

Do Water Levels Affect Fuel Prices?

Evidence from High-Frequency Data on German Waterways

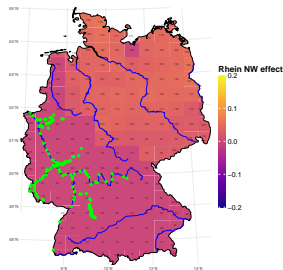
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Takeaway

- **Low water levels \Rightarrow fuel price spikes.**
On Rhine and other major rivers, Diesel and E10 rise *immediately* after low-water events.
- **High water & non-navigable levels also disrupt,** but magnitudes differ by river (heterogeneous effects).
- **Rivers still matter for prices:** transport bottlenecks show up at the pump.



Example: *Diesel, Rhine, estimated marginal effects of low water (only coefficients with p-value below 1% sig. level).*

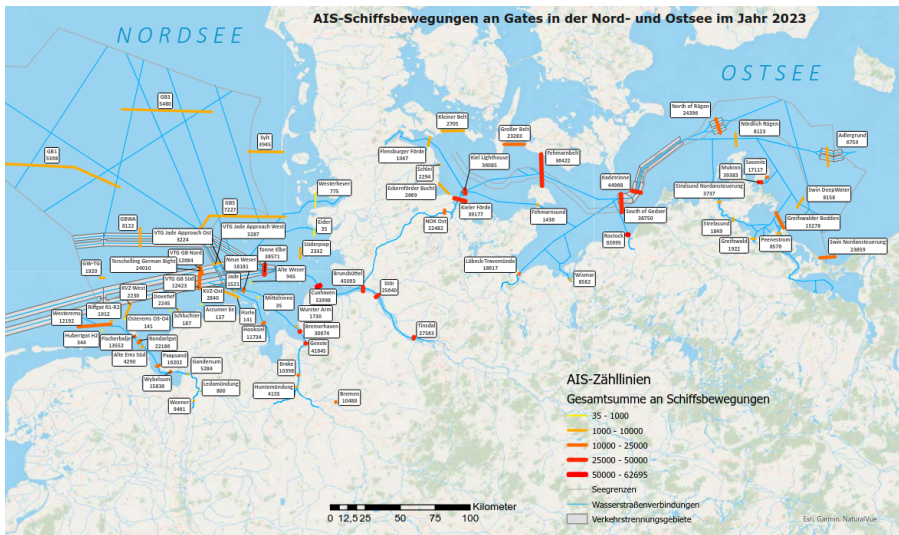
Why rivers may matter for fuel prices?

- Major rivers (e.g., Rhine, Elbe) are critical corridors for transporting fuels by barge.
- 38.1 Mt of "mineral oil and coke-oven products" had been transported in 2019 by ship
- Approximate estimates: 100 Mt via pipelines and 80–120 Mt via road tankers

≈ 20% of oil products are transported via ships

- + **Large Volumes, Low Cost:** bulk transport of fuels, lower costs compared to rail or road.
- + **Strategic Locations:** Refineries and tank farms often near rivers.

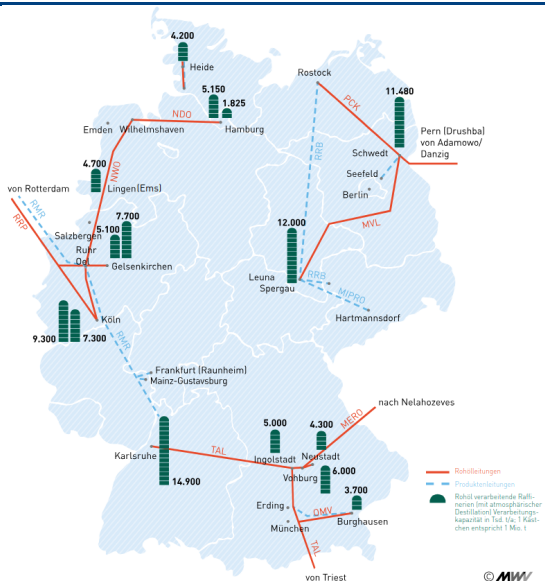
BUT: **Vulnerability to Water Levels:** Low or high water can disrupt fuel deliveries, local shortages or price spikes.



Kartographie: Fachstelle für Geodäsie und Geoinformatik der WSV (FGeoWSV), Dienstort Aurich, Juli 2024

Quelle der Seegrenzen, Wasserstraßenverbindungen und Verkehrstrennungsgebiete: Bundesamt für Seeschifffahrt und Hydrographie (BSH)

Pipelines



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Integrated:

- Tankerkönig – Fuel price data since June 2014 for 17.592 gas stations (all price changes)
- pegelonline (WSV – Wasserstraßen und Schifffahrtsverwaltung des Bundes) – Water level data since the year 2000 (high-frequency)
- River basin GIS data Environmental Systems Research Institute, Inc. (ESRI)
- Shape files for borders Natural Earth Data
- Precipitation and Temperature from the Deutsche Wetterdienst (DWD)

⇒ In total ~ 160 GB data.

Planned: Integration of AIS data

Prior Considerations

Features of the data

- repeated, multiple types of treatments (events), i.e., absence of an absorbing state
- non-binary treatment (share of measurement stations)
- different treatments: high and low water levels
- data not plagued by identification problem of TWFE found in staggered event studies (absence of untreated units)

Further considerations

- temporary treatment → transitory effect
- (in absence of un-treated units, treatment effects cannot be distinguished from (common) time trend)
- (implicit assumptions of homogeneity of treatment effect (all units, all horizons same effect) → treatment-time FE interactions lead to multicollinearity)

Event-Study Designs: TWFE Baseline



TWFE

- All units, all periods kept.
- Relies on not-yet/never-treated as controls.
- With heterogeneous effects: biased weights. (cf. Sun and Abraham 2021)

Event-Study Designs: Stacked



Stacked Design

- Discussed in Cunningham (2021), Cengiz, Dube, Lindner and Zentler-Munro (2022) and Baker, Larcker and Wang (2022)
- Define first treatment, recenter at $k = 0$.
- Keep only window $[-14, +14] \setminus \{-14\}$.
- Stack cohorts, drop outside data.
- Clean but can be data-inefficient.
- Extension: Keep all observations. Observations outside the event window contribute to FE/controls, but not to ES coefficients. (We find no big differences.)

Model 1: Stacked Event Study Design

$$\underbrace{y_{it}}_{\text{log price}} = \mu_{is} + \lambda_{ms} + \sum_{\substack{k=-K_{\text{pre}} \\ k \neq -14}}^{K_{\text{post}}} \left(\beta_{kg} + \gamma_{kg} \underbrace{\text{dose}_s \cdot \mathbb{1}\{k \geq 0\}}_{\text{post-only intensity}} \right) \mathbb{1}\{K_{its} = k\} \\ + \rho \bar{y}_{i,t,[14:44]} + \mathbf{m}'_{it} \boldsymbol{\theta} + \varepsilon_{it}.$$

K_{its}	relative event time (days) within stack s ; $k = 0$ on first extreme; reference $k = -1$ omitted
g	group index: family $\in \{\text{HW}, \text{NW}, \text{NSB}\}$ crossed with river
μ_{is}	<i>stack-specific unit FE</i> (grid cell $i \times$ stack s)
λ_{ms}	<i>stack-specific month FE</i> (calendar year-month $m \times$ stack s)
dose_s	event intensity for stack s (enters only for $k \geq 0$)
$\bar{y}_{i,t,[14:44]}$	30-day moving average from lag 14 to lag 44
\mathbf{m}_{it}	meteorology: mean precipitation P_{it} , mean temperature T_{it}

Notes: Stacks are cohorts defined by the first extreme (HW/NW/NSB) for a given river after a quiet period of 14 days. Within each stack we estimate river \times family-specific ES paths $\{\beta_{kg}\}$ and dose-slope $\{\gamma_{kg}\}$. Confidence bands are built around β_{kg} (baseline) and around $\beta_{kg} + \gamma_{kg} \cdot \text{dose}$ for a chosen dose.

Identification & Assumptions

- **Parallel trends within stacks**

Treated and not-yet-treated cells follow similar trends.

Check: pre-event coeffs ($k < 0$) jointly ≈ 0 (no pre-trends).

- **Strong fixed effects**

$\mu_{i \times s}$: absorb all time-invariant differences across grid cells within each stack (e.g., refinery proximity, baseline demand).

$\lambda_{m \times s}$ (or $\lambda_{m \times s}$): absorbs common shocks within each stack at *monthly* resolution (e.g., Brent, taxes, refinery outages).

- **Controls for short-run shocks**

Meteorology (P_{it}, T_{it}) and 30-day moving average of past prices $\bar{y}_{i,t,[14:44]}$ capture demand seasonality, local persistence, and slow adjustment.

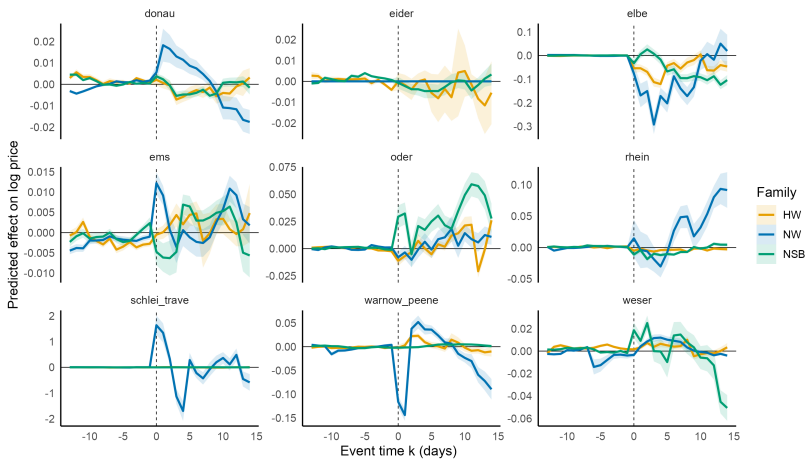
Identification & Assumptions

- **Event definition & overlap**

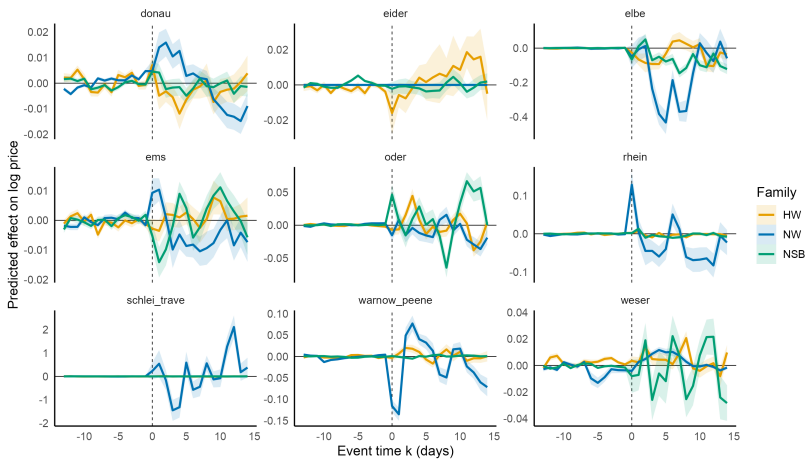
Quiet period (14 days) before first extreme per stack reduces overlap and endogenous timing; results robust to alternative windows.

⇒ Within-stack cross-cell differences in response to common shock provide the event-study coefficients (i.e., treatment effects relative to $k = -14$).

Results: Diesel – Dose: 0.8 – CI: 0.95



Results: E10 – Dose: 0.8 – CI: 0.95



⇒ **Diesel & E10 & NW:**

Donau, Ems, Oder, Rhine, Schlei/Trave, Warnow/Peene and Weser show significant positive effects on prices in the post event window

⇒ **Diesel & E10 & (HW | NSB):**

Ems, Oder, Rhein (small), Schlei/Trave, Warnow/Peene and Weser show pronounced positive spikes for high water levels in the post event window

⇒ Extreme water level events seem to increase volatility.

⇒ Effects of water level events vary for each river and over time.

BUT: How are different regions affected?

Model 2: Wide TWFE Design

$$y_{it} = \alpha + \mu_i + \lambda_t + \mathbf{x}'_{tf}\beta + \mathbf{w}'_{it}\delta + \rho\bar{y}_{i,t,t-14,t-44} + \mathbf{m}'_{it}\theta + \varepsilon_{it},$$

y_{it} daily log average fuel price (diesel, e5, or e10) for grid cell i

μ_i fixed effect for grid cell i

λ_m fixed effect for month m

\mathbf{x}_{tf} daily river basin f specific water level variables

– standardised average level \bar{z}_{tf} at t

– propensity \underline{s}_{tf} of high-water level measurements (HW)

– propensity \bar{s}_{tf} of low-water level measurements (NW)

– propensity \bar{s}_{tf}^* of non-navigable level measurements (NSB)

\mathbf{w}_{it} set of interactions between all variables in \mathbf{x}_{tf} with grid cells

\mathbf{m}_{it} meteorology at grid cell i , day t (DWD):

– mean precipitation P_{it} (mm)

– mean temperature T_{it}

$\bar{y}_{i,t}$ 30-day moving average starting at lag 14 ranging to lag 44

Approximate Regional Marginal Effects

The marginal effects can be approximated contemporaneously (with water level information at t).

$$\begin{aligned}\mathbb{E}[y_{it} \mid \text{Normal } f] - \mathbb{E}[y_{it} \mid \text{Low } f] &\approx (\beta_{0f} + \delta_{0fi}) (\bar{z}_{tf|\text{Normal}} - \bar{z}_{tf|\text{Low}}) \\ &\quad + (\beta_{2f} + \delta_{2fi}) \text{avg}_t(\underline{s}_{tf}),\end{aligned}$$

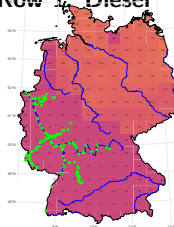
$$\begin{aligned}\mathbb{E}[y_{it} \mid \text{High } f] - \mathbb{E}[y_{it} \mid \text{Normal } f] &\approx (\beta_{0f} + \delta_{0fi}) (\bar{z}_{tf|\text{High}} - \bar{z}_{tf|\text{Normal}}) \\ &\quad + (\beta_{1f} + \delta_{1fi}) \text{avg}_t(\bar{s}_{tf}),\end{aligned}$$

$$\begin{aligned}\mathbb{E}[y_{it} \mid \text{NSB } f] - \mathbb{E}[y_{it} \mid \text{Normal } f] &\approx (\beta_{0f} + \delta_{0fi}) (\bar{z}_{tf|\text{NSB}} - \bar{z}_{tf|\text{Normal}}) \\ &\quad + (\beta_{2f} + \delta_{2fi}) \text{avg}_t(\bar{s}_{tf}) \\ &\quad + (\beta_{3f} + \delta_{3fi}) \text{avg}_t(\bar{s}_{tf}^*).\end{aligned}$$

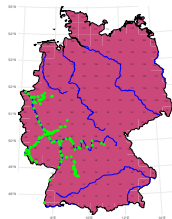
(Preliminary) Results

Rhine – Contemporaneous Extreme Water Event – 1% sig. level

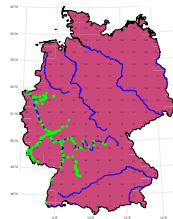
Row 1: Diesel



low water

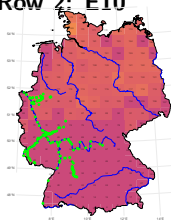


high water

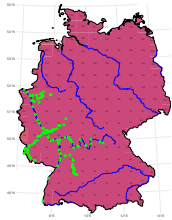


non-navigable

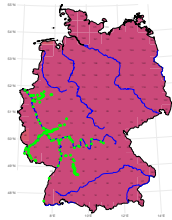
Row 2: E10



low water



high water

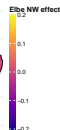
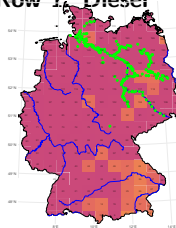


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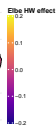
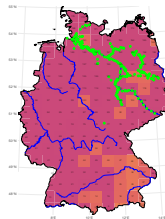
(Preliminary) Results

Elbe – Contemporaneous Extreme Water Event – 1% sig. level

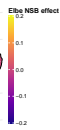
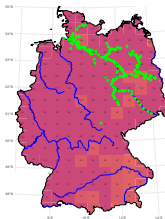
Row 1: Diesel



low water

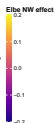
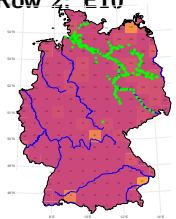


high water

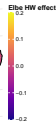
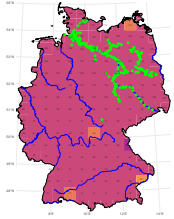


non-navigable

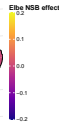
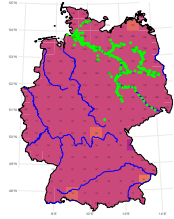
Row 2: E10



low water



high water

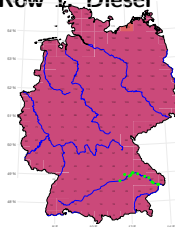


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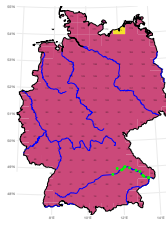
(Preliminary) Results

Donau – Contemporaneous Extreme Water Event – 1% sig. level

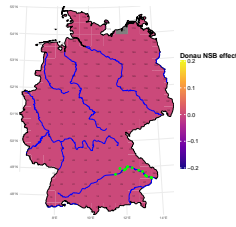
Row 1: Diesel



low water

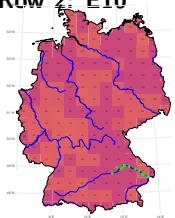


high water

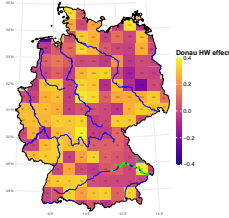


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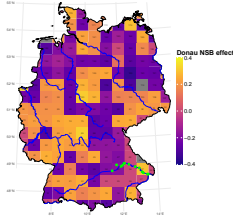
Row 2: E10



low water



high water

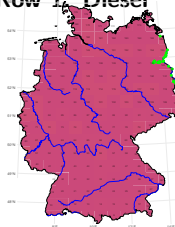


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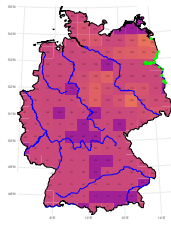
(Preliminary) Results

Oder – Contemporaneous Extreme Water Event – 1% sig. level

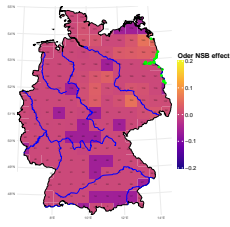
Row 1: Diesel



low water

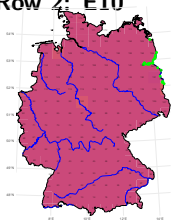


high water

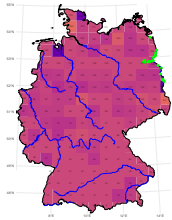


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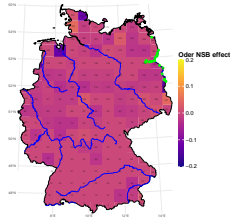
Row 2: E10



low water



high water

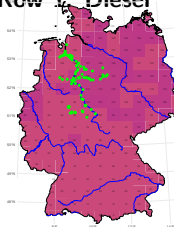


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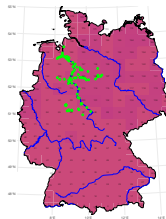
(Preliminary) Results

Weser – Contemporaneous Extreme Water Event – 1% sig. level

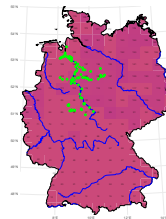
Row 1: Diesel



low water

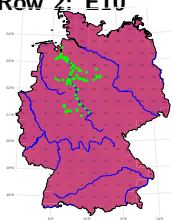


high water

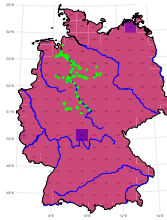


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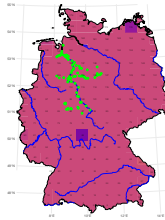
Row 2: E10



low water



high water

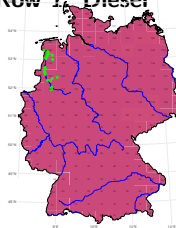


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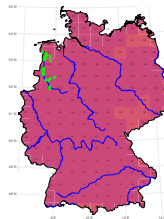
(Preliminary) Results

Ems – Contemporaneous Extreme Water Event – 1% sig. level

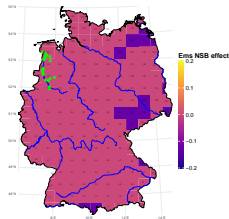
Row 1: Diesel



low water

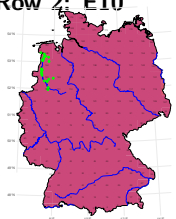


high water

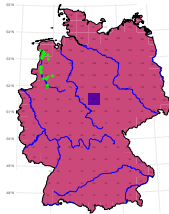


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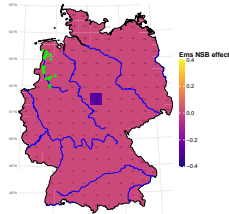
Row 2: E10



low water



high water

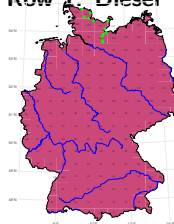


non-navigable

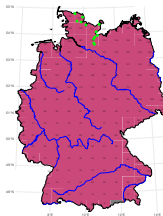
(Preliminary) Results

Schlei/Trave – Contemporaneous Extreme Water Event – 1% sig. level

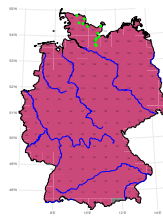
Row 1: Diesel



low water

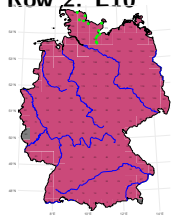


high water

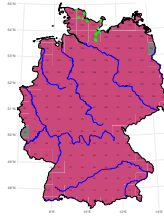


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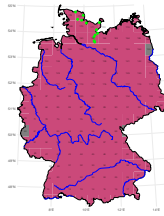
Row 2: E10



low water



high water

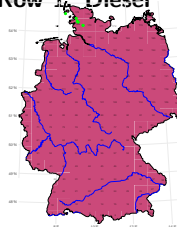


non-navigable

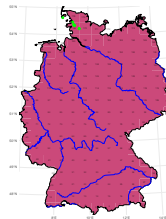
(Preliminary) Results

Eider – Contemporaneous Extreme Water Event – 1% sig. level

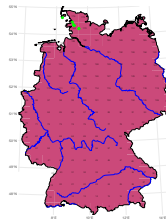
Row 1: Diesel



low water

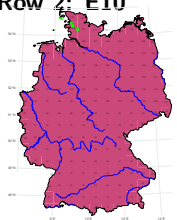


high water

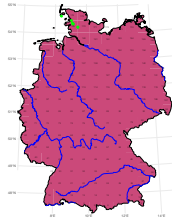


non-navigable

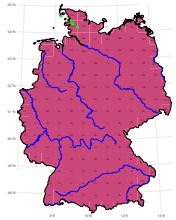
Row 2: E10



low water



high water

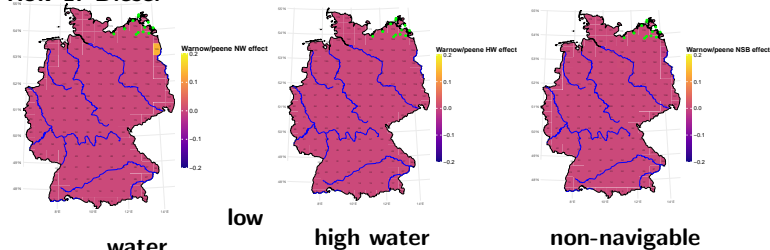


non-navigable

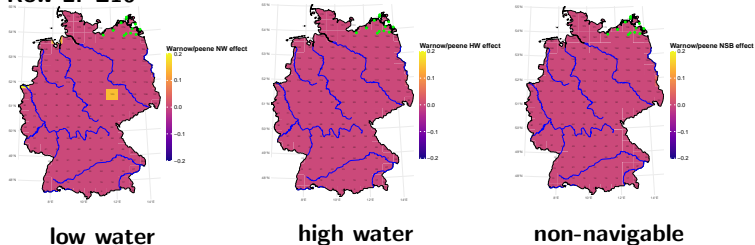
(Preliminary) Results

Warnow/Peene – Contemporaneous Extreme Water Event – 1% sig. level

Row 1: Diesel



Row 2: E10



Open Questions & Future Work

- **Importance weighting of HW, NW, NSB at different measuring stations?** (AIS data)
- **Does the grid convention matter for regional patterns?**
- **Did inland water transportation lose importance?**
 - Low water levels (e.g. 2018, 2022): hinder large barge operations, forcing cargo to road/rail
⇒ freight quantities or historical AIS data
 - Ageing fleet & infrastructure: old vessels, insufficient channel depths and bridge underpasses reduce competitiveness
 - Road transport growth: nowadays trucks carry far more freight; IWT share of tonnage is only $\sim 10 - 12\%$ overall
 - Policy & modal shift lacking: Despite environmental advantages, limited investment has slowed the shift from road to IWT
- **How much does a 7 day drought / flood cost at the gas station?**

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