

Cost-based Road Safety Dynamics Under an Exogenous Mobility Shock: Evidence from Interrupted Time Series and Difference-in-differences on Rural Roads

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Abstract

This study investigates cost-based road safety dynamics on rural roads under an exogenous mobility shock using an exposure-adjusted Accident Cost Rate (ACR). The analysis focuses on curve-related injury crashes on Category B rural roads in two Austrian states during 2012–2023. Geocoded crash records were integrated with official traffic counts to construct exposure-adjusted safety indicators at monthly, road, and road-segment levels. The mobility disruption beginning in March 2020 was treated as an exogenous intervention and analysed using interrupted time series models, complemented by difference-in-differences, count-data, and two-part models to evaluate regional heterogeneity and the robustness of the findings. The results show a statistically significant immediate reduction in the Accident Cost Rate following the onset of the mobility shock, mainly driven by reduced traffic exposure. However, the post-intervention period reveals a gradual recovery of cost-based crash risk despite persistently lower traffic volumes, indicating increased conditional crash severity when crashes occurred. These findings demonstrate that reductions in traffic volume do not necessarily result in sustained improvements in road safety when crash severity is considered alongside exposure. To support the interpretation of crash mechanisms, the study introduces a physically interpretable risk factor based on the ratio between operating speed and the critical curve speed derived from vehicle dynamics. Higher values of this indicator are consistently associated with increased Accident Cost Rates, linking roadway operating conditions with economic crash consequences.

The findings highlight the value of exposure-adjusted, cost-based safety indicators for evaluating rural road safety and supporting evidence-based infrastructure management and transportation safety decision-making.

Keywords

road safety analysis, Accident Cost Rate, traffic exposure, interrupted time series, difference-in-differences, rural roads, critical curve speed, risk factor

1 Introduction

Crashes on rural road networks continue to account for a disproportionate share of severe and fatal traffic outcomes, despite comparatively low traffic volumes. In particular, horizontal curves on lower-class rural roads represent locations where modest deviations in speed choice or vehicle control can translate into large differences in crash severity. Limited sight distance, increased lateral acceleration demands, and restricted recovery space make these environments especially sensitive to changes in operating conditions (Bauer and Harwood, 2013; Elvik and Strandvik Haugvik, 2023; Fitzpatrick and Collins, 2000; Hassan and Easa, 2003).

In Austria, Category B rural roads form a substantial component of the secondary road network and are characterised by heterogeneous alignment quality, mixed traffic composition, and frequent horizontal curvature. Although traffic demand on these roads is typically lower than on primary corridors, injury crashes occurring in curves are associated with elevated severity levels. As a result, curve-related crashes on rural roads remain a critical focus for transport safety monitoring and infrastructure management.

A central challenge in evaluating safety developments on such networks lies in disentangling changes in traffic exposure from changes in crash occurrence and crash severity.

Conventional safety indicators based on crash counts or injury frequencies provide only a partial view, particularly when traffic demand varies strongly over time. Reductions in exposure may coincide with shifts in operating conditions and behavioural adaptation – such as changes in speed choice and speed variance – that alter crash severity, leading to ambiguous interpretations when frequency-based indicators are used in isolation (Aarts and van Schagen, 2006; Sekadakis et al., 2021; Vanlaar et al., 2021).

Cost-based, exposure-adjusted indicators offer an alternative perspective. The Accident Cost Rate (ACR) expresses socio-economic crash costs per unit of traffic exposure and integrates information on both crash frequency and severity within a single metric. Such indicators are widely applied in road safety monitoring and economic appraisal in European practice (OECD/ITF, 2018). By construction, the ACR is well suited to contexts in which severity shifts are expected to offset changes in crash frequency. At the same time, cost-based indicators require careful interpretation, as uncertainty in unit cost parameters and non-linear exposure–risk relationships limit their suitability for absolute cross-sectional comparisons, emphasising longitudinal analysis within consistent networks (OECD/ITF, 2018).

Sudden system-wide changes in traffic demand create a particularly informative setting for examining the behaviour of exposure-adjusted safety indicators. Abrupt reductions in traffic volumes alter congestion levels, attainable speeds, traffic composition, and enforcement conditions, thereby affecting both the probability and the consequences of crashes. Empirical evidence from pandemic-related studies indicates sharp declines in crash counts during restriction

phases, while findings on severity are mixed, with several studies reporting stable or increased shares of serious and fatal crashes despite lower exposure (Marshall et al., 2023; Sekadakis et al., 2021). These patterns suggest that exposure reductions alone do not guarantee proportional safety gains, particularly on rural roads where reduced congestion directly translates into higher attainable speeds.

The mobility disruptions beginning in early 2020 constitute a rare example of an externally induced, largely exogenous shock to traffic systems. For transport safety analysis, this episode provides a natural experiment in which exposure and operating conditions changed rapidly and at scale, without being directly targeted at specific road segments or safety treatments. Importantly, the analytical interest lies not in the evaluation of individual policy measures, but in understanding how safety outcomes and indicators respond to abrupt changes in traffic demand and operating environments.

Against this background, this study examines the response of a cost-based, exposure-adjusted safety indicator to an exogenous mobility shock, focusing on curve-related injury crashes on Category B rural roads in two Austrian states over the period 2012–2023. The analytical workflow integrates crash data, traffic exposure, and cost information to derive Accident Cost Rates at multiple aggregation levels (Fig. 1). Using a long monthly time series, interrupted time series models are applied to identify immediate level changes and post-intervention trend dynamics following the onset of the shock in March 2020 (Eq. (7)). To assess regional heterogeneity between the two states, the analysis is complemented by a difference-in-differences design with state and time fixed effects (Eq. (8)).

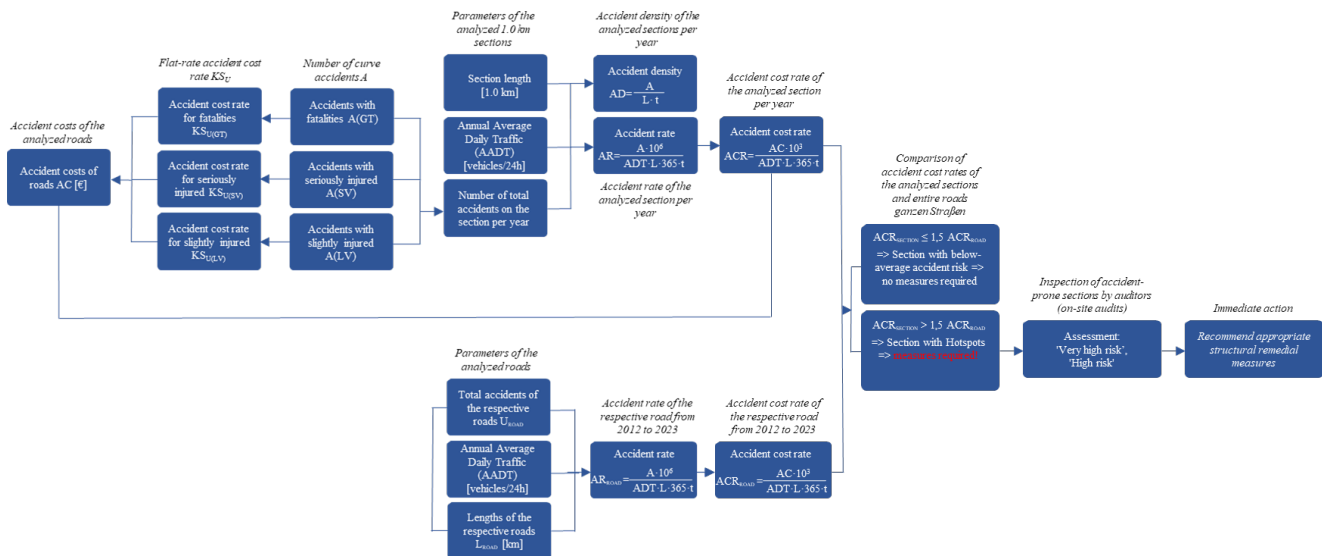


Fig. 1 Workflow for identifying crash hotspots and computing exposure-adjusted crash risk indicators

To distinguish between changes in crash occurrence and changes in crash severity, the study further employs two-part models and count-data specifications as robustness and mechanism checks (Eqs. (9) to (11)). These models allow the decomposition of cost-based safety dynamics into an occurrence component and a conditional severity component, addressing the limitations of frequency-based indicators when exposure varies strongly over time. In addition, a vehicle-dynamics-based stability indicator is introduced to link physical curve characteristics with observed crash outcomes. Descriptive developments of exposure, crashes, and Accident Cost Rates over the study period are presented in Fig. 2. An overview of curve-related injury crashes by crash type and year is provided in Table 1, while Table 2 summarises the key descriptive indicators for the pre-COVID and COVID periods. The formal estimates of intervention effects are reported in Tables 3–5, with additional robustness and sensitivity analyses summarised in Table 6.

By concentrating on a well-defined rural road environment and by emphasising indicator behaviour rather than policy evaluation, the study contributes to the transport safety literature in three ways. First, it demonstrates how cost-based, exposure-adjusted indicators respond to sudden changes in traffic demand, highlighting dynamics that may be obscured by crash counts alone. Second, it illustrates the value of combining time-series and quasi-experimental methods when analysing system-wide shocks in transport safety data. Third, it provides empirical evidence on the heterogeneity of safety responses across regions operating under similar external conditions. The findings are intended to inform methodological practice in transport safety analysis and applied road safety monitoring, and the analytical framework is transferable to other contexts in which abrupt changes in traffic demand challenge the interpretation of conventional safety indicators.

2 Literature review

2.1 Curve-related crashes on rural roads

Horizontal curves are consistently identified as locations with elevated crash risk and disproportionately high injury severity on rural road networks. Compared with tangential sections, curves impose increased demands on vehicle dynamics and driver perception, limit available sight distance, and reduce recovery space, thereby increasing the likelihood of loss-of-control and run-off-road crashes (Bauer and Harwood, 2013; Fitzpatrick and Collins, 2000; Hassan and Easa, 2003). These mechanisms are particularly pronounced on lower-class rural roads, where geometric standards are more heterogeneous and roadside protection is often limited.

Empirical studies show that geometric characteristics such as curve radius, curvature change rate, and alignment consistency are key determinants of both crash occurrence and severity. Small radii and abrupt transitions between curves are associated with higher crash frequencies, while inconsistent alignment increases driver workload and expectancy violations (Bauer and Harwood, 2013; Elvik and Strandvik Haugvik, 2023; Hassan and Easa, 2003). On rural roads, these effects are amplified by mixed traffic composition, narrower cross-sections, and limited forgiving roadsides, leading to comparatively severe outcomes even at lower traffic volumes (Abdi et al., 2019).

2.2 Speed, behavioural adaptation, and crash severity

Speed is a central determinant of crash severity, with a well-established non-linear relationship between impact speed and injury risk. Even modest increases in speed can lead to disproportionately higher probabilities of serious and fatal injuries, particularly in environments with limited lateral and longitudinal recovery space such as horizontal curves (Aarts and van Schagen, 2006). As a result, changes

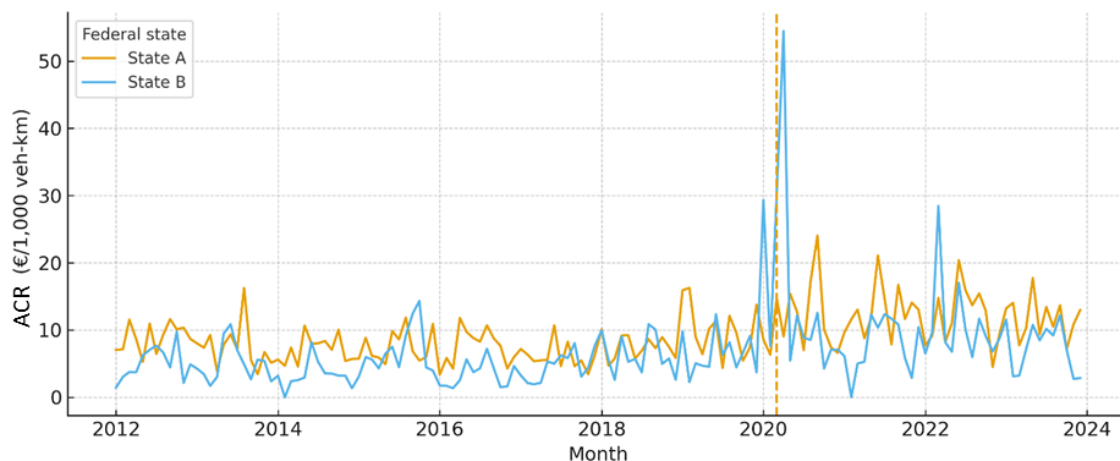


Fig. 2 Monthly development of the Accident Cost Rate on Category B rural roads, 2012–2023, with COVID-19 intervention marked (March 2020)

Table 1 Accidents on Category B rural roads (2012–2023) by crash type (curve crashes). Own calculations based on personal communication (Vogel, 2025)

Crash types (curves)	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
012 Run-off road to the right, in right curve	101	92	96	84	87	99	88	87	84	81	71	73
013 Run-off road to the right, in left curve	364	374	356	331	374	314	369	335	313	293	292	330
022 Run-off road to the left, in right curve	189	171	175	155	171	172	182	162	128	134	148	148
023 Run-off road to the left, in left curve	82	80	72	75	61	82	65	67	43	39	38	59
222 Run-off road to the right due to oncoming vehicle, in right curve	12	7	6	5	8	4	3	4	1	1	–	3
223 Run-off road to the right due to oncoming vehicle, in left curve	16	8	5	6	13	11	8	6	5	5	1	2
225 Run-off road to the left due to oncoming vehicle, in right curve	50	38	41	34	39	34	3	4	2	–	1	3
226 Run-off road to the left due to oncoming vehicle, in left curve	20	20	12	21	10	9	–	–	2	–	–	1
232 Side collision, in a curve	60	76	65	62	68	55	91	94	81	73	98	104
242 Head-on collision, in a curve	96	80	62	70	72	76	146	143	110	110	120	122
265 Head-on or side collision while overtaking, in right curve	7	6	12	10	15	10	19	23	14	13	15	18
266 Head-on or side collision while overtaking, in left curve	4	5	3	8	6	4	11	6	8	7	8	5
Total	1,001	957	905	861	924	870	985	931	791	756	792	868

Table 2 Key indicators for the pre-COVID period (2012–2019) and the COVID phase (2020–2023)

Period	Months	Total cost [€]	Total vehicle-km	Total crashes	Mean monthly ACR [€/1,000 veh-km]	Mean monthly AR [per million veh-km]	Overall ACR [€/1,000 veh-km]
Pre-COVID (2012–2019)	96	167,600,813	24,081,347,833	48,527	6.86	1.864	6.96
COVID-Phase (2020–2023)	48	123,979,757	11,416,040,442	26,684	10.693	2.045	10.86

Table 3 Interrupted Time Series (ITS) regression results for the Accident Cost Rate

State	δ (level shift)	95% CI (δ)	p (δ)	γ (trend)	95% CI (γ)	p (γ)
State A	4.945	[3.860, 6.031]	< 0.001	–0.024	[–0.058, 0.011]	0.175
State B	6.887	[1.481, 12.293]	0.013	–0.126	[–0.301, 0.049]	0.159

Note: The level-shift estimates (δ) and their confidence intervals are reported as positive magnitudes of the estimated immediate decreases in the Accident Cost Rate. The corresponding regression coefficients are negative. Post-intervention trend-change estimates (γ) retain their original signs.

Table 4 Difference-in-differences (DiD) estimates for the Accident Cost Rate

Predictor	Estimate	95%-CI	p
B $\times$ Post	6.499	[2.987, 10.012]	0.000

in speed choice and speed variance play a critical role in shaping safety outcomes on rural curved road segments.

Behavioural research indicates that drivers adapt their speed choice to perceived risk, traffic density, and enforcement intensity. Under low-traffic conditions, drivers tend to select higher speeds and exhibit greater speed dispersion, which increases both crash probability and crash severity (Bella, 2014; Chen et al., 2018). These mechanisms are especially relevant on rural roads, where reductions in congestion directly translate into higher attainable speeds and fewer external constraints on driver behaviour.

A formal framework for understanding behavioural adaptation in curve negotiation is provided by the concept of risk compensation (Wilde, 1982). Within this framework, drivers adjust their speed choice in response to perceived risk, maintaining a target level of risk rather than strictly adhering to posted speed limits or design standards. Consequently, improvements in roadway geometry or pavement friction may be partially offset by behavioural adaptation, whereby drivers increase their operating speed in response to perceived safety improvements. This behavioural mechanism has important implications for curve safety assessment, as it implies that static speed limits may not adequately reflect actual operating conditions on high-quality pavement surfaces with favourable geometric design.

Table 5 Two-part model and zero-inflated negative binomial results

Two-part logit (OR Post)	95% CI(OR)	<i>p</i> (logit)	Two-part gamma (multiplier post)	95% CI (multiplier)	<i>p</i> (Gamma)	ZINB (IRR, Post)	95%CI(IRR)	<i>p</i> (NB)
1.291	[1.123, 1.484]	0.000	1.344	[1.166, 1.551]	0.000	1.207	[1.130, 1.289]	0.000

Table 6 Summary of robustness and sensitivity analyses

Check	Main result	Direction	Pass
NB (with Offset)	Direction unchanged	$\delta < 0$; Rebound	✓
Event study (no pre-trends)	No significant pre-trend	$\delta < 0$; $\gamma \geq 0$	✓
Quarterly aggregation	Direction unchanged	$\delta < 0$; $\gamma \geq 0$	✓
UPS $\pm 10\%$	Level shift, stable effect	$\delta < 0$; $\gamma \geq 0$	✓
Placebo cut-offs (2019-07 and 2019-10)	Significant placebo level shifts observed	Placebo effects present	No

2.3 Operating environment: pavement condition, weather, and visibility

Road surface condition and environmental factors substantially influence crash risk and severity on rural curves. Reduced pavement friction under wet or winter conditions increases stopping distances and lateral instability, thereby elevating the likelihood of loss-of-control crashes (Qiu and Nixon, 2008). Weather conditions such as precipitation, fog, and snow further impair visibility and friction, while darkness exacerbates risk by limiting driver perception and reaction time (Theofilatos and Yannis, 2014; Yannis et al., 2013). Using provincial panel data from China covering 2006–2021, Zou et al. (2024) further demonstrated that rainfall and temperature are associated with road traffic casualties, with effects differing between the short and long term.

Interactions between road geometry, surface condition, and environmental factors are particularly strong in curves, where drivers already operate close to the limits of lateral friction. Although infrastructure measures such as high-friction surface treatments and improved delineation can mitigate these risks, behavioural adaptation may partially offset safety gains if drivers respond to improved conditions by increasing speed (Cafiso et al., 2021).

2.4 Mobility shocks and road safety outcomes

Large-scale mobility disruptions provide a natural experiment for examining the relationship between traffic exposure, crash frequency, and crash severity. The COVID-19 pandemic resulted in abrupt and substantial reductions in traffic volumes across many countries, often exceeding 40–60% during early restriction phases (Hale et al., 2021; Paez, 2020). For Austria, Heiler et al. (2023) documented changes in population mobility during the initial COVID-19 lockdown using aggregated mobile-phone data. Numerous studies document sharp declines in crash counts during these periods (Qureshi et al., 2020).

However, findings regarding crash severity are mixed. Several analyses report stable or increasing proportions of serious and fatal crashes despite lower exposure, suggesting that reduced traffic demand does not automatically translate into proportional safety improvements (Marshall et al., 2023; Sekadakis et al., 2021). Increased operating speeds on less congested networks, changes in enforcement intensity, and behavioural adaptation have been identified as key explanatory mechanisms, particularly on rural roads where congestion effects are otherwise limited (Vanlaar et al., 2021).

Using an interrupted time series framework, Jima and Sipos (2023) documented the long-term dynamics of road traffic crashes in Budapest, reporting a pronounced immediate reduction in crash counts followed by a gradual return towards pre-pandemic levels, which aligns with the exposure-driven dynamics observed in the present study on rural roads.

Most pandemic-related road safety studies rely on crash counts or injury severity categories as outcome measures. While informative, these indicators capture only parts of the safety picture and may mask offsetting effects between exposure, frequency, and severity during periods of rapidly changing traffic demand.

2.5 Cost-based safety indicators and exposure adjustment

Cost-based safety indicators are widely used in road safety management and economic appraisal to integrate crash frequency and severity into a single outcome measure. By expressing safety outcomes in monetary terms, such indicators facilitate comparison across locations, time periods, and intervention contexts (OECD/ITF, 2018). The Accident Cost Rate, defined as socio-economic crash costs per unit of traffic exposure, is commonly applied in network screening and cost-benefit analysis, particularly in European practice.

By combining information on crash occurrence and severity, cost-based rates provide a more comprehensive assessment of safety developments than frequency-based indicators alone, especially when severity shifts are expected (Aarts and van Schagen, 2006). At the same time, cost-based indicators inherit known limitations of rate measures. Uncertainty in unit cost estimates and non-linear relationships between exposure and crashes limit their suitability for absolute cross-sectional comparisons, highlighting the importance of longitudinal interpretation within consistent networks (OECD/ITF, 2018).

The importance of integrating crash frequency and severity into a single analytical framework has been reinforced by recent European-level assessments, which highlight the limitations of fatality-only targets in capturing actual risk exposure (Pauer and Ötvös, 2025).

From an economic perspective, the ACR should not be interpreted as a direct welfare measure. The unit costs used in its construction represent average valuations (based on the Austrian WTP approach) rather than marginal social costs. Variations in the ACR therefore do not necessarily correspond to changes in marginal welfare, which is the relevant metric for economic policy evaluation. However, as a descriptive index for longitudinal network monitoring and as a decision-support tool for infrastructure prioritisation, the ACR remains valuable. The Safe System approach (OECD/ITF, 2008) provides an overarching policy framework in which infrastructure is designed to tolerate human error, and the risk factor RF offers a direct indicator of the extent to which curve design accommodates this principle.

2.6 Methodological approaches to intervention analysis

Interrupted time series analysis is a well-established method for evaluating population-level interventions with a clearly defined start date. ITS models estimate changes in outcome levels and trends following an intervention while controlling for pre-existing trends, seasonality, and serial correlation (Lopez Bernal et al., 2017). Difference-in-differences designs complement ITS by enabling comparative evaluation between treated and reference groups and by capturing regional heterogeneity in intervention effects (Brodersen et al., 2015).

When applied to crash data characterised by overdispersion and excess zeros, these approaches are often combined with two-part and count-data models to distinguish between changes in crash occurrence and changes in outcome intensity (Cameron and Trivedi, 2013). Such decompositions are particularly valuable when exposure

varies strongly over time and when severity dynamics are expected to play a central role.

2.7 Research gap

In summary, existing literature provides strong evidence of exposure-driven reductions in crash counts during large-scale mobility disruptions but offers mixed conclusions regarding crash severity, particularly on rural roads and in horizontal curves. Research explicitly focusing on curve-related crashes under abrupt mobility shocks remains limited. Moreover, cost-based, exposure-adjusted indicators such as the Accident Cost Rate are well established in safety monitoring practice but remain under-represented in formal time-series and quasi-experimental intervention analyses. Furthermore, few studies explicitly link physical stability indicators – such as critical curve speed – with cost-based safety outcomes in a time-series framework. This study addresses this gap by integrating a vehicle-dynamics-based risk factor ($RF = V_{act} / V_{crit}$) with exposure-adjusted ACR dynamics.

This study addresses these gaps by applying a cost-based outcome measure within a robust time-series and quasi-experimental framework to examine safety dynamics on rural curves under an exogenous mobility shock.

3 Data and methodology

3.1 Study area, data sources, and sample definition

3.1.1 Study area and analytical framework

The empirical analysis focuses on curve-related injury crashes on Category B rural roads in two Austrian states, anonymised as State A and State B, over the period 2012–2023. Category B roads represent a substantial part of the secondary rural road network and are characterised by heterogeneous geometric standards, mixed traffic composition, and frequent horizontal curvature.

The overall analytical workflow applied in this study is illustrated in Fig. 1. The workflow integrates crash data, traffic exposure, and cost information to derive exposure-adjusted Accident Cost Rates at multiple aggregation levels. It further outlines the distinction between pre-intervention and post-intervention periods and the application of complementary modelling approaches to identify level changes, trend dynamics, and underlying mechanisms.

The observation period covers eight full years prior to the mobility disruption in March 2020 and nearly four years thereafter. This long pre-intervention period supports the identification of baseline trends and seasonal patterns, while the extended post-intervention period allows the examination of medium-term dynamics following the initial shock.

3.1.2 Crash data

Crash data were obtained from official police-reported statistics provided by Statistics Austria. The dataset includes information on crash date and time, geographic coordinates (WGS-84), posted speed limits, and injury outcomes, including fatalities, serious injuries, and slight injuries. Additional variables describe environmental and operating conditions such as weather, precipitation, road surface condition, and lighting.

The analysis is restricted to curve-related injury crash types coded as 012, 013, 022, 023, 222, 223, 225, 226, 232, 242, 265, and 266, representing the most frequent and severe crash configurations occurring in horizontal curves on Category B rural roads. An overview of crash frequencies by crash type and year for the period 2012–2023 is provided in Table 1.

All crashes were geocoded and assigned to homogeneous road sections based on official network referencing. Road identifiers were anonymised in accordance with data protection requirements. No major reclassification or geometric realignments occurred on the analysed road sections during the study period, ensuring longitudinal consistency of crash data.

3.1.3 Road geometry and network data

Road and geometric characteristics were obtained from official road authority databases and project documentation. Available attributes include road length, number of lanes, lane width, shoulder configuration, posted speed limits, and horizontal alignment characteristics. A detailed description of the RoadSTAR parameters, including geometric and pavement-related variables, is provided in Table S2 of the Supplement.

Horizontal curves were identified using official alignment records. Only curves that remained unchanged with respect to radius and alignment throughout the study period were included. This restriction ensures that observed changes in crash outcomes can be attributed to changes in traffic demand and operating conditions rather than to infrastructure modifications, consistent with the analytical logic presented in Fig. 1.

3.1.4 Traffic exposure data

Traffic exposure was quantified using vehicle-kilometres travelled derived from official traffic count data. Annual Average Daily Traffic (AADT) values were obtained from permanent and short-term counting stations and assigned to the corresponding homogeneous road sections.

Monthly exposure values were estimated by applying standard seasonal adjustment factors to the AADT series and multiplying the result by section length. This procedure ensures that safety outcomes are evaluated relative to changes in traffic demand over time and corresponds to the exposure normalisation component shown in Fig. 1.

3.2 Outcome variables

3.2.1 Accident Cost Rate (ACR)

The primary outcome variable is the Accident Cost Rate (ACR), defined as the total socio-economic cost of injury crashes per unit of traffic exposure. Crash costs were calculated by assigning standardised unit costs to crashes according to injury severity, reflecting medical costs, production losses, human costs, and material damage.

The ACR is computed as:

$$ACR = (AC \cdot 10^3) / (ADT \cdot L \cdot 365 \cdot t), \quad (1)$$

where AC denotes total accident costs [€], ADT is the average daily traffic volume [veh/24 h], L is the road section length [km], and t is the observation period [years].

For comparison, the conventional Accident Rate (AR), defined as the number of crashes per million vehicle-kilometres, is also reported:

$$AR = (U \cdot 10^6) / (ADT \cdot L \cdot 365 \cdot t), \quad (2)$$

where U denotes the number of injury crashes observed during the study period.

Accident cost parameters are derived from official Austrian socio-economic accident cost schedules for personal injury crashes (UPS; reference years 2011, 2016, and 2021), differentiated by road type and injury severity (Herry Consult et al., 2012; Herry Consult and KFV, 2017; Sedlacek et al., 2023). Intermediate years are linearly interpolated using a price index. The applied cost parameters are documented in Table S1 in the Supplement.

3.2.2 Aggregation levels

Three variants of the Accident Cost Rate are used in the analysis:

- **ACR_Segment:** annual ACR computed for standardised 1.0-km road segments, used to examine spatial heterogeneity.
- **ACR_Road:** annual ACR aggregated at the road level (road · year panel), used in panel-based robustness analyses.
- **ACR_Month:** monthly ACR aggregated at the state level, serving as the primary outcome for interrupted time series analysis.

3.2.3 Critical curve speed and risk factor (RF)

To link physical curve characteristics with crash outcomes, a vehicle-dynamics-based stability indicator is introduced. The critical curve speed V_{crit} represents the maximum speed at which a vehicle can negotiate a curve without exceeding available lateral friction and losing stability.

The derivation follows from the equilibrium of forces acting on a vehicle during curve negotiation. When a vehicle negotiates a horizontal curve, the centrifugal force $F_c = m \cdot v^2 / R$ acts outward, where m is vehicle mass, v is speed, and R is curve radius. This force must be balanced by the lateral friction force $F_f = \mu \cdot N$ (where μ is the pavement friction coefficient and N is the normal force) and the component of gravity due to superelevation $G_q = m \cdot g \cdot q$ (where g is gravitational acceleration and q is cross-slope expressed as a decimal, e.g., 5% = 0.05).

The equilibrium condition can be written as:

$$m \cdot v^2 / R = \mu \cdot m \cdot g \cdot \cos \alpha + m \cdot g \cdot \sin \alpha, \quad (3)$$

where α is the superelevation angle. For small cross-slopes ($q \ll 1$, i.e., $q < 0.1$ or 10%), we can approximate $\sin \alpha \approx q$ and $\cos \alpha \approx 1$. Solving for v and converting from m/s to km/h (multiplication by 3.6) yields the critical curve speed:

$$V_{crit} = \sqrt{[R \cdot g \cdot (\mu + q) / (1 - \mu \cdot q)]} \cdot 3.6. \quad (4)$$

Equation (4) accounts for both the beneficial effect of superelevation (q in the numerator) and the reduction in normal force due to superelevation ($\mu \cdot q$ in the denominator). The approximation $\cos \alpha \approx 1$ is valid for typical superelevation values ($q \leq 0.07$ or 7%), where the error remains below 0.25%.

To account for driver behaviour, an operating speed proxy V_{act} is defined based on the posted speed limit V_{limit} and a behavioural adjustment factor f . Following empirical studies on rural roads, drivers often exceed posted speed limits by 5–12 km/h on curves following long tangent sections (De Oña and Garach, 2012). The behavioural factor $f = 0.85$ is applied to capture systematic speeding behaviour:

$$V_{act} = V_{limit} + f \cdot (V_{limit} - V_{crit}). \quad (5)$$

The risk factor RF is then defined as the ratio between estimated operating speed and critical speed:

$$RF = V_{act} / V_{crit}. \quad (6)$$

RF values less than 1.0 indicate that estimated operating speeds remain within the physical stability margin. Values approaching 1.0 suggest reduced stability reserves, while $RF > 1.0$ indicates that the estimated operating speed exceeds the critical stability threshold, representing

a potentially unstable driving condition. For practical engineering interpretation, RF is classified into four stability-based risk levels:

- $RF < 1.0 \rightarrow$ Low risk (stable);
- $1.0 \leq RF < 1.2 \rightarrow$ Moderate risk (limited stability reserve);
- $1.2 \leq RF < 1.4 \rightarrow$ High risk (reduced stability reserve);
- $RF \geq 1.4 \rightarrow$ Very high risk (critical instability).

This indicator provides a direct engineering link between roadway geometry (R, q), pavement condition (μ), driver behaviour (V_{limit}, f), and the economic crash outcomes captured by the ACR. For a detailed derivation including the full force equilibrium without the small-angle approximation, see Hrapović (2025).

3.3 Modelling approach

3.3.1 Interrupted time series analysis

To identify level and trend changes associated with the mobility disruption beginning in March 2020, interrupted time series (ITS) models are estimated separately for each state using monthly ACR data. The baseline specification is:

$$ACR_t = \alpha + \delta \{t \geq \text{March 2020}\} + \gamma \cdot \text{PostTrend}_t + \beta^T X_t + \varepsilon_t, \quad (7)$$

where δ captures the immediate level change at the intervention and γ captures the post-intervention trend change. The covariate vector X_t includes exposure controls, winter indicators, darkness share, and month fixed effects.

Serial correlation is addressed using either parsimonious autoregressive terms within an ARIMAX framework or heteroskedasticity- and autocorrelation-consistent (Newey–West) standard errors. Model selection is based on AIC_c and residual autocorrelation is assessed using Ljung–Box tests.

3.3.2 Difference-in-differences design

To examine regional heterogeneity, a two-way fixed effects difference-in-differences (DiD) model is estimated:

$$ACR_{s,t} = \alpha + \theta \cdot [B_s \cdot \text{Post}_t] + \lambda_s + \tau_t + \varepsilon_{s,t}, \quad (8)$$

where B_s indicates State B, λ_s are state fixed effects, and τ_t are month fixed effects. The interaction coefficient θ measures the differential post-intervention change in State B relative to State A.

3.3.3 Two-part and count-data models

To distinguish between changes in crash occurrence and changes in crash severity, two-part models are estimated at

the road · year level. The first part models the probability of observing at least one injury crash using a logit specification, while the second part models conditional crash cost intensity using a gamma generalised linear model with log link:

$$P_r(U_{i,t} > 0) = \text{logit}^i(\alpha_i + \tau_t + Z_{it}^T \theta), \quad (9)$$

$$E\{ACR_{i,t} | U_{i,t} > 0\} = \exp(\alpha_i + \tau_t + Z_{it}^T \phi), \quad (10)$$

where α_i is the road fixed effects, τ_t is the year fixed effects, Cluster-robust SEs at the road level.

In addition, zero-inflated negative binomial (ZINB) models are estimated for crash counts using monthly data, with vehicle-kilometres travelled included as an offset:

$$U_{s,t} \sim \text{ZINB}(\mu_{s,t}, k), \log(\mu_{s,t}) \\ = \alpha_s + \tau_t + Z_{s,t}^T k + \log(\text{veh-km}_{s,t}). \quad (11)$$

These models address overdispersion and excess zeros commonly observed in crash data.

3.3.4 Robustness and validation

Robustness checks include alternative intervention windows, quarterly aggregation, placebo cut-offs prior to 2020, variation in accident cost parameters, and event-study specifications to test for pre-trends. The direction and stability of main findings across these checks are summarised in Table 6, with detailed results provided in Tables S4 to S6 and Figs. S1 to S3 in the Supplement.

3.4 Reproducibility

All outcome construction, model specifications, and estimation procedures follow a transparent and reproducible workflow. Variable definitions and coding are consolidated in Table S3 in the Supplement, and all figures and tables report the exact model specifications used.

4 Results

4.1 Descriptive development of exposure, crashes, and Accident Cost Rates

Fig. 2 illustrates the monthly development of the Accident Cost Rate on Category B rural roads in both Austrian states over the period 2012–2023. Pronounced seasonal variation is visible throughout the pre-intervention period, with higher ACR values typically observed during winter months. A clear structural break occurs in March 2020, coinciding with the onset of the mobility disruption.

Table 2 summarises key descriptive indicators for the pre-intervention period (2012–2019) and the post-intervention period (2020–2023). Traffic exposure, measured in vehicle-kilometres travelled, declined sharply during

the initial restriction phase. Injury crash counts also decreased, but the reduction was less pronounced than the decline in exposure. As a result, both the mean monthly and overall Accident Cost Rate increased in the post-intervention period, indicating higher cost-based risk conditional on traffic activity.

These descriptive patterns suggest that changes in crash frequency alone do not fully capture safety developments during periods of strongly varying traffic demand and motivate the use of exposure-adjusted, cost-based indicators.

The relationship between the risk factor RF and the Accident Cost Rate reveals a pronounced nonlinear gradient. Descriptive analysis of the integrated road segment dataset ($n = 1,048$ 1.0-km segments) shows that curves classified as very high risk ($RF \geq 1.4$) exhibit ACR values more than seven times higher than stable curves ($RF < 1.0$). This gradient confirms that the RF indicator successfully captures locations where physical instability coincides with increased economic crash costs.

4.2 Interrupted time series results

Fig. 3 compares the observed monthly Accident Cost Rate with the counterfactual continuation of the pre-intervention trend derived from the interrupted time series model specified in Eq. (7). A distinct level change is observed at the intervention point in March 2020, indicating an immediate reduction in the Accident Cost Rate following the mobility disruption.

Table 3 reports the estimated interrupted time series coefficients for each state. The intervention parameter δ indicates a statistically significant level shift at the onset of the disruption in both states. For interpretability, δ is reported as the absolute magnitude of the level decrease in the Accident Cost Rate, while the underlying model coefficients are negative.

The post-intervention trend-change parameter γ is negative in both state-specific specifications but not statistically significant. This result suggests no clear evidence of a systematic trend change in the state-specific time series beyond the immediate level shift. Consequently, medium-term post-intervention dynamics are interpreted primarily using descriptive trajectories and robustness analyses.

4.3 Difference-in-differences results

Regional heterogeneity in post-intervention developments is examined using the difference-in-differences model specified in Eq. (8). The key parameter of interest is the interaction term between the state indicator and the post-intervention period.

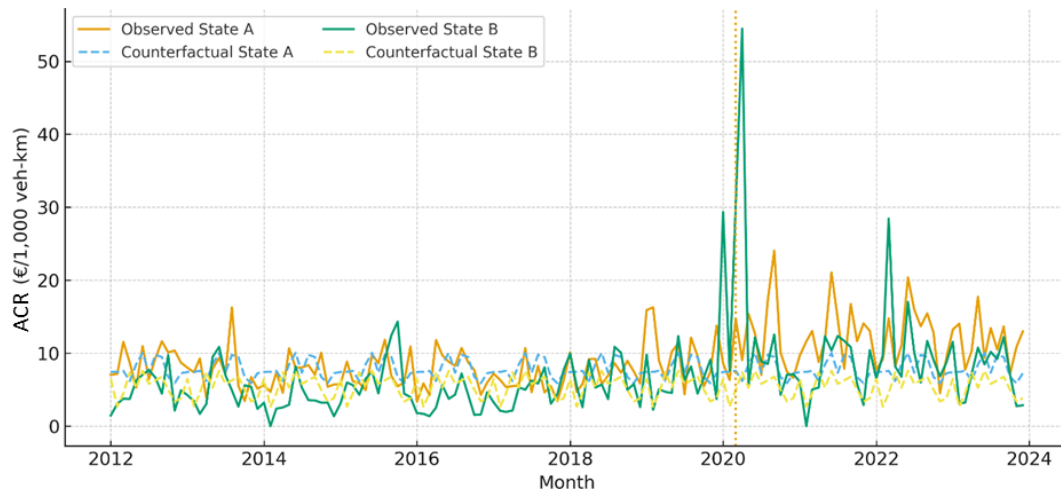


Fig. 3 Interrupted time series of the Accident Cost Rate: observed values and counterfactual continuation of the pre-intervention trend

Table 4 reports the difference-in-differences estimate for the Accident Cost Rate. The interaction coefficient is positive and statistically significant, indicating that State B experienced a larger increase, or a smaller reduction, in the Accident Cost Rate relative to State A in the post-intervention period. This finding implies that cost-based crash risk evolved differently across the two states under the same system-wide mobility conditions.

4.4 Two-part model results

Table 5 presents the results of the two-part model, which decomposes changes in the Accident Cost Rate into a crash occurrence component and a conditional crash cost intensity component, as specified in Eqs. (9) and (10).

The occurrence component, estimated using a logit model, shows that the post-intervention indicator is associated with a statistically significant increase in the probability of observing at least one injury crash after controlling for exposure and fixed effects. This result indicates higher crash occurrence in the post-intervention period, conditional on traffic exposure.

The intensity component, estimated using a gamma generalised linear model conditional on crash occurrence, reveals a statistically significant increase in crash cost intensity in the post-intervention period. This implies that, when crashes occurred, their average socio-economic cost was higher than in the pre-intervention period.

4.5 Count-data model results

Results from the zero-inflated negative binomial model specified in Eq. (11) are also reported in Table 5. The estimated post-intervention incidence rate ratio is significantly greater than one, indicating higher expected crash

counts in the post-intervention period after accounting for exposure through the vehicle-kilometre offset.

The consistency between the count-data results and the two-part occurrence component supports the interpretation that post-intervention changes in the Accident Cost Rate reflect not only recovering traffic exposure but also changes in crash frequency and severity.

4.6 Cross-model comparison and robustness

Fig. 4 summarises the estimated effects of the mobility disruption across the different modelling approaches applied in this study, including interrupted time series, difference-in-differences, two-part, and count-data models. Across all specifications, the immediate effect of the intervention on the Accident Cost Rate is consistently negative, indicating a short-term reduction in cost-based crash risk.

At the same time, post-intervention dynamics consistently point towards a rebound in the Accident Cost Rate, although the magnitude varies across model classes. The direction and persistence of the main findings remain stable across robustness and sensitivity checks.

Table 6 summarises the results of these robustness analyses, including alternative intervention windows, placebo cut-offs, quarterly aggregation, and variation in accident cost parameters. Detailed robustness results are provided in the Supplement (Tables S4 to S6 and Figs. S1 to S3).

4.7 Summary of results

In summary, the results indicate a statistically significant immediate reduction in the Accident Cost Rate following the onset of the mobility disruption in March 2020. This initial decline coincides with a sharp reduction in traffic exposure. However, the reduction is not sustained uniformly

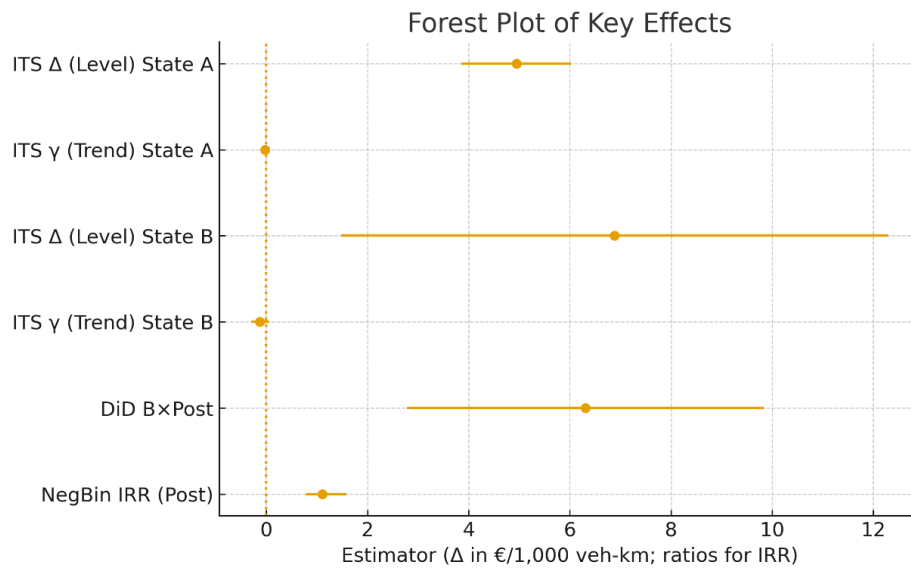


Fig. 4 Comparison of estimated COVID-19 effects across modelling approaches (forest plot)

over time. Post-intervention dynamics reveal a rebound in cost-based crash risk driven by both higher crash occurrence and increased conditional crash cost intensity. Regional heterogeneity across the two Austrian states further indicates that safety responses to system-wide mobility shocks are not spatially uniform. The integration of the vehicle-dynamics-based risk factor RF demonstrates that curves with reduced stability margins ($RF > 1.2$) are disproportionately represented in higher ACR classes, linking physical instability directly to economic crash outcomes.

5 Discussion

5.1 Immediate effects of an exogenous mobility shock on cost-based safety outcomes

The results indicate a clear and statistically significant reduction in the Accident Cost Rate at the onset of the mobility disruption in March 2020. This immediate level shift is consistently identified in the interrupted time series analysis (Fig. 3; Table 3) and coincides with the abrupt contraction in traffic exposure observed during the initial restriction phase. From the perspective of an exposure-adjusted indicator, this finding suggests that reduced traffic demand translated into a short-term reduction in cost-based crash risk on rural roads.

However, the magnitude of the ACR reduction is smaller than the contemporaneous decline in vehicle-kilometres travelled (Table 2). This divergence implies that exposure reductions alone do not fully explain observed safety outcomes. Changes in operating conditions, such as increased attainable speeds and altered traffic composition under low-demand conditions, appear to have moderated the short-term safety gains. The result highlights the

analytical value of cost-based indicators, which integrate frequency and severity effects that may offset each other when demand changes rapidly.

5.2 Post-intervention dynamics and rebound in cost-based risk

Although the initial reduction in the Accident Cost Rate is pronounced, it is not sustained uniformly over time. Descriptive trajectories of the monthly ACR (Fig. 2) and the results of robustness analyses (Table 6) indicate a recovery of cost-based crash risk during the post-intervention period. State-specific interrupted time series trend-change estimates are not statistically significant (Table 3), suggesting that longer-term dynamics are better interpreted through the combined evidence of descriptive patterns and complementary model specifications.

The decomposition provided by the two-part and count-data models offers insight into the mechanisms underlying this rebound. The two-part occurrence component indicates a higher probability of observing injury crashes in the post-intervention period after accounting for exposure (Table 5). At the same time, the conditional intensity component shows a substantial increase in average crash cost given crash occurrence (Table 5). Consistently, the count-data model yields a post-intervention incidence rate ratio greater than one after controlling for exposure through the vehicle-kilometre offset (Table 5).

Taken together, these findings suggest that the rebound in the Accident Cost Rate reflects both increased crash occurrence and higher severity conditional on crash involvement. This pattern is compatible with behavioural adaptation and altered operating conditions on rural roads

following the initial disruption phase, rather than being driven solely by recovering traffic volumes.

The empirical analysis remains largely reduced-form, without linking observed outcomes to a structural interpretation of incentives, constraints, or equilibrium adjustments. However, the observed patterns are consistent with risk compensation mechanisms (Wilde, 1982): under lower traffic volumes, drivers may increase their operating speeds, thereby reducing the available stability margin on curves. This interpretation is supported by the RF analysis, which shows that curves with $RF > 1.2$ (i.e., where estimated operating speeds approach or exceed critical stability thresholds) are associated with significantly higher ACR values. Nevertheless, direct empirical evidence on speed choice, enforcement intensity, or driver behaviour is not available in the current dataset. The interpretation of behavioural mechanisms therefore remains inferential and should be validated with supplementary data sources in future research.

5.3 Regional heterogeneity in safety responses

The difference-in-differences results demonstrate that post-intervention developments in the Accident Cost Rate were not spatially uniform across the two Austrian states (Table 4). The positive and statistically significant interaction effect indicates that State B experienced a less favourable evolution of cost-based crash risk relative to State A under the same system-wide mobility conditions.

This heterogeneity suggests that regional characteristics – such as network structure, traffic composition, enforcement intensity, or behavioural responses – can shape how abrupt mobility shocks translate into safety outcomes. The finding underscores the importance of accounting for spatial context when interpreting population-level safety indicators and evaluating system-wide disruptions. Moreover, differences in the distribution of high-risk curves ($RF \geq 1.2$) between the two states may contribute to the observed heterogeneity, as State B exhibits a higher proportion of sharp curves with limited stability reserves.

5.4 Consistency across modelling approaches

A key strength of the analysis lies in the consistency of findings across multiple modelling approaches. As summarised in Fig. 4, the immediate effect of the mobility disruption on the Accident Cost Rate is negative across interrupted time series, difference-in-differences, two-part, and count-data models. Similarly, post-intervention dynamics consistently point towards a rebound in cost-based risk, although effect magnitudes differ across specifications.

The main findings are broadly consistent across several model specifications and cost-parameter sensitivity analyses. However, the significant placebo level shifts indicate that the intervention-specific interpretation requires caution.

The agreement in effect direction across model classes supports the robustness of the main conclusions and indicates that the observed rebound is not an artefact of a particular modelling choice. Instead, it reflects a systematic response of cost-based safety outcomes to abrupt changes in traffic demand and operating conditions.

5.5 Methodological implications of cost-based indicators

The results illustrate both the strengths and limitations of using the Accident Cost Rate as a primary safety indicator. By integrating crash frequency and severity, the ACR captures offsetting dynamics that remain hidden in frequency-based analyses. This feature is particularly valuable in contexts characterised by rapid and large changes in traffic exposure.

At the same time, the findings highlight the need for careful interpretation of cost-based rates. Non-linear relationships between exposure and crash outcomes, as well as uncertainty in unit cost parameters, limit the suitability of the ACR for absolute comparisons across networks or jurisdictions. Longitudinal analysis within consistent networks, supported by robustness checks such as those reported in Table 6 and, is therefore essential.

From an economic perspective, the ACR should not be interpreted as a direct welfare measure. The unit costs used in its construction represent average valuations (based on the Austrian WTP approach) rather than marginal social costs. Variations in the ACR therefore do not necessarily correspond to changes in marginal welfare, which is the relevant metric for economic policy evaluation. However, as a descriptive index for longitudinal network monitoring and as a decision-support tool for infrastructure prioritisation, the ACR remains valuable.

Beyond traditional time-series approaches, advanced predictive modelling using artificial intelligence and neural networks has been shown to capture complex, non-linear interactions between mobility shocks and crash occurrence, as demonstrated by Gorzelańczyk (2024) in the context of post-pandemic traffic safety analysis.

5.6 Implications for transport safety monitoring

From a transport safety monitoring perspective, the results suggest that reductions in traffic demand alone do not guarantee sustained safety improvements on rural roads.

Temporary decreases in exposure may reduce crash frequency, but behavioural adaptation and changes in operating conditions can increase crash severity, particularly on curve-prone rural networks.

Cost-based, exposure-adjusted indicators such as the Accident Cost Rate can support more nuanced monitoring by revealing emerging severity-driven risk patterns that are not visible in crash counts alone. When combined with complementary modelling approaches, these indicators provide a robust basis for interpreting safety dynamics under rapidly changing traffic conditions. The integration of the vehicle-dynamics-based RF indicator offers an additional layer of engineering interpretability, allowing road authorities to identify curves where the available stability margin is critically low ($RF \geq 1.2$) and to prioritise infrastructure interventions accordingly.

6 Conclusions

This study analysed how a cost-based, exposure-adjusted road safety indicator responds to a sudden system-wide mobility disruption, using the Accident Cost Rate (ACR) applied to curve-related injury crashes on Category B rural roads in two Austrian states over the period 2012–2023. By combining a long pre-intervention time series with interrupted time series and difference-in-differences designs, complemented by two-part and count-data models, the analysis provides a comprehensive assessment of short-term and medium-term safety dynamics under an exogenous shock.

The results show a statistically significant immediate reduction in the Accident Cost Rate at the onset of the mobility disruption in March 2020, coinciding with a sharp decline in traffic exposure. This initial decrease indicates that reduced traffic demand translated into a short-term reduction in cost-based crash risk on rural roads. However, the reduction was not sustained uniformly over time. Post-intervention dynamics reveal a rebound in the Accident Cost Rate, driven by both higher crash occurrence after accounting for exposure and increased conditional crash cost intensity when crashes occurred.

The decomposition of cost-based outcomes demonstrates that changes in crash severity played a central role in shaping post-intervention safety dynamics. These findings illustrate that frequency-based indicators alone may provide an incomplete or even misleading picture when exposure varies strongly over time. Cost-based, exposure-adjusted indicators are therefore particularly valuable

for capturing offsetting effects between crash frequency and severity during periods of rapid change.

The introduction of a vehicle-dynamics-based risk factor ($RF = V_{act} / V_{crit}$) provides a direct engineering link between roadway geometry, pavement friction, driver behaviour, and economic crash outcomes. The analysis demonstrates that curves with $RF \geq 1.2$ (reduced stability margin) are associated with disproportionately higher ACR values, confirming that physical instability translates into increased crash costs. This finding has practical implications for infrastructure management: curves with $RF \geq 1.2$ should be prioritised for safety interventions such as high-friction surface treatments, advisory speed reductions, or geometric redesign.

The analysis further reveals regional heterogeneity in post-intervention developments between the two Austrian states, indicating that safety responses to system-wide mobility shocks are not spatially uniform. This heterogeneity underscores the importance of accounting for regional context when interpreting population-level safety indicators and highlights the limitations of assuming homogeneous effects across networks.

From a methodological perspective, the study demonstrates the value of combining time-series and quasi-experimental approaches with indicator decomposition to analyse safety dynamics under abrupt changes in operating conditions. The consistent direction of effects across modelling approaches supports the robustness of the main findings and suggests that the observed rebound is not an artefact of model specification.

The Safe System approach (OECD/ITF, 2008) provides an overarching policy framework in which infrastructure is designed to tolerate human error. The RF indicator directly measures the extent to which curve design accommodates this principle: where $RF < 1.0$, the infrastructure provides sufficient stability margin for typical operating speeds; where $RF > 1.2$, the design no longer tolerates expected driver behaviour. The observed rebound in ACR during the post-intervention period suggests that reduced traffic volumes may have encouraged higher operating speeds, thereby reducing the effective safety margin on curves – a pattern consistent with risk compensation.

Overall, the results emphasise that reductions in traffic demand alone do not guarantee sustained safety improvements on rural roads. Cost-based, exposure-adjusted indicators such as the Accident Cost Rate provide important

additional insight by explicitly integrating crash frequency and severity. The analytical framework applied in this study is transferable to other contexts in which abrupt changes in traffic demand challenge the interpretation of conventional safety indicators and can support more resilient and informed transport safety monitoring.

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