Temporal trends of transport-related injuries on New Zealand roads

Siobhan Isles, Michael Keane, Joanna F Dipnall, Ben Beck

ABSTRACT

AIM: This observational study aimed to investigate temporal trends in transport-related injuries in New Zealand by mode of transport and explore whether specific population groups and localities have a relatively higher incidence of injury. These trends provide insight into changes in injury patterns from road trauma.

METHODS: A retrospective study of hospitalised road trauma in New Zealand was conducted between 1 July 2017 to 30 June 2021. Data were obtained from the National Minimum Dataset of hospital admissions and the New Zealand Trauma Registry (NZTR). Road trauma was identified using ICD-10 coding, and major trauma using Abbreviated Injury Scale (AIS) coding. Analysis included road trauma by mode, ethnicity, rurality and population rates. Statistical analysis included Interrupted Time Series (ITS) analysis to account for the impact of COVID-19 on road trauma.

RESULTS: Over the 4-year period there were 20,607 incidents of transport-related injury that resulted in admission to a New Zealand hospital. Of these, 14.5% (2,992) involved injuries that were classified as major trauma. Car occupants accounted for 62% of hospitalisations, followed by motorcyclists (23%), pedestrians (9%) and pedal cyclists (4%). Temporal trends showed no reduction in injuries from cars, pedal cyclists and pedestrian injuries, but an increase in motorcycling injuries. Māori had an age-standardised incidence rate almost 3.5 times higher than the rate for Asian peoples.

CONCLUSION: The increases in motorcycling injuries and no changes in pedestrian and cycling injuries, as well as demographic variation, highlight the need to focus on vulnerable road users. Effective and targeted initiatives on vulnerable road users will support objectives to reduce deaths and serious injury on New Zealand roads. Enhanced exposure data is needed for vulnerable road users to account for mobility changes over time. Linked data across population-based datasets is an important asset that enhances our understanding of road traffic injuries and allows evidence-based countermeasures to be developed.

Death and serious injury involving transport are important metrics for monitoring and evaluating road safety initiatives. New Zealand has a higher rate of road fatalities than comparable countries[1] and, after a downward trend in fatalities and serious injuries since the mid-1980s, the number of people killed or seriously injured on New Zealand roads has been increasing since 2013.[2] To reverse this trend, investment in road safety strategies have been launched with the aim to reduce annual deaths and serious injury caused by road transport.[3] The focus of these strategies are motorised modes of personal transport such as cars and motorbikes, and also public transport, cycling and walking. Policies are influenced by the successes observed in countries such as the Netherlands and Sweden, which have changed approaches from being an individual's responsibility to take a systems-approach to addressing road safety issues. The "safe system" approach is focussed on three principles: people make mistakes, roads and vehicles need to be designed to minimise the impact of crashes and road safety is a shared responsibility.[4]

Accurate and comprehensive data is important to monitoring performance against targets, evaluating road safety interventions and setting future priorities. However, complete transport injury information is not centralised in any single source. While serious car crashes in New Zealand are typically documented in the Crash Analysis System,[5] moderate and minor road incidents, particularly those involving a non-motorised mode of transport such as cycling and walking, are not always captured by police.[6]

Covering a 4-year period using data from hospital admission and the New Zealand Trauma Registry (NZTR), the present study investigated temporal trends in injury-causing crashes in New Zealand and explored whether specific population groups have an increased incidence of injury. These trends provide insight into changes in injury patterns from road trauma.

The study period included the COVID-19 pandemic and resultant changes to daily life following the introduction of the COVID-19 Alert System. This study explored the impact of the lockdown on injury rates during and after the restrictions.

Methods

This observational study of hospitalised patients in New Zealand used existing data from national collections and no additional information was obtained from individuals. The study covers the period between 1 July 2017 to 30 June 2021.

Data sources

Hospitalisations were identified within the Hospital Events National Minimum Dataset (NMDS),[7] a national collection of all hospital admission data. Using ICD-10-AM[8] external cause codes, which are linked to individual hospital events, admissions coded as being caused by road traffic injury were identified. Road traffic injury was defined as "traffic" codes in the range V010 to V899, as well as a small number of X and Y codes. Non-traffic codes (e.g., mountain biking) were excluded.

Events were excluded if the patient was discharged home from the emergency department, or the patient was admitted to hospital over 14 days after the crash, or the admission was arranged and the clinical specialty was Maternity Services, or no overnight stay occurred, or the clinical specialty was Mental Health Services or arranged or waitlist.

Mode of transport was identified using the ICD-10-AM coding in the NMDS and categorised into car (driver or passenger, and passenger cars only), motorcycle (driver or passenger), pedal cycle and pedestrian. The last category was "Other", and included any mechanised vehicle not classified as a car such as a truck, van, light or bus, and incidents involving horses or other animals on a road.

Major trauma incidents were linked to the hospitalisation dataset using National Health Index (NHI) in the NZTR,[9] a population-based registry that collects data on all major trauma patients who have a threat to life and are admitted to acute hospitals. Matching cases between the NMDS and the NZTR enabled stratification analyses by major and non-major trauma.

Statistics New Zealand population projections for relevant periods and for all population subgroups and rural/urban classifications were used. The 2013 Census estimated population for Māori was used as the reference population.

Prioritised ethnicity data associated with the NHI was used.

Rural/urban classification is based on University of Otago's Geographic Classification of Health[10] using the patient's domicile code of residence and Census data. This does not reflect where the injury occurred.

The study period included the COVID-19 pandemic and the introduction of the lockdowns that were first put in place from 26 March 2020 to 27 April 2020, with strong restrictions on transport. Legally, individuals had to stay home other than for essential personal movement. These restrictions resulted in a dramatic decrease in traffic volume to around 15% of usual rates during the lockdown period.[11] Auckland city was subject to further lockdowns at other periods during the pandemic.

The Health and Disability Ethics Committee approved this study (2022 EXP 12993) and the Data Governance Groups of the NZTR and Manatū Hauora – Ministry of Health approved the use of their respective data.

Statistical analysis

Age standardisation was applied to all ethnicity rates, with 95% confidence intervals calculated using the Dobson method.[12] Incidence rates were calculated using the 2022 Census data and presented as an event rate per 100,000 population, as robust exposure data were unavailable for all modes of transport. Temporal trends were not analysed for pedestrians and cyclists due to insufficient numbers.

Due to the disruption to usual transport activity by the COVID-19 restrictions in 2020, an interrupted time series analysis (ITSA) was used to determine changes in the number of incidents over the study period.[13] The ITSA models accounted for seasonality and were compared to the counterfactual to investigate if the disruption altered the post-COVID trends. Two models were used for the modes of transport with sufficient incidents to analyse: one for motorcycle, and one for car occupant. Further details are described in the Appendices. Analysis was performed using R statistical software[14] and statistical significance was defined as $p<0.05$.

Results

Over the 4-year period there were 20,607 incidents of transport-related road trauma that resulted in a hospital admission in New Zealand. Of these, 14.5% (2,992) involved injuries that were classified as major trauma.

Car occupants accounted for 62% of incidents, followed by motorcyclists (23%), pedestrians (9%) and pedal cyclists (4%) (Table 1). Males made up 63% of the cohort and the median age was

Table 1: Age, ethnicity, sex and period of road trauma cohort by mode of transport, 2017/2018–2020/2021. Q1= first quartile, Q3= third quartile.

		Mode of transport			
	All road trauma	**Car**	**Motorcycle**	**Pedal cycle**	**Pedestrian**
N =	20,607	12,664	4,709	910	1,802
Age (years), median (Q1–Q3)	38 (23, 59)	36 (22–60)	41 (26–55)	48 (28–60)	39 (20–64)
Ethnicity					
Māori	5,097 (25%)	3,355 (26%)	1,077 (23%)	115 (13%)	441 (24%)
Pacific peoples	1,287 (6.2%)	898 (7.1%)	187 (4.0%)	24 (2.6%)	149 (8.3%)
Asian peoples	1,516 (7.4%)	1,005 (7.9%)	192 (4.1%)	50 (5.5%)	217 (12%)
European/ other	12,707 (62%)	7,406 (58%)	3,253 (69%)	721 (79%)	995 (55%)
Sex					
Female	7,707 (37%)	5,886 (46%)	620 (13%)	205 (23%)	760 (42%)
Male	12,900 (63%)	6,778 (54%)	4,089 (87%)	705 (77%)	1,042 (58%)
Period					
2017/2018	5,256 (26%)	3,341 (26%)	1,093 (23%)	223 (25%)	478 (27%)
2018/2019	5,353 (26%)	3,272 (26%)	1,183 (25%)	257 (28%)	497 (28%)
2019/2020	4,784 (23%)	2,939 (23%)	1,130 (24%)	201 (22%)	379 (21%)
2020/2021	5,214 (25%)	3,112 (25%)	1,303 (28%)	229 (25%)	448 (25%)

Note: "Other" mode of transport was excluded because of low numbers.

Figure 1: Monthly count of road trauma hospitalisations by mode of transport, 2017/2018–2020/2021. Note: Y-axis uses a logarithmic scale.

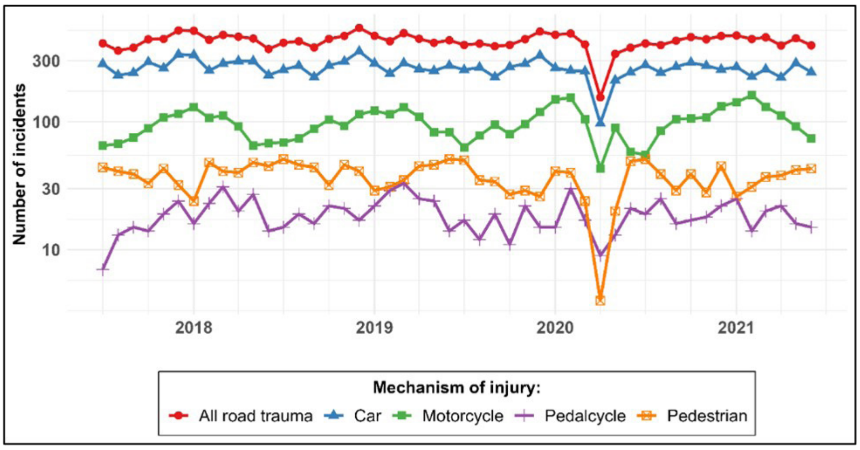


Table 2: Incidence rate of transport-related hospitalisations per 100,000 people by event type and mode of transport, 2017/2018–2020/2021. Parentheses contain 95% confidence interval.

Injury severity	**2017/2018**	**2018/2019**	**2019/2020**	**2020/2021**
Non-major trauma hospitalisation	94.5 (91.8–97.3)	93.8 (91.1–96.6)	82.7 (80.2–85.3)	88.3 (85.7–91.0)
Major trauma	14.9 (13.8–16.0)	15.9 (14.8–17.0)	14.0 (12.9–15.0)	15.7 (14.6–16.8)
Mode of transport				
Car	69.6 (67.2–72.0)	67.1 (64.8–69.4)	59.4 (57.2–61.6)	62.1 (59.9–64.3)
Motorcycle	22.8 (21.4–24.2)	24.3 (22.9–25.7)	22.8 (21.5–24.2)	26.0 (24.6–27.4)
Pedal cycle	4.6 (4.1–5.3)	5.3 (4.6–6.0)	4.1 (3.5–4.7)	4.6 (4.0–5.2)
Pedestrian	10.0 (9.1–10.9)	10.2 (9.3–11.1)	7.7 (6.9–8.5)	8.9 (8.1–9.8)
Other	2.5 (2.1–3.0)	3.0 (2.5–3.5)	2.7 (2.3–3.2)	2.4 (2.0–2.9)
Total	**109.5 (106.5–112.5)**	**109.7 (106.8–112.7)**	**96.6 (93.9–99.4)**	**104.0 (101.2–106.9)**

Table 3: Incidence rate of transport-related hospitalisations per 100,000 people by rural urban classification and ethnicity, 2017/2018–2020/2021. Parentheses contain 95% confidence interval.

Rural Urban Classification	**Rate per 100,000 (95% confidence interval)**
Urban 1	92.0 (90.3–93.7)
Urban 2	108.9 (105.5–112.3)
Rural 1	127.8 (123.3–132.4)
Rural 2	131.8 (125.0–138.9)
Rural 3	198.3 (179.7–218.3)
Ethnicity	**Age-standardised rate per 100,000 (95% confidence interval)**
Māori	155.9 (151.6–160.2)
Pacific peoples	94.0 (88.9–99.3)
Asian peoples	45.1 (42.6–47.6)
European/other	90.7 (88.8–92.6)

38 years (IQR: 25, 59). Those of European/other ethnicities made up 62% of incidents, followed by Māori (25%), Asian peoples (7.4%) and Pacific peoples (6.2%).

A sharp decline in deaths and serious injury in early 2020 was observed and coincided with the period of the COVID-19 Alert Level 4 lockdown, which was in place from March 2020 to April 2020 (Figure 1).

The incidence rate of all transport-related hospitalisation was lowest in 2019/2020, at 96.6 per 100,000 people (95% CI: 93.6–99.4), although motorcycle incidents were highest in 2020/2021 than in any other period prior (Table 2).

The rate of transport-related hospitalisation varied between age groups within different modes of transport. Those aged 80 years and older had the highest rate of incidents as car occupants, followed by those aged 20–24 years. Pedal cyclist incidents were highest for those aged 55–59 years. An increase in the incidence rate of motorcycling injuries was observed for males aged 10–19 and 60–69 years (Appendix Table 1).

Asian peoples had a substantially lower rate of transport-related hospitalisation than other ethnicity groups, with around half the incidence rate of NZ European/other for both injury severity categories (Table 3). Māori had an age-standardised incidence rate almost 3.5 times higher than the rate for Asian peoples.

Incidence rates for road trauma hospitalisation were higher in people living in rural areas relative to people living in urban areas. People living in the remotest rural areas (rural 3) had over twice the rate of hospitalisation (198.3, 95% CI: 179.7–218.3) than those living in the densest urban areas (92.0, 95% CI: 90.3–93.7; Table 3).

Car model

The seasonal model best captures the car injury hospitalisations patterns for both the pre-COVID and post-COVID periods (refer red line predictions in Figure 2). Again, the sharp drop-off of car injury hospitalisations at the start of the COVID-19 period appeared to be only a minor interruption as the expected pre-COVID seasonal pattern returned.

During the pre-COVID period, there was no change over time in the number of car occupant hospitalisation injuries (IRR= 1.000, 95% CI: 0.999–1.000, p= 0.326). The car model detected a fall in the rate of car injury hospitalisations of between 3% to 68% into the initial week of COVID-19 (IRR= 0.565, 95% CI: 0.320–0.997, p= 0.049). However, the average car rate returned to the counterfactual by first week into the post-COVID period, with no difference between the post-COVID and counterfactual detected (IRR= 1.032, 95% CI: 0.918–1.161, p= 0.595) (Appendix Table 2).

Motorcycle model

The seasonal model captured the seasonal pattern in motorcycle hospitalisation counts for both the pre-COVID and post-COVID periods, as seen by the predictions in Figure 3. The sharp drop-off of motorcycle-related hospitalisations at the start of the COVID-19 period appeared to be only a minor interruption as the expected pre-COVID seasonal pattern returned, albeit initially lower than the counterfactual model, but returned by the end of the period.

During the pre-COVID period there was an increase in the number of weekly motorcycle injury hospitalisations (*IRR*= 1.001, *95% CI:* 1.000–

Figure 2: Predicted outcome from seasonally adjusted and non-seasonally adjusted car model, with counterfactual scenario (dashed lines).

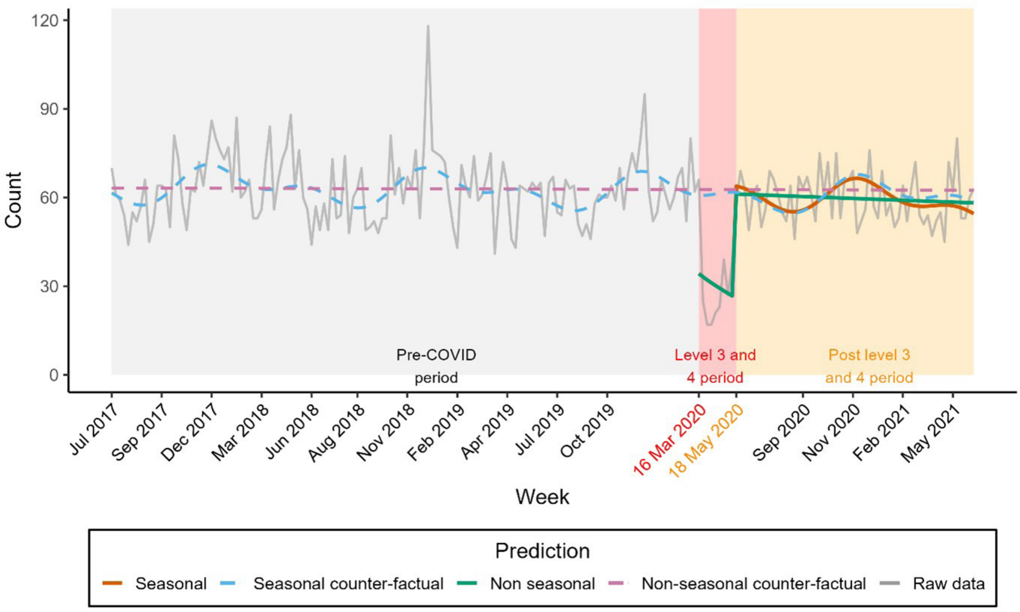
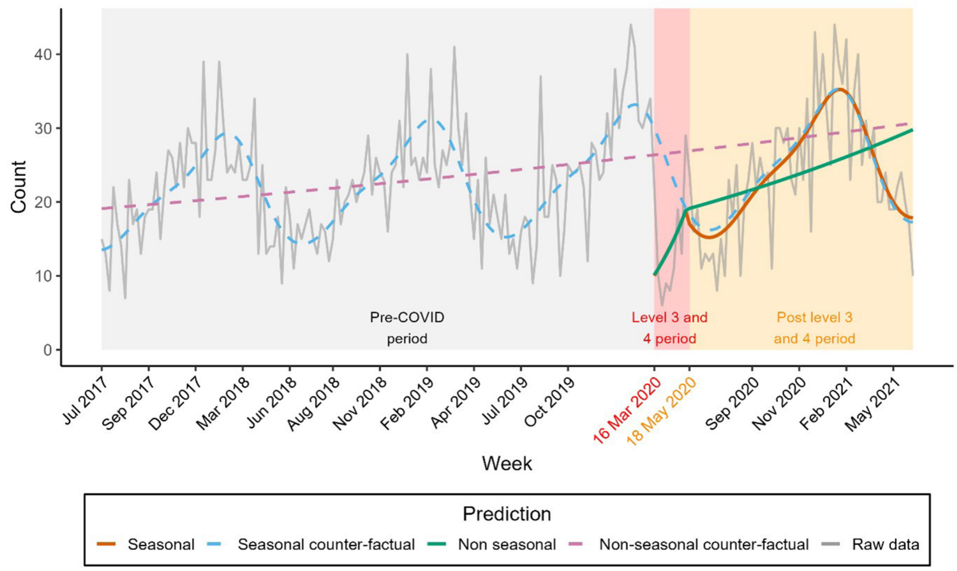


Figure 3: Predicted outcome from seasonally adjusted and non-seasonally adjusted motorcycle model, with counterfactual scenario (dashed lines).



1.002, *p*= 0.009). As expected, the COVID-19 period was associated with a large decrease in the count of motorcycle injury hospitalisations into the first week of between 33% to 83% (IRR= 0.334, 95% CI: 0.167–0.667, p= 0.002), which was an initial deviation from the counterfactual. However, post-COVID, motorcycle hospitalisations were similar to the predicted rate using data from a pre-COVID period. (Appendix Table 3).

Discussion

This study has highlighted the difference in rates across modes, and across ethnicity groups, and has described the impact of COVID-19. The results are unique to the New Zealand context, although many results are consistent with the findings in international studies of this nature.[15–17]

The rate of motorcycle injury hospitalisations increased over the study period and were over 10% higher in 2020/2021 than in 2017/2018, and largely occurred in men. This is despite investment in initiatives to reduce motorcycle injuries, such as rider competency training.[18] The incidence rate is nearly double for motorcycle injury for those who live rurally compared to urban domicile, but to the best of our knowledge there is scant research to understand why the difference occurs. The results suggest two quite distinct demographic groups who are being injured on motorcycles: males aged between 10–19 and 60–69 years, where significant increases in the rate of injury were observed, and males aged between 20–59 that had high rates of injury. Motorcycle exposure data shows a reduction of 18 million kilometres over the 4 years of this study.[19] This suggests that while motorcycling injuries are increasing, that increase is *not* necessarily associated with increased exposure.

The converse pattern is observed for pedal cyclists. The number of cycling injuries has remained stable, but the number of cyclists has increased, at least in the urban areas on key cycling routes.[20–22] One possible explanation is that the infrastructure spending by local councils and the transport agencies to build dedicated cycle lanes separated from cars and other vehicles may be successful in reducing cycling injuries. Another possibility is that cycling injuries are not being captured well in the data, which is discussed further below.

There is distinct variation in the patterns of transport-related injury by ethnicity. We found that Asian peoples have a much lower rate of transport-related road trauma. There is a dearth of research to provide insight into what influences among Asian peoples lead to this low rate of injury. While Asian peoples may be more urban than the total population, this does not explain the difference, as both major and non-major trauma rates in Asian peoples are approximately half of the rates in the urban 1 category.

A study by Randal et al. showed a faster rate of increase of transport-related deaths and serious injury for Māori than non-Māori between 2014 and 2017.[23] Our study shows this upward trend has continued unabated over the subsequent 4 years after their study. There is a substantial long-term negative impact on Māori health at a similar level due to the effects of tobacco and obesity.[24] The relationship between age, rurality and Māori ethnicity indicate there are specific geographical locations where serious injury is particularly high.

The differences of hospitalisation rate across ethnicities, sex and age groups provide some impetus to the aims of *Road to Zero*. Given the evidence that there is variation between some groups within the population on the magnitude of the 40% target, this implies that the aims are achievable in principle, and that a focus on reducing inequities is a worthy endeavour.

Strengths and weaknesses

The use of ICD-10-AM external cause codes alone appears to be insufficient for identifying all relevant hospitalisations that occurred during the study period. The coding system distinguishes between "traffic" and "non-traffic" events, and analysis suggests hospitalised pedal cyclists and pedestrians not involved in a collision with another vehicle are often coded as "non-traffic" events, even if the incident occurred on a public road. All but one of the 910 pedal cycle incidents captured in this study have an external cause code indicating a collision with another vehicle. The NMDS collects information on place of occurrence (which can be identified as a road/street or highway) of injury and external cause codes for falls, which taken together could be used to identify transport incidents that have been coded as "non-traffic" in future studies. Previous work investigating pedestrian injuries in Victoria, Australia using this method identified approximately 65 times more pedestrian falls than were present in the Victorian Police report Road Crash Data.[25]

Better exposure data, and agreement on how to interpret that data, is needed for all modes of transport to understand whether changes over time can be attributed to changes in usage. Differences between modes with respect to the number of kilometres, travel time, number of trips and vehicle registrations contribute to analysis of exposure rates. Notwithstanding this limitation, trend analysis, such as analysed in this paper, is important particularly in the context of reducing deaths and serious injuries for all road users.

Conclusions

This study has highlighted critical differences in road trauma rates and explored trends over time. The increases in motorcycling injuries and no changes in car, pedestrian and cycling injuries, as well as demographic variation, highlight the need to focus on vulnerable road users. Effective and targeted initiatives for vulnerable road users will support the aims to reduce deaths and serious injury on New Zealand roads. More clearly defined exposure data is needed to provide an accurate denominator. Linked data across population-based datasets is an important asset that enhances our understanding of road traffic injuries and allows evidence-based countermeasures to be developed.

COMPETING INTERESTS

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Appendices

Appendix Table 1: Incidence rate of motorcycle transport-related hospitalisations per 100,000 people by age group, 2017/2018–2020/2021. Parentheses contain 95% confidence interval.

	Period			
Age (years)	**2017/2018**	**2018/2019**	**2019/2020**	**2020/2021**
0–9	1.3 (0.5–2.5)	1.7 (0.9–3.1)	3.0 (1.8–4.7)	1.7 (0.9–3.1)
10–19	16.5 (13.5–20.0)	17.5 (14.4–21.1)	19.1 (15.9–22.8)	23.8 (20.2–27.9)
20–29	38.2 (33.7–43.1)	39.0 (34.5–43.9)	31.2 (27.2–35.7)	36.0 (31.7–40.8)
30–39	28.0 (24.0–32.5)	28.9 (24.9–33.4)	26.7 (22.9–30.9)	27.2 (23.4–31.4)
40–49	31.4 (27.1–36.1)	30.4 (26.2–35.0)	30.6 (26.4–35.3)	30.4 (26.2–35.0)
50–59	34.4 (30.0–39.4)	37.8 (33.1–42.9)	34.6 (30.2–39.5)	38.7 (34.0–43.9)
60–69	18.7 (15.1–22.9)	25.9 (21.6–30.6)	26.0 (21.8–30.7)	35.1 (30.3–40.5)
70–79	9.9 (6.8–14.0)	11.5 (8.2–15.7)	12.1 (8.8–16.3)	15.0 (11.3–19.5)
80+	7.5 (4.0–12.9)	5.1 (2.3–9.6)	3.3 (1.2–7.1)	11.5 (7.2–17.3)

Appendix Table 2: Estimated incident rate ratios, 95% confidence intervals and p-values for car seasonal and non-seasonal model.

	Seasonal model			Non-seasonal model		
Characteristic	**IRR[1]**	**95% CI[1]**	**p-value**	**IRR[1]**	**95% CI[1]**	**p-value**
Pre-COVID period slope change	1.000	0.999, 1.000	0.326	1.000	0.999, 1.001	0.906
COVID-19 period level change	0.565	0.320, 0.997	0.049	0.545	0.306, 0.971	0.040
COVID-19 period slope change	0.967	0.860, 1.088	0.575	0.970	0.862, 1.091	0.608
Post-COVID period level change	2.474	1.352, 4.526	0.003	2.361	1.309, 4.257	0.004
Post-COVID period slope change	1.032	0.918, 1.161	0.595	1.030	0.916, 1.159	0.617
Seasonal parameters (Fourier)						
Fourier 1	0.973	0.939, 1.008	0.131			
Fourier 2	0.963	0.932, 0.995	0.026			
Fourier 3	0.935	0.901, 0.970	0.000			
Fourier 4	1.039	1.001, 1.078	0.042			

[1]IRR = Incidence Rate Ratio, CI = Confidence Interval

Appendix Table 3: Estimated incident rate ratios, 95% confidence intervals and p-values for motorcycle seasonal and non-seasonal model.

	Seasonal model			Non-seasonal model		
Characteristic	**IRR[1]**	**95% CI[1]**	**p-value**	**IRR[1]**	**95% CI[1]**	**p-value**
Pre-COVID period slope change	1.001	1.000, 1.002	0.009	1.002	1.000, 1.005	0.063
COVID-19 period level change	0.334	0.167, 0.667	0.002	0.385	0.196, 0.754	0.006
COVID-19 period slope change	1.144	1.010, 1.296	0.035	1.078	0.953, 1.220	0.232
Post-COVID period level change	0.829	0.490, 1.402	0.483	0.940	0.508, 1.738	0.842
Post-COVID period slope change	0.876	0.773, 0.993	0.039	0.933	0.824, 1.055	0.268
Seasonal parameters (Fourier)						
Fourier 1	0.884	0.843, 0.927	0.000			
Fourier 2	1.051	1.006, 1.097	0.025			
Fourier 3	0.736	0.706, 0.766	0.000			
Fourier 4	0.925	0.889, 0.962	0.000			

[1]IRR = Incidence Rate Ratio, CI = Confidence Interval

Statistical analysis

Motorcycling and car occupant data was collapsed into weekly counts and plotted as a time series graph to establish the appropriate ITSA period segments: pre-COVID period included weeks up to 16 March 2020 and considered the counterfactual; COVID-19 period corresponded to Level 4 and 3 restrictions and included weeks 16 March 2020 to 17 May 2020; post-COVID period included weeks 18 May 2020 to 27 June 2021. Three days were excluded from the start and end of the period due to containing incomplete weekly data. Quasi-Poisson generalised linear models (GLM) were used in the ITSA due to the presence of overdispersion in the count data. The Quasi-Poisson uses the mean regression and variance functions from the standard Poisson model but allows the dispersion parameter to be unrestricted and estimated from the data so the standard errors are scaled appropriately in the presence of overdispersion.[26] The ITSA models of the count of incidents included the time since start of study, dummy variables representing the COVID-19 and post-COVID periods and the interaction of period and time. To account for seasonal trends in the data, a Fourier term was included that allowed for regular seasonal shifts in the number of incidents.[27] Since the presence of autocorrelation and heteroskedasticity of the residuals was detected from model diagnostics, a Newey–West standard error adjustment was made to handle autocorrelation in addition to possible heteroskedasticity with the maximum lag set according to Stock and Watson's[28] rule-of-thumb. Post-estimation model diagnostics included deviance and autocorrelation graphs. The predicted count level change from the first week of the post-COVID period from the pre-COVID period (counterfactual) were performed to establish the potential impact of the preceding COVID-19 period. Predicted counts for each ITSA segment from the models were graphed against the counterfactual. Poisson tests and GLM models using the *stats* package, age standardisation using the method in the *dsrTest* package.[29] Counterfactual comparisons were performed using the *multicomp*[30] package.