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CAMA Working Paper 57/2018
November 2018

Rohan Best
Department of Economics, Macquarie University

Paul J. Burke
Centre for Applied Macroeconomic Analysis, ANU

Abstract

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Keywords

fuel price, road accident death, road accident injury

JEL Classification

Q41, Q48, R41

Address for correspondence:

(E) cama.admin@anu.edu.au

ISSN 2206-0332

Fuel prices and road accident outcomes in New Zealand

Rohan Best[*,**] and Paul J. Burke[**]

[*] Department of Economics, Macquarie University, Sydney, NSW 2109, Australia. rohan.best@mq.edu.au
[**] Centre for Applied Macroeconomic Analysis, Australian National University, ACT 2601, Australia. paul.j.burke@anu.edu.au

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Recent years have seen a spike in New Zealand's road death toll, a phenomenon also seen in some other countries such as Australia. This paper analyses the short-run impact of fuel prices on road accident outcomes in New Zealand, including the numbers of road deaths, accidents, and injuries. Using data for the period 1989–2017, we find a negative relationship between fuel prices and key road-risk outcome variables, including the number of road deaths. There are similar results for models in levels and first differences. The number of serious injuries to cyclists tends to increase when fuel prices are high, however. Lower fuel prices appear to have contributed to New Zealand's recent uptick in road accidents, pushing against the long-term trend of improved road safety.

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Acknowledgements: We are grateful for feedback from anonymous reviewers and seminar participants at the Australian National University, and econometric advice from several colleagues. Funding was received from the Australian Research Council (DE160100750).

1. Introduction

Around seven people per 100,000 population are killed in road crashes in New Zealand every year, a higher rate than Australia (five per 100,000 population; OECD, 2017). The annual total social cost of road crashes in New Zealand – including costs of injury – has been estimated at over 3.7 billion New Zealand dollars (New Zealand Ministry of Transport, 2013, 2017). There has been an uptick in road crashes and deaths in New Zealand in recent years, a phenomenon also seen in some other developed countries including Australia, the United States, and Great Britain. This has drawn renewed attention to what has long been considered a pressing policy priority.

At the centre of New Zealand's road safety policy is the Safer Journeys campaign, launched in 2010. Safer Journeys is a multi-pronged strategy with the goal of "a safe road system increasingly free of death and serious injury" (New Zealand Ministry of Transport, 2013, p. 3). New Zealand also has more specific goals such as "zero fatalities and reduced serious injuries for people who cycle" (Cycling Safety Panel, 2014, p. 8).

Road accidents are a function of factors including road user behaviour, road characteristics, vehicle characteristics, and the distances driven on roads by different types of drivers. Research has also shown that, behind the scenes, economic variables can affect underlying road accident risk exposure. Among these, fuel prices and key macroeconomic measures such as the unemployment rate have been the focus of prior studies of road accidents in the United States (e.g. Grabowski and Morrisey, 2006; Chi *et al.*, 2011; 2012; 2013; 2015; Robertson, 2018) and other countries (e.g. Ahangari *et al.*, 2014; Burke, 2014; Burke and Nishitateno, 2015; Burke and Teame, 2018).

The most obvious channel via which fuel prices might influence the number of road accidents is by affecting travel distances. When fuel prices are low, people are likely to drive more, exposing themselves to additional road accident risks.

Fuel prices could also influence the number of road accidents per kilometre travelled. For example, lower fuel prices could free up space in household budgets for spending on alcohol, which could lead to more alcohol-related accidents. Lower fuel prices may also induce more dangerous driving styles involving more rapid accelerating and braking, on account of reduced concern over fuel economy. The demographic mix of drivers could also evolve when fuel prices change; lower fuel prices could lead to a disproportionate increase in road travel by young drivers, for instance, who are statistically more likely to crash.

The effects of fuel prices on road accidents may vary by transport mode. When fuel prices are high, drivers may substitute to fuel-efficient modes such as motorcycles and bicycles. One might expect fewer car accidents, but more motorcyclist and cyclist accidents, although we note that the number of motorcyclist and cyclist accidents is also affected by the number of cars and other vehicles on the road. Studies for the United States show that higher gasoline prices can indeed lead to more motorcycle fatalities in that country (Hyatt *et al*., 2009; Wilson *et al*., 2009; Zhu *et al*., 2015). Motorcyclists and cyclists are particularly vulnerable road users (Nishitateno and Burke, 2014), although they only accounted for 24% and 3% of road-crash hospitalisations in New Zealand in 2016, respectively.

In this paper we present the first detailed analysis of the effect of fuel prices on a range of short-run road accident outcomes in New Zealand. A report to the New Zealand Ministry of Transport (Keall *et al*., 2012) and a follow-up report by Infometrics (2013) investigated factors causing a dramatic drop in the number of road fatalities in New Zealand in 2011, but did not investigate the effect of fuel prices on outcomes other than fatalities. These reports found that the drop in road deaths was due to a return to trend, higher fuel prices, higher real wage rates (real wages per unit of time), lower motor cycle registrations, and a substantial unexplained component. Other studies for New Zealand have found some evidence that real gross domestic product per capita is a significant short-run factor in explaining fatal crashes (Scuffham and Langley, 2002; Scuffham, 2003).

This paper is a companion to a paper for Australia (Burke and Teame, 2018), for which strikingly similar results are reached: a short-run fuel price elasticity of road deaths of around –0.2 to –0.3. The Australian paper formed a submission to the country's 'Inquiry into progress under the National Road Safety Strategy 2011-2020'. The first item on the Terms of Reference for this Inquiry was to 'Identify the key factors involved in the road crash death and serious injury trends including recent increases in 2015 and 2016'.[1]

Our empirical approach uses national time-series data. We obtain generally similar results using several estimation approaches, including an instrumental variable strategy and a

[1] See http://roadsafety.gov.au/performance/files/ToR-Inquiry-into-National-Road-Safety-Strategy-2011-2020.pdf.

specification in first differences. Our approach complements international studies using cross-sectional or panel data for a sample of countries (e.g. Ahangari *et al*., 2014; Burke and Nishitateno, 2015).

Figure 1 shows New Zealand's annual number of road deaths since 1921. Deaths peaked in 1973, and then declined subsequent to the international oil price rises and due to factors such as strengthened seatbelt laws and lower speed limits (New Zealand Ministry of Transport 2016).[2] Road deaths rose again in the early 1980s. There has since been a general decline since the late 1980s. Unfortunately, recent years have seen the largest increase in road deaths since the 1980s. From a low of 253 in 2013, annual road deaths increased by 30% by 2016, reaching 328. Road deaths increased further in 2017, reaching 379 (New Zealand Ministry of Transport, 2018). There have also been increases in the numbers of road accidents and serious injuries.

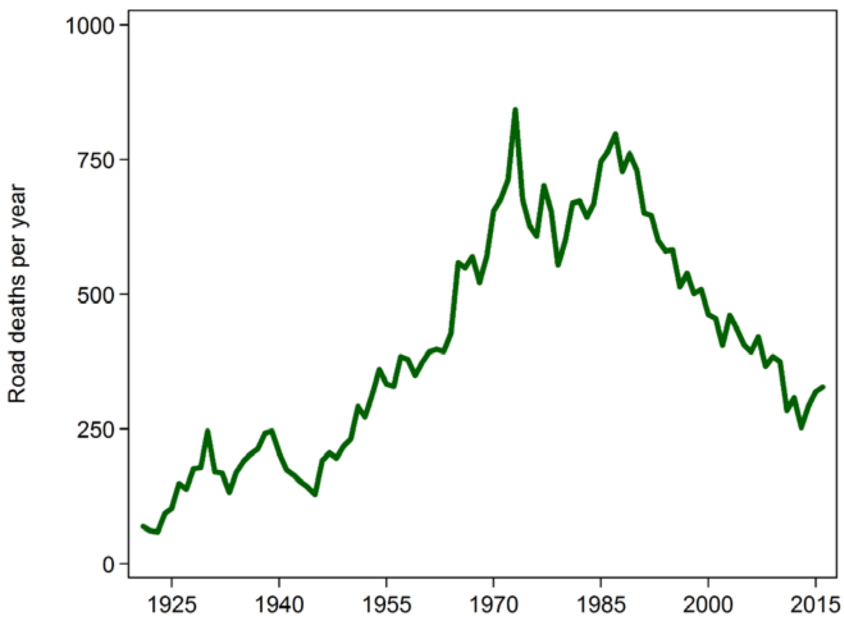


Figure 1. Road deaths in New Zealand, 1921–2016. Source: New Zealand Ministry of Transport (2018).

Figure 2 shows road deaths and the real gasoline price in New Zealand from the mid-1970s. The second half of the 1980s and the 1990s saw declines in both real gasoline prices and road

[2] The open-road speed limit was reduced to 50 miles per hour (80 kilometres per hour) in 1973, from 55 or 60 miles per hour. It was subsequently increased to 100 kilometres per hour in 1985 (New Zealand Ministry of Transport, 2016).

deaths. Since 2000, an inverse relationship between road deaths and real gasoline prices is observable. After the fall in pump prices due to the world oil price crash in late 2014, the annual number of road deaths has increased every year since. The onset of the increase in road deaths closely coincided with the fall in pump prices: the road toll in the final quarter of 2014 exceeded the road toll in the final quarter of 2013 by 30 (45%). In contrast, the number of road deaths in the third quarter of 2014 came in below the number of road deaths in the third quarter of 2013.

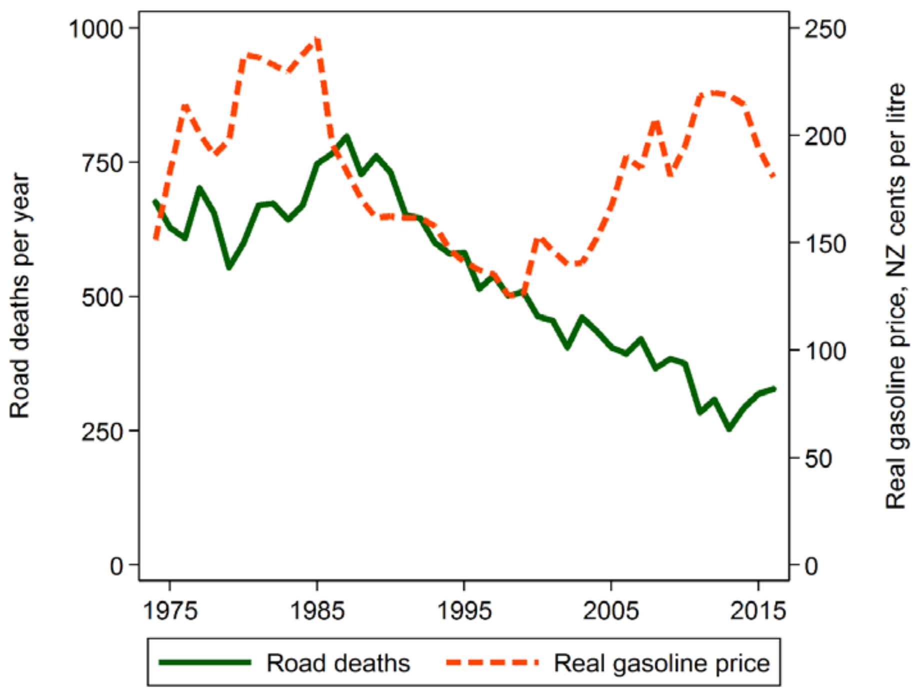


Figure 2. Road deaths and real gasoline prices in New Zealand, 1974–2016. Sources: New Zealand Ministry of Transport (2018), New Zealand Ministry of Business, Innovation & Employment (2017).

One advantage of studying New Zealand is that relatively comprehensive road transport data are available, including data on vehicle-kilometres travelled by the motor vehicle fleet (including motorcycles) in recent years. The vehicle-kilometres travelled data are estimates based on odometer readings taken during inspections for certificates of fitness or warrants of fitness (New Zealand Ministry of Transport, 2018). The data indicate that the increase in New Zealand's road death toll was not solely due to an increase in vehicle-kilometres driven. Comparing 2016 to 2013:

- Road deaths increased by 30%.

- The number of vehicle-kilometres driven increased by 11%.
- The number of road deaths per vehicle-kilometre driven increased by 19%.
- The average real fuel price fell by 23% (among other developments).

The rate of increase in road deaths has differed for different road-user types, road types, and regions. Comparing 2016 to 2013, road deaths increased for drivers, passengers, and motorcyclists. They decreased for pedestrians and cyclists. Deaths on open roads increased by 70, while deaths on urban roads increased by only five. The Waikato region accounted for over 60% of the increase in New Zealand's road deaths (New Zealand Ministry of Transport, 2018). Nationally, there were 118 road deaths related to alcohol and drugs in 2016, compared to 76 in 2013.

Figure 3 shows quarterly data on New Zealand's deaths, serious injuries, and minor injuries from road accidents. The series display indications of seasonality, and each has ticked up over recent years. Figure 3 also draws attention to the fact that we are using time-series data, for which careful handling of issues associated with potentially non-stationary data is required.

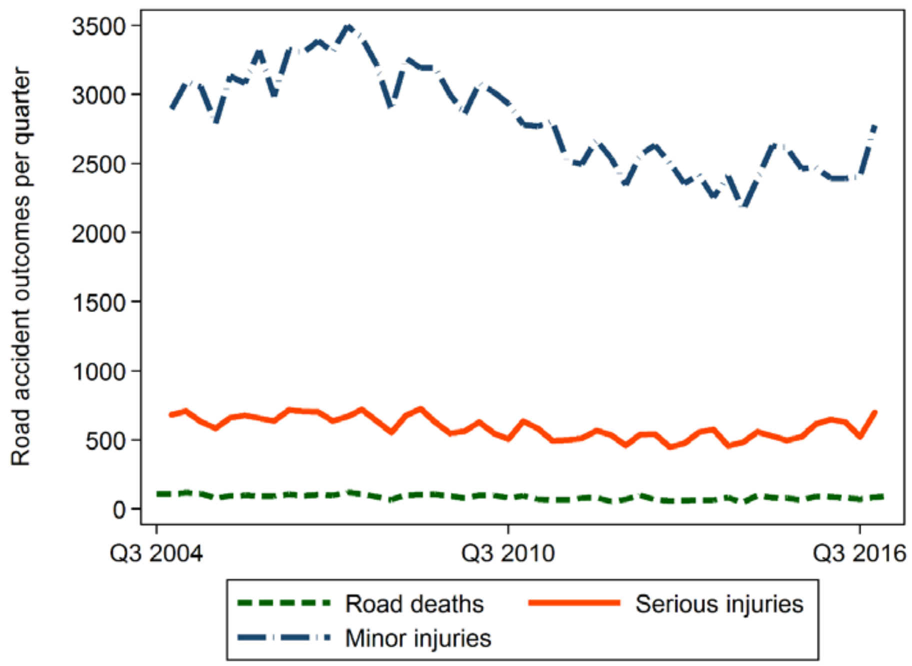


Figure 3. Road accident outcomes in New Zealand per quarter. Sources: New Zealand Ministry of Transport (2018), New Zealand Transport Agency (2017).

Lower fuel prices likely bring a number of costs outside the sphere of road safety, including road congestion and pollution from additional road transport flows. Using New Zealand data, Shaw *et al*. (2018) find suggestive evidence of a modest (albeit non-significant) reduction in air pollutants when petrol prices rise. We also note that there are numerous benefits of lower fuel prices, including expanded consumption possibilities for consumers. Producers also often benefit, especially when fuel costs are important inputs to production. Our focus in this paper is on implications for road safety rather than broader effects on overall consumer welfare.

2. Method and data

2.1 Unit root tests

Before proceeding to select a model form, we first conducted tests for unit roots in our key data series. We use a two-step process. The first is to deseasonalise the data by estimating the following equation:

$$\ln y_t = \alpha + \sum_{i=1}^{i=11} \phi_i B_{i:t} + \varepsilon_t \tag{1}$$

where $\ln y_t$ is the natural logarithm of a road crash outcome variable or the real fuel price, and B is a set of binary variables for the month of the year. There are 11 monthly binary variables, with i = 1 to 11, as one month is dropped to avoid perfect collinearity. We save the residuals, $\hat{\varepsilon}_t$.

The second step involves augmented Dickey and Fuller (1979) regressions on $\hat{\varepsilon}_t$, choosing a lag order p, as in equation 2. We utilise lag lengths chosen by the Bayesian information criterion so as to address potential serial correlation in the error term. We restrict the maximum number of lags to six to avoid low test power. There has been considerable debate about the many different options for choosing the lag length and the maximum lag length for unit root tests, and it has been noted that these tests can be sensitive to specification choices (Ng and Perron, 1995; Ng and Perron, 2001). We include trend terms for variables that appear to display a trend, based on Figure A.1 in the Appendix. This includes our main dependent variable (log road deaths). Our unit root tests use the maximum series length that we have access to for each variable, and data of monthly frequency in order to utilise as large a dataset as possible.

$$\Delta\hat{\varepsilon}_t = \alpha + \lambda t + \gamma\hat{\varepsilon}_{t-1} + \delta_1\Delta\hat{\varepsilon}_{t-1} + \cdots + \delta_{p-1}\Delta\hat{\varepsilon}_{t-p+1} + u_t \tag{2}$$

The results of the augmented Dickey-Fuller tests for each of the dependent variables and the key independent variable of the log real fuel price are shown in Table 1. The tests reject the null of a unit root at the 5% level for most of the variables. Importantly, for our two key variables (log road deaths, and the log real fuel price), a unit root is rejected at the 5% level. Note that a unit root could not be rejected at the 5% level for the *nominal* fuel price, but that our analysis uses the deflated series.

As a check on the augmented Dickey-Fuller tests, we also carried out alternative unit root tests. A Phillips and Perron (1988) test rejects the null of a unit root in log road deaths at the 1% level of significance. Using the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test (Kwiatkowski et al. 1992), we cannot reject the null of stationarity of log road deaths at the 1% level. These tests thus provide evidence against strong unit root behaviour in our dependent variable, instead pointing towards trend stationarity. In contrast, an Elliot, Rothenberg, and Stock (1996) test cannot reject the null of a unit root in log road deaths at the 1% level of significance. We thus have somewhat conflicting results. All of these tests are available in the online Stata code.

Given the evidence from the augmented Dickey-Fuller test (and two of the additional tests) that log road deaths is a trend stationary variable, we initially estimate a model in levels. Noting the sensitivity of unit root testing, however, and as a check on the robustness of our results, we will also show estimates in first differences. Our high-level findings are similar using either approach. Note that Burke and Teame (2018) also did not find strong evidence in favour of unit root behaviour in log road deaths or the log real gasoline price for the case of Australia. Unit roots are also rejected for monthly traffic crashes in a study for Minnesota in the US (Chi *et al*. 2013).

Table 1. Augmented Dickey-Fuller unit root tests, monthly data

Residual for:	Observations	Lags	Trend	Test statistic	*p*-value
Ln road deaths	627	5	Yes	–4.21	0.00
Ln real fuel price	155	1	No	–3.08	0.03
Ln road deaths (alcohol/drugs)	447	5	Yes	–5.01	0.00
Ln road deaths (not alcohol/drugs)	447	5	Yes	–5.82	0.00
Ln road deaths: open roads	447	5	Yes	–5.44	0.00
Ln minor injuries from road crashes	447	2	No	–2.97	0.04
Ln serious injuries from road crashes	447	5	Yes	–1.69	0.76
Ln road accidents	339	2	No	–2.28	0.18
Ln serious injuries (light vehicles)	447	5	Yes	–3.12	0.10
Ln serious injuries (cyclists)	447	3	Yes	–5.95	0.00
Ln serious injuries (motorcyclists)	447	2	Yes	–2.77	0.21
Ln serious injuries (pedestrians)	447	5	Yes	–5.25	0.00

Notes: Tests are based on equation (1) and (2). Lag length chosen by Bayesian information criterion (BIC), with a maximum lag length of six. Inclusion of a trend term is based on visual inspection of Figures for each variable (shown in the Appendix). The critical values at the 10% level of significance are –3.13 when a trend is included and –2.57 when there is no trend. Test statistics that are more negative than the critical value allow rejection of the null hypothesis that there is a unit root. Each sample uses the maximum length of monthly observations that we have access to.

2.2 Empirical models

We first estimate the model in levels, with a trend explanatory variable, as shown in equation 3. This is a straightforward approach for trend-stationary variables, and is usually the preferred option (Hill et al., 2008). We use Newey-West (1987) estimates that assume the error structure is heteroskedastic and possibly autocorrelated up to some lag. The Newey-West procedure uses a lag length of four, based on the suggestion of using the smallest integer greater than or equal to the sample size to the power of the fourth root (Greene, 2012).

$$\ln D_t = \alpha + \beta \ln F_t + \gamma t_t + \sum_{i=1}^{3\ or\ 11} \phi_i B_{i:t} + \mu E_t + \chi L_t + \delta U_t + \theta C_t + \zeta V_t + u_t \qquad (3)$$

D is road deaths in time period t (a month or quarter). F is the average fuel price in real terms (March 2017 prices), measured as a weighted average of the average gasoline and diesel retail prices. t is a time trend. B is a set of binary variables for month or quarter of the year. E is an Easter binary variable. L is a binary variable equal to 1 for the appropriate quarter or month of leap years (to account for the extra day). U is the unemployment rate. C is the consumer confidence index (when using monthly data) or the log of real average weekly earnings (when using quarterly data), to control for the economic cycle. V is the number of international visitor arrivals per capita, an important control due to New Zealand's large tourist industry relative to the domestic population, and also because travelling to New Zealand should be cheaper when oil prices are lower. The per capita calculation uses New Zealand's working age population. u is an error term.

Studies for other countries (e.g. Burke and Teame, 2018) usually focus on road deaths because the data are typically more complete and accurately measured than data on other road crash outcomes, such as injuries. Given the availability of suitable data for New Zealand, we supplement fatality data with dependent variables equal to the log number of accidents, serious injuries, and minor injuries. The number of accidents includes minor accidents that are reported to police. We also assess dependent variables that focus on specific types of transit: motorcyclists, cyclists, and pedestrians. The data on accidents and injuries are subject to some degree of time-varying reporting error (Infometrics, 2013).

The road, vehicle safety, and emergency care improvements that have occurred over time are partly accounted for by our time trend control. The monthly or quarterly binary variables are important because there may be varying numbers of road accidents due to weather, holidays, and the different numbers of days in each month/quarter. The Easter binary variable accounts for the possibility of having more road accidents during Easter, a holiday that does not always fall in the same month/quarter. A summary of the data is provided in Appendix Table A.1.

We also use an alternative model in first differences (equation 4) as a robustness check. These specifications also include additional lags of the first-differenced log fuel price term so as to assess lagged impacts. We consider lags of up to four quarters.[3] $\boldsymbol{X}_t$ in equation 4 is a vector of controls used in equation 3. $\boldsymbol{B}_t$ is a vector that includes the seasonal variables from equation 3. There is no time trend in equation 4, as this disappears on differencing.

$$\ln D_t - \ln D_{t-1} =$$

$$\alpha + \gamma_1(\ln F_t - \ln F_{t-1}) + .. + \gamma_4(\ln F_{t-3} - \ln F_{t-4}) + (\boldsymbol{X}'_t - \boldsymbol{X}'_{t-1})\lambda' + \boldsymbol{B}'_t\theta' + u_t \qquad (4)$$

We also present quarterly estimates that decompose the effect of fuel prices on road deaths into two components: the effect on (1) distance travelled, and (2) road deaths per vehicle-kilometre travelled. These estimates use vehicle-kilometre travelled estimates, available on a quarterly basis from 2001. It should be noted that this variable is not precisely measured, as not all odometers are read each quarter. In particular, the variable misses some fluctuations in vehicle-kilometres travelled. Our decomposition results should thus be interpreted as exploratory. In the future, more accurate measures of vehicle-kilometres travelled may become available for this type of analysis (based on satellite technology, rather than manual readings of odometers).

Our decomposition starts by noting:

$$D_t = (D_t/K_t).K_t \qquad (5)$$

where D is road deaths in period t and K is vehicle-kilometres travelled in period t. Taking the logs of both sides and differentiating with respect to the log of the real fuel price shows that the fuel price elasticity of road deaths equals the sum of the fuel price elasticity of road deaths per vehicle-kilometre travelled plus the fuel price elasticity of vehicle-kilometres travelled:

$$\partial \ln D_t/\partial \ln F_t = \partial \ln(D_t/K_t)/\partial \ln F_t \ + \ \partial \ln K_t/\partial \ln F_t \qquad (6)$$

[3] A prior study using US data found both contemporaneous and lagged effects of gasoline prices on road crashes of up to 10 months (Chi et al., 2015)

2.3 Econometric issues and interpretation

One potential challenge is that it is possible for road transport demand to have an influence on local retail fuel prices. If so, there could be an endogeneity issue affecting our estimates. We use an instrumental variable approach to address this issue. Following previous studies (Burke and Nishitateno, 2013, 2015; Burke and Teame, 2018), we use the log of the real world oil price to instrument New Zealand's log average real fuel price. The logic is that the world oil price is exogenous to New Zealand, and has a direct and tangible effect on local pump prices.

Our estimates will represent relatively short-run effects, as our models do not allow adequate time-to-response for long-run effects to be fully captured. In theory, long-run effects on road accident outcomes are likely to be larger, as some of the impacts of higher real fuel prices – such as people moving closer to their workplaces, and more dense urban development (Creutzig, 2014) – take time to be fully realised. Burke (2014) and Burke and Nishitateno (2015) used between variation across a large sample of countries to identify long-run effects of fuel prices on road deaths. Their approach avoided time-series econometric issues and the specification of lag lengths. Empirical evidence also indicates that long-run price elasticities of gasoline demand exceed short-run elasticities in absolute terms (Brons et al., 2008; Havranek et al., 2012).

2.4 Data and sources

We combine data from a number of sources. Data on road accidents and injuries are from the Crash Analysis System of the New Zealand Transport Agency (2017). Real pump prices of gasoline and diesel are from the New Zealand Ministry of Business, Innovation & Employment (2017), available on a quarterly basis from 1974.[4] For the monthly series, we use nominal weekly prices, available from 2004, to calculate monthly averages, and then convert into real terms using the monthly New Zealand consumer price index. Our fuel price measure uses weights of 60% for gasoline and 40% for diesel, based on the fuel shares of New Zealand's road transport sector during 2000–2014 according to the International Energy Agency (2017).

[4] The Ministry of Business, Innovation & Employment construct real fuel price series using Statistics New Zealand's retail fuel pump price and consumer price index data. Diesel and petrol prices are collected by Statistics New Zealand from fuel companies at several locations around New Zealand.

Data for the unemployment rate, average weekly earnings, international visitor arrivals, working age population, and consumer price index are from Statistics New Zealand (2017). Data for the world oil price, in United States dollars, are from the International Monetary Fund (2017). We converted this into real terms using the US consumer price index from the Federal Reserve Bank of St Louis (2017). Consumer confidence data are from ANZ-Roy Morgan (2017). The variable descriptions and sources are summarised in Appendix Table A.2.

There is a trade-off between using monthly data of higher frequency or quarterly data that cover a longer time series. We alternate between both approaches. We commence with quarterly specifications for a longer time period, then proceed to monthly data. For the quarterly analysis, data are available for each of the variables from 1989. The exception is data on vehicle-kilometres travelled, which are available from 2001.

3. Results and discussion

As augmented Dickey-Fuller tests (Table 1) could reject the null of unit roots for our main variables, we start with levels estimates. Table 2 presents estimates for the period from March 1989 to March 2017 using quarterly data. The coefficient for the log of fuel prices in the first column is –0.3, significant at the 1% level. The coefficient of –0.3 implies that a 1% increase in fuel prices on average leads to a 0.3% decrease in road deaths, holding the other variables constant. This is similar to the finding of Burke and Teame (2018) for Australia. The results on the fuel price elasticity of road deaths in Table 2 are also similar to the estimate of –0.2 for traffic crashes in Alabama (Chi *et al*., 2012), –0.3 for British road casualties (Harvey and Durbin, 1986), and are at the lower bound of the range for the long-run fuel price elasticity of road deaths of –0.3 to –0.6 reported by Burke and Nishitateno (2015) for an international sample.

Table 2. Results for road deaths, quarterly data, March 1989–March 2017

Dependent variable:	Ln road deaths$_t$	Ln road deaths$_t$ (IV)	Ln road deaths (alcohol/ drugs)$_t$	Ln road deaths (not alcohol/ drugs)$_t$	Ln road deaths on urban roads$_t$	Ln road deaths on open roads$_t$
Log real fuel price, NZ c/l$_t$	-0.278***	-0.280***	-0.027	-0.426***	-0.167	-0.339***
	(0.056)	(0.070)	(0.163)	(0.078)	(0.181)	(0.082)
Time trend$_t$	-0.016***	-0.016***	-0.025***	-0.010***	-0.020***	-0.014***
	(0.001)	(0.001)	(0.003)	(0.001)	(0.004)	(0.001)
Log avg. weekly earnings$_t$	2.798***	2.803***	6.153***	0.919*	3.776***	2.409***
	(0.326)	(0.351)	(1.083)	(0.521)	(0.930)	(0.479)
Unemployment rate$_t$	-0.014**	-0.014**	0.006	-0.026***	-0.011	-0.016
	(0.007)	(0.007)	(0.016)	(0.008)	(0.016)	(0.010)
International visitors p.c.$_t$	1.728**	1.722**	1.699	1.543*	1.246	2.231**
	(0.667)	(0.751)	(1.750)	(0.876)	(2.066)	(1.096)
Observations	113	113	113	113	113	113
R^2	0.885	0.885	0.768	0.833	0.715	0.796
Wu-Hausman test *p*-value	0.964	0.964	0.263	0.196	0.692	0.798
Instrumented variable:		Ln real fuel price				
Instrument:		Ln real world oil price				
Coefficient on instrument		0.32***				
F statistic on instrument		501.85				

Notes: ***, **, * show statistical significance at 1, 5 and 10 % level respectively. Newey-West standard errors with lag order four are in brackets below the coefficients (robust standard errors for instrumental variable (IV) column). Coefficients for constants, quarterly binary variables, February leap-year binary variable, and an Easter binary variable are not shown. Variable definitions and units are in the Appendix. The Stock-Yogo test statistic (10% maximal IV size) is 16.38 for the instrumental variable results in the second column. If the *F* statistic on the instrument exceeds this critical value, the null hypothesis of a weak instrument can be rejected. The Wu-Hausman test has a null hypothesis that the fuel price is exogenous. The *p*-values indicate that the null of exogeneity is not rejected at the 1% level. The instrument is the same for all columns.

The second column of Table 2 shows a similar result when instrumenting the log real fuel price with the log real world oil price. The first-stage coefficient for the log of the real world oil price is 0.3, significant at the 1% level. This is reasonable given that pump prices in New Zealand need to cover refining costs, a retail margin, a tax component, and so on, and also given that the instrument is in United States dollar terms. The F statistic on the instrument of 502 exceeds the Stock-Yogo critical value (Stock and Yogo, 2005) of 16.38 (5% level of significance, 10% maximal instrumental variable size), suggesting that there is not a weak instrument problem.

The remaining columns in Table 2 show impacts on road deaths of various types. The fuel price variable does not have a significant coefficient in explaining deaths related to alcohol and drugs, a finding that differs to that of Chi *et al*. (2011) for Mississippi. The estimate has a relatively large standard error, however. The column for road deaths unrelated to alcohol and drugs has a significant coefficient of –0.4. The coefficient in the open-road deaths column is also negative and significant at –0.3. In contrast, the coefficient for urban-road deaths is not estimated precisely. Perhaps holiday driving is more responsive to fuel prices than regular urban trips.

A considerable share of the variation in the dependent variables in Table 2 is explained by the explanatory variables in our model, including 89% of the variation in total log road deaths. The null hypothesis of fuel price exogeneity is not rejected at the 10% level in any column, using the Wu-Hausman test (Wu, 1974; Hausman, 1978) and the same instrument as in the second column. As the results are similar with and without the instrument, it appears that the issue of endogeneity is not in the end a consequential concern. We thus proceed to show single-equation estimates henceforth. The ordinary least squares estimator is able to generate more efficient estimates than instrumental variable estimation (on account of it being the best linear unbiased estimator).

The time trend has negative coefficients in Table 2, suggestive of a secular downward trend in road deaths at a pace of around 1.6% per quarter, holding the other variables constant. This likely reflects factors such as technological improvements in vehicles and improved road design. The effect is even larger for deaths related to alcohol and drug consumption. Adding a quadratic or cubic time trend, or using the log of the working age population instead of the linear time trend, produces similar fuel price coefficients (results available in Stata code).

There are significant coefficients for some of the other explanatory variables in Table 2. The coefficients for the log of average weekly earnings are positive and significant at the 1% level in five of the columns, perhaps because road deaths are more likely when drivers have more income to spend on fuel. This is consistent with evidence from other countries that road deaths tend to spike during economic booms (e.g. International Transport Forum, 2015). Specifically, a 1% increase in average weekly earnings tends to be associated with an increase in road deaths of around 2.8%, *ceteris paribus*. The coefficient in the column for alcohol- and drug-related deaths is larger than the coefficients in the other columns, perhaps because higher incomes relieve budget constraints for both fuel purchases and alcohol/drug consumption. The unemployment rate has a negative and significant coefficient in three of the six columns, perhaps because higher unemployment leads to less road travel for commuting purposes. A similar effect has been observed in Australia (Burke and Teame, 2018) and the United States (He, 2016). There are also positive and significant coefficients for the number of international visitor arrivals per capita.

Has the fuel price elasticity of road deaths evolved over time? To explore this issue, we estimated a specification similar to column 1 of Table 2, but with an additional variable equal to the interaction of the fuel price term and the time trend. The interaction term has a negative coefficient of –0.007 (significant at the 10% level), suggesting that the fuel price elasticity of road deaths has become larger. As will be discussed below, restricting the estimation period to more recent years also provides a larger fuel-price elasticity of road deaths.

Table 3 shows results in first differences, using quarterly data for June 1989–March 2017. This is the same period as for Table 2, but the first observation is lost in the differencing. Column (1) has a negative and significant coefficient of –0.5 for the contemporaneous fuel price coefficient when only controlling for seasonal dummy variables. The negative coefficient for the contemporaneous change in fuel prices remains in column (2) when adding a lag of the fuel price variable. Columns (3) and (4), with additional lags, show a negative and significant coefficient for the fuel price variable lagged one period. The sum of the contemporaneous and lagged fuel price coefficients is shown in the base of Table 3, and ranges from –0.2 to –0.8. This is the point estimate of the fuel price elasticity of road deaths when responses over a year are considered. Only two of the sums in the first four columns are significantly different from zero at the 10% level. The estimates in first differences are less precise than our estimates in levels.

Columns (5)–(8) of Table 3 add the controls. These lead to smaller absolute magnitudes for the contemporaneous change in fuel prices, but larger absolute values for the significant coefficients for the fuel price variable lagged one period. The sum of the fuel price coefficients in columns (5)–(8) ranges from –0.2 to –0.6. This range encompasses the levels estimate of –0.3 in Table 2.

Table 4 shows results for 2001–2017, the period for which data on vehicle-kilometres travelled are available. The same-year fuel price elasticity of road deaths in the first column of Table 4 (point estimate = –0.30) can be decomposed into the impact on deaths per vehicle-kilometre travelled (elasticity = –0.19) and the impact on vehicle-kilometres travelled (elasticity = –0.11, significantly different from zero at the 1% level). While these magnitudes are not estimated precisely and this decomposition analysis is exploratory in nature due to imprecision in the vehicle-kilometre travelled data, the estimates provide an indication that the effect of fuel prices on road deaths may be larger than the effect on vehicle-kilometres travelled alone.

Table 5 uses monthly data from May 2004 to assess road accident outcomes using the model in equation 3 (in levels). The coefficient for fuel prices in the road deaths column is –0.7 and in the accidents column is –0.4, with both significantly different from zero at the 1% level. The fuel price elasticity of road deaths is higher in absolute magnitude than the coefficient in column 1 of Table 2, which used quarterly data for a longer estimation period. We also obtain a relatively high fuel price elasticity of road deaths if the quarterly estimates are restricted to later years. For example, restricting the estimate in column 1 of Table 2 to the period from 2007 onwards provides a fuel price elasticity of road deaths of –0.6 (see Stata code). These findings support the conclusion that the link between fuel prices and road deaths might have become larger in more recent years.

The remaining columns of Table 5 investigate effects on injuries. We do not find a significant effect on minor injuries, but obtain a fuel price elasticity of serious injuries from road crashes of –0.3. We also split serious injuries into different transit modes: light vehicle, motorcycle, cycling, and pedestrian. Light vehicles include cars, station wagons, sport utility vehicles (SUVs), vans, utilities, and taxis. The coefficient for the log of fuel prices for serious injuries from light vehicles, –0.4, is larger in absolute value than that for total serious injuries. A positive coefficient (0.5) is obtained for cyclist injuries, perhaps because some people substitute from cars to bicycles when fuel prices increase in order to save on fuel.

Table 3. Results for first difference of log of road deaths, quarterly data, June 1989–March 2017

Dependent variable: d.Ln road deaths$_t$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
d.Ln real fuel price$_t$	-0.549*	-0.522*	-0.391	-0.385	-0.227	-0.198	-0.153	-0.172
	(0.300)	(0.301)	(0.299)	(0.304)	(0.238)	(0.228)	(0.224)	(0.229)
d.Ln real fuel price$_{t-1}$		-0.244	-0.311**	-0.326*		-0.391***	-0.433***	-0.405**
		(0.152)	(0.148)	(0.180)		(0.147)	(0.163)	(0.198)
d.Ln real fuel price$_{t-2}$			0.485**	0.494**			0.249	0.226
			(0.216)	(0.249)			(0.257)	(0.300)
d.Ln real fuel price$_{t-3}$				-0.054				0.117
				(0.293)				(0.285)
d.Ln average weekly earnings$_t$					2.002	1.714	1.503	1.453
					(2.427)	(2.338)	(2.330)	(2.343)
d.Unemployment rate$_t$					-0.019	-0.021	-0.016	-0.018
					(0.033)	(0.033)	(0.033)	(0.032)
d.International visitors p.c.$_t$					1.224	1.094	0.860	0.855
					(0.740)	(0.789)	(0.924)	(0.940)
Sum of fuel price coefficients	-0.549*	-0.766**	-0.218	-0.272	-0.227	-0.589**	-0.337	-0.234
p-value for test that sum of coefficients equals to 0	0.07	0.01	0.57	0.50	0.34	0.04	0.31	0.51
Observations	112	112	112	112	112	112	112	112
R^2	0.031	0.038	0.060	0.060	0.336	0.350	0.355	0.356

Notes: ***, **, * show statistical significance at 1, 5 and 10 % level respectively. Newey-West standard errors with lag order four are in brackets below the coefficients. Coefficients for constants, quarterly binary variables, February leap-year binary variable, and an Easter binary variable are not shown. The data start in Q1 1989, but the first quarter is lost in the differencing, because the weekly earnings data only start in Q1 1989. The sample thus starts in Q2 1989 (i.e. June 1989).

Table 4. Results decomposition, quarterly data, June 2001–March 2017

Dependent variable:	d.Ln road deaths$_t$	d.Ln road deaths per vehicle-kilometre travelled$_t$	d.Ln vehicle-kilometre travelled$_t$
d.Ln real fuel price$_t$	-0.193	-0.149	-0.044***
	(0.353)	(0.348)	(0.014)
d.Ln real fuel price$_{t-1}$	-0.307	-0.283	-0.024
	(0.271)	(0.265)	(0.015)
d.Ln real fuel price$_{t-2}$	0.245	0.285	-0.040***
	(0.364)	(0.361)	(0.011)
d.Ln real fuel price$_{t-3}$	-0.045	-0.044	-0.001
	(0.361)	(0.358)	(0.009)
d.Ln average weekly earnings$_t$	2.865	2.933	-0.068
	(4.562)	(4.506)	(0.271)
d.Unemployment rate$_t$	0.014	0.023	-0.009***
	(0.068)	(0.067)	(0.003)
d.International visitors p.c.$_t$	0.446	0.479	-0.033
	(1.884)	(1.909)	(0.082)
Sum of fuel price coefficients	-0.299	-0.190	-0.109***
p-value for test that sum of coefficients equals 0	0.56	0.71	0.00
Observations	64	64	64
R^2	0.368	0.344	0.842

Notes: ***, **, * show statistical significance at 1, 5 and 10 % level respectively. Newey-West standard errors with lag order four are in brackets below the coefficients. Coefficients for constants, quarterly binary variables, February leap-year binary variable, and an Easter binary variable are not shown. The data start in Q1 2001, but the first quarter is lost in the differencing, because the distance data only start in Q1 2001. The sample thus starts in Q2 2001 (i.e. June 2001).

Table 5. Results for number of injuries and accidents, monthly data, May 2004–March 2017

Dependent variable:	Ln road deaths$_t$	Ln accidents$_t$	Ln minor injuries$_t$	Ln serious injuries: all$_t$	Ln serious injuries: light vehicles$_t$	Ln serious injuries: motorcycles$_t$	Ln serious injuries: cyclists$_t$	Ln serious injuries: pedestrians$_t$
Log real fuel price$_t$	-0.703***	-0.367***	-0.143	-0.256***	-0.417***	-0.181	0.506**	-0.051
	(0.152)	(0.089)	(0.102)	(0.082)	(0.117)	(0.194)	(0.200)	(0.173)
Time trend$_t$	-0.002***	-0.001*	-0.002***	-0.001***	-0.002***	0.002*	0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Consumer confidence$_t$	-0.003*	-0.004***	-0.004***	-0.004***	-0.004***	-0.006***	-0.006**	-0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Unemployment rate$_t$	-0.025	-0.044**	-0.026	-0.054***	-0.059***	-0.055	-0.099***	-0.036
	(0.029)	(0.020)	(0.021)	(0.012)	(0.016)	(0.040)	(0.032)	(0.024)
International visitors p.c.$_t$	4.376	3.199	0.917	7.563**	8.415**	0.922	-4.237	8.073
	(3.818)	(2.818)	(3.198)	(2.962)	(3.567)	(4.428)	(6.429)	(5.641)
Observations	155	155	155	155	155	155	155	155
R^2	0.432	0.735	0.673	0.670	0.661	0.602	0.338	0.330

Notes: ***, **, * show statistical significance at 1, 5 and 10 % level respectively. Newey-West standard errors with lag order four are in brackets below the coefficients. Coefficients for constants, monthly binary variables, February leap-year binary variable, and an Easter binary variable are not shown. Light vehicles (four-wheeled) includes cars, station wagons, SUVs, vans, utilities, and taxis. Motorcycles include mopeds. Variable definitions and units are in the Appendix. Using quarterly data for the time period May 2004–March 2017 produces an insignificant coefficient for log real fuel price in explaining log road deaths.

Appendix Figure A.2 replicates the log fuel price coefficient for the first column of Table 2, but using rolling 10, 15, and 20 year sub-samples. There are negative and significant coefficients for the log of the real fuel price in explaining the log of road deaths in each 20-year sub-sample, starting with 1989–2009 and ending with 1997–2017. 15-year windows also produce negative coefficients in each case. 10-year windows produce negative coefficients in most cases (14 out of 19). Tighter confidence intervals are obtained when using larger estimation samples. Our point estimate of –0.3 from Table 2 falls within the confidence intervals for the estimates using 15 and 20 year sub-samples, and within 90% of the confidence intervals for the estimates using 10-year sub-samples.

To better visualise the relationship between road deaths and fuel prices, we obtained the residual from regressing log road deaths on all of the control variables from Table 2 *excluding* the log real fuel price. We then plotted this residual against the log real fuel price. An inelastic, statistically significant negative association can be seen (Figure 4). Note that the log real fuel price does not explain all of the variation in the residual. Our regressions in Table 2 have high R^2 values, but they do not equal 1.

We pursued a number of other robustness checks. We continue to obtain a negative and significant coefficient of –0.3 in the first column of Table 2 if we de-trend the dependent variable before carrying out the estimation (and exclude the time trend from the regression). Also, the fuel price elasticity of road deaths is similar if data from 2013 onward are excluded from the estimation (see our Stata code, available online). We also obtain similar results if we include a lagged dependent variable in our levels estimates. The coefficient for the lagged dependent variable is close to zero and insignificant, consistent with our earlier finding that log road deaths do not follow a strongly autoregressive process.

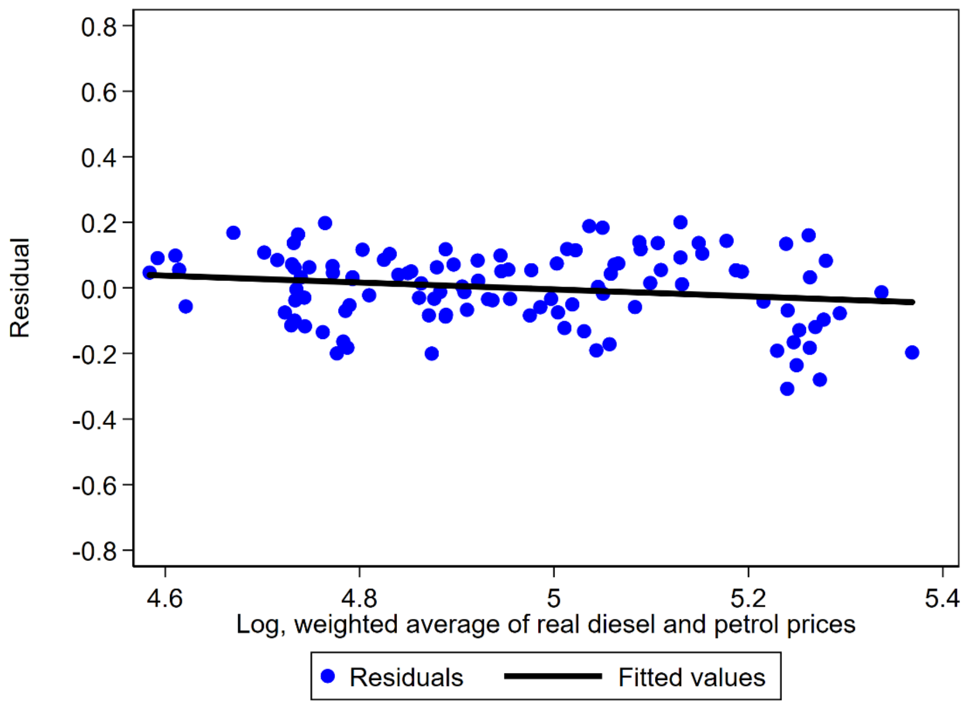


Figure 4. Residual from regressing log road deaths on all of the control variables from Table 2 excluding the log real fuel price, *versus* the log real fuel price. The fitted values are from an ordinary least squares regression.

4. Conclusion and policy implications

This paper quantified the short-run impact of fuel prices on road accident outcomes in New Zealand. The work was motivated by the rise in New Zealand's road deaths in recent years, which coincided with a fall in fuel prices. Some other countries such as Australia have also seen an increase in road deaths. We find a negative effect of fuel prices on road deaths and serious injuries, holding other variables constant. For a 1% decrease in the real fuel price, the average increase in New Zealand's road deaths tends to be in the range 0.2–0.8%, based on the first-differenced regressions in Table 3. The response to fuel price shocks appears to predominantly occur during the current and the subsequent quarter. Focusing on short-run effects with the levels model, the average fuel price elasticity of road deaths is –0.3 over the full estimation period. The inelastic estimates of the effect of fuel prices on road deaths reconcile well with the fact that demand for fuel is price inelastic (Brons et al., 2008; Havranek et al., 2012; Burke and Nishitateno, 2013). Our estimates suggest that the elasticity has increased over the sample period. Our paper has not analysed long-run effects, and we do not extrapolate to make long-run forecasts.

How large a contribution did lower fuel prices make to the increase in New Zealand's road death toll since 2013? The real retail fuel price decreased by approximately 23% from 2013 to 2016. If one were to apply the average fuel price elasticity of road deaths over the period May 2004–March 2017 (Table 5), this would be associated with an increase in the level of road deaths of approximately 16%. It is thus conceivable that around half of the overall increase in road deaths over the period was due to lower fuel prices.

What other factors may have contributed to New Zealand's increase in road deaths? Our results suggest that road deaths are positively associated with average weekly earnings and international visitor numbers per capita. Comparing 2016 to 2013, real average weekly earnings increased by 5% and international visitor numbers per capita increased by 23%. The slight decline in New Zealand's unemployment rate, from 6.0% in 2013 to 5.3% in 2016, also appears to have likely contributed to the increase in road deaths.

Increased use of technology such as smartphones and navigation devices is another potential contributor to New Zealand's rising road death toll in recent years, and one that we have not included in our modelling due to measurement challenges. The share of New Zealanders owning or having access to a smartphone increased from 48% in 2013 to 70% in 2015 according to data from Research New Zealand (2015). Augmented reality games, such as Pokemon Go, are an additional potential distraction (Ayers *et al*. 2016; Barbieri *et al*. 2017), although we note that the commencement of the uptick in road deaths in late 2014 preceded the release of Pokemon Go. In the United States, increases in road accidents involving bicyclists, motorcyclists, and pedestrians have been presented as a clue that increasing smartphone use is contributing to more road accidents (Bloomberg, 2017). In New Zealand, cyclist and pedestrian deaths slightly declined over the period 2013–2016. It is increased deaths of drivers, passengers, and motorcyclists that has led to the increase in New Zealand's road toll.

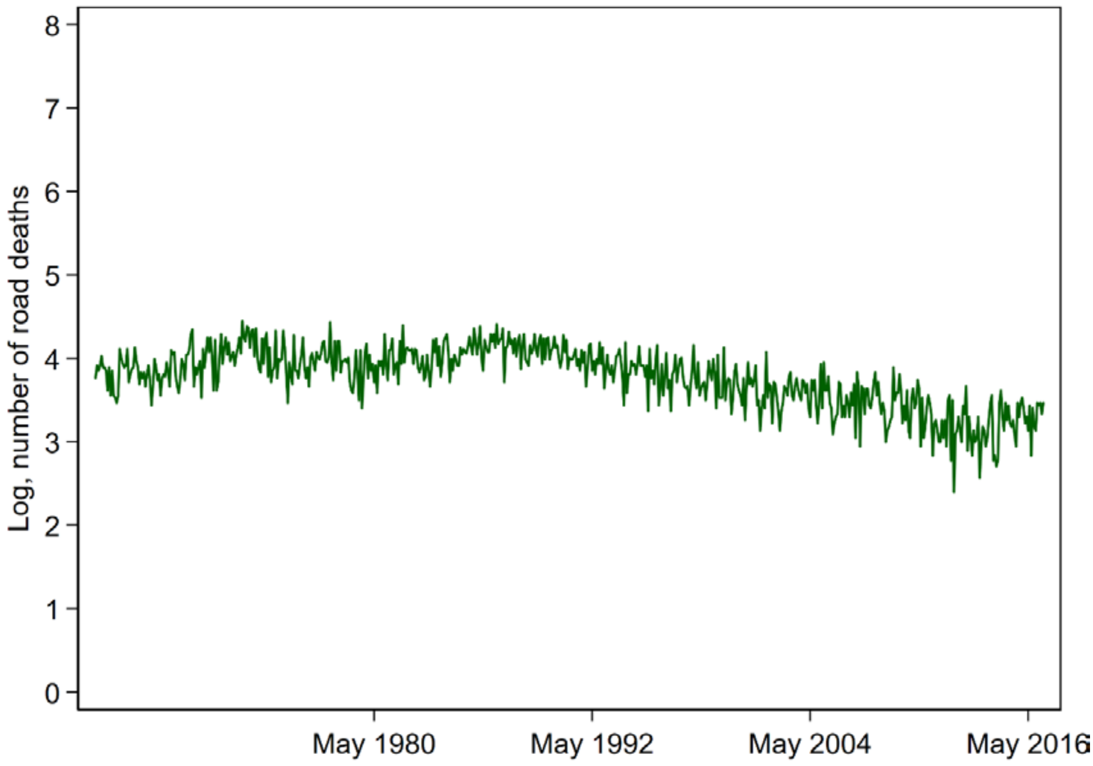
Our finding of a positive relationship between fuel prices and cyclist accident outcomes is an expected effect, due to a likely substitution from driving to cycling when fuel prices increase. Note, however, that cyclists are the minority of road accident victims, and that our overall results indicate that higher fuel prices lead to improved overall road safety outcomes.

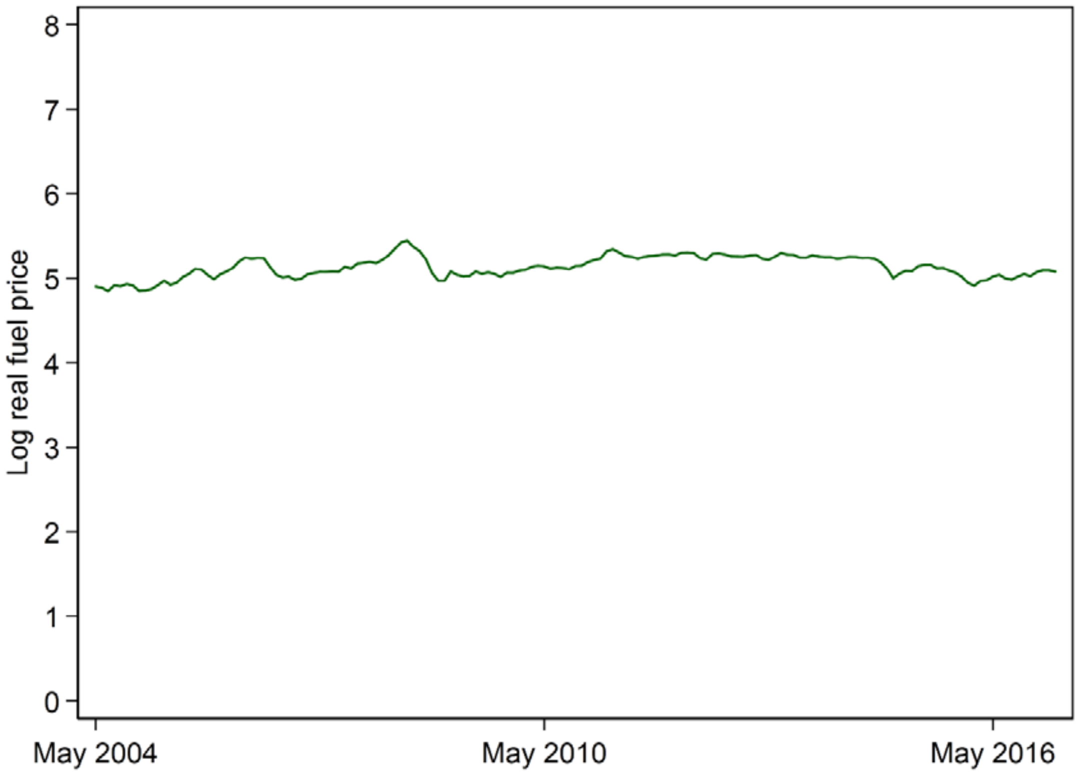
Road accident risks imposed on others are one type of negative externality from road use, providing a justification for taxing road and/or fuel use. Other justifications include reducing pollution and congestion, and raising revenue (Parry and Small, 2005; Parry *et al*., 2014). We do not make conclusions on the optimal gasoline taxation rate for New Zealand in this paper, but do provide confirmatory evidence that higher fuel prices indeed tend to be associated with reduced road safety risks in the short run.

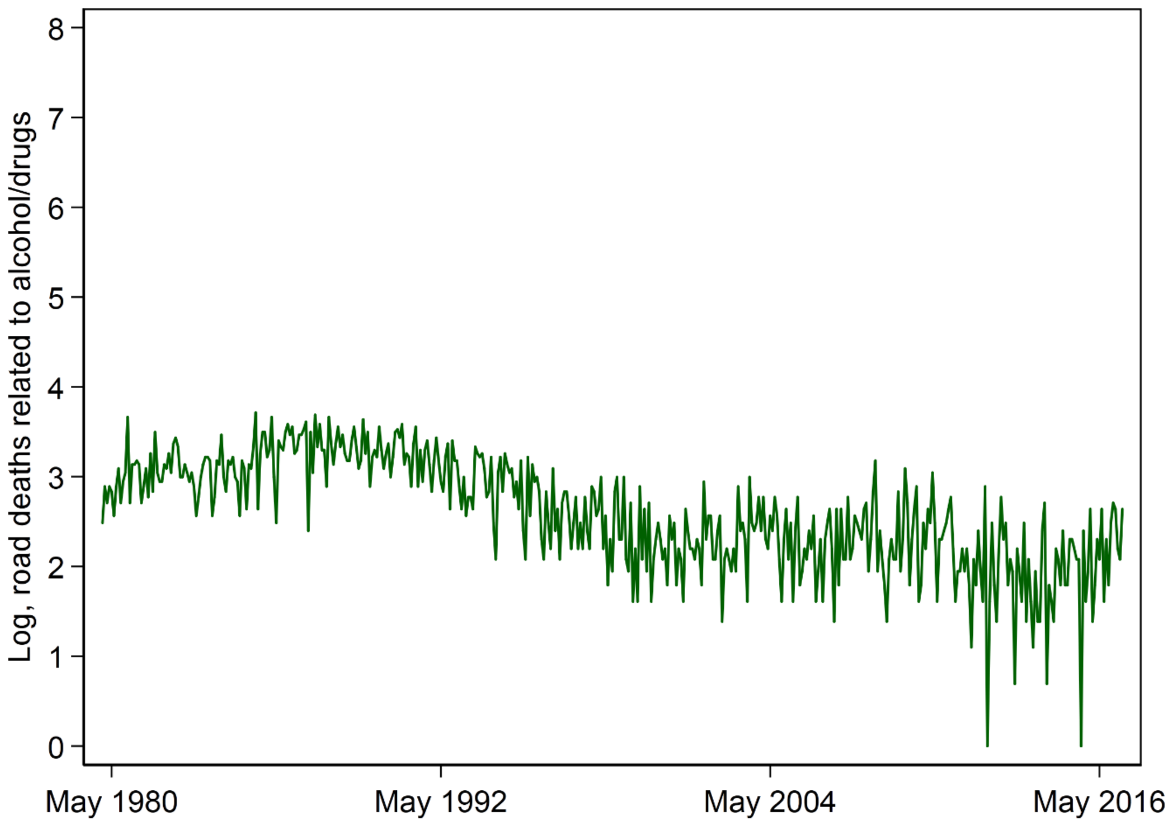
An implication of our results is that there could be the potential for calibrating the focus of road safety campaigns according to whether fuel prices are high or low. It would make sense for road safety advertising expenditure to increasingly target cyclist safety at times when fuel prices are high. Greater focus on motor vehicle drivers, and on open-road driving, appears to be warranted when fuel prices fall.

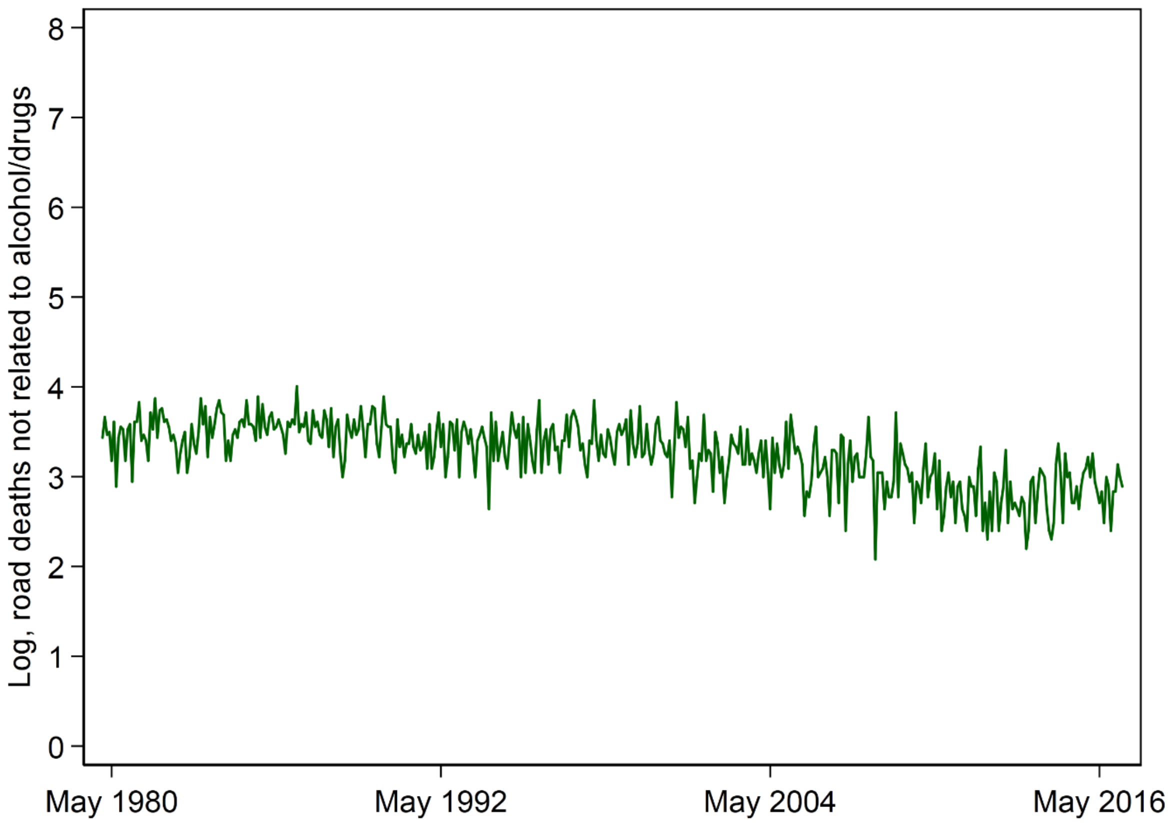
Appendix

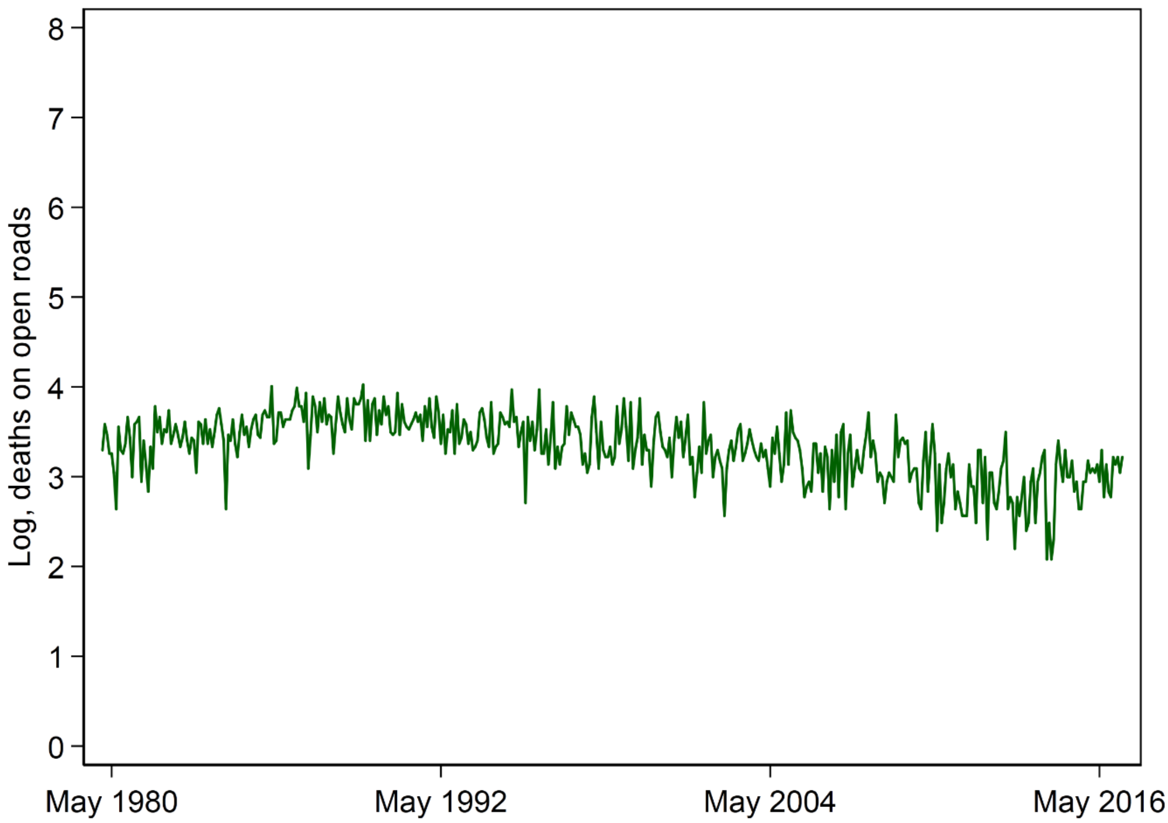
Figure A.1. Log road accident outcomes in New Zealand using monthly data.






Log, road deaths related to alcohol/drugs
0
1
2
3
4
5
6
7
8
May 1980
May 1992
May 2004
May 2016

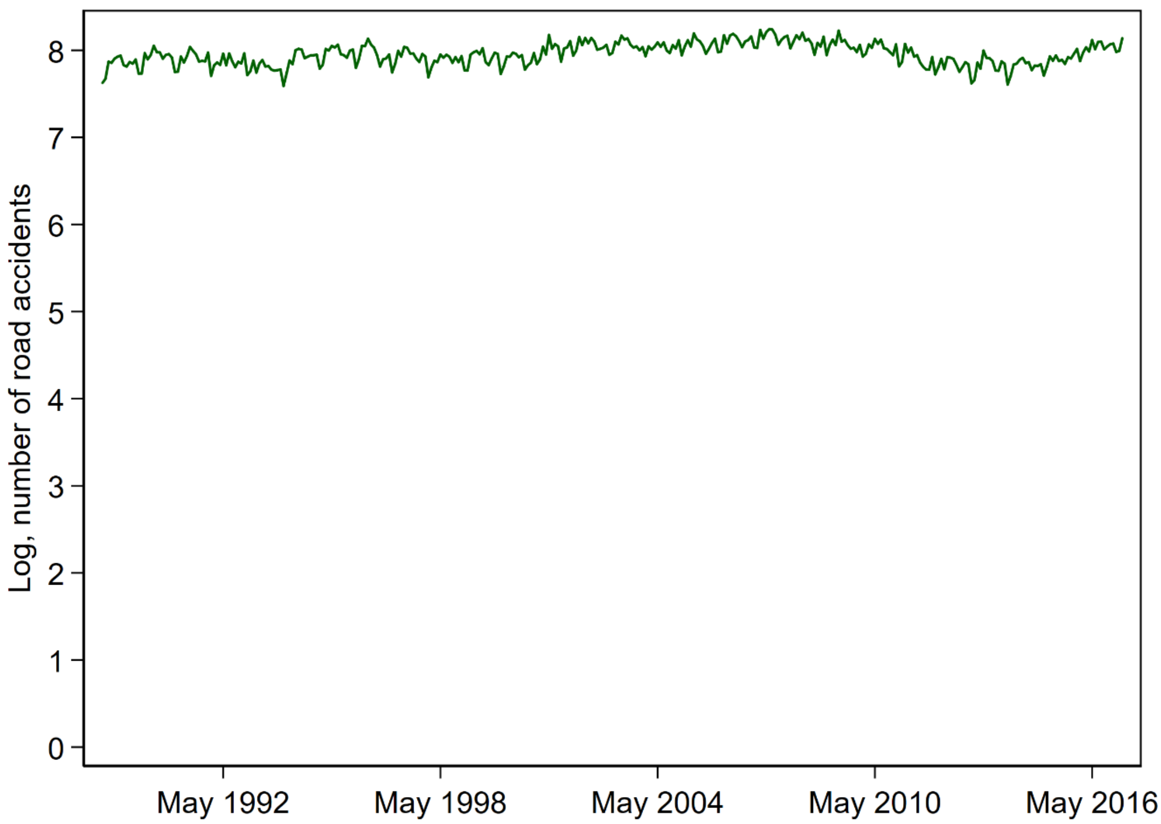

Log, road deaths not related to alcohol/drugs
0
1
2
3
4
5
6
7
8
May 1980
May 1992
May 2004
May 2016



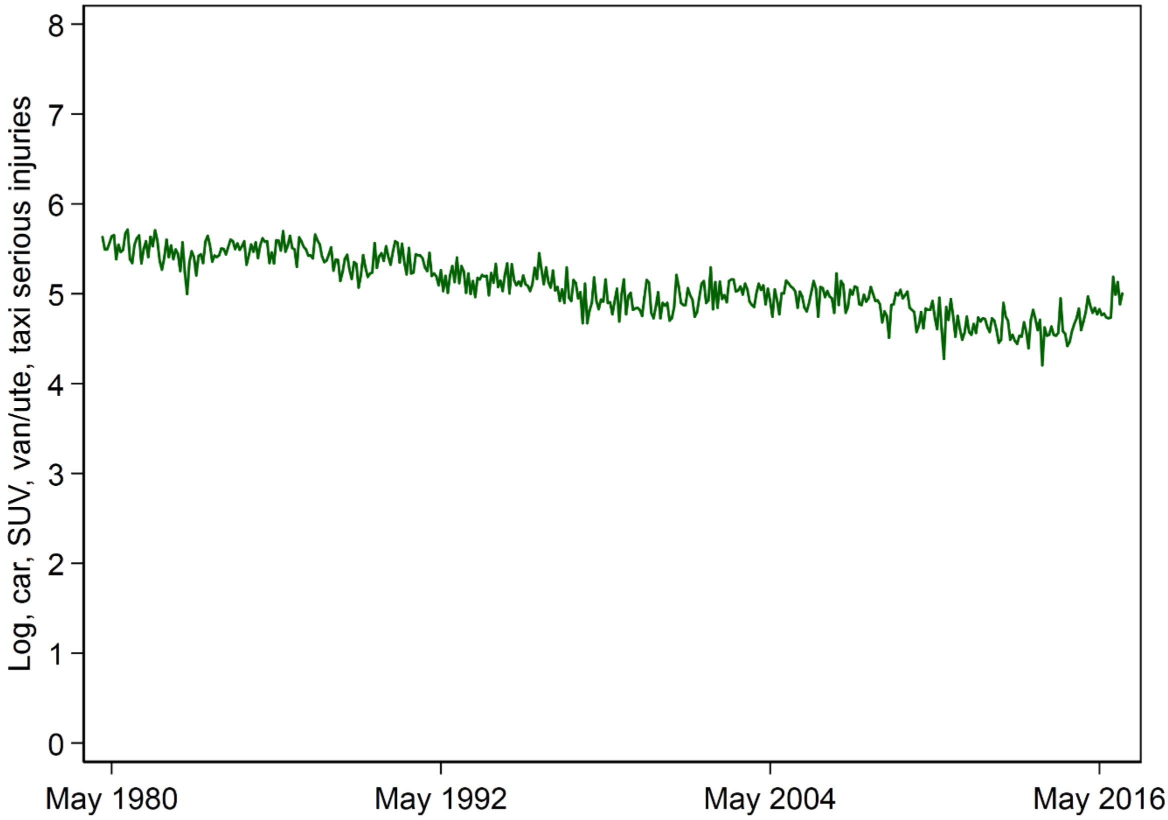
Log, deaths on open roads
May 1980
May 1992
May 2004
May 2016

Log, number of minor injuries
May 1980
May 1992
May 2004
May 2016

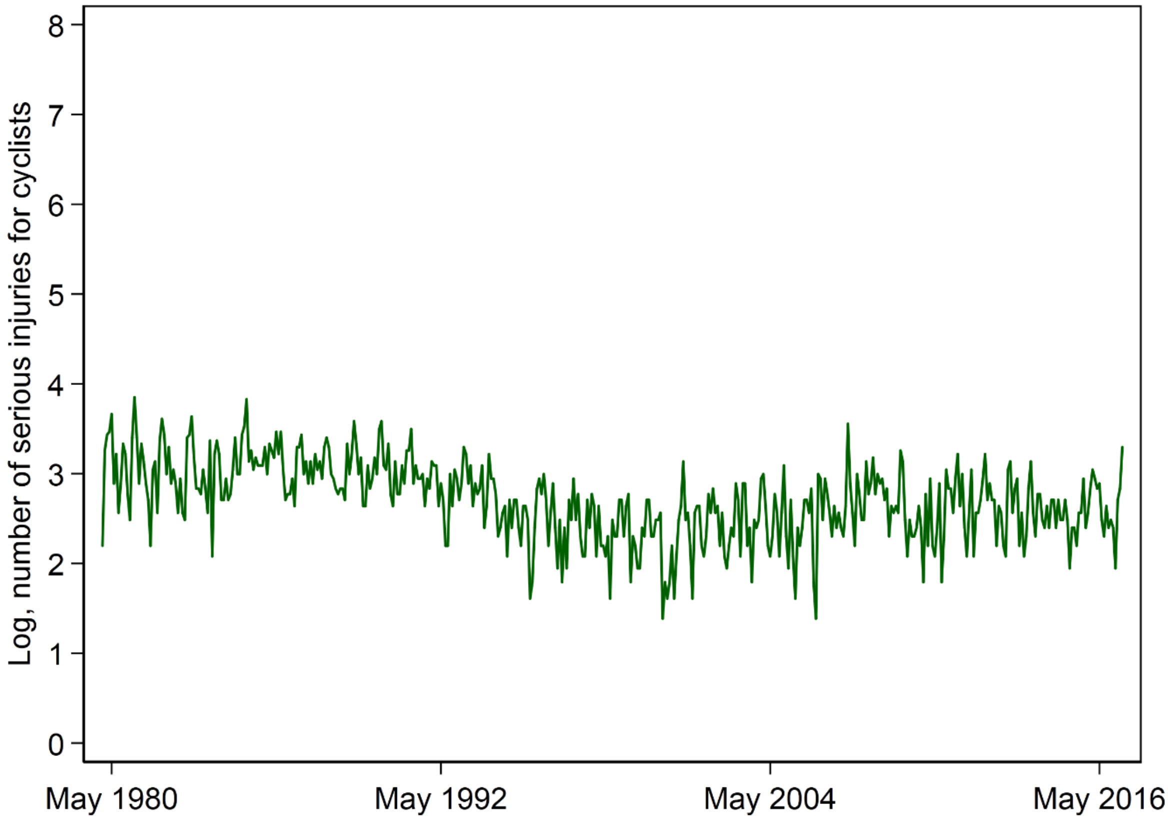
Log, number of serious injuries
8
7
6
5
4
3
2
1
0
May 1980
May 1992
May 2004
May 2016



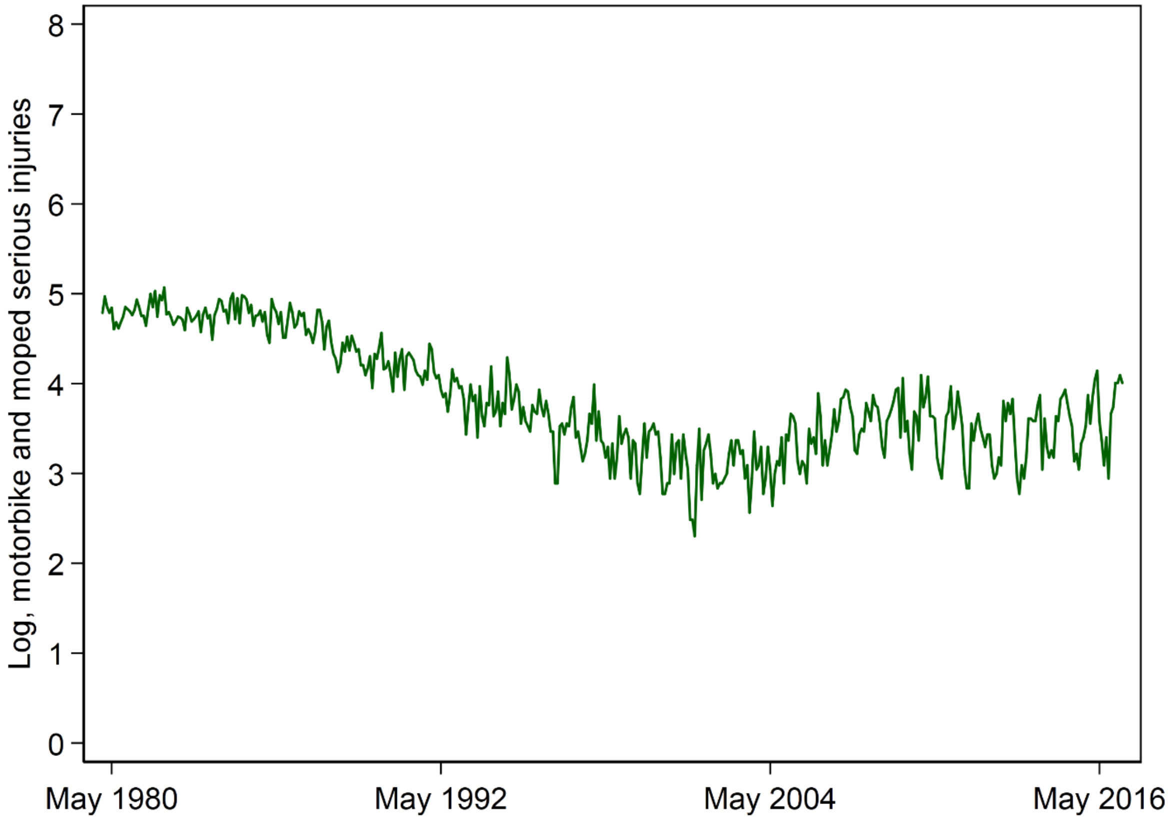
Log, number of road accidents
8
7
6
5
4
3
2
1
0
May 1992
May 1998
May 2004
May 2010
May 2016



Log, car, SUV, van/ute, taxi serious injuries
0
1
2
3
4
5
6
7
8
May 1980
May 1992
May 2004
May 2016



Log, number of serious injuries for cyclists
0
1
2
3
4
5
6
7
8
May 1980
May 1992
May 2004
May 2016


Log, motorbike and moped serious injuries
0
1
2
3
4
5
6
7
8
May 1980
May 1992
May 2004
May 2016

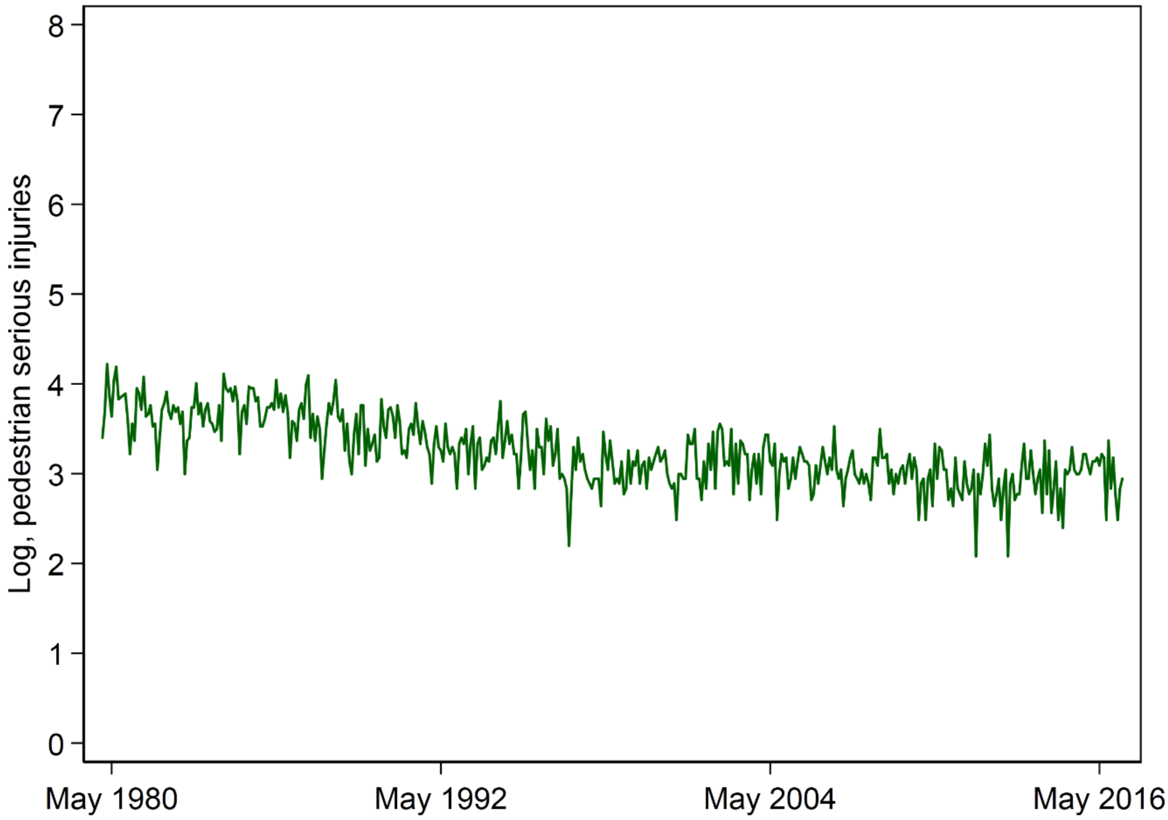
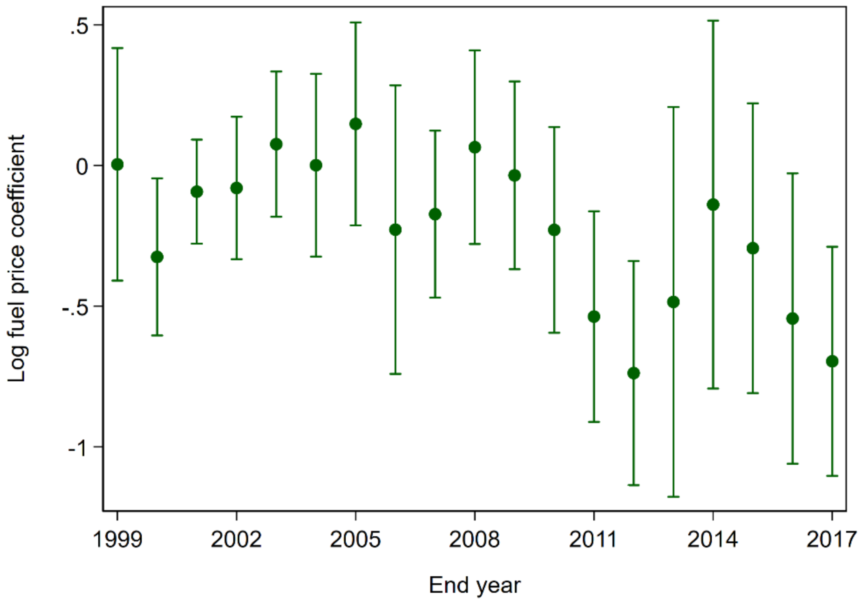
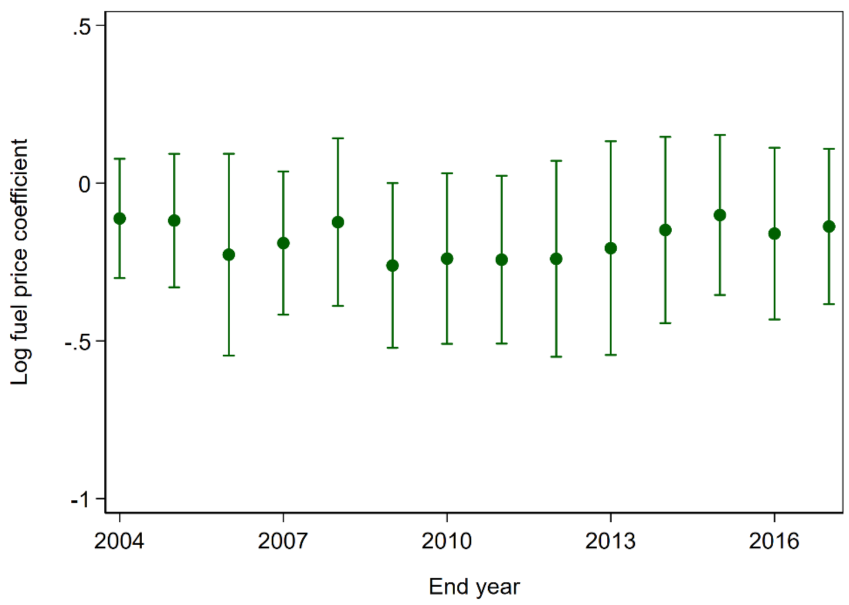

Log, pedestrian serious injuries
0
1
2
3
4
5
6
7
8
May 1980
May 1992
May 2004
May 2016

Figure A.2. Log fuel price coefficients and 95% confidence intervals for Table 2, but for rolling sub-samples.

A. 10-year rolling periods



B. 15-year rolling periods



C. 20-year rolling periods

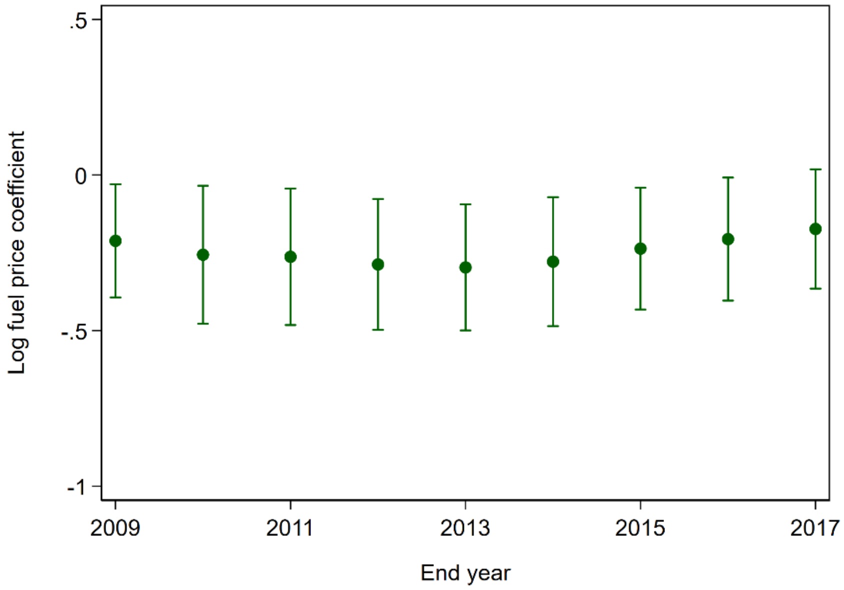


Table A.1. Descriptive statistics

Variable	Frequency	Observations	Minimum	Mean	Maximum
Road accident deaths	Quarterly	113	48	115.5	199
Road accident deaths (alcohol/drugs)	Quarterly	113	15	39.8	101
Road deaths (not alcohol/drugs)	Quarterly	113	33	75.7	123
Road accident deaths: open roads	Quarterly	113	30	83.3	138
Real fuel price	Quarterly	113	97.9	144.9	214.5
International visitor arrivals	Quarterly	113	168,048	506,996	1,104,901
Unemployment rate	Quarterly	113	3.3	6.4	11.6
Average weekly earnings	Quarterly	113	785.9	861.5	998.4
Minor injuries from road crashes	Monthly	155	657	938.8	1243
Serious injuries from road crashes	Monthly	155	115	198.5	267
Road accidents	Monthly	155	2013	2973.7	3800
Serious injuries (light vehicles)	Monthly	155	67	122.9	186
Serious injuries (cyclists)	Monthly	155	4	14.1	35
Serious injuries (motorcyclists)	Monthly	155	14	34.3	63
Serious injuries (pedestrians)	Monthly	155	8	20.2	34
Consumer confidence	Monthly	155	83.9	118.8	140.9

Table A.2. Description of variables

Variable	Source	Description
Road accident deaths	NMT	Deaths within 30 days of an accidental road crash.
Road accident deaths (alcohol or drug related)	NTA	Number of road accident deaths with alcohol or drugs as a factor.
Road accident deaths: open roads	NTA	Number of road accident deaths on open roads.
Road accidents	NTA	Number of road accidents reported to police.
Vehicle-kilometres travelled	NMT	Vehicle-kilometres travelled (by both heavy and light vehicles, and motorcycles). Estimated from odometer readings.
Serious injuries from road crashes	NTA	Number of serious injuries from road crashes reported to police. Includes broken bones, concussion, and others.
Minor injuries from road crashes	NTA	Number of minor injuries from road crashes reported to police. Includes cuts, sprains, bruises, and others.
Real fuel price	MBI	Weighted average of the real gasoline (weight = 60%) and real diesel (40%) pump prices. Real prices are average retail prices in March 2017 prices. The weights are based on the average of International Energy Agency road energy data for gasoline and diesel proportions of road fuel use in New Zealand from 2000–2014. We converted the nominal monthly fuel price into real terms using the interpolated monthly New Zealand consumer price index from Statistics New Zealand.
Real world oil price	IMF	Crude oil (petroleum) price index, with underlying data in USD, 2005=100, simple average of three spot prices: Dated Brent, West Texas Intermediate, and Dubai Fateh, converted into real terms (March 2017 prices) using US consumer price index from the Federal Reserve Bank of St. Louis, and converted into quarterly averages from the original monthly data for quarterly regressions.
Time trend	-	Increases by one in each time period.
Working age population	SNZ	The non-institutionalised, New Zealand resident population aged 15 years and over. There is no official retirement age in New Zealand.
Consumer confidence	ARM	ANZ-Roy Morgan New Zealand consumer confidence rating.
International visitor arrivals divided by working age population	SNZ	Overseas residents arriving in New Zealand for a stay of less than 12 months during the quarter/month, divided by the working age population (which is representative of the driving-age population).
Unemployment rate	SNZ	Unemployment rate, original series, based on labour force status for people aged 15 to 64 years. Available on a quarterly basis. We interpolated to create monthly data.
Average weekly earnings	SNZ	Average weekly earnings (employees), total, based on a survey, all industries and both sexes,

		trend series, converted into real terms using consumer price index.
Easter binary variable	-	Binary variable equal to one for time periods including Easter Sunday.
February leap year binary variable	-	Binary variable equal to one for periods that include a leap-year February.
Month or quarter of year binary variable	SNZ	A set of 3 binary variables for the quarterly data and 11 binary variables for the monthly data. Binary variable equal to one for relevant month or quarter.

Sources: NMT: New Zealand Ministry of Transport (2018), NTA: New Zealand Transport Agency (2017), MBI: Ministry of Business, Innovation & Employment (2017), IMF: International Monetary Fund (2017), ARM: ANZ Roy Morgan (2017), SNZ: Statistics New Zealand (2017).

References

Ahangari, H., Outlaw, J., Atkinson-Palombo, C. & Garrick, N.W. (2014). Investigation into impact of fluctuations in gasoline prices and macroeconomic conditions on road safety in developed countries. *Transportation Research Record*, 2465, 48–56.

ANZ-Roy Morgan (2017). *ANZ-Roy Morgan New Zealand consumer confidence* [Data set]. Retrieved May 31, 2017, from website: http://www.roymorgan.com/morganpoll/consumer-confidence/anz-roy-morgan-new-zealand-consumer-confidence.

Ayers, J.W., Leas, E.C., Dredze, M., Allem, J., Grabowski, J.G., & Hill, L. (2016). Pokemon GO – A new distraction for drivers and pedestrians. *JAMA Internal Medicine*, 176(12), 1865–1866.

Barbieri, S., Vettore, G., Pietrantonio, V., Snenghi, R., Tredese, A., Bergamini, M., Previato, S., Stefanati, A., Gaudio, R.M., & Feltracco, P. (2017). Pedestrian inattention blindness while playing Pokemon Go as an emerging health-risk behaviour: A case report. *J Med Internet Res*, 19(4): e86.

Bloomberg (2017). Smartphones are killing Americans, but nobody's counting. October 17, 2017, by Kyle Stock, Lance Lambert, and David Ingold, from website: https://www.bloomberg.com/news/articles/2017-10-17/smartphones-are-killing-americans-but-nobody-s-counting.

Brons, M., Nijkamp, P., Pels, E., & Rietveld, P. (2008). A meta-analysis of the price elasticity of gasoline demand. A SUR approach. *Energy Economics*, 30, 2105–2122.

Burke, P.J., & Nishitateno, S. (2013). Gasoline prices, gasoline consumption, and new-vehicle fuel economy: Evidence for a large sample of countries. *Energy Economics*, 36, 363–370.

Burke, P.J. (2014). Green pricing in the Asia Pacific: An idea whose time has come? *Asia & the Pacific Policy Studies*, 1(3), 561–575.

Burke, P.J., & Nishitateno, S. (2015). Gasoline prices and road fatalities: International evidence. *Economic Inquiry,* 53(3), 1437–1450.

Burke, P.J., & Teame, A. (2018). Fuel prices and road deaths in Australia. *Economic Papers* 37(2), 146–161.

Chi, G, Zhou, Z., McClure, T.E., Gilbert, P.A., Cosby, A.G., Zhang, L., Robertson, A.A., & Levinson, D. (2011). Gasoline prices and their relationship to drunk-driving crashes. *Accident Analysis and Prevention*, 43, 194–203.

Chi, G., McClure, T.E., & Brown, D.B. (2012). Gasoline prices and traffic crashes in Alabama, 1999–2009. *Traffic Injury Prevention*, 13(5), 476–484.

Chi, G., Quddus, M.A., Huang, A., & Levinson, D. (2013). Gasoline price effects on traffic safety in urban and rural areas: Evidence from Minnesota, 1998–2007. *Safety Science*, 59, 154–162.

Chi, G., Brown, W., Zhang, X., & Zheng, Y. (2015). Safer roads owing to higher gasoline prices: how long it takes. *American Journal of Public Health*, 105(8), e119–e125.

Creutzig, F. (2014). How fuel prices determine public transport infrastructure, modal shares and urban form. *Urban Climate*, 10, 63–76.

Cycling Safety Panel (2014). *Safer journeys for people who cycle: Cycling Safety Panel final report and recommendations* (December 2014). Retrieved from Safer Journeys website: http://www.saferjourneys.govt.nz/resources/.

Dickey, D.A., & Fuller, W.A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366), 427–431.

Elliot, G.R., Rothenberg, T.J., & Stock, J.H. (1996). Efficient tests for an autoregressive unit root. *Econometrica*, 64, 813–836.

Federal Reserve Bank of St. Louis (2017). *Consumer price index: Total all items: Wage earners for the United States* [Data set]. Retrieved July 7, 2017, from website: https://fred.stlouisfed.org/.

Grabowski, D.C., & Morrisey, M.A. (2006). Do higher gasoline taxes save lives? *Economic Letters*, 90, 51–55.

Greene, W.H. (2012). Econometric Analysis. International Edition. Seventh Edition. Pearson Education Limited.

Harvey, A.C., & Durbin, J. (1986). The effects of seatbelt legislation on British road casualties: A case study in structural time series modelling. *Journal of the Royal Statistical Society. Series A (General)* 149, 187–227.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica* 46, 1251–1271.

Havranek, T., Irsova, Z., & Janda, K. (2012). Demand for gasoline is more price-inelastic than commonly thought. *Energy Economics*, 34, 201–207.

He, M.M. (2016). Driving through the Great Recession: Why does motor vehicle fatality decrease when the economy slows down? *Social Science & Medicine*, 155, 1–11.

Hill, R.C., Griffiths, W.E., & Lim, G.C. (2008). Principles of Econometrics, Third Edition. John Wiley & Sons, Inc.

Hyatt, E., Griffin, R., Rue III, L.W., & McGwin Jr., G. (2009). The association between price of regular-grade gasoline and injury and mortality rates among occupants involved in motorcycle- and automobile-related motor vehicle collisions. *Accident Analysis and Prevention*, 41, 1075–1079.

Infometrics (2013). Further econometric investigation of the 2011 reduction in road fatalities. Retrieved July 30, 2017, from website: http://www.transport.govt.nz/research/roadtoll/analysisofthe2011roadtoll/.

International Energy Agency (2017). *IEA World energy statistics and balances* [Data set]. Retrieved July 2, 2017, from website: http://www.oecd-ilibrary.org/.

International Monetary Fund (2017). *IMF primary commodity prices* [Data set]. Retrieved May 30, 2017, from website: http://www.imf.org/external/np/res/commod/index.aspx.

International Transport Forum (2015). *Why Does Road Safety Improve When Economic Times Are Hard?* Organisation for Economic Co-operation and Development, Paris.

Keall, M., Stroombergen, A., Sullivan, C., Cameron, M., & Weiss, H. (2012). An analysis of potential factors behind the 2011 reduction in New Zealand road fatalities. Retrieved from website: http://www.transport.govt.nz/assets/Uploads/Research/Documents/Analysis-of-traffic-fatality-trends-final-7-Sept-2012.pdf.

Kwiatkowski, D., Phillips, P.C.B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics*, 54, 159–178.

Lin, M.B., & Huang, Y. (2017). The impact of walking while using a smartphone on pedestrians' awareness of roadside events. *Accident Analysis and Prevention*, 101, 87–96.

Newey, W.K., & West, K.D. (1987). A simple, positive semi-definite, heteroscedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55, 703–708.

New Zealand Ministry of Business, Innovation & Employment (2017). *Energy prices* [Data set]. Retrieved May 30, 2017, from website: http://www.mbie.govt.nz/info-services/sectors-industries/energy/energy-data-modelling/statistics/prices.

New Zealand Ministry of Transport (2013). *Safer journeys: New Zealand's road safety strategy 2010–2020.* Retrieved from Safer Journeys website: http://www.saferjourneys.govt.nz/resources/.

New Zealand Ministry of Transport (2016). *Road safety progress*. Retrieved July 30, 2017, from website: http://www.transport.govt.nz/research/roadtoll/road-safety-progress/.

New Zealand Ministry of Transport (2017). *Social cost of road crashes and injuries 2016 update.* Retrieved July 2, 2017, from website: http://www.transport.govt.nz/research/roadcrashstatistics/thesocialcostofroadcrashesandinjuries/.

New Zealand Ministry of Transport (2018). *Road toll* [Data set]. Retrieved March 5, 2018, from Ministry of Transport website: http://www.transport.govt.nz/research/roadtoll/.

New Zealand Transport Agency (2017). *Crash analysis system* [Data set]. Retrieved July 21, 2017, from website: https://www.nzta.govt.nz/safety/safety-resources/crash-analysis-system.

Ng, S., & Perron, P. (1995). Unit root tests in ARMA models with data-dependent methods for the selection of the truncation lag. *Journal of the American Statistical Association*, 90 (429), 268–281.

Ng, S., & Perron, P. (2001). Lag length selection and the construction of unit root tests with good size and power. *Econometrica*, 69 (6), 1519–1554.

Nishitateno, S., & Burke, P.J. (2014). The motorcycle Kuznets curve. *Journal of Transport Geography*, 36, 116–123.

OECD (Organisation for Economic Co-operation and Development (2017). *Road accidents*. Retrieved August 1, 2017 from website: https://data.oecd.org/transport/road-accidents.htm.

Parry, I.W.H., Heine, D., Lis, E., & Li, S. (2014). Getting energy prices right: From principle to practice. International Monetary Fund, Washington D.C.

Parry, I.W.H., & Small, K.A. (2005). Does Britain or the United States have the right gasoline tax? *American Economic Review*, 95(4), 1276–1289.

Phillips, P.C.B., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, 75, 335–346.

Research New Zealand (2015). A report on a survey of New Zealanders' use of smartphones and other mobile communication devices 2015. Research New Zealand, Wellington, New Zealand.

Robertson, L. (2018). Reversal of the road death trend in the U.S. in 2015–2016: An examination of the climate and economic hypotheses. *Journal of Transport & Health*, 9, 161–168.

Scuffham, P. A. (2003). Economic Factors and Traffic Crashes in New Zealand. *Applied Economics*, 35(2), 179–188.

Scuffham, P.A., & Langley, J.D. (2002). A model of traffic crashes in New Zealand. *Accident Analysis and Prevention* 34, 673–687.

Shaw, C., Hales, S., Edwards, R., Howden-Chapman, P., & Stanley, J. (2018). What can fuel price increases tell us about the air pollution health co-benefits of a carbon price? *Journal of Transport & Health*, 8, 81–90.

Statistics New Zealand (2017). *Various items* [Data set]. Retrieved May 30, 2017, from website: http://www.stats.govt.nz/infoshare/.

Stock, J. H., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. In Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg, ed. D. W. K. Andrews and J. H. Stock, 80–108. New York: Cambridge University Press.

Wilson, F.A., Stimpson, J.P., & Hilsenrath, P.E. (2009). Gasoline prices and their relationship to rising motorcycle fatalities, 1990–2007. *American Journal of Public Health*, 99(10), 1753–1758.

Wu, D.-M. (1974). Alternative tests of independence between stochastic regressors and disturbances: Finite sample results. *Econometrica* 42, 529–546.

Zhu, H., Wilson, F.A., & Stimpson, J.P. (2015). The relationship between gasoline price and patterns of motorcycle fatalities and injuries. *Injury Prevention*, 21, 153–158.