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Do higher fuel prices help reduce road traffic accidents?

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ABSTRACT

Road traffic accidents have decreased in most developed nations over the last decade. This has been attributed to improvements in vehicle and road design, medical technology and care, and driver education and training. Recent evidence however indicates that fuel price changes also have a significant impact on road traffic accidents through other mediating factors such as reductions in driver exposure through less car travel and more fuel-efficient driving e.g. speed reduction on high-speed roads. So far though, no study has examined the effects of changing fuel prices on road traffic accidents in a country such as Great Britain where fuel prices are kept artificially high for public policy reasons. Consequently, this study was designed to quantify the effects of fuel price on road traffic accident frequency through changes and adjustments in travel behaviour. For this purpose, weekly fuel prices (between 2005–2015) have been used to study the effects on road traffic accidents using the Prais-Winsten model of first order autoregressive (AR1) and the Box and Jenkins seasonal autoregressive integrated moving average models (SARIMA). The study found that with every 1% increase in fuel price there is a 0.4% reduction in the number of fatal road traffic accidents. In light of this, one concern raised was that recent UK government plans to phase out petrol and diesel vehicles by 2040 may also risk a rise in fatal road traffic accidents, and hence this will need to be addressed.

1. Introduction

More than 1.25 million people die on the world's roads and millions more suffer serious injuries each year as a result of road traffic accidents, which cost most nations around 3 % of their GDP (Toroyan et al., 2015), with the average societal benefit of preventing a fatal accident on British roads for example, being estimated to be just over £2 million (Blincoe et al., 2015; Department for Transport, 2016a). Preventing road traffic accidents has therefore been a key transport policy for many countries. In the context of Great Britain, even though the roads are considered to be amongst the safest in the world, there were still 1720 reported road deaths and 174,510 casualties of all severities in 2017 (Department for Transport, 2018). That said, the number of fatalities was still some 42% less when compared with the figure in 2006 (Department for Transport, 2015a), and this begs the question, why?

One thought is that periods of economic recession (such as those in 1990–1992 and in 2006–2010) coupled with high fuel prices over the same period have played an important part in reducing road accident fatalities (Department for Transport, 2015b). Thus Fig. 1 shows how the number of road traffic accidents has fallen in Great Britain between 2005 and 2015 along with corresponding petrol and diesel price fluctuations.

This understanding is especially important in the British context where fuel prices are relatively high compared to other countries (Noel et al., 2016). These higher fuel prices are largely due to high rates of fuel duty which for many years have been targeted at two main policy objectives. First, higher fuel prices are aimed at reducing road externalities (carbon dioxide, air pollution, congestion and accidents) and second, at generating tax revenues (some £27.9 billion in 2017/2018 according to *RAC Foundation*, 2017) of which some has been spent on road safety schemes (Parry, 2001; Santos et al., 2010). Consequently, if higher fuel prices do lead to fewer accidents, then this relationship needs to be better understood.

This issue is especially pertinent at the moment, because political sensitivities about poor air quality and climate change are now pushing Government in the direction of scrapping vehicles powered by internal combustion engines, with one recent announcement proposing a complete ban on petrol and diesel vehicles in the UK by 2040 (BBC, 2017), and this coupled with rapid recent developments in alternative power source technologies mean that sales of diesel vehicles in particular are already declining. Thus car registration data show that diesel vehicle sales fell from 103,564 to 74,361 (i.e. by 28.2%) between June 2017 and June 2018, with the demand replaced with 15,866 (12.3%) more petrol vehicles and 4828 (45%) more alternative fuel vehicles (AFV)

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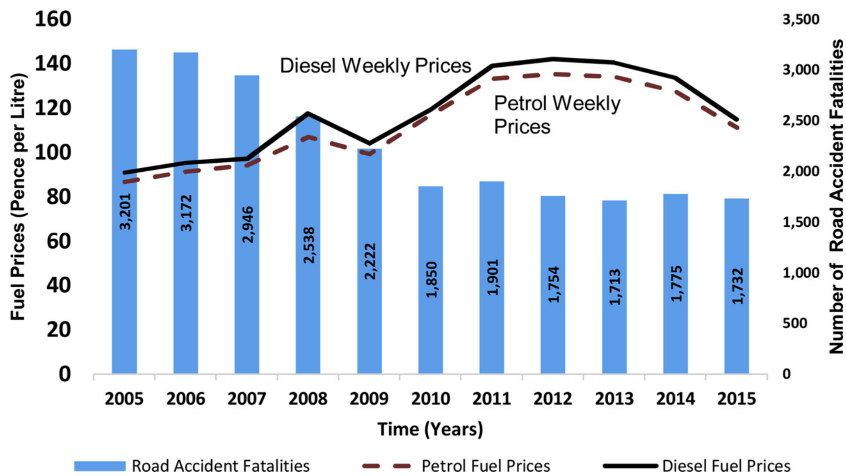

Fig. 1. Road Accident Fatalities and Fuel Price Fluctuation in Great Britain (2005–2015).

(The Society of Motor Manufacturers and Traders (SMMT, 2018). Bluntly, whilst such a shift from the internal combustion engine could well improve health outcomes and reduce energy use and carbon emissions, it may also inadvertently lead to an increased number of accidents, firstly by encouraging more and longer vehicle trips, and secondly by reducing fuel tax revenues and thus cutting spending on road safety improvement schemes.

Hence this question of how fuel price changes affect the number of road accidents in Great Britain forms the focus of this paper. The paper is structured as follows: Section 2 presents previous research, Section 3 details the data, and Section 4 describes the methodology. Section 5 outlines the results, and Section 6 provides a discussion and the conclusions.

2. Previous research

Overall, only a small number of studies have looked specifically at the relationship between fuel price changes and the level of road safety, specifically between fuel prices and the number of road accident fatalities (e.g. Burke and Nishitateno, 2015; Grabowski and Morrisey, 2004a, 2004b), else between fuel prices and the number of road traffic accidents (Chi et al., 2012; Rodríguez-López et al., 2016). So far, the overarching finding is that fuel prices are negatively related to road traffic accidents, i.e. that the number of road traffic accidents or fatalities falls as fuel becomes more expensive. For instance, a worldwide study found that an increase of 1% in fuel prices will cause a corresponding reduction in road accident fatalities of between 3% and 6% (Burke and Nishitateno, 2015). This variation in fatalities across different countries depends upon country specific characteristics e.g. medical technology and care, vehicle design, fuel price policy and regulations (fuel subsidies and fuel taxes).

Meanwhile an American study found that with every 1% increase in gasoline prices there is an immediate 0.25% reduction in the total accident rate (Chi et al., 2010), with the most impact being recorded on young people of age group (16–19) years old as compared to any other age group due to financial dependency. Next, a longitudinal study of data between 2004 and 2012 found that whilst the fuel price immediately affected the number of accidents for young people, it had no effect for people aged 25–34 and was only significant after a 9–10 month lag for people aged 75 years old and above (Chi et al., 2015). Chi et al. (2013) studied the fuel price effects on road traffic accidents per million VMT in Minnesota (USA), and found a 10% increase in petrol price reduced total crashes by 4.1% in rural areas but by only 2.8% in urban areas. Similarly, it reported that a 10% increase in petrol prices led to a decrease in the number of injury-only accidents by 2% in rural areas and 1.1% in urban areas, and in property damage only accidents of 5.2% in rural areas and 3.6% in urban areas. There was no significant difference between rural and urban fatal crash numbers.

In taking a broader view, there is a significant body of literature relating to the various ways in which drivers react to changes in fuel

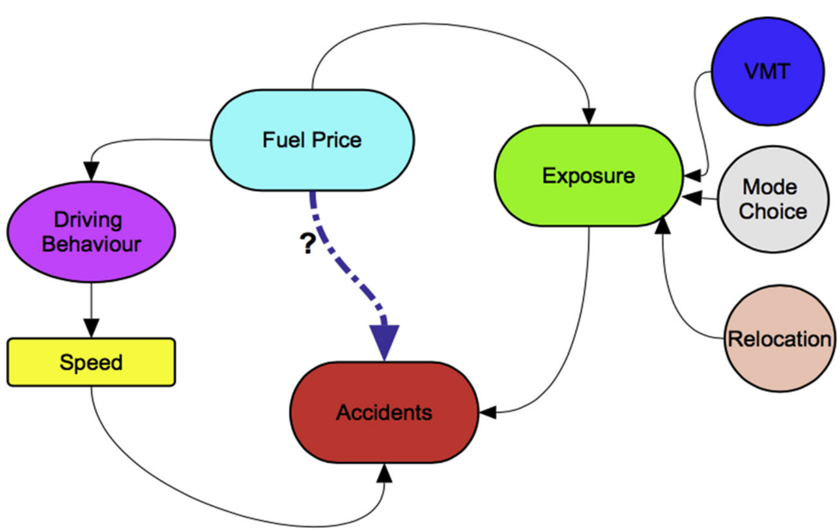

Fig. 2. Causal Diagram of Fuel Price and Road Traffic Accidents.

prices (see Fig. 2), particularly from elasticity studies on how they affect travel demand (e.g. Graham and Glaister, 2004; Musso et al., 2013) and fuel consumption (Goodwin et al., 2004), but also in other indirect ways (Burke and Nishitateno, 2015; Grabowski and Morrisey, 2004a, 2004b). Also important, given the assumption that speed and severity of accident are correlated, is a study of the fuel price and speed relationship which found that with every 1 US Dollar increase in fuel price there will be corresponding reduction of 0.27 mph in speed (Wolff, 2014). However, Burger and Kaffine (2015) reported the opposite by noting that a rise in fuel price of 1 US Dollar on freeways in peak periods actually increased average freeway speed by 3.3 mph during rush hours by persuading some people not to drive, thus freeing up road space and reducing congestion. Moreover, they speculated there was a disconnect between fuel buying decisions and choices about driver behaviour, and that drivers were generally unaware of the relationship between driver behaviour and fuel efficiency.

Crucially, in understanding what is actually an indirect relationship between fuel price changes and the number of accidents, it is necessary to consider several forms of variables (Elvik, 2003). In this 'causal chain' arrangement, these are the dependent variable, the independent variable, and a third type, which can then be denoted as being either (1) confounding (sometimes called confounder) variables, (2) mediator (sometimes called intermediate) variables, or (3) effect modifier (sometimes called moderator) variables (Kamangar, 2012). Of these, confounding variables can be defined as being as "*a predictor of the outcome, but is also associated with exposure*" (Bauman et al., 2002). Examples in this case could include such elements as GDP and weather conditions. For instance, whilst GDP might increase accident numbers by increasing the level of vehicle miles travelled (and hence exposure, (Jokscfi, 1984)), it may also lead to higher investment in road safety and hence reduce the number of accidents (Bishai et al., 2006). Meanwhile the economic growth of a country as measured by GDP will also influence fuel price levels, though fuel prices do not affect GDP directly at least (though crude oil prices may do), and thus GDP is a potential confounding factor candidate. Based on these arguments, a causal diagram is developed to demonstrate how fuel price changes may affect road traffic accidents (Fig. 2).

As for the effects of weather, whilst driving is generally less dangerous during daylight hours and in dry conditions, people also tend to drive more thus increasing their exposure (Department of Transport, 2014). Also, weather can influence fuel prices but remains unaffected by fuel price changes and accidents, and hence was identified as a second confounder for this study.

Mediating or intermediate factors are represented by variables which lie in the path of a causal chain of exposure and outcome, unlike a confounder variable (Kamangar, 2012), and for the purpose of this study may include variables such as vehicle miles travelled. Lastly, moderating or effect modifier variables affect the strength of a relationship without being a part of that relationship. An example here would be population, as a change in population would not fit in the casual chain between fuel price and accident relationship, though it would impact on the level of traffic exposure and thus on the number of accidents (Department for Transport, 2016b).

Table 1 presents the results of a series of previous studies illustrating how drivers change their driving behaviour, trip making behaviour or their lifestyles in response to fuel price changes; and then reporting how these responses affect the number of accidents.

In conclusion, the current literature is primarily focused on the United States, with only one or two exceptions, such as the world-wide study (Burke and Nishitateno, 2015). To the best of our knowledge, no analysis has been carried out in Great Britain, an environment where the price of fuel is kept artificially high for reasons of policy.

3. Data

From the review of the literature, the causal diagram (Fig. 2) and

Table 1
Conceptual Framework of Fuel Price Changes and Traffic Accidents.

Fuel Price Response		Source	Potential Implications For Accidents	Source
Changes in traffic dynamics; Changes in driving behaviour (immediate responses)	Fuel efficient driving (Drive slower and smoother)	(Blomquist, 1984)	Reduce likelihood of accidents	(Elvik, 2013)
	Reduce Speed	(Wolff, 2014)		
Changes in driving behaviour (short-medium term responses)	Trip chain, make multi-purpose trips	(Chi et al., 2013)	Reduce exposure	(Fridstrøm et al., 1995)
	Make shorter trips/less trips			
	Share vehicle/ car pool			
	Change mode	(Currie and Phung, 2007; Haire and Machemehl, 2007)		
Life Style changes (medium-long term responses)	Sell vehicle/ replace with new vehicle	(Busse et al., 2009)	Increase severe accidents	(Ahmad and Greene, 2005)
	Move house to be closer to work	(Chi et al., 2017)	Reduce exposure	(Fridstrøm et al., 1995)

Table 2
Variable Description of Data Collected for Great Britain*.

Data Type	Variable	Description	Available Frequency	Type	Source
Road & Traffic	Accidents	Accidents per week	Hourly	Dependent	(Department for Transport, 2015c)
	Vehicle miles travelled (VMT)	Separate VMT variables for Total, Cars, HGV and LGV	Quarterly	Mediator	(Department for Transport (2015, 2017)
	Road length	Total GB road length in miles	Annual	Moderator	(Department for Transport, 2016c)
Socio- economic	Unemployment rate	Rate of unemployment per capita	Monthly	Mediator	(Office of National Statistics, 2017a)
	GDP	Economic growth per capita	Quarterly	Confounder	(Office of National Statistics, 2017b)
	Population	Population aged 16 plus in thousands	Monthly	Moderator	(Office of National Statistics, 2018)
	Fuel price	Pump price of petrol and diesel in pence per litre	Weekly	Main independent variable	(Department for Business Energy and Industrial, 2018)
Weather	Temperature (^{0}C)	Average minimum, maximum and mean temperature of GB	Monthly	Confounder	(Met Office, 2017)
	Rainfall (mm)	Average rainfall of GB			
	Sunshine hours	Average sunshine hours of GB			
Specific event	Indicator for the Christmas period	Dummy variable (0,1) to control for unusual accident patterns. 0 = 51 Not a Christmas week 1 = 52 Christmas week	Weekly	Indicator	Manual

* Data sources links have been provided in the above Table 2 as and when necessary.

the conceptual framework (Table 1), a number of factors were identified, and a dataset was formulated. The dataset of 15 variables was constructed from a range of secondary data sources, with observations taken from January 2005 to December 2015 for GB (England, Wales and Scotland). The variable characteristics are displayed in Table 2, with more detailed comments provided below where necessary.

Accident and Traffic Data: The dependent variable is the number of accidents per week which was obtained from the so-called STATS19 database (Department for Transport, 2015c.) This contains detailed records of each accident e.g. location, number of vehicles involved, time (year, month, day, hour), the severity of accidents and number of casualties. The data is based on police records and is not matched with hospital data. It also does not include property damage accidents nor some minor injury accidents that have not been reported to the police. The raw daily data for total, fatal, serious and slight accidents was converted to weekly counts to use in the statistical analysis. Only one accident is recorded even if there are multiple victims or vehicles involved. Data for vehicle miles travelled for cars, light goods vehicles, and heavy goods vehicles were only available quarterly from the department for transport (DfT) converted to weekly data using annual average daily traffic (AADT) data, whilst those for road lengths was only available annually (Department for Transport, 2016c, 2017).

Socio-economic Data: Monthly data for unemployment rate data, quarterly gross domestic product GDP per capita and monthly population data for those aged 16 or over was collected for Great Britain from the Office of National Statistics website (Office of National Statistics, 2018, 2017a, 2017b).

Meanwhile, weekly fuel price data for unleaded petrol (ULSP) and unleaded diesel (ULSD) was obtained from the Department for Business, Energy and industrial Strategy (Department for Business Energy and Industrial, 2018). This data is updated every Monday from six participating companies covering 65% of the UK market and is used as a proxy for the average pump price pence per litre across the country.

Weather data comprising of minimum, maximum, mean temperature, rainfall and sunshine hours was taken from the Met Office weather summaries for each month (Met Office, 2017). One limitation with the data is that values for the whole of Great Britain are not directly available, and so an average of values from England, Scotland and Wales was used instead. According to the Department for Transport, the number of road traffic accidents in Great Britain increases during the summer months with a corresponding decrease in winter (Department of Transport, 2015c, 2015d, e).

One anomaly appears in the data each year for the week around Christmas, which shows a major reduction in accidents (an average of 12% less weekly accidents) and is possibly due to the combined effects of the holiday and accompanying bad weather. Specifically, daily averages of Christmas Day (25th of December) and Boxing Day (26th of December) have been found to have 56 percent and 42 percent less total accidents respectively when compared to daily average accident counts. To mitigate the effect of Christmas week a dummy variable for the Christmas week has been introduced.

4. Method

The purpose of this study is to develop a relationship between fuel price and road traffic accidents while controlling for other related factors for GB. Based upon the available data and other modelling issues appropriate accident prediction methods have been investigated and developed in this study.

A Poisson distribution was found to be appropriate for analysing count data (Noland and Karlaftis, 2005). However, there is an important and unique property of Poisson regression models which is the equi-dispersion (whereby variance = mean), though this is rarely true for accident count data which is mostly found to be over-dispersed (i.e. variance > > mean). The negative binomial (NB) distribution is therefore the next best choice to deal with the over-dispersion in the data, and variants have been used in many studies to analyse count data (Noland, 2005). However, whilst Poisson regression or NB regression models and its extensions are useful for analysing cross-sectional data with an assumption that observations are independent of each other and have been used in the previous studies to control serial correlation by introducing a time trend variable (Chi et al., 2013, 2010; Noland and Karlaftis, 2005), these models are not really suitable for time series data and can result in the incorrect estimation of parameters. This is potentially problematic in this case because the accident data used in this study is aggregate-level weekly time series count data for Great Britain from 2005 to 2015 and so could well be serially correlated. Quddus (2008) proposed that when the analysis units of observation (spatial and temporal) are relatively large (e.g. country-wide weekly or monthly traffic collisions) with a high value of the mean count (say greater than 50) then the data is termed as being highly aggregated time-series data. Therefore, addressing the inherent serial correlation is more important than preserving the properties of count data (e.g. the Poisson or NB process). Hence statistical models suitable for controlling serial correlation are considered in this study.

There are many different statistical models that are used in handling serial autocorrelation. In safety analysis, two models have primarily been used: (i) Prais-Winsten AR(1) model (Chi et al., 2010) and (ii) ARIMA models and their extensions (Hyatt et al., 2009). First, the Prais-Winsten regression model is able to account for any serial correlation present in a time series dataset but is more complex. These models estimate through a generalized linear square (GLS) regression function and can be used to transform a data series to resolve the issues of first order autoregressive (AR1) correlation which makes the residual stationary resulting in more reliable and accurate predictions. The important statistic to look for here is the Durbin-Watson *d*-value. The value of '*d*' statistics should be between 0–4, where 0 indicates a perfect negative correlation, a value equals to 2 represents no autocorrelation and a value moving towards 4 means a positive correlation.

$$Y_{\ell} = \beta_o + \sum_{j=1}^{k} \beta_j X_{j\ell} + \mu_{\ell} \text{ where } \mu_{\ell} = \rho\mu_{\ell-1} + e_{\ell} \tag{1}$$

Y_{ℓ} = Number of weekly crashes in time “

μ_{ℓ} = model error term; where ℓ = 1, ……, n

$X_{j\ell}$ = Vector of explanatory variables

k = Number of explanatory variables

ρ = Autocorrelation coefficient of order 1 (i.e. AR1) and $\rho = 1$ means that there is a perfect correlation among residuals ('perfect' means residuals are identical);

β_o, β_j = Parameters to be estimated;

e_{ℓ} = Refers to the independently and identically distributed error term with zero-mean and constant variance.

The second approach is to use time series modelling as introduced by Box and Jenkins (1970) which have been used in the last few years to analyse road safety data as compared to cross-sectional studies historically (Box and Jenkins, 2008; Lavrenz et al., 2018). These are well developed and these autoregressive integrated models (ARIMA) and so-called seasonal autoregressive integrated models (SARIMA) have been effectively used to estimate and forecast time series data. Subsequently they were extended to study the effects of exogenous variables on time series along with trend and seasonality (Box and Tiao, 1975).

As mentioned earlier, this study has time series count data which consists of dependent accident variable and independent time series of different control variables, and due to the presence of serial correlation in the series negative binomial models are unsuitable to use in this analysis. To deal with the problem of autocorrelation, dependencies of adjacent values in the time series data, and seasonality-periodic behaviour of the series- ARIMA and SARIMA models have been used in this study.

Overall then, the time series model can be defined as:

$$\mathcal{Y}_{\ell} = \beta\mathcal{X}_{\ell} + N_{\ell} \tag{2}$$

In cases in which ℓ is the discrete time (week in this case), $\mathcal{Y}_{\ell}$ is the appropriate Box-Cox transformation of $\mathcal{Y}_{\ell}$, say in log $\mathcal{Y}_{\ell}$, $\mathcal{Y}_{\ell}{}^{2}$ or $\mathcal{Y}_{\ell}$ itself (Box and Cox, 1964), $\mathcal{Y}_{\ell}$ is the dependant variable (i.e. accident counts/frequency) for a particular time *t*, $\beta\mathcal{X}$ is the deterministic part of the equation which to account for the effects of independent control variables ($\mathcal{X}$) and N_{ℓ} is the stochastic or noise component. The stochastic or noise component N_{ℓ} is ARIMA(p,d,q) and SARIMA $(p,d,q)(P,D,Q)_S$ where *p* is the order of the non-seasonal[1] autoregressive (AR) process, *d* is the order of the non-seasonal difference, *q* is the order of the non-seasonal moving average (MA) process and *P* is the order of the seasonal autoregressive (AR) process, *D* is the order of the seasonal difference, *Q* is the order of the seasonal moving average (MA) process and subscript 's' represents the periodicity or length of seasonality (in this weekly study s = 52).

$$N_{\ell} = \frac{\theta(B)\Theta(B)\mu_{\ell}}{\varnothing(B)\Phi(B_s)(1-B)d(1-B_s)D} \tag{3}$$

Eq. (3) is mathematical representation of SARIMA model where “∅” and Φ are non-seasonal and seasonal AR components and θ and Θ are seasonal and non-seasonal MA components, B and B_s represents backward shift operator, $u\ell$ is uncorrelated random term with zero mean and constant variance σ^2.

This study ran two types of models: one for petrol fuel prices and the other for diesel fuel prices, for each type of accident severity (fatal, serious and slight). This study developed weekly accident models for all accident severity levels.

5. Findings

Two separate models were developed: (i) petrol and (ii) diesel. This was necessary due to the high correlation between diesel and petrol prices which meant that it was not possible to include both variables in the same model (see Section 5.2 for more details). Each of the models has been further classified into three accident categories of fatal, serious and slight accidents. For ease of interpretation of the model coefficients, all three dependent variables were transformed into a logarithmic scale. Since the models are based on a time-series regression, a stationarity test is necessary before conducting the regression analysis. A stationarity test of a dependent variable is required as Granger and Newbold (1974) postulated that regression models for non-stationary variables give spurious results. Stationarity of time series is examined by the commonly employed Dickey-Fuller of Augmented Dickey-Fuller Unit Root Test (Dickey and Fuller, 1979). The results are presented in Table 3. As can be seen, the null hypothesis of a unit root at all common significance level (i.e. 1%, 5% and 10%) can be overwhelmingly rejected, confirming that the dependent variables are stationary.

Overall 12 different accident models were applied: two separate modelling techniques (Prais-Winsten AR(1) model and seasonal ARIMA); were applied to two different fuel types (diesel and petrol); at three different accident levels (fatal, serious and slight). All explanatory variables shown in Table 2 were initially included in the models but only the statistically significant variables were retained in the final models. Table 4 shows descriptive statistics for the variables that appeared in the final models. The exception here was 'rainfall', which is only significant for the fatal accident model and therefore was removed from the other accident models. Based on the model goodness of fit (i.e. Schwarz Information Criterion or Bayesian Information Criterion, BIC), the optimal specification for the ARIMA model was found to be SARIMA $(0,0,1)(0,0,1)_{52}$ with 1 non-seasonal and 1 seasoanl MA terms.

Table 5 presents the modelling results for all the models. Since each

[1] 'Non-seasonal' means that a term relates to every consecutive observation whereas 'Seasonal' means that a term relates to the seasonal length of 52 weeks in our study

Table 3
Stationarity Test for Unit Root.

Dependent Variable	Test Statistic Z(t)	1% Critical Value	5% Critical Value	10% Critical Value
Ln(weekly fatal accidents)	−10.551	−3.430	−2.860	−2.570
Ln(weekly serious accidents)	−10.574	−3.430	−2.860	−2.570
Ln(weekly slight accidents)	−8.306	−3.430	−2.860	−2.570

Table 4
Descriptive Statistics of Variables Used in the Statistical Analysis*.

Variable	Mean	Variance	Std. Dev.	Min.	Max.
Weekly total accident counts	3,086	264,736.51	514.53	1589	4,519
Weekly fatal accident counts	40	160.72	12.67	16	75
Weekly serious accident counts	419	4,556.17	67.50	162	588
Weekly slight accident counts	2,627	201,483.00	448.87	1305	3,930
Weekly petrol price (pence per litre)	112.58	328.07	18.11	78.93	142.17
Weekly diesel price (pence per litre)	117.68	355.90	18.86	83.87	148.04
GB population aged 16 and over (million)	48.73	1.59	1.26	46.45	50.81
Cars VMT (billions)	179.96	102.129	10.11	153.57	199.00
Rainfall (mm)	110.96	2,304.104	48.00	23.6	265.63

* There are 572 total observations for each variable included in the above.

Table 5
Modelling Results:
Prais –Winsten AR(1) Model and SARIMA $(0,0,1)(0,0,1)_{52}$ Model.

Prais-Winsten AR(1) model

Dependent variable: ln(weekly accidents inGB)	Petrol model						Diesel model					
	Fatal		Serious		Slight		Fatal		Serious		Slight	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
ln(petrol price)	−0.453	−4.04	0.021	−0.23	−0.119	−1.20	−0.391	−3.45	0.000	0.00	−0.127	−1.28
ln(car VMT)	1.094	5.58	1.188	7.83	0.341	2.21	1.048	5.23	1.189	7.79	0.327	2.11
ln(population)	−6.326	−8.88	−3.030	−5.18	−3.991	−6.31	−6.671	−9.34	−3.136	−5.43	−3.962	−6.34
ln(rainfall)	0.050	2.16	–	–	–	–	0.052	2.21	–	–	–	–
Christmas	0.153	2.53	0.081	2.36	0.110	4.01	0.153	2.55	0.081	2.36	0.110	4.01
Constant	24.433	9.75	11.725	5.68	22.155	9.97	25.731	10.41	12.036	6.01	22.156	10.25
Auto correlation coefficient of order 1, ρ	0.239		0.443		0.568		0.250		0.443		0.569	

Seasonal ARIMA models $(0,0,1)(0,0,1)_{52}$

Dependent variable: ln(weekly accidents in GB)	Petrol model						Diesel model					
	Fatal		Serious		Slight		Fatal		Serious		Slight	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
ln(petrol price)	−0.437	−3.95	−0.025	−0.31	−0.094	−1.54	−0.368	−3.26	0.003	0.04	−0.102	−1.57
ln(car VMT)	1.129	5.69	1.329	9.39	0.605	4.90	1.091	5.44	1.333	9.38	0.5918	4.78
ln(population)	−6.411	−8.89	−3.049	−5.37	−4.231	−9.35	−6.789	−9.29	−3.187	−5.51	−4.203	−9.08
ln(rainfall)	0.053	2.48	–	–	–	–	0.0561	2.59	–	–	–	–
Christmas	0.161	3.48	0.072	3.40	0.103	6.78	0.162	3.54	0.073	3.42	0.102	6.74
Constant	24.497	9.59	11.088	5.49	21.604	12.81	25.837	10.07	11.471	5.67	21.602	12.74

of the dependent variables were transformed into the logarithmic scale, the coefficient values in Table 5 indicate ‘elasticities’ rather than ‘slope coefficients’ for the continuous explanatory variables. Although Prais-Winsten AR(1) models controlled for serial correlation through an autoregressive term of order 1 and SARIMA models controlled it through two moving average terms (one non-seasonal of order 1, MA1 and one seasonal of order 1, SMA1), the results are identical with respect to the set of statistically significant variables and the magnitudes of the estimated parameters. Since the Prais-Winsten AR(1) model is more parsimonious, the interpretation of the results is primarily based on this model. All Durban-Watson d-statistic values from the Prais-Winsten models have found to be close to 2 which indicates that the models have been successful in controlling serial correlation in the data.

5.1. Fuel price and accident frequency

One of the key objectives is to investigate how fuel price changes affect road accident frequency while controlling for related factors. From Fig. 3 a trend is noticeable that across the decade 2005–2015 there was a broadly negative relationship between fuel price and the number of road accidents. Thus, between 2005 and 2007 when fuel prices were relatively low there was an increase in road traffic accidents whilst during 2009–2012 when prices rose there was a corresponding reduction in accidents.

This negative relationship is clearly reflected in our results for both the diesel and petrol model analyses, such that fuel prices were linked to the number of fatal accidents by an elasticity value of ‘-0.45 and ‘-0.39’ respectively i.e. that for every 1% increase in fuel price, the

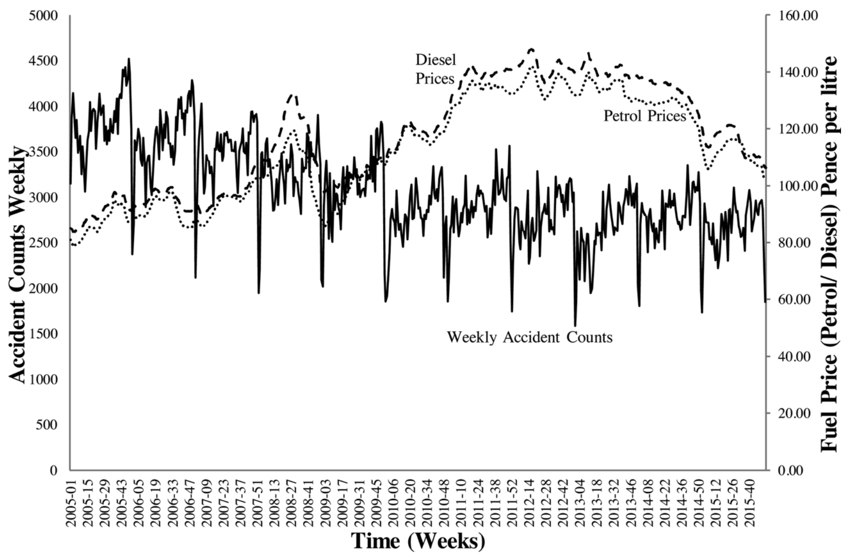

Fig. 3. Fuel Price and Accident Frequency (GB 2005–2015).

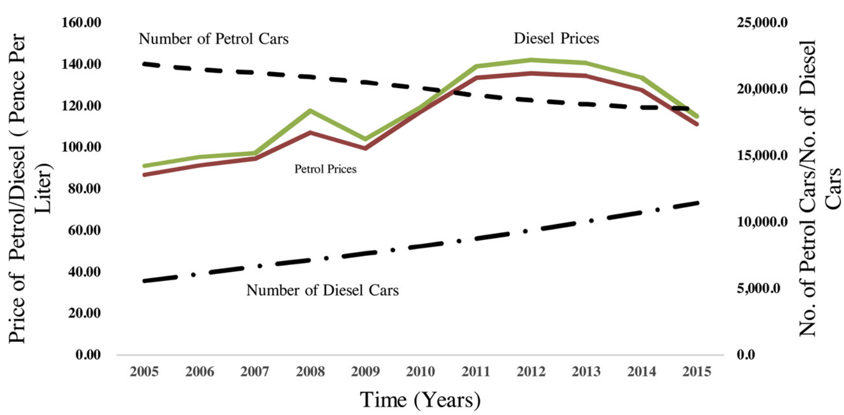

Fig. 4. Changes in Numbers of Cars Based Upon Fuel Type.

number of fatal accidents fell by 0.4% (see Table 5). These results have been obtained at the mean price values of petrol and diesel, which were 112.58 pence per litre and 117.68 pence per litre respectively. These results are consistent with the previous studies that analysed fuel price and accident rate/ fatalities rate in other parts of the world (Chi et al., 2017; Grabowski and Morrisey, 2004a, 2004b) suggesting that fuel prices do affect road safety through a reduction in fatalities which is an important road safety target around the world. In understanding this, there seem to be two major possible links through which fuel prices affect accidents; through changes in driver behaviour, and through changes in exposure.

In terms of driver behaviour, in the short term, one might expect to see drivers slowing down, and driving more smoothly in order to use less fuel which could also help lead to less accidents (Wolff, 2014). In terms of exposure meanwhile, drivers will likely seek to reduce the money they spend on fuel, and thus reduce their VMT, and this could play out in several ways. In the short term, drivers might change their route to minimise distance, congestion, or stopping and starting (route assignment); switch modes for certain trips – i.e. walk, cycle, use public transport, or share their cars with other people (mode choice); start trip chaining, reducing peak period trips by car, or travel to/from activities that are closer to home (trip distribution); or replace trips altogether by working at home or shopping on-line (trip generation). In the longer term, some drivers might be expected to change their vehicles to be more fuel efficient or to a 'cleaner' power source; and to move their job and/or their house so as to reduce the distance they have to travel and the money they spend on fuel. With regard to exposure, it is important to understand that such changes will likely impact different groups and different geographical areas in different ways. For example, higher fuel prices will probably disproportionately deter many younger people from driving and thus reduce the number of people from this 'risky driver' group on the roads and stop accidents from happening (Department for Transport, 2015a). Geographically too there are differences, whereby rural drivers have been shown to be more sensitive to fuel price changes than urban drivers (Chi et al., 2013), which in the Great Britain context has been where most accidents occur due to greater speed variability and poorer road conditions (Department of Transport, 2015).

5.2. Comparison of petrol and diesel models

There has been a decline in the number of petrol cars over the study period (2005–2015) in Great Britain from 21.8 million (79.5% of total cars) to 18.1 million (61.2%) in 2015 (see Fig. 4). At the same time, the number of diesel cars numbers grew from 5.6 million (20.3 % of total cars) in 2005 to 11.4 million (36.2% of total cars) in 2015.

This shift was driven due to the better fuel efficiency and carbon emission performance of diesel vehicles (Department for Transport, 2015c), and was encouraged by Government tax policy on CO_2 reduction which subsidised diesel fuel cars from 2001. However, increased public health concerns (especially in children) caused by poor local air quality, have seen a recent policy switch away from incentivising the use of diesel powered vehicles, which have largely generated the increased levels of nitrogen dioxide NO_2 and particulates.

Accident elasticities from both these separate models are shown in Table 5. The elasticity value remains approximately the same, with the slightly higher value for petrol elasticity perhaps being due to there being more petrol cars on British roads. Thus, both model results can be interpreted such that the fuel price effects on accidents remains negative i.e. that a 1% increase in fuel price will reduce road traffic accidents by 0.45% for petrol price and 0.39% for diesel at the 95 % confidence interval.

5.3. Variables selected for the final model

Throughout the literature, fuel price has been conceptualized to affect accidents e.g. through changes in factors such as vehicle miles travelled (VMT), changes in fuel consumption through less travel and more rational driving behaviour etc. In this study, VMT has been used as an exposure variable and car VMT are found to be significant for fatal accidents model (elasticity value = 1.09) which is consistent with the previous literature and explains that changes in fuel prices can affect changes in accidents through variation in VMT. GDP has not been found statistically significant in this study and was thus excluded from the final models. The population of an area can affect number of accidents through increased travel demand (Department for Transport, 2013), and therefore population of all 16 plus of GB residents was included in the model. It is to a certain degree surprising that population has a negative association with all types of road traffic accidents. This is because an increase in population indicates more travel activities and therefore a positive association is expected. While this may be true for cross-sectional data, population represents 'trend' in time-series analysis of accidents. This is evident as population has steadily increased over the study period in GB while traffic accidents have decreased during the same period. Rainfall was used as the most influential weather control variable and was found to be a statistically significant predictor affecting fatal accidents only as in rainfall becomes insignificant for other types of accidents (serious and slight) and therefore, removed from those models. More specifically, a 1% increase in rainfall will increase fatal accidents by 0.05%.

6. Discussion and conclusion

A reduction in road accident fatalities around the world has previously been linked with the economic downturn (Interenational Transport Forum, 2015). In the British case, an additional explanation for this is the parallel trend in fuel prices, whereby petrol and diesel became more expensive during the recession period of 2008–2010 (Department for Transport, 2015b). This paper is original in that whilst there is international evidence on the accident and fuel price relationship, so far there have not been any studies on this topic in coutries with relatively high fuel prices. Thus, fuel prices in Great Britain are impacted through the implementation of relatively high rates of fuel duty and fuel tax (VAT on top of duty). They are the 11th highest for petrol and 3rd highest for diesel in the whole of the EU (May 2018), and are double those in the USA.

This formed the rationale for an investigation on how much accidents have been controlled through fuel prices in Great Britain and hence is the focus of this paper. The rigour of the method was derived from applying two separate modelling techniques (Prais-Winsten AR(1) model and seasonal ARIMA); to two different fuel types (diesel and petrol); at three different accident levels (fatal, serious and slight); to national-level weekly data collected over the course of a decade.

The study found that fuel prices are only significant for fatal accidents and not for serious and slight accidents. Changing fuel prices affected fatal road accidents not only during recession but also throughout the whole time period of the study from 2005 to 2015. The petrol and diesel price levels were found to have almost the same negative effect on fatal accidents. In addition, two different statistical models were applied to the same data, but an almost identical impact was obtained. This ensures an efficacy of the findings. Increase in fuel price perhaps captures changes in exposure and driving behaviours of motorists through reducing speed, travelling less and a reduction in the 'risky driver' population.

Finally, this study is significant in that it lays the foundation of future road safety policy and practice by proving an evidence regarding the significance of fuel price in the GB in mitigating road traffic accidents. This is important because high fuel taxes are seen as being a core policy tool that aims to reduce air and noise pollution, congestion and road accidents through a reduction in traffic exposure, whilst part of the revenue generated from the fuel taxes is spent on road safety improvement projects. Moreover, the changing composition of the vehicle fleet from fossil fuelled engines to hybrid and electric cars and the corresponding loss of tax revenue could lead to more road safety issues, and possibly to more road accidents than currently. Fundamentally, this evidence can help policy makers to better understand the implications of fuel price policy on road accidents, and to devise new and better transport pricing policies in the near future for controlling fatal accidents that are currently supressed by high fuel prices.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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