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Shocks, Reforms, and Infrastructure Investment in Turkish Rail Freight: Interrupted Time Series and Bayesian Counterfactual Evidence, 2000–2024

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Abstract

Governments invest in railways expecting freight traffic to follow, yet evidence on whether it does — and on how traffic withstands large shocks — remains thin for middle-income countries. We assemble a continuous national series of Turkish rail freight traffic (net tonne-kilometres, 2000–2024) from harmonised official sources and evaluate four policy and shock events: the first high-speed rail opening (2009), the 2013 liberalisation-and-Marmaray regime change, the COVID-19 pandemic, and the February 2023 Kahramanmaraş earthquakes, with the 2001 and 2008–2009 recessions as context. Identification triangulates segmented-regression interrupted time series, ARIMA-based ITS, and Bayesian structural time-series counterfactuals with spike-and-slab variable selection, supported by placebo-date distributions and definition-consistent sensitivity series. Three results stand out. First, neither the high-speed rail opening nor the 2013 reform package was associated with the traffic gains that motivated them; point estimates for both are negative, a pattern stable across estimation windows. Second, rail freight did not contract during the pandemic: relative to Bayesian counterfactuals, monthly traffic ran above its expected path under both seasonal (+ 6.6%, 95% CI [− 0.5, 15.1]) and non-seasonal (+ 10.3%, 95% CI [1.4, 20.1]) specifications. Third, 2023 brought the sharpest contraction in a quarter century — a compound shock combining earthquake destruction with severe macroeconomic tightening — of − 15.8% (95% CI [− 19.2, − 12.2]) over 23 months, an effect larger than every one of 14 placebo dates; the fall was deepest in the epicentral rail region (Malatya − 44%) though it extended beyond the earthquake zone, and cement traffic rose 50% against the general decline, consistent with reconstruction flows. To our knowledge this is the first counterfactual estimate of a disaster-driven contraction in a national rail freight series. The findings caution against infrastructure-led modal-shift optimism and argue for disaster-resilient network planning.

Introduction

Rail freight sits at an awkward intersection of transport policy. Governments count on it to decarbonise land transport and relieve congested road corridors, yet in most middle-income countries its market share has been shrinking for decades, often despite substantial public investment. The COVID-19 pandemic sharpened this tension. While passenger rail collapsed almost everywhere and recovered slowly (Vickerman, 2021), the freight side of the railway behaved differently: European system-level assessments pointed to disrupted but comparatively resilient goods flows, and to a window of opportunity for rail where road haulage faced border closures and driver shortages (Gray, 2020; Tardivo et al., 2021). Understanding when rail freight demand absorbs shocks and when it does not is therefore more than an academic exercise; it speaks directly to how much confidence policymakers can place in modal-shift targets. Recent European work reflects this concern from two directions: the performance of modal-shift policy instruments has itself become the subject of systematic evaluation (Takman & Gonzalez-Aregall, 2024), and shift-share decomposition tools have been developed precisely because observed changes in rail's share mix policy-driven modal shift with structural change in the freight market (Jonkeren et al., 2019).

Türkiye offers an unusually rich setting for this question. Over the past quarter century the country has run one of the largest railway investment programmes among emerging economies: the first high-speed line opened between Ankara and Eskişehir in March 2009, the Marmaray tunnel created a rail link beneath the Bosphorus in October 2013, and Law No. 6461 of 2013 formally liberalised railway transport, with private freight operators becoming visible in national statistics from the late 2010s onwards. The same period contained an exceptional sequence of exogenous shocks: the 2001 financial crisis, the 2008–2009 global recession, the COVID-19 pandemic, and the devastating Kahramanmaraş earthquakes of February 2023, which struck provinces traversed by several major freight corridors. The aggregate outcome is sobering. Between 2000 and 2024, road freight on the national network more than doubled, from roughly 162 to 348 billion tonne-kilometres, while rail freight grew by about a third, from 9.9 to 13.3 billion tonne-kilometres; rail's share of the road–rail market consequently fell from just under 6% to below 4%. Investment, in other words, coincided with absolute growth but relative decline — a pattern familiar from high-speed rail experiences elsewhere, where expectations have often outrun realised demand (Beria et al., 2018), and one consistent with the parallel expansion of Türkiye's road network, whose trade-generating effects have been documented at the firm level (Coşar & Demir, 2016).

What the literature offers on Turkish rail freight demand is surprisingly thin. The most direct antecedent remains Çekerol and Nalçakan (2015), who modelled domestic rail freight demand within the logistics sector using ridge regression to handle severe multicollinearity among macroeconomic drivers. That study predates the liberalisation's effects, the pandemic, and the earthquakes, and its estimation framework — while well suited to correlated regressors — does not address structural change over time. Studies of demand determinants in comparable settings, such as Khan and Khan's (2020) time-series analysis for Pakistan, confirm the centrality of income and trade activity but likewise stop short of shock evaluation. On the shocks side, the COVID-era transport literature concentrated on passengers, aviation, and maritime trade (Notteboom et al., 2021; Vickerman, 2021), and the emerging work on the 2023 earthquakes has documented geotechnical and building damage (Gökçeoğlu, 2023; Şenol Balaban et al., 2025) without, to our knowledge, quantifying consequences for rail freight flows. Methodologically, interrupted time series designs and Bayesian structural time-series (BSTS) counterfactuals are now standard tools for policy evaluation in epidemiology and public policy (Bernal et al., 2017; Brodersen et al., 2015; Papadogeorgou et al., 2023; Schaffer et al., 2021; Scott & Varian, 2014), yet their application to national freight series remains rare. The European literature on railway liberalisation, for its part, has concentrated on productive efficiency and industrial organisation (Growitsch & Wetzel, 2009; Lerida-Navarro et al., 2019) rather than on what reform did to freight demand — precisely the outcome policymakers care about.

This paper assembles a continuous national rail freight series for 2000–2024 from official Turkish sources, harmonising TCDD statistical yearbooks, TCDD Taşımacılık publications, and Ministry of Transport (UHDGM) operator-level data, and asks three questions. First, which macroeconomic and competitive factors are associated with rail freight demand over the long run, and do the variables identified by Çekerol and Nalçakan (2015) retain their relevance when selection is performed by Bayesian spike-and-slab priors — the natural Bayesian counterpart to their ridge shrinkage? Second, did

the identifiable policy interventions — the high-speed rail openings and the 2013 liberalisation-and-Marmaray regime — coincide with detectable level or slope changes in demand? Third, how did the two great shocks of the 2020s differ: did COVID-19 depress rail freight at all once a counterfactual is constructed, and how large and how persistent was the earthquake effect? We answer these questions with a triangulation of segmented-regression ITS, ARIMA-based ITS, and BSTS/CausalImpact models, supported by a region- and commodity-level decomposition of the 2023 break and by data-driven changepoint detection as a check on our theoretically chosen dates.

The novelty of the study lies in four elements, each of which we state precisely because each is falsifiable. First, the dataset itself is new: no continuous national rail freight series spanning Türkiye's institutional reorganisation existed before this study, because the three official reporting regimes (TCDD to 2016, TCDD Taşımacılık from 2017, ministry operator-level statistics from 2019) had never been harmonised; the resulting 2000–2024 series, cross-validated across overlapping official publications, is itself a contribution that subsequent research can build on. Second, Türkiye's flagship rail interventions — the high-speed programme and the 2013 liberalisation — have to our knowledge never been evaluated against realised freight traffic; the existing literature either models demand without structural change (Çekerol & Nalçakan, 2015) or discusses the interventions' potential without testing outcomes (Zeybek, 2021). Third, the paper provides what our systematic search indicates is the first counterfactual estimate of a disaster-driven contraction in a national rail freight series; the nearest antecedents quantify hazard vulnerability of train operations (Fabella & Szymczak, 2021) or disaster effects on trade flows (Osberghaus, 2019), not freight-traffic displacement against a modelled counterfactual. Fourth, the pandemic finding runs against the grain of the COVID-transport literature, which documented collapse in passenger rail and disruption in maritime trade (Notteboom et al., 2021; Vickerman, 2021): we show a national rail freight system that ran above its expected path through the pandemic — evidence, we argue, that reframes what the binding constraint on rail freight growth in such settings is. Methodologically, it illustrates how BSTS with spike-and-slab selection can serve simultaneously as a demand model and as a structural-change instrument, connecting a regularisation tradition in transport demand analysis to modern Bayesian policy evaluation.

Six hypotheses guided the analysis. H1: rail freight demand is positively associated with real GDP, industrial production, and trade volumes, contracting in the 2001 and 2008–2009 crises. H2: high-speed passenger line openings from 2009 are associated with a positive shift in freight demand on the conventional network, via capacity released by migrating passenger traffic (Boehm et al., 2021; Zeybek, 2021). H3: the 2013 regime change is associated with a gradual, slope-type increase, strengthening after private operators entered the market. H4: against a pre-pandemic counterfactual, COVID-19 is associated with a null or positive effect; we refrained from imposing a negative prior. H5: the February 2023 earthquakes are associated with a large negative level shift, concentrated in affected regions and heavy-industry commodities, with commodity-level evidence of a reconstruction-demand channel. H6: road freight volume is negatively associated with rail freight demand, while the association of energy prices is treated as an empirical question.

Method

Data

The dependent variable is annual net tonne-kilometres (millions) carried on the Turkish railway network, 2000–2024. No single official source spans the period, because institutional reorganisation changed who reports what: until 2016 the integrated incumbent TCDD was the sole operator and reporter; from 2017 the operating company TCDD Taşımacılık published statistics excluding the private operators licensed after liberalisation; and from 2019 the Ministry of Transport and Infrastructure (UHDGM) published operator-level monthly statistics covering the full market. We therefore constructed the national series from three official segments. For 2000–2016 we used the modal transport table reproduced in TCDD statistical yearbooks (original source: TurkStat), with overlapping five-year yearbook windows providing internal cross-validation. For 2017–2018 we used TCDD Taşımacılık publications (grand totals including departmental traffic), noting that private-operator traffic — still small then — is not covered; sensitivity analyses probe this caveat. For 2019–2024 we aggregated UHDGM monthly operator-level data, which sum TCDD Taşımacılık and private operators; reporting units, which differ across UHDGM vintages, were standardised to million tonne-kilometres. The monthly UHDGM sub-series (2019M1–2025M12, 84 observations) serves as the outcome for the monthly counterfactual analyses.

Data sources and retrieval. All series were retrieved from publicly accessible official sources in July 2026; Table A1 lists each source with its access address. The monthly operator-level freight statistics (2019–2025) were downloaded as annual Excel workbooks from the Ministry of Transport and Infrastructure's UHDGM statistics portal (https://uhdgmistatistik.uab.gov.tr/demiryolu-yuk-tasima-istatistikleri). Annual figures for 2000–2016 were extracted from the TCDD statistical yearbooks, published as five-year PDF volumes on the incumbent's server (https://static.tcdd.gov.tr/webfiles/userfiles/files/, e.g., 20122016yillik.pdf); because consecutive yearbooks overlap, every year between 2000 and 2016 appears in at least two volumes, and all overlapping values were cross-checked before entering the dataset. Figures for 2017–2018, together with the regional and commodity tables used in Section 3.4, come from TCDD Taşımacılık's annual statistical publications (https://www.tcddtasimacilik.gov.tr/sayfa/istatistikler/). Road freight tonne-kilometres were taken from Table UE04 of the General Directorate of Highways' statistical yearbook (https://www.kgm.gov.tr, *Karayolu Ulaşım İstatistikleri 2024*); the exact agreement of its 2000–2016 values with the TurkStat modal table reproduced in the TCDD yearbooks provided an independent quality check across agencies. Macroeconomic aggregates were obtained through the World Bank's World Development Indicators API (https://api.worldbank.org; series NY.GDP.MKTP.KN, NV.IND.TOTL.KN, NE.EXP.GNFS.KN, NE.IMP.GNFS.KN). Monthly exchange rates, the Brent spot price, the domestic producer price index, and the industrial production index were retrieved from the Central Bank of the Republic of Türkiye's Electronic Data Delivery System, EVDS (https://evds3.tcmb.gov.tr; series TP.DK.USD.A.YTL, TP.BRENTPETROL.EUBP, TP.TUFE1YI.T1, TP.TSANAYMT2021.Y1). Table extraction from PDF sources, unit harmonisation (UHDGM workbooks report net tonne-kilometres in raw units up to 2022 and in

millions thereafter), and all series-linking steps were performed in code and are reproducible from the replication archive.

Covariates fall into three groups. Macroeconomic activity: real GDP, industrial value added, and export and import volumes (constant prices, World Bank World Development Indicators); at monthly frequency, the calendar- and seasonally adjusted industrial production index (2021 = 100) from the Central Bank's EVDS system. Competition and costs: road freight tonne-kilometres from the General Directorate of Highways (KGM Table UE04; its 2000–2016 portion matches the TurkStat modal table exactly), the monthly average USD/TRY rate and Brent spot price (EVDS), and a lira-denominated energy cost proxy (Brent × exchange rate). Policy and shock indicators: level and slope-change terms for the 2008–2009 recession, the first high-speed line (March 2009), the 2013 regime change (Law No. 6461 in May and Marmaray in October, not separable at annual frequency and modelled jointly), COVID-19 (March 2020), and the Kahramanmaraş earthquakes (February 2023). To interpret the 2023 break we additionally extracted from TCDD Taşımacılık's 2024 statistical publication the regional distribution of tonnage and the commodity composition of tonne-kilometres (2020–2024); these tables cover TCDD Taşımacılık traffic only, which we state wherever they are used. Table 1 reports descriptive statistics.

Table 1
Descriptive Statistics for Annual Series, 2000–2024 (N = 25)

Variable	***M***	***SD***	**Min**	**Max**
Rail freight (billion tonne-km)	11.47	2.40	7.22	16.19
Road freight (billion tonne-km)	224.42	61.70	150.91	347.81
Real GDP (trillion constant TL)	1.37	0.51	0.69	2.34
Industrial value added (trillion TL)	0.35	0.14	0.15	0.57
Exports (trillion TL)	0.33	0.13	0.14	0.55
Imports (trillion TL)	0.31	0.10	0.12	0.49
Brent crude (USD/barrel)	66.69	27.75	24.45	111.62
Exchange rate (TRY/USD)	5.24	7.83	0.62	32.78

Note. Rail freight: author's harmonised series (TCDD yearbooks 2000–2016; TCDD Taşımacılık 2017–2018; UHDGM 2019–2024). Road freight: KGM Table UE04. Macroeconomic aggregates: World Bank WDI, constant prices. Brent and exchange rate: CBRT EVDS, annual means of monthly averages.

Analytic Strategy

No single design is credible alone with 25 annual observations, so identification triangulates three approaches. All analyses were conducted in R 4.5.2 (R Core Team, 2025) with a fixed random seed; full code accompanies the paper. We used the packages *forecast* 9.0.0 (Hyndman et al., 2026) for ARIMA estimation, *tseries* 0.10–59 (Trapletti & Hornik, 2026) for unit-root tests, *sandwich* 3.1-1 (Zeileis et al.,

2020) and *lmtest* 0.9–40 (Zeileis & Hothorn, 2002) for HAC inference and diagnostics, *zoo* 1.8–15 (Zeileis & Grothendieck, 2005) for time-series handling, *changepoint* 2.3 (Killick & Eckley, 2014) for PELT detection, *bsts* 0.9–11 (Scott, 2025) for Bayesian structural time-series estimation, and *CausalImpact* 1.4.1 (Brodersen et al., 2015) for counterfactual inference.

Segmented-regression ITS. Following Bernal et al. (2017, as amended in their 2020 corrigendum), we regressed log tonne-kilometres on a linear trend, an event indicator (level change), and time since the event (slope change). Because a saturated model would spend ten parameters on 25 observations, the primary analyses estimate event-specific models on windows around each intervention (2002–2012 for the 2009 opening; 2009–2019 for the 2013 regime; 2014–2022 for COVID-19, ending before the earthquakes; 2017–2024 for the earthquakes), with the full multi-event model as a sensitivity check. Autocorrelation was addressed with Newey–West standard errors (Newey & West, 1987), using bandwidths of one to two lags chosen to ensure positive-definite covariance estimates, and diagnosed with Durbin–Watson tests.

ARIMA-based ITS. Following Schaffer et al. (2021), intervention terms entered as exogenous regressors in an ARIMA model selected by corrected AIC. Unit-root pretests indicated behaviour consistent with an integrated series (in levels, ADF $p = .466$ and KPSS rejects stationarity at $p \leq .01$; in first differences KPSS is consistent with stationarity at $p \geq .10$ while ADF remains inconclusive), acknowledging the limited power of such tests at $n = 25$.

BSTS and counterfactual impact. The core specification is a Bayesian structural time-series model (Scott & Varian, 2014) whose state comprises a local linear trend and, at monthly frequency, a seasonal component, plus a static regression with spike-and-slab priors (Ishwaran & Rao, 2005), so that variable selection and estimation occur jointly and inference averages over models (Hoeting et al., 1999). The choice is deliberate: our direct antecedent handled multicollinearity among Turkish freight-demand drivers with ridge regression (Çekerol & Nalçakan, 2015), and the spike-and-slab prior is the Bayesian counterpart of that shrinkage strategy. Models were estimated with 20,000 MCMC draws (20% burn-in; expected model size 3, with 5 as a sensitivity). Causal effects of the two 2020s shocks were estimated with the counterfactual framework of Brodersen et al. (2015): a model trained on the pre-event monthly series is projected over the post-event window, and the difference between observed and predicted paths, with posterior intervals, is the estimated impact. For COVID-19 the pre-period is short (2019M1–2020M2, 14 months), a limitation we flag; for the earthquakes it spans 49 months (2019M1–2023M1). Finally, because our event dates are institutionally chosen, we applied PELT changepoint detection (Killick & Eckley, 2014) as a data-driven check — on the national series and, to rule out artefacts of source-linking, on a definition-consistent TCDD-only series — and ran robustness analyses: a placebo distribution obtained by re-estimating the counterfactual at every pseudo-event month from January 2021 to February 2022 (14 dates, 12-month post-windows), re-estimation of the earthquake window on the TCDD-only series, window-width variations for the 2013 event, a non-seasonal specification for the COVID counterfactual (whose 14-month pre-period cannot fully identify a monthly seasonal component), and alternative expected model sizes. Because four events are tested with level and slope terms across

two designs, we refrain from emphasising any single p-value and read the evidence at the level of patterns. To position the earthquake contribution we also searched OpenAlex for counterfactual or interrupted time-series estimates of earthquake impacts on national rail freight series (Kobe, Wenchuan, Tōhoku and generic disaster terms) and found none. All effect estimates are model-based counterfactual contrasts in an observational design and are phrased as associations throughout.

Results

Descriptive Patterns and Trend

Figure 1 plots the harmonised series against the candidate events. Rail freight grew from 9.9 billion tonne-kilometres in 2000 to a peak of 16.2 billion in 2022, before falling to 13.1 billion in 2023. The 2001 financial crisis illustrates the series' pro-cyclicality at the start of the period: traffic fell 24% in 2001 and bottomed at 7.2 billion in 2002 — 27% below its 2000 level — before recovering to within 5% of that level by 2004. The full-period trend corresponds to approximately 3% annual growth (full ITS model: $b = 0.030$ log points per year, Newey–West $SE = 0.012$, $p = .030$; Durbin–Watson = 1.77), with recovery-era growth between 3.9% and 5.4% per year across the window models' pre-event segments. Over the same years road freight grew 115%, so rail's share of the road–rail market declined from 5.8% to 3.7%. Unit-root pretests place the log series where a trending aggregate is expected to sit: the ADF test fails to reject a unit root in levels (statistic − 2.28, $p = .466$) while KPSS rejects level stationarity (0.80, $p \leq .01$); in first differences KPSS no longer rejects (0.09, $p \geq .10$), while the ADF remains inconclusive (− 2.52, $p = .376$) — unsurprising with 24 differenced observations. The pattern is consistent with an I(1) process examined by tests of limited power, which is one reason the analysis leans on designs that do not require a stationarity verdict. In the monthly series, the earthquake month itself is unmistakable: traffic fell from 1,301 million tonne-kilometres in January 2023 to 779 million in February, a 40% single-month drop.

Interrupted Time Series Estimates

Table 2 reports the event-window segmented-regression estimates with Newey–West standard errors, together with the saturated ARIMA-ITS model. Three of the four events fail to show the pattern their policy rationale predicts. The 2009 high-speed opening is associated with a marginally significant *negative* level shift ($b = − 0.067$, $SE = 0.032$, $p = .072$) and no slope change, contrary to H2. The 2013 liberalisation-and-Marmaray regime is associated with a significant negative level shift ($b = − 0.144$, $SE = 0.053$, $p = .030$) and no subsequent slope change, contrary to H3. The COVID-19 indicator is positive but not significant in the window model ($b = 0.051$, $SE = 0.041$, $p = .268$). Only the 2023 earthquakes show a large, robust displacement: a level drop of − 0.290 log points ($SE = 0.021$, $p < .001$), approximately − 25%, accompanied by a further negative slope ($b = − 0.038$, $SE = 0.005$, $p = .002$). The saturated ARIMA-ITS (white-noise residuals; Ljung–Box $p = .400$) tells the same story with wider uncertainty: only the trend ($b = 0.030$, $SE = 0.009$, $p < .001$) and the earthquake level shift ($b = − 0.236$, $SE = 0.122$, $p = .053$) approach conventional significance, as expected when ten parameters meet 25 observations. The 2013 estimate

is not an artefact of one window: across four alternative windows (2007–2017, 2009–2016, 2009–2019, 2011–2021) the level shift ranges from − 0.091 to − 0.144 (*p* between .015 and .039), and it survives (− 0.113, *p* = .087) when additional 2016 and 2018 indicators — the years private-operator entry and the currency crisis might otherwise absorb — are included, though with four events tested across two designs we deliberately read these estimates as a pattern rather than leaning on any single p-value.

Table 2
Interrupted Time Series Estimates for Log Rail Freight (Net Tonne-Kilometres)

Parameter	Window *b* (*SE*)[a]	Window *p*	ARIMA *b* (*SE*)[b]	ARIMA *p*
Pre-event trend (per year)	—	—	0.030 (0.009)	< .001
HSR 2009: level	−0.067 (0.032)	.072	0.010 (0.074)	.888
HSR 2009: slope	−0.015 (0.013)	.312	0.009 (0.031)	.777
Regime 2013: level	−0.144 (0.053)	.030	−0.144 (0.094)	.126
Regime 2013: slope	0.002 (0.013)	.856	0.002 (0.033)	.941
COVID-19 2020: level	0.051 (0.041)	.268	0.072 (0.083)	.388
COVID-19 2020: slope	−0.023 (0.014)	.152	−0.015 (0.049)	.753
Earthquakes 2023: level	−0.290 (0.021)	< .001	−0.236 (0.122)	.053
Earthquakes 2023: slope	−0.038 (0.005)	.002	−0.010 (0.106)	.928

Note. [a]Separate segmented regressions on windows around each event (2002–2012, 2009–2019, 2014–2022, 2017–2024) with Newey–West standard errors; each window model also includes its own intercept and pre-event trend (not shown). [b]Regression with ARIMA(0,0,0) errors on the full 2000–2024 series; Ljung–Box *p* = .400. [c]The earthquake slope in the window model rests on only two post-event years (2023–2024) and should be read as descriptive.

Bayesian Variable Selection

Figure 2 and Table 4 display posterior inclusion probabilities from the annual BSTS model with spike-and-slab priors over ten candidate predictors. No macroeconomic driver dominates: with a flexible local linear trend absorbing long-run movement, the collinear macro block — GDP, industrial value added, exports, imports, road freight, energy costs — clusters between .16 and .22, with the earthquake indicator highest at .27. The internal spread of the macro block is .01 at the default prior and .02 at the looser prior — the posterior is, for practical purposes, indifferent among these six variables. Raising the expected model size to five roughly doubles all probabilities and preserves the ordering (earthquake .54; macro block .43; energy .30) without separating the macro variables from one another. This is the Bayesian model-averaging counterpart of the multicollinearity that forced Çekerol and Nalçakan (2015) into ridge regression: the data can identify the trend and the earthquake break, but cannot apportion the trend among near-collinear macroeconomic drivers. We therefore read the evidence on H1 as supporting

a strong common growth component rather than any specific driver, and the evidence on H6 (road competition) as indeterminate.

Counterfactual Impacts of the Pandemic and the Earthquakes

Figure 3 presents the CausalImpact estimates on the monthly series. Relative to a counterfactual trained on the 14 pre-pandemic months, rail freight during March 2020–December 2021 averaged + 6.6% above its expected path (95% credible interval [− 0.5, 15.1]; posterior tail probability p = .034). Because a monthly seasonal component cannot be fully identified from 14 pre-event observations, we re-estimated the counterfactual without seasonality; the estimate strengthens to + 10.3% (95% CI [1.4, 20.1], p = .012). In cumulative terms the observed path exceeded the counterfactual by roughly 1.8 billion tonne-kilometres over the 22 post-onset months. We nonetheless read the pandemic evidence conservatively: the defensible claim is that there is no evidence of a contraction and that point estimates are positive across specifications, supporting H4 and consistent with the annual models.

The earthquake-period counterfactual, trained on 49 pre-event months, is far more precise: from February 2023 to December 2024 traffic averaged − 15.8% below its expected path (95% CI [− 19.2, − 12.2]; p = .0001), supporting H5. The anatomy of the shock is instructive. The gap opens immediately and at maximum width: in February 2023 itself, observed traffic was 779 million tonne-kilometres against a counterfactual of 1,109 million, a 30% shortfall in the event month. It then narrows only partially and stabilises rather than closes — over the final quarter of 2024, 22 months after the event, observed traffic still ran 17% below its expected path, so the series shows no sign of reverting to its pre-event trajectory within our sample. Cumulatively, the shortfall sums to approximately 4.6 billion tonne-kilometres over 23 months, equivalent to roughly a third of a typical year's national rail freight. Two falsification exercises discipline this estimate. First, re-estimating the counterfactual at every pseudo-event month from January 2021 to February 2022 (14 dates, 12-month post-windows) produced placebo effects ranging from + 0.017 to + 0.074 log points; the observed 2023 effect (− 0.172) is larger in magnitude than all 14, and of opposite sign. Second, re-estimating the earthquake window on the TCDD-only series — which removes the series-linking caveat — reproduced the result (level shift − 0.238, SE = 0.014, p < .001).

The regional and commodity decomposition sharpens the earthquake interpretation, with the caveat that it covers TCDD Taşımacılık traffic only (Table 3). Between 2022 and 2023, tonnage originating in the Malatya region — which contains the epicentral corridors — fell 43.7%, and the Adana region fell 15.6%, against + 0.7% in Ankara; declines in regions outside the earthquake zone (e.g., İstanbul − 14.7%) indicate that macroeconomic conditions contributed to the 2023 fall as well. The commodity pattern is asymmetric in an informative way: heavy-industry flows collapsed (iron and steel products − 40%, construction materials − 65%, clinker − 42%, coal − 27%), whereas cement was the one major commodity

to move against the decline (+ 50% in 2023), consistent with reconstruction demand in the affected provinces.

Table 3

TCDD Taşımacılık Traffic Around the February 2023 Earthquakes

Panel A: Region (thousand tonnes)	**2022**	**2023**	**Change**
Malatya (epicentral corridors)	5,257	2,961	−43.7%
Adana (affected)	4,189	3,536	−15.6%
İstanbul	4,776	4,074	−14.7%
İzmir	3,941	3,476	−11.8%
Sivas	2,572	2,326	−9.6%
Ankara	8,428	8,483	+ 0.7%
National total (TCDD)	32,241	27,071	−16.0%
Panel B: Selected commodities (million tonne-km)	2022	2023	Change
Iron ore	3,411	2,859	−16%
Coal	1,320	969	−27%
Iron and steel products	592	358	−40%
Construction materials	215	76	−65%
Clinker	587	338	−42%
Cement	218	328	+ 50%

Note. Source: TCDD Taşımacılık 2024 statistical publication (Tables 2.2.3 and 2.2.7); excludes private operators. Region labels denote TCDD operating regions (traffic directorates), not provinces; the Malatya region contains the corridors closest to the February 2023 epicentres.

Data-Driven Breakpoints

PELT changepoint detection on the log series located breaks at 2007, 2016, 2018, and 2022 — none exactly at our theoretically chosen dates. Because the national series changes reporting source in 2017 and 2019, breaks near those years could in principle be splice artefacts; re-running PELT on the definition-consistent TCDD-only series, which involves no source change in 2019 and a single institutional relabelling in 2017, returned the identical break set (2007, 2016, 2018, 2022), indicating that the breaks reflect the traffic process rather than the data-linking. The 2022 break is the pre-earthquake peak, consistent with the counterfactual evidence. The 2016 and 2018 breaks bracket the years in which private operators entered the market following the 2013 law, suggesting that if liberalisation affected traffic it did so with a lag, through entry, rather than at the legal date itself. No breakpoints were detected in the differenced series, indicating a stable growth regime punctuated by level displacements.

Table 4

Posterior Inclusion Probabilities From the Spike-and-Slab Regression (20,000 MCMC Draws, 20% Burn-In)

Predictor	Expected model size = 3	Expected model size = 5
Earthquakes (2023+)	.27	.54
log industrial value added	.22	.43
log exports	.22	.43
log road tonne-km	.21	.43
log GDP	.21	.43
log imports	.21	.43
log energy price (TL)	.16	.30
HSR (2009+)	.12	.20
Liberalisation regime (2013+)	.09	.17
COVID-19 (2020+)	.06	.10

Note. State specification: local linear trend. Doubling the prior expected model size raises all probabilities roughly proportionally without changing the ordering or separating the macroeconomic block, whose members remain within .01–.02 of one another.

Discussion

Three findings organise the discussion. The first concerns what did *not* happen. Neither the arrival of high-speed rail in 2009 nor the 2013 liberalisation-and-Marmaray package was followed by the demand gains that motivated them; the point estimates are negative, significantly so for 2013. We are careful not to read these associations causally — the 2009 window sits atop the global financial crisis recovery, and 2013 was a year of currency stress — but the pattern is consistent with the broader record of infrastructure-led expectations outrunning realised freight demand (Beria et al., 2018) and reinforces the case for evaluating — rather than assuming — the performance of modal-shift instruments (Takman & Gonzalez-Aregall, 2024). The capacity-release mechanism articulated for Türkiye by Zeybek (2021) and for Europe by Boehm et al. (2021) may still operate, but if it does, its effects have been too small to surface in national totals against competing forces — chief among them a road network whose freight volumes more than doubled over the same period (Coşar & Demir, 2016, document the trade side of that expansion). The data-driven breakpoints add a nuance with policy content: the breaks PELT locates in 2016 and 2018, rather than 2013, are where private-operator entry became quantitatively visible. Liberalisation's imprint on Turkish rail freight, such as it is, appears in the composition of supply — private operators carried 20.8% of national tonne-kilometres in 2024 (author's calculation from UHDGM operator-level data) — and possibly in a delayed, entry-driven channel, rather than in an immediate demand response to the legal reform; the identical PELT breaks on the TCDD-only series rule out the possibility that this timing merely reflects the change of reporting source. This echoes the European

finding that reform effects travel through industrial organisation before they travel through output (Growitsch & Wetzel, 2009; Lerida-Navarro et al., 2019).

The second finding reverses the pandemic narrative that motivated this study's original framing. Turkish rail freight did not merely withstand COVID-19; relative to a counterfactual it ran above its expected path while the economy's industrial production index collapsed and recovered. The estimate is imprecise, and the short pre-period warrants humility, but the direction is corroborated by the raw series (national tonne-kilometres rose 4.6% in 2020) and aligns with sector-level accounts of rail freight's operational continuity under lockdown conditions — trains crossing borders without driver quarantines, agriculture and bulk flows sustained (Gray, 2020; Tardivo et al., 2021). Where maritime studies found disruption-with-recovery (Notteboom et al., 2021) and passenger rail found collapse (Vickerman, 2021), national rail freight in Türkiye looks like a modest beneficiary. For policy, the episode functions as a natural stress test passed: the constraint on Turkish rail freight is evidently not demand fragility.

The third finding is, to our knowledge, the first counterfactual quantification of a disaster-driven contraction in a national rail freight series — with an important qualification that we place at the centre of the interpretation rather than in a footnote. The year 2023 combined earthquake destruction with a severe macroeconomic tightening, and an aggregate counterfactual cannot separate the two; what it measures is the compound shock: a − 15.8% average monthly displacement sustained over 23 months, larger in magnitude than every one of 14 placebo dates. The regional and commodity evidence then apportions this compound effect. The fall was deepest where the network was physically damaged (Malatya − 44%) and in the heavy-industry commodities that dominate eastern corridors, but regions outside the earthquake zone also declined (İstanbul − 15%), so the seismic component is bounded below the headline number; the roughly 30-point gap between the epicentral region's decline and the national average is the most defensible earthquake-specific signal in our data. Nearest-neighbour studies quantify hazard vulnerability of train operations (Fabella & Szymczak, 2021) or disaster effects on trade flows (Osberghaus, 2019); neither provides a freight-traffic counterfactual, which is the gap this estimate fills. Two features deserve emphasis. The persistence — a 17% gap against the counterfactual still open in the final quarter of 2024, and a cumulative shortfall of some 4.6 billion tonne-kilometres — indicates an extended reduction in effective network capacity and regional economic activity, of the kind the transport-resilience literature warns about (Wan et al., 2018). And the asymmetry — cement rising 50% against a general collapse — is a signature of post-disaster logistics, where reconstruction flows surge into damaged regions even as ordinary freight collapses (Holguín-Veras et al., 2012).

The variable-selection result carries a methodological message for the demand-modelling literature. A decade after Çekerol and Nalçakan (2015) resorted to ridge regression because Turkish macroeconomic drivers were too collinear to separate, Bayesian model averaging reaches the same verdict by a different route: posterior inclusion probabilities spread almost uniformly across GDP, industrial output, trade, road competition, and energy costs. With 25 annual observations and a flexible trend, "which macro variable drives rail freight" is not an answerable question in Türkiye — and analyses that report a single significant

driver from this family should be read with corresponding caution. What is answerable, and what our design answers, is how the series responds to discrete, dateable events.

Limitations follow from the setting. The annual series has 25 observations; power is limited and saturated models are indicative only. The national series splices three official sources, and although overlapping windows reconcile, the TCDD-only re-estimations reproduce both the earthquake result and the PELT break set, the 2017–2018 segment omits then-small private traffic. The COVID counterfactual rests on 14 pre-months, and although the non-seasonal specification strengthens rather than weakens the estimate, the pre-period remains short. The 2023 estimate is a compound shock by construction; a synthetic-control design using unaffected corridors, or wagon-level data, could separate the seismic from the macroeconomic component. Finally, all estimates are associations against modelled counterfactuals in an observational design; no randomisation underwrites them. As to generality beyond Türkiye, the setting is in one respect typical of middle-income countries — a state-dominated railway facing a fast-growing road sector under an ambitious modal-shift plan — and in another respect unusual, in the density of shocks and reforms within a single quarter century; the transferable lesson is methodological as much as substantive, namely that national freight series can support credible event evaluation where they cannot support driver-attribution.

For transport policy, the implications are uncomfortable but useful. Türkiye's 2053 targets, like the EU's, assume that infrastructure plus liberalisation will bend the modal split toward rail. A quarter century of data shows absolute growth of about 3% per year that never outpaced road, no detectable demand dividend at the dates of the flagship interventions, a delayed and supply-side imprint of liberalisation, resilience through the pandemic, and deep vulnerability to seismic shock along exactly the corridors that carry the network's heavy industry. The actionable reading is threefold: modal-shift projections should be benchmarked against demand elasticities actually observed, not engineering capacity; reform evaluation should track operator entry and composition, not legal milestones; and disaster-resilient design of eastern corridors — redundancy, rapid-repair capability, and pre-positioned reconstruction logistics — deserves a priority commensurate with the − 16% national loss the 2023 earthquakes imposed for nearly two years.

Declarations

Author note. Data availability: all series derive from publicly available official sources (TCDD, TCDD Taşımacılık, UHDGM, KGM, CBRT EVDS, World Bank); the harmonised dataset, download scripts, and full R replication code will be deposited in a public repository (OSF) with a persistent identifier upon acceptance [DOI to be inserted]. Declarations of interest: none. This manuscript has not been published or submitted elsewhere.

References

1. Beria P, Grimaldi R, Albalate D, Bel G (2018) Delusions of success: Costs and demand of high-speed rail in Italy and Spain. Transp Policy 68:63–79. https://doi.org/10.1016/j.tranpol.2018.03.011
2. Bernal JL, Cummins S, Gasparrini A (2017) Interrupted time series regression for the evaluation of public health interventions: A tutorial. Int J Epidemiol 46(1):348–355. https://doi.org/10.1093/ije/dyw098
3. Bernal JL, Cummins S, Gasparrini A (2020) Corrigendum to: Interrupted time series regression for the evaluation of public health interventions: A tutorial. Int J Epidemiol 49(4):1414. https://doi.org/10.1093/ije/dyaa118
4. Boehm M, Arnz M, Winter J (2021) The potential of high-speed rail freight in Europe: How is a modal shift from road to rail possible for low-density high value cargo? Eur Transp Res Rev 13., Article 4. https://doi.org/10.1186/s12544-020-00453-3
5. Brodersen KH, Gallusser F, Koehler J, Remy N, Scott SL (2015) Inferring causal impact using Bayesian structural time-series models. Annals Appl Stat 9(1):247–274. https://doi.org/10.1214/14-AOAS788
6. Coşar AK, Demir B (2016) Domestic road infrastructure and international trade: Evidence from Turkey. J Dev Econ 118:232–244. https://doi.org/10.1016/j.jdeveco.2015.10.001
7. Çekerol G, Nalçakan M (2015) Lojistik sektörü içerisinde Türkiye demiryolu yurtiçi yük taşıma talebinin ridge regresyonla analizi [Ridge regression analysis of Turkey's domestic rail freight transport demand within the logistics sector]. Marmara Üniversitesi İktisadi ve İdari Bilimler Dergisi 31(2):321–344
8. Fabella VM, Szymczak S (2021) Resilience of railway transport to four types of natural hazards: An analysis of daily train volumes. Infrastructures 6(12). Article 174. https://doi.org/10.3390/infrastructures6120174
9. Gökçeoğlu C (2023) 6 February 2023 Kahramanmaraş – Türkiye earthquakes: A general overview. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLVIII-M-1-2023*, 417–424. https://doi.org/10.5194/isprs-archives-xlviii-m-1-2023-417-2023
10. Gray RS (2020) Agriculture, transportation, and the COVID-19 crisis. Can J Agric Econ 68(2):239–243. https://doi.org/10.1111/cjag.12235
11. Growitsch C, Wetzel H (2009) Testing for economies of scope in European railways: An efficiency analysis. J Transp Econ Policy 43(1):1–24. https://doi.org/10.3828/jtep.2009.43.1.1
12. Hoeting JA, Madigan D, Raftery AE, Volinsky CT (1999) Bayesian model averaging: A tutorial. Stat Sci 14(4):382–417. https://doi.org/10.1214/ss/1009212519
13. Holguín-Veras J, Jaller M, Van Wassenhove LN, Pérez N, Wachtendorf T (2012) On the unique features of post-disaster humanitarian logistics. J Oper Manag 30(7–8):494–506. https://doi.org/10.1016/j.jom.2012.08.003
14. Hyndman R, Athanasopoulos G, Bergmeir C, Caceres G, Chhay L, O'Hara-Wild M, Petropoulos F, Razbash S, Wang E, Yasmeen F (2026) *forecast: Forecasting functions for time series and linear models* (Version 9.0.0) [Computer software]. https://pkg.robjhyndman.com/forecast/

15. Ishwaran H, Rao JS (2005) Spike and slab variable selection: Frequentist and Bayesian strategies. Annals Stat 33(2):730–773. https://doi.org/10.1214/009053604000001147
16. Jonkeren O, Francke J, Visser J (2019) A shift-share based tool for assessing the contribution of a modal shift to the decarbonisation of inland freight transport. Eur Transp Res Rev 11:8. https://doi.org/10.1186/s12544-019-0344-x
17. Khan MZ, Khan FN (2020) Estimating the demand for rail freight transport in Pakistan: A time series analysis. J Rail Transp Plann Manage 14:100176. https://doi.org/10.1016/j.jrtpm.2019.100176
18. Killick R, Eckley IA (2014) changepoint: An R package for changepoint analysis. J Stat Softw 58(3). https://doi.org/10.18637/jss.v058.i03
19. Lerida-Navarro C, Nombela G, Tranchez-Martin JM (2019) European railways: Liberalization and productive efficiency. Transp Policy 83:57–67. https://doi.org/10.1016/j.tranpol.2019.09.002
20. Newey WK, West KD (1987) A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55(3):703–708. https://doi.org/10.2307/1913610
21. Notteboom T, Pallis T, Rodrigue J-P (2021) Disruptions and resilience in global container shipping and ports: The COVID-19 pandemic versus the 2008–2009 financial crisis. Maritime Econ Logistics 23:179–210. https://doi.org/10.1057/s41278-020-00180-5
22. Osberghaus D (2019) The effects of natural disasters and weather variations on international trade and financial flows: A review of the empirical literature. Econ Disasters Clim Change 3. https://doi.org/10.1007/s41885-019-00042-2
23. Papadogeorgou G, Menchetti F, Choirat C, Wasfy JH, Zigler CM, Mealli F (2023) Evaluating federal policies using Bayesian time series models: Estimating the causal impact of the hospital readmissions reduction program. Health Serv Outcomes Res Method 23:266–279. https://doi.org/10.1007/s10742-022-00294-8
24. R Core Team (2025) *R: A language and environment for statistical computing* (Version 4.5.2) [Computer software]. R Foundation for Statistical Computing. https://www.R-project.org/
25. Schaffer AL, Dobbins TA, Pearson S-A (2021) Interrupted time series analysis using autoregressive integrated moving average (ARIMA) models: A guide for evaluating large-scale health interventions. BMC Med Res Methodol 21:58. https://doi.org/10.1186/s12874-021-01235-8
26. Scott SL (2025) *bsts: Bayesian structural time series* (Version 0.9.11) [Computer software]. https://CRAN.R-project.org/package=bsts
27. Scott SL, Varian HR (2014) Predicting the present with Bayesian structural time series. Int J Math Modelling Numer Optimisation 5(1–2):4–23. https://doi.org/10.1504/ijmmno.2014.059942
28. Şenol Balaban M, Doğulu C, Akdede N, Akoğlu H, Karakayalı O, Yılmaz S, Yılmaz S, Ajobiewe T, Güzel S, İkizer G, Akin M, Ünal Y, Karancı AN (2025) Emergency response, and community impact after February 6, 2023 Kahramanmaraş Pazarcık and Elbistan earthquakes: Reconnaissance findings and observations on affected region in Türkiye. Bull Earthq Eng 23:1053–1081. https://doi.org/10.1007/s10518-024-01867-3

29. Takman J, Gonzalez-Aregall M (2024) Public policy instruments to promote freight modal shift in Europe: Evidence from evaluations. Transp Reviews 44(3):612–633. https://doi.org/10.1080/01441647.2023.2279219
30. Tardivo A, Carrillo Zanuy A, Sánchez Martín C (2021) COVID-19 impact on transport: A paper from the railways' systems research perspective. Transp Res Rec 2675(5):367–378. https://doi.org/10.1177/0361198121990674
31. Trapletti A, Hornik K (2026) *tseries: Time series analysis and computational finance* (Version 0.10–59) [Computer software]. https://CRAN.R-project.org/package=tseries
32. Vickerman R (2021) Will Covid-19 put the public back in public transport? A UK perspective. Transp Policy 103:95–102. https://doi.org/10.1016/j.tranpol.2021.01.005
33. Wan C, Yang Z, Zhang D, Yan X, Fan S (2018) Resilience in transportation systems: A systematic review and future directions. Transp Reviews 38(4):479–498. https://doi.org/10.1080/01441647.2017.1383532
34. Zeileis A, Grothendieck G (2005) zoo: S3 infrastructure for regular and irregular time series. J Stat Softw 14(6). https://doi.org/10.18637/jss.v014.i06
35. Zeileis A, Hothorn T (2002) Diagnostic checking in regression relationships. R News, *2*(3). https://CRAN.R-project.org/doc/Rnews/
36. Zeileis A, Köll S, Graham N (2020) Various versatile variances: An object-oriented implementation of clustered covariances in R. J Stat Softw 95(1). https://doi.org/10.18637/jss.v095.i01
37. Zeybek H (2021) Evaluation of the possible use of the Ankara-Sivas high-speed railway line for freight transport. J Transp Logistics 6(1):1–15. https://doi.org/10.26650/jtl.2021.0017

Figures

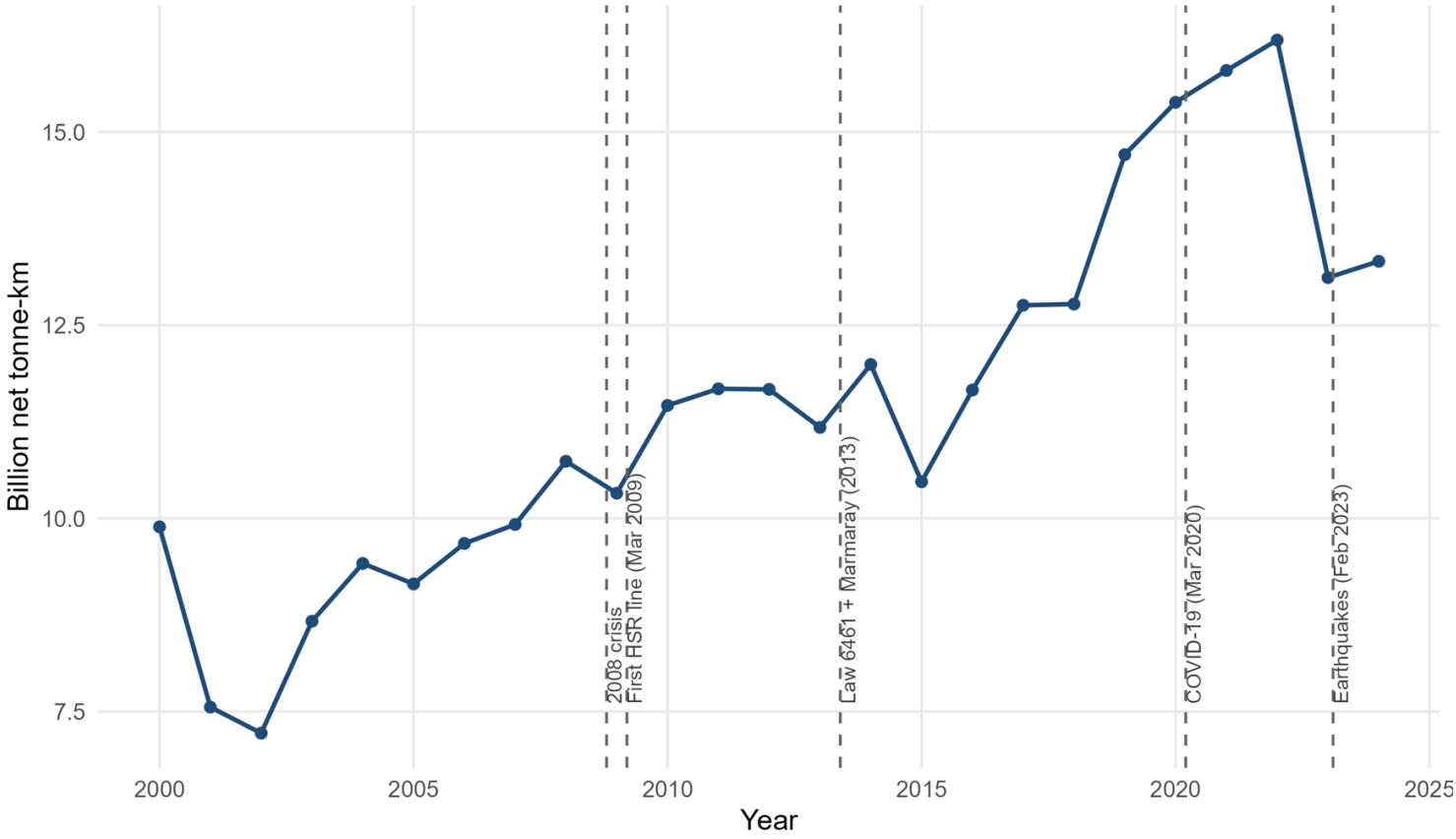


Figure 1

Turkish rail freight traffic (national total, billion net tonne-kilometres), 2000–2024, with candidate structural breaks.

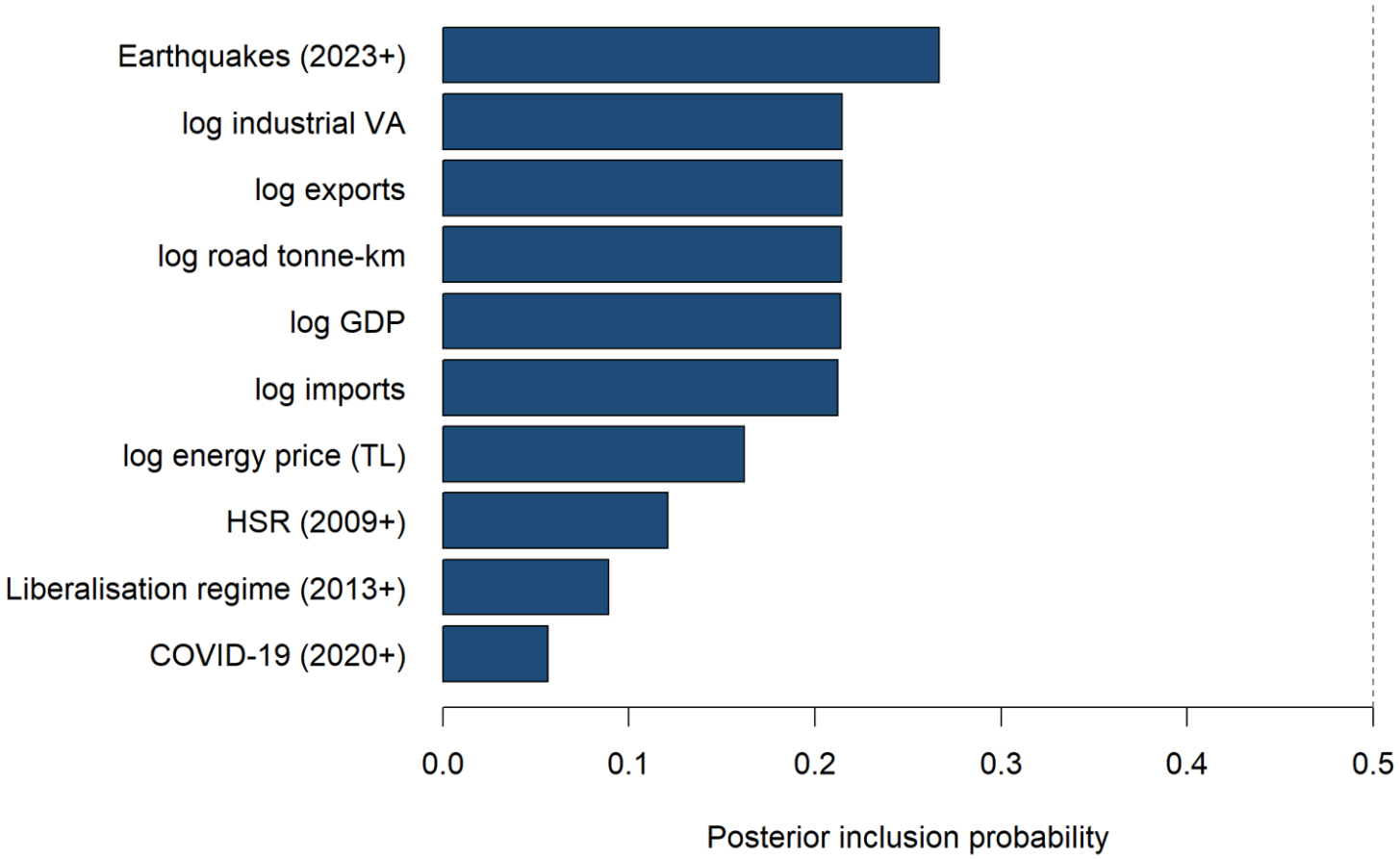


Figure 2

Posterior inclusion probabilities from the spike-and-slab regression component of the annual BSTS model (expected model size = 3; 20,000 draws).

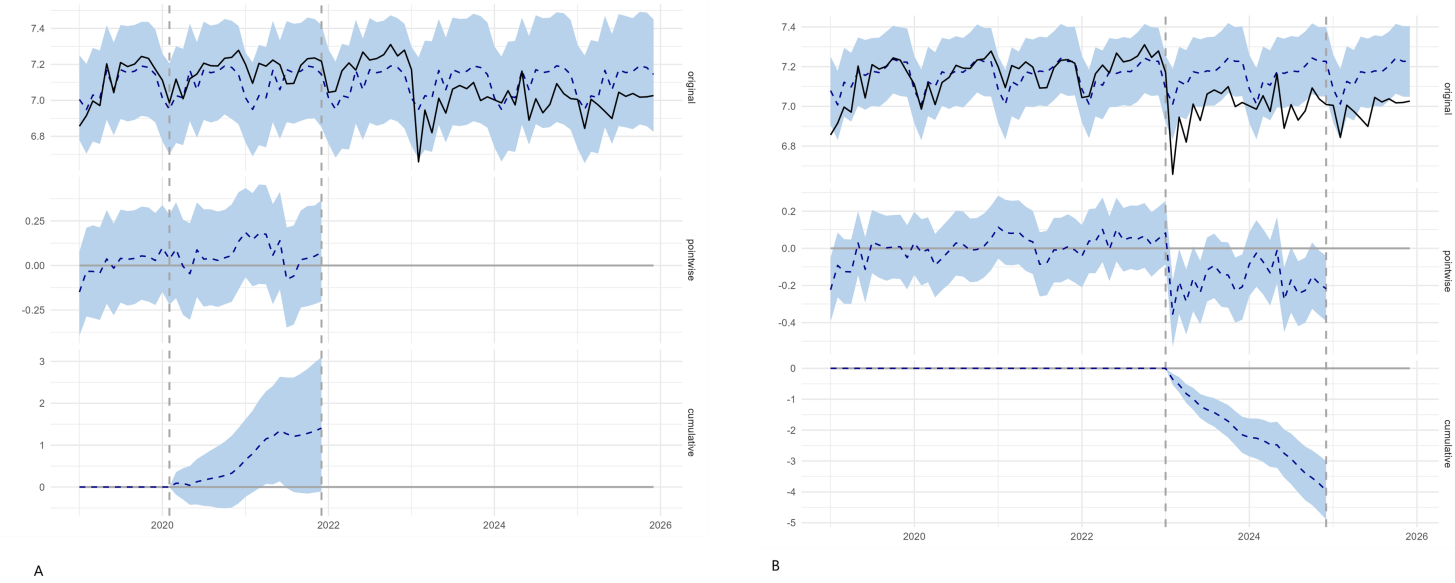


Figure 3

a. Observed versus counterfactual monthly rail freight around COVID-19 (pre-period 2019M1–2020M2; post-period 2020M3–2021M12): original series, pointwise effects, and cumulative effect (log scale).

b. Observed versus counterfactual monthly rail freight around the February 2023 earthquakes (pre-period 2019M1–2023M1; post-period 2023M2–2024M12).