduced more strongly to domestic buyers in comparison to international buyers. Purchases, on the contrary, are reduced more strongly from international partners. Friedt (2021) examines the consequences of Hurricane Katrina. The analysis focuses on the transport infrastructure and, thus, uses port-level data. The author finds large and lasting trade reductions in affected ports, while adjacent ports benefit. In a similar vein, Hamano and Vermeulen (2020) analyze the case of the 2011 Tsunami in Japan on the port-level. They set up a microfounded model of firms and ports, and find strong overall declines in port activity, since only 40% of the reduction was substituted by other ports. The open question remains whether the capacity to shift port activity within the country only applies to developed countries with a high number of ports and a dense network of roads between them. In the present paper, we move beyond the existing case studies to a global analysis of storm exposure on trade and port substitution.

This study also relates to the literature on transportation costs. Instead of assuming that bilateral transportation costs are constant, this literature examines the regionally- and time varying dimensions of transportation. The seminal study by Hummels and Schaur (2013) finds that additional transportation time raises costs by 0.6 to 2.1 percent of traded value. Furthermore, Clark and Kozlova (2020) argue that higher uncertainty in arrival time of imports leads to higher buffer stock holdings which reduces bilateral trade. We provide details on one source of delayed and uncertain time of transportation: natural disasters. A recent strand of the literature has also focused on the effects of dynamics of the shipping network on trade. Authors investigate the effect of market power (Hummels et al., 2009), search frictions (Brancaccio et al., 2020), the Panama Canal expansion (Heiland et al., 2019), the

Suez Canal closing (Feyrer, 2021), piracy (Sandkamp et al., 2022), scale effects in the shipping network (Ganapati et al., 2020) and oil price (Felbermayr and Stamer, 2022). To this most recent strand we contribute the study of storms at sea that provide unparalleled exogenous variation to behavior of the shipping industry.

This paper is structured as follows: Section 3 gives a brief background on the container shipping industry and then describes the data sources and the empirical approach. Next, Section 4 presents our main results of the empirical analyses at the country-level and investigates various potential adjustment mechanisms by the exporter. Section 5 explores whether the results can be explained by the ships' behavior at sea. Section 6 discusses alternative specifications and, finally, Section 7 concludes.

3 Data and empirical approach

3.1 Shipping data

We measure trade from three angles: First, we employ standard aggregate monthly bilateral trade flows from *Comtrade* between 2015 to 2019. Second, we enrich the analysis using port-pair level container ship transactions with monthly volume and per-container or per-ton prices, separately for *HS2*-product categories, between 2015 to 2018. Third, we complement the prior analysis using individual container ship voyages reconstructed from geo-localized ship positions between 2015 to 2021, yielding 6.5 million observations. This subsection describes the data sets and the following subsection outlines the combination of ship and storm data.

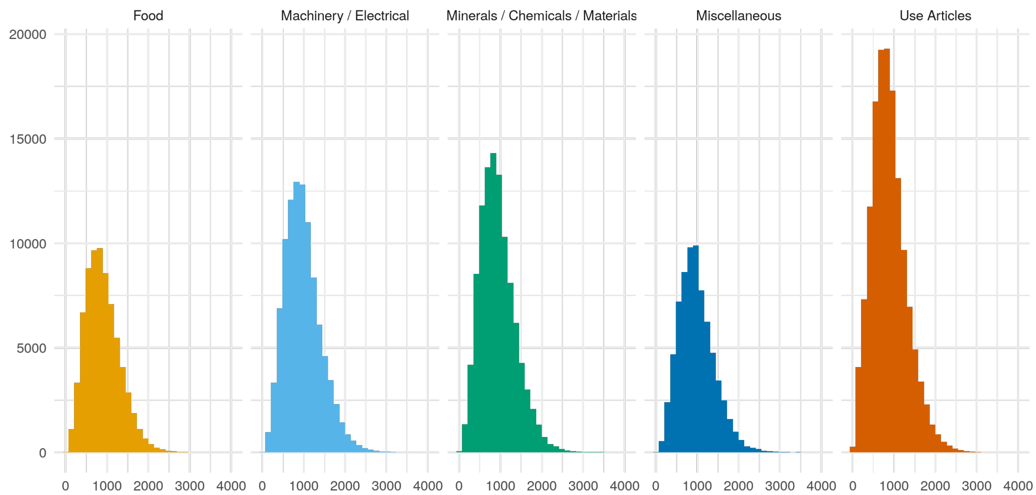
While *Comtrade* data is widely used in the trade arena, the other two datasets are unique to our analysis and deserve more attention.

Container transaction data. We leverage monthly transaction data for the years 2015 to 2018 from one of the largest global container shipping companies.[3] The data includes shipping costs and shipping volumes. The shipping firm at hand belongs to the five leading shipping liners, which control almost two thirds of the global market. In the years following the Great Recession in particular, the maritime indus-

[3] Due to the sensitivity of the freight rate information in the proprietary data, we can not refer to the shipping firm by name.

try consolidated significantly leading to the high market power today. The shipping firms are further organized into alliances which share transportation capacity among alliance members. Hence, the monthly transaction data used includes transportation of goods across the entire network spanned by the alliance. Notwithstanding a slight concentration on developed markets, Felbermayr and Stamer (2022) show that the transaction data is geographically evenly distributed.

Figure (1) Distribution of freight costs across product categories



Notes: Histograms of freight costs in USD per container per product category. Based on monthly container shipping transactions, per port-pair.

Figure 1 shows the distribution of freight prices for a standard 20 footlong container with different product categories. assign the HS2 product groups into five broader categories. Freight prices do not differ to a large extent, however, summary statistics reveal that it is cheapest to ship final consumption goods like food and use articles. Machinery and Materials are more expensive to ship. However, the histograms cover different routes so that the freigh prices are not narrowly comparable.

Tracing cargo flows directly has great advantages over tracking the container ships. Container ships carry goods on fixed routes that include several stops at ports to load or unload cargo, so called port calls[4]. We consider the transportation of cargo to be "direct" if the same container ship carries goods from an origin to the destination port regardless of intermediate port calls. If, however, the origin port and destination port do not lie on the same shipping route, the containers are

[4]Unlike bulk ships, that operate like taxi cabs, contracting for a specific trip as exploited by (Brancaccio et al., 2023, 2020)

unloaded at a port to be transferred to a different ship on another line. This process is called transshipment, which makes tracing good flows impossible with container ship movements alone. The data set from the shipping firm remedies this as it also contains information on the transshipment locations of cargo flows.

The volume of goods is measured in tons. The more than 206,000 observations are organized at the port pair, year, month and HS-2-product level. In order to arrive at a balanced dataset, we fill in the missing values with zeros, which implies that no shipping has taken place by the shipping company, indeed a relevant case in our setting with storms in the extreme case discouraging trading altogether. It may well be that another shipping company "fills in" for the lost trade, which is why we contrast these data with the aggregate Comtrade data.

Container ship voyages. We additionally construct global container ship voyages, i.e. the information at what time a particular container ship cruises from a start port to an end port. Our data is derived from the maritime Automatic Identification System (AIS) which emits a ship's position to avoid collision at sea. We make use both of port calls and positional information at high sea, which we connect using a shortest-path algorithm which avoids shallow waters such as atolls and coastal lines, but can traverse navigable rivers and canals. This allows us to trace the exact vessel movements between a start port and an end port as example connections illustrate in Figure 2. The calculation of the data set is described in more detail in Felbermayr and Stamer (2022). For the available time period 2015 to mid-2021, the data amounts to 6.5 million voyages connecting a given port pair at a specific point in time. Additionally, the reconstructed routes provide information on the vessel's traveled distance, speed, average draught and share of capacity loaded. The level of observation for the voyage data set is port pair, vessel, date and time.

The information on voyages also allows us to compute approximations of good flows: For instance, using the average draught of the ship for the voyage, we derive the share of capacity utilized[5] and multiply this value with the carrying capacity of the ship in number of containers. This yields an approximation for the volume of trade measured in Twenty-foot Equivalent Units (TEU).

[5]Share of capacity used equals actual draught minus minimum draught divided by maximum draught minus minimum draught

Figure (2) Cargo Shipping Trips

Notes: The map shows examples of container ship trips in the data set.

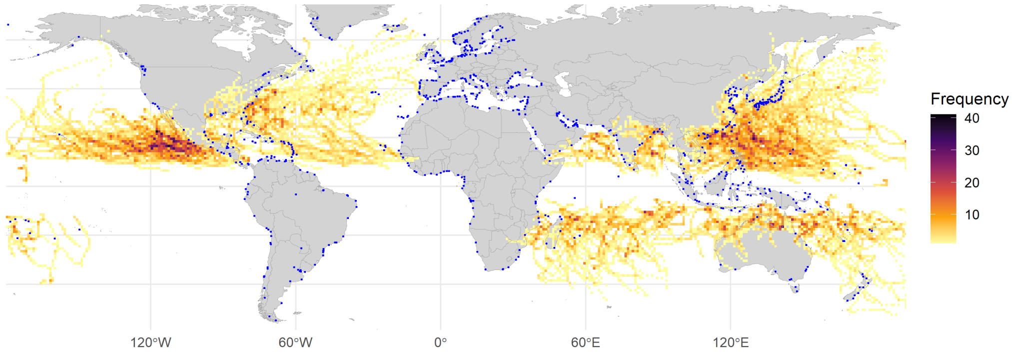
The average container is transported more than 14 thousand kilometers at sea - a combination of voyages that in total take almost 28 days at an average speed of 26.2 km/h. A whole round trip around the globe would correspond to the maximum measured distance of more than 43,000 km. On average, vessels stop 5.6 times including the destination and transshipment port to transport the monthly mean shipments of 35 containers tons for approximately 76 thousand US Dollars revenue. Hence, the average freight rate amounts to 990 USD per container.

3.2 Tropical cyclone data

For natural disaster exposure, we use the daily tracks of tropical cyclones from the International Best Track Archive for Climate Stewardship (IBTrACS). A tropical cyclone (TC) consists of a rotating cloud system that forms in tropical or subtropical waters and sustains a positive windspeed. TCs are further classified into tropical depressions (less than 62 km/h maximum sustained windspeed), tropical storms (above 63 km/h, but less than 118 km/h) and tropical cyclones (above 119 km/h). Only the last group is classified as "hurricanes" in North America or "typhoons" in the Western Pacific. We keep all tropical cyclones in the data set and, somewhat inaccurately, use "storm" synonymously with cyclone.

We apply a wind field model around the tracks that takes into account air pressure and temperature (Holland, 2008). Figure 3 shows a map of cyclone frequencies at the pixel-level between 1980 and 2020. The darker the color, the more cyclones have

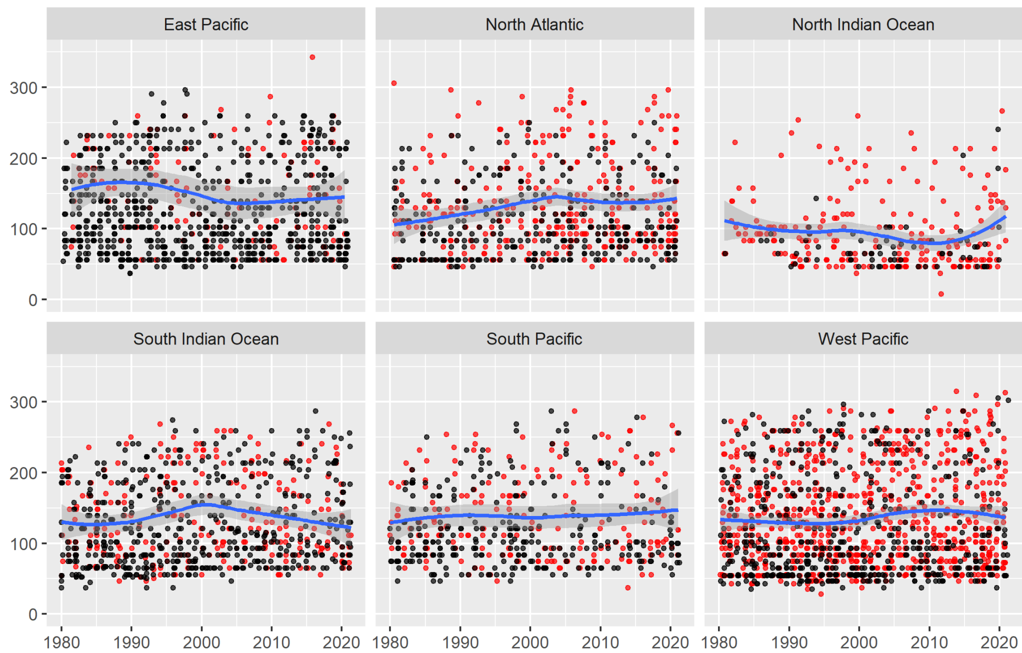
Figure (3) Frequency of Tropical Cyclones since 1980



Notes: Global cyclone frequencies based on IBTrACS between 1980 and 2020. Blue dots are deep water ports.

occurred in that location. Note the high frequency of storms in the South China Sea and Philippine Sea, as well as to the West of Mexico and to the South East of the United States. These regions prone to cyclones are also important to various shipping routes such as connections between major shipping hubs in East Asia and the rest of the world. Note also the occurrence of tropical cyclones in other basins such as the Indian Ocean and the Arabian Sea.

Figure (4) Maximal attained windspeeds of tropical cyclones since 1980, by basin



Notes: Maximal attained windspeeds in km/h. Red dots indicate tropical cyclones that eventually make landfall, while black dots indicate that the cyclone only occurred at sea. The blue line is based on a locally weighted scatterplot smoothing with 95-percent confidence intervals in gray.

To further illustrate the geographic distribution and intensity of cyclones, Figure 4 draws one point for every cyclone from 1980 to 2020 by basin and depicts the maximum attained wind speed on the y-axis. In particular the West Pacific basin shows a very high number of average cyclones and cyclones reaching sustained wind-speeds of 150 km/h. The trend lines by basin do not show a significant uptick of wind speeds in the past four decades. Note the high share of cyclones that never make landfall, that is reflected by the black dots as opposed to the cyclones that eventually hit land indicated by the red dots.

One will wonder whether trading occurs according to seasonal storm hazards. If tropical cyclones have a clear seasonal pattern, shipping companies might try to circumvent storm risks by trading outside of storm seasons. In **??**, the blue line shows the number of cyclones per month (left scale), the orange bars show the count of departing ships per month (right scale). This is shown separately for each ocean basin. We detect a clear seasonality in the storm occurrences: As a example, in the North Atlantic, most storms occurr between August to October with September featuring (infamously) as "peak Hurricane" month. The trading pattern also exhibits a seasonal pattern. More goods are traded across the North Atlantic in October prior to the holidays (i.e. Black Friday shopping, Christmas shopping). In several ocean basins, the month with the most cyclones also exhibits slightly less oceanic ship departures as compared to the adjacent months. Yet, the pattern is very weak. In sum, shipping patterns are hardly counter-cyclical (if at all). This implies that shipping companies seem to anticipate storm seasons only to very small extent but rather operate based on consumer demand and production cycles. In our analysis, we abstract from this seasonality by including monthly fixed effects to focus on abnormal deviations away from monthly expected patterns.

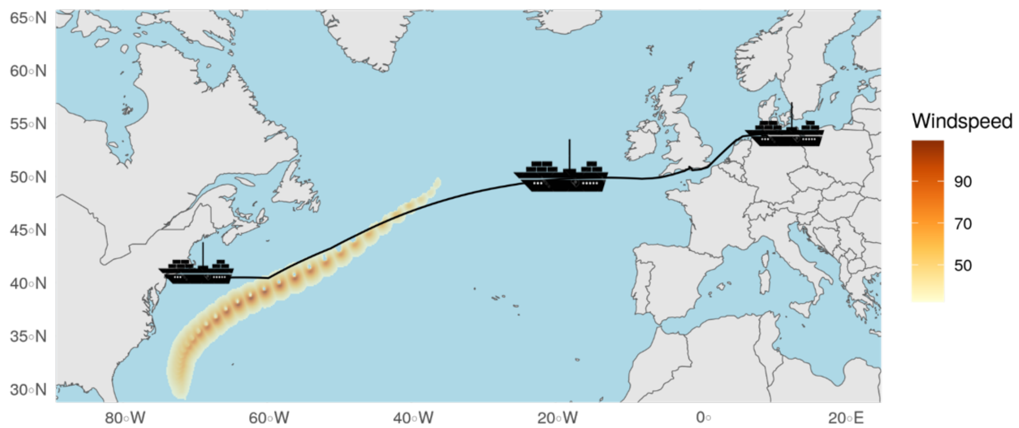
Figure (5) Seasonality of tropical cyclones vs. trade volume

Notes: Orange bars reflects the count of departing ships in each ocean basin. Blue line reflects the number of tropical cyclones in each basin based on iBTrACS.

3.3 Linking storms to trading routes

As a last step, this subsection outlines the derivation of the storm treatment, i.e. the mapping of ship voyages and tropical cyclones. This is conceptionally not trivial, because vessels likely sail detours when a storm is headed for the typical route. Precisely when a storm interferes with voyages, the vessels' paths may not show any spatial intersection with the cyclone. To overcome this, we identify a representative route across the entire observation time for every port pair. This representative route is the connection that marks the 10th percentile shortest route for every port pair. Note that our definition aligns with that of Dunbar et al. (2023). Hence, the chosen route marks an ideal route without detours for port calls or storms, but does not constitute an extreme outlier. If the cyclone's windfield spatially overlays with the representative route, we consider the route from origin port, o, to destination port, d, to be intersected and the dummy $StormOnRoute_{od,ym}$ takes on the value 1.

Figure (6) Linking storms to routes



Notes: Route from Hamburg, DE, to New York, US. Hurricane *Gert* forms on August 12 2017 and dissolves on August 18, 2017. According to iBTrACS, it reaches windspeeds up to 176 km/h. It starts in the South and moves Northwards.

The $StormOnRoute_{od,ym}$ dummy variable equals to 1 for trading if the cyclone formation falls into this the month. Note that limits the ability of exporters to redirect cargo flows at time t to other transport modes: Exporters are typically advised to book shipment for cargo one to two weeks before the ready date, at which point the container must arrive at the origin port.[6] At least two more days follow in

[6] See, for instance, guidance by Maersk, the largest shipping company in

which the cargo passes customs, is being moved to the docking site and eventually loaded onto the vessel. The exact number of days depends on whether the goods arrive to the port already in a container. During the month of the vessel sailing and the export customs clearance, the storm forms many thousand kilometers away at high sea and may intersect the shipping route days or even weeks later. Hence, for the vast majority of cargo flows during the treatment month, the information that the cyclone may affect the container ship will be known too late to change the transportation of the export goods. As the destructive forces of the cyclone only last a few days, in actuality only a small number of voyages is impacted by the storm. Results should, therefore, be interpreted not as an effect on a single voyage, but explicitly on monthly observations affected by storms at some point during the month.

Overall, affected ships are not expected to change their itinerary altogether. Instead, they will try to follow their fixed routes as closely as possible, adjusting their speed and their path, changing their port stops as minimally as possible so that the loaded cargo reaches their customers at the least additional costs.

3.4 Estimation

The gravity-type equation in the event-study framework, which we estimate with the Poisson Pseudo Maximum Likelihood (PPML) estimator, is represented as follows:

$$
\begin{aligned}
log(Trade_{od,ym}) = \sum_{t=-3}^{3} \; & \beta_t[StormOnRoute_{od,ym+t}] \\
& + \mu_{o,ym} + \mu_{d,ym} + \mu_{od,m} \; + \; \epsilon_{od,ym}
\end{aligned}
$$

$Trade_{od,ym}$, reflects the trade in terms of value and weight from an origin o to a destination d in a specific year y and month m. The main treatment indicators are $StormOnRoute_{od,ym+t}$. These indicators signify whether a storm affected the route between the origin and destination at time $t = 0$, the event-study window is running from $t = -3$ (prior to storm) to $t = +3$ (after storm). Each indicator has

the world, to finalize a booking at least five days before the ready date https://www.maersk.com/news/articles/2021/08/25/guidance-set-containers-pick-up-date-refresher a separate coefficient β_t. All coefficients are estimated relative to the pre-treatment period $t = -1$. Additionally, the equation includes a rigorous set of fixed effects: $\mu_{od,m}$ for Origin x Destination x Month, that crucially not only capture differences in levels between origin-destination pair but also month-of-year seasonality at the origin-destination level (like pre-holiday trading, or potentially cyclone anticipation). Moreover, $\mu_{o,ym}$ are fixed effects for Origin x Year x Month, $\mu_{d,ym}$ for Destination x Year x Month, to tease out different trading trajectories over time. $\epsilon_{od,ym}$ reflects the standard errors, clustering is performed within Origin-Destination pairs.

One empirical issue deserves more discussion: The recent difference-in-differences literature has raised important points. One notable concern is the presence of multiple overlapping storms, which introduces the risk of comparing a treated observation to an already treated observation, resulting in a "Forbidden comparison". This situation could lead to a negative weighting problem, posing challenges in the estimation process. In response to these challenges, new estimators have emerged (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). However, these methods are not well-suited for the Poisson Pseudo Maximum Likelihood (PPML) estimation, particularly crucial in our application given the prevalence of zero values in the trade data.

A potential solution is presented in a paper by (Nagengast and Yotov, 2024). The authors incorporate standard gravity model practices into Wooldridge (2023) *Extended Two-Way Fixed Effects* approach, which has also been implemented in statistical software[7].

Meanwhile, as an ad-hoc solution applicable for the present, we propose restricting the analysis to isolated treatment events with no other storm occurrences within 3 months prior or after the specific event. This approach aims to mitigate the challenges associated with overlapping storms and facilitates a more robust empirical estimation.

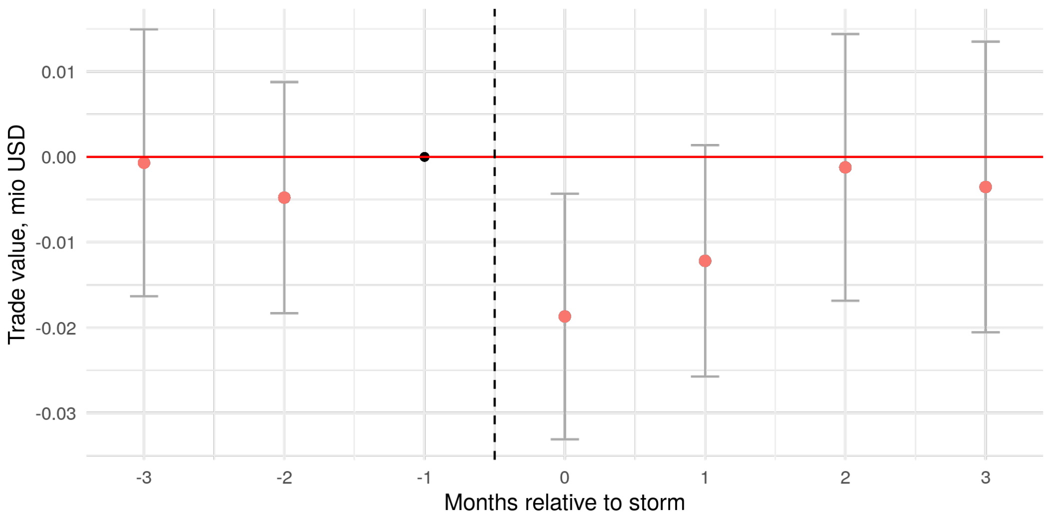
[7]Encouragingly, discussions with the authors of Nagengast and Yotov (2024) indicate that this promising development will be available soon.

4 Results

4.1 Aggregate effect

Country-level estimates using COMTRADE trade by value across all transportation modes serve as the baseline results. Figure 7 presents the findings. Given the rigorous fixed effect system, the identifying variation comes from nonseasonal storms at the country-pair level. The identifying assumption holds if the resulting error term is uncorrelated with economic events that impact non-seasonal trade flows at the country-pair level and simultaneously correlated with the non-seasonal tropical cyclones. Furthermore, we restrict exposures to those storms that did not have any other storm during the 3 prior months.

Figure (7) Storm effect on trade, country-pair level



Notes: Regression of Trade in mio USD value include fixed effects for Country Pair, Month, Country Pair x Month, End Country x Year x Month and Start Country x Year x Month. Only episodes with no storm prior to the storm month. Estimated with PPML. 95-percent confidence intervals shown, where standard errors are clustered at the country-pair-level. Detailed regression results in Table A1.

All coefficients in the event-study graph are relative to period -1, the month just before the storm. The regressions in the table overall show a decline in trade across all transportation modes due to a storm. The coefficient for *Months from Storm = 0*, is -0.019, implying an almost 2% decrease in trade overall during a month affected by an unexpected storm. Trade remains dampened for one additional month. Yet, during subsequent months after the storm, trade rebounds back to zero.

As a test of the parallel trends assumption, we find that the pre-treatment coefficients are insignificant from zero. This is reassuring that treated country-pair observations are not systematically different from the comparison observations prior to the storm. No anticipation of the storm seems to take place.

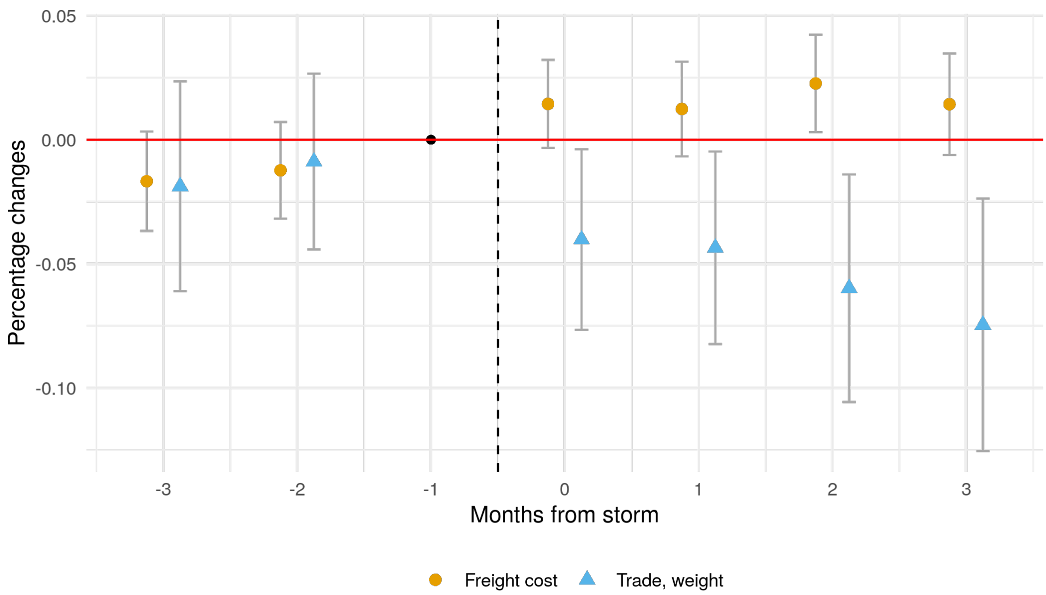
In this aggregate view, any anticipation of the storm and mitigation responses may occur *within* the period of treatment. So these aggregate results capture the average monthly effect of storms and include any potential adjustments such as substitution between transport modes and port pair routes. In what follows, we open the black box to understand the margins of substitution, the time dynamics.

4.2 Port-pair transactions

We now turn towards an examination of monthly port-pair-level transactions by one of the largest shipping companies worldwide. In Figure 8, the coefficients, represented by blue points denoting trade estimates in weight units and orange points signifying freight costs, reveal a temporal pattern. Prior to the storm, both trade and freight costs are statistically insignificant; however, a noteworthy divergence emerges in the aftermath of the storm. Trade undergoes an initial 4% reduction, followed by a continual diminishing trend, while freight costs transition from insignificance to a persistent positive effect. This pattern aligns coherently with a price-demand model, where higher prices coincide with lower demand for shipping. The intriguing interpretation of these findings suggests a dual impact of the storm on trade dynamics: a first-order effect of direct reduction in trade, and a second-order effect wherein higher prices appear to amplify the adverse consequences of the storm on trade.

Next, we distinguish in our analysis by product categories. We group the provided HS2-product categories into four distinct classifications: Machinery/Electrical, Minerals/Chemicals/Materials, Consumer End Products, and Food Items. A negative effect pervades all four product categories; however, the magnitude and statistical significance varies, with particularly strong effect in the categories "Machinery" and "Food." These two categories, not only exhibit a pronounced negative impact but also emerge as the primary groups dealing with a significant rise in freight costs. Again, the decline in port-pair level trade together with the contemporaneous rise in freight costs in these specific categories pins down thes economic second-order

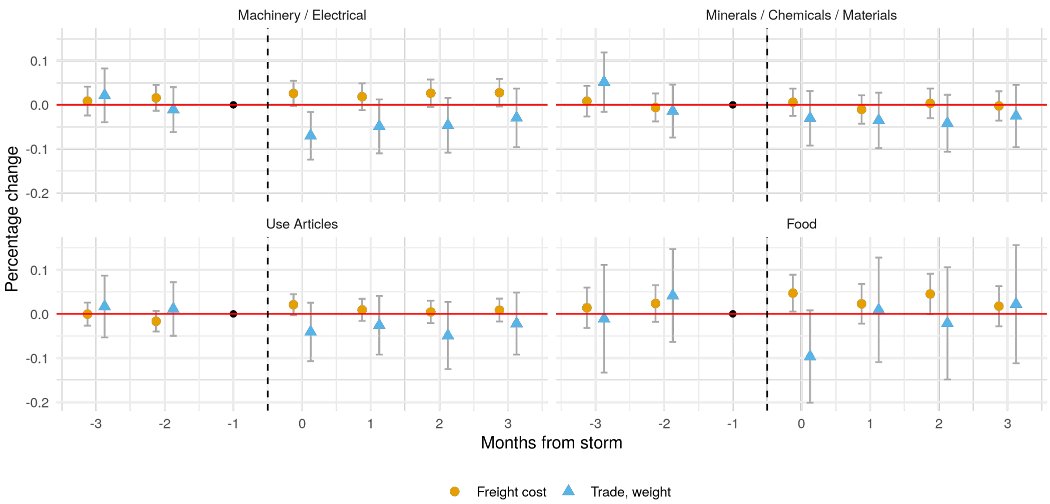
Figure (8) Port-pair transactions: quantity vs. price



Notes: Regression of trade by weight (PPML) or freight costs (OLS) with fixed effects for Port-pair, Month, Port-pair x Month, Origin Country x Month and Destination Country x Month. Standard errors are clustered at the port-pair-level. Detailed regression results in Table A4.

effects.

Figure (9) Port-pair transactions: not all goods are equal

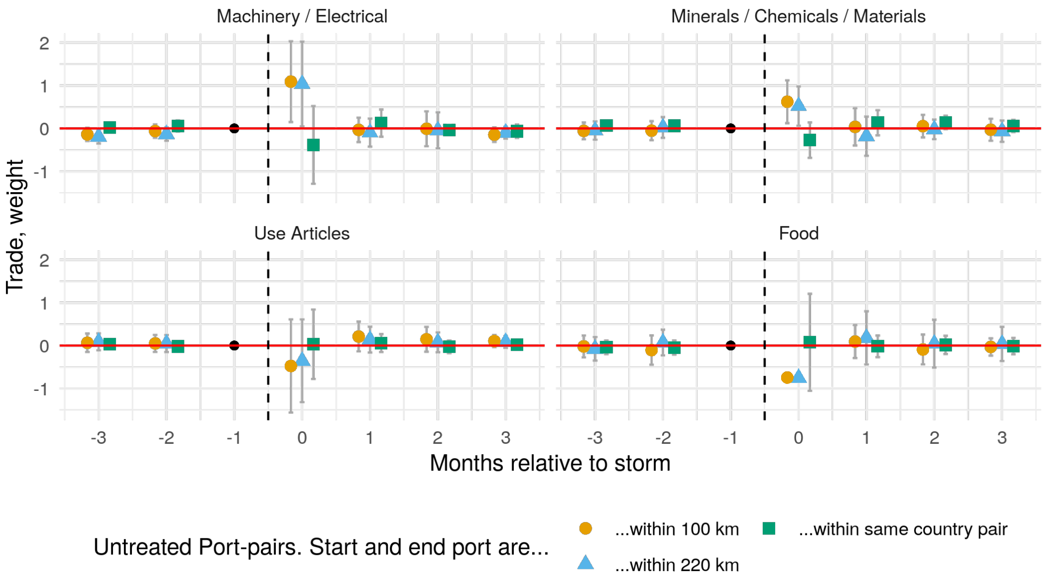


Notes: Regression of trade by weight (PPML) or freight costs (OLS) with fixed effects for Port-pair, Month, Port-pair x Month, Origin Country x Month and Destination Country x Month. Standard errors are clustered at the port-pair-level. Product categories: **Machinery/Electrical**: Machinery / Electrical, Transportation. **Minerals/Chemicals/Materials**: Mineral Products, Chemical and Applied Industries, Stone/Glass, Metals. **Use Articles**: Plastics and Rubber, Raw Hides, Skins, Leather and Furs, Wood and Wood Products, Textiles, Footwear/Headgear. **Food**: Animal and Animal Products, Vegetable Products, Foodstuffs.

4.3 Substitution from closeby routes

How do adjacent port-pairs react? Do they dampen or even aggravate the immediate negative effect?

Figure (10) Port-pair transactions: substitution from closeby routes



Notes: Regression of trade by weight (PPML) with fixed effects for Port-pair, Month, Port-pair x Month, Origin Country x Month and Destination Country x Month. Standard errors are clustered at the port-pair-level. Product categories: **Machinery/Electrical**: Machinery / Electrical, Transportation. **Minerals/Chemicals/Materials**: Mineral Products, Chemical and Applied Industries, Stone/Glass, Metals. **Use Articles**: Plastics and Rubber, Raw Hides, Skins, Leather and Furs, Wood and Wood Products, Textiles, Footwear/Headgear. **Food**: Animal and Animal Products, Vegetable Products, Foodstuffs.

In Figure 10, we next investigate the effect on *unaffected* substitution routes within affected country-pairs, or, alternatively, within a specified radius of 110km or 220km. The result unfold a nuanced pattern of response within various product categories. Notably, for machinery and minerals, there is a marked and substantial increase in traded volumes, reaching up to 100%. This surge suggests a discernible trend of short-term substitution toward alternative routes within the affected regions. Conversely, for final consumer goods, encompassing non-food products and food items, a reduction in traded volumes is observed even in non-affected port-pairs. We find the substitution patterns for geographically proximate routes, rather than for unaffected routes between the same country-pair more widely. The overarching interpretation implies that strategically or industrially significant products, such as machinery and minerals, receive priority in re-routing strategies. In contrast, food and final consumption goods experience a more pronounced disruption, either being sourced through alternative means or facing a lapse in supply. In sum, this analysis underscores that the unit of substitution is not the entire country but rather a geographically narrow area, revealing a spatially nuanced strategy on part of the shipping companies to mitigating the impacts of disruptions in trade routes. We do not find an uniform price reaction in the surrounding substitution port pairs: Figure A1 shows a marked increase in the variance in freight costs during the storm month, that hint towards both rises and declines in prices charged.

5 Channels

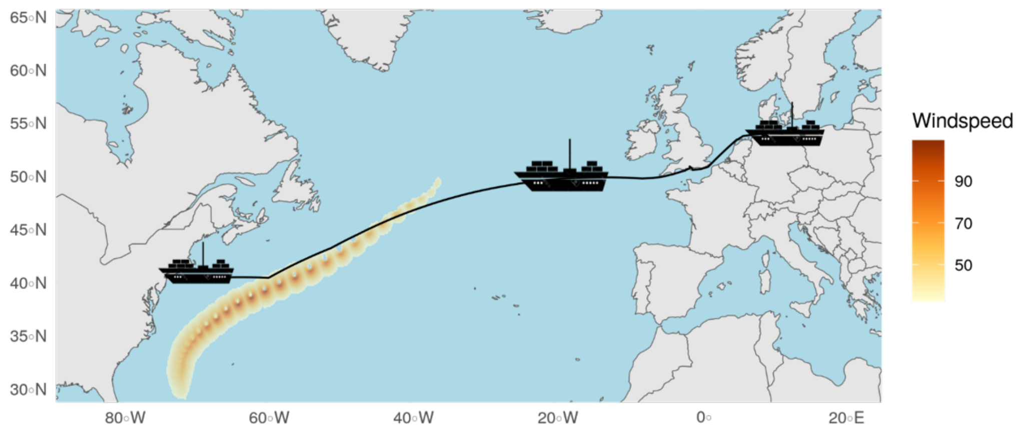
To sum up the prior results: The analysis of the trade dynamics within bilateral country-pair relationships has revealed a discernible contraction, registering a 2% decrease. A more granular analysis at the level of port-pairs unveiled a steeper decline, averaging 4%, together with a notable surge in freight prices. This interplay suggests a potential amplification of the initial adverse effect on trade. However, a mitigating factor emerged as geographically proximate port-pairs strategically substitute for a portion of the diminished trade. Notably, this substitution phenomenon is more pronounced for industrially-relevant intermediate goods, indicating a strategic prioritization in the rerouting of critical supply chains. Conversely, final consumption goods appeared to be less subject to this substitution dynamic, underscoring a heterogeneous spatial and sectoral variability in the resilience of trade networks.

The subsequent chapter tests whether the detected trade pattern can be rationalized through an examination of micro-level ship behavior. An important aspect includes to understanding how ships navigate in the face of storms. Importantly, it shall be explicitly clarified that hardly any ships regularly navigates into the center of hurricanes. Rather, due to advancements in hurricane predictions, rendering them more accurate over time, ships have the scope to adapt their navigational parameters, such as adjusting the specific detour route and speeds. This adaptive behavior of maritime logistics operators might serve as an explanation for the observed shifts in macroeconomic trade patterns.

5.1 Ship behavior

We now turn towards investigating container ship behavior, based on the entirety of container ships, with a particular focus on comparing differences in trip characteristics due to storms, including parameters such as distance traveled, speed, and time of transport. Figure 11 illustrates how the position of a ship may be related to the cyclone wind field. First, a ship may have already passed the storm field area (reflected by the ship on the left in the illustration). These voyages act as a placebo and, thus we can test whether the ship adjusts even if it has already passed a storm. We will later refer to these voyages as "before" the storm. Second, positioned in the middle, a ship is may be currently en route towards a storm, we will refer to these voyages as "during" a storm window. Third, the ship on the right, exemplifies a trip where the ship has yet to embark on its journey, designating the trip as occurring "after" the storm. This would be reflective of a spillover effect.

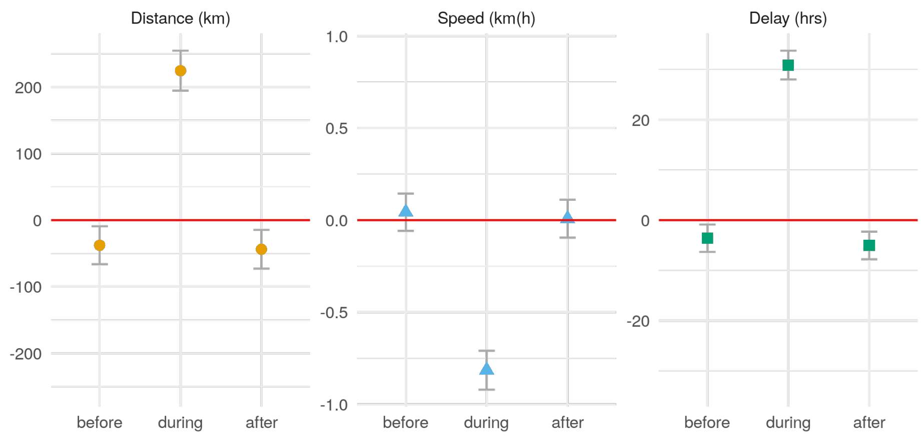
Figure (11) Example of trip



Notes: Route from Hamburg, DE, to New York, US. Hurricane *Gert* forms on August 12 2017 and dissolves on August 18, 2017. According to iBTrACS, it reaches windspeeds up to 176 km/h. It starts in the South and moves Northwards.

The key variables that we now examine include distance traveled in km (longer distances reflect a "detour"), speed in km/h, and the resulting time delay in hours. All effects are estimated such that voyages occurring 90 days before or after a storm serve as reference category. Figure 12 shows that voyages which happen during a storm exhibit additional 200 km of route. They also experience a reduction in speed by 0.8 km/h. As a result, these trips incur an added time delay of 30 hours. To assess the potential anticipation effect, the coefficient on "before" acts as a placebo test. It reflect voyages within the 90-day period prior to the cyclone, confirming the absence of storm anticipation if the ship have already passed the storm field area. Furthermore, voyages within 90 days "after" a cyclone reveals no lasting effects during a 90-day post-cyclone period, underscoring the transitory nature of the observed impacts within this temporal range.

Figure (12) Ship behavior



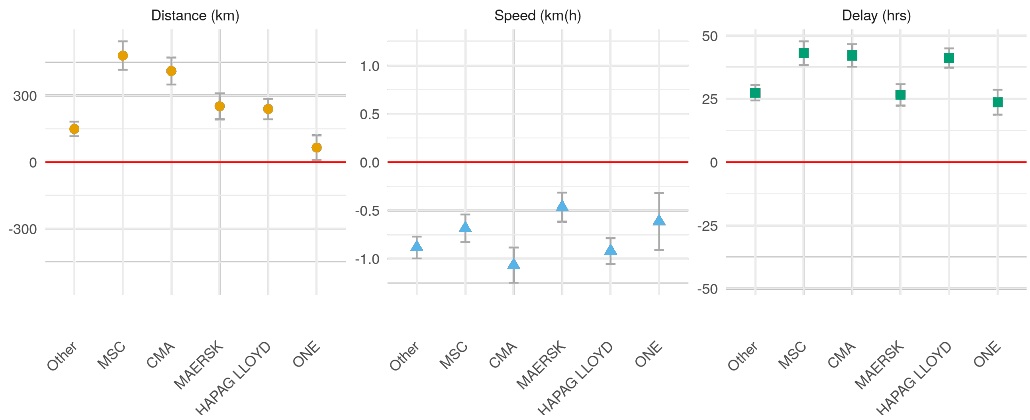
Notes: Trips which take place within 90 before/ during/ within 90 days after a tropical cyclone occurrence. Regressions include fixed effects for port-pairs, month and port-pair x month. Reference category are trips 90 days away from any storm. $N = 6,155,273$. Standard errors clustered at the port-pair-level. 95-percentile confidence intervals shown.

5.2 Ship behavior, by shipping company

The investigation into heterogeneity within the shipping industry, specifically among the top 5 shipping companies globally, unveils insightful differences in shipping performance.

In Figure 13, we focus exclusively on the effect on voyages taking place during a storm. Comparing among shipping companies within the same route (i.e. fixed effects for Port-pairs) and taking into account the seasonal patterns (fixed effects for Port-pair x Month) replicates the pattern where all examined shipping companies experience heightened delivery delays. However, the strategies employed by these companies diverge. For instance, MSC, adopts a risk-averse approach characterized

Figure (13) Ship behavior, by shipping company



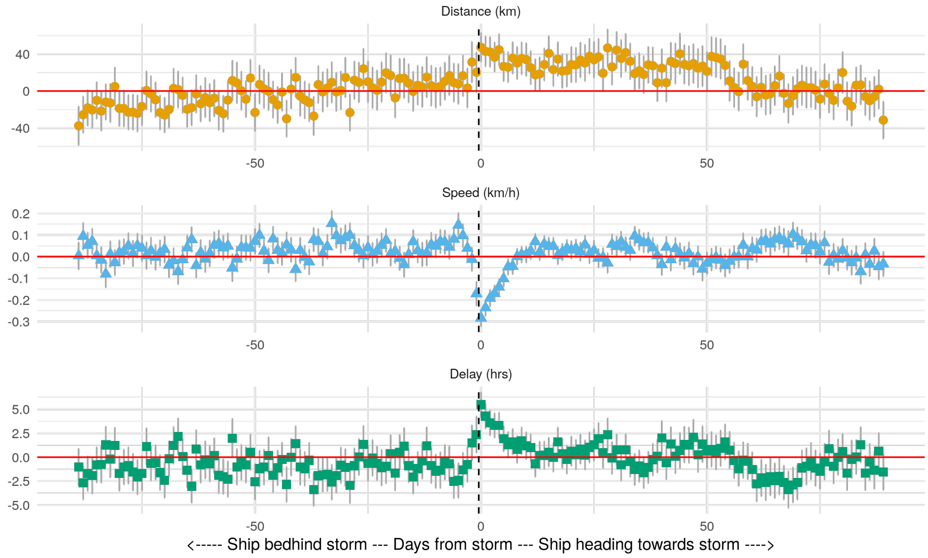
Notes: Trips which take place during a tropical cyclone occurrence. Regressions include fixed effects for port-pairs, month and port-pair x month. Reference category are trips 90 days away from any storm. Standard errors clustered at the port-pair-level. 95-percentile confidence intervals shown.

by a considerable detour, leading to substantial delays in delivery. In contrast, ONE, strategically minimizes course alterations and instead opts for reducing speed, resulting in relatively fewer delays. Notably, while within-route differences are evident, it is unclear whether these difference are indeed due to risk-aversion or due to distinct fleet characteristics among the top shipping companies, or due to different value of the transported goods.

5.3 Ship behavior, time dynamic, daily

As a final step of our investigation, we employ an analysis with daily intervals as the temporal unit and the ship's proximity to the wind field as the key determinant. In Figure 14, the horizontal axis delineates two groups: on the left, vessels that have already traversed the wind field, serving as a placebo or control group (In the illustration in Figure 11, this corresponds to the ship on the left side). On the right side of Figure 14 are vessels currently navigating toward a storm, constituting the treatment group under scrutiny (In the illustration in Figure 11, this would corresponds to the ship on the right side). Our empirical findings yield detailed insights into the operating dynamics. First, there is a discernible absence of effects on ships that have already passed through the storm field, substantiating a valid placebo effect. Second, we observe the most substantial delays of ships that are located within the 7-10 day time frame preceding the storm, primarily attributable to variations in ship speed during this critical period. Remarkably, delays extend beyond temporal proximity, as even vessels positioned up to 50 days in advance towards the storm field exhibit considerable delays.

Figure (14) Ship behavior, time dynamic, daily



Notes: Regressions include fixed effects for port-pairs, month and port-pair x month, as well as start-port x Year x Month and end-port x Year x Month. Reference category are trips that are more than 90 days away from any storm. $N = 6,155,273$. Standard errors clustered at the port-pair-level. 95-percentile confidence intervals shown.

6 Robustness

We conclude the analysis by reporting the results of a series of robustness tests for our main findings.

Isolated storm events. To address the concern that cyclone exposures may overlap with earlier cyclone exposures, and thus create a "forbidden comparison", we introduce an additional restriction. In addition to the previous constraint that we only examine those storm exposures episodes that did not have any storm during the three months prior, we now also restrict to isolated treatment events with no other storm occurring 3 months prior *or after* that event. Table A2 shows similar results for those isolated storm events. Although, trade rebounds slightly more quickly as in the baseline results and trade even turns positive in the second months after storm. This would be compatible with dynamic shifting of trade to offset the initial shock.

Consecutive storm events. A route might not be affected just once, but there may be multiple consecutive storms one month after another. In Table A3 we examine the additional impact of consecutive storms. The coefficient on period "0" reflects the impact of the first storm, the coefficient in period "1" reflects the impact of a second additional storm et cetera. Consequently, we find that the trade impediment lasts much longer than in the baseline case.

7 Conclusion

In a global setting, we quantify the impact of tropical cyclones on container shipping trade with unprecedented time and spatial resolution. Main results show that tropical storms reduce trade at the country level by approximately 2%. The according effect size at the port-pair level is two times as large approximately 4%. The most prominent coping strategies of exporters are found to be delaying goods with lower unit value such as final consumption goods and to reroute goods to other destination ports in neighboring countries. Results indicate that substitution of the destination port should be strengthened by building, for instance, better onshore infrastructure between ports. Additionally, storms lead to higher transport times and to longer distances traveled and as a result to higher freight rates in the months following the storm. Our findings have severe repercussions for quantifying the costs of climate change. With warming oceans, strong tropical cyclones are projected to become more frequent, leading to large prospective costs for shipping companies with implications for consumers and producers.

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A Appendix

A.1 Detailed Results

Table (A1) Storm effect on trade, country-pair level

Model:	Trade values (1)
Variables	
Time from storm = -3	-0.0007
	(0.008)
Time from storm = -2	-0.005
	(0.007)
Time from storm = 0	-0.019***
	(0.007)
Time from storm = 1	-0.012*
	(0.007)
Time from storm = 2	-0.001
	(0.008)
Time from storm = 3	-0.004
	(0.009)
Fixed-effects	
Country Pair	✓
Month	✓
Country Pair x Month	✓
End Country x Year x Month	✓
Start Country x Year x Month	✓
Fit statistics	
Observations	1,313,306
Pseudo R^2	0.988

Notes: Estimated with PPML. *** p<0.01, ** p<0.05, * p<0.1

Table (A2) Isolated storm events, country-pair level

Model:	Trade values (1)
Variables	
Months to Storm = -3	-0.005
	(0.013)
Months to Storm = -2	-0.007
	(0.013)
Months to Storm = 0	-0.032*
	(0.016)
Months to Storm = 1	-0.009
	(0.014)
Months to Storm = 2	0.028**
	(0.014)
Months to Storm = 3	-0.016
	(0.016)
Fixed-effects	
Country Pair	✓
Month	✓
Country Pair x Month	✓
End Country x Year x Month	✓
Start Country x Year x Month	✓
Fit statistics	
Observations	1,473,864
Pseudo R^2	0.987

Notes: Estimated with PPML. *** p<0.01, ** p<0.05, * p<0.1

Table (A3) Cumulative storm events, country-pair level

Model:	Trade values (1)
Variables	
Months from Storm = -3	0.018**
	(0.009)
Months from Storm = -2	-0.012
	(0.008)
Months from Storm = 0	-0.018***
	(0.007)
Months from Storm = 1	-0.015*
	(0.009)
Months from Storm = 2	-0.013
	(0.010)
Months from Storm = 3	-0.008
	(0.012)
Months from Storm = 4	0.0006
	(0.009)
Months from Storm = 5	-0.005
	(0.013)
Fixed-effects	
Country Pair	✓
Month	✓
Country Pair x Month	✓
End Country x Year x Month	✓
Start Country x Year x Month	✓
Fit statistics	
Observations	1,473,864
Pseudo R^2	0.987

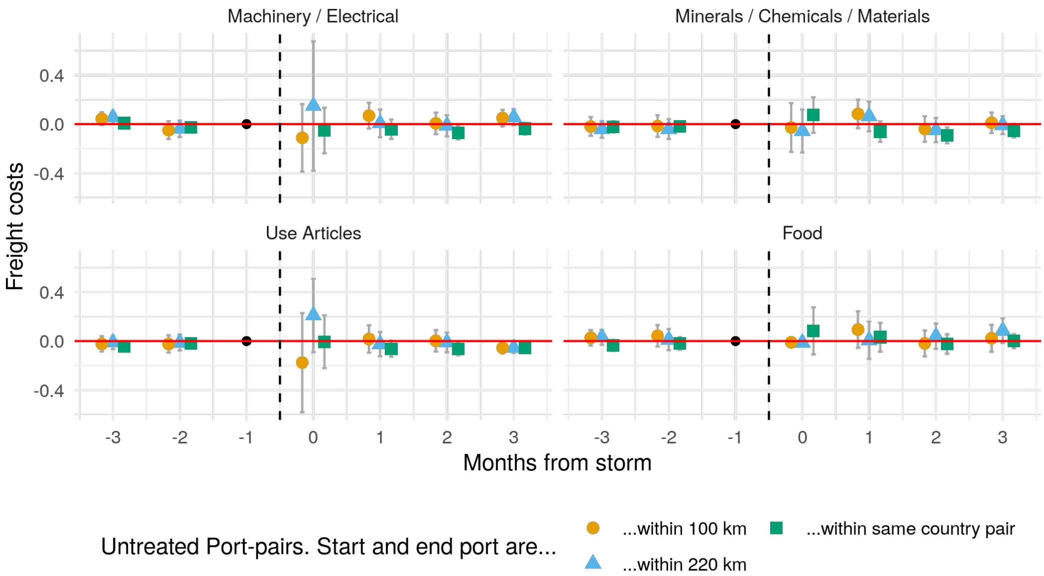
Notes: Estimated with PPML. *** p<0.01, ** p<0.05, * p<0.1

Table (A4) Port-pair transactions: quantity versus price

Model:	Trade weight (1) Poisson	Freight cost (2) OLS
Variables		
Time from storm = -3	-0.019	-0.017*
	(0.021)	(0.010)
Time from storm = -2	-0.009	-0.012
	(0.018)	(0.010)
Time from storm = 0	-0.040**	0.014
	(0.018)	(0.009)
Time from storm = 1	-0.044**	0.012
	(0.019)	(0.010)
Time from storm = 2	-0.060***	0.023**
	(0.023)	(0.010)
Time from storm = 3	-0.075***	0.014
	(0.025)	(0.010)
Fixed-effects		
Port Pair	Yes	Yes
Month	Yes	Yes
Port Pair x Month	Yes	Yes
End Country x Year x Month	Yes	Yes
Start Country x Year x Month	Yes	Yes
Fit statistics		
Observations	662,445	206,378
Pseudo R^2	0.840	0.781

Notes: *** p<0.01, ** p<0.05, * p<0.1

Figure (A1) Port-pair-transactions: Price spillovers to closeby routes?



Notes: Regression freight costs (OLS) with fixed effects for Port-pair, Month, Port-pair x Month, Origin Country x Month and Destination Country x Month. Standard errors are clustered at the port-pair-level. Product categories: **Machinery/Electrical**: Machinery / Electrical, Transportation. **Minerals/Chemicals/Materials**: Mineral Products, Chemical and Applied Industries, Stone/Glass, Metals. **Use Articles**: Plastics and Rubber, Raw Hides, Skins, Leather and Furs, Wood and Wood Products, Textiles, Footwear/Headgear. **Food**: Animal and Animal Products, Vegetable Products, Foodstuffs.