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Navigating Supply Chain Disruptions: How Firms Respond to Low Water Levels

SASKIA MEUCHELBÖCK

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Saskia Meuchelböck†

Aarhus University & Kiel Institute for the World Economy

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Abstract

This paper studies how firms adjust to temporary infrastructure disruptions, using a period of exceptionally low water levels on European inland waterways as a natural experiment. Linking monthly trade and transport data for Germany, I show that firms relying on inland shipping for imports reduced the value, variety, and geographic scope of their exports. These effects were strongest among firms with limited transport diversification and cannot be explained by demand shocks or export constraints, highlighting the role of supply bottlenecks. Affected firms adapted by persistently switching to alternative transport modes, showing that even short-lived shocks can induce lasting behavioural change.

Keywords: extreme weather events; global supply chains; firms; infrastructure; transport mode; low water; climate change; adaptation; Germany.

JEL-Classification: F14, F18, Q54, R4.

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† sameu@econ.au.dk

1 Introduction

Disruptions to transport infrastructure can have major consequences for firms and the wider economy. Even short-lived breakdowns in logistics systems can constrain input access, delay production, and generate ripple effects through production networks. A growing source of such disruptions are extreme weather events, whose frequency and severity are expected to rise due to climate change (IPCC, 2021). A recent survey of 3,500 executives identified supply and transport bottlenecks as major climate-related risks to their supply chains (The Economist, 2024). How do firms react to such bottlenecks? How is their performance affected? Do they adjust their sourcing strategies in response? While prior research documents how supply shocks transmit across firms and borders at the micro level (Barrot and Sauvagnat, 2016; Boehm et al., 2019; Lafrogne-Joussier et al., 2022), and recent macro-level work highlights the role of infrastructure in propagating climate shocks internationally (Feng et al., 2025), we know little about how firms respond to temporary disruptions in transport capacity and the behavioural margins along which they adjust.

This paper examines how firms respond to a temporary weather-induced shock to transport infrastructure. I exploit a period of critically low water levels on Germany's inland waterways as a natural experiment. Caused by prolonged drought, water levels on the Rhine – one of Europe's most important inland shipping routes – and other rivers fell below navigable thresholds in the second half of 2018, sharply constraining freight transport.[1] Inland shipping is a cost-efficient, low-emission mode of moving bulk goods, making it a key logistics channel for heavy and upstream industrial inputs such as coal, ores, and chemicals.[2] Disruptions to these inputs can significantly impact downstream production, especially for firms reliant on just-in-time deliveries. As the shock left physical capital and production capacity intact, it

[1]Similar disruptions have also occurred on other major waterways, including the Panama Canal and Mississippi River in 2022 and 2023 (The Economist, 2023; US Department of Transportation, 2022).

[2]Emissions for freight transported by inland waterways, rail, and maritime shipping are substantially lower than for road or air freight (European Environment Agency, 2021). As a result, the European Commission aims to increase the modal share of inland waterways as part of its transport decarbonisation strategy (European Parliamentary Research Service, 2022).

offers a rare opportunity to isolate the effects of a temporary infrastructure disruption.

To analyse the shock's economic impact, I use a novel firm level dataset for Germany that links trade flows to information on transport. The monthly data cover most of Germany's exports and imports, recorded at the firm-product-country level, and indicate the transport mode used to ship each product. The granularity of the data allows me to leverage the timing of the 2018 low water shock to estimate the causal impact of the disruption on firms' export performance and sourcing decisions in a difference-in-differences and event study framework.

The paper makes three main contributions. First, it provides novel firm-level evidence that temporary infrastructure disruptions transmit along supply chains, reducing export performance through input supply constraints. Second, it shows that firms respond to a short-lived disruption – without any physical capital destruction – by switching to alternative transport modes, with effects lasting even after water levels normalised. This behavioural persistence challenges standard modelling assumptions of symmetric or reversible effects in response to transitory shocks. Third, while most existing studies focus on supplier choice or geographic reallocation (Khanna et al., 2022; Castro-Vincenzi et al., 2024; Balboni et al., 2024), this paper highlights transport mode choice as a distinct and underexplored margin of adjustment to infrastructure disruptions.

The empirical analysis proceeds in three parts. First, I show that international trade via inland shipping declined sharply during the low water period. Firms' exports on inland waterways fell by nearly 20 percent, while imports declined by 12 percent. While exports rebounded, inland waterway imports remained subdued even after water levels normalised, suggesting a persistent change in sourcing behaviour. Second, I examine how the shock propagated along supply chains, constraining downstream performance through supply bottlenecks.[3] Firms that had relied on inland waterways for importing reduced their exports,

[3] I use exports as a proxy for downstream performance. This is common in the literature investigating the international transmission of supply disruptions. For example, Boehm et al. (2019) use exports to Mexico and Canada to proxy production of US firms when analysing the effects of supply disruption due to the

regardless of how those exports were transported. These effects, seen in export value, variety, and destination scope, were concentrated among firms with low transport diversification, consistent with supply-side constraints. I rule out alternative explanations including export capacity shortages, product-specific demand shocks, and regulatory changes. Third, I examine adaptive behaviour. Affected firms substituted away from inland shipping toward other transport modes, and this shift persisted well beyond the initial shock. Switching was most common for time-sensitive products such as intermediate inputs and non-durable goods, and increased with the product's importance in a firm's import portfolio.

Taken together, these findings provide new insights into how firms respond to short-term shocks, providing evidence that even temporary disruptions can lead to persistent changes in firm behaviour. The results also highlight that climate resilience strategies must account for the fragility of transport networks that underpin modern production.

The paper is organized as follows. Section 2 reviews the related literature. Section 3 provides background information on the incidence of low water and the specific shock under study. Section 4 describes the data. Section 5 presents the empirical analysis. Finally, Section 6 concludes.

2 Related Literature

This paper contributes to multiple strands of the literature. First, it relates to the broader work on the economic effects of extreme weather events and climate shocks. Studies using aggregate annual data have found mixed results, with negative effects often concentrated in developing countries and affecting measures such as GDP, industrial production, and exports (Jones and Olken, 2010; Dell et al., 2014). To better capture the localized and short-term nature of such shocks, researchers increasingly use high frequency (Heinen et al.,

Great East Japan earthquake. Lafrogne-Joussier et al. (2022) investigate how missing imports from China due to a Covid-19 lockdown affect exports of French firms. I discuss the caveats of relying on foreign trade data in Section 4.

2019; Ademmer et al., 2023; Kim et al., 2025) and disaggregated data, exploring effects at the local (Strobl, 2011; Felbermayr et al., 2022) and firm level (De Mel et al., 2012; Gröschl and Sandkamp, 2023). These studies quantify the effects of shocks like floods or hurricanes, but the underlying mechanisms through which these events harm the economy remain underexplored. Most work emphasizes capital destruction and production capacity losses. A recent macro-level study by Feng et al. (2025) shows that climate disasters affecting ports reduce trade and GDP in directly hit countries but also in their main trading partners, pointing toward infrastructure as a transmission channel. Ademmer et al. (2023) find that low water levels reduce industrial production in Germany at the macro level. I complement that work by providing firm level evidence from an advanced economy on how a temporary weather-induced disruption to transport capacity affects firms and their supply chains.

Second, this paper contributes to the literature studying the propagation of shocks through production networks at the firm level. A growing number of studies show that shocks – including natural disasters (Barrot and Sauvagnat, 2016; Carvalho et al., 2021; Boehm et al., 2019), the Covid-19 pandemic (Lafrogne-Joussier et al., 2022), or regulatory changes (Demir et al., 2024) – transmit through supplier-buyer relationships, both domestically and internationally. Unlike these studies, the shock I analyse is short-lived and truly temporary in nature, with low water levels occurring for a limited period without physical infrastructure destruction or shifts in the geopolitical or regulatory environment. The monthly frequency of my data allows me to analyse adjustment dynamics during and after the shock and to test whether it propagated through input bottlenecks. I find that firms reliant on inland shipping for imports reduced their exports, consistent with supply chain transmission.

Third, the paper relates to a growing literature on firm responses to supply chain risk. Khanna et al. (2022) find that firms in India shifted to larger and better-connected suppliers following regional Covid-19 lockdowns. Korovkin et al. (2024) document supply chain reconfiguration during the 2014 Russia-Ukraine war. Focusing on firms' responses to extreme weather events, Hayakawa et al. (2015) find little long-run change in local sourcing after floods in Thailand, while Castro-Vincenzi et al. (2024) show that Indian firms anticipate monsoon risk and diversify sourcing accordingly. Balboni et al. (2024) argue that firms are imperfectly informed about climate risk, as they relocate production and purchases to less exposed areas only after flood events in Pakistan. My contribution lies in examining whether and how firms adjust to a temporary infrastructure shock, both on impact and over a longer time period. While most existing work focuses on supplier choice and geographic diversification, I emphasize adjustments in transport mode choice as an overlooked margin of firm response.

Finally, the paper connects to the literature on the role of transportation in international trade. This includes work on the determinants of firms' mode choice (Harrigan, 2010; Hummels and Schaur, 2013; Coşar and Demir, 2018), and studies examining infrastructure shocks. For example, Heiland et al. (forthcoming) study the Panama Canal expansion, Martincus and Blyde (2013) document export losses from road destruction, and Besedeš et al. (2024) show that airspace closures reduce trade by increasing flight distances and costs. Friedt (2021) finds that infrastructure destruction leads to persistent changes in port usage. Closest to the present paper, Sandkamp et al. (2022) show that piracy incidents lower ocean freight volumes as firms substitute toward air shipping. More broadly, Allen and Arkolakis (2022) develop a general equilibrium framework showing how infrastructure shapes trade and welfare highlighting, the role of transport networks in shaping economic outcomes.

3 Background: Inland waterway transport and low water in Germany

Inland waterway transport accounts for a comparatively low share of goods carried in Germany. In 2017, the year before the low water period analysed in this paper, inland waterway transport made up 4.7 percent of the total volume (measured in tons) of goods transported in Germany according to aggregate freight data by the Federal Statistical Office. With a share of almost 80 percent, the large majority of the freight volume is transported by road, followed by rail with 8.5 percent and sea with around 6 percent.[4] The Rhine river is the most important waterway in Germany, carrying around 80 percent of the total volume of freight transported on inland waterways (BDB, 2019) but also other rivers including the Danube, Main, Moselle, and Elbe are relevant for freight transport. Figure A1 in the Appendix shows the freight traffic density of maritime and inland navigation on the main network of federal waterways in a map of Germany.

Despite accounting for a small portion of the total freight volume, inland waterways play a crucial role in transporting essential industrial goods. Products with a comparatively high share of inland waterway transport include metal ores, coal, crude oil, refined petroleum products, basic and fabricated metals, chemical goods, and agricultural products. These low value-to-weight products are typically located upstream in supply chains (Ganapati and Wong, 2023). Disruptions in the transport of these goods – for example due to low water levels – can therefore have a significant impact on downstream production stages, particularly when firms rely on just-in-time production methods.

In general, low water situations are not an unusual occurrence in river systems, and there have been several instances of low water events in recent decades. Between 1991 and 2019,

[4] The reported statistics include both national and international transport. Unsurprisingly, the sea transport volume is almost exclusively generated by international trade. The remaining share is made up by mail and fixed transport facilities such as pipelines.

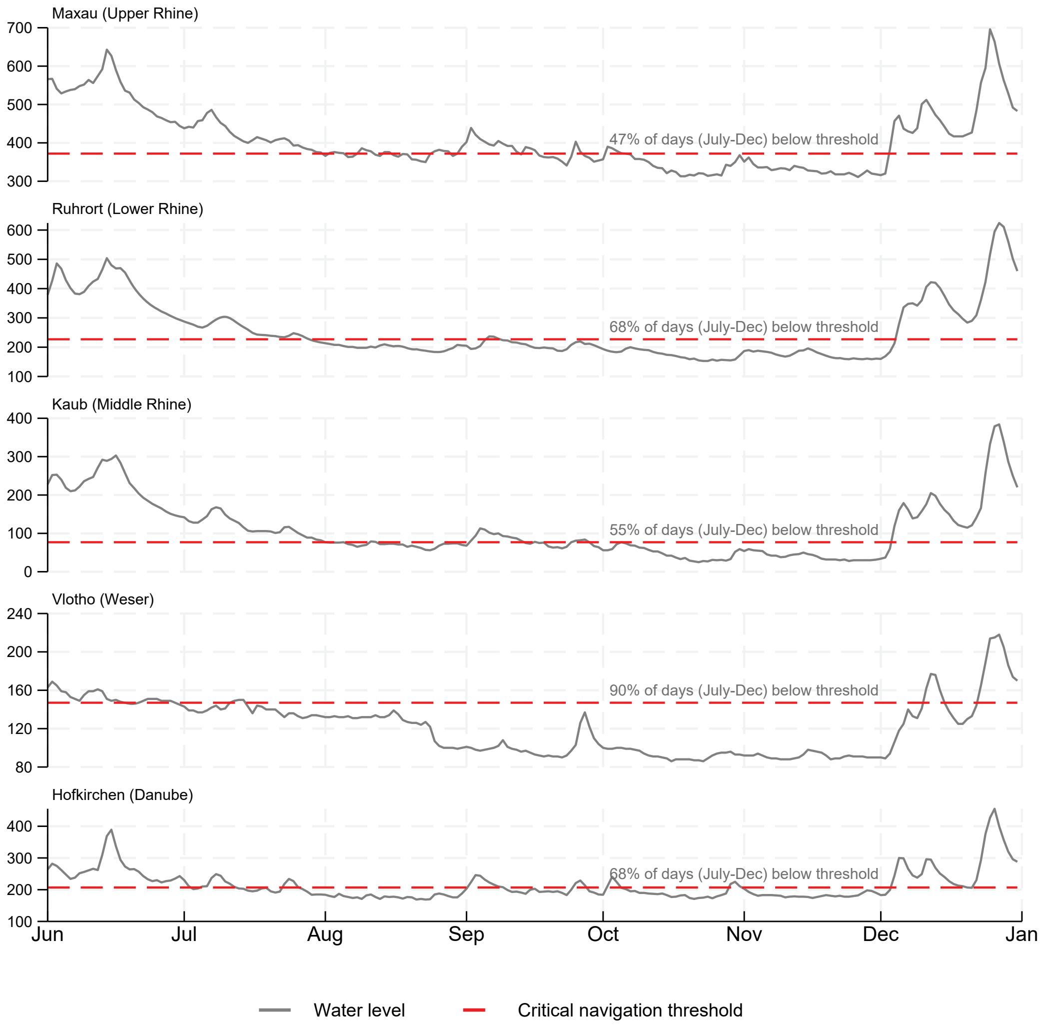
Kaub – a gauging station critical for navigation on the Rhine – recorded 14 low water events, most of which lasted between less than one and up to three months. Low water can be defined as a situation in which the gauge level on a river drops below a certain threshold, the so-called "equivalent water level". According to the German Federal Institute of Hydrology, river-specific equivalent water levels "are of major importance as reference values for [...] navigation, especially during low-flow." At these gauge levels, ships' draught and thus cargo capacity is markedly reduced compared with regular water levels. Additionally, transport companies usually charge an additional fee ("low water surcharge") and do not guarantee their services any more when gauge levels fall below these thresholds.

The macroeconomic effects of low water have been investigated by Ademmer et al. (2023). Using time-series data over the past three decades, they show that low water levels lead to a substantial drop in freight volume transported on inland waterways, as well as a significant impairment of industrial production. In a month with 30 days of critically low water levels, aggregate industrial production in Germany is reduced by about 1 percent. This effect is driven by lower production in sectors that heavily rely on inland waterway transport including the manufacture of non-metallic mineral products and the chemical industry.

In this paper, I leverage the 2018 low water period – an exceptionally severe and long-lasting event – as a natural experiment to examine its effects at the level of the firm. The low water period was characterized by extensive territorial coverage, and notably the Rhine river, by far the most important waterway for freight transport, was also strongly affected. In 2018, a prolonged drought in Germany resulted in a significant decrease in water levels throughout the year. Already from April onward, nationwide precipitation was only about half of the long-term average; as a consequence, water levels of rivers fell first in the north and east of Germany, and later on also in the south and west, increasingly affecting inland navigation in the course of the year (German Federal Institute of Hydrology, 2019). Figure 1 plots the development of water levels at different gauging stations on German waterways in the second half of 2018, and benchmarks them against the “equivalent water levels”. In late June 2018, water levels on some rivers already reached their critical reference values. The greatest restrictions to navigation were observed in the fall, particularly in November, when water levels reached new historical lows. In December rainfall finally brought the low water situation to an end after five consecutive months. Overall, the low water period in 2018 was unprecedented in severity, duration, and geographic scope in the 21st century.[5] Unlike in 2018, in 2019 inland freight navigation was not impaired by low water levels at a broad scale over extended periods of time. Importantly, water levels at the Rhine river fell below critical thresholds only for very few days (CCNR, 2020).

[5]Low water periods of similar or greater intensity and duration – as measured by the number of days the critical threshold for navigation was undercut in Kaub – occurred, for example, in 1920/21, 1949, and 1962; the low water period in 2018 was the most severe since 1971 (Kriedel, 2019).

Figure 1. Development of water levels at different gauging stations in Germany, 2018



The graph shows the development of water levels over time of selected waterways in Germany (solid line). The dashed lines represent critical gauge-specific reference values for low water levels. Source: German Federal Institute of Hydrology (2019) based on data by the German Federal Waterways and Shipping Agency (WSV).

4 Data

The main source of data for the empirical analysis of this paper is a novel firm level dataset on foreign trade for Germany provided by the Federal Statistics Office. The dataset covers a large majority of transactions of goods involving a Germany company and a non-German partner at the monthly level. Data for transactions with countries outside the EU are collected by the customs administration ("Extrastat" system) and cover the universe of extra-EU trade transactions. Data on the cross-border movements of goods between EU member states are collected through the "Intrastat" reporting system, which requires firms to provide information on their trade activities only if they exceed a certain reporting threshold. In this paper, I use monthly data from July 2017 through December 2019, the latest month for which the data is available at the time of writing.[6] For the sample period, the reporting thresholds for intra-EU trade were set at 500,000 euros for exports and 800,000 euros for imports. Firms with annual trade below these thresholds were not required to report their transactions, whereas firms exceeding the thresholds had to report all their transactions. These thresholds were designed such that 97 percent of the total annual exports and 93 percent of total imports are covered.[7]

For each export and import observation in the dataset, I observe a unique identifier for the Germany company that is involved in the trade flow, the direction of trade, the product category, the partner country, the value of the shipment in euros, as well as its physical quantity. Products are classified according to the EU's Combined Nomenclature (CN) at the 8-digit level; the first six digit correspond to the code of the Harmonized System (HS) administrated by the World Customs Organization. The physical quantity is measured by two variables: the first one reports the weight in kilograms and it is mandatory to report this information for all transactions in the "Extrastat" system. In the "Intrastat" system, reporting the weight in kilograms is optional if a supplementary physical unit – such as litres, number of parts or square meters – exists for a specific product category. I generate

[6]While extending the analysis to include years beyond 2019 is possible as additional data becomes available, the onset of the Covid-19 pandemic in 2020 presents significant challenges. Lockdown measures and trade restrictions likely introduced transport-specific disruptions, potentially confounding the analysis of longer-term effects.

[7]While the German Statistical Office uses VAT data to reconstruct trade flows for firms below these thresholds, information on these trade flows is much less detailed. As neither information on the product category nor on the mode of transport used is available, I cannot include these trade flows into my analysis. Another caveat of the "Intrastat" system is that the reporting unit is not always a firm. Instead, it can also be the corporate group in the case of VAT groups, in which case the Federal Statistical Office redistributes the foreign trade flows reported by the VAT group to the individual firm level using VAT data. Kruse et al. (2021) provide more information on the methodology used.

a new measure from these variables that corresponds to the supplementary physical unit, if available, and the weight in kilograms otherwise.

Moreover – and importantly for my analysis – the data also contain information on the mode of transport for each observation. For intra-EU trade, the transport mode is recorded at the German border. For extra-EU trade, it is recorded at the EU border but in addition, the mode of transport used *within* Germany is reported. The variables distinguish between the following modes: sea, rail, road, air, and inland waterway transport, as well as mail, fixed transportation facilities (such as pipelines) and own propulsion. The last three transport modes are grouped together and referred to as "other". I classify a trade flow as exposed to inland shipping if the transport mode is reported to be inland waterway transport *within* Germany in the case of extra-EU trade and at the German border in the case of intra-EU trade. Figure A1 in the Appendix shows that border crossings on inland waterways are most likely to occur on the rivers Rhine (Switzerland, Netherlands), Moselle (Luxembourg, France), Danube (Austria), Oder (Poland), or Elbe (Czech Republic). It is likely that goods crossing the border on an inland waterway continue to be shipped on inland waterways *within* Germany, at least for some part of their journey.

Exploiting the transport mode allows me to identify firms that use inland shipping to import and/or export certain products and are therefore potentially affected by low water levels. However, there are several caveats associated with the data. First, monthly data on production and domestic sales is not available, restricting my analysis to imports and exports. Second, I only observe international transactions in the data but some firms might be affected by low water levels due to disruptions in national transport. Aggregate goods transport statistics by the Federal Statistical Office, however, show that a relatively large part of the total volume of inland waterway transport is related to international transactions. In 2017, the year before the low water period under study, almost half (46 percent) of the quantity (in tons) transported on inland waterways were imports, and almost one quarter (23 percent) were exports.[8] Purely national transactions accounted for 25 percent of the total volume transported on inland waterways, which might be generated by firms that are not active in international trade and are therefore not recorded in the dataset used for the empirical analysis. Another option is that trading firms use this transport mode (also) within Germany, for example to source inputs from another part of the country. If a firm in my dataset uses inland waterway transport for national transactions only, I would wrongly assign it to the control group, neglecting that it is exposed to the low water shock due to disrupted *national* transactions. As a consequence, the estimates of the following empirical analysis would be biased towards zero.

Table 1. Summary statistics at the firm-transportation mode level: Imports

	# observations	Mean	Median	SD
All modes of transportation				
ln(value)	3,246,615	9.74	9.89	2.91
ln(quantity)	3,164,884	6.89	6.80	3.88
ln(# products)	3,246,615	1.16	0.69	1.21
ln(# countries)	3,246,615	1.31	1.10	1.33
ln(# shipments)	3,246,615	1.40	1.10	1.40
# firms	184,047			
Inland waterway transportation				
ln(value)	16,836	11.93	12.05	2.69
ln(quantity)	16,794	12.08	12.13	3.20
ln(# products)	16,836	0.76	0.69	0.95
ln(# countries)	16,836	0.90	0.69	1.02
ln(# shipments)	16,836	0.99	0.69	1.07
# firms	2,124			

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

Only few firms use inland waterway transport to import or export. In the estimation sample, 2,124 firms use this mode to import, which corresponds to 1.2 percent of all firms (Table 1).

[8]In addition, 7 percent were goods in transit which are not included in foreign trade statistics.

1,324 or 0.9 percent of exporters use inland waterways to ship their goods abroad (Table 2). Compared with other modes, average values and quantities transported on inland waterways per firm are much larger, with a similar distribution observed for exports and imports. At the same time, inland waterway transport is used for fewer products, partner countries and shipments.[9] Note that firms primarily active in services sectors (NACE Rev. 2 Section I-U) are excluded from the sample.

Table 2. Summary statistics at the firm-transportation mode level: Exports

All modes of transportation				
	# observations	Mean	Median	SD
ln(value)	2,370,421	10.89	10.92	2.43
ln(quantity)	2,339,247	7.90	7.94	3.41
ln(# products)	2,370,421	1.28	1.10	1.35
ln(# countries)	2,370,421	1.86	1.61	1.70
ln(# shipments)	2,370,421	1.92	1.61	1.75
# firms	143,114			
Inland waterway transportation				
ln(value)	10,115	11.90	12.04	2.83
ln(quantity)	10,082	12.08	12.38	3.52
ln(# products)	10,115	0.70	0.00	1.04
ln(# countries)	10,115	0.99	0.69	1.30
ln(# shipments)	10,115	1.07	0.69	1.39
# firms	1,324			

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

[9]The dataset does not report each individual transaction but monthly observations. If one particular firm exports the same product to the same destination country using the same mode of transport several times per month, only the aggregate monthly value and quantity is reported. The number of shipments thus does not reflect the number of individual transactions but rather the number of individual firm-product-country-transport mode combinations per month.

5 Empirical analysis

This paper aims to examine empirically the impact of a temporary transport disruption due to low water levels on firms' export and import behaviour. While a growing body of research investigates the effects of shocks on international trade and supply chains, these shocks typically have a lasting nature. For example, supply chain reconfiguration and, more generally, trade responses have been investigated in the context of natural disasters including the Tōhoku earthquake and tsunami in Japan (Freund et al., 2022; Kawakubo and Suzuki, 2022) or floods in China (Gröschl and Sandkamp, 2023). While these shocks are short-term events, they are associated with the destruction of physical capital in the form of infrastructure and production facilities. In contrast, low water levels are a temporary phenomenon that only disrupts transport for a limited period. My empirical strategy utilizes the monthly dynamics of exports and import to analyze the impact of the shock on exposed trade flows and firms, respectively, both *during* and *after* the low water period in a difference-in-differences framework. This approach allows me to investigate the immediate impact of the shock as well as whether a temporary shock has lasting consequences even after it has ended.

I structure my empirical analysis in three parts. First, I examine whether the low water period in 2018 disrupted imports and exports via inland waterway transport. Second, I investigate whether the shock propagated down the supply chain. In particular, I compare the development of exports of firms importing by inland waterways to the development of exports of firms that do not rely on this transport mode before, during, and after the low water period in the second half of 2018. Finally, I focus on firms that rely on inland shipping as a transport mode for importing and analyze if they adjust their sourcing behaviour in response to the shock. I use data from July 2017 through December 2019. For the difference-in-differences regressions, I define two treatment periods: the first treatment period ranges from July 2018 through December 2018 and is denoted *2018H2*. It captures the immediate impact of the transport disruption. The second treatment period is defined as the year 2019 (denoted *2019*) and captures any effects prevailing after the shock is over.

The identifying assumption for my analysis is that the interaction terms of interest in the difference-in-differences regression are uncorrelated with the error term, conditional on the fixed effects included. As low water levels result from a combination of meteorological and hydrological events, they can plausibly be interpreted as an exogenous shock disrupting the transport of goods. The long duration and severity of the 2018 period were also not anticipated. Furthermore, it is crucial for identification that the parallel trends assumption holds in the difference-in-differences framework. Specifically, this means that there should be no significant disparities in the pre-treatment trends of the dependent variable between the treated and control group. I complement the difference-in-differences analysis with event study regressions which confirm the parallel trends assumption.

5.1 Does low water disrupt inland waterway transport?

In a first step, I examine whether the period of low water in 2018 caused any disturbances to the transport of internationally traded goods on inland waterways. To do so, I collapse the data to the firm-transport mode level (distinguishing between rail, road, air, inland waterways, sea, and an "other" category) and estimate the following difference-in-differences regression for imports and exports separately:

$$
\begin{aligned}
ln(Y_{fmt}) = &\beta_1(IWT_{fm} \times 2018H2_t) + \\
&\beta_2(IWT_{fm} \times 2019_t) + \delta_{fm} + \delta_t + \epsilon_{fmt},
\end{aligned} \tag{1}
$$

where f denotes firm, m denotes transport mode and t denotes time on a monthly basis. IWT is an abbreviation for inland waterway transport, and IWT_{fm} is a dummy variable equal to one for imports and exports of firm f by inland waterways. Several trade performance indicators serve as the dependent variable Y_{fmt}. It is either the value (in euros) traded by firm f by transport mode m at time t, the quantity, the number of products or the number of product-country pairs. To fully capture the extensive margin as well, I additionally estimate a linear probability model using as an outcome variable a binary indicator that takes the value one if a firm uses a specific transport mode in a given month and is zero for all other months.

The main coefficients of interest are the coefficients on the interaction terms $IWT_{fm} \times 2018H2_t$ and $IWT_{fm} \times 2019_t$. They capture the differential effect of the low water period on trade flows on inland waterways in comparison with trade flows by other transport modes. The estimates thus reflect a combination of two effects: on the one hand imports and exports via inland waterways are likely to drop due to the low water levels, and on the other hand imports and exports via other transport modes are likely to increase somewhat as firms might switch to other modes. However, Ademmer et al. (2023) do not find a strong increase in road and rail transport in the aggregate suggesting that impairments on inland waterways cannot be fully compensated by other modes of transport in the short run. In all regressions, I include a set of fixed effects: δ_{fm} control for any time-invariant factors that are specific to a firm and transport mode. Monthly time dummies δ_t control for everything affecting all firms and transport modes equally in a given month. Standard errors are clustered at the firm-transport mode level.

Table 3 reports the results for the export side. The low water levels during the second half of 2018 had a statistically significant and quantitatively large impact on both the intensive and extensive margins of exports by inland shipping relative to other transport modes and in comparison with the baseline time period, i.e. the year before the low water occurred. The value of goods exported on inland waterways dropped by 18.5 percent (column 1, $(e^{-0.204} - 1) * 100$), while the physical quantity traded exhibited a slightly larger decline (column 2). Moreover, the number of products and the number of product-destination combinations exported by inland shipping declined by approximately 8 (column 3) and 11 percent (column 4), respectively. The probability of exporting by inland shipping decreased by 3.4 percent (column 5) relative to other modes. There is no evidence that the effects lasted beyond the low-water period, as the estimations show no statistically significant impact on any outcome variable in 2019.

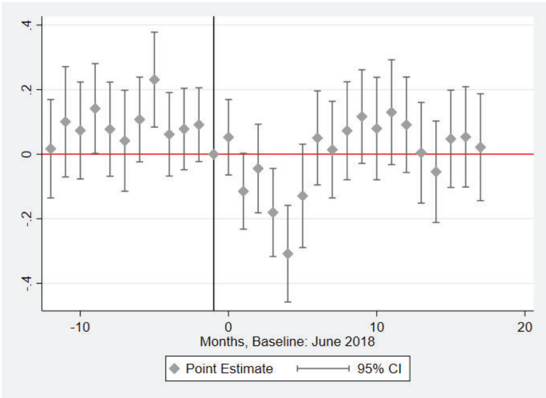
Table 3. Exports, firm-transport mode level estimations

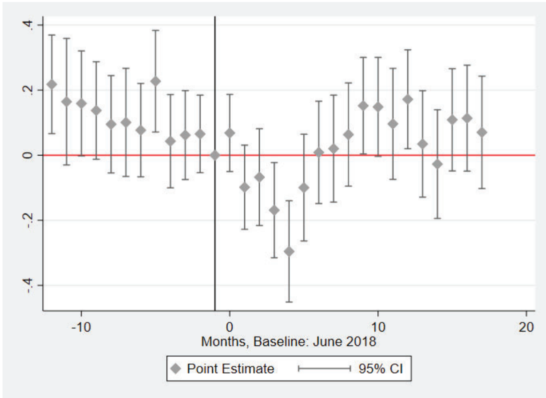
	(1) value	(2) KG	(3) #products	(4) #shipments	(5) probability
Inland shipping	-0.201***	-0.216***	-0.082***	-0.116***	-0.033***
$\times$ 2018H2	(0.038)	(0.039)	(0.014)	(0.020)	(0.005)
Inland shipping	-0.031	-0.030	-0.017	-0.037	-0.002
$\times$ 2019	(0.051)	(0.052)	(0.022)	(0.030)	(0.007)
# obs.	2,326,365	2,295,570	2,326,365	2,326,365	5,785,830
δ_{fm}	Yes	Yes	Yes	Yes	Yes
δ_t	Yes	Yes	Yes	Yes	Yes
R^2	0.852	0.891	0.894	0.911	0.612

Robust standard errors clustered at the firm-transport mode level are in parenthesis. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

Figure 2 mirrors the results presented in Table 3 by showing for several outcome variables the dynamics of exports by inland shipping in comparison with other transport modes before, during, and after the low water period. Importantly for the analysis, there is no sign of systematic, significant pre-trends for any of the outcome variables used. From July 2018 onward, the estimates reflect the development of water levels and the geographic extent of the low water situation. The negative effects are strongest in November, when water levels reached historical lows, including at decisive gauging stations on the Rhine, the most important river for freight navigation in Germany. In December, when the low water situation eased, the negative impact becomes smaller. From January 2019 onward, exports via inland shipping relative to other transport modes have fully recovered, reflected by coefficients very similar to those estimated for the pre-shock period.

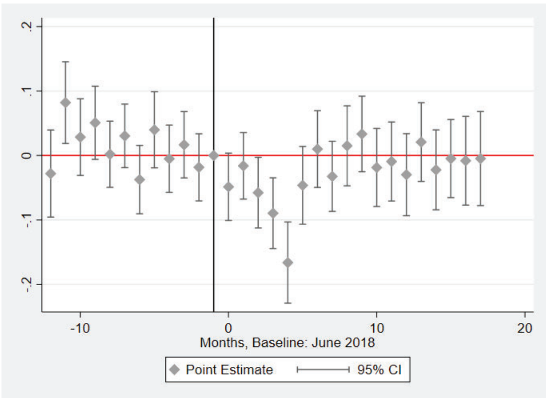
Figure 2. Exports, firm-transport mode level estimations, event study graphs

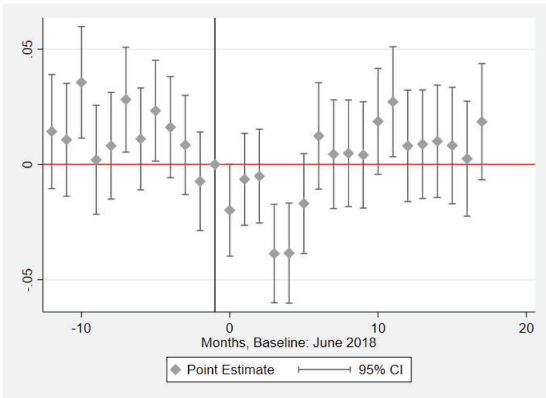




Export value

Export quantity





products

Probability of exporting

The figure shows the dynamics of exports by inland shipping in comparison with other transport modes before, during, and after the low water period. The estimation equation reads:

$$ln(Y_{fmt}) = \sum_{i=-12}^{18} \beta_i (IWT_{fm} \times Time_{it}) + \delta_{fm} + \delta_t + \epsilon_{fmt},$$

where $Time_{it}$ is a dummy equal to one i periods before/after the shock and IWT_{fm} is one for exports by inland waterway transport. The baseline period ($i = -1$) is June 2018. All β_i's – i.e. one for each month in the regression sample – are displayed. Y_{fmt} is the value of exports in euro (upper left panel), quantity exported (upper right panel), the number of products exported (lower left panel) or the probability of using inland shipping as the mode of transport for exporting (lower right panel). Confidence intervals are defined at 5%.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

The results for the import side are presented in Table 4 and show a somewhat different picture. The low water period also had a statistically significant, large impact on the intensive and extensive margins of importing via inland waterways relative to other transport modes. However, in comparison with the export side, the effects are smaller. The value and quantity of goods imported on inland waterways fell by 12.0 and 14.1 percent (columns 1 and 2), respectively. The decline was 3.4 percent for the number of products (column 3) and somewhat larger for the number of product-destination pairs (column 4). The probability of importing by inland shipping decreased by 2.3 percent (column 5). Depending on the outcome variable used, the coefficients for the same regressions for exports are between 1.5 and 2.5 times larger (see Table 3).

Table 4. Imports, firm-transport mode level estimations

	(1) value	(2) quantity	(3) #products	(4) #shipments	(5) probability
Inland shipping	-0.127***	-0.151***	-0.034**	-0.048***	-0.024***
× 2018H2	(0.033)	(0.033)	(0.013)	(0.016)	(0.005)
Inland shipping	-0.090**	-0.078*	-0.043***	-0.043**	-0.012**
× 2019	(0.041)	(0.043)	(0.015)	(0.018)	(0.006)
# obs.	3,170,823	3,090,423	3,170,823	3,170,823	9,182,730
δ_{fm}	Yes	Yes	Yes	Yes	Yes
δ_t	Yes	Yes	Yes	Yes	Yes
R^2	0.845	0.892	0.853	0.869	0.558

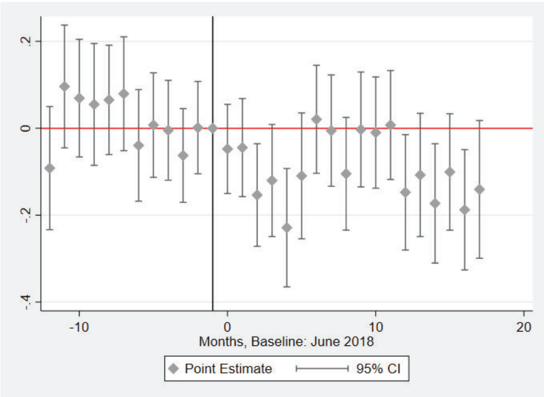
Robust standard errors clustered at the firm-transport mode level are in parenthesis. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

There are two possible explanations for why the effects are smaller on the import side. First, there is a time lag between the purchase and the arrival of goods in Germany. Especially in the beginning of the low water period, the shipment modalities are likely to have been arranged before transport on inland waterways was impaired, and it might be difficult to change the transport mode at short notice. Second, firms relying on inputs typically imported via inland waterways have high incentives to prevent shortages of decisive import goods in order to avoid constraints to production due to missing inputs. When water levels are low, inland shipping is not prohibited by the authorities. It only becomes much more difficult and expensive to carry goods: due to a reduced cargo capacity, more ships are needed to transport the same amount of goods, and transport companies charge additional fees. Both factors can make shipping on inland waterways uneconomical. However, importers might be more willing to bear additional costs to receive as much of their freight as possible to avoid production losses than exporters who may try to postpone the shipment.

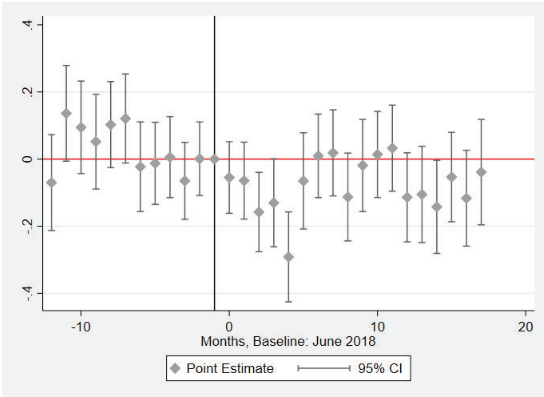
Interestingly, in contrast to the export side, the negative effect on imports via inland waterways persists in the year after the low water period. Although the size of the coefficient decreases compared to the second half of 2018 when the value, quantity, and probability of importing via inland shipping are the dependent variables, the coefficient *increases* when the number of products is the outcome. It remains almost unchanged for the number of product-destination combinations. These results provide the first evidence that firms continue to adjust their sourcing behaviour even after the shock is over, potentially to mitigate supply chain risks.

Figure 3 presents the associated event study graphs, indicating that the findings reported in Table 4 are not due to a systematic downward trend that already began before the low water period. The temporal pattern of the low water levels is again reflected in the monthly estimates, although it is not as distinct as on the export side, particularly when the number of products in the dependent variable. While the coefficients become statistically insignificant and close to zero in the first half of 2019, they turn negative and, in some cases, statistically significant again in the second half of 2019, i.e. in the months generally most prone to low water. Note that this pattern was neither observed as a seasonal trend in the year before the low water period, nor for exports, pointing toward a persistent import-specific adjustment of firms' transport mode choice.

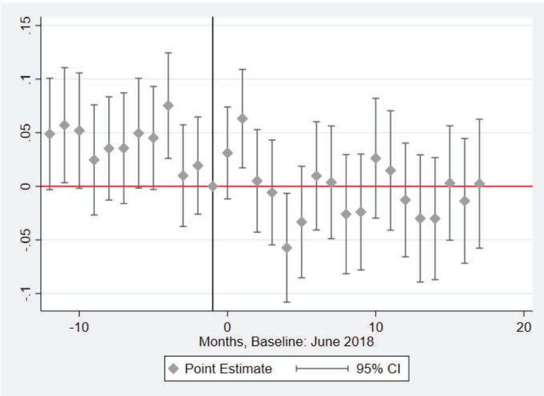
Figure 3. Imports, firm-transport mode level estimations, event study graphs



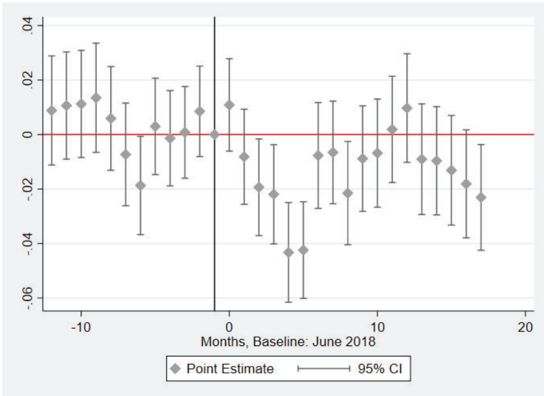
Import value



Import quantity



\# products



Probability of importing

The figure shows the dynamics of imports by inland shipping in comparison with other transport modes before, during, and after the low water period. The estimation equation reads:

$$ln(Y_{fmt}) = \sum_{i=-12}^{18} \beta_i (IWT_{fm} \times Time_{it}) + \delta_{fm} + \delta_t + \epsilon_{fmt},$$

where $Time_{it}$ is a dummy equal to one i periods before/after the shock and IWT_{fm} is one for exports by inland waterway transport. The baseline period ($i = -1$) is June 2018. All β_i's – i.e. one for each month in the regression sample – are displayed. Y_{fmt} is the value of imports in euro (upper left panel), quantity imported (upper right panel), the number of products imported (lower left panel) or the probability of using inland shipping as the transport mode for importing (lower right panel). Confidence intervals are defined at 5%.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

5.2 Does the shock propagate along the supply chain?

5.2.1 Empirical strategy

The previous section demonstrated that the low water period in 2018 significantly disrupted the transport of goods via inland waterways. Given the sizable and persistent effect on imports, the remainder of the paper examines how firms react in response. In this section, I focus on analyzing whether the supply shock propagates along the supply chain to downstream trade partners as firms that rely on imports via inland shipping might face input shortages, forcing them to scale back production and exports. For this purpose, I compare the development of exports of firms importing via inland waterways to the development of exports of firms that do not import via this mode of transport.[10] If firms relying on inland waterways for imports were able to fully offset the supply distortions caused by low water levels by switching to alternative transport modes or substituting imports from other sources or inventory, there should be no significant difference between exports of treated and untreated firms. I aggregate the data to the firm-product level and estimate the following difference-in-differences regression at the firm-product level:

$$\begin{aligned} lnY_{fpt} =&\beta_1(Treated^c_f \times 2018H2_t)+ \\ &\beta_2(Treated^c_f \times 2019_t) + \delta_{fp} + \delta_t + \epsilon_{fpt}, \end{aligned} \tag{2}$$

where f denotes firm, p denotes product and t denotes time on a monthly basis. Y_{fpt} is an indicator of export performance. I use the exported value (in euro), the quantity as well as the number of countries a firm f sells product p to as an outcome. Moreover, I aggregate the data to the firm level in an alternative specification to be able to use the number of products exported as an additional outcome variable.

Treatment is defined at the firm level, where $Treated^c_f$ is a binary indicator that equals one

[10]To the extent that the control group is subject to negative spillover effects from treated firms – for example as production problems lead to missing deliveries to other firms in Germany which, in turn, might weigh on their exports – , the following estimate represents an upper bound of the negative export effect.

if a firm is in the treatment group. I classify a firm as treated if it imported at least one product by inland shipping in the year before the low water, i.e. between July 2017 and June 2018. In the estimation sample, 1,231 firms are classified as treated. They are characterized by higher average values and quantities per firm-product combination than untreated firms, and are more diversified in terms of export partners and transport modes (Table 5).

Table 5. Firm-product level: Exports, by treatment status

	# observations	Mean	Median	SD
Not treated				
ln(value)	2.59e+07	7.32	7.16	2.65
ln(quantity)	2.36e+07	4.09	3.66	3.06
ln(# countries)	2.59e+07	0.73	0.00	0.95
# transportation modes	2.59e+07	1.09	1.00	0.33
# firms	141,883			
Treated				
ln(value)	1,447,068	7.96	7.73	3.06
ln(quantity)	1,349,533	5.43	5.01	3.64
ln(# countries)	1,447,068	1.13	0.69	1.15
# transportation modes	1,447,068	1.24	1.00	0.60
# firms	1,231			

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

To account for different dimensions of treatment heterogeneity, I consider various treatment categories c when estimating the effect. First, treatment intensity is measured by firm level exposure to the shock. Firms that only import sporadically or in very small quantities are not likely to be severely affected by the low water period. Thus, I differentiate between high and low exposure to the shock based on the share of imports via inland shipping in total imports in the year before treatment. I use a cutoff of 1 percent, which puts roughly $1/3$ of the treated firms into the low exposure category and $2/3$ into the high exposure category.[11]

[11]Lafrogne-Joussier et al. (2022) provide orientation for the choice of the cutoff. They use the same

Second, treatment intensity at the firm level is defined based on product level transport mode diversification. Diversification in terms of transport modes at the product level is likely to matter. If a firm imports a specific product exclusively by inland waterways it might be particularly difficult to switch to other modes of transport in the short-run, e.g. in the case of bulk goods. To the extent that this product is a crucial input for the firm, it can have significant consequences for production and exports, even if it constitutes only a small share of the firm's total imports. Therefore, I also differentiate between high and low exposure to the shock based on the maximum share of imports via inland shipping in total imports of a particular product in the year before treatment (also based on the import value in euros). Firms with high exposure are those that import at least 90 percent of at least one product via inland waterways (around 1/3 of all treated firms).

In the estimation, I again differentiate between two treatment periods: the second half of 2018, to capture the immediate effects of supply chain disruptions due to the low water, and the year 2019, to account for longer-lasting consequences. I include firm-product fixed effects (δ_{fp}) to control for all constant factors that are specific to a firm and product. Monthly time fixed effects (δ_t) control for everything that affects all firms and products equally in a month. Standard errors are clustered at the firm level in all regressions.

5.2.2 Baseline results

Table 6 presents the estimations based on Equation 2, using a firm's ex-ante import exposure to inland waterway transport as the measure of treatment intensity. The results reveal a negative impact of low water levels on all aspects of export performance, but only for firms with relevant exposure to the shock, characterized by a share of inland shipping in total imports of above 1 percent. Firms that import only a small proportion of their total imports

threshold to "abstract from secondary goods that are imported infrequently or in tiny quantities" (p. 186) in their analysis of the export response of French firms to the early lockdown in China. Note that employing a low threshold is useful to capture the average treatment effect while mitigating the distortion caused by firms that engage in sporadic or minimal import activities through inland shipping.

via inland waterways do not show statistically significant effects. Specifically, highly exposed firms experienced an average decrease in export value of 3.6 percent during the second half of 2018 compared to unaffected firms (column 1). The decline in exported quantity was slightly larger (column 2), while the number of destination markets served and the number of products exported each decreased by approximately 2 percent (columns 3 and 4). These estimates are statistically significant at the 1 and 5 percent levels, respectively. The effects were primarily temporary, as there is no evidence of sustained negative consequences or significant catch-up effects after the low water period. Only when the number of products is the dependent variable, a negative coefficient statistically significant at the 10 percent level remains in 2019.

Table 6. Impact of supply disruptions due to low water levels on export performance, by treatment intensity based on firm level import exposure

	(1) value	(2) quantity	(3) # countries	(4) # products
Low exposure	0.012	0.000	0.001	-0.001
× 2018H2	(0.015)	(0.015)	(0.013)	(0.012)
Low exposure	0.004	-0.020	0.013	-0.003
× 2019	(0.030)	(0.027)	(0.019)	(0.017)
High exposure	-0.039***	-0.042***	-0.020***	-0.023**
× 2018H2	(0.014)	(0.012)	(0.005)	(0.011)
High exposure	0.003	0.009	-0.009	-0.027*
× 2019	(0.024)	(0.023)	(0.011)	(0.015)
# obs.	26,167,390	23,886,966	26,167,390	1,993,797
δ_{fp}	Yes	Yes	Yes	δ_f
δ_t	Yes	Yes	Yes	Yes
R^2	0.857	0.883	0.857	0.895

Firms with high (low) exposure are those with a share of imports via inland waterways in total imports of above (below) 1%. Robust standard errors clustered at the firm level are in parenthesis. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

Similarly, Table 7 examines treatment intensity based on the diversification of transport modes at the product level. Firms with low exposure, which import via inland waterways but with each product's share of inland shipping remaining below 90 percent, experience no significant effects from low water levels. In contrast, firms heavily reliant on inland shipping for imports of specific products exhibit a statistically significant and economically substantial decline in export performance during the low water period. The coefficients in this case are somewhat larger in size compared to those in Table 6, although the confidence intervals are overlapping. Yet, the results underscore the importance of ex-ante transport mode diversification in mitigating the supply shock.

Table 7. Impact of supply disruptions due to low water levels on export performance, by treatment intensity based on product level transport mode diversification

	(1) value	(3) quantity	(5) # countries	(6) # products
Low exposure	0.017	0.006	0.005	0.000
× 2018H2	(0.013)	(0.013)	(0.011)	(0.010)
Low exposure	0.012	-0.010	0.022	-0.010
× 2019	(0.028)	(0.026)	(0.016)	(0.014)
High exposure	-0.045***	-0.050***	-0.024***	-0.029**
× 2018H2	(0.015)	(0.014)	(0.009)	(0.013)
High exposure	-0.009	-0.006	-0.022	-0.021
× 2019	(0.028)	(0.028)	(0.018)	(0.020)
# obs.	26,167,390	23,886,966	26,167,390	1,993,797
δ_{fp}	Yes	Yes	Yes	δ_f
δ_t	Yes	Yes	Yes	Yes
R^2	0.857	0.883	0.857	0.895

Firms with high exposure are those that import at least 90 percent of at least one product via inland waterways. Firms with low exposure are other firms importing via inland waterways. Robust standard errors clustered at the firm level are in parenthesis. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

In summary, the findings provide empirical evidence that supply chain disruptions caused by low water levels have a statistically significant and economically meaningful negative effect on export performance. A likely explanation for these findings is that a lack of necessary inputs hampers the production of affected firms, leading to decreases in export value, quantity, and the number of destination markets and products exported. These disruptions propagate along the supply chain and can potentially have ripple effects in other countries. However, the observed effects are generally temporary and diminish once the transport disruption is resolved.

5.2.3 Alternative channels and robustness

In the following, I address and eliminate several alternative channels that could potentially drive the observed negative impact on export performance, beyond the absence of crucial inputs in the production process. First, I dismiss the lack of transport options for exports as an explanatory factor for the observed negative effects on export performance. Second, I demonstrate the robustness of the results by controlling for product-specific demand shocks. Lastly, I provide evidence to refute the notion that the results are driven by the introduction of the "Worldwide Harmonized Light-Duty Vehicles Test Procedure" (WLTP) on September 1, 2018, which also lead to production problems and coincided with the low water period.

Exporting by inland waterways. One potential alternative explanation for the findings presented in Tables 6 and 7 is that firms relying on inland waterway transport for imports also employ this transport mode for their exports. In this case, the observed negative effect could be attributed to a lack of transport options for exporting, rather than production issues arising from the unavailability of crucial inputs. To investigate this hypothesis, I conduct additional regressions at the firm-product level using a restricted sample, wherein all firm-product combinations that were exported at least once via inland waterway transport during the sample period are excluded. Table 8 provides evidence against this explanation, as the estimated coefficients exhibit minimal changes in comparison with the baseline estimations. Although some regressions yield slightly smaller coefficients, the overall results remain remarkably robust. It appears that, for firms importing via inland waterways, a lack of transport options for exporting via the same mode is a minor concern.

Table 8. Impact of supply disruptions due to low water levels on export performance, excluding products typically exported by inland waterways

	(1) value	(2) quantity	(3) # countr.	(4) value	(5) quantity	(6) # countr.
Exposure	firm	firm	firm	product	product	product
Low exposure	0.011	-0.002	0.000	0.015	0.003	0.004
× 2018H2	(0.015)	(0.015)	(0.012)	(0.013)	(0.013)	(0.01)
Low exposure	0.013	-0.009	0.016	0.021	0.000	0.025*
× 2019	(0.026)	(0.023)	(0.017)	(0.023)	(0.021)	(0.014)
High exposure	-0.038***	-0.039***	-0.019***	-0.043***	-0.046***	-0.023**
× 2018H2	(0.014)	(0.013)	(0.005)	(0.016)	(0.015)	(0.009)
High exposure	0.007	0.014	-0.005	-0.004	0.000	-0.018
× 2019	(0.025)	(0.024)	(0.012)	(0.029)	(0.028)	(0.018)
# obs.	26,015,719	23,737,991	26,015,719	26,015,719	23,737,991	26,015,719
δ_{fp}	Yes	Yes	Yes	Yes	Yes	Yes
δ_t	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.856	0.881	0.856	0.856	0.881	0.856

In columns (1)-(3), firms with high (low) exposure are those with a share of imports via inland waterways in total imports of above (below) 1%. In columns (4)-(6), firms with high exposure are those that import at least 90 percent of at least one product via inland waterways. Firms with low exposure are other firms importing via inland waterways. Robust standard errors clustered at the firm level are in parenthesis. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

Product-specific demand shocks. Another potential concern is whether the observed negative effect is influenced by demand factors rather than supply factors. It is possible that firms classified as highly exposed to low water levels may also experience a simultaneous demand shock. If these firms predominantly sell specific products and there is a decline in demand for those products during the same period, it could contribute to the observed negative effects on export performance. To address this concern, I introduce product-time fixed effects (δ_{pt}) instead of just time fixed effects (δ_t) in Equation 2 and re-estimate the regressions. The inclusion of δ_{pt} captures any factors that affect a particular product in a given month, regardless of whether the product is sold by a firm exposed to the low water shock or not. This accounts for the possibility of a general drop in global demand for a product. The results in Table 9 provide evidence against this channel. Although the coefficients are slightly smaller compared to the baseline regressions, the overall findings remain unchanged. This confirms that negative product-specific demand shocks are not the primary driver of the observed effects.

Table 9. Impact of supply disruptions due to low water levels on export performance, alternative fixed effects

	(1) value	(2) quantity	(3) # countr.	(4) value	(5) quantity	(6) # countr.
Exposure	firm	firm	firm	product	product	product
Low exposure	0.014	0.003	0.003	0.018	0.008	0.007
× 2018H2	(0.015)	(0.015)	(0.013)	(0.013)	(0.014)	(0.011)
Low exposure	-0.005	-0.017	0.016	0.014	-0.007	0.025
× 2019	(0.029)	(0.027)	(0.019)	(0.027)	(0.026)	(0.016)
High exposure	-0.034**	-0.035***	-0.016***	-0.040***	-0.042***	-0.021**
× 2018H2	(0.014)	(0.013)	(0.005)	(0.015)	(0.014)	(0.010)
High exposure	0.007	0.015	-0.004	-0.006	0.001	-0.018
× 2019	(0.024)	(0.023)	(0.011)	(0.028)	(0.027)	(0.018)
# obs.	26,154,042	23,873,231	26,154,042	26,154,042	23,873,231	26,154,042
δ_{fp}	Yes	Yes	Yes	Yes	Yes	Yes
δ_{pt}	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.860	0.886	0.860	0.860	0.886	0.860

In columns (1)-(3), firms with high (low) exposure are those with a share of imports via inland waterways in total imports of above (below) 1%. In columns (4)-(6), firms with high exposure are those that import at least 90 percent of at least one product via inland waterways. Firms with low exposure are other firms importing via inland waterways. Robust standard errors clustered at the firm level are in parenthesis. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

WLTP introduction. On September 1, 2018, the "Worldwide Harmonized Light-Duty Vehicles Test Procedure" (WLTP) became a requirement for the registration of new passenger cars in the European Union. Due to bottlenecks in the implementation of the test procedure, production of motor vehicles was hampered, in particular during the summer (Jannsen and Kallweit, 2018). Due to the temporal overlap of the reform with the low water period, I check the robustness of the results by excluding the sector "Manufacture Of Motor Vehicles, Trailers And Semi-Trailers" (code 29 according to the International Standard Industrial

Classification of All Economic Activities, Rev. 4). Table 10 presents the estimations and shows that they are robust to the exclusion of the automobile sector.

Table 10. Impact of supply disruptions due to low water levels on export performance, excluding the automobile sector

	(1) value	(2) quantity	(3) # countr.	(4) value	(5) quantity	(6) # countr.
Exposure	firm	firm	firm	product	product	product
Low exposure	0.015	0.003	0.003	0.020	0.010	0.007
× 2018H2	(0.015)	(0.016)	(0.014)	(0.013)	(0.014)	(0.012)
Low exposure	0.026	0.003	0.020	0.035	0.013	0.029*
× 2019	(0.026)	(0.023)	(0.020)	(0.022)	(0.020)	(0.015)
High exposure	-0.039***	-0.042***	-0.020***	-0.045***	-0.049***	-0.024***
× 2018H2	(0.014)	(0.012)	(0.005)	(0.015)	(0.014)	(0.009)
High exposure	0.002	0.008	-0.009	-0.009	-0.006	-0.022
× 2019	(0.024)	(0.023)	(0.011)	(0.029)	(0.028)	(0.018)
# obs.	25,590,222	23,352,915	25,590,222	25,590,222	23,352,915	25,590,222
δ_{fp}	Yes	Yes	Yes	Yes	Yes	Yes
δ_t	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.856	0.883	0.854	0.856	0.883	0.854

In columns (1)-(3), firms with high (low) exposure are those with a share of imports via inland waterways in total imports of above (below) 1%. In columns (4)-(6), firms with high exposure are those that import at least 90 percent of at least one product via inland waterways. Firms with low exposure are other firms importing via inland waterways. Robust standard errors clustered at the firm level are in parenthesis. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

5.3 Do firms adjust their sourcing behaviour in response to the shock?

5.3.1 Empirical strategy

So far, the empirical analyses of the impact of the low water period have shown a significant decrease in exports and imports via inland shipping compared to trade through other transport modes, with a more lasting impact observed on imports rather than exports. Moreover, the low water shock propagated along the supply chain. Firms depending on imports via inland shipping experienced a decline in exports that goes beyond the direct impact of reduced transport options for exporting, suggesting that the supply of critical inputs was disrupted. The adverse effects are particularly pronounced for firms with limited diversification in terms of transport at the product level. These findings are in line with macroeconomic evidence presented by Ademmer et al. (2023), who establish a negative impact of low water on industrial production. Going one step further, the question arises whether firms adjust their sourcing strategies with respect to their mode choice during and after the low water shock.

To address this question, the sample is now restricted to firms classified as treated in Section 5.2, i.e. firms that imported at least once via inland waterways in the year before the low water period. I redefine treatment at the firm-product level, considering that certain products are more likely to be imported by inland shipping, such as bulk goods or heavy and/or large products.

The analysis compares the transport mode choice of treated firms for those products imported via inland shipping in the year before the low water to those products imported via other transport modes. In particular, I estimate the probability of switching to an alternative mode for a product previously imported by inland shipping in comparison with the products in the control group. The linear probability model takes the following form:

$$\begin{aligned} Y_{fpt} =&\beta_1(Treated_{fp} \times 2018H2_t)+ \\ &\beta_2(Treated_{fp} \times 2019_t) + \delta_{fp} + \delta_t + \epsilon_{fpt}, \end{aligned} \tag{3}$$

where the dependent variable, Y_{fpt} is a dummy variable for the transport mode used in a given month, and it is zero for all other months. I distinguish between road, train, sea, and air transport. In an alternative specification, I use a dummy variable that takes the value one if a product was imported by *either* of these four modes of transport. The binary treatment indicator at the firm-product level $Treated_{fp}$ takes the value one if a firm-product pair was imported by inland shipping in the year before the low water period and is zero otherwise. I restrict the sample to only include products imported in the year before the low water to avoid any compositional effects due to changes in a firm's product portfolio. The coefficients of interest are β_1 and β_2. They capture the differences in the probability of using a specific transport mode when comparing products previously imported by inland shipping to all other products before, during, and after the shock. Standard errors are clustered at the firm-product level in all regressions, i.e. at the level at which treatment is defined.

5.3.2 Baseline results

The results, presented in Table 11, indicate that the probability of importing a product by train, road, air, and sea in a given month increases during the low water period for products previously imported by inland shipping, relative to products not imported by this mode in the year before the shock. The increase is largest for road transport, with a probability increase of 2.3 percent (column 2). The increases in the probability of importing by train, air or sea are below 1 percent (columns 1, 3, and 4). All coefficients are statistically significant at common levels. Looking at all four transport modes simultaneously, the probability of using one of them increases by 3.2 percent when comparing products previously imported by inland shipping to all other products before and during the low water period (column

5). Figure 4 shows the dynamics of the effect over time when "all modes" is the dependent variable. There is no significant and systematic pre-trend visible, suggesting that indeed the low water situation lead to an adjustment of the transport mode choice for imports.[12]

Table 11. Imports, firm-product level estimations, diversion to other transport modes

	(1) train	(2) street	(3) air	(4) sea	(5) all modes
IWT product	0.003**	0.023***	0.008***	0.004***	0.032***
× 2018H2	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
IWT product	-0.009***	0.018***	0.007***	0.007***	0.026***
× 2019	(0.002)	(0.003)	(0.001)	(0.001)	(0.003)
# obs.	4,060,320	4,060,320	4,060,320	4,060,320	4,060,320
δ_{fp}	Yes	Yes	Yes	Yes	Yes
δ_t	Yes	Yes	Yes	Yes	Yes
R^2	0.561	0.540	0.497	0.489	0.516

Robust standard errors clustered at the firm-product level are in parentheses. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

Notably, the probability of using alternative transport modes instead of inland waterway shipping remains elevated even *after* the low water period is over, although the coefficients mostly decrease in size. The observed persistence of the switching effect is in line with previous evidence on infrastructure disruptions. Friedt (2021) documents that Hurricane Katrina lead to a persistent rerouting of international cargo to ports unaffected by the disaster, pointing to path dependencies in shipping patterns. Similarly, Balboni et al. (2024) find that flood events in Pakistan lead firms to persistently switch away from suppliers reached via flood-prone roads.

Several demand-side explanations may account for this phenomenon. First, the low wa-

[12]The respective graphs for each transport mode separately can be found in the Appendix (Figure A3). The negative coefficient on $Treated_{fp} \times 2019_t$ for transport by train in Table 11 is partly driven by a sharp and unexpected drop in November and December 2019.

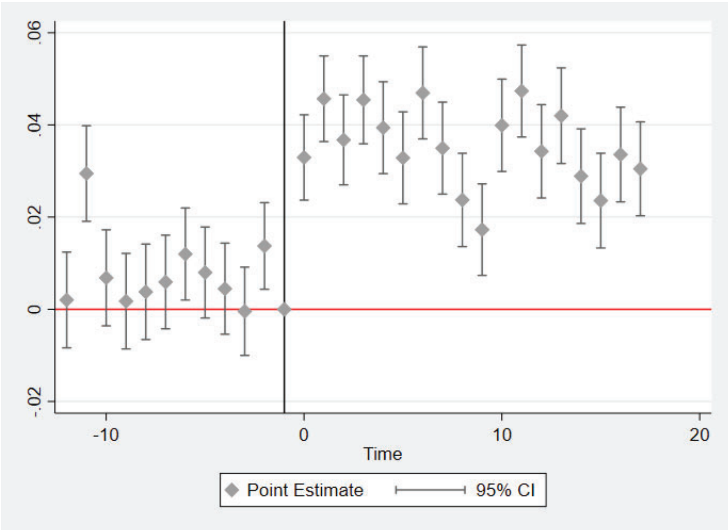
ter period might lead to increased uncertainty about the future reliability of inland waterway transport in particular in light of climate change increasing the probability of extreme weather conditions. Firms might therefore reassess the costs, benefits, and risks associated with inland shipping, prompting them to mitigate the potential for disruptions by diversifying their transport options. Second, switching to alternative modes is likely associated with sunk costs – e.g. as firms need to find new suppliers or carriers –, making it less appealing to revert back to inland waterway shipping after the low water period is over. Finally, it might be the case that the transport mode choice of firms was not optimal prior to the low water period, and the "forced experimentation" during the disruption revealed previously unrecognized benefits.[13]

Alternatively, supply-side factors could contribute to the observed persistence in transport mode switching. If shipping providers exited the market following the low water shock, the resulting reduction in shipping capacity could lead to lower availability and higher prices for inland waterway transport. To assess this potential mechanism, I examine the development of transport equipment. Eurostat provides data on the number, load capacity, and nationality of vessels used for inland waterway transport in Germany. Figure A2 plots the evolution of inland waterways transport equipment from 2013 to 2019.[14] While the number of vessels has slightly declined over time, overall capacity has remained stable. Notably, there is no evidence of a substantial reduction in capacity following the low water period under study, suggesting that supply-side constraints are unlikely to be the primary driver of persistence in transport mode switching.

[13]Larcom et al. (2017) highlight the "benefits of forced experimentation" in the context of disruptions to transport in a different setting. They show that a significant share of commuters in London permanently adjust their travel routine in response to a strike on the London Underground, suggesting that their previous routes were not optimal.

[14]The figure reports aggregate inland water transport equipment for Germany and the Netherlands. In 2017 – the year preceding the low water shock – nearly 90 percent of inland waterway freight in Germany (measured in tonnes) was carried by Dutch (58 percent) and German (30 percent) vessels.

Figure 4. Imports, firm-product level estimations, diversion to other transport modes: Event study graphs



The figure shows the dynamics of the probability of importing a product by an alternative transport mode had it been imported at least once by inland shipping in the year before the low water period, relative to all other products. The estimation equation reads:

$$Y_{fpt} = \sum_{i=-12}^{18} \beta_i (Treated_{fp} \times Time_{it}) + \delta_{fp} + \delta_t + \epsilon_{fpt},$$

where $Time_{it}$ is a dummy equal to one i periods before/after the shock and $Treated_{fp}$ takes the value one if a firm-product pair was imported by inland shipping in the year before the low water period and is zero otherwise. The baseline period ($i = -1$) is June 2018. Y_{fpt} is a dummy variable if street, train, sea or air is used in a given month, and it is zero for all other months. Confidence intervals are defined at 5%. Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

5.3.3 Heterogeneity of the switching effect

In the following, I explore the heterogeneity of the transport mode switching effect across product and firm characteristics. For this purpose, I use the composite transport mode variable, which indicates whether a product is imported by either train, street, air, or sea, as the outcome variable in all specifications and re-estimate Equation 3 for different subsamples.

First, I investigate whether the switching effect varies across product groups. Table 12 reveals that during the low water period in the second half of 2018 the probability to import a product previously shipped via inland waterways using another mode increases across product groups. The effect is strongest for intermediate goods, agricultural products, and non-durable consumer goods, with an increase by more than 3 percent that is statistically significant at the 1 percent level. This finding aligns with expectations, as firms are more likely to modify their sourcing strategies when dealing with critical products that require timely delivery, such as imported inputs in just-in-time supply chains or perishable goods like foodstuffs. The likelihood of importing via alternative transport modes remains higher in 2019 for all three product groups, although the coefficients decrease in magnitude compared to the low water period.

The picture is somewhat different for capital goods, durable consumption goods, and energy products. The probability of importing capital goods through alternative transport modes rather than inland waterways increases by 2 percent during the low water period. However, and in contrast to intermediate, agricultural, and non-durable products, the effect becomes *larger* in the aftermath of the disruption. One reason could be that firms prioritize intermediate and non-durable products in the presence of capacity constraints, with investment goods catching up only later on. A similar pattern may apply to energy goods, for which a significant switching effect is only present after the low water period, while the effect during the disruption is negligible and statistically insignificant. In contrast, the switching effect for durable consumption goods is only temporary. Since these goods are neither perishable nor critical inputs for production, this result is in line with firms reassessing the risks in their supply chain and making permanent adjustments only when necessary.

Next, I investigate whether the probability of using alternative transport modes for importing varies along the firm size dimension. It is unclear ex-ante whether small or large firms are more likely to adjust their sourcing behaviour. On the one hand, small firms typically deal with lower import quantities compared to large firms, which makes it easier for them to accommodate alternative means of transport such as trucks. On the other hand, large firms

Table 12. Imports, firm-product level estimations, diversion to other transport modes, by product groups

	Dependent variable: alternative modes dummy					
	(1) agricultural goods	(2) intermediate goods	(3) capital goods	(4) consumer durables	(5) consumer non-durables	(6) energy goods
IWT product	0.035***	0.036***	0.020***	0.023**	0.031***	0.006
× 2018H2	(0.011)	(0.003)	(0.006)	(0.009)	(0.005)	(0.012)
IWT product	0.025**	0.028***	0.032***	0.003	0.023***	0.030**
× 2019	(0.011)	(0.004)	(0.006)	(0.012)	(0.006)	(0.015)
# obs.	74,760	2,224,890	754,260	157,830	726,240	34,050
δ_{fp}	Yes	Yes	Yes	Yes	Yes	Yes
δ_t	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.504	0.512	0.536	0.529	0.501	0.513

Robust standard errors clustered at the firm-product level are in parentheses. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

have extensive supplier networks, which might facilitate short-term adjustments. Table 13 presents the results for subsamples of small, medium-sized, and large firms. The switching effect is most pronounced and persistent for small firms. The probability of using alternative transport mode for goods imported on inland waterways before the low water period increases by 5.2 percent during the disruption and remains at this level after the shock subsides (column 1). In the case of medium-size firms, adjusting their sourcing strategy takes longer, with the switching effect growing from 2.1 percent during the low water period to 4.2 percent in the aftermath (column 2). Large firms exhibit a 3.7 percent increase in the probability of using alternative modes for products previously imported via inland shipping, and the effect diminishes slightly after the disruption (column 3).

Finally, Table 14 examines the role of transport mode diversification at the product level and the relevance of a product in a firm's import portfolio for the switching effect. As the latter requires the introduction of triple interaction terms, I facilitate the analysis by

Table 13. Imports, firm-product level estimations, diversion to other transport modes, by firm size

	Dependent variable: alternative modes dummy		
	(1) small firms	(2) medium-sized firms	(3) large firms
IWT product	0.052***	0.021***	0.037***
× 2018H2	(0.006)	(0.005)	(0.003)
IWT product	0.050***	0.042***	0.032***
× 2019	(0.006)	(0.005)	(0.003)
# obs	195,510	577,590	3,235,146
R^2	0.417	0.458	0.530

Robust standard errors clustered at the firm-product level are in parentheses. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

introducing a dummy variable $Post_t$ that takes the value of one from July 2018 onward instead of distinguishing between two treatment periods. I classify a product as diversified if inland waterway transport accounted for less than 70 percent of the total imports of the respective product in the year before the low water period. Products with a higher share of inland shipping in total imports are classified as non-diversified. Maybe unsurprisingly, the switching effect is entirely driven by a large and statistically highly significant increase in the probability of using alternative transport modes for ex-ante non-diversified products (column 2), which is not observed for diversified products (column 1).

Additionally, I explore the heterogeneity of the switching effect based on the importance of a product for a firm. Products imported in small quantities or irregularly should be less crucial inputs for firms, while products accounting for a significant share of overall imports are probably more relevant so that an adjustment regarding sourcing these products is more likely. To test this hypothesis, I introduce triple interaction terms involving the share of a specific product in a firm's overall import value and quantity. As expected, the probability of adopting alternative modes of transport increases with the share of the respective product in overall imports, as the large and highly statistically significant triple interaction terms confirm (columns 3 and 4).

Table 14. Imports, firm-product level estimations, diversion to other transport modes, by product characteristics

	Dependent variable: alternative modes variable			
	(1) low IWT share	(2) high IWT share	(3) product relevance	(4) product relevance
IWT product × post	-0.003	0.078***	0.028***	0.028***
	(0.003)	(0.003)	(0.002)	(0.002)
... × value share			0.089***	
			(0.019)	
... × quantity share				0.080***
				(0.019)
# obs.	4,060,320	4,060,320	4,060,320	4,060,320
δ_{fp}	Yes	Yes	Yes	Yes
δ_t	Yes	Yes	Yes	Yes
R^2	0.516	0.516	0.516	0.516

Robust standard errors clustered at the firm-product level are in parentheses. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

6 Conclusion

This paper provides evidence that a temporary supply shock can propagate along the supply chain and trigger persistent adjustments in firms' sourcing strategies. Leveraging a period of critically low water levels on major shipping routes in Germany as a natural experiment, I examine how disruptions to transport infrastructure caused by extreme weather events can inflict economic harm on advanced economies and how firms adapt in response. During the low water period, the inland shipping volumed declined substantially relative to other transport modes, with imports more persistently affected than exports. Using detailed firm level data, I investigate the extent to which disruptions to import supply due to the low water affect exports, thereby transmitting the shock internationally. The results show that firms relying on inland waterway transport for importing experienced a temporary decline in exports of 3.6 percent, on average, during the low water period. Firms with limited transport mode diversification at the product level were affected most. These findings are robust when accounting for the role of inland waterway transport in exporting, product-specific demand shocks, and simultaneous regulatory changes in the automotive sector.

Investigating whether firms adjusted their sourcing strategies in response to the shock reveals that they substituted away from inland shipping toward alternative transport modes, particularly for time-sensitive products such as intermediate inputs and non-durable goods. Notably, this switching effect persisted even after the severe low water period had ended, pointing towards path dependencies in firms' decision-making. The findings imply that even short-lived disruptions – without physical capital destruction or permanent changes in the external environment – can lead to lasting adjustments to supply chains. This challenges the common assumption of symmetric effects often employed in modelling frameworks when analysing shocks and underscores the importance of understanding supply chain dynamics and firms' resilience to temporary disruptions.

More broadly, the findings contribute to the growing literature on how climate-related disruptions affect economic activity by highlighting infrastructure vulnerabilities as a transmission channel. Inland waterways are generally considered a cost-effective and low-emission transport mode, and feature prominently in European decarbonisation strategies. Yet the results show that extreme weather can reduce the reliability of these environmentally favourable options, potentially undermining sustainability goals. Understanding firms' responses to infrastructure vulnerabilities is therefore important for assessing economic resilience and informing efforts to strengthen climate-adaptive transport systems and supply chains.

References

Ademmer, M., N. Jannsen, and S. Meuchelböck (2023): "Extreme weather events and economic activity: The case of low water levels on the Rhine river," *German Economic Review*, 24, 121–144.

Allen, T. and C. Arkolakis (2022): "The welfare effects of transportation infrastructure improvements," *The Review of Economic Studies*, 89, 2911–2957.

Balboni, C., J. Boehm, and M. Waseem (2024): "Firm Adaptation in Production Networks: Evidence from Extreme Weather Events in Pakistan," Mimeo.

Barrot, J.-N. and J. Sauvagnat (2016): "Input specificity and the propagation of idiosyncratic shocks in production networks," *The Quarterly Journal of Economics*, 131, 1543–1592.

BDB (2019): "Bundesverband der Deutschen Binnenschifffahrt e.V. (BDB) – Daten und Fakten 2018/2019," `https://www.binnenschiff.de/wp-content/uploads/2019/11/191125-Daten-Fakten_2018-19_final.pdf`, accessed 2023/04/06.

Besedeš, T., J. Chu, and A. P. Murshid (2024): "Fly the unfriendly skies: The role of transport costs in gravity models of trade," *Journal of International Economics*, 152, 103994.

Boehm, C., A. Flaaen, and N. Pandalai-Nayar (2019): "Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake," *Review of Economics and Statistics*, 101, 60–75.

Carvalho, V. M., M. Nirei, Y. U. Saito, and A. Tahbaz-Salehi (2021): "Supply chain disruptions: Evidence from the Great East Japan earthquake," *The Quarterly Journal of Economics*, 136, 1255–1321.

Castro-Vincenzi, J., G. Khanna, N. Morales, and N. Pandalai-Nayar (2024): "Weathering the storm: Supply chains and climate risk," NBER Working Paper No. w32218.

CCNR (2020): "Annual Report of the Central Commission for the Navigation of the Rhine (CNNR) 2020: Inland Navigation in Europe – Market Observation." Tech. rep.

Coşar, A. K. and B. Demir (2018): "Shipping inside the box: Containerization and trade," *Journal of International Economics*, 114, 331–345.

De Mel, S., D. McKenzie, and C. Woodruff (2012): "Enterprise recovery following natural disasters," *The Economic Journal*, 122, 64–91.

Dell, M., B. F. Jones, and B. A. Olken (2014): "What do we learn from the weather? The new climate-economy literature," *Journal of Economic Literature*, 52, 740–98.

Demir, B., B. Javorcik, T. K. Michalski, and E. Ors (2024): "Financial constraints and propagation of shocks in production networks," *Review of Economics and Statistics*, 106, 437–454.

European Environment Agency (2021): "Briefing no. 01/2021 – Rail and waterborne — best for low-carbon motorised transport," https://www.eea.europa.eu/publications/rail-and-waterborne-transport, accessed 2024/04/07.

European Parliamentary Research Service (2022): "Inland waterway transport in the EU," https://www.europarl.europa.eu/RegData/etudes/BRIE/2022/698918/EPRS_BRI(2022)698918_EN.pdf, PE 698.918, accessed 2024/04/07.

Eurostat (2024): "Transport Database," https://ec.europa.eu/eurostat/web/transport/database, accessed: 2025-01-25.

Felbermayr, G., J. Gröschl, M. Sanders, V. Schippers, and T. Steinwachs (2022): "The economic impact of weather anomalies," *World Development*, 151, 105745.

Feng, A., H. Li, and Y. Wang (2025): "We are All in the Same Boat: Cross-Border Spillovers of Climate Shocks through International Trade and Supply Chains," *The Economic Journal*, 135, 1433–1466.

Freund, C., A. Mattoo, A. Mulabdic, and M. Ruta (2022): "Natural disasters and the reshaping of global value chains," *IMF Economic Review*, 70, 590–623.

Friedt, F. L. (2021): "Natural disasters, aggregate trade resilience, and local disruptions: Evidence from Hurricane Katrina," *Review of International Economics*, 29, 1081–1120.

Ganapati, S. and W. F. Wong (2023): "How far goods travel: global transport and supply chains from 1965–2020," *Journal of Economic Perspectives*, 37, 3–30.

German Federal Institute of Hydrology (2019): "Low-Flow in 2018," https://www.bafg.de/DE/05_Wissen/04_Pub/04_Buecher/niedrigwasser_2018_dokument_EN.pdf, accessed 2023/04/06.

Gröschl, J. and A. Sandkamp (2023): "Flood Events and Plant Level Trade: A Chinese Experience," *ifo Working Paper Series*, 389.

Harrigan, J. (2010): "Airplanes and comparative advantage," *Journal of International Economics*, 82, 181–194.

Hayakawa, K., T. Matsuura, and F. Okubo (2015): "Firm-level impacts of natural disasters on production networks: Evidence from a flood in Thailand," *Journal of the Japanese and International Economies*, 38, 244–259.

Heiland, I., A. Moxnes, K. H. Ulltveit-Moe, and Y. Zi (forthcoming): "Trade From Space: Shipping Networks and The Global Implications of Local Shocks," *Review of Economics and Statistics*.

Heinen, A., J. Khadan, and E. Strobl (2019): “The Price Impact of Extreme Weather in Developing Countries,” *The Economic Journal*, 129, 1327–1342.

Hummels, D. L. and G. Schaur (2013): “Time as a trade barrier,” *American Economic Review*, 103, 2935–2959.

IPCC (2021): *Climate change 2021: the physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change*, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Jannsen, N. and M. Kallweit (2018): “Auswirkungen des neuen WLTP-Prüfverfahrens,” *Wirtschaftsdienst*, 98, 831–832.

Jones, B. F. and B. A. Olken (2010): “Climate shocks and exports,” *American Economic Review*, 100, 454–59.

Kawakubo, T. and T. Suzuki (2022): “Supply Chain Dynamics and Resilience of the Economy during a Crisis,” *RIETI Discussion Paper Series*, 22-E-070.

Khanna, G., N. Morales, and N. Pandalai-Nayar (2022): “Supply chain resilience: Evidence from Indian firms,” NBER Working Paper No. w30689.

Kim, H. S., C. Matthes, and T. Phan (2025): “Severe weather and the macroeconomy,” *American Economic Journal: Macroeconomics*, 17, 315–341.

Korovkin, V., A. Makarin, and Y. Miyauchi (2024): “Supply Chain Disruption and Reorganization: Theory and Evidence from Ukraine’s War,” *Available at SSRN 4825542*.

Kriedel, N. (2019): “Macroeconomic effects of low water levels on the Rhine – a statistical analysis,” `https://www.ccr-zkr.org/files/documents/workshops/wrshp261119/03_Kriedel_en.pdf`, accessed 2023/04/06.

Kruse, H., A. Meyerhoff, and A. Erbe (2021): “Neue Methoden zur Mikrodatenverknüpfung von Außenhandels- und Unternehmensstatistiken,” *WISTA-Wirtschaft und Statistik*, 73, 53–63.

Lafrogne-Joussier, R., J. Martin, and I. Mejean (2022): “Supply shocks in supply chains: Evidence from the early lockdown in China,” *IMF Economic Review*, 1–46.

Larcom, S., F. Rauch, and T. Willems (2017): “The benefits of forced experimentation: striking evidence from the London underground network,” *The Quarterly Journal of Economics*, 132, 2019–2055.

Martincus, C. V. and J. Blyde (2013): “Shaky roads and trembling exports: Assessing the trade effects of domestic infrastructure using a natural experiment,” *Journal of International Economics*, 90, 148–161.

Sandkamp, A., V. Stamer, and S. Yang (2022): “Where has the rum gone? The impact of maritime piracy on trade and transport,” *Review of World Economics*, 158, 751—-778.

Strobl, E. (2011): "The economic growth impact of hurricanes: Evidence from US coastal counties," *Review of Economics and Statistics*, 93, 575–589.

The Economist (2023): "Severe drought is constraining the Panama Canal," https://www.economist.com/the-americas/2023/11/23/severe-drought-is-constraining-the-panama-canal, 2023/11/23, accessed 2024/04/07.

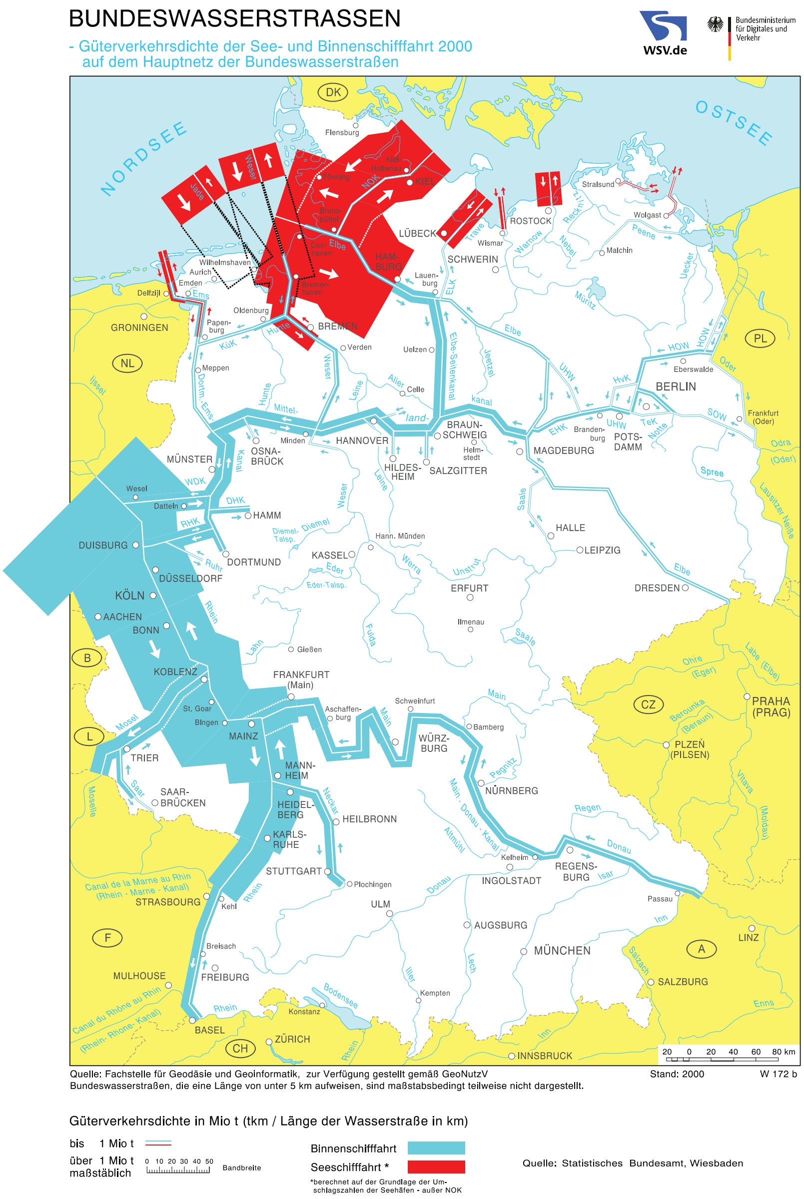
——— (2024): "Climate change's disruptive impact on global supply chains and the urgent call for resilience," Economist Impact, https://impact.economist.com/projects/trade-in-transition/climate_change, accessed 2024/04/07.

US Department of Transportation (2022): "Low Water on the Mississippi Slows Critical Freight Flows," https://www.bts.gov/data-spotlight/low-water-mississippi-slows-critical-freight-flows, 2022/11/16, accessed 2024/04/07.

A Appendix

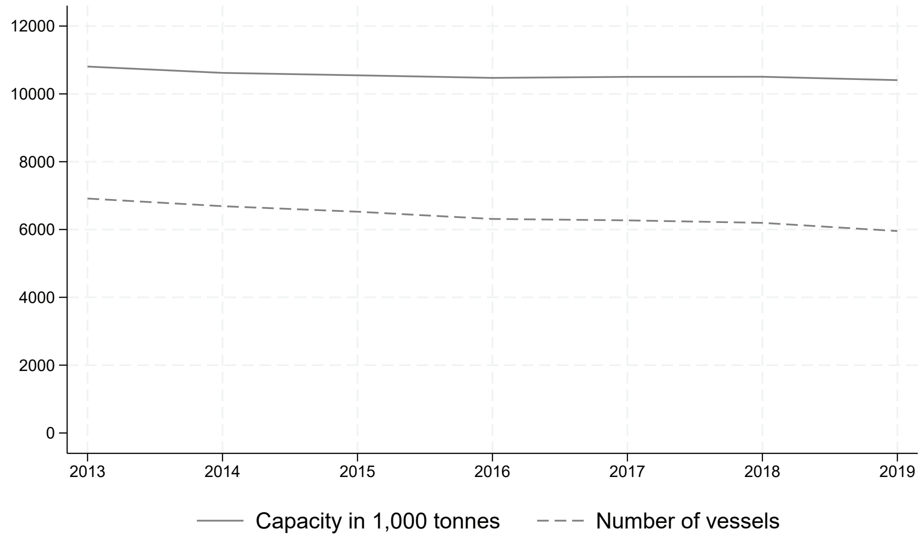
A.1 Inland waterway transportation in Germany

Figure A1. Freight traffic density of maritime and inland navigation on the main network of federal waterways



Source: German Statistical Office.

Figure A2. Development of inland water transport equipment, 2013-2019



The graph shows the development of available equipment for inland waterway transportation from 2013 to 2019. It displays the aggregate number of self-propelled, dumb, and pushed vessels available in Germany and the Netherlands, as well as their total load capacity. The joint fleet capacity of Germany and the Netherlands is displayed as these two countries account for nearly 90 percent of total inland waterway fright transport (measured in tonnes) in Germany, when classified by the nationality of the vessel. Source: Eurostat (2024).

A.2 Firm-transport mode level estimations

Table A1. Exports, firm-transport mode level estimations

	(1) value	(2) KG	(3) #products	(4) #shipments	(5) probability
Inland shipping	-0.201***	-0.216***	-0.082***	-0.116***	-0.033***
× 2018H2	(0.038)	(0.039)	(0.014)	(0.020)	(0.005)
Inland shipping	-0.031	-0.030	-0.017	-0.037	-0.002
× 2019	(0.051)	(0.052)	(0.022)	(0.030)	(0.007)
# obs.	2,326,365	2,295,570	2,326,365	2,326,365	5,785,830
δ_{fm}	Yes	Yes	Yes	Yes	Yes
δ_t	Yes	Yes	Yes	Yes	Yes
R^2	0.852	0.891	0.894	0.911	0.612

Robust standard errors clustered at the firm level are in parenthesis. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

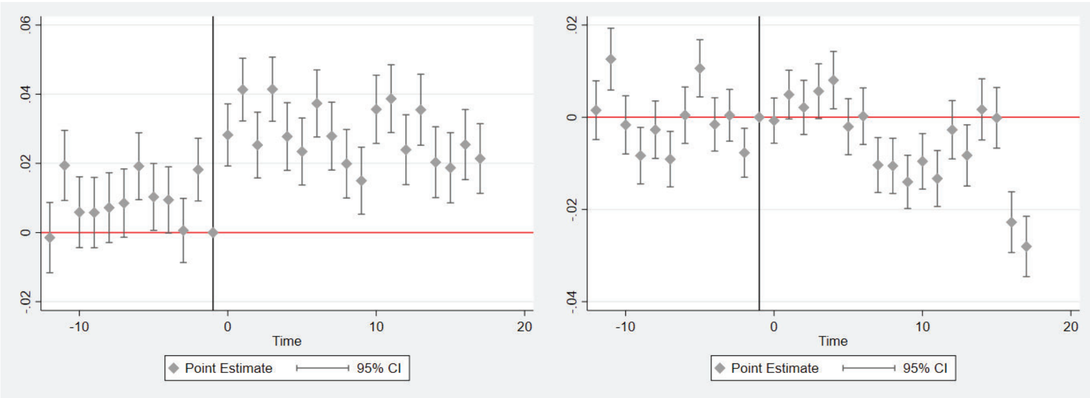
Table A2. Imports, firm-transport mode level estimations

	(1) value	(2) quantity	(3) #products	(4) #shipments	(5) probability
Inland shipping	-0.127***	-0.151***	-0.034**	-0.048***	-0.024***
× 2018H2	(0.033)	(0.033)	(0.013)	(0.016)	(0.005)
Inland shipping	-0.090**	-0.078*	-0.043***	-0.043**	-0.012**
× 2019	(0.041)	(0.043)	(0.015)	(0.018)	(0.006)
# obs.	3,170,823	3,090,423	3,170,823	3,170,823	9,182,730
δ_{fm}	Yes	Yes	Yes	Yes	Yes
δ_t	Yes	Yes	Yes	Yes	Yes
R^2	0.845	0.892	0.853	0.869	0.558

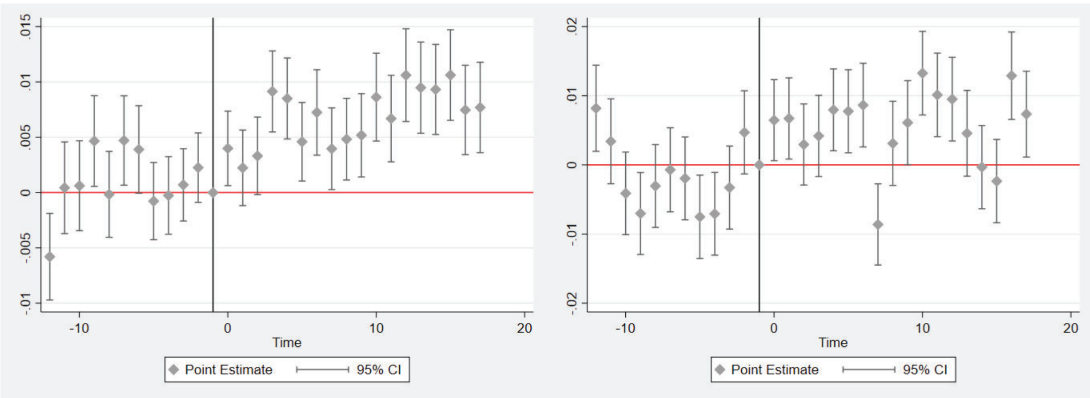
Robust standard errors clustered at the firm level are in parenthesis. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

A.3 Firm-product level estimations

Figure A3. Imports, firm-product level estimations, diversion to other transport modes: Event study graphs



Street Train



Sea Air

Notes: The figure shows the dynamics of the probability of importing a product by an alternative mode of transportation had it been imported at least once by inland shipping in the year before the low water period, relative to all other products. The estimation equation reads:

$$Y_{fpt} = \sum_{i=-12}^{18} \beta_i (Treated_{fp} \times Time_{it}) + \delta_{fp} + \delta_t + \epsilon_{fpt},$$

where $Time_{it}$ is a dummy equal to one i periods before/after the shock and $Treated_{fp}$ takes the value one if a firm-product pair was imported by inland shipping in the year before the low water period and is zero otherwise. The baseline period ($i = -1$) is June 2018. All β_i's – i.e. one for each month in the regression sample – are displayed. Y_{fpt} is a dummy variable if the respective mode of transportation – street (upper left panel), train (upper right panel), sea (lower left panel) or air (lower right panel) is used in a given month, and it is zero for all other months. Confidence intervals are defined at 5%.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

Table A3. Imports, firm-product level estimations, diversion to other transport modes, alternative clustering

	(1) train	(2) street	(3) air	(4) sea	(5) all modes
IWT product	0.003	0.023***	0.008**	0.004	0.032***
× 2018H2	(0.006)	(0.005)	(0.003)	(0.004)	(0.005)
IWT product	-0.009	0.018*	0.007**	0.007	0.026***
× 2019	(0.008)	(0.011)	(0.003)	(0.007)	(0.010)
# obs.	4,060,320	4,060,320	4,060,320	4,060,320	4,060,320
δ_{fp}	Yes	Yes	Yes	Yes	Yes
δ_t	Yes	Yes	Yes	Yes	Yes
R^2	0.561	0.540	0.497	0.489	0.516

Robust standard errors clustered at the firm level are in parentheses. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

Table A4. Imports, firm-product level estimations, diversion to other transport modes, by product groups, alternative clustering

	Dependent variable: alternative modes dummy					
	(1) agricultural goods	(2) intermediate goods	(3) capital goods	(4) consumer durables	(5) consumer non-durables	(6) energy goods
IWT product	0.035	0.036***	0.020**	0.023*	0.031***	0.006
× 2018H2	(0.026)	(0.005)	(0.008)	(0.013)	(0.009)	(0.012)
IWT product	0.025	0.028***	0.032**	0.003	0.023	0.03
× 2019	(0.029)	(0.009)	(0.014)	(0.034)	(0.021)	(0.019)
# obs.	74,760	2,224,890	754,260	157,830	726,240	34,050
δ_{fp}	Yes	Yes	Yes	Yes	Yes	Yes
δ_t	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.504	0.512	0.536	0.529	0.501	0.513

Robust standard errors clustered at the firm level are in parentheses. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

Table A5. Imports, firm-product level estimations, diversion to other transport modes, by firm size, alternative clustering

	Dependent variable: alternative modes dummy		
	(1) small firms	(2) medium-sized firms	(3) large firms
IWT product	0.052***	0.021**	0.037***
× 2018H2	(0.011)	(0.011)	(0.005)
IWT product	0.050***	0.042***	0.032**
× 2019	(0.015)	(0.011)	(0.012)
# obs	195,510	577,590	3,235,146
R^2	0.417	0.458	0.530

Robust standard errors clustered at the firm level are in parentheses. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Foreign Trade Statistics, own calculations.

ABOUT RETHINK-GSC

The project ‚Rethinking Global Supply Chains: Measurement, Impact and Policy' (RETHINK-GSC) captures the impact of knowledge flows and service inputs in Global Supply Chains (GSCs). Researchers from 11 institutes are applying their broad expertise in a multidisciplinary approach, developing new methodologies and using innovative techniques to analyse, measure and quantify the increasing importance of intangibles in global supply chains and to provide new insights into current and expected changes in global production processes.

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