Quantifying Waterway Supply Chain Shocks: Regional Propagation in the Rhine Area *

– *Working Paper* –

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Abstract

Transportation restrictions on waterways due to high or low water level events lead to disruptions of supply chains, which are exogenous to the current state of the economy. This paper proposes a novel method to exploit and quantify these surprising transportation restrictions which lead to regional supply chain disruptions and applies the method to the river Rhine. A surprising decrease of the Rhine's shipping capacity leads to a short-lived but significant decrease in economic activity, not only in the bordering federal states but entire Germany. This effect is more pronounced in industries and regions that rely more heavily on the Rhine and the goods shipped on it. Also, we document a substitution towards suppliers that do not rely on the Rhine to deliver their goods.

Keywords: Regional Supply Chain Disruptions, Waterway Restrictions, Rhine.
JEL Codes: E32, Q41.

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In recent years, there has been a surge in academic efforts to understand the effects of supply chain disruptions, but a robust identification of these shocks has turned out to be challenging. Bai et al. (2024) present a promising approach to capture the causal effect of global supply chain disruptions. Yet, supply chain disruptions do not necessarily only occur at the country-level, but also between different regions of a country. The lack of convincingly identified regional supply chain shocks in the literature has prevented research to explore the resilience of countries to these shocks. Therefore, we propose a novel microfounded approach to quantify regional supply chain shocks by exploiting an exogenous variation in the transportation capacity of waterways.

To this end, we compute a shock measure that captures transportation capacity restrictions caused by high- and low-level water events and employ our method to the Rhine, the most important river in Germany in terms of transported goods volume. These waterway transportation restrictions, caused by high or low water level events and exogenous to the current state of the economy, occur with notable frequency. This allows us to provide a comprehensive and microfounded analysis of the economic consequences of disruptions on the Rhine, which is also replicable to other waterway systems.

The objective of our research is to assess the macroeconomic impact by estimating the response of industrial production to transport capacity restrictions in a local projection framework. We find a significant temporary contraction in industrial production of 0.14% following a waterway transportation capacity shock of one standard deviation. This negative effect is larger and more persistent in energy-intensive sectors. Against our supposition, we do not find any transportation substitution from cargo ships to trucks or trains on impact, which might be due to the typically short duration of restrictions in combination with the special nature of the goods transported. However, we find a substitution pattern with respect to the countries of origin for the import of fossil fuels. On impact, imports from Russia increase, which are primarily transported via pipelines. In contrast, imports from the Netherlands, which heavily depend on waterway transportation, decrease. These findings raise the question about increasing future welfare effects of regional supply chain shocks since fossil fuel imports from Russia to the EU have been halted in 2022.

Related Literature. Following the transformation towards international value chains and increased trade in intermediate inputs since the 1980s (Antràs and Chor, 2022), there has been a growing interest in studying the macroeconomic impact of global supply chain disruptions. The empirical literature attempts to identify exogenous variations in global supply chains by utilizing SVAR models with sign and narrative restrictions (e.g., Fink and Tillmann, 2022; Bai et al., 2024). Their findings show that these disruptions can result in a significant reduction in trade and economic output. Another avenue of the literature analyzes the impact on global supply chains induced by trade cost shocks (e.g., Feyrer, 2021). Since the onset of the COVID-19 pandemic, policy makers and academic researchers became more keen about consumer goods shortages caused by supply chain disruptions and congestion effects. Meier and Pinto (2024) provide empirical evidence on the economic effects following the anti-COVID-19 measures. Bonadio et al. (2021) find that a one-sided repeal of these measures in large economies could lead to a GDP growth of up to 2.5% for their smaller trading partners.[1]

With respect to regional supply chain disruptions, the literature has relied on case studies as outlined in Elliott and Golub (2022). For example, Carvalho et al. (2021) show how the propagation of the Great East Japan Earthquake depended on input-output linkages. In a similar vein, Barrot and Sauvagnat (2016) scrutinized major natural disasters in the US and how they propagated through production networks.[2] However, to the best of our knowledge, there is no approach to capture systematic exogenous supply chain disruptions at a specific location. Ademmer et al. (2023) have previously proposed using water level data at single measuring stations as a proxy for trade flow disruptions. While the method can provide some suitable intuition for the effect of low water events, it does not account for potential sources of bias such as regionally heterogeneous transportation restrictions and anticipation effects. Having this in mind, our approach accounts for several dimensions of heterogeneity by constructing a shock series that utilizes data from multiple measuring stations along the river and incorporates a trade flow weighting system to account for the relevance of specific passage closures. Consequently, our project will complement the literature by providing a methodology to construct a time-varying measure that captures regional supply chain shocks by exploiting waterway transportation restrictions.[3]

The structure of the paper is as follows. First, we provide an overview of the Rhine river and the trade flows it supports. Next, we present our approach for quantifying transport restrictions on the Rhine using administrative data. We incorporate these findings into a local projection framework to estimate the macroeconomic impacts of waterway restrictions. Finally, we conclude the paper with a summary of our findings.

[1] The pandemic has also induced a surge in the theoretical literature regarding supply chain disruptions (e.g., Baqaee and Farhi, 2022; Bigio and La'o, 2020)

[2] Firm-level linkages have been proposed as major determinant in the transmission of these disruptions (e.g., Acemoglu and Tahbaz-Salehi, 2020; Elliott et al., 2022; Alfaro-Urena et al., 2022).

[3] Our project also relates to papers from the field of transport economics, which have analyzed the impact of low water levels and the interaction with climate change on waterway transport companies (e.g., Jonkeren et al., 2007; Beuthe et al., 2014).

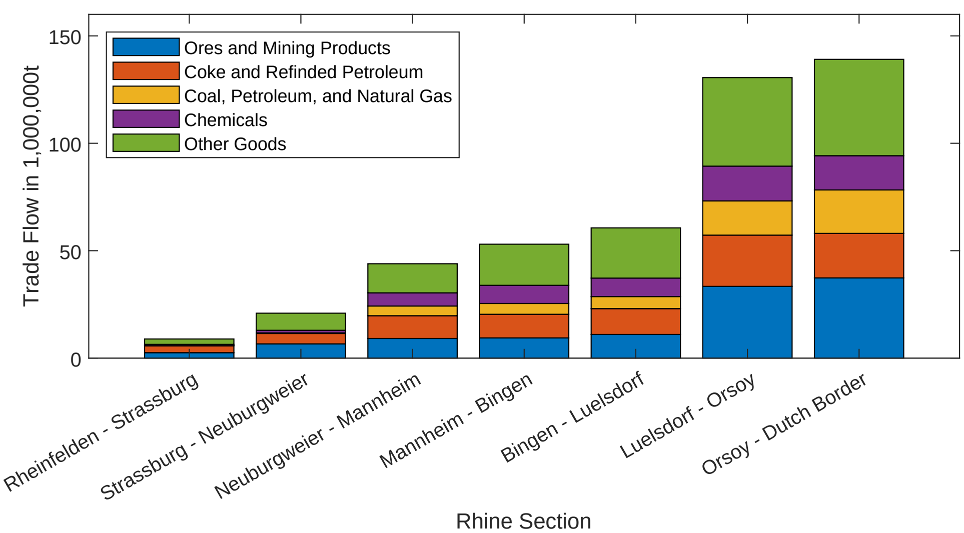
1 Data

Our approach requires daily data on water levels at multiple measuring stations and information on the trade flows at specific sections of the waterway. We have chosen the Rhine to conduct our analysis, which is a major European river running through Switzerland, France, Germany, and the Netherlands.[4] It is one of the longest rivers in Europe and has a total length of approximately 1,230 kilometers. The Rhine is an important transportation route and largely used for primary and intermediary goods. The following subsections present information regarding the traded goods on the Rhine together with water level data. This is indicative for which sectors and regions one should expect to be more severely affected by transportation restrictions.

1.1 Trade Flow

To construct the capacity shock series and to enhance the interpretation of our results, it is useful to have an impression of the transportation patterns along the Rhine. This subsection presents trade flow data for the Rhine obtained from the *Federal Statistics Office Germany*. The data is available at a yearly frequency and contains information regarding the transport volume of 20 goods categories in seven Rhine subsections.

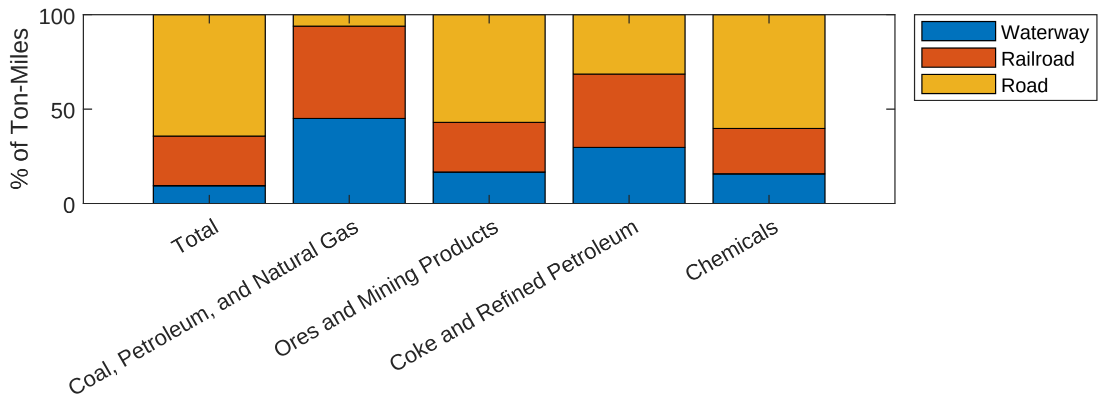
Figure 1: Overview of Goods Transported for each Rhine Section.



Note: Trade flows on the seven administrative Rhine sections - ordered from South to North - in 2021. Goods categories according to NST-2007 classification. (Source: Federal Statistics Office Germany)

[4]Other rivers frequently encountering waterway transportation restrictions stemming from high or low water levels, and thus suitable for our approach, include the Mississippi in the United States, the Danube in Europe, and the Yangtze River in China.

Figure 2: Means of Transportation for certain Goods Categories.



Note: This figure shows the share of goods transported by different means of transportation. The shares are computed relative to the total ton-miles in that goods category. (Source: Federal Statistics Office Germany)

Figure 1 summarizes the data. The horizontal axis reports the different Rhine sections. The corresponding bars indicate the respective trade volume per category, whereby the four most important categories (in terms of volume) are singled out from the remaining categories.

Two observations stand out. First, the largest share of transported goods is processed in the two sections of the Lower Rhine close to the Dutch border. Second, the most important goods categories are primary and intermediary goods, especially energy sources. A detailed breakdown for each goods category at the specific Rhine sections is presented in Appendix A.2.

The Rhine accounts for 86% of the amount of goods shipped on German inland waterways. This amount constitutes to 5%-8% of the total goods transportation in Germany.[5] This share, however, varies considerably across goods categories. Figure 2 highlights the differences in means of transportation for specific categories. The Rhine's four most important goods categories are disproportionately transported through waterways, with the exception of ores and mining products. For example, more than 40% of coal, petroleum, and natural gas are transported via waterways. Additionally, according to the freight statistics of German inland shipping, the majority of goods transported via the Rhine are shipped to or from overseas ports in the Netherlands.[6]

[5] Compare press statement from the Federal Statistics Office Germany in April 2022. [Link accessed: 06.03.2024]

[6] More information available in the 'Freight Statistics of German Inland Shipping, December 2022' [Link accessed: 06.03.2024]

1.2 Water Levels

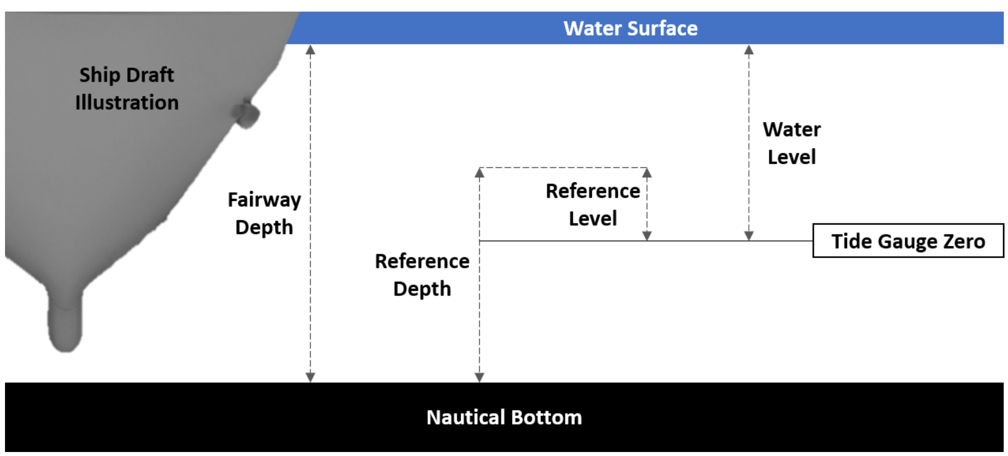
In the following subsection, we present the water level data employed in our analysis to quantify high and low water events. We obtain raw water levels at a daily frequency from the *Federal Waterways and Shipping Agency (WSV)*, which provides information for all administratively relevant measuring stations along the Rhine.[7] Additionally, we collect information from legal and historical documents about reference water level, depth at the reference level and high level threshold at each station.

By dropping stations without such specified values, we obtain a sample of 13 stations with data available from November 1971 to October 2022. However, raw water levels are not comparable across stations.[8] Therefore, we compute the *fairway depth*, which is comparable across time and locations, as follows:

$$depth_{dj} = level_{dj} - reference\_level_{dj} + reference\_depth_{dj},$$

where $level_{dj}$ is the raw water level at day d measured in location j. The $reference\_level_{dj}$ is a reference value determined every ten years for each station representing the water level at which the $reference\_depth_{dj}$ is secured, which represents the fairway depth at the reference water level. Figure 3 illustrates these nautical definitions.

Figure 3: Nautical Definitions.



Note: Illustration how the nautical definitions of fairway depth, reference depth, reference level, and water level are related. (Source: Author's own illustration)

[7]Daily water levels represent the average of three measurements each day at the same time.

[8]Water levels refer to the tide gauge zero which does not contain comparable information regarding the passability for cargo ships.

2 Shock Construction

The raw water level and fairway depth data presented in the previous section do not provide direct insight into the potential supply chain disruptions following low or high water events on the Rhine. To this end, this section proposes a two-step approach to quantify surprising (shipping) capacity restrictions. In the first step, we introduce a measure of shipping capacity for a given day and Rhine section. In the second step, we aggregate and clean this measure to obtain a monthly series for the German Rhine that accounts for seasonal and autoregressive effects.

2.1 Capacity Restrictions

Two important challenges arise in quantifying shipping capacity restrictions. First, the measurement has to be consistent for high as well as for low water events. Second, we do not only want to determine the presence of a restriction but also quantify its severity. To resolve these problems, we define the daily shipping capacity at day d and location j as $cap_{dj} \in [0, 100]$. By normalizing the magnitude in this way, we measure the shipping capacity of the respective Rhine section in percent relative to a day where no legal restriction was in place. Three different events are possible:
For high water events there is a clear legal framework. If the water level at a station j exceeds the legal high water threshold $\bar{\ell}_j$, shipping the respective section is prohibited (§ 10.01 RheinSchPV). Consequently, we set

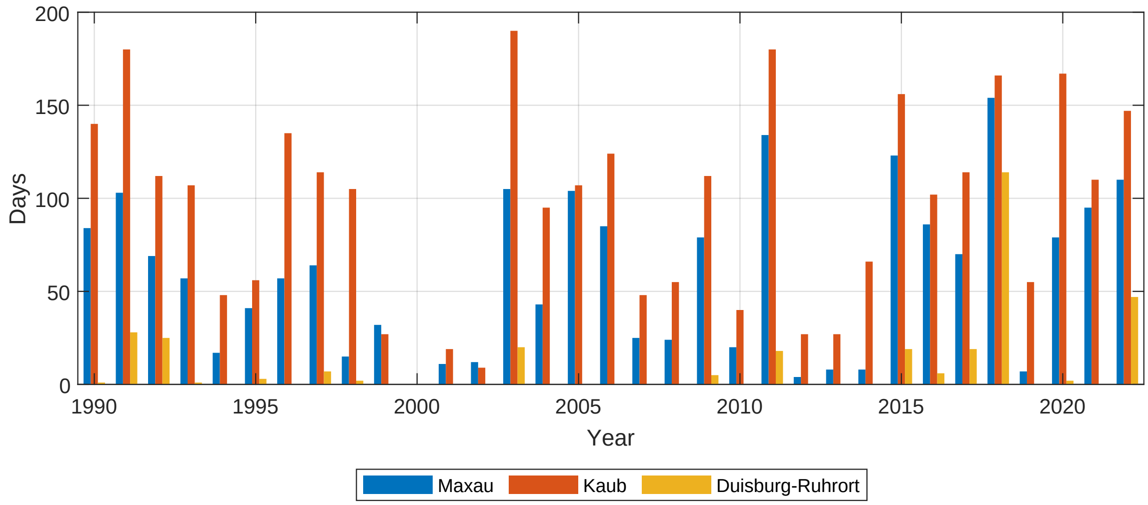
$$cap_{dj} = 0 \quad \text{if } level_{dj} > \bar{\ell}_j$$

For low water events, the restrictions evolve more smoothly. For instance, even if the water level is unusually low, it might still be possible to ship 50 % of the goods that would have been shipped under normal conditions. Crucially, there are no sharp legal thresholds for low water closures; rather, each skipper decides on the draft of their ship based on the current fairway depth. To formalize this relationship, we define a continuous function f capturing (effective) loading restrictions due to low water such that:

$$cap_{dj} = f(depth_{dj}) < 100 \quad \text{if } depth_{dj} < \underline{\ell}$$

We determine the function's properties by exploiting information on low water events from

Figure 4: Number of Days with Restrictions at Selected Stations.



Note: Number of days with transportation restrictions per year caused by high or low water level events for three selected measuring stations that are located along the Rhine.

Contargo.[9] $\underline{\ell}$ is the lowest fairway depth at which there is just no restriction in place.[10] In all other cases, no restriction is in place, i.e., we define

$$cap_{dj} = 100 \quad \text{otherwise}$$

Figure 4 shows the historic restrictions for three selected locations. For better accessibility, the figure only shows the total number of days with restrictions (i.e., days with $cap_{dj} < 100$) within each year. The key observation is a very pronounced regional heterogeneity: While Kaub faced 24 years with more than 50 days with restrictions, there is only a single year where there were more than 50 days with restrictions in Duisburg.[11] However, as discussed in section 2, there is significantly more traffic on the Rhine sections around Duisburg. Consequently, even few days with restrictions there have a large impact on the total shipping volume of the Rhine.

2.2 Shock Construction

Aggregation. Up til now, the capacity measure we have constructed is location-specific. However, to examine, for example, how industrial production in Germany responds to Rhine

[9] Contargo is a major Rhine shipping company that published information on low water surcharge. [Link accessed: 06.03.2024]

[10] We fix it at the fairway depth of 260cm at which Contargo starts charging low water fees. We set $f(depth_{dj}) = 0$ once Contargo is not obliged to ship anymore, which corresponds to a fairway depth of $\approx$ 190cm. In between we interpolate linearly, again following Contargo.

[11] Kaub is located in the flattest German Rhine section between Mainz and Koblenz.

capacity restrictions, it is necessary to have an aggregate capacity series for the entire German Rhine. Given the pronounced regional heterogeneity with respect to traffic shares (Figure 1) and restrictions (Figure 4), selecting a single measuring station only gives an incomplete image of the current shipping restrictions on the German Rhine. Hence, we compute the aggregate capacity measure by taking a weighted average of the location-specific measures. The weights depend on two factors:

1. Restrictions in sections with high traffic have a greater impact on the shipping capacity of the entire German Rhine compared to restrictions in sections with low traffic. Therefore, we use the data set on trade flows introduced in section 2 to compute the traffic share of each Rhine section (tons of goods shipped in that section divided by tons of goods shipped on all German Rhine sections)[12] to quantify the importance of each station.

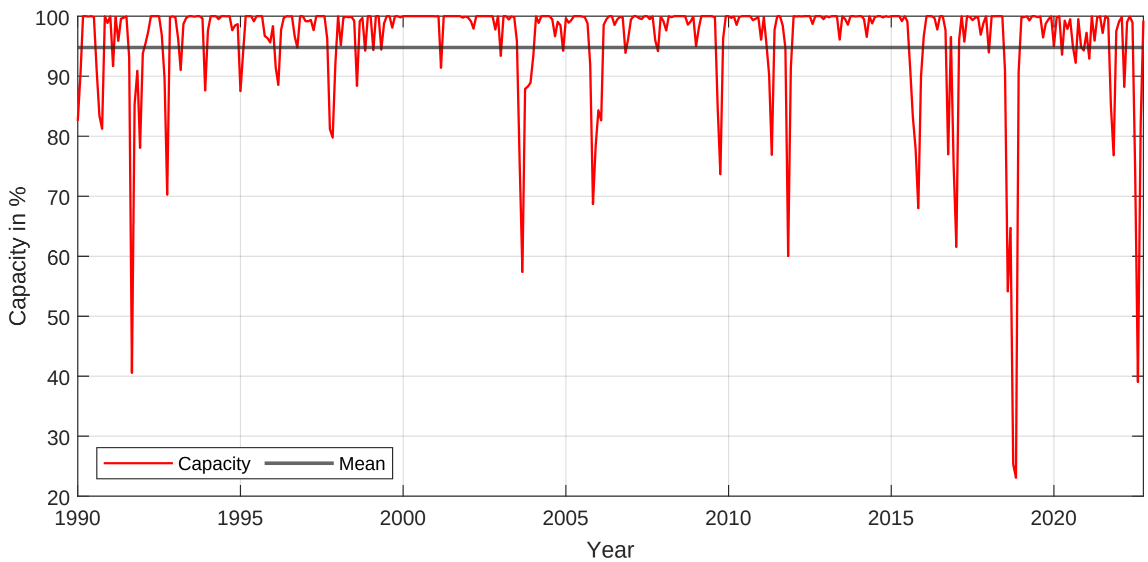
2. Since the Rhine sections in the data set at hand are broader than the legal Rhine sections, we frequently observe multiple stations within the same section. To prevent overstating the role of these stations, we correct for the number of stations within each section.

Hence, the weights we use are given by $\frac{traffic\ share\ in\ section}{\#stations\ in\ section}$. Since all outcome variables of interest are at a monthly frequency, we also compute monthly averages of the daily measure to obtain the monthly aggregate capacity series cap_t.
Figure 5 shows the resulting time series from 1990 until 2022. The series still has the interpretation of being the Rhine's shipping capacity relative to a month in which there was no restriction in place at any day or station. Three sources of variation drive the series: (I) Variation in the number of days and (II) the number of stations at which there was a restriction, as well as (III) the severity of these restrictions as outlined in subsection 2.1.
The average shipping capacity is approximately 95%. The drought between July and December 2018 stands out as the most extreme event, with a capacity reduction down to 23% at the peak in November. Appendix A.2 contains more disaggregated figures of the capacity measure, which highlight that the shipping capacity is mainly driven by low water events and not by high water events (which occur less frequently and last only for very few days).

Anticipation Effects. Importantly, some of the fluctuations visible in Figure 5 might be expected in advance. For example, agents might expect low water events to be more likely in fall than in spring. Moreover, the capacity in a given month might have predictive power

[12] Given the data set, we compute these weights for all years between 2010 and 2020 and then average over the years. While the absolute quantities vary a lot over time, the shares are relatively stable.

Figure 5: Aggregate Monthly Capacity



Note: The figure depicts the aggregate monthly transportation capacity on the Rhine. The horizontal bar in black indicates the mean capacity.

for the capacity in the following month. Conducting an impulse response analysis in the following section requires to control for these effects. We do so by regressing the capacity measure on a full set of monthly dummies (to address seasonal effects) and on its first lag (to address its predictive power):

$$cap_t = \boldsymbol{\alpha}_0' \, \mathbf{month}_t + \alpha_1 \, cap_{t-1} + s_t$$

In the upcoming section, we use the residual of this regression s_t as our shock measure, which is illustrated in Appendix B.8. Of course, other specifications of this step are possible, e.g., including temperature or precipitation data. We have conducted a series of robustness specifications and our findings remain unchanged. The results for these specifications can be found in Appendix A.1.

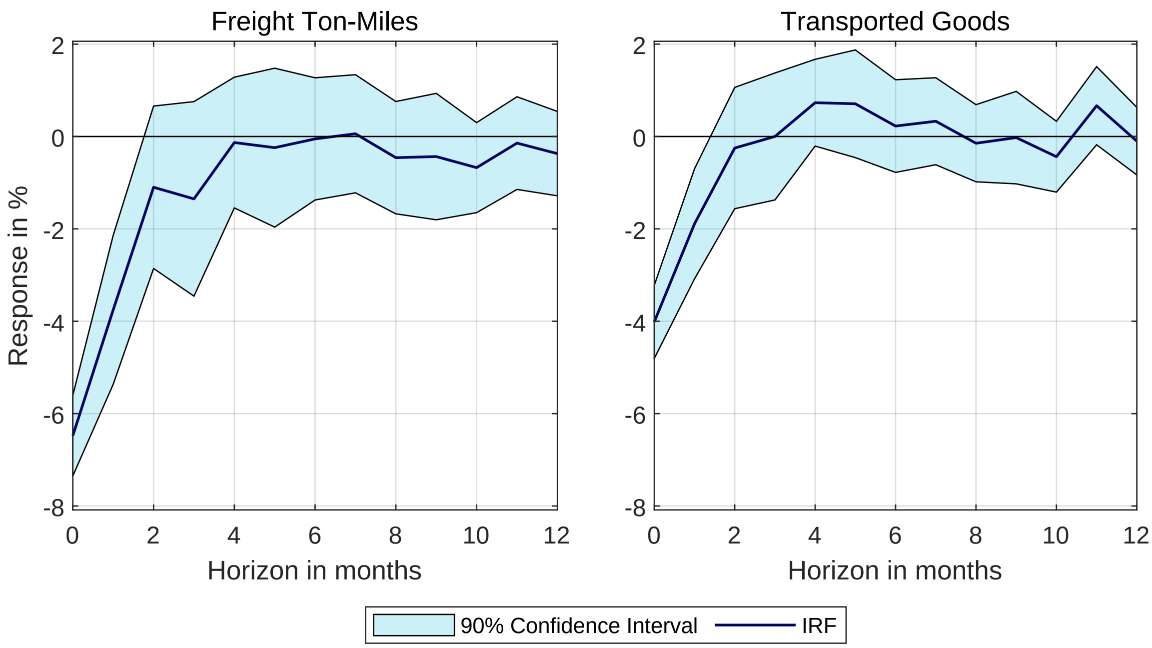
2.3 Shock Diagnostics

Ensuring the validity of our constructed shock measure requires the fulfillment of two conditions. First, it has to capture the decrease in transportation capacity and no confounding factors. And second, it should be exogenous to the current state of the economy and not predictable by other economic or climate indicators.[13] With respect to the first condition,

[13]This approach is related to Ramey (2016), who states that a robust series of high-frequency surprises must fulfill several properties: (I) No auto-correlation, (II) no predictability, and (III) no correlation with

we use our shock series in a local projection framework and estimate the impulse response of cross-border receiving after a negative Rhine capacity shock of one standard deviation ($\approx 8.3\%$).[14] Figure 6 plots the results for two common waterway transportation measures, namely freight ton-miles and transported goods in tons. On impact, we observe a significant contraction by about 6.5% and 4%, respectively. In the subsequent months, the outlined transportation measures recover; being not significantly different from zero two months after the shocks onwards, which highlights the short-lived nature of our identified shocks. These findings are reasonable considering the magnitude of the shock and confirm that we are actually capturing transportation contractions induced by unexpected waterway transportation restrictions.[15]

Figure 6: IRF of Goods Transportation on the Rhine (Cross-Border Receiving)



Note: IRFs (dark blue) of freight ton-miles (left panel) and transported goods (right panel) after a one standard deviation negative Rhine capacity shock. 90% confidence intervals depicted in light blue.

The second condition requires us to ensure that our shock series is exogenous to the current state of the economy and not predictable because otherwise firms could adapt their

other shocks.

[14] We have chosen cross-border receiving, which are majorly primary and intermediate goods, and therefore, should induce cascade effects within their supply chains. German exports shipped on the Rhine, however, are primarily final goods and should not induce cascade effects within the value chain.

[15] Another concern could be that Rhine capacity restrictions are no fundamental shocks but rather driven by temperature or precipitation shocks that also impact the economy through other channels. In section 3.2, we outline our empirical approach that shows how our results are actually driven by waterway transportation restrictions.

behavior.[16] Given that waterway transportation restrictions critically depend on hydrological events which occur independently of economic activities, we are reasonably confident that our shock series is exogenous to the current state of the economy.[17] However, the most obvious threat to our identification lies in the possibility that water levels, and therefore, waterway transportation restrictions can be predicted. Clearly, a certain part of this threat is addressed by our shock construction itself. We identify a variation in transportation restrictions that are orthogonal to information obtained from the previous period and the seasonality in which the shock occurs.[18] A remaining threat to our identification arises if it would be possible to construct valid long-term predictions for transportation restrictions. There are state-of-the-art machine learning approaches that attempt to forecast water levels months ahead.[19] However, both the precision of water levels predictions and even more so the predictions for extensive and intensive margins of transportation restrictions seem to be quite imprecise for a longer horizon. Therefore, we remain confident with respect to the validity of our constructed shock measure.

3 Empirical Framework

Given the shock series constructed in the previous section, it is natural to ask for its propagation effects on the economy. More precisely, how does the economy responds to an unexpected change in the Rhine's shipping capacity? To this end, we introduce the relevant outcome variables (3.1) and our empirical framework (3.2).

3.1 Outcome Variables

The first collection of data sets we use contains the index of industrial production, which is a monthly index of the output produced in four 1-digit sectors (Mining & Quarrying, Manufacturing, Energy Supply, Construction).[20] On the federal level, we obtain data from January 1991 to December 2019 at varying granularity. Since we also want to examine

[16] For example, if waterway transportation restrictions occur quite frequently in a given month, companies might be inclined to ship their goods in earlier or later months. In such a case, the impulse response would not capture a reaction to the shock but rather a transportation pattern that is observable irrespective of the occurence of waterway transportation shocks.

[17] At this point, one could also check the autocorrelation with monetary, fiscal, or technology shocks. Since it appears very unlikely to find any correlation with these shocks, we haven't conducted this analysis yet but attempt to do so at a later point.

[18] Our robustness checks also include additional information from the period in which the shock occurs.

[19] Wee et al. (2021) provide an overview of machine learning algorithms to forecast water levels. Yueling et al. (2019) apply one of these models to make within-month water level forecasts.

[20] See Appendix B.3 for a breakdown of the relative sizes of these sectors.

regional heterogeneity in the responses, we also collect data at the state level. Currently, we have data for two out of the four Rhine neighboring states (Baden-Wurttemberg and North Rhine-Westphalia) from January 2000 to December 2019. Unfortunately, the data is less granular than that at the federal level.

To examine changing transportation patterns in response to Rhine capacity reductions, we collect data on the truck index at the federal level (January 2009 - December 2019) and train transportation data at the federal level (January 1991 - December 2022).[21] In the given context, there are two effects on trucks and trains utilization after a Rhine capacity reduction: On the one hand, there is a positive input effect, i.e., firms demand more of these services to cope with the reduced shipping capacity of the Rhine on the input side. On the other hand, there is a negative output effect, i.e., firms produce less, so they need fewer truck and train services to transport their output to their customers. Since our interest lies in the first effect, we will discuss in section 3.2 how it can be isolated empirically. In the same vein, we scrutinize the effect on imports of specific goods that are primarily transported on the Rhine. Since we know that a large share of these goods are fossil fuels, we expect to observe some substitution patterns in order to mitigate the impact on the economy. For this exercise, we collected data on the imports of (un-)refined petroleum and crude oil by the country of origin (January 2008 - October 2022).[22] By comparing changes in the import behavior, we attempt to unveil substitution patterns following a waterway transportation restriction. Finally, we want to analyze how prices react to our constructed shock series. To this end, we collect CPI components of goods that are primarily transported on the Rhine (January 2000 - October 2022).

3.2 Empirical Strategy

As we already have a series of shocks capturing unexpected changes in the Rhine's shipping capacity, the most natural empirical strategy to estimate impulse response functions is the local projection framework (e.g. Jordà, 2005; Plagborg-Møller and Wolf, 2021). Since all outcome variables are highly persistent[23], a model in first differences seems appropriate. The local projection framework offers a convenient way to directly estimate cumulative impulse response functions (IRF from now on) with a model in differences in the background. More

[21] The truck index is computed based on toll data on kilometers of trucks driven on German highways.

[22] Unfortunately, data for natural gas imports was not retrievable from the *Federal Statistics Office Germany* its database at the time we have conducted our analysis.

[23] An ADF test does not reject the null hypothesis of a unit root for any of the series we consider.

concretely, the model for the industrial production index reads as

$$\underbrace{\Delta^{h+1} ip_{t+h}}_{=ip_{t+h}-ip_{t-1}} = \alpha^h + \beta^h s_t + \gamma^h \underbrace{\Delta ip_{t-1}}_{=ip_{t-1}-ip_{t-2}} + v_t\,, \quad \text{for } h = 0, 1, ..., 12$$

where ip_t denotes the logarithm of industrial production in period t. In words, we consider a shock to Rhine shipping capacity occurring in period t and its effect on the industrial production index h periods after the shock has occurred. The regressions are augmented by the first lag of the first difference of (log) industrial production following Ramey (2016). We run a sequence of these regressions up to a horizon of 1 year. By considering log differences of industrial production, the sequence of IRF coefficients $\{\beta^h\}_{h=0}^{12}$ measures the response of industrial production in percent. For the graphical representation later on, we multiply by 100 to obtain results in percentages. We also compute standard errors robust to serial correlation following Newey and West (1987), which are appropriate for this type of model according to Jordà (2005).
The models for the other (log) outcome variables, i.e., means of transportation and imported goods (y in the following), are specified in a similar way:

$$\underbrace{\Delta^{h+1} y_{t+h}}_{=y_{t+h}-y_{t-1}} = \alpha^h + \beta^h s_t + \gamma^h \underbrace{\Delta y_{t-1}}_{=y_{t-1}-y_{t-2}} + \delta^h \underbrace{\Delta^{h+1} ip_{t+h}}_{=ip_{t+h}-ip_{t-1}} + v_t\,, \quad \text{for } h = 0, 1, ..., 12$$

Note that the regressions are augmented by the change in (log) industrial production between one period before and h periods after the shock has occurred. As discussed in section 3.1 and similar to the previous equation, this additional term is added to isolate the input effect from the output effect. Put differently, by controlling for the effect of changing output on the demand for transportation services or imported goods, β^h only captures the effects related to changing transportation or imported goods patterns caused by supply chain disruptions.

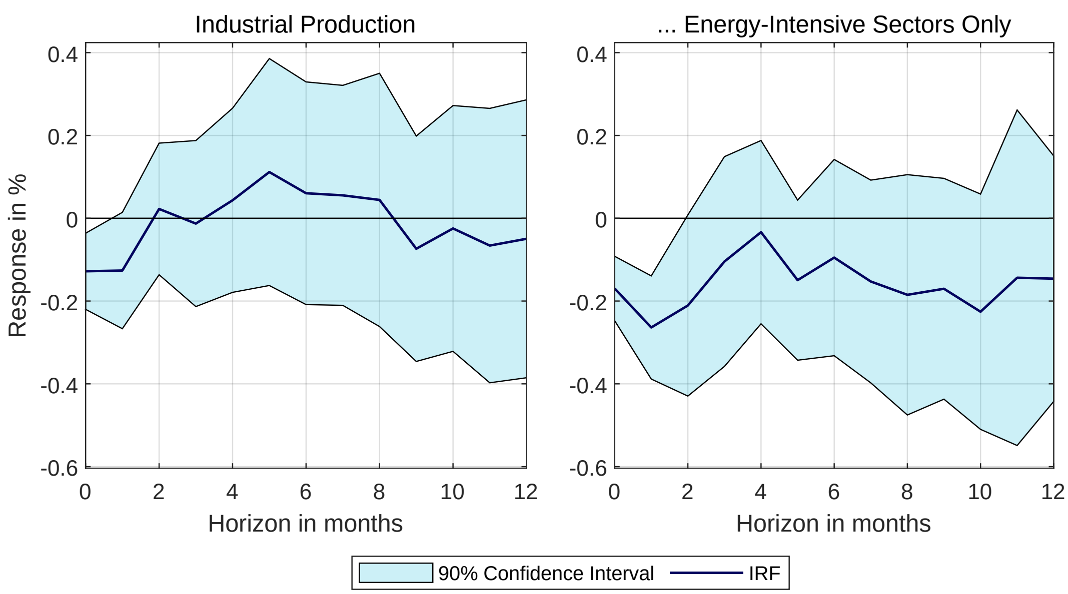
Causality. Before turning to our empirical results, we want to address the causality of our estimates. The largest Rhine capacity shocks in our sample (e.g., that of fall 2018) are caused by unexpectedly hot and dry summers. Hence, it is not entirely clear whether the estimated coefficients actually capture the supply chain disruptions related to the Rhine capacity reduction or just weather effects on output (e.g., declining labor productivity due to heat). One possible defense of interpreting our shocks as supply chain disruptions is the lagging behavior of water levels. Referring back to figure 5, nearly all of the most extreme capacity reduction (which will govern the estimators' behavior) reach their peak in fall (September - November), when the most severe heat is already over. Since agricultural sectors are not included in the industrial production index, additional effects of low precipitation seem unlikely. Nevertheless, we also conduct a series of robustness checks and include controls for temperature in the baseline regressions. The main findings remain unchanged and are presented in Appendix A.2. Therefore, we are reasonably confident that our approach isolates the causal channel of regional supply chain disruptions via waterway transportation restrictions.

4 Empirical Results

4.1 Industrial Production

This subsection discusses the response of the industrial production index following a Rhine capacity shock. The presentation is organized from broad to specific: We first discuss aggregate industrial production in Germany. In a second step, we explore regional and sectoral heterogeneity in the response patterns.

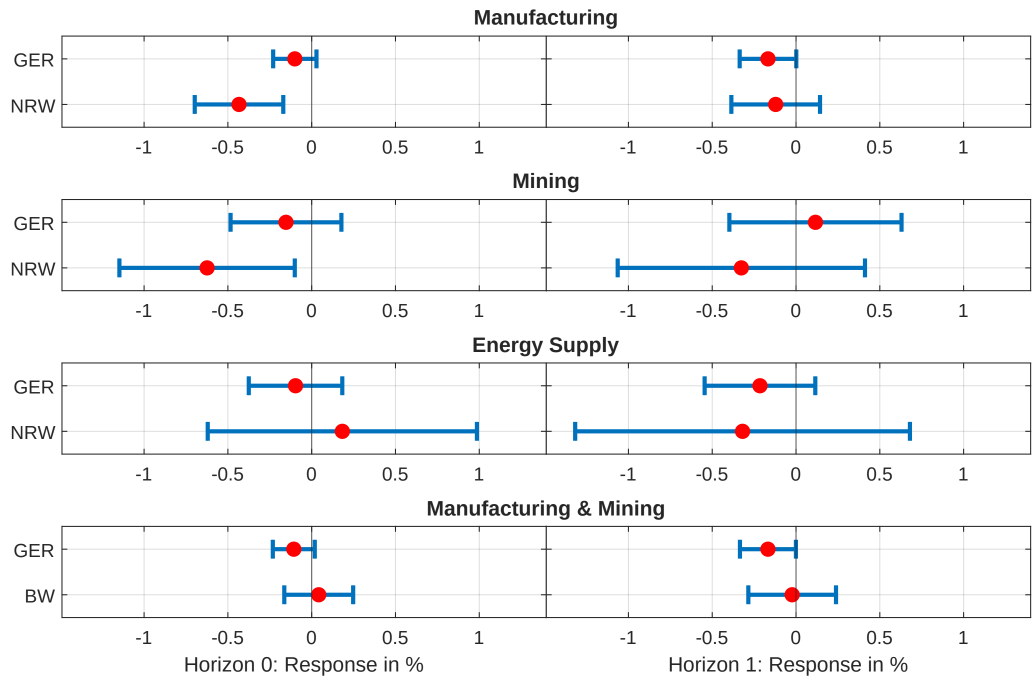
Figure 7: IRFs of German Industrial Production



Note: IRFs (dark blue) of industrial production (left panel) and industrial production of energey-intensive sectors only (right panel) after a one standard deviation negative Rhine capacity shock. 90% confidence intervals depicted in light blue.

The left panel of Figure 7 shows the impulse response function of the industrial production index in Germany after a negative Rhine capacity shock of one standard deviation ($\approx 8.3\%$). On impact, industrial production decreases by -0.14%. This point estimate is significantly different from 0 at the 90% level. However, from one month after the shock onwards the response is no longer significantly different from zero. As shipping on the Rhine mainly involves energy sources, an obvious extension is to focus on sectors that are more heavily reliant on these goods. Therefore, the right panel in Figure 7 only includes those subsectors, which are energy-intensive in their production processes. As expected, the impact response of -0.19% is more pronounced than that of the aggregate industrial production index and decreases even further down to -0.29% in the following month. Both of these coefficients are significantly different from zero, but none at horizons larger than one are.

Figure 8: IRF of Industrial Production for Different States and Sectors



Note: The figure shows the IRFs of the industrial production index after a one standard deviation negative Rhine capacity shock together with 90% (Newey-West) confidence bands. The left panels show the response on impact; the right panels show the response one month after the shock occurred (GER: Germany, NRW: North Rhine-Westphalia, BW: Baden-Wurttemberg).

To explore how these results differ across regions and sectors, Figure 8 plots the IRF coefficients together with the 90% confidence intervals (again normalized for a negative one standard deviation Rhine capacity shock) for different state-sector pairs. The first three panels compare the results on the federal level with state-level results in North Rhine-Westphalia (NRW in the following; the largest Rhine neighboring state in terms of economic output). The fourth panel compares Germany with Baden-Wurttemberg (BW in the following). Since none of the coefficients is significantly different from zero from horizon two onwards, the figure only shows the responses at horizon zero and one for better accessibility. Given the shorter data sample at the state level (c.f. section 3.1), we conduct all regressions on a sample from January 2000 until December 2019.

The first panel compares the response of the manufacturing sector of NRW to that in Germany. Since manufacturing makes up the largest part of the industrial production index (c.f. Appendix B.3), the results for Germany are similar to those presented in Figure 7: The impact response is at around -0.11% and then decreases further to -0.17%, however, none of them is statistically significant at the 90% level. The impact response of -0.47% in NRW is notably larger than that for entire Germany (and also significantly different from zero). Such a result was to be expected given that NRW appears to be most dependent on the Rhine for transportation, as discussed in section 1.1. However, this difference vanishes one month after the shock.

The second panel again compares the response in NRW and Germany but for the mining sector. While the response in Germany is not significantly different from zero, the impact response in NRW (-0.68%) is the largest point estimate (in absolute terms) among all estimates presented in this section. One possible narrative is again related to the composition of goods shipped on the Rhine (c.f. section 1.1), since mining activities require energy, chemicals, and gases.

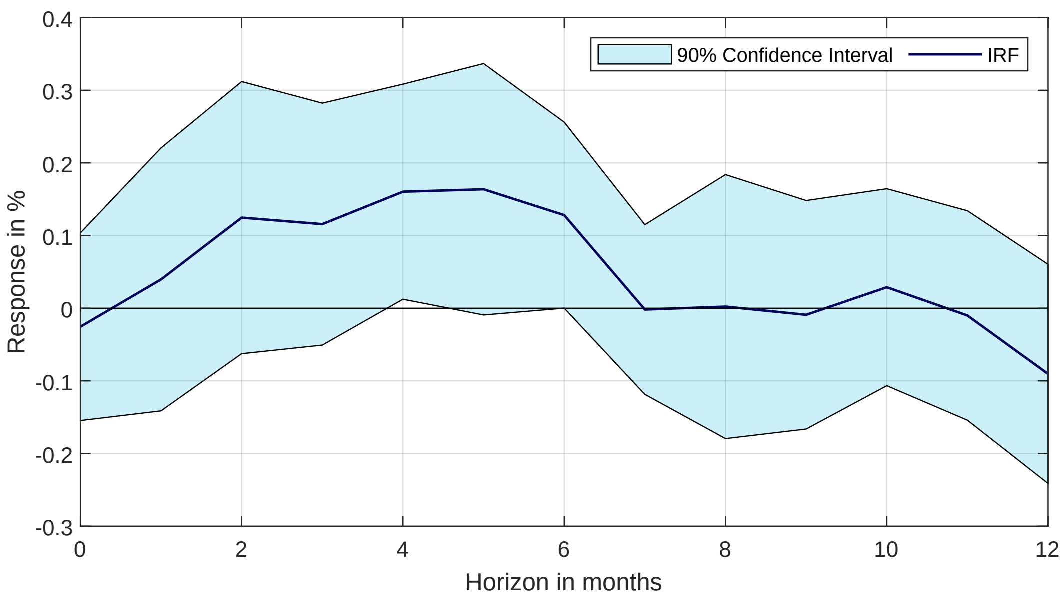
The third panel considers the energy supply sector in NRW and Germany. Here, none of the four coefficients is significantly different from zero at the 90% level. This might be a surprise given that primarily energy sources are shipped on the Rhine. Two potential narratives might rationalize this result: On the one hand, confounding weather effects (c.f. section 3.2) might be important here, e.g., surprisingly hot and dry periods lead to rising electricity demand. On the other hand, energy suppliers are systemically relevant and consequently better insured against these events, e.g., they might hoard energy sources to cope with shipping restrictions.

The last panel focuses on the manufacturing and mining sector jointly (due to data limitations), comparing BW and Germany. Since the mining sector is close to negligible compared to manufacturing (c.f. Appendix B.3), the results for Germany are very similar to those in the first panel. Surprisingly, the coefficients for BW are extremely close to zero (0.04 and -0.02) for both horizons. Referring back to Figure 1, there are way fewer goods transported on the Rhine in BW than in NRW (by a factor between 4 and 7), i.e. the supply chains in BW might be less dependent on the Rhine as those in NRW. Moreover, our aggregation scheme introduced in section 2.2 gives relatively large weights to stations in NRW. This could imply that the shock series is 'tailor-made' for NRW and thus does not capture the effective restrictions firms face in BW very well. Hence, a potential extension of the current analysis is to construct state-specific shock series using more granular trade flow data, which was unavailable at this project stage.

4.2 Truck Index

The results discussed above already suggest that firms are not able to perfectly switch to other means of transportation after a Rhine capacity shock (at least on impact and at equal cost). To further explore the response in transportation patterns, Figure 9 shows the IRF of the truck index for Germany. As discussed in section 3.2, these regressions control for the change in industrial production to isolate the substitution effect on the input side of production. Hence, one would expect a positive response after a negative Rhine capacity shock due to higher demand for truck services for transporting input goods.

Figure 9: IRF of Truck Index



Note: The figure shows the IRF of the truck index for Germany after a one standard deviation negative Rhine capacity shock together with 90% (Newey-West) confidence bands.

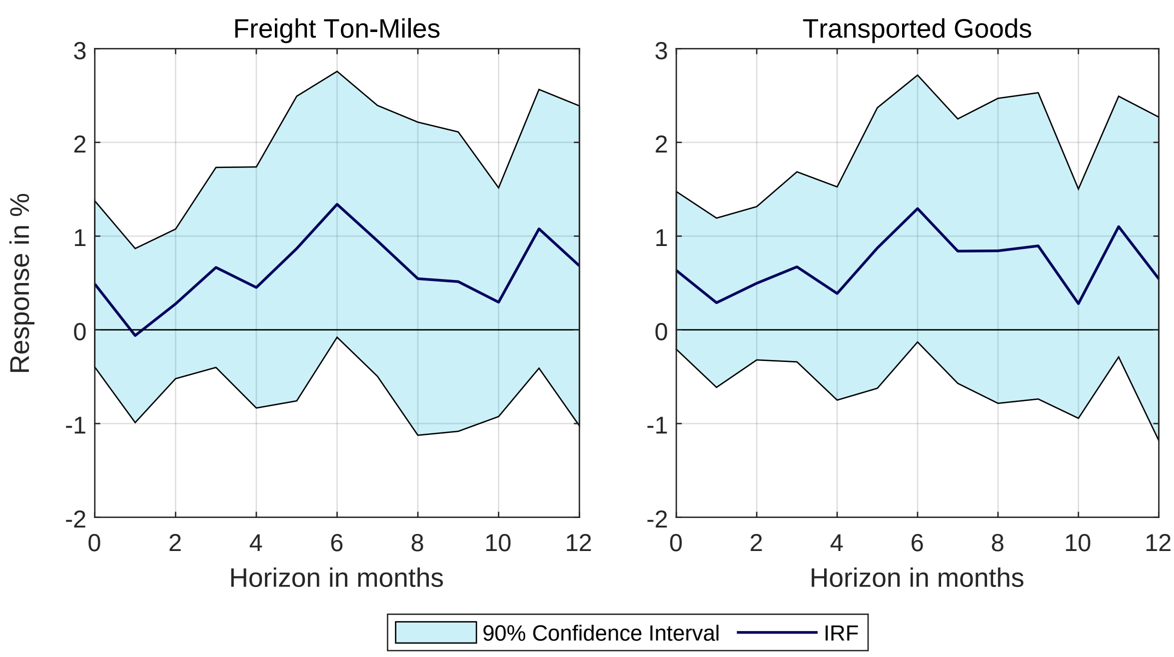
One apparent feature of the IRF shown in Figure 9 is its sluggish behavior compared to the responses of industrial production. The impact response is close to zero and then builds up over time until it reaches its peak between four and five months after the shock at around 0.15%. Afterwards, the IRF declines back to zero rapidly. Note that the point estimates are significantly different from zero only at horizons four and six (at the 90% level).

Two conclusions emerge from this exercise: First, the periods in which the truck index exhibits a strong and positive response (horizons two to six) correspond to the periods in which industrial production starts to recover again (c.f. Figure 7). Referring to the discussion in section 3.2, this provides suggestive evidence that the estimates do indeed capture the supply chain disruptions caused by Rhine capacity shocks and not just other channels of extreme weather events. Second, the results suggest that firms cannot flexibly switch means of transportation right after a Rhine capacity shock occurs. First, a single Rhine ship can transport as many goods as 150 trucks, which might not be available on the spot. Second, coal, gas, and chemicals are not shipped in containers but on specialized ships. This makes it even more difficult to switch to trucks since special loading terminals and truck types are needed. These arguments could rationalize, why the estimated response is close to zero on impact and only builds up over time.

4.3 Train Transportation

Another way of substituting the mode of transportation could be to transfer input goods with trains during the waterway transportation restrictions. Therefore, we present IRFs of train transportation in Figure 10. Similar to the analysis of the truck index response, we do not find evidence for any substitution patterns on impact. The point estimates of freight ton-miles and transported goods are positive but at no horizon significantly different from 0 at a 90% confidence level. As outlined before, one possible explanation for this finding could be the special transportation requirements of the input goods which impede the short-term substitution with trains. Further, not all inland waterway ports are connected to the railway network which makes a substitution of goods to trains impossible.

Figure 10: IRF of Train Transportation (Cross-Border Receiving)

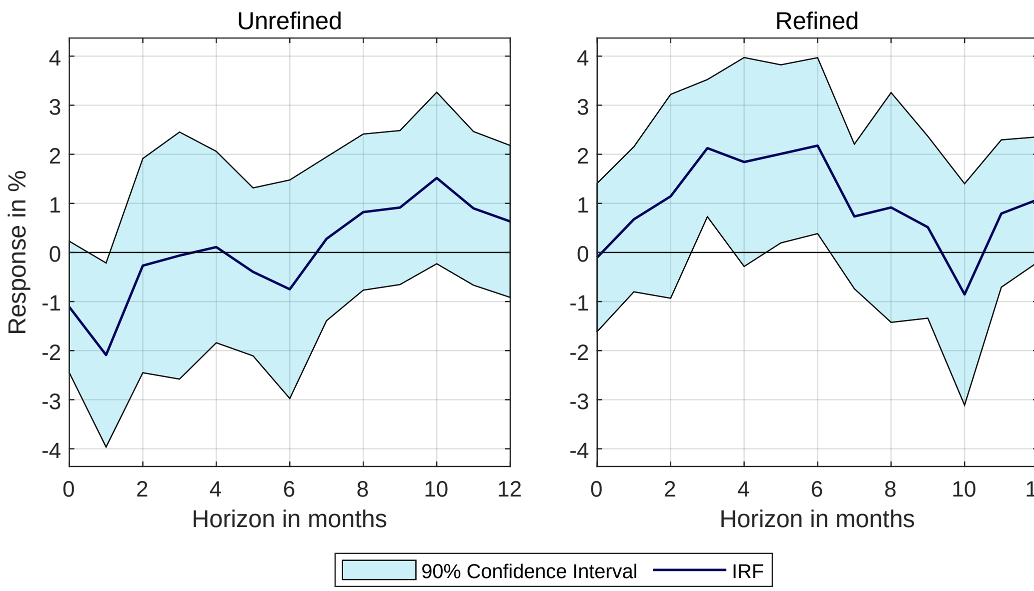


Note: IRFs (dark blue) of cross-border receiving via train transportation for Germany measured in freight ton-miles (left panel) and transported goods in tons (right panel) after a one standard deviation negative Rhine capacity shock. 90% confidence intervals depicted in light blue.

4.4 Energy Imports

Given the importance of the Rhine for the transportation of energy imports, we present evidence on the total imports and the substitution patterns with respect to the countries of origin of those goods. To this end, we compute the IRFs for total German imports of petroleum and crude oil, which are important primary goods for the German economy. Figure 11 illustrates the results.

Figure 11: IRF of Petroleum and Crude Oil Imports

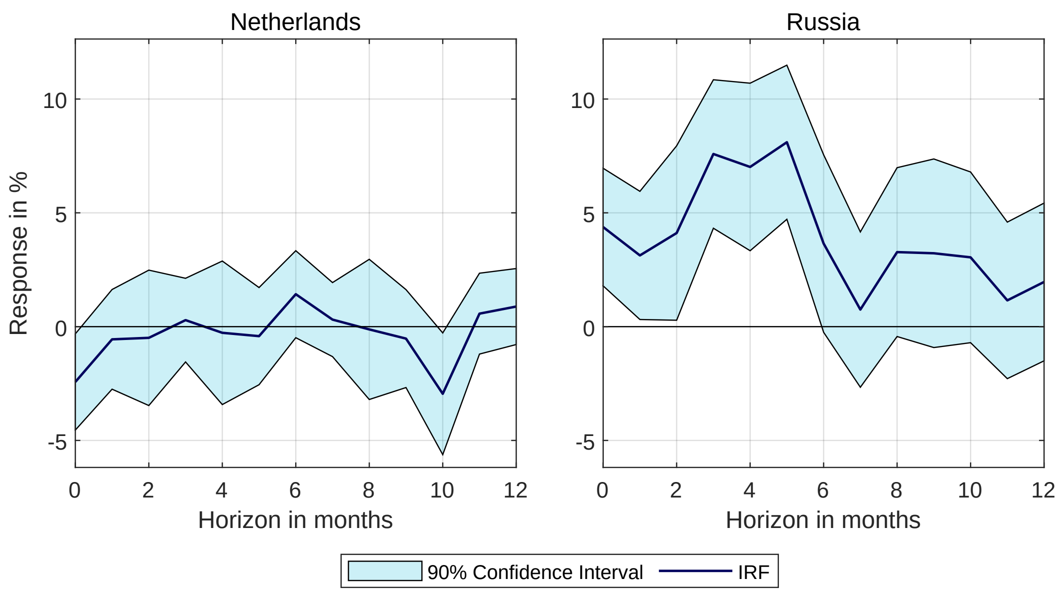


Note: IRFs (dark blue) of total German imports of unrefined (left panel) and refined (right panel) petroleum and crude oil after a one standard deviation negative Rhine capacity shock. 90% confidence intervals depicted in light blue.

For unrefined imports, the impulse response in the left panel indicates a contraction on impact (-1.1%) and one month after (-2.1%) while recovering subsequently. Besides horizon 1, however, the estimates are not statistically significant. The pattern for refined imports in the right panel look quite different. Here, we observe a prolonged increase of imports reaching its peak at around 2.1% at horizon three and remaining at this level until horizon six before normalizing afterwards. The point estimates are statistically significant in the periods three, five, and six. These findings are surprising. On impact, we would have expected a decrease for both kinds of goods given the relevance of the Rhine for the transportation of fossil fuels as outlined in section 1.1.

To rationalize the increase in refined crude oils, we compute the IRFs of German imports from each exporting country separately. Figure 12 presents the IRFs for the Netherlands and Russia, which had been the major countries of origin for German imports of refined petroleum and crude oil. For imports from the Netherlands, we find a statistically significant decrease of 2.4%. From horizon 1 onwards, the point estimates are approximately zero and not statistically significant.[24] For Russian imports, however, the results indicate a different pattern. On impact, we observe an statistically significant increase by 4.4%. Thereafter, Russian imports continued to increase up until horizon 5, reaching a peak of 8.1% and normalizing afterwards. These findings indicate that there is a substitution pattern in German imports with quite an overshooting following the negative transportation capacity shock. There are two lines of arguments that could rationalize our outcomes. First, the short-termed increase in imports from Russia is only possible with certain contractual agreements that require a prolonged increase in imports of those goods. Another possible explanation is that economic agents become aware of these shocks and start stockpiling due to a precautionary motive.

Figure 12: IRF of Refined Petroleum and Crude Oil Imports by Country



Note: IRFs (dark blue) of total German imports of refined petroleum and crude oil from the Netherlands (left panel) and Russia (right panel) after a one standard deviation negative Rhine capacity shock. 90% confidence intervals depicted in light blue.

4.5 Energy Prizes

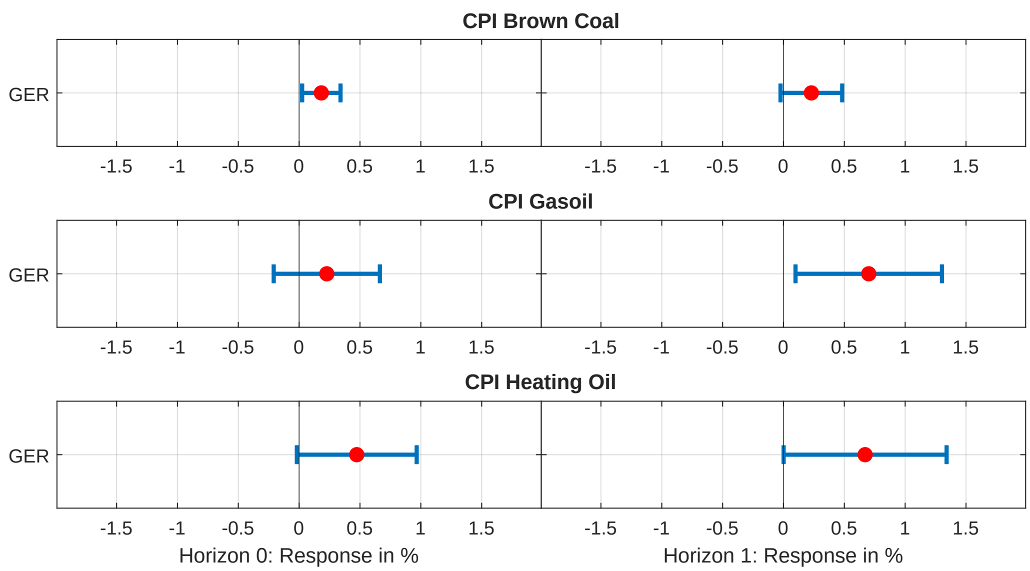
Following our findings, it is reasonable to assume that the goods shortages and short-term substitution patterns are associated with increasing costs. Therefore, we want to know

[24]One exemption is the estimate for horizon 10. However, due to the relatively short sample size, we assume that this finding is more of a statistical nature rather than being associated with any economical meaning.

whether economic agents might be affected through price changes following the regional supply chain disruptions. To this end, we compute the impulse response for the CPI components of brown coal, gasoil, and heating oil. The results are presented in Figure 13. Since we do not find any results of significance after horizon 1, the left side of the figure shows the effect on impact and the right side of the figure indicates the response after 1 month. On impact we observe a significant increase of the brown coal CPI component by 0.81%. The impulse response estimates for the gasoil and the heating oil CPI components are also positive but not significantly different from 0 at a 90% level. However, one month after the shock, the results for the CPI components of gasoil and heating oil indicate an increase of 0.7% and 0.67%, respectively, and are statistically significant at a 90% level. Also the point estimate of the brown coal CPI component increases further one month after the shock but is not statistically significant anymore.

Given these findings, we conclude that prices react to the regional supply chain disruptions followed by substitution patterns with respect to the countries of origin of fossil fuel imports.

Figure 13: IRF of CPI components



Note: The figure shows the IRFs of various CPI components after a one standard deviation negative Rhine capacity shock together with 90% (Newey-West) confidence bands. The left panels show the response on impact; the right panels show the response one month after the shock occurred (GER: Germany).

5 Conclusion

We present a new approach to measure regional supply chain disruptions by exploiting waterway transportation restrictions and apply it to the river Rhine. By using administrative trade flow data, we assign weights to the impact of certain passage closures and calculate an overall shock measurement that can be used to assess the macroeconomic effects of disruptions in waterway supply chains.

By incorporating this shock series into a local projection framework, we find that transportation restrictions have a temporary contractionary effect on industrial production in bordering federal states and Germany as a whole. This effect is more pronounced and more permanent when considering only energy-intensive sectors, which are likely reliant on natural gas, and therefore, disproportionately affected by transport restrictions on waterways. Our results also suggest significant differences in the impact of disruptions across states and sectors, which may be due to variations in industry structures or reliance on waterway transportation in the supply chains of different states.

Controlling for the effect of reduced output, we find evidence that cargo is substituted with trucks only with a lag of two to four months. This observation might be due to the specialized nature of the goods being transported, such as fossil fuels that require specific terminals and cannot be easily transferred from ships to trucks. However, we do not find any evidence for ship-train substitution patterns

However, we observe a substitution pattern with respect to the country of origin from the imported goods. During supply chain disruptions caused by waterway transportation restrictions, fossil fuels imports from Netherlands, often shipped through the Rhine, decrease. In contrast, imports from Russia increase, which are primarily transported via pipelines. The observable increase of Russian imports is also quite persistent, for which there are two possible explanations. First, the short-termed demand increase of these goods is only possible with a contractual obligation to increase imports for a prolonged horizon. The second explanation of this finding could be a precautionary motive, such that economic agents insure themselves against possible regional supply chain shocks in the nearby future. These findings raise the question, to what degree these regional supply chain shocks will affect the economy in the future since the possibility to substitute with Russian imports will not be available anymore in the nearby future.

Finally, we also present evidence on how households are affected by these regional supply chain shocks through prices changes. We find short-lived increases in CPI components of goods that are primarily transported via the Rhine.

Our constructed shock series paves the way for more research on the effects of regional supply chain disruptions. Especially, any research that employs firm-level data to analyze the propagation through firm-linkages seems promising.

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Appendix

A. Robustness Checks

A.1 Shock Regression

As outlined in subsection 2.2, there are other reasonable ways to formulate the regression from which we derive our shock series. To mitigate concerns that our results hinge on the chosen regression specification of our shock construction, we present robustness specifications and repeat the main empirical steps of our project.

Precipitation. A major concern has been that companies can predict waterway transportation restrictions due to precipitation in the same month. Therefore, we adjust our shock regression as follows:

$$cap_t = \boldsymbol{\alpha}_0' \, \mathbf{month}_t + \alpha_1 \, cap_{t-1} + \alpha_2 \, prec_t + s_t^{prec},$$

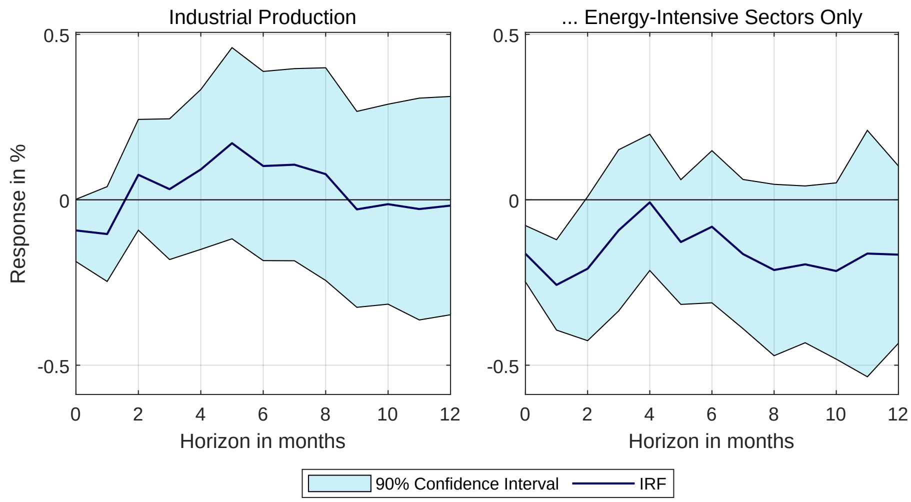
where $prec_t$ is the average level of precipitation in Germany in period t. Similar to before, we use s_t^{prec} as shock measure. When computing the IRF of waterway cross-border receiving as shock diagnostics, we can again observe a statistically significant contraction on impact of freight ton-miles and transported goods in tons. Both the magnitude and the recovery afterwards are also similar to the results of our baseline shock specification.

Figure A.1: IRF of Goods Transportation on the Rhine with Adjusted Shock Series (Cross-Border Receiving)

Note: IRFs (dark blue) of freight ton-miles (left panel) and transported goods (right panel) after a one standard deviation negative Rhine capacity shock. 90% confidence intervals depicted in light blue.

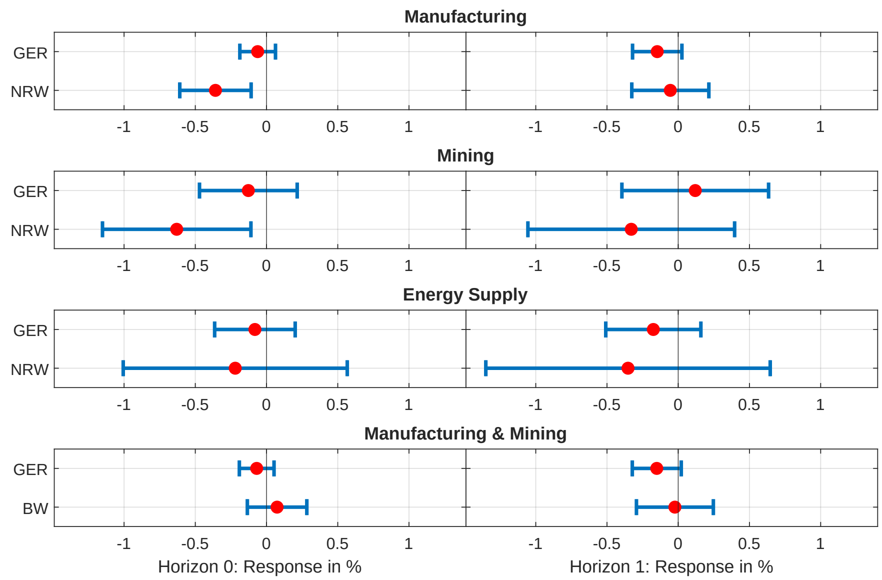
In the following we repeat the empirical analysis from the main part and present the outcomes without further comments. The main takeaway from these figures is that our conclusions derived previously do not hinge on the design of our shock regression.

Figure A.2: IRF of German Industrial Production with Adjusted Shock Series



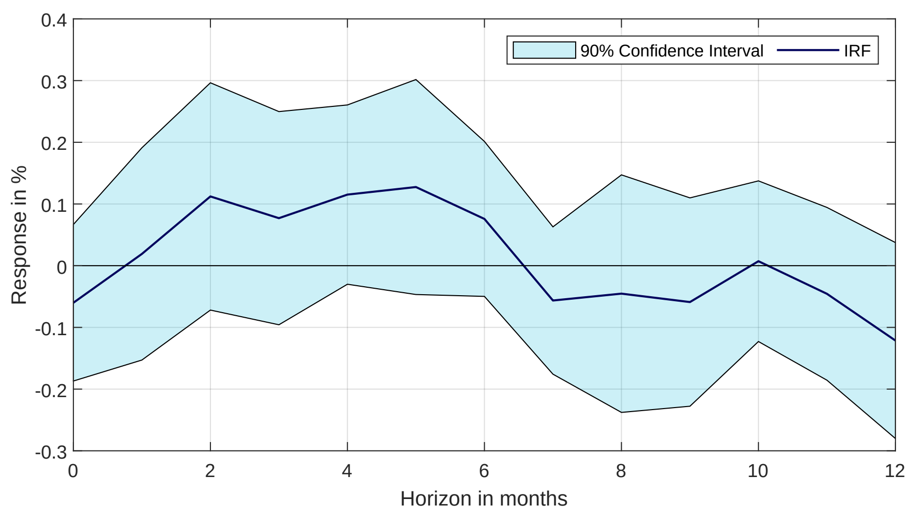
Note: IRFs (dark blue) of industrial production (left panel) and industrial production of energey-intensive sectors only (right panel) after a one standard deviation negative Rhine capacity shock. 90% confidence intervals depicted in light blue.

Figure A.3: IRF of Industrial Production for States and Sectors with Adjusted Shock Series



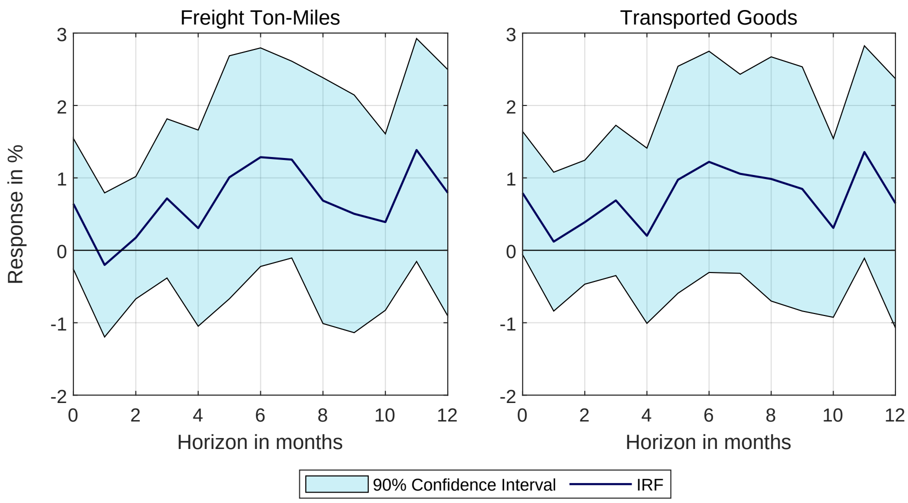
Note: The figure shows the IRFs of the industrial production index after a one standard deviation negative Rhine capacity shock together with 90% (Newey-West) confidence bands. The left panels show the response on impact; the right panels show the response one month after the shock occurred (GER: Germany, NRW: North Rhine-Westphalia, BW: Baden-Wurttemberg).

Figure A.4: IRF of Truck Index with Adjusted Shock Series



Note: The figure shows the IRF of the truck index for Germany after a one standard deviation negative Rhine capacity shock together with 90% (Newey-West) confidence bands.

Figure A.5: IRF of Train Transportation with Adjusted Shock Series (Cross-Border Receiving)

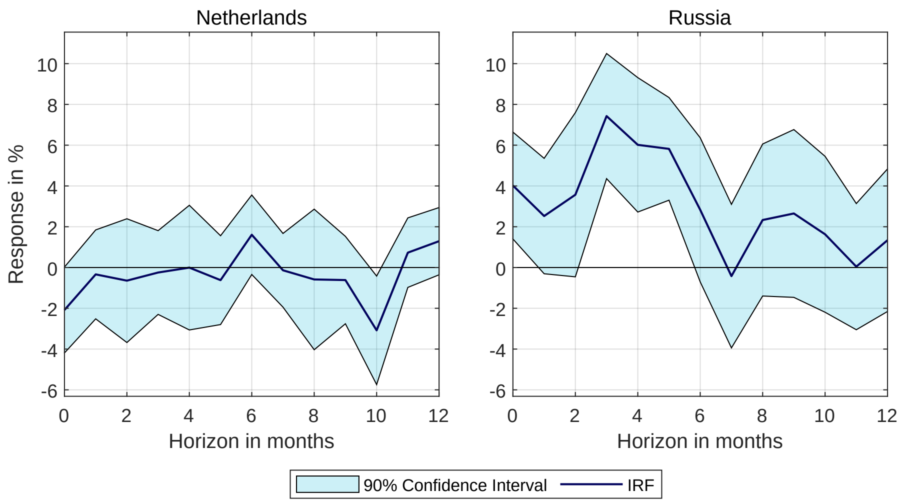


Note: IRFs (dark blue) of cross-border receiving via train transportation for Germany measured in freight ton-miles (left panel) and transported goods in tons (right panel) after a one standard deviation negative Rhine capacity shock. 90% confidence intervals depicted in light blue.

Figure A.6: IRF of Petroleum and Crude Oil Imports with Adjusted Shock Series

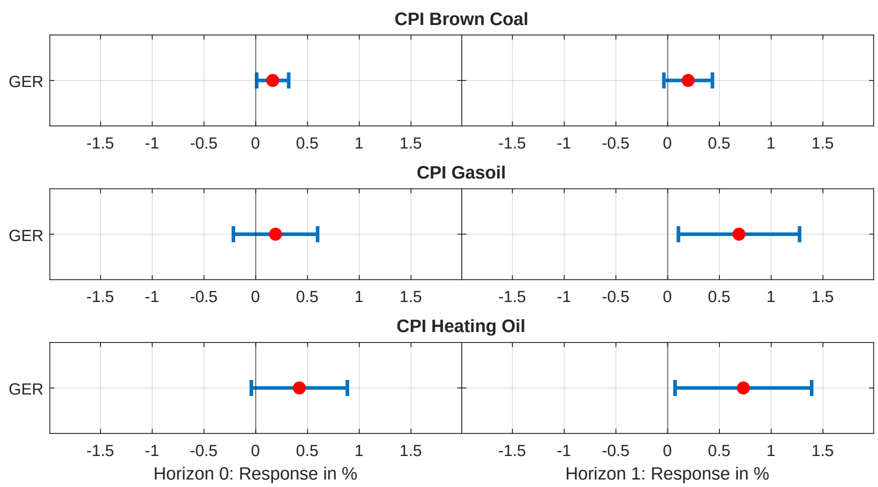
Note: IRFs (dark blue) of total German imports of unrefined (left panel) and refined (right panel) petroleum and crude oil after a one standard deviation negative Rhine capacity shock. 90% confidence intervals depicted in light blue.

Figure A.7: IRF of Refined Petroleum and Crude Oil Imports by Country with Adjusted Shock Series



Note: IRFs (dark blue) of total German imports of refined petroleum and crude oil from the Netherlands (left panel) and Russia (right panel) after a one standard deviation negative Rhine capacity shock. 90% confidence intervals depicted in light blue.

Figure A.8: IRF of German CPI components with Adjusted Shock Series

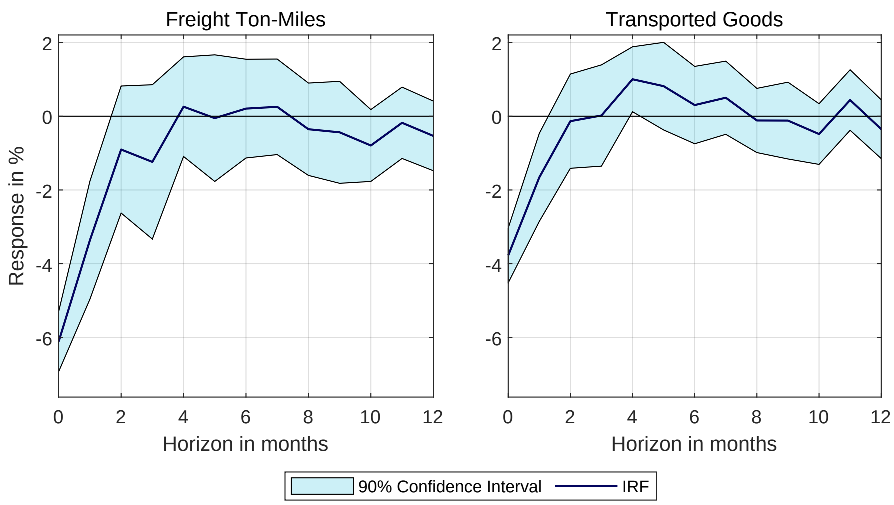


Note: The figure shows the IRFs of various CPI components after a one standard deviation negative Rhine capacity shock together with 90% (Newey-West) confidence bands. The left panels show the response on impact; the right panels show the response one month after the shock occurred (GER: Germany).

Precipitation x Temperature Interaction. The effect of precipitation could also be mediated through temperature in the respective month. For this reason, we include an interaction term to account for this effect.[25]

$$cap_t = \boldsymbol{\alpha}_0' \, \mathbf{month}_t + \alpha_1 \, cap_{t-1} + \alpha_2 \, prec_t + \alpha_3 \, prec_t \times temp_t + s_t^{inter}$$

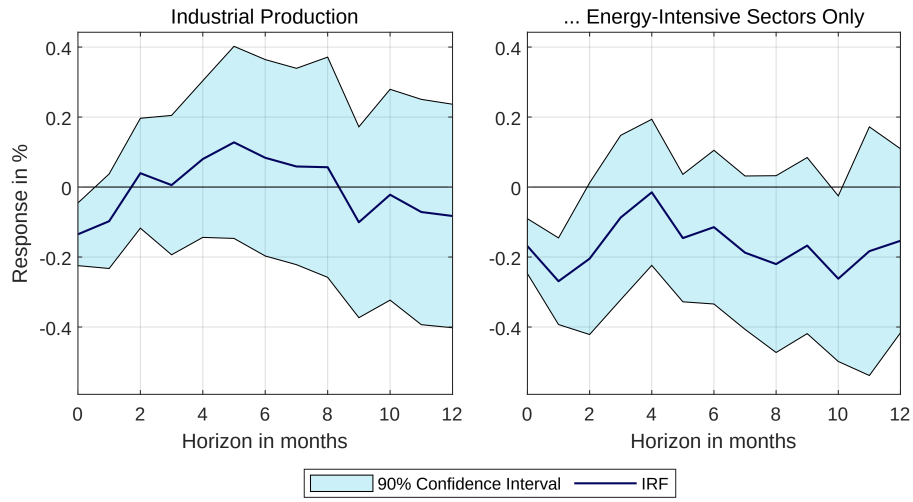
Figure A.9: IRF of Goods Transportation on the Rhine with Adjusted Shock Series (Cross-Border Receiving)



Note: IRFs (dark blue) of freight ton-miles (left panel) and transported goods (right panel) after a one standard deviation negative Rhine capacity shock. 90% confidence intervals depicted in light blue.

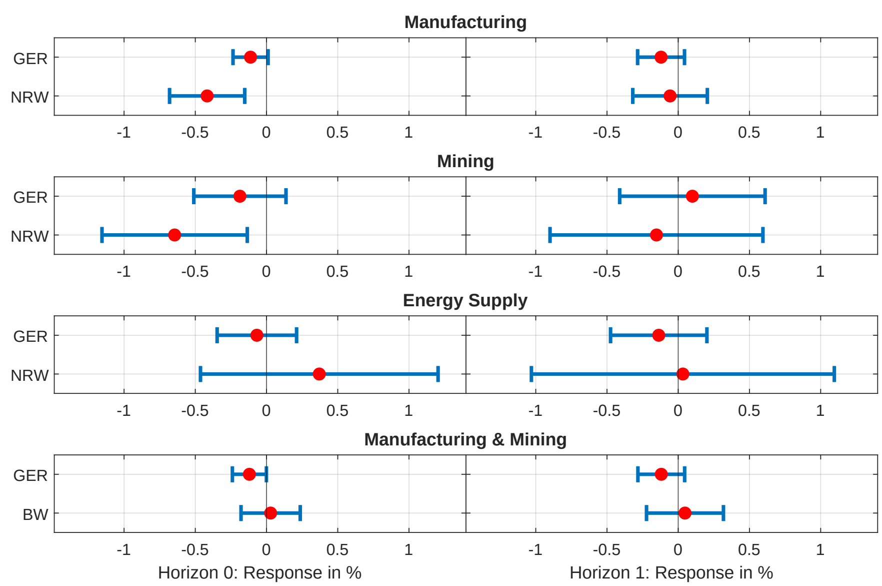
[25] Temperature is to a larger degree captured by the monthly dummy variable compared to precipitation. Therefore, we do not include temperature as single variable.

Figure A.10: IRF of German Industrial Production with Adjusted Shock Series



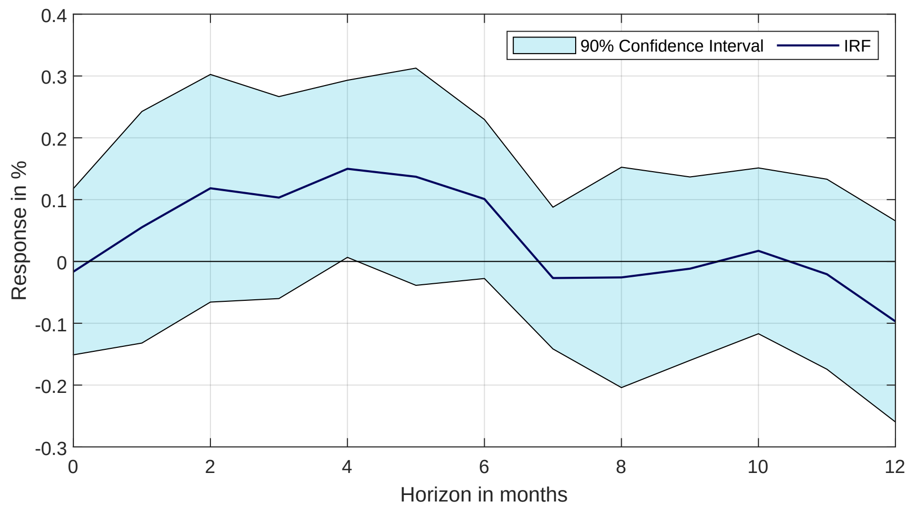
Note: IRFs (dark blue) of industrial production (left panel) and industrial production of energey-intensive sectors only (right panel) after a one standard deviation negative Rhine capacity shock. 90% confidence intervals depicted in light blue.

Figure A.11: IRF of Industrial Production for States and Sectors with Adjusted Shock Series



Note: The figure shows the IRFs of the industrial production index after a one standard deviation negative Rhine capacity shock together with 90% (Newey-West) confidence bands. The left panels show the response on impact; the right panels show the response one month after the shock occurred (GER: Germany, NRW: North Rhine-Westphalia, BW: Baden-Wurttemberg).

Figure A.12: IRF of Truck Index with Adjusted Shock Series

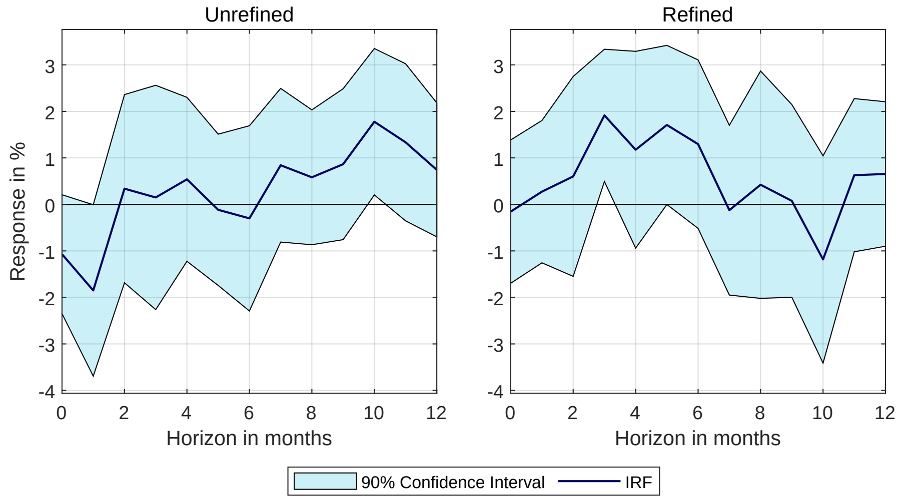


Note: The figure shows the IRF of the truck index for Germany after a one standard deviation negative Rhine capacity shock together with 90% (Newey-West) confidence bands.

Figure A.13: IRF of Train Transportation with Adjusted Shock Series (Cross-Border Receiving)

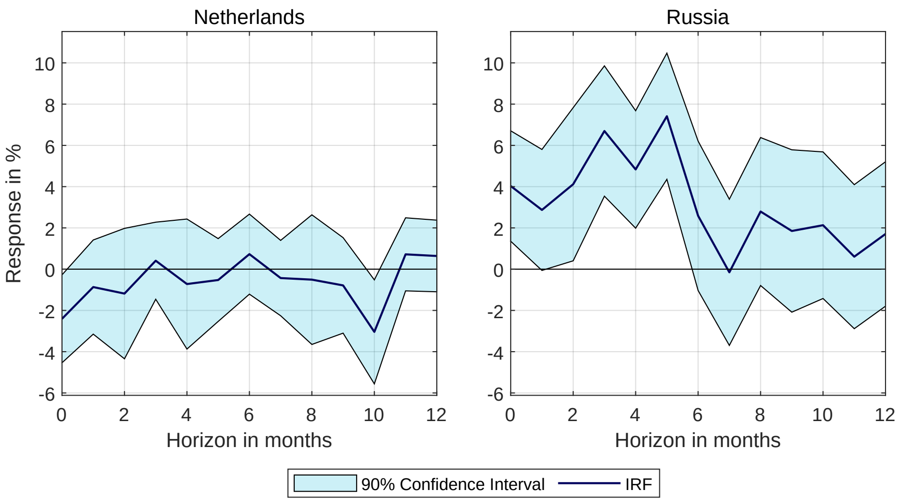
Note: IRFs (dark blue) of cross-border receiving via train transportation for Germany measured in freight ton-miles (left panel) and transported goods in tons (right panel) after a one standard deviation negative Rhine capacity shock. 90% confidence intervals depicted in light blue.

Figure A.14: IRF of Petroleum and Crude Oil Imports with Adjusted Shock Series



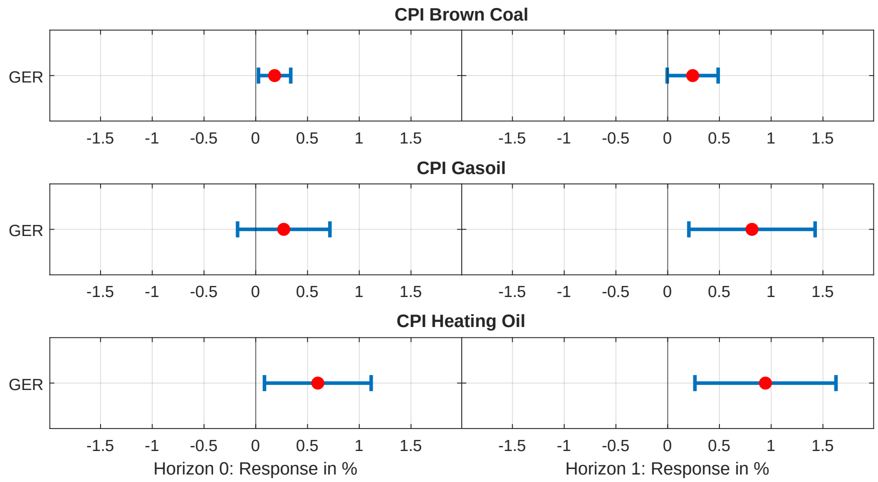
Note: IRFs (dark blue) of total German imports of unrefined (left panel) and refined (right panel) petroleum and crude oil after a one standard deviation negative Rhine capacity shock. 90% confidence intervals depicted in light blue.

Figure A.15: IRF of Refined Petroleum and Crude Oil Imports by Country with Adjusted Shock Series



Note: IRFs (dark blue) of total German imports of refined petroleum and crude oil from the Netherlands (left panel) and Russia (right panel) after a one standard deviation negative Rhine capacity shock. 90% confidence intervals depicted in light blue.

Figure A.16: IRF of German CPI components with Adjusted Shock Series



Note: The figure shows the IRFs of various CPI components after a one standard deviation negative Rhine capacity shock together with 90% (Newey-West) confidence bands. The left panels show the response on impact; the right panels show the response one month after the shock occurred (GER: Germany).

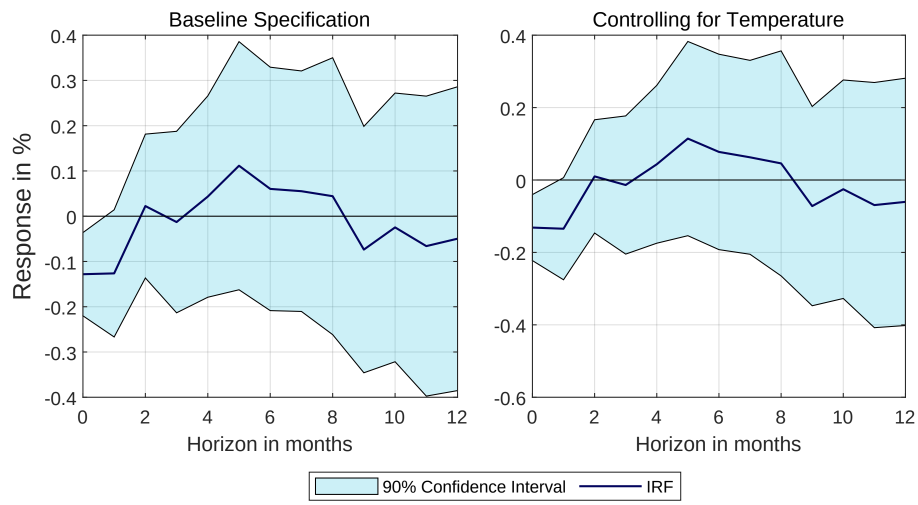
A.2 Baseline Specification

To identify the causal effect of our series of regional supply chain disruptions, we need to ensure that the effect on economic output is actually driven by our identified series of supply chain shocks and not some other confounding variables. A valid concern has been that instead of the waterway transportation restrictions, it is actually the temperatures that lead to a drop, since high temperatures and waterway restrictions might be correlated. To mitigate this concern we enhance our baseline regression as follows:

$$\Delta^{h+1} ip_{t+h} = \alpha^h + \beta_1^h s_t + \gamma^h \Delta ip_{t-1} + \beta_2^h temp_t + v_t\,, \quad \text{for } h = 0, 1, ..., 12$$

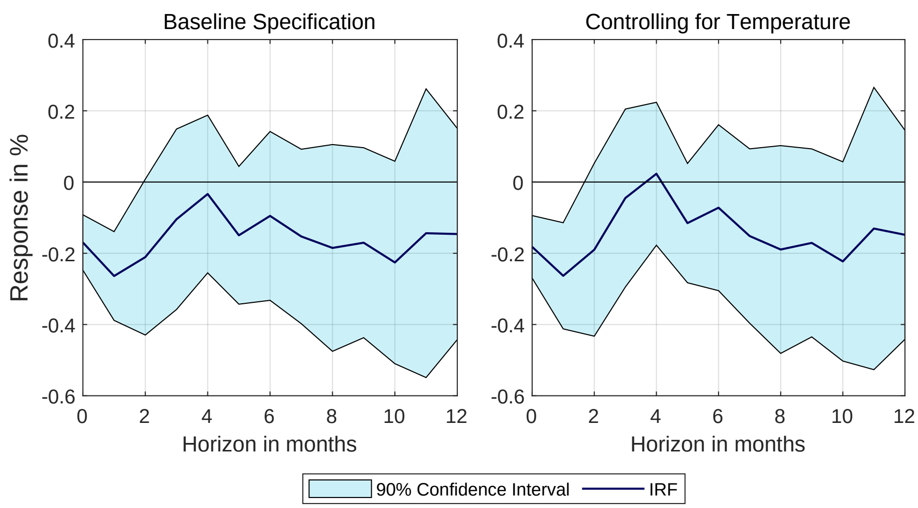
By accounting for temperature $temp_t$, we ensure that output contractions are not driven by temperature changes. The results are presented in Figure A.17 and Figure A.18 without further comments.

Figure A.17: IRF of German Industrial Production



Note: IRFs (dark blue) of industrial production with the baseline specification (left panel) and industrial production controlling for temperature (right panel) after a one standard deviation negative Rhine capacity shock. 90% confidence intervals depicted in light blue.

Figure A.18: IRF of German Industrial Production (Energy-Intensive Sectors Only)



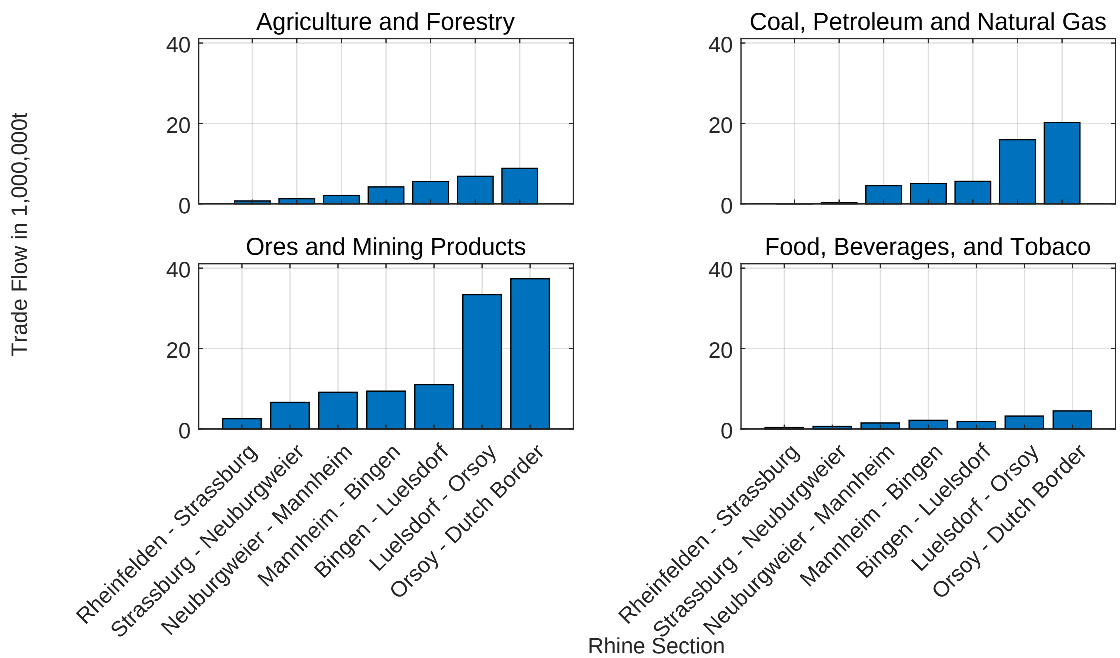
Note: IRFs (dark blue) of industrial production in energy-intensive sectors only with the baseline specification (left panel) and industrial production controlling for temperature (right panel) after a one standard deviation negative Rhine capacity shock. 90% confidence intervals depicted in light blue.

B. Data Details

B.1 Trade Flow Data

The trade flow data is published by the *Federal Statistical Office Germany* and we retrieved the data from *Destatis*.[26] The data set includes yearly trade volume for seven defined Rhine subsubsections: (1) Rheinfelden-Straßburg, (2) Straßburg-Neuburgweier, (3) Neuburgweier-Mannheim, (4) Mannheim-Bingen, (5) Bingen-Lülsdorf, (6) Lülsdorf-Orsoy, (7) Orsoy-Dutch Border. The trade data subdivides the trade volume into 20 goods categories following the NST-2007 classification. Further, the data differentiates between hazardous and non-hazardous goods. For the purpose of our project, we work with the total transport volume. The data is available for the years 2011-2021. The absolute volume of the transported goods changes over the years; however, the relative shares remain relatively stable. Figures B.1, B.2, and B.3 summarize the trade flow data.

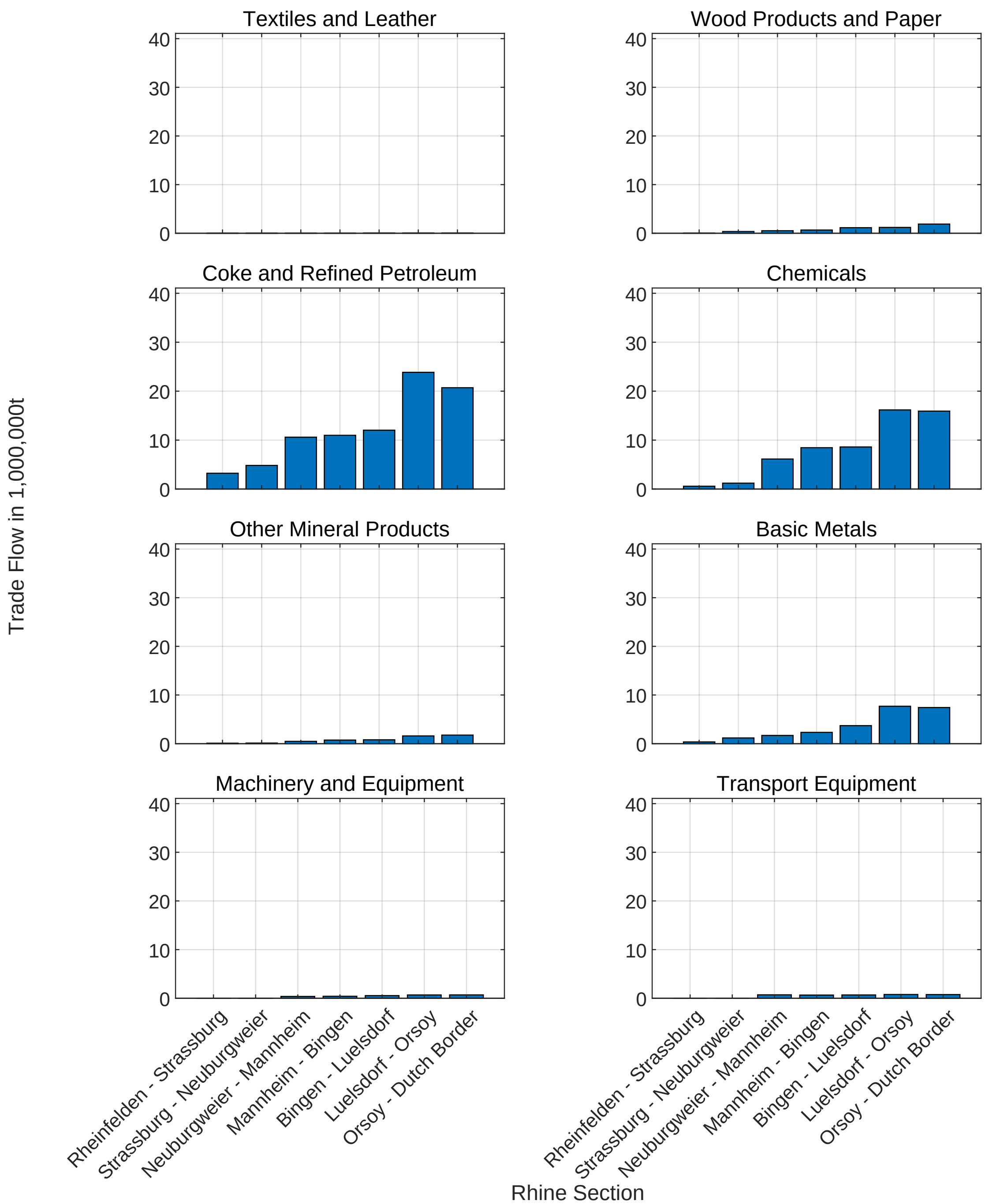
Figure B.1: Trade Flows by Category and Rhine subsubsection in 2021 (1/3)



Note: Each figure contains the trade flows for a specific goods category on every of the seven Rhine sections. The Rhine sections are ordered from South (Swiss border) to North (Dutch border). (Source: German Statistical Office)

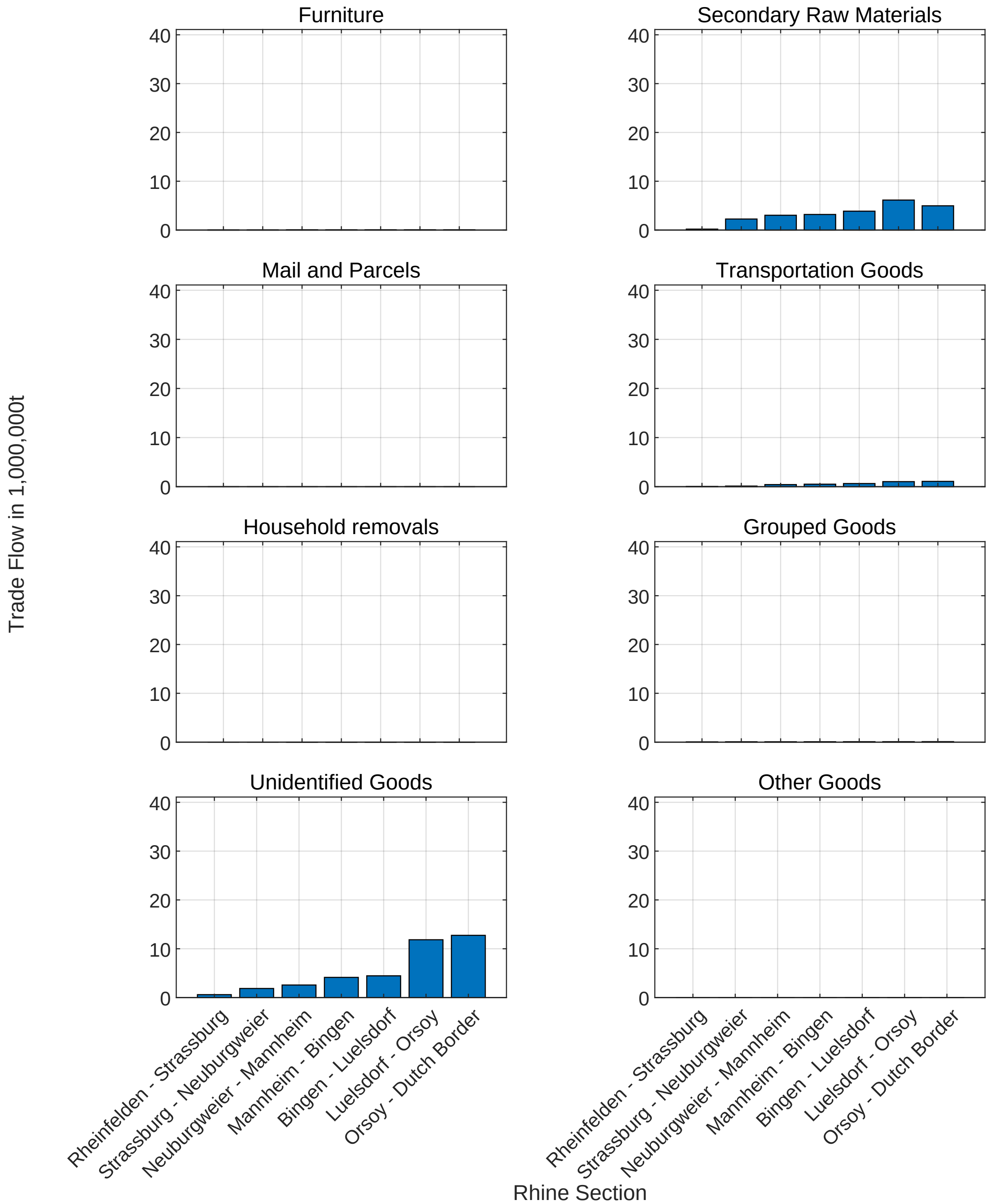
[26] Table 46321-0013, accessed 17.11.2022

Figure B.2: Trade Flows by Category and Rhine subsubsection in 2021 (2/3)



Note: Each figure contains the trade flows for a specific goods category on every of the seven Rhine sections. The Rhine sections are ordered from South (Swiss border) to North (Dutch border). (Source: German Statistical Office)

Figure B.3: Trade Flows by Category and Rhine subsubsection in 2021 (3/3)



Note: Each figure contains the trade flows for a specific goods category on every of the seven Rhine sections. The Rhine sections are ordered from South (Swiss border) to North (Dutch border). (Source: German Statistical Office)

B.2 Water Level and Related Data

Water Levels. We obtain the raw water level data from the *German Federal Waterways and Shipping Agency*. On request, they provided us with daily observations for administratively relevant measuring stations along the Rhine. The daily water level represents an average of three observations taken each day at every station at the same time. The period of observations varies across the measuring stations, going back as far as to the beginning of World War II.

Reference Level and High Level Threshold. The legal high water level thresholds did not change over time and are available at the *German Federal Waterways and Shipping Agency*[27]. The reference water levels ('Gleichwertiger Wasserstand'/'GlW' in German) are determined every ten years by the *Central Comission for the Navigation of the Rhine*. However, some of these changes were irregular or delayed. To precisely determine the dates of the changes, we rely on resolutions of the *Central Comission for the Navigation of the Rhine*, which we received upon request[28].

Reference Depth. For the reference depth ('Solltiefe unter GlW' in German) we rely on two types of sources. The current reference depth (minimum guaranteed fairway depth at the reference level) is publicly available at the *German Federal Waterways and Shipping Agency*[29]. For the historic changes in the reference depth, we exploit the information contained in two historical studies by Langschied (1990) and Meurer (2000).

As outlined in the paper, we include only those measuring stations for which the previous variables have been defined. As a result, we obtain water level data for 13 relevant measuring stations along the Rhine (sorted South to North): Maxau, Speyer, Mannheim, Worms, Mainz, Kaub, Koblenz, Andernach, Köln, Düsseldorf, Ruhrort, Wesel, Emmerich.

B.3 Outcome Variables

Industrial Production. The industrial production index is published by the *Federal Statistical Office Germany* and by some of the statistical offices of the states. It includes sectors B (Mining and Quarrying), C (Manufacturing), D (Energy Supply) and F (Construction) according to the WZ2008 classification, which is closely related to the international NACE Rev. 2 classification.[30] All series used in our analysis are normalized to 100 in 2015.

[27] Overview of Stations and High Water Thresholds ('HSW' in the table), accessed 18.11.2022

[28] The relevant resolutions are 1932-II-12, 1952-II-18, 1962-IV-49, 1973-I-28, 1976-II-40, 1984-II-40, 1992-I-32, 1996-I-34, 1998-I-27, 2002-II-26, 2012-II-18, 2014-II-17

[29] Overview: Reference Levels, accessed 18.11.2022

[30] More information available in the quality reports of the Federal Statistics Office Germany. [Link accessed: 14.03.2024]

Germany. We retrieve the data from *Destatis*[31]. The index is available for all four sectors as an aggregate and also for several subsets of sectors, including the ones discussed in subsubsection 4.1. We use the series that is cleaned for seasonal and calendar effects according to the X-13 JDemetra+ procedure. The series spans a time interval from January 1991 to September 2022.

NRW. We retrieve the data from the database of the *Statistical Office in North Rhine-Westphalia*[32]. The index is available for sectors B, C and D individually (or the corresponding sectors in the preceding sector classification schemes) but not as an aggregate index for all four sectors. The raw data contains overlapping subsamples corresponding to different base years. We unify the base year by rescaling the individual series using a simple splicing method to obtain a time series spanning January 1995 - September 2022. The raw data is already cleaned for calendar effects. We use the X-13 procedure in JDemetra+ to clean for seasonal effects using the same specification as the one described in the quality reports of the Federal Statistics Office Germany.

BW. We obtain data upon request from the *Statistical Office in Baden-Wurttemberg*. The index is only available for sectors B and C jointly, but not as an aggregate index for all four sectors, nor for individual sectors. The raw data contains overlapping subsamples corresponding to different base years. We unify the base year by rescaling the individual series using a simple splicing method to obtain a time series spanning January 2000 - September 2022. We use the X-13 procedure in JDemetra+ to clean for seasonal and calendar effects using the same specification as the one described in the quality reports of the Federal Statistics Office Germany.

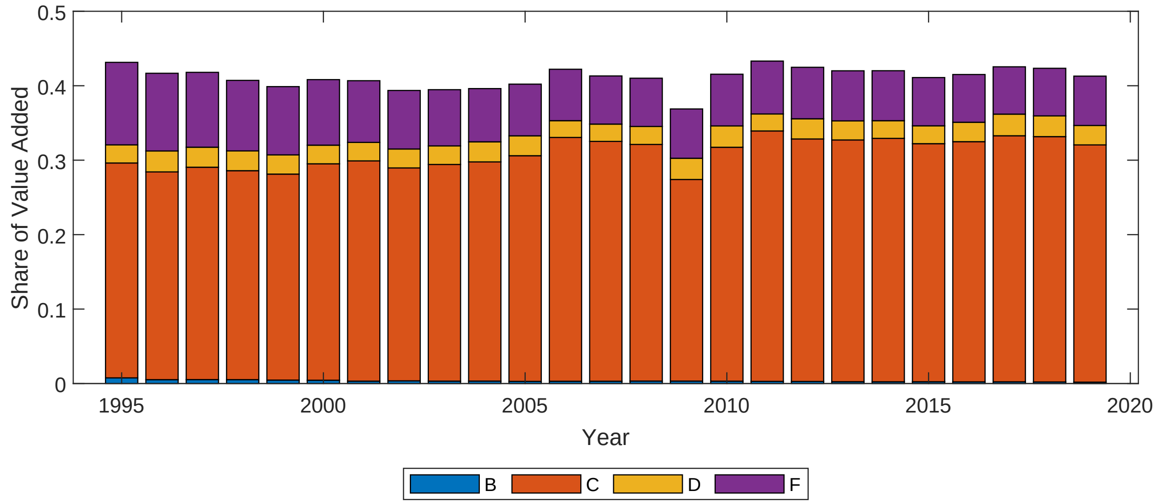
Value Added. Figure B.4 shows the relative sizes of the four sectors contained in the index of industrial production. More precisely, the figure shows the value added generated in each of the four sectors relative to the value added generated in the entire market economy[33]. The four sectors included in the industrial production index jointly account for roughly 40% of value added in the market economy. The manufacturing sector accounts for the largest share among them (around 30%). The shares are stable over time, except for 2009 where the manufacturing sector was affected more severely by the great recession in relative terms.

[31] Table 42153-01. [Link accessed: 14.03.2024]

[32] Tables 42153-03i, 42153-06i, 42153-09i, 42153-16i. [Link accessed: 14.03.2024]

[33] The data is taken from EUKLEMS, Release 2021, Growth Accounts Basic, Germany (accessed 07.12.2022)

Figure B.4: Sector Shares of Value Added



Note: Each bar represents the relative size of the value added of the four industrial production sectors (B, C , D, and F) from 2005 to 2019. (Source: LUISS Lab of European Economies)

Truck Index. We use the monthly truck index (*LKW-Maut-Fahrleistungsindex*) published by the *Federal Statistical Office*. The index uses toll data on kilometers of trucks driven on German highways. We retrieve the data from *Destatis*.[34] We use the series that is cleaned for seasonal and calendar effects according to the X-13 JDemetra+ procedure. The series spans a time interval from January 2005 to October 2022.

Train Transportation. We obtain information on train transportation in Germany by the *Federal Statistical Office*. The series spans a time interval from January 2008 to December 2022. We retrieve data from *Destatis*.[35]

Imported Goods. To illustrate the effects of supply chain disruptions on the Rhine on imported goods, we use data of refined and unrefined crude oil and petroleum imports published by the *Federal Statistical Office*. We retrieve data from *Destatis*.[36] The series spans a time interval from January 2008 to December 2022. The data provides information of the total amount of imports together with a partitioning of imports by countries of origin.

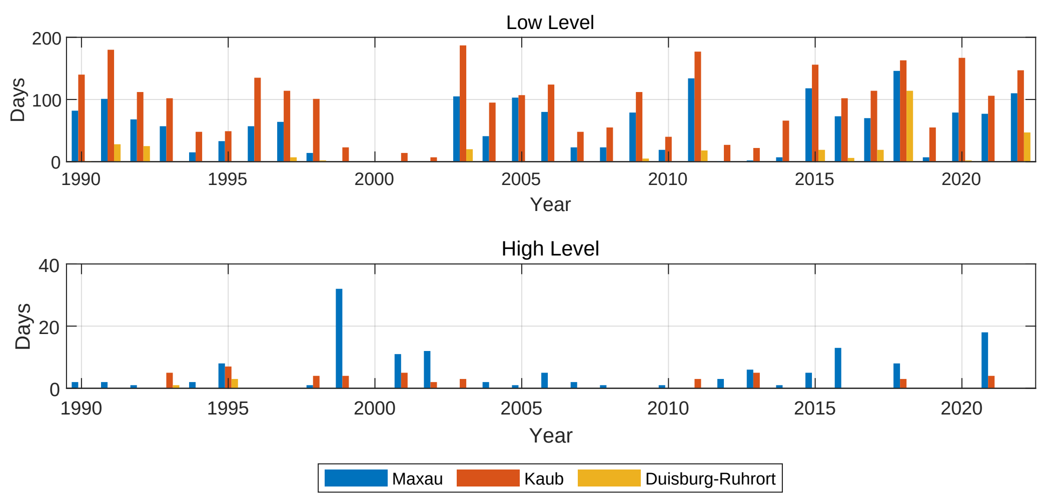
[34] Table 42191-01 (accessed 03.12.2022)
[35] Table 46131-0006 (accessed 25.04.2024)
[36] Table 51000-0011 (accessed 25.04.2024)

CPI. We use the monthly CPI publications from the *Federal Statistical Office Germany*. The data provides information for each sub-category of the CPI basket. Within our analysis, we consider the components *Brown Coal, Gasoil, and Heating Oil*. The data is retrieved from Destatis.[37]

B.4 Capacity and Shock Series

Figure B.5 presents an extension of figure 4, which distinguishes between restrictions due to high vs. low water. The figure shows the total number of days at which a restriction (due to low water in the upper panel, due to high water in the lower panel) was in place within the respective year at three selected stations. Two key observations stand out. First, the regional heterogeneity is very pronounced for both types of events. Second, low water events occur way more frequently than high water events. In addition, high water restrictions typically only last for few days, while low water restrictions can last for several months. Even though high water restrictions lead to more severe capacity restrictions (complete closure of the passage as opposed to low water events that usually just limit the loading capacity), this implies our results are mostly driven by low water events.

Figure B.5: Number of days with restrictions at selected stations

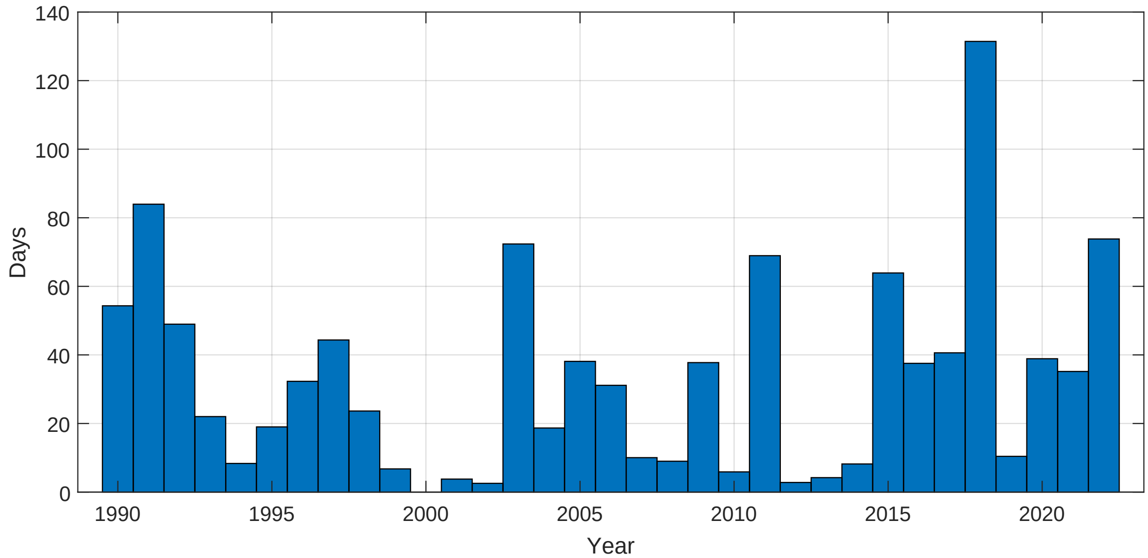


Note: Number of days with waterway transportation restrictions caused by low level water events (top panel) and high water level events (bottom panel) at the measuring stations Maxau, Kaub, and Duisburg-Ruhrort from 1990 until 2022.

Figures B.6 and B.7 replicate figures 4 and B.5 but average over locations using the weighting scheme presented in subsubsection 3. The conclusions drawn above and in subsubsection 3 carry over to these figures.

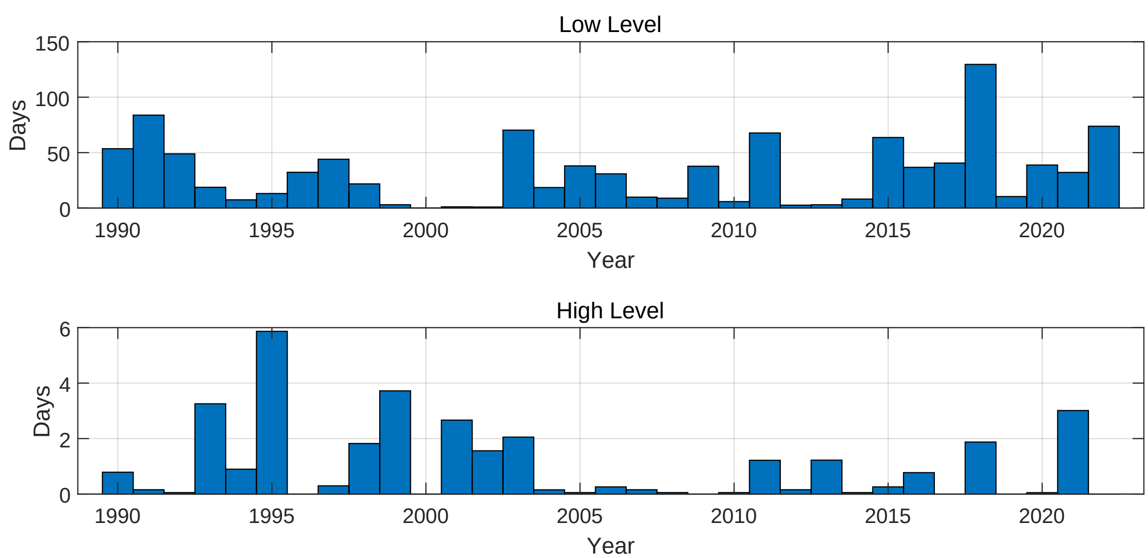
[37] Table 61111-0004 (accessed 25.04.2024)

Figure B.6: Average Number of Days with Restrictions



Note: Average number of days with restrictions at all measuring stations for every year between 1990 and 2022.

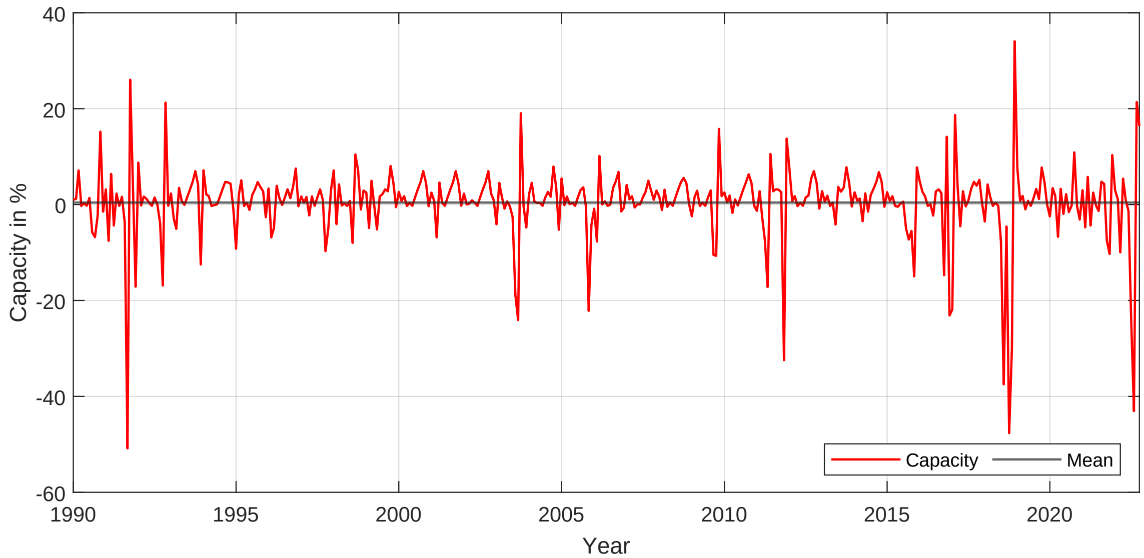
Figure B.7: Average Number of Days with Restrictions (High vs. Low Water Levels)



Note: Average number of days with restrictions caused by low water level events (top panel) and high water level events (bottom panel) at all measuring stations for every year between 1990 and 2022.

Figure B.8 shows the final shock series used for the impulse response analysis. The series is obtained by regressing the aggregate capacity series (c.f. figure 5) on a full set of monthly dummies and on its first lag, as discussed in subsubsection 2.2. The qualitative behavior is similar to that of the aggregate capacity series, with the notable difference that the final shock series also contains positive shocks (mostly occurring at the end of low water episodes).

Figure B.8: Final Rhine Capacity Shock Series



Note: Resulting shock series from our constructed series. The red line indicates the monthly shock realizations between 1990 and 2022 and the black line indicates the mean over the entire observation period.