Economics of road accidents and fatalities in Britain

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Abstract

In Britain each year, enormous costs stem from death and injury caused by road accidents, making driving behaviours of critical importance to health economists and others. Efforts to reduce accidents and their severity require knowledge of individual behaviour in response to changes in incentives induced by the economic environment and government policy. As such, accidents may be consequences of other factors.

There is a growing interest in the link between economic activity and road accidents. Using data for British regions over 23 years, we find a procyclical relationship between accidents and fatalities and employment with an effect size in the order of 2%. Strongest results are found for accidents involving motorcycles or goods vehicles or accidents occurring at night. Strong results are also found for drivers of unknown age and sex (likely from accidents reported after the fact). Fatalities involving motorcycles, on motorways or A(M) roads or occurring at night also show strong relationships with economic activity. Traffic volumes and risky driver behaviour are the most likely mechanisms at work.

Having established the link between economic activity and numbers of accidents for Britain, we then consider the relationship with accident severity at the individual driver/vehicle level. There is a significant procyclical relationship when we compare slight to serious or fatal accidents leading up to the Global Financial Crisis (GFC), consistent with risky driving behaviour. However, no procyclical relationship thereafter suggests traffic volumes and congestion predominate. We find accidents on motorways remain procyclical after the GFC (in contrast to the results for other characteristics), suggesting more risky behaviour on motorways over this period. A significant countercyclical relationship is found post-GFC when we consider driver characteristics, although insignificant relationships for accidents involving alcohol or drugs at that time suggests a preponderance of risky driving behaviours.

There is a limited literature on the relationship between stock markets and road accidents, which are thought to link through anxiety and stress, leading to driver fatigue and distraction and consequent accidents. From 1985–2015, we find overall accidents increase with positive and negative changes in FTSE100 returns with effects up to 1%. For fatal accidents, larger negative returns are associated with fewer fatal accidents but increases in returns leave numbers unaffected. Similar results occur by driver/vehicle characteristics. Accidents in richer counties

increase in response to ‘good news’ from the stock market, although the effect is small. There is no significant relationship between fatal accidents and returns for either rich or poor counties.

Penalties are designed to deter certain behaviours. In Britain in 2017, penalties for mobile use doubled and in England and Wales speeding fines increased by 50%. We evaluate the effects of these interventions over a two-year time horizon using Regression Discontinuity in Time and Difference-in-Difference analysis, employing data on virtually all injury accidents for Britain. After rigorous analysis we find no effect of either intervention on numbers of serious or fatal accidents at the aggregate level. However, the speed intervention has a small effect on motorways relative to non-motorways.

Declaration

This thesis is an original work of my research and contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

Jane M. Fry

Date: 14 September 2020

Presentations during enrolment

Chapter	Date	Forum	Discussant
2 Economic activity, road accidents and fatalities in Britain	20 Feb 2018	Confirmation milestone	
	6 Jun 2018	Griffith Business School seminar series, Griffith University	
	1 Nov 2018	31st PhD Conference in Economics and Business, UNSW	Prof. Denzil G. Fiebig
3 The economy and road accident severity in Britain	5 May 2020	Pre-submission seminar	
4 Stock market returns and road accidents in Britain	25 Sept 2018	Australian Health Economics Society Conference, Hobart	
	28 Nov 2018	Monash Business School Doctoral Colloquium	
	19 Feb 2019	Mid Candidature Review milestone	
	12 Apr 2019	Economics, Finance & Marketing seminar, RMIT University	
	29 May 2019	Department of Management, Marketing and Entrepreneurship and Department of Economics and Finance seminar, University of Canterbury	
	5 May 2020	Pre-submission seminar	
5. Penalties and behaviour: road accidents and the introduction of harsher driving penalties in Britain	25 Sept 2019	Australian Health Economics Society Conference, Melbourne	
	5 May 2020	Pre-submission seminar	

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Chapter 1: Introduction

As sanitation has improved and medicine has advanced over time, health behaviours have become critical to improving health and wellbeing. Indeed, in the US, almost half of all deaths are thought to be the result of behavioural factors (Glanz & Stryker, 2008). Health behaviours can be defined as an individual's action that affects own or others' health (Cawley & Ruhm, 2011). These behaviours are determined by the utility maximising behaviour of individuals, in which marginal benefits are equated to marginal costs. Such behaviours may change in response to a variety of factors that affect benefits and/or costs. These factors may result from deliberate attempts to manipulate behaviour (such as targeted government actions) or from incidental means (potentially unanticipated consequences of other events). If we are to improve the health of individuals, we need to understand the effects of these interventions and other events.

One aspect of health that is of intense interest is death and injury arising from road accidents. As of 2016, road accidents have become the 8th leading cause of death globally and the top cause of death for individuals aged 15–29. Each year more than 1.35 million people die from road accidents and up to 50 million are injured (World Health Organization, 2018). Vulnerable road users such as pedestrians, bicyclists and motorcyclists are particularly at risk. In recognition of the enormity of this problem, in 2010, the United Nations General Assembly declared the following decade (2011–2020) to be the Decade of Action for Road Safety (World Health Organization, 2013). Substantially reducing such deaths and injuries became one of the United Nations' Sustainable Development Goals (set in 2015). Sustainable Development Goal number three is designed to 'ensure healthy lives and promote well-being for all at all ages' and relates to road safety as it has an ambitious target to 'halve the number of global deaths and injuries from road traffic accidents' by 2020 (World Health Organization, 2015, p. 3). As a follow up, in 2017 Member States agreed to a set of performance targets for 2030 for road safety risk factors and service delivery mechanisms (World Health Organization, 2018). Road accidents are therefore a major public health issue — for each fatality there are dozens of injured who suffer short term or permanent disabilities that restrict their productivity, participation and/or quality of life more generally (Peden et al., 2004). Additionally, there are direct costs associated with initial and ongoing medical care and rehabilitation. Then there are the lives of carers and family that are also affected. Understanding the determinants of these costs can help policy makers target areas for interventions to lessen the impacts.

Research on road accidents has been conducted over a long period by government departments, research centres and academics (see, for example, Erlander, Gustavsson, & Lárusson, 1969). However, much of the literature focusses on engineering, science or technology. Relatively little of this body of work considers the economics of individual risky behaviour in the context of traffic accidents (see Cawley & Ruhm, 2011; Green, Heywood, & Navarro, 2014; Lam & Piérard, 2017; Ruhm, 2015) and tends not to use econometric techniques. In the past 10 years or so, relevant publications have appeared in the two leading health economics journals (Journal of Health Economics and Health Economics). Although these papers focus in some way on the economics of road accidents/fatalities (see, for example, García-ferrer, de Juan, & Poncela, 2007; Ruhm, 2015, 2016), most papers use US data and there remain fundamental gaps in knowledge in relation to accidents and economic factors.

This thesis investigates a number of key issues and policy-related questions relating to the economics of road accidents and fatalities using the world class British Stats19 database, which records details of every road accident that involves personal injury and at least one vehicle and that is reported to police in Britain. These data are very rich and span more than 30 years, permitting investigation of a variety of issues using modern econometric modelling techniques. The richness and structure of these data have been combined with data from other sources such as the UK Labour Force Survey, stock market data and Google trends search information to enable each study.

1.1 Background

Driving has both benefits and costs. Most journeys are undertaken by road and, in Britain at least, the majority of these — some 90% — are by car or van (UK Department for Transport, 2016b). Driving allows individuals to commute to and from work, purchase consumption goods and services from other locations and to travel for leisure purposes (Couture, Duranton, & Turner, 2018).[1] Driving also facilitates the movement of goods and services (freight) from point of production to point of sale/consumption. In Britain, almost 75% of transported goods are moved by road (UK Department for Transport, 2016b). Road transport is therefore critical to the functioning of the economy. However, driving also has significant costs via road safety. In

[1] Driving may also have intrinsic consumption value to individuals.

Britain in 2017, for example, there were almost 130,000 accidents involving injury or death that were reported to police, of which about 106,000 (81%) were slight, 22,500 (17%) were serious and 1,676 (1.3%) were fatal (UK Department for Transport, 2018). On average, the cost of accident prevention was some £2.1m for fatal accidents, £244,000 for serious and £25,500 for slight accidents, resulting in a total cost of £11.7bn (UK Department for Transport, 2018).[2]

What is known about road safety? There is no single factor that determines the number of road accidents and their severity. Rather, a number of interrelated factors play a role, including distance travelled (which is, in turn, affected by economic conditions, such as fuel costs, unemployment and incomes), the mix of transport modes used and their safety standards/vehicle technology, individual (driver, rider and pedestrian) behaviour, the mix of road user groups (such as child cyclists and pedestrians, newly qualified drivers or older people) and other external effects such as light and weather conditions and road surface conditions (UK Department for Transport, 2016a). Improvements in emergency response and medical care can also reduce the severity of casualties by reducing fatalities. Accidents are considered to be largely preventable and predictable (Peden et al., 2004).

Extensive research indicates one of the main factors causing accidents is human behaviour (Broughton & Stone, 1998). Human error contributes to some 90% of road accidents and responds to the environment surrounding the behaviour (Peden et al., 2004). In the road safety literature, the environment typically refers to road design, layout and other safety features as per the Haddon matrix (Haddon, 1968; Peden et al., 2004). However, in an economic framework the environment could also be defined more broadly to include other influences on driver behaviour, such as economic conditions. These other influences are thought to work through exposure to risk (the need to travel), accident involvement and accident severity. Critical aspects of driver behaviour include speeding, drinking alcohol, drug taking, distraction (including mobile phone use), driving anger/aggression and fatigue. Each is likely to contribute in a significant way to accident numbers and their severity.

Efforts to reduce accidents and their severity require in depth knowledge of the determinants of the number of accidents, risks and the effectiveness of policies designed to reduce the

[2] A further £19bn was associated with accidents not reported to police (UK Department for Transport, 2018).

number of deaths and severity of injuries that comprise the ‘road toll’. In an economic framework, these determinants are mostly linked to accident outcomes via individual decisions weighing up costs and benefits associated with different behaviours. If individuals deem benefits of risky driving behaviours to exceed costs, accidents may ensue. This result can arise for several reasons. Individuals might inaccurately assess benefits and costs associated with risky driving due to a lack of relevant information. For example, they may not know the true risks associated with exceeding the speed limit. Alternatively, they might suffer optimism bias in which they know population risks but underestimate personal risks (Cawley & Ruhm, 2011) — ‘it can’t happen to me’. Drivers may also fail to take into account the costs of accidents to others such as passengers. That is, there are externalities that result in a wedge between private costs and benefits and social costs and benefits and this will lead to an overprovision of (risky) driving from society’s perspective. If drivers do not personalise the risks associated with risky driving, improvements in general information on the consequences of risky driving may have limited effects on behaviour. There might also be differences arising from different cognitive processing limitations (perhaps proxied by education). In such cases, we might expect those with higher levels of cognitive skills to better grasp the consequences of risky driving and drive more conservatively. Different risk preferences may lead some individuals to drive in a more risky manner than others. The rate of time preference can also affect driving behaviour. For individuals seeking to maximise the present value of discounted lifetime utility, a higher rate of time preference indicates less patience on the part of a driver (preferring utility today rather than tomorrow), potentially leading to more reckless behaviour in order to save time in transit. The rate of time preference can change with different situations (Cawley & Ruhm, 2011), allowing individuals to drive differently as, say, economic or other conditions change.

In weighing up costs and benefits, risky behaviours may still result. Where there are externalities, economics tells us that behaviour may not result in pareto optimal outcomes and government intervention may be required to cut numbers of accidents and/or reduce their severity. Government intervention may comprise information provision on links between behaviour, accident risk and harmful health outcomes, or it may be targeted more specifically at driver incentives (such as changing penalties associated with certain — potentially harmful — behaviours). Penalty instruments include fines and penalty points for law breaking, policing of illegal behaviours and increased car insurance premiums associated with convictions for illegal behaviours. The idea here is to have drivers internalise social costs associated with accidents. There are high costs associated with accidents: to victims, carers, related others and the health system. It is therefore crucial to understand influences on driver behaviour that can lead to accidents. This is important as improving the health of the nation requires that we understand the pathways through which we can affect health. The aim of this thesis is to make a substantive contribution to this knowledge base.

1.2 Thesis overview

In Britain in 2018, there were 160,597 casualties (individuals injured or killed) and the casualty-related costs associated with all injury road accidents were £29.2b or 1.6% of GDP (UK Department for Transport, 2019).[3] Road accidents were the second leading cause of death for individuals aged 5–19 and the third leading cause of death for individuals aged 20–34 in England in 2017 (Public Health England, 2017). As such accidents are potentially avoidable, this represents a large cost to individuals and the health system that should be reduced. The health of the British population is therefore substantially affected by road accidents and this thesis aims to understand how accident volumes and severities are impacted by individual behaviour in response to changes in incentives induced by the economic environment and government policy. Our focus is on accidents (or lack thereof) and severity as consequences of other factors. We begin our inquiry by considering the (perhaps unanticipated) consequences of changes in how the economy is performing in chapters 2 and 3. We then examine effects of movements in the stock market in chapter 4, before finally investigating effects of specific changes in incentives/penalties for particular driving behaviours in chapter 5. The four empirical chapters are written to be self-contained pieces of analysis each of which will be shortened into a research paper. Necessarily, therefore, there may be some repetition in background and data sections.

1.2.1 Chapter 2

There is a growing interest in how changes in the macroeconomy affect population health. Since the early work of Ruhm (2000), this literature has found a consistent procyclical relationship with road accidents: both accidents and fatalities increase in good economic times (see for example García-ferrer, Bujosa, de Juan, & Sánchez-Mangas, 2019; Lin, 2009;

[3] This figure includes costs associated with accidents reported to police and estimates for those not reported to police.

Neumayer, 2004; Ruhm, 2015; Stevens, Miller, Page, & Filipski, 2015). These studies tend to show that, in response to a 1% increase in unemployment rates, estimates of road fatalities fall nationally by about 2–3% and regionally by about 1–3%. These results are partly attributed to road user behaviour (OECD/ITF, 2015; UK Department for Transport, 2016a; Wagenaar, 1984). However, none of these studies focus on Britain and, given the considerable costs associated with road injuries and fatalities, it is important to obtain accurate estimates of how accidents and fatalities respond to the economic cycle.

This chapter then considers how macroeconomic performance affects health as represented by road accidents in Britain. Using the very rich and unique Stats19 dataset, comprising characteristics of all road accidents involving personal injury in Britain, we model the association between economic activity and regional road accidents and fatalities on a quarterly basis over an extended period that includes the Global Financial Crisis, which had a large effect on economic activity. Disaggregations of the total number of accidents and fatalities provide further insights. We examine the extent to which accident rates rise after a recovery and identify potential mechanisms in order to target groups and/or situations for potential road safety interventions.

Aligning with the available economic data, in this analysis, the accidents data span some 23 years (from 1992 to 2015) and allow us to explore variations in the estimated effects by testing whether the overall relationship holds for different types of road accident. This helps identify explanations that may not have been distinguished in the extant literature due to data limitations and the scope of analysis. The analysis is conducted at the region level for England and the country level for Scotland and Wales. At the macro level, we use a panel data model to capture fixed effects and trends, isolating the effects of the macroeconomy. That is, we take away the effects of other (confounding) characteristics to see how accidents and fatalities respond to macroeconomic conditions. Having looked at the overall relationship we then disaggregate the total and make hypotheses about mechanisms that might be determining the differences. Robustness is examined in relation to the measure of the macroeconomic cycle (unemployment) and the form of relationship (semi-logarithmic). A final analysis considers the relationship between the macroeconomic cycle and the ratio of serious or fatal accidents to total accidents.

1.2.2 Chapter 3

In chapter 2 we established the link between economic activity and numbers of road accidents for Britain. Although many studies, including ours, explore the relationship between economic performance and numbers of accidents or fatalities, few studies have examined whether road accident severity is also procyclical. For example, Gerdtham and Johannesson (2005) considered the relationship between unemployment and death from road accidents and Noland (2003) examined the link between per capita income and road fatalities and injuries, with both studies suggesting to some extent the relationships may be procyclical. However, this link could occur through changes in traffic volumes and congestion or changes in drivers' risky behaviour, or both. During economic expansions, traffic volumes increase and raise the probability of accidents. However, at certain times, increased volume could lead to congestion, lowering average speeds and reducing severity. At the same time, drivers may adopt more risky behaviours such as speeding (where possible), excessive lane changing, drink driving and using mobile phones while driving. These factors have been linked with increased accident severity. As the most severe accidents place a greater burden on individuals and the health care system it is important to understand ways in which we might 'lighten the load'.

In this chapter, we use unique driver-level data from Stats19 on approximately 8.6 million vehicles involved in injury accidents reported to police in Britain over the period 1992–2015 (the time period over which economic data are available) and a novel empirical approach stemming from the macroeconomic cycle/health literature. Our fixed effects model removes time, region (and in some cases vehicle type) variations from the data, allowing us to focus on the effects of the regional economic cycle on individual accident severity. The model identifies the impact of economic conditions on accident outcomes using within-region variations in severity relative to other regions. Our measure of accident severity is the probability that the accident results in at least one serious injury or fatality, relative to just slight injuries.

We investigate the link between the economy and accident severity and consider accident characteristics and driver/vehicle characteristics to determine whether it is due to traffic characteristics (volumes (exposure) and congestion (speed)) and/or driving behaviour. We further seek to identify characteristics of individuals who change their behaviour, how they change their behaviour and their accident outcomes. Driver demographics can indicate likely behaviours affecting accident severity and severity of accidents involving particular types of cars gives some idea of the effects of driver SES. Comparing outcomes of accidents involving alcohol or drugs gets us closer to driver behaviour.

1.2.3 Chapter 4

In this chapter we investigate how driving behaviour reacts to economic news. There is growing interest in the relationship between stock market movements and health, dating back to about 2010.[4] Both stock holders and non-stock holders are subject to the effects of changes in the stock market as a real-time indicator of economic conditions, and through wealth channels (Angrisani & Lee, 2016) although the effect is likely to be smaller for individuals with less exposure to the stock market. Since most individuals are aware of economic uncertainty (Kalcheva, McLemore, & Sias, 2017), it is likely that changes in the stock market can lead to short-run anxiety about future prospects (Frijters, Johnston, Shields, & Sinha, 2015), even for those not invested in the stock market.

Considering road accidents, there are only two papers to date that consider the relationship with the stock market (Cotti, Dunn, & Tefft, 2015; Giulietti, Tonin, & Vlassopoulos, 2020), both focussing on the US. The results suggest that there is a negative relationship (accidents increase as the market falls), which is likely to be causal. The efficient markets hypothesis maintains that stock prices incorporate all currently available information about firms and their performance and are both variable and unpredictable (Ratcliffe & Taylor, 2015). Seasonal effects aside, this implies large changes in the stock market represent an exogenous shock which may causally affect individuals' driving behaviour. Daily stock market movements (particularly negative shocks) could affect driving performance through judgement errors and lapses in concentration resulting from psychological distress (Giulietti et al., 2020).

This chapter investigates the relationship between movements in a stock market index and road accidents in British regions. Direct health outcomes such as heart attacks and strokes have already been considered, but the indirect impact on driving behaviours has remained largely unaddressed. Again, we use data on accidents from the Stats19 administrative data on all police-reported injury accidents. Using available data, we construct a daily series from 1985 to 2015, split by region, yielding some 124,000 observations. We use daily returns (closing prices)

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[4] See, for example, Chen, Chen, Liu, and Lin (2012), Fiuzat, Shaw, Thomas, Felker, and O'Connor (2010) and Ma, Chen, Jiang, Song, and Kan (2011).

for the FTSE100 index as our measure of the stock market as it is widely reported in the British and international media. Having 30 years of data allows us to investigate the relationship over a long period, which experienced a great deal of variation to be used for identification. In modelling, accidents are aggregated into 7 time periods within a week. Each period begins at 5pm after the market has closed. For consistency with weekdays, weekend periods begin at 5pm. For each period, accidents are related to the most recent daily return. Our model is estimated for the whole week, weekdays and weekends on total numbers of accidents and numbers of fatal accidents. Again, using a very tightly identified fixed effects model, the effects of the stock market are identified by variation in the number of accidents within regions within a week. Region fixed effects account for factors varying by region, such as road lengths and the geography of the area. Time fixed effects account for variables like national economic trends and vehicle safety standards. In trading off using additional information (variables that might be of interest — such as traffic volumes — are not available on a daily basis) against tight identification, we gain greater precision in our analysis, having removed a lot of potentially confounding variation. Although there are many confounding factors that are hard to measure or get data on, this model differences these factors away.

1.2.4 Chapter 5

In analysing the economics of crime, penalties — such as fines — are designed to modify behaviour according to the socially optimum/efficient outcome by internalising externalities (Pigou, 1932). In making decisions, individuals compare the expected benefits and expected costs associated with different behaviours. Penalties are designed to deter certain behaviours through increasing expected costs associated with committing an offence. One type of crime that can have significant health impacts via road accidents is behavioural driving offences, such as using a mobile phone while driving and speeding. Being distracted by a mobile phone while driving can increase the risk of an accident by four times (World Health Organization, 2018) and the power model of Nilsson (2004) postulates that the change in numbers of fatal accidents is determined by the fourth power of the change in mean speed (see, for example, Elvik, 2012). Although one way of potentially reducing accident numbers is to control driver behaviour, introducing laws governing mobile phone use and setting speed limits does not guarantee compliance. A system of harsh penalties for drivers caught using mobiles or exceeding the speed limit is therefore required to induce would-be offenders to obey the laws and to penalise violations.

In 2017 there were two such road safety interventions targeted at drivers using a mobile phone or speeding. The first intervention involved increasing the fine from £100 to £200 and doubling penalty points from 3 to 6 for drivers caught using a hand-held mobile phone while driving in Britain. The second intervention involved increasing fines for extreme speeding from 100% to 150% of weekly income for drivers in England and Wales. Most analyses of such interventions would only consider the effects on numbers of offences committed. However, since the interventions are essentially designed to improve road safety, in this chapter we focus on identifying the ultimate effects on numbers of accidents, particularly fatal or serious accidents. These interventions had the potential to reduce such severe accidents: of the 18,936 accidents classified as fatal or serious in Britain in 2016, about 1% were associated with using a mobile phone while driving and some 8% were associated with speeding.

In this chapter we investigate the effects of the 2017 interventions on numbers of serious or fatal accidents using Stats19 data in the year before and after the policies. Our treatments comprise the introduction on 1 March 2017 of larger fines and penalty points for using a mobile phone while driving in England, Wales or Scotland and the introduction on 24 April 2017 of larger fines for the most serious category of speeding in England and Wales. After accounting for longer term trends and seasonal effects, we use Regression Discontinuity in Time (RDiT) analysis to see what happened in the affected countries before and after the interventions and we use difference-in-difference (DiD) analysis to compare areas or groups affected by an intervention with areas or groups unaffected to identify 'treatment' effects over a two-year time horizon. We aggregate to daily observations on numbers of serious or fatal accidents for each Local Authority in England and Wales (and in some cases Scotland) for our analysis. UK Met Office weather data (daily precipitation, maximum and minimum temperatures) for each Local Authority area account for any unusual weather events that might have affected accidents at the time of the interventions.

In order to identify the effects of the interventions, our modelling strategy involves a two-step process similar to that used in related literature (Castriota & Tonin, 2019; De Paola, Scoppa, & Falcone, 2013; Hausman & Rapson, 2018). The first step involves estimating and removing long term effects of trend, seasonal, public holiday and weather factors from the raw data to create an adjusted series. The second step involves either an RDiT or DiD analysis of the intervention. We focus on accidents in which someone is seriously injured or killed.

1.3 Contribution

Each empirical chapter makes a substantive contribution to the existing limited literature. The chapters explore accidents and their severity as consequences of other ‘events’. These consequences may not have been foreseen, but these analyses allow driver behaviours to be better anticipated and aid in designing policies aimed at averting accidents and/or reducing their severity. The analysis adds new knowledge in the field of health economics on the way certain events influence health outcomes through driving behaviours.

Chapter 2 complements other studies linking the economy and road deaths or numbers of accidents but provides several important points of difference. To our knowledge, this chapter represents the first attempt to model the relationship between fatalities and the economic cycle for British regions using panel data and to explore the link with accident characteristics. Using data on every road accident reported to police over 23 years provides strength to the analysis. While most papers use unemployment as the main measure of economic circumstances, this chapter considers employment as a more relevant measure of economic activity. Rather than using annual data, our data are disaggregated to quarterly level, providing another point of difference for the analysis. Understanding how economic change influences accidents and their severity can help policy makers and economists identify how to improve population health during economic upturns, which could crucially avoid major increases in road deaths and reduce the burden on the health system.

In chapter 3 we further add to the existing literature by providing a very detailed examination of the link between accident severity and the economic cycle. With such high costs associated with the more severe accidents, it is important to understand how economic activity affects individual accident severity through traffic volumes and congestion and individual driver risky behaviour. Understanding who is affected, and how, allows governments to design targeted policies to lessen the economic and emotional burden of accidents. This represents the first known direct study of accident severity and the economy for Britain. A novel driver-level analysis goes some way to identifying individual behaviours associated with accident severity and further insights are gained through our use of accident contributory factors. Severity of accidents involving particular types of cars gives some idea of the effects of driver SES and makes this analysis unique.

Chapter 4 extends the small literature linking health and the stock market. We believe that we are the first to consider the relationship between movements in the stock market and road accidents in Britain. We find that both positive and negative stock market returns increase accidents at the region level and suggest that this is linked to driver distraction. Allowing for asymmetric effects of (continuous) positive and negative daily returns represents an innovation over the categorical measures of returns adopted by Giulietti et al. (2020). Our parsimonious and tight empirical specification of daily variations within the same month in the same year in the same region also improves on the extant literature. Using daily data also represents an improvement over the monthly data used by Cotti et al. (2015) and our application to all road accidents extends our coverage beyond just fatal car accidents studied to date.

Analysis of penalties often involves simply gauging the impact on numbers of infringements, such as fines issued. However, driving-related penalties are ultimately designed to reduce numbers of accidents and their severity and, to our knowledge, chapter 5 represents the first attempt to investigate these effects for specific changes in penalties. We comprehensively examine the effects of two road safety interventions — harsher mobile phone penalties and speeding fines — on numbers of serious or fatal accidents. As the literature only considers the effects of specific penalties on infringement notices rather than accidents, we have no point of comparison for our results. In linking specific changes in penalties to accident outcomes, our research question is unique. We also make a methodological contribution by introducing the two-step difference-in-difference approach in which long-term trend and seasonal factors are removed prior to comparing treatment and control groups before and after the speed intervention.

1.4 Summary

In applying a health economics perspective to comprehensive analysis of the economic influencers of road accidents in Britain, this thesis provides a number of original contributions. By seeking to understand driver behaviours, their causes and consequences, we are able to provide a unique body of strong evidence from which policymakers can influence health outcomes. This thesis also comprises a unique set of empirical studies linked via a single dataset which has never been explored in this context.

References

Angrisani, M., & Lee, J. (2016). Health effects of short-term fluctuations in macroeconomic conditions: the case of hypertension for older Americans. *Health Economics, 25*(S2), 113-125. doi:10.1002/hec.3374

Broughton, J., & Stone, M. (1998). *A new assessment of the likely effects on road accidents of adopting SDST*. TRL Report 368. Berkshire.

Castriota, S., & Tonin, M. (2019). *Stay or flee? Probability versus severity of punishment in hit-and-run accidents*. IZA Discussion Paper No. 12693. IZA. Bonn.

Cawley, J., & Ruhm, C. J. (2011). Chapter three - the economics of risky health behaviors. In M. V. Pauly, T. G. McGuire, & P. P. Barros (Eds.), *Handbook of Health Economics* (Vol. 2, pp. 95-199): Elsevier.

Chen, C.-C., Chen, C.-S., Liu, T.-C., & Lin, Y.-T. (2012). Stock or stroke? Stock market movement and stroke incidence in Taiwan. *Social Science & Medicine, 75*(11), 1974-1980. doi:https://doi.org/10.1016/j.socscimed.2012.07.008

Cotti, C., Dunn, R., A., & Tefft, N. (2015). The Dow is killing me: risky health behaviors and the stock market. *Health Economics, 24*(7), 803-821. doi:10.1002/hec.3062

Couture, V., Duranton, G., & Turner, M. A. (2018). Speed. *The Review of Economics and Statistics, 100*(4), 725-739. doi:10.1162/rest_a_00744

De Paola, M., Scoppa, V., & Falcone, M. (2013). The deterrent effects of the penalty points system for driving offences: a regression discontinuity approach. *Empirical Economics, 45*(2), 965-985. doi:10.1007/s00181-012-0642-9

Elvik, R. (2012). Speed limits, enforcement, and health consequences. *Annual Review of Public Health, 33*(1), 225-238. doi:10.1146/annurev-publhealth-031811-124634

Erlander, S., Gustavsson, J., & Lárusson, E. (1969). Some investigations on the relationship between road accidents and estimated traffic. *Accident Analysis & Prevention, 1*(1), 17-64. doi:https://doi.org/10.1016/0001-4575(69)90004-9

Fiuzat, M., Shaw, L. K., Thomas, L., Felker, G. M., & O'Connor, C. M. (2010). United States stock market performance and acute myocardial infarction rates in 2008–2009 (from the Duke databank for cardiovascular disease). *The American Journal of Cardiology, 106*(11), 1545-1549. doi:https://doi.org/10.1016/j.amjcard.2010.07.027

Frijters, P., Johnston, D. W., Shields, M. A., & Sinha, K. (2015). A lifecycle perspective of stock market performance and wellbeing. *Journal of Economic Behavior & Organization, 112*, 237-250. doi:https://doi.org/10.1016/j.jebo.2015.02.004

García-ferrer, A., Bujosa, M., de Juan, A., & Sánchez-Mangas, R. (2019). *The relationship between traffic accidents and real economic activity revisited: old targets and new policy implications*. Unpublished manuscript. Universidad Autónoma de Madrid. Madrid, Spain.

García-ferrer, A., de Juan, A., & Poncela, P. (2007). The relationship between road traffic accidents and real economic activity in Spain: common cycles and health issues. *Health Economics, 16*(6), 603-626. doi:10.1002/hec.1186

Gerdtham, U.-G., & Johannesson, M. (2005). Business cycles and mortality: results from Swedish microdata. *Social Science & Medicine, 60*(1), 205-218. doi:https://doi.org/10.1016/j.socscimed.2004.05.004

Giulietti, C., Tonin, M., & Vlassopoulos, M. (2020). When the market drives you crazy: Stock market returns and fatal car accidents. *Journal of Health Economics, 70*, 102245. doi:https://doi.org/10.1016/j.jhealeco.2019.102245

Glanz, K., & Stryker, J. E. (2008). Health Behavior and Risk Factors. In V. Patel, A. Woodward, V. L. Feigin, H. K. Heggenhougen, & S. Quah (Eds.), *International Encyclopedia of Public Health* (pp. 146-152). Amsterdam: Elsevier.

Green, C. P., Heywood, J. S., & Navarro, M. (2014). Did liberalising bar hours decrease traffic accidents? *Journal of Health Economics, 35*, 189-198. doi:http://dx.doi.org/10.1016/j.jhealeco.2014.03.007
Haddon, W., Jr. (1968). The changing approach to the epidemiology, prevention, and amelioration of trauma: the transition to approaches etiologically rather than descriptively based. *American journal of public health and the nation's health, 58*(8), 1431-1438. doi:10.2105/ajph.58.8.1431
Hausman, C., & Rapson, D. S. (2018). Regression discontinuity in time: considerations for empirical applications. *Annual Review of Resource Economics, 10*(1), 533-552. doi:10.1146/annurev-resource-121517-033306
Kalcheva, I., McLemore, P., & Sias, R. (2017). *Stock market uncertainty and unhealthy choices*. Mimeo. The A. Gary Anderson Graduate School of Management, University of California, Riverside.
Lam, J.-P., & Piérard, E. (2017). The time-varying relationship between mortality and business cycles in the USA. *Health Economics, 26*(2), 164-183. doi:10.1002/hec.3285
Lin, S.-J. (2009). Economic fluctuations and health outcome: a panel analysis of Asia-Pacific countries. *Applied Economics, 41*(4), 519-530. doi:10.1080/00036840701720754
Ma, W., Chen, H., Jiang, L., Song, G., & Kan, H. (2011). Stock volatility as a risk factor for coronary heart disease death. *European Heart Journal, 32*(8), 1006-1011. doi:10.1093/eurheartj/ehq495
Neumayer, E. (2004). Recessions lower (some) mortality rates: evidence from Germany. *Social Science & Medicine, 58*(6), 1037-1047. doi:http://dx.doi.org/10.1016/S0277-9536(03)00276-4
Nilsson, G. (2004). *Traffic safety dimensions and the power model to describe the effect of speed on safety*. Bulletin 221. Lund Institute of Technology. Lund, Sweden.
Noland, R. B. (2003). Traffic fatalities and injuries: the effect of changes in infrastructure and other trends. *Accident Analysis & Prevention, 35*(4), 599-611. doi:https://doi.org/10.1016/S0001-4575(02)00040-4
OECD/ITF. (2015). *Why does road safety improve when economic times are hard?* Research Report. OECD/ITF. Paris.
Peden, M., Scurfield, R., Sleet, D., Mohan, D., Hyder, A. A., Jarawan, E., & Mathers, C. (2004). *World report on road traffic injury prevention*. World Health Organization. Geneva.
Pigou, A. C. (1932). *The Economics of Welfare*. London: Macmillan.
Public Health England. (2017). *Health profile for England: 2017*. Public Health England. London.
Ratcliffe, A., & Taylor, K. (2015). Who cares about stock market booms and busts? Evidence from data on mental health. *Oxford Economic Papers, 67*(3), 826-845. doi:10.1093/oep/gpv030
Ruhm, C. J. (2000). Are recessions good for your health? *The Quarterly Journal of Economics, 115*(2), 617-650. doi:10.1162/003355300554872
Ruhm, C. J. (2015). Recessions, healthy no more? *Journal of Health Economics, 42*, 17-28. doi:http://dx.doi.org/10.1016/j.jhealeco.2015.03.004
Ruhm, C. J. (2016). Health effects of economic crises. *Health Economics, 25*(S2), 6-24. doi:10.1002/hec.3373
Stevens, A. H., Miller, D. L., Page, M. E., & Filipski, M. (2015). The best of times, the worst of times: understanding pro-cyclical mortality. *American Economic Journal: Economic Policy, 7*(4), 279-311. doi:10.1257/pol.20130057
UK Department for Transport. (2016a). *Reported road casualties Great Britain 2015: annual report*. Department for Transport. London.

UK Department for Transport. (2016b). *Road use statistics Great Britain 2016*. Department for Transport. London.

UK Department for Transport. (2018). *Reported road casualties Great Britain: 2017 annual report*. Department for Transport. London.

UK Department for Transport. (2019). *Reported road casualties Great Britain 2018: annual report*. Dpeartment for Transport. London.

Wagenaar, A. C. (1984). Effects of macroeconomic conditions on the incidence of motor vehicle accidents. *Accident Analysis & Prevention, 16*(3), 191-205. doi:http://dx.doi.org/10.1016/0001-4575(84)90013-7

World Health Organization. (2013). *Global status report on road safety 2013*. WHO. Geneva.

World Health Organization. (2015). *Global status report on road safety 2015*. WHO. Geneva.

World Health Organization. (2018). *Global status report on road safety 2018*. WHO. Geneva.

Chapter 2: Economic activity, road accidents and fatalities in Britain

2.1 Introduction

Economists have long been interested in the business cycle and the factors that influence it as well as the factors that it influences. Among this research there is a growing interest in the impact of the macroeconomy on population health. In particular, we might think about how health changes in times of recession versus economic growth. Since the work of Ruhm (2000), this literature has found a relationship with various health conditions, suicides and also road accidents. This chapter contributes to the latter using a powerful dataset that will allow us not only to understand the relationship between accidents and the business cycle but also to look at how this relationship varies by a number of accident characteristics such as accident severity, vehicle involvement, when and where the accident occurred, involvement of alcohol or drugs, weather conditions and driver age and sex.

Economic conditions contribute to road accidents via traffic volumes as GDP and traffic broadly move in the same direction (UK Department for Transport, 2016). Greater traffic volumes tend to result in more accidents, although the number and severity of these accidents can be at least partly offset by better training in anticipation of economic expansions, vehicle standards, enforcement and engineering (UK Department for Transport, 2016). Distances travelled tend to be longer when the economy is performing well, and, as travel is a 'normal' good (it increases with income), we expect accidents to increase (W. Evans & Graham, 1988).

In terms of the economic cycle, the number of accidents and their severity may be reduced in times of recession through lower traffic volumes, reduced exposure of high risk road user groups (e.g. shorter distances travelled by younger drivers) and reductions in risky behaviour as individuals drive more slowly to conserve fuel or tend not to drink and drive (UK Department for Transport, 2016). Reduced driving exposure implies shorter trips might also reduce numbers of accidents, although research shows most accident injuries occur close to home anyway (Steinbach, Edwards, & Grundy, 2013).[1]

[1] That paper showed, for example, some 53% of car occupants in England were injured within 5km of home.

Understanding the factors influencing accidents and their severity can help policy makers and road safety professionals identify strategies to improve road safety in economic upturns, avoiding major increases in road deaths (Noble et al., 2015 in OECD/ITF, 2015). This would also alleviate the additional burden on the health system in dealing with the often traumatic injuries occurring because of road accidents. To this end, we should examine the extent to which accident rates rise after a recovery and identify mechanisms at work in order to target groups/situations for potential interventions. For example, in better economic times the government could invest in various road safety initiatives, including policing, and promote good driving behaviours. Additional expenditure on emergency management services (such as ambulances and emergency medical personnel) could also help reduce fatalities occurring after accidents.

Key studies look at a couple of accident types, for example hit-and-run (French & Gumus, 2015) and motorcycle accidents (French & Gumus, 2014), or only study fatalities (Ruhm, 2016; Stevens, Miller, Page, & Filipski, 2015).However. this chapter uses detailed data on the universe of accidents reported to police allowing greater coverage and providing more depth to the analysis. The British data used is very rich and spans some 23 years (95 quarters)[2], permitting investigation of a variety of accident characteristics over a long period. These data allow us to explore heterogeneity in the estimated effects by breaking down these accidents more finely and testing whether the overall relationship holds up for different types of accident. If so, this helps identify explanations and pathways which may not have been identified before due to data limitations and the level of disaggregation adopted (or the depth of analysis). Heterogeneity is important because we can learn things from different types of accidents and drivers. For example, some types of accidents or drivers may be more strongly tied to the macroeconomic cycle than others. Therefore we expect the relationship between macroeconomic conditions and accidents and fatalities to differ by characteristics of the accidents and drivers.

This chapter complements other studies, which have investigated links between the economy and road deaths or numbers of accidents. According to OECD/ITF (2015), most studies focus on road deaths and there is very little information about economic conditions and road injuries. Studies typically focus on other countries. UK-specific studies typically focus at the national

[2] Our analysis sample is limited by the availability of economic data.

level and are often descriptive rather than explanatory. Using a very rich dataset comprising characteristics of all personal injury road accidents occurring in Britain, we model the links between economic activity (primarily employment) and road accidents and fatalities at the region level and on a quarterly basis over a period that includes the Global Financial Crisis (GFC), which had a large effect on economic activity.[3] Regions are defined as Government Office Regions (GORs) in England and other countries in Britain (Scotland, Wales).

Among papers using panel estimation methods, this chapter represents the first attempt to model the relationship between fatalities and the macroeconomic cycle for regions in Britain. It is also the first attempt to investigate the link between various accident characteristics and the macroeconomic cycle. While most papers use unemployment as the main variable to proxy economic circumstances (although income is also used — see, for example, French & Gumus, 2014; Noland, 2003), this chapter considers the employment to population ratio as a more relevant measure of economic activity as the employment rate takes account of so-called discouraged workers and added workers who transition from or to being out of the labour force, although unemployment is used as a robustness check (Fuchs & Weber, 2013). Other papers tend to use annual data but our data are disaggregated to quarterly level, providing another point of difference for the analysis. In providing a detailed breakdown in the nature and type of traffic accidents, we can learn more about the mechanisms determining accidents and mortality than in previous studies.

2.2 Background and literature review

Several studies have used a regional fixed effects specification to control for changes over time (with year fixed effects) and region-specific influences that were fixed over time to model the relationship between state level unemployment rates for the US and causes of death. These studies identified the average (within state) effect and rely on the assumption that unobserved factors that influence the relationship are time invariant. They found a procyclical relationship for most causes of death (Edwards, 2008; Miller, Page, Stevens, & Filipski, 2009; Ruhm, 2000; Tapia Granados, 2005a). In particular, Ruhm (2000) found evidence of a procyclical

[3] According to Reinhart and Rogoff (2009), throughout the 20th century financial crises around the world have been associated with large reductions in output and employment which usually last about 4 years.

relationship between unemployment and mortality (i.e. recessions are good for health) in the US. The key exception appears to be suicide, reflecting a countercyclical relationship. Similar procyclical relationships with most major causes of death have been found for Nordic regions (Haaland & Telle, 2015), German states (Neumayer, 2004), OECD countries (Gerdtham & Ruhm, 2006), Spanish provinces (Tapia Granados, 2005b), in Asia-Pacific countries (Lin, 2009) and in Japan (Tapia Granados, 2008). Stevens et al. (2015) also found procyclical overall death rates for the US, but (for non-motor vehicle accidents) attribute them to cyclical movements in quality of health care among the older age groups rather than 'own group' changes in unemployment rates. Overall mortality for regions of the US (Lindo, 2013) and of Canada (Ariizumi & Schirle, 2012) were also procyclical.

However, Gerdtham and Johannesson (2005) showed no significant relationship between unemployment and overall and cause specific mortality risk at the individual level for Sweden. Considering 26 EU countries, Stuckler, Basu, Suhrcke, Coutts, and McKee (2009) found no effect on most causes of death.

Using more recent data, Ruhm (2015) found the overall death rate in the US was unrelated to economic conditions. In terms of causes of death, deaths from cardiovascular disease and transport accidents were procyclical but deaths from cancer and external causes (such as accidental poisonings) had become countercyclical. In a study of Mexican states, Gonzalez and Quast (2011) found a countercyclical relationship between economic activity and mortality from cancer. Hollingsworth, Ruhm, and Simon (2017) found deaths from opioid abuse were countercyclical for the US. Muazzam and Nasrullah (2011) found most cause-specific injury mortality rates (such as falls, drownings and homicides) for 18 OECD countries were countercyclical.

Several studies have also shown many aspects of health to be countercyclical. For example, smoking and obesity were procyclical and physical activity and 'diet quality' were countercyclical (Ruhm, 2000). In a more disaggregated analysis, Ruhm (2003) showed physical health was countercyclical with the largest effects for prime working age individuals and men. Mental health was suggested to be procyclical. Haaland and Telle (2015) also found countercyclical health for regions in Norway. In particular, they found procyclical relationships for onset of disability, overweight and personal injury traffic accidents, although the result for mental health/behavioural/poisoning was not significant.

However, some studies have shown health to be procyclical (or in some cases shown no relationship to economic conditions). Charles and DeCicca (2008) investigated the relationship between health and health behaviours and local labour market conditions (unemployment rates) for 58 metropolitan statistical areas in the US. They found evidence of a procyclical relationship with weight-related health (represented by reduction in Body Mass Index) and mental health for African-American males and with mental health for less educated males. Most health behaviours (alcohol consumption and exercise) were not significant — except smoking, which is countercyclical (i.e. non-smoking is procyclical). Hollingsworth et al. (2017) studied opioid abuse leading to emergency department visits in the US and found what amounts to ill health associated with opioid abuse to be countercyclical.

The big picture on macroeconomic conditions and health, mortality and morbidity has been studied since, for example, Ruhm (2000). Although there is general ambiguity in the relationship, there is consensus that traffic accidents and associated fatalities increase in good economic times, largely because there is more traffic on the roads. Most literature has focussed on mortality rather than accidents. Relevant publications in leading health economics journals over the last ten years or so (such as Green, Heywood, & Navarro, 2014; Haaland & Telle, 2015; Lam & Piérard, 2017; Ruhm, 2015) focus on the economics of road accidents/fatalities (in some cases identifying the effects of specific interventions and changes in incentives), and using data in novel and policy-relevant ways. However, most papers use US data and there remain research gaps.

Recent research by Ruhm and others has identified a procyclical relationship between motor vehicle fatalities and the economic cycle (see, for example, Ruhm, 2015; Stevens et al., 2015). Indeed, 'one of the most consistent previous research findings is that transport fatalities are procyclical' (Ruhm, 2015, p. 25). These studies provide compelling evidence of this relationship as they use longitudinal data and apply panel econometric techniques to control for region-specific time invariant and overall time varying influences. These papers are more relevant to the current study than those adopting simple linear regression (such as Partyka, 1984, 1991; Tapia Granados, 2005a), time series methods (such as W. Evans & Graham, 1988; García-ferrer, Bujosa, de Juan, & Sánchez-Mangas, 2019; García-ferrer, de Juan, & Poncela, 2007; Hanewald, 2011; Lam & Piérard, 2017; Reinfurt, Stewart, & Weaver, 1991; Scott, 1986; Scuffham, 2003; Wagenaar, 1984), modelling at the individual level (such as Edwards, 2008; Gerdtham & Johannesson, 2005; Haaland & Telle, 2015), using cross section data (such as

Traynor, 2008) or modelling incidence relative to exposure (such as Amoros, Martin, & Laumon, 2003).

Among those papers adopting a panel estimation methodology to investigate the relationship between fatalities and economic circumstances (summarised in table 2.1), in response to a 1 percentage point increase in unemployment rates, road traffic fatalities have been estimated to fall nationally by about 2–3% in the US (W. N. Evans & Moore, 2012), OECD countries (Gerdtham & Ruhm, 2006), and Asia-Pacific countries (Lin, 2009). Similar procyclical results have been mostly found with regional breakdowns for France (Buchmueller, Grignon, & Jusot, 2006), Germany (Neumayer, 2004), Spain (Tapia Granados, 2005b) and the US (Cotti & Tefft, 2011; W. Evans & Graham, 1988; French & Gumus, 2014; He, 2016; Miller et al., 2009; Ruhm, 1995, 2000, 2016; Stevens et al., 2015) with results typically ranging from 1–3%.[4] Maheshri and Winston (2016) also found similar results, although they modelled the effects on fatalities per daily vehicle mile travelled.

The relationship between unemployment and motor vehicle deaths may be changing over time. Ruhm (2015) examined US states and found a response to unemployment of -2.7% in an earlier sample (1976–1995) but only -0.9% in a later sample period (1991–2010). However, 'there is also suggestive evidence that the procyclicality of mortality might have increased slightly in the most recent analysis periods that include the severe 2007–2009 recession' (p. 27).

Considering different levels of spatial aggregation, Lindo (2013) modelled the relationship between employment and motor vehicle deaths at the region, state and county level for the US and found statistically significant semi-elasticities of 0.035 (regions), 0.021 (state) 0.006 (county).

While a procyclical relationship has been found for fatalities, the relationship is yet to be established for all accidents and there is scope for the relationship to vary by accident or driver characteristics. This is where our analysis comes to the fore.

[4] Stuckler et al. (2009) also found a procyclical relationship across 26 EU countries although their model specification included rates of change making the results difficult to compare with those based on levels (or logs).

Table 2.1: Studies investigating the relationship between unemployment or employment and road fatalities using a fixed effects model

Study	Data	Time	Semi-elasticity	Dependent variable	Other control variables
Buchmueller et al (2006)	96 French Départements (metro)	1982-2002	-0.02; -0.055 if national unemployment rate is included in the model; -0.0161 if average income is included.	log fatality rate	average area income, national unemployment rate
Cotti & Tefft (2011)	US states	2003-2009	-1.63% overall; -2.84% alcohol-related fatal accidents; similar effects for drivers aged 16-59, no significant effects for drivers aged 60+. For alcohol-related fatal accidents, largest effect for drivers aged 30-59 (-3.55%).	log fatality rate per capita	real per capita personal income, real beer taxes, gas taxes, blood alcohol content (BAC) limit legislation.
Evans & Graham (1988)	US states	1946-1985	No semi-elasticities reported. Elasticity -0.121 for total motor vehicle fatalities; strongest effects for car occupants and 'others' including bicyclists & motorcyclists.	log fatalities	vehicle miles travelled (VMT)
Evans & Moore (2012)	US states	1976-2004	-3.19%	log fatality rate (/100,000 pop)	age, race (black)
French & Gumus (2014)	US states	1988-2010	-1.4 to -2.4%	log motorcycle fatality rate (/100,000 pop)	motorcycle registrations, VMT, BAC limit, helmet law, licence revocation law, real beer excise taxes, avg temp, avg precip. Real gas prices, state-specific time trend.
Gerdtham & Ruhm (2006)	23 OECD countries	1960-1997	-2.11%	log fatality rate (/100,000 pop)	age, sex distribution of population, country specific linear time trends.
He (2016)	US states	2003-2013	overall -2.88%. -8.37% large trucks, -5.03% speeding, -3.62% drunk driving	log fatality rate (/100,000 pop)	beer tax, gas prices, safety laws (texting, handheld mobile, BAC limit, seat belts, graduated licensing program)
Lin (2009)	8 Asia-Pacific countries	1976-2003	-3.4%	log fatality rate (/100,000 pop)	age, gender, urban population and medical care resources. Country specific time trends.
Lindo (2013)	US regions, states, counties	1968-1997	No unemployment results. Employment: 3.47% at region level, 2.09% state level, 0.55% county level.	fatality rate (/100,000 pop)	ethnicity, age, SES.
Maheshri & Winston (2016)	88 counties in Ohio, US	2009-2013	-14% effect on fatalities per daily VMT	fatalities per daily VMT	state-county subsidies and capital transfers, temperature
Miller et al (2009)	US, states	1978-2004	-2.94%	log fatality rate	age, race, ethnicity
Neumayer (2004)	Germany, 11/16 states	1980-2000	-1.3%; -2.05% females, -0.82% males.	log fatality rate	age, foreigners. Also uses Gini coefficient as a measure of income inequality.
Ruhm (1995)	48 US states	1975-1988	-3.16% (2.84% for employment) -2.06% if income included. Stronger effects for 21-24 yo at night, 21-24 yo all times	log fatality rate (/100,000 pop)	beer taxes, min legal drinking age per capita personal income
Ruhm (2000)	US, states	1972-1991	-3.02% state unemployment; -1.80% state unemployment and income, -3.19% state with national unemployment rates.	log fatality rate (/100,000 pop)	education, ethnicity, age, income
Ruhm (2015)	US, states	1976-2010	-2.65% (1976-1995), -0.86% (1991-2010).	log fatality rate (/100,000 pop)	state specific linear time trend, age, sex, race/ethnicity.
Ruhm (2016)	US states	1976-2013	-2.62 to -3.11%, depending on specification of additional economic crisis variable.	log fatality rate (/100,000 pop)	sex, race, age
Stevens et al (2015)	US states	1978-2006	-2.54%; -2.75% age <25, -2.54% aged 25-64, -2.20% aged 65+	log fatality rate; log age adjusted fatality rate	age, education, race/ethnicity, state specific time trends
Tapia Granados (2005b)	50 Spanish provinces	1980-1997	-1.96% province unemployment, -1.60% national unemployment	log fatality rate (/100 000 pop)	age structure, real GDP per capita

2.2.1 Mechanisms

The mechanisms linking economic conditions and road accidents are not well understood (Ariizumi & Schirle, 2012; OECD/ITF, 2015) and 'there is no firm economic theory indicating which explanatory variables should appear in a causal model of fatal crashes' (Scuffham, 2003, p. 180). Therefore, this section presents some potential explanations based on (in some cases, extrapolation of) available literature and intuition about potential behavioural factors. The explanations are split between those affecting health outcomes (accidents and fatalities) and those related to driver characteristics. The latter extends the analysis of others such as Ruhm (2000, 2015). Table 2.2 details likely mechanisms linking employment rates and accidents of various types, as well as expected effects.

2.2.1.1 Health outcomes

Accidents of all severity types are likely to rise when the economy expands, due to increased traffic volumes and risky driving behaviours. In particular, the higher value of time means people drive more intensively (faster/riskier) (Beland & Brent, 2018; OECD/ITF, 2015). In economic upturns, worsening in work conditions can affect health due to long hours, work hazards (for transport workers) and less attention to safety (Haaland & Telle, 2015). Individuals may also experience more mental stress leading to more aggressive driving and increasing accident rates (Wagenaar, 1984). People might also be angrier when there are larger traffic volumes (Beland & Brent, 2018), resulting in more accidents due to road rage. In good times, individuals can afford to upgrade vehicles to newer, safer models (Wegman et al., 2017) and this could result in increased driver confidence being compensated by driving more recklessly, although unfamiliarity with a new vehicle could increase accident risk (OECD/ITF, 2015). Risky driving behaviours (such as speeding and drink driving) may also be more likely when the economy is performing well (W. Evans & Graham, 1988). For example, alcohol and recreational driving after drinking alcohol may be normal goods (increasing with income in good economic times) and budget constraints during recessions may lead individuals to drink at home rather than at pubs and restaurants, leading to drink driving being procyclical. Speeding might be more likely in economic upturns, as wages are higher and individuals attempt to reduce (unpaid) commuting time. However, drivers might be less likely to undertake risky driving behaviour when the economy is expanding if they perceive they have more to lose or if stress associated with unemployment or precarious employment leads to more risk taking (W. Evans & Graham, 1988).

Slight severity accidents are more likely when the economy is expanding as there is more traffic on the roads and congestion at certain times might lead to accidents at those times occurring at lower speeds and being less severe. That is, road congestion can change accident risk (Stevens et al., 2015). Driver inattention due to stress might also increase the number of less serious accidents. However, underreporting of these less severe accidents is more likely when the economy is performing well, as individuals may be too busy to go to a police station and report the accident.

More serious accidents are also likely to rise as the vehicle mix on the roads changes to favour more risky forms of transport such as heavy goods vehicles (HGVs). At certain times, congestion limits might not be reached, increasing the scope for excessive speed to play a role thereby increasing the severity of accidents.

Fatal accidents are also likely to rise during economic expansions as driver behaviours become more risky, for example with drink driving (Cotti & Tefft, 2011). Risky behaviours are positively associated with time pressures and work-related stress that rises with economic activity. In addition, high risk drivers may be more sensitive to economic conditions than low risk drivers (Maheshri & Winston, 2016; Wegman et al., 2017).

2.2.1.2 Accident characteristics

Use of some vehicle types is more closely associated with the economic cycle. For example, as incomes rise, commuters can afford to purchase and drive cars rather than ride bicycles or use mass-transit options like the bus or the train. As economic activity expands, more use is made of HGVs rather than vans for moving goods around the country. These two effects change the vehicle mix on the roads and potentially lead to different accident and fatality rates. HGV accidents involve high energy collisions with a higher chance of fatalities (Massie, Campbell, & Williams, 1995). There are likely to be more accidents and more severe accidents as the volume of HGVs (number and share of fleet) leads to more accidents involving HGVs during economic expansions. Alongside the increase in overall accidents there are likely to be more severe accidents due to the nature of HGVs, implying more fatalities as HGV traffic expands when the economy is performing well. The use of motorcycles might increase with economic expansions if individuals believe they can save time by negotiating congested roads (making accidents and fatalities more likely). To a lesser extent there might also be additional freight traffic on motorcycles. Motorcycle accidents are more responsive on weekends, as recreational riding is more sensitive than work-related travel (French & Gumus, 2014). As most bicycle traffic is likely to involve children, it is unlikely that this form of transport will respond strongly to the economic cycle. Similarly, most other vehicles (such as minibuses, horses, trams, and motor caravans) are less likely to respond to changing economic circumstances.

French and Gumus (2015) modelled the relationship between unemployment and hit-and-run and non-hit-and-run fatalities for US states and found significant negative effects (incidence rate ratios less than one) on non-hit-and-run fatalities (although the effect is small: approx. 0.99 or a 1% reduction). 'Intoxicated drivers might flee a crash scene due to severe driving-under-the-influence (DUI) sanctions, which are often more stringent than non-DUI hit-and-run penalties' (French & Gumus, 2015, p. 1). As the economy expands and individuals drink more alcohol, we might expect the number of hit-and-run accidents (and fatalities) to increase, although French and Gumus (2015) only found an effect for the non-hit-and-run fatalities.

Motorways and A roads are designed to carry higher volumes of traffic and for longer distances than B and C roads. Therefore, in response to increased economic activity we would expect to see more traffic (commuting, business trips and transport of goods) and more accidents on motorways and A roads relative to B and C roads.[5] However, increased traffic can lead to congestion and lower vehicle speeds, resulting in less serious accidents and therefore fewer fatalities than might be expected.

Most traffic associated with economic activity flows during the day, as evidenced by commuter traffic and the movement of goods (freight). There are likely to be more accidents due to larger traffic volumes from discretionary (holidays) and non-discretionary (commuting) traffic in the daytime during economic expansions. Fatalities are likely to vary less than accidents as (given increased traffic volumes) we expect congestion to reduce speed and therefore accident severity (although for the same level of congestion there may be a larger effect on severity at low speeds). There are likely to be more accidents due to larger traffic volumes at night during economic expansions as discretionary traffic at night is also likely to respond to higher incomes available when economic times are good.[6] Fatalities are likely to vary in line with accidents due to lower road use and congestion than occurs in daytime. At night, both accidents and

[5] Although there could also be some diversionary traffic as people use B and C roads as shortcut alternatives to congested main roads.

[6] Although French and Gumus (2014) find no difference in responsiveness of daytime and nighttime fatalities for motorcycle riders.

fatalities are also likely to rise when the economy expands due to fatigue associated with time pressures and potentially longer working hours.

Larger traffic volumes during weekday peak times would increase the likelihood of accidents. During economic expansions there is likely to be larger than usual traffic volumes and drivers may be stressed and tired by long working hours and have their decision-making impaired. Time pressure might also lead drivers to drive more erratically and increase their speed (W. Evans & Graham, 1988). However, larger traffic volumes can also lead to congestion which slows traffic speeds making accidents less severe and leading to relatively fewer fatalities. Therefore, fatalities are unlikely to increase due to congestion limiting vehicle speeds. In addition to larger traffic volumes, in weekday off peak times there might be increased drink driving as incomes rise when the economy is performing well, which would lead to more accidents and fatalities. There are likely to be more accidents during weekends when the economy is expanding due to increased leisure traffic. For example, French and Gumus (2014) find such a weekend effect for motorcycles with no significant effect for weekdays. Fatalities are also likely to rise as alcohol consumption increases.

Drink driving is also likely to become a factor when the economy is performing well. Alcohol consumption is an important part of the accident/risky behaviour literature. Indeed, it has long been recognised that alcohol and drugs (such as antihistamines, sedatives, anxiolytics, antidepressants and illicit drugs) contribute to accidents by impairing driving ability (Alonso, Esteban, Montoro, & Tortosa, 2014). If alcohol and drugs are normal goods, then we expect their consumption to increase with income. Conversely, as the economy worsens, pressure on budget constraints induce individuals to drink less and drink at home rather than at pubs, bars and restaurants (OECD/ITF, 2015). However, binge drinking by drivers could also increase as economic conditions worsen (Traynor, 2008). There is evidence that the relationship between alcohol consumption and drink-drive fatalities is procyclical (French & Gumus, 2014; Ruhm, 2006). Therefore, as the economy expands and incomes rise, we might expect higher involvement of alcohol and drugs in traffic accidents. These factors could also be associated with vehicles travelling at greater speeds, increasing the likelihood of fatalities.

Driving conditions are worse in bad weather. Therefore, in good economic times we are likely to see a greater volume of traffic in good weather relative to inclement weather as individuals attempt to travel in favourable weather or avoid travel in bad weather, increasing the chances of accidents in good weather. Moreover, in better weather some individuals substitute towards travel modes — such as bicycles and motorcycles (Mais, Lloyd, & Davies, 2016) — that make them more vulnerable road users and therefore more susceptible to fatal accidents.[7] However, increases in traffic volumes might also reduce accidents and their severity as traffic congestion lowers vehicle travelling speeds (Fridstrøm, Ifver, Ingebrigtsen, Kulmala, & Thomsen, 1995). Also, under the risk compensation hypothesis, individuals modify their driving habits to offset increased hazards due to adverse weather (Fridstrøm et al., 1995). In bad weather there may be reductions in vehicle speeds and more cautious driving, leading to lower accident rates and less severe accidents (UK Department for Transport, 2014). For these reasons it is important to control for the effects of weather on accident outcomes.

2.2.1.3 Driver characteristics

Males tend to be more involved in fatal accidents and females in less severe accidents as a result of 'men's increased propensity to drive in a risky manner' (Massie et al., 1995, p. 84). However, with men's higher labour force participation and employment rates, small changes in the economic cycle can have larger effects for women than men. Neumayer (2004) found a significant procyclical effect for women but no effect for men, suggesting women are more affected by the economic cycle than men. On average, women drive less than men, leading women to have less driving experience (Massie et al., 1995). With less experience, women are less proficient at driving and therefore less able to avoid accidents. Women may also have slower reaction times and be more prone to distraction and perceptual errors (Bazargan-Hejazi et al., 2017; Bellinger, Budde, Machida, Richardson, & Berg, 2009; Bone & Mowen, 2006; Massie et al., 1995). There are therefore likely to be more accidents involving women as the economy expands due to higher traffic volumes as women's employment rises further from a lower base than men's. Accidents and fatalities involving men are also likely to rise as men adopt increasingly risky behaviours when the economy performs well. Whether the effects for men and women differ is an empirical question. Stuckler et al. (2009) found no significant difference in the procyclical effects of unemployment on transport-related deaths for men and women across 26 EU countries.

Most papers that consider age do so in the context of overall mortality, rather than road fatalities (see, for example, Ariizumi & Schirle, 2012; Gonzalez & Quast, 2011). Business cycles affect

[7] Although such substitution is less likely when the economy is expanding as individuals work longer hours and therefore have less time available for commuting using time-intensive forms of transport such as bicycles.

the age composition of drivers and risky behaviour. While showing overall effects in the region of a 1–3% reduction, further investigation of fatalities by Stevens et al. (2015) reveals that effects weaken slightly with age of the fatality, likely due to younger people being disproportionately affected by labour market circumstances (Stevens et al., 2015), which reduces exposure for young people during recessions (UK Department for Transport, 2016). Young men are more likely to engage in risky driving behaviours, such as speeding, driving aggressively, going through amber lights, travelling closer to the vehicle in front, turning across oncoming traffic, driving without seatbelts and drink driving (Massie et al., 1995; Traynor, 2008), which would increase the number of fatalities during economic expansions.[8]

Based on the results of Stevens et al. (2015), we might expect a procyclical effect on accidents that declines with age as older people are less affected by labour market conditions, and perhaps show increased risk awareness, compensatory behaviour, and lower alcohol use (Massie et al., 1995). Fatalities are likely to increase more in younger people due to risky driving and other behaviours and being disproportionately affected by changes in the economy. Fatalities in older people are likely to rise in line with accidents due to the aging process making these people more frail and therefore more physically vulnerable in accidents (Massie et al., 1995).

In summary, evidence from around the world suggests road accidents and fatalities are procyclical, resulting from increased traffic volumes and risky behaviour in good times. It also appears that disaggregating accidents and fatalities by accident and driver characteristics is likely to reveal procyclical relationships of varying strength as some factors are associated with the economic cycle to a greater or lesser extent (see table 2.2).

[8] For traffic fatalities, Miller et al. (2009) found similar semi-elasticities across age groups and conclude that these fatalities are more likely to be the result of externalities associated with the economic cycle such as increased traffic flows, rather than behavioural factors.

Table 2.2: Expected effects of employment on accidents by characteristic, driver types and mechanism

Characteristic/driver type	Mechanism	Expected effect
Total accidents	Longer working hours, less attention to safety	Procyclical
	Mental stress/aggressive driving	Procyclical
	Reckless driving in compensation for improved safety when vehicles are upgraded	No effect
	Speeding associated with time pressures	Procyclical
	Drink driving associated with higher incomes	Procyclical
Slight accidents	Driver inattention	Procyclical
Serious accidents	Vehicle mix: more HGV, increased use of cars, motorcycles)	Procyclical
	Bicycles, other vehicles	No effect
Fatal accidents	Risky behaviour – drink/drug driving	Procyclical
Accident characteristic		
Vehicle type	Vehicle mix switches to more risky forms of transport	Procyclical
Hit/run	Time pressures, increased alcohol use	Procyclical
Motorways/A roads	Traffic volume but congestion/lower speeds	No effect
Daytime	Traffic volumes but congestion	No effect
Nighttime	Traffic volumes/discretionary travel/higher incomes	Procyclical
	Fatigue	Procyclical
Weekday peak	Stress/fatigue/speed from time pressures/longer working hours, more commuting	Procyclical
	Congestion	No effect
Weekday off peak,	Leisure traffic	Procyclical
Weekends	Drink driving	Procyclical
Alcohol	Impaired driving, speeding?	Unknown
Drugs	Impaired driving	Unknown
Good weather	Volumes/vehicle mix	Procyclical
Driver type		
Males	Risky behaviour	Procyclical
Females	Less driving experience, distraction, perceptual errors	Procyclical
Young drivers	Sensitivity to economic conditions, driving inexperience	Procyclical
Older drivers	Physical vulnerability, less safe cars but more driving experience, lower alcohol use	No effect

2.3 Data

In this chapter, British Stats19 administrative data are used to analyse accidents and fatalities (Department for Transport, 2016, Police reported personal-injury road accident data (Stats19), available at: www.data.gov.uk/dataset/road-accidents-safety-data). The power of these data lies in being able to look at both accidents and fatalities and to be able to look at specific characteristics of accidents (such as those occurring at night or involving alcohol). Breaking down totals by accident characteristics allows us to start to ask which types of accidents (and fatalities) are most affected by the macroeconomic cycle and to start to think about the behavioural and environmental mechanisms that might be determining any overall cyclical relationship.

Stats19 records details of every personal injury accident on public roads in Britain reported to the police within 30 days of occurrence. At least one vehicle (of any type, including bicycles and horses) must be involved in the accident (which may involve pedestrians). Data are collected either by police at the scene of the accident or (in about one third of cases) are reported by a member of the public at a police station after the accident. Further details of the variables collected are available in UK Department of the Environment (2001). Comparisons with other data sources indicate very few fatalities are not reported to police (compared with death registrations).

These data identify circumstances of accidents, including types of vehicles involved, whether the accident was a hit-and-run, road type, timing, contributory factors to the accidents (such as alcohol, licit and illicit drugs), weather conditions, driver characteristics, and casualties. Accident severity is classified as fatal, serious or slight according to the most severe casualty. Casualty severity is determined by the most serious status (within 30 days of the accident). Under the Vienna Convention, a fatality is defined as 'an individual who dies at the scene of the crash or within 30 days following the crash' (García-ferrer et al., 2007, p. 605). In Stats19, serious injury is defined as 'an injury for which a person is detained in hospital as an inpatient, or any of the following injuries whether or not they are detained in hospital: fractures, concussion, internal injuries, crushings, burns (excluding friction burns), severe cuts, severe general shock requiring medical treatment and injuries causing death 30 or more days after the accident' (UK Department for Transport, 2016, p. 71).

Vehicle classification in Stats19 is very detailed and changed over the sample period. For analytical purposes, a small but consistent set of the main vehicle types was created, comprising bicycles, motorcycles, cars, buses, goods vehicles and other vehicles (details of the vehicle categories are given in Table A.2.1 in the appendix).

There are many accident characteristics recorded in the data. Accidents are split between hit-and-run and no-hit-and-run. 'Hit-and-run' refers to a vehicle for which the driver does not stop at the scene of an accident to aid victims or to make a report to the police, although the driver might be pursued and caught later. No-hit-and-run refers to vehicles whether in, or contributing to, the accident that stop at the scene or vehicles that were involved in or contributed to the accident and did not or was not hit but left the scene. The latter is not considered hit-and-run as the driver might not be aware of the accident (UK Department of the Environment, 2001). Motorways and A(M) roads were aggregated as they involve similar road conditions and traffic volumes. Remaining roads are classified in Stats19 as A (major arterials), B (‘connectors’), C (minor roads within estates) and Unclassified roads (local roads and country laneways). Stats19 records light conditions according to whether or not there was daylight, whether or not there was lighting and whether the lights were lit. These categories were aggregated into daytime and night. The data also include the time and day of the accident and this information was used to categorise accidents into weekday peak (Monday–Friday 7–9am and 4–7pm), weekday off-peak (Monday–Friday 7pm–7am and 9am–4pm) and weekends (Saturday and Sunday) to capture effects of peak commuter traffic volumes, non-commuter traffic volumes and weekend leisure traffic.

There are some 77 factors from which officers are able to select up to six as potential accident influencers (UK Department for Transport, 2013). Analysis in this chapter includes the two contributory factors for which data were made available, namely alcohol and drugs (including prescription drugs).[9]

Weather at the time of the accident was classed as either high winds or no high winds and either fine, raining or snowing. Fog or mist and an ‘other’ weather category were also specified. These categories were aggregated into fine weather (with no high winds), adverse weather (rain or snow with no high winds, any conditions with high winds, and fog/mist), and other/unknown weather. Unknown weather is likely to be associated with accidents later reported to police.

Driver characteristics used are sex and age. Driver sex is recorded in Stats19 as male, female and unknown. The latter category is included to allow for occasions when the sex of the driver is not known, for example if the driver did not stop at the accident scene. Driver age is recorded in single years that are aggregated for analysis into 1–17 years, 18–24 years, 25–49 years, 50–64 years, 65 years and over, and an unknown category. These categories should capture different behaviours exhibited by drivers in different broad age groups and are similar to those used in Gonzalez and Quast (2011). We separate young adults aged 18–24 to capture behavioural/risk factors that are more likely to apply to this age group.[10]

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[9] Data on the remaining contributory factors was not made available due to the introduction of the Data Protection Act 2018 (the UK’s implementation of the EU General Data Protection Regulation).

[10] Although individuals aged 17 can get a driving licence, only about 10% did so in 2012. See: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/306500/young-car-drivers-2012.pdf.

Although our data are world-class, there remain some limitations. Damage-only accidents are not included and less severe casualties are underreported (based on comparison with hospital, survey and compensation claims data) (UK Department for Transport, 2016).[11] Casualty severity is determined by police using information available at the scene of the accident or shortly afterwards and there may be some misclassification of severity.[12] Contributory factor data are recorded for about 80 per cent of accidents (UK Office of National Statistics, n.d.) but are based on the police officer's judgement on arriving at the scene of the accident. This judgement may be incorrect if for example something was not apparent at the time of the accident (like hidden vehicle defects) or became apparent after more detailed investigation. Differences in judgement may also arise if officers have different levels of knowledge/experience in traffic conditions. Unfortunately, only data on the involvement of alcohol or drugs could be used as data on some 75 other contributory factors — such as speeding, driver using mobile phone or driver/rider careless — were not made available, owing to the introduction of the UK's Data Protection Act.

Analysis in this chapter is based on accidents and fatalities from 1992–2015. Data are aggregated over time (quarters) and space (Government Office Regions, GORs) (see Figure A.2.1 in appendix). This level of regional aggregation is used as many journeys are likely to extend beyond regional boundaries at lower levels of aggregation (such as accidents occurring on motorways), potentially confounding regional effects. The information collected in the Stats19 dataset is reviewed and revised every 5 years, resulting in some changes in variables and/or characteristics collected over time. As a result, some accident characteristics (vehicle types and weather) were aggregated for comparability over time. For each quarter and region, the total number of accidents and fatalities is analysed and this total is then broken down by the following accident characteristics: accident severity (accidents only), vehicle type, hit-and-

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[11] See: https://www.gov.uk/government/collections/road-accidents-and-safety-statistics. Underreporting occurs because 'as long as drivers exchange details there is no legal obligation to report a road traffic collision even if someone is injured' (UK Department for Transport, 2013, p. 2). The extent of underreporting might also vary by mode of transport, for example with bicycle accidents being most likely to be underreported (Fridstrøm et al., 1995).

[12] In some cases the full severity is not known until some time after the accident, when the police are no longer present. 'Research has found that the police tend to underestimate the severity of injury' (UK Department for Transport, 2013, p. 10). Severity will not necessarily reflect the results of a medical examination or medical expertise (unless, for example, medical personnel attended the accident or police officers attend the hospital with the casualty). Furthermore, there could be misclassifications between serious and sight injuries in the data, which makes distinguishing casualty severity difficult (UK Department for Transport, 2016).

run, road type, light conditions, time and day, contributory factor (alcohol, drugs) and weather. At the vehicle level, driver sex and age are also examined. Over the sample period there was a total of 4,709,725 accidents, 8,595,540 vehicles and 70,205 fatalities in Britain.

In considering the relationship between accidents (or fatalities) and the economic cycle, there are two key variables that can capture movements in the economic cycle, namely employment and unemployment rates. Although these two variables fluctuate with economic activity, there were large changes around the time of the GFC (circa 2008). The economic data therefore comprise employment to working age (16–64 years) population ratios and unemployment rates calculated from the UK Labour Force Survey (UK Office of National Statistics, 2016). Data were available quarterly from 1992:2 to 2015:4 and were aggregated to GOR level. For each GOR, population aged 16 and over was also collected to scale accidents, vehicle drivers and fatalities in per capita terms (per 100,000 population).[13] Although it is common to measure economic activity using unemployment, we use employment as our primary proxy for macroeconomic conditions as it accounts for the effects of discouraged workers who exit the labour market in bad times (rather than remaining unemployed) and the 'added workers' who enter employment from outside the labour force (Fuchs & Weber, 2013). In this way, employment is more closely tied to economic activity as measured by, say, GDP than is unemployment. However, we also present the main results using unemployment rates as a robustness check.

The data were supplied in a complex format, and extensive data processing was required before analysis could be carried out. Table A.2.2 in the appendix lists the data processing tasks that were required.

Quarterly British employment rates and accident and fatality rates are shown in figure 2.1. Polynomial trends are used to show smoothed trends in accidents and fatalities. These aggregate data show changes associated with the recovery after the 1991 recession and the effects of the GFC that began in about 2008. Employment rates show cyclical patterns associated with variations in economic activity, although there are differences between the regions (see Figure A.2.2). Deviating from the overall downward trend, accidents show a weak procyclical relationship associated with the 1991 recovery. During the early 2000s, there is a

[13] 'Risk' can be measured in terms of population, distance or time. However, 'it is largely impossible to determine distance and time travelled for a large-scale analysis of road safety' (Anderson, 2010, p. 2197).

longer term downward trend while employment is relatively stable, perhaps associated with improvements in vehicle safety features and longer-term road safety initiatives rather than directly associated with the economic cycle. The downward trend in accidents more or less continues when employment sharply declines during the GFC and then levels off as employment rises post-GFC. Fatalities show a slightly different pattern. Fatality levels change little as the economy recovers from the 1991 recession and in the immediate aftermath, although the decline is modest. This suggests longer term trends in vehicle safety have more than offset the effects of economic circumstances over this period. There is a sharp decline in fatalities during the GFC (indicating a procyclical relationship), followed by a levelling off in fatalities as the economy recovers. Relative to an overall downward trend, this flattening may reflect a procyclical relationship with employment. The relationship between accidents and fatalities and employment is difficult to interpret from these charts due to the influence of trend and seasonal patterns. In our modelling we control for these effects so that the cyclical components of the series can be compared.

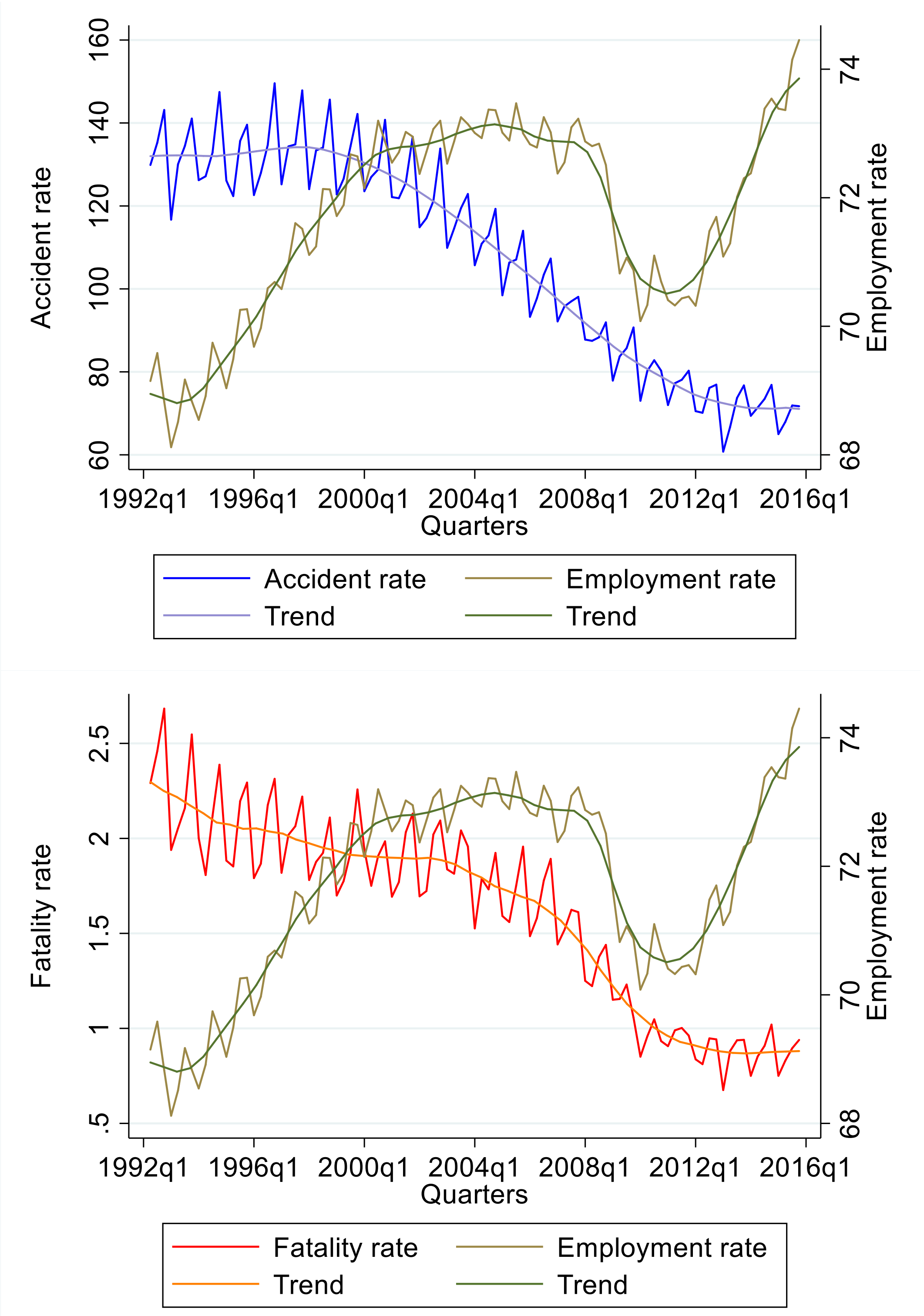

Figure 2.1: Accidents, fatalities and employment for Britain, 1992–2015[a]

[a] Accidents and fatalities are measured per 100,000 population aged 16 and over. Employment rates are calculated as the number employed divided by the working aged population (aged 16–64).

Tables 2.3 and 2.4 provide descriptive statistics for per capita accidents and fatalities and for vehicle drivers, broken down by accident (or driver) characteristics. All data on accidents, vehicle drivers and fatalities were measured per 100,000 regional population aged 16 and over. Of the 104 accidents on average per quarter per region (per 100,000 population), the majority (88 accidents, 84%) involve only slight injuries. Some 93 accidents (89%) involve at least one car, with motorcycles (12, 11%) and goods vehicles (13, 13%) also relatively common. Most accidents do not involve hit-and-run (96, 92%). About 47 accidents (45%) occur on A roads and 31 (29%) on Unclassified roads. Most accidents occur in daylight hours (77, 73%) and/or during off-peak times on weekdays (47, 45%). Alcohol is deemed to contribute to only 3 accidents (3%) and drugs 0.36 accidents (<1%) per region per quarter per 100,000 population. Most accidents occur in fine weather (82, 79%).

Similar patterns emerge for the 1.6 fatalities per quarter per GOR (per 100,000 population), although there is a higher relative prevalence of fatalities than accidents where motorcycles and goods vehicles are involved and on A roads. There are relatively fewer fatalities than accidents on Unclassified roads. Although most fatalities occur during the day, there are relatively more fatalities than accidents at night, indicating night accidents are more severe than those occurring during the day.

In terms of vehicle drivers and riders involved in accidents (again, per quarter, per GOR, per 100,000 population), most are male and/or aged 25–49 years, although drivers aged 18–24 are also a large group.

Table 2.3: Descriptive statistics for numbers of accidents and fatalities per 100,000 population per GOR per quarter, by accident characteristics[a]

	Accidents				Fatalities			
	Mean	SD	Q1	Q3	Mean	SD	Q1	Q3
Total	104.83	28.77	82.49	124.02	1.64	0.65	1.08	2.10
Severity (accidents only)								
Fatal	1.50	0.57	1.01	1.92				
Serious	15.26	5.22	11.14	19.03				
Slight	88.07	24.35	69.04	103.47				
Vehicle involvement in accident								
Bicycle	10.36	4.25	7.28	12.53	0.08	0.06	0.04	0.11
Motorcycle	12.04	6.15	8.00	14.79	0.29	0.17	0.16	0.39
Car	93.30	25.36	73.34	111.07	1.33	0.57	0.85	1.74
Bus	4.94	2.80	3.01	6.61	0.07	0.06	0.02	0.09
Goods	13.35	4.28	10.11	16.71	0.38	0.20	0.22	0.50
Other/unknown vehicle	2.61	1.13	1.75	3.24	0.06	0.06	0.02	0.09
Hit-and-run								
Yes	10.24	3.66	7.82	12.17	0.06	0.05	0.02	0.09
No	96.26	25.94	76.64	113.43	1.61	0.63	1.08	2.05
Road type								
Motorway/A(M) road	3.75	2.18	2.03	5.16	0.08	0.07	0.03	0.12
A road	47.33	17.16	35.09	54.53	0.95	0.41	0.62	1.20
B road	13.55	3.63	10.71	16.40	0.23	0.13	0.13	0.32
C road	9.31	5.67	4.52	14.01	0.13	0.11	0.05	0.18
Unclassified road	30.89	10.43	22.93	37.45	0.25	0.14	0.15	0.34
Light conditions, time and day								
Daytime	76.54	23.67	58.35	92.48	0.95	0.45	0.59	1.24
Night	28.27	16.39	15.60	40.03	0.69	0.39	0.40	0.90
Peak weekday	31.38	8.56	24.81	36.99	0.32	0.18	0.19	0.43
Off-peak weekday	47.43	13.52	36.89	55.93	0.78	0.34	0.52	1.02
Weekend	26.01	7.20	20.28	31.34	0.53	0.23	0.35	0.69
Contributory factor								
Alcohol	3.19	1.29	2.41	3.81	0.10	0.07	0.05	0.14
Drugs	0.36	0.16	0.25	0.44	0.03	0.03	0.00	0.04
Weather								
Fine, no wind	82.40	23.99	64.80	99.00	1.34	0.53	0.89	1.72
Adverse weather	18.85	8.61	12.54	23.75	0.26	0.17	0.13	0.35
Other/Unknown weather	3.58	2.31	1.84	4.85	0.04	0.05	0.00	0.06

[a]Number of observations 1045 (1992–2015), except for alcohol and drugs which have 484 observations (2005–2015) and hit-and-run which have 1001 observations (1992–2014) due to shorter observation timeframes. Q1 and Q3 are the first and third quartiles, respectively.

Table 2.4: Descriptive statistics for numbers of vehicles per 100,000 population per GOR per quarter, by driver characteristics[a]

	Vehicles			
	Mean	SD	Q1	Q3
All drivers	191.13	52.97	148.90	228.66
Driver sex				
Male	128.72	38.54	97.26	155.74
Female	52.16	13.45	41.53	61.28
Unknown	10.25	3.34	7.92	12.01
Driver age				
0–17	7.43	3.44	4.55	9.83
18–24	33.07	10.80	23.69	41.15
25–49	95.87	30.15	71.52	115.38
50–64	26.57	5.32	22.47	30.51
65+	10.36	2.49	8.56	12.10
Unknown age	17.83	9.96	10.86	22.77

[a] Number of observations 1045 (1992–2015). Q1 and Q3 are the first and third quartiles, respectively.

2.4 Empirical strategy

Based on results from the previous international literature (table 2.1) and the potential mechanisms linking accidents and employment (table 2.2), we hypothesise:

H1 there will be a procyclical relationship between employment and total accidents and this relationship varies according to accident characteristics based on the strength of mechanisms such as fatigue/stress from longer working hours, less attention to safety, drink driving, speeding, inattention,

H2 a procyclical relationship between employment and fatalities (fatal casualties), with the strength of relationship varying by accident characteristic according to mechanisms mentioned earlier, and

H3 a procyclical relationship between employment and the number of vehicles involved in accidents, with variations according to mechanisms linked to driver demographics (such as general risky behaviour, driving experience, distraction/inattention, alcohol use and general sensitivity to economic conditions).

Our strategy is to remove as much time series and other confounding variation from the data as possible. A fixed effects modelling approach was used, as is most commonly used in the literature using panel data (see table 2.1). In this model the impact of the macroeconomic cycle is identified by modelling the average of (within region) changes in employment rates against numbers of accidents or fatalities, while controlling for secular changes (via year fixed effects).

The addition of GOR-specific time trends makes the analysis even more nuanced. This allows us to isolate the cyclical component of macroeconomic activity as our explanatory variable of interest: the employment coefficient measures the effect of intra-region movements in macroeconomic conditions and is based on the premise that economic conditions vary between GORs (Buchmueller et al., 2006; Ruhm, 2000). This is evident from Figure A.2.2.

Importantly, the fixed effects model allows unobserved characteristics embodied in the region fixed effects (such as road lengths or policing effects) and the time fixed effects (such as seasonality or vehicle safety levels) to be correlated with observed characteristics. The fixed effects control for a range of unobserved confounders that vary by region or by time. The model differences away these influences, which, combined with a linear trend, helps us identify the causal effect of employment within regions within quarters on accidents and fatalities.

Time fixed effects capture factors affecting all regions in the same way over time such as national macroeconomic conditions, knowledge on how to avoid accidents and reduce their severity, vehicle safety standards (Fridstrøm et al., 1995) and national trends in mortality (Buchmueller et al., 2006).[14] Region fixed effects capture institutional, economic or demographic differences such as variations in police activity, differences in road length and topography and region geography. Congestion may vary by time and region, so is not captured. Using a fixed effects model removes the bias that would be induced from a variable that is fixed over regions or over time being omitted.

Region specific time trends capture the effects of variables that are (within region) 'spatially stable, but [with a] temporally monotonic pattern of variation' (Fridstrøm et al., 1995, p. 7). These time trends account for the fact that numbers of accidents and fatalities are not stable over time and there might be 'behavioural adaptation to changes in vehicle safety technologies' as well as macroeconomic conditions (Behnood & Mannering, 2015, p. 8). There might also be changes in police reporting practices (such as opinions) over time (Behnood & Mannering, 2015) and 'changes in police-reporting over time may be a source of temporal instability. For example, temporal instability could result if police agencies change the probabilities of assigning certain driver conditions to more severe crashes (for example, becoming more likely to assign fatigue or distracted driving as a primary cause of severe crashes) which could be the

[14] Time dummies also capture the effects of seasonal variation.

result of changes in police policy, the influence of court cases, or other factors' (Behnood & Mannering, 2015, p. 28).

Our model exploits within-region variations in employment that are independent of regional time trends and inter-regional differences in time invariant unobservables affecting accidents and fatalities. This model improves on aggregate time series analysis if there are large variations between GOR-based employment rates.

Our main specification for the estimating equation takes the form:

$$O_{it} = \beta_1 E_{it} + T_{it} + \alpha_i + \lambda_t + \varepsilon_{it}$$

(i=1, … , 11; t=1992:2, … , 2015:4) (1)

where O_{it} is the health outcome: number of accidents per 100,000 population (aged 16 and over) in GOR i in quarter t; number of vehicles involved in accidents in GOR i in quarter t; number of fatalities (casualties) in GOR i in quarter t. E_{it} is the employment to working age population ratio for GOR *i* in quarter *t*, T_{it} is a linear time trend for GOR *i* to capture the overall downward trend in accidents and fatalities in each GOR over time, ε_{it} is an error term. α_i and λ_t are GOR and time fixed effects (dummy variables). The equation is estimated for each of the three outcomes (accidents, drivers and fatalities).

In our main specification we use levels rather than natural logarithms as the dependent variable because some of the smaller regions have zero values for the dependent variables in at least some quarters. However, we later test for robustness by modelling the logarithm of the accident rate against the employment rate, and the level of accidents against the unemployment rate. We also investigate the effects of the GFC by splitting the sample into a pre-GFC period (1992–2008) and a post-GFC period (2008–2015) and modelling the relationship between accident levels and employment rates.

Building on a literature that focuses on overall accidents or fatalities, the model is re-estimated for various breakdowns of total accidents and fatalities according to accident characteristics, comprising vehicle types involved in the accidents, whether the accident/fatality involved a hit-and-run, road type on which the accident occurred, light conditions and time/day when the accident occurred, whether alcohol or drugs contributed to the accident, weather conditions at the time of the accident and accident severity (accidents models only). The model is also estimated for the vehicle driver's (or rider's) sex and broad age group. This detailed analysis provides some initial indication of what behaviours might be involved in the link between accidents and economic activity.

Standard errors are clustered at the GOR-quarter level to account for heterogeneity within GOR-quarters.[15] That is, structure is imposed as accidents are likely to be correlated within regions within seasons, so the error terms are independent across clusters but correlated within clusters (Cameron & Miller, 2015). Without controlling for such correlation, standard errors could be misleadingly small and p values too small, implying coefficients appear significant when in fact they are not. Such 'cluster-robust' standard errors require the assumption that the number of clusters is large. With 11 GORs and 4 quarters in the year, we have 44 clusters and assume this is sufficient to obtain cluster-robust standard errors.[16]

All estimation was carried out using Stata15.

2.5 Results

The relationships between employment and accidents, fatalities and driver characteristics are explored below. For ease of interpretation, results are reported in tables 2.6 and 2.7 in terms of semi-elasticities. Confidence intervals for the semi-elasticities are reported in the text as they are more informative than standard errors for coefficients, although both coefficient estimates and standard errors are given in Table A.2.3 and Table A.2.4 in the appendix. Semi-elasticities show the percentage change in accidents or fatalities from a 1 percentage point change in the employment rate and are calculated from a levels model as the coefficient divided by the mean of the dependent variable:

$$\frac{\beta_1}{\overline{O_{\iota t}}} \qquad (i=1, \dots, 11;\ t=1992{:}2, \dots, 2015{:}4) \quad (2)$$

[15] According to Cameron and Miller (2015), 'the clustering should not be based on state-year pairs because, for example, the error for California in 2010 is likely to be correlated with the error for California in 2009' (p. 323). However, we cluster by GOR-qtr (i.e. four clusters per GOR) so correlation should not be a problem.

[16] According to Cameron and Miller (2015), 'there is no formal test of the level at which to cluster. The consensus is to be conservative and avoid bias and to use bigger and more aggregate clusters when possible, up to and including the point at which there is concern about having too few clusters' (p. 333).

2.5.1 *Accidents*

Consistent with the literature, overall accident levels show a procyclical relationship with the economic cycle over the 95 quarters studied. This period is significant for the measurement of economic activity, as it includes the GFC. On average there are 104 accidents per GOR per quarter and all accident variables are scaled by population (100,000) to account for different sized regions. A one percentage point rise in the employment rate increases the number of accidents by 2.2 per cent (95% CI: 1.1 to 3.2%) (table 2.6).[17]

Similar statistically significant patterns are observed when accidents are broken down by severity, likely due to increased traffic volumes and riskier driving behaviours. The bulk of accidents are slight (on average 88 of the 105 accidents (84%) result in slight casualties). A one percentage point rise in employment increases slight accidents by 2.2% (95% CI: 0.9 to 3.4%). Serious accidents show procyclical patterns with employment increasing accidents by 2% (95% CI: 1.4 to 2.6%). This smaller than overall result suggests congestion might be turning some of the potentially more serious accidents into slight accidents. Fatal accidents are few (averaging 1.5 per GOR per quarter, 1%) and increase by 2.6% (95% CI: 1.3 to 4%) as employment rises by one percentage point. The stronger effect on fatal accidents is consistent with the effects of riskier driving behaviours outweighing the effects of congestion from increased traffic flows.

In terms of vehicle types involved in accidents (again per 100,000 population), all vehicle types show procyclical relationships with employment and for all but buses the relationship is significant. This lack of significance for buses might reflect a capacity issue, as there is more patronage of buses as the economy expands but potentially not sufficient an increase to warrant extra services. Therefore the number of bus services would remain stable with a relatively constant accident rate.

The bulk of accidents involve at least one car (on average 93 out of 104 accidents, 89%) and the number of accidents rises by 2.1% (95% CI: 1.0 to 3.2%) as employment rises by one percentage point. This tally is likely to comprise both leisure and commuting traffic, both of which are likely to be procyclical. As incomes rise there is more opportunity to fund

[17] These results should be interpreted bearing in mind that underreporting of accidents (particularly less severe ones) is likely to vary with economic activity.

discretionary travel (holidays/road trips), leading to increased traffic volumes. As employment opportunities increase, commuter traffic also increases and at least part of this will be accounted for by cars. Time pressures and stress also rise when the economy expands due to more employment and potentially longer work hours, leading to more erratic driving behaviours (such as speeding or general reckless driving) and more accidents. This category includes taxis, which respond to income (people catch a taxi rather than drive due to consumption of alcohol or for convenience) and economic activity (say, travelling between meetings/workplaces). The smaller than overall result might reflect some substitution between cars and taxis (which are potentially safer as they might be somewhat insulated from risky behaviours) as economic activity expands. The procyclical relationship is consistent with the findings of W. Evans and Graham (1988) although their study focussed on fatalities and unemployment.

The strongest relationship occurs for goods vehicles (13.4 accidents, 13%) and the number of these accidents rises with employment (3.3%, 95% CI: 2.2 to 4.4%). This category includes vans, small and large goods vehicles. Such traffic is mostly associated with movement of goods as a fundamental part of economic activity. Hence the procyclical relationship with traffic volumes. As with commuters, drivers are likely under time pressure for quick deliveries during economic expansions, leading to speeding and more erratic driving behaviours and therefore more accidents. Although studying the effects of unemployment on fatalities, He (2016) also found a large procyclical effect (-8.37%) for large goods vehicles (trucks).

Motorcycles are involved in about 12 accidents per GOR per quarter (11%) and increase by 3% (95% CI: 1.0 to 5.1%) as employment rises. Again, commuting and to a lesser extent leisure purposes are likely explanations for these trips, although there could be some small freight also associated with motorcycle deliveries. This relatively strong effect is consistent with an increase in risky behaviour and, to a lesser extent, increased traffic volumes when the economy is performing well. W. Evans and Graham (1988) also found strong procyclical effects on ‘other’ fatalities (which included motorcycle riders). Mobility scooters are included in this category and are likely to represent non-work related travel and be less sensitive to the economic cycle.

About 10 of 104 accidents (10%) involve bicycles and this figure rises by 1.7% (95% CI: 0.3 to 3.1%) as employment increases. A somewhat weaker relationship to the economic cycle is evident as some of this traffic will be associated with students commuting to school, although bicycles are also used by some individuals to commute to work and as leisure vehicles which both respond to economic activity in terms of traffic volumes and rider behaviour.

Accidents involving 'other vehicles' represent an average of 2.6 accidents per GOR per quarter (2%) and rise by 1.6% (95% CI: -0.1 to 3.3%) as employment rises by one percentage point. This category includes the minibus, ridden horse, agricultural vehicle, tram, motor caravan, other and unknown vehicles. Most of these forms of transport are less likely to respond to the economic cycle as measured by changes in employment, therefore this result is likely driven by agricultural vehicles which would be the form of transport in this group most likely to respond to economic conditions.

Table 2.5: Employment semi-elasticities for accident and fatality models, including vehicle types[a]

	Accidents	Fatalities
Total	0.022***	0.022***
Severity		
Fatal	0.026***	
Serious	0.020***	
Slight	0.022***	
Vehicle involvement in accident		
Bicycle	0.017**	0.002
Motorcycle	0.030***	0.031**
Car	0.021***	0.023**
Bus	0.008	0.021
Goods	0.033***	0.018
Other vehicle	0.016*	0.048

[a]Sample runs from 1992–2015. Dependent variables are measured in levels per 100,000 population (for each GOR and quarter). Robust standard errors were clustered at the GOR-quarter level. Each cell represents a separate regression. Coefficients and standard errors are provided in Table A.2.3 in the appendix. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

2.5.1.1 Accident characteristics

Both hit-and-run and non-hit-and-run accidents appear to be procyclical. On average, 10 out of 104 accidents (9%) are hit-and-run. The remaining 96 accidents (91%) are either non-hit-and-run or involve a hit that the driver was unaware of. Non-hit-and-run accidents are likely to respond to changes in economic activity via traffic volumes on the roads and we find such accidents increase by 2.1% (95% CI: 1.0 to 3.2%) as employment expands by 1 percentage point. This result is consistent with the findings of French and Gumus (2015). Hit-and-run accidents are less sensitive to the economic cycle with only a 1.6% (95% CI: 0.4 to 2.8%) increase for each percentage point change in employment. This effect is somewhat surprising as we might expect as employment and incomes increase, individuals are more likely to have licences and registered vehicles, leading to fewer hit-and-run accidents. Perhaps the positive effect is due to individuals being under time pressure and making poor decisions when the economy is doing well. Drink driving could also be a factor here. These effects might partly offset each other, explaining why we get a smaller effect for hit-and-run accidents relative to non-hit-and-run accidents. A smaller (i.e. insignificant) effect is, however, what French and Gumus (2015) found.

Accidents on all road types are procyclical. Most accidents occur on A roads (47.3 per GOR per quarter, 45%). The number of accidents on A roads increases by 2.7% (95% CI: 1.4 to 4.1%) as employment increases by one percentage point. Accidents on B roads (13.6, 13%) increase by 1.6% (95% CI: 0.6 to 2.7%) as employment increases. Accidents on C roads respond positively to employment (2.3%, 95% CI: 0.2 to 4.3%). Motorway/A(M) road accidents are less common (3.75 accidents per GOR per quarter, 4%) and respond relatively strongly to changes in employment (2.7%, 95% CI: 1.3 to 4.1%). The weakest relationship with economic activity occurs on Unclassified roads, for which accidents increase by 1.4% (95% CI: 0.5 to 2.3%) as employment increases by one percentage point. Strong effects on motorways/A(M) roads and A roads relate to the very large volumes of traffic these roads carry as the economy expands. The relatively strong result for C roads could be due to individuals seeking short cuts or less congested routes when their time is at a premium at the height of the economic cycle.

Accidents occurring during daylight hours make up the bulk of accidents (76.5 out of 104.8, 73%) and increase by 1.8% (95% CI: 0.7 to 2.9%) as employment increases by one percentage point. Accidents occurring at night respond positively and relatively strongly to employment (3.2%, 95% CI: 1.7 to 4.6%). This suggests when the economy expands there might be more socialising in terms of post-work drinking in pubs and restaurants leading to more traffic and risky behaviour (alcohol and speed) at night and resulting in more accidents. This ‘night’ effect is stronger than the 1.3% effect found by Ruhm (1995), although that paper focussed on fatalities.

Time and day are split between weekday peak (7–9am and 4–7pm Monday–Friday), weekday off-peak (7pm–7am and 9am–4pm Monday–Friday) and weekends (all day Saturday and Sunday). Although weekday off-peak has the highest number of accidents (47 out of 104, 45%), relative to the number of hours covered, weekday peak has the highest accident rate per hour. The three time and day categories all respond procyclically to changes in employment and with similar semi-elasticities[18], although they likely have different explanations. Accidents during weekday peak hours are likely due to increased commuting when employment expands, whereas weekday off-peak is more likely due to movement of goods during the day and perhaps socialising at night. The response of weekend accidents is slightly more muted and likely results from increased leisure traffic as incomes increase with employment.

Accidents involving alcohol and/or drugs do not respond significantly to economic conditions (although there are very few accidents in these two categories and there might be some under reporting if some of these less severe accidents are not attended by police or police do not report the involvement of these two contributory factors). This result is somewhat surprising as we might expect (based on the findings of Ruhm, 2006) the use of alcohol and drugs to increase with income as the economy expands. Similarly, a significant procyclical effect of unemployment of -2.84% on fatalities by Cotti and Tefft (2011) also suggests there are differences from the US literature. Perhaps there is increased use of alcohol, but it remains under the drink-driving threshold and/or individuals increase their use of taxis (or designated non-drinking drivers) as income rises.

Weather conditions play a role in how accidents respond to changing economic circumstances. Most accidents occur in fine weather (averaging 82.4 per GOR per quarter, 79%) and these accidents increase as employment increases (2.2%, 95% CI: 1.2 to 3.3%). Accidents during adverse weather conditions (18.9, 18%) increase by 1.2% (95% CI: 0.0 to 2.3%) as employment increases, suggesting the increased volume of traffic when the economy expands favours travel in fine weather (or individuals delay travel in adverse weather). The few accidents for which the weather conditions are unknown respond very strongly to changes in employment (almost 6%, 95% CI: 1.9 to 10.0%) and might be accidents that police did not attend that were reported later. These are likely to be less severe accidents, perhaps where the other driver was unaware and did not stop and/or reported for insurance purposes as time pressures increased and decisions became poorer when the economy was performing well.

[18] Weekday peak 2.4%, 95% CI: 1.3 to 3.5%; weekday off-peak 2.1%, 95% CI: 0.9 to 3.2%; weekend 2.0%, 95% CI: 1.0 to 3.0%.

Table 2.6: Employment semi-elasticities for accident and fatality models, by accident characteristic[a]

	Accidents	Fatalities
Total	0.022***	0.022***
Hit-and-run		
Yes	0.016**	0.042
No	0.021***	0.023***
Road type		
Motorway/A(M)	0.027***	0.074**
A	0.027***	0.02*
B	0.016***	0.009
C	0.023**	0.022
Unclassified	0.014***	0.027**
Light conditions, time and day		
Daytime	0.018***	0.007
Night	0.032***	0.044***
Weekday peak	0.024***	0.009
Weekday off peak	0.021***	0.024**
Weekend	0.020***	0.028**
Contributory factor		
Alcohol	-0.009	-0.002
Drugs	-0.009	0.09
Weather		
Fine no wind	0.022***	0.023***
Adverse weather	0.012**	0.012
Other/unknown weather	0.059***	0.053

[a]Sample runs from 1992–2015, except for hit-and-run (1992–2014) and contributory factors (2005–2015). Dependent variables are measured in levels per 100,000 population (for each GOR and quarter). Robust standard errors were clustered at the GOR-quarter level. Each cell represents a separate regression. Coefficients and standard errors are provided in Table A.2.3 in the appendix. *** p < 0.01, ** p < 0.05, * p < 0.1.

So, as we can see from tables 2.5 and 2.6, there is a significant procyclical relationship between accidents and employment rates at the aggregate level as well as by most characteristics.

2.5.2 Fatalities

The average number of fatalities per GOR per quarter is 1.64. Again, fatalities are scaled per 100,000 population. Overall, fatalities are procyclical and increase by 2.2% (95% CI: 0.8 to 3.7%) as the employment rate increases by one percentage point (table 2.6). This corresponds to the previous literature, for example, for the US, Lindo (2013) found the fatality rate increased by 2.09% at state level and Ruhm (1995) found fatalities increased by 2.84% in response to a 1 percentage point increase in the employment rate. The bulk of the literature focusses on unemployment rates and also finds a significant procyclical relationship with fatalities, with effects ranging from about -1 to -3%.

When overall fatalities are broken down by types of vehicles involved in the accidents, there is a procyclical relationship with economic activity for some vehicle types and no significant relationship for others. Accidents involving cars have the largest number of fatalities (1.33, 81%). Fatalities from such accidents rise with employment rates (2.3%, 95% CI: 0.6 to 3.9%) and are likely to be associated with larger volumes of commuter and leisure traffic rather than the movement of goods (it is also likely that there is a constant fatality rate per accident for cars, but that the increase is driven by traffic volumes). This is consistent with the strong procyclical relationship found by W. Evans and Graham (1988). Accidents involving motorcycles average 0.29 fatalities (18%) and are likely due to lack of protection of the rider. These fatalities increase with employment rates (3.1%, 95% CI: 0.7 to 5.6%) and may be associated with increased speed, erratic driving behaviour and general vulnerability of the riders. These results are comparable with those of French and Gumus (2014), who find a 2.4% effect. Fatalities from accidents involving bicycles, buses, goods vehicles and other/unknown vehicles show no significant association with the economic cycle. This result for goods vehicles is in contrast with that of He (2016), who finds a larger effect in the US for accidents involving goods vehicles (trucks) than those without. These results could be due to bicycle accidents occurring at very low speeds and the offsetting effects in goods vehicle accidents of increased driver protection but more severe impacts on other vehicles (Massie et al., 1995).[19]

Most fatalities are not associated with hit-and-run accidents (1.61, 98%) but respond significantly to changes in employment (2.3%, 95% CI: 0.8 to 3.7%). These fatalities might be due to risky behaviour (speeding, driver inattention) and traffic volume associated with rising employment. Although hit-and-run fatalities have a large percentage effect (4.2%, 95% CI: -0.7 to 9.1%), it is not significant likely due to the small sample size (0.06 fatalities on average (4%), per GOR per quarter). This finding is consistent with French and Gumus (2015), who found non-hit-and-run fatalities procyclical, with fatalities declining by 1% as unemployment rose by 1 percentage point.

Although the number of fatalities on motorways and A(M) roads is small (0.08, 5%), this category of road shows the strongest response to changes in employment (7.4%, 95% CI: 1.3 to 13.5%) and such fatalities are likely due to traffic volumes, vehicle composition and speed, all of which respond to economic activity and increase the likelihood of fatalities in accidents.

[19] Some of these fatalities involve pedestrians being struck by vehicles, most likely cars.

Most fatalities occur on A roads (0.95, 58%) and such fatalities increase by 2% (95% CI: -0.1 to 4.1%) as employment rates increase by one percentage point. Lower speeds than apply to motorways and A(M) roads are likely to limit the likelihood of fatalities in accidents occurring on A roads. Fatalities on Unclassified roads respond to changes in employment (2.7%, 95% CI: 0.3 to 5.2%). Unclassified roads tend to have less traffic and lower speed limits but tend to have more horses and agricultural machinery as traffic, with less protection afforded to the drivers/riders. As overall traffic volumes increase with economic activity, fatalities are likely to rise. Fatalities on B and C roads do not significantly respond to economic activity.[20]

Fatalities occurring during the day (0.95, 58%) do not respond to changes in the economic cycle, suggesting that the increased number of accidents in good times does not translate fully into fatalities. However, fatalities occurring at night (0.69, 42%) increase by 4.4% (95% CI: 2.1 to 6.6%) with increases in the employment rate. French and Gumus (2014) find a qualitatively similar result for motorcycles. Risky behaviour is likely to result in night-time accidents (which are strongly procyclical) translating into fatalities. Although we found the number of fatal accidents was procyclical, there is no significant association between economic activity and the number of fatalities occurring during daytime. This indicates the procyclical nature of fatal accidents is driven by nighttime activity. This is in contrast to Ruhm (1995), who found a stronger procyclical effect of unemployment for all times (-3.16%) than for nighttime (-1.3%), suggesting results are driven by fatalities during the day.

There is no significant association between employment and fatalities occurring during weekday peak times, suggesting congestion leads to lower speeds involved and accidents are less severe. The procyclical nature of fatalities is driven by fatalities occurring during weekday off-peak times and the weekend, with responses of 2.4% (95% CI: 0.4 to 4.4%) and 2.8% (95% CI: 0.7 to 4.9%), respectively. These fatalities could be driven by nighttime activity.

Fatalities from accidents involving alcohol and drugs do not respond to economic activity. This suggests that although there might be more alcohol consumed when the economy is expanding, that it is not in sufficient quantities to trigger accidents (see earlier) or fatalities and be recorded

[20] While accidents on C roads responded to changes in the economy, fatalities did not. This suggests the response is driven by less serious accidents.

as a contributory factor. This result is in contrast to that of He (2016) who found a significant procyclical effect of -3.6% (unemployment).[21]

Most fatalities occur when the weather is fine (1.34, 82%) and are procyclical. This finding would be consistent with the risk compensation hypothesis in which individuals adopt more risky driving behaviours when the weather is good (Fridstrøm et al., 1995). Fatalities increase by 2.3% (95% CI: 0.8 to 3.9%) as employment rates increase by one percentage point. The few fatalities that occur in adverse weather and other/unknown weather are not significantly associated with the economic cycle, although this is likely due to small sample sizes.

In summary, a significant procyclical relationship is observed between fatalities and most accident characteristics.

2.5.3 Vehicles

With many accidents involving multiple vehicles, analysis of driver sex and age needs to be conducted at the vehicle level rather than at accident level. On average per GOR per quarter (per 100,000 population) there were 191.13 vehicles involved in 104 accidents (table 2.4). Most vehicles were driven by males (128.72, 67%) and this number increased by 2% (95% CI: 1.0 to 2.9%) as employment rose by 1 percentage point (table 2.7, figure 2.2). This figure is likely to represent more risky behaviour exhibited by males in their driving as the economy expands and these individuals face time pressures and stress. Female drivers accounted for 52.16 vehicles (27%) on average, although the response to changes in employment was slightly less than for males (1.8%, 95% CI: 0.7 to 2.9%), representing more conservative behaviours.[22] Such close results for the two sexes is consistent with the findings of Stuckler et al. (2009) for 26 European countries combined. However, our results differ from those of Neumayer (2004), who found that although fatalities in Germany were procyclical in terms of unemployment (-1.3%), the -2.1% effect for females was significant but for males was not significant. However, it should be borne in mind that those results related to fatalities rather than drivers and those two groups do not completely overlap. There were 10.25 vehicles (5%) driven by

[21] Ruhm (2006) found alcohol consumption for the US was procyclical, and this may indicate a procyclical relationship with fatalities.

[22] When these driver sex variables used the corresponding (smaller) population in the per capita denominator, similar but slightly larger semi-elasticities resulted (0.032 for males and 0.028 for females). Both semi-elasticities remained significant.

individuals of unknown sex and this category responded strongly to changes in employment (5.5%, 95% CI: 3.6 to 7.3%). With increased pressure on their time and perhaps impaired decision-making when employment increases, some of these drivers might have been unaware of their involvement in a less serious accident that was later reported to police.

As employment rises, drivers and riders of all but the youngest ages (under 18) significantly increase their accident involvement. Those aged under 18 are mostly bicycle riders and not in the labour force so we would not expect them to respond to changing economic circumstances.[23] Similarly, individuals aged 65 and over are most likely retired and less likely to respond to changes in the broad economy (1.2%, 95% CI: 0.5 to 1.8%).[24] A weaker result for these older individuals is consistent with US evidence from Cotti and Tefft (2011) and, to a lesser extent, Stevens et al. (2015). Although most drivers in accidents are aged 25–49 (50%), they have a below average response to changes in employment (1.9%, 95% CI: 0.6 to 3.1%), suggesting their behaviour is not as risky as that of other age groups. This is a smaller effect than for unemployment in Cotti and Tefft (2011) (30–59 year olds, -3.55%) and Stevens et al. (2015) (25–64 year olds, -2.54%).

Although not the largest group, drivers aged 50–64 have one of the strongest responses to changes in the economy (2.8%, 95% CI: 1.7 to 3.9%), perhaps because they are more affected than middle aged individuals by economic circumstances. For example, when the economy is in decline, they might be among the first to lose their jobs and be less able to find another job thereby reducing their income and the potential for driving. Drivers aged 18–24 have the highest accident involvement rate per year of age (4.75 vehicles per year of age) likely due to their well-known risk-taking behaviour and relative lack of driving experience. They respond significantly to changes in employment (2.2%, 95% CI: 0.8 to 3.6%).[25] This result is on par

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[23] However, there is a tendency to delay getting a licence for the under 25s, so they have a lower rate of vehicle registration. Therefore, if we could have divided by the number of registrations we would get a larger response for the under 25s.

[24] There is no age limit on driving a car in the UK, however, once individuals reach age 70, they must renew their licence every three years. See https://www.gov.uk/renew-driving-licence-at-70. Drivers of trucks, minibuses and buses aged 45 or over need to renew their licence every 5 years. From age 65, they need to renew their licence every year. See https://www.gov.uk/driving-licence-renewal-after-45-lorry-minibus-bus. These 'hurdle' ages potentially limit the relevant population age group from 65+ to potentially something like 65–80 years.

[25] As a robustness exercise (not shown), where possible we used a variant of the per capita age variables using the corresponding population in the denominator (individuals aged 18–24, 25–49, 50–64 and 65 and over). Quarterly regional population estimates were not available for the under 18s. When these alternative driver age variables

with that of Stevens et al. (2015) who found an unemployment effect of -2.75% for individuals aged under 25. This age group is also known to be disproportionately affected by changes in economic circumstances. Gaining a job affects income and therefore the amount of driving (due to higher income leading to greater affordability and a higher requirement for commuting). However, this group has the lowest income of all working age groups and therefore is likely to use cheaper forms of transport for which they are not the driver (bus, train), partly offsetting the effect of additional income. Again, we see that drivers of unknown age have the strongest response to changing economic circumstances (3.1%, 95% CI: 1.4 to 4.7%) and some of these are likely to be drivers unaware of their involvement in an accident that is later reported to police.

In contrast to our results, although Stevens et al. (2015) found fatalities were procyclical with an unemployment effect of -2.5%, they also found the effect weakened with age, whereas our results show an inverted U-shape in effect sizes. Again, those results relate to fatalities rather than drivers although there is likely to be some overlap in the two groups.

Table 2.7: Employment semi-elasticities for vehicle models[a]

	Semi-elasticity
All drivers	0.021***
Driver sex	
Male	0.02***
Female	0.018***
Unknown	0.055***
Driver age	
Under 18	0.011
18–24	0.022***
25–49	0.019***
50–64	0.028***
65 or over	0.012***
Unknown	0.031***

[a]Sample runs from 1992–2015. Dependent variables are measured in levels per 100,000 population (for each GOR and quarter). Robust standard errors were clustered at the GOR-quarter level. Each cell represents a separate regression. Coefficients and standard errors are provided in Table A.2.4 in the appendix. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

were used, larger (and significant) semi-elasticities resulted. For the three oldest age groups the semi-elasticities were approximately five times larger (ranging from 0.05 to 0.11). For individuals aged 18–24, the semi-elasticity was about ten times larger (0.210). This much larger effect shows how the youngest adult age group is disproportionately represented in accidents.

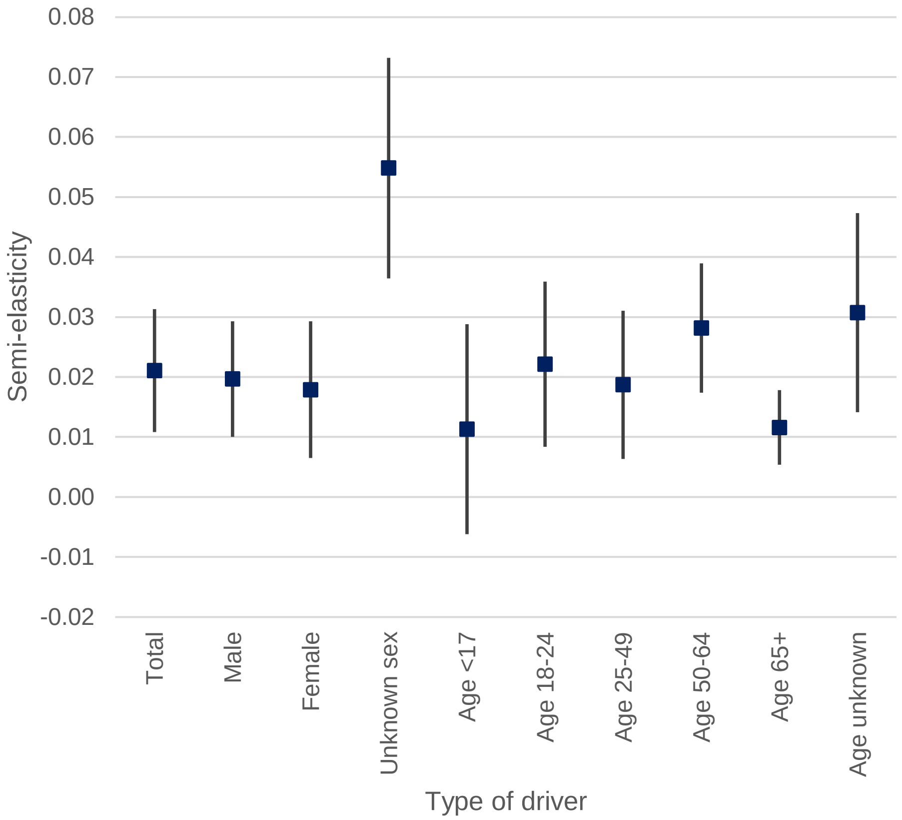

Figure 2.2: Semi-elasticities for employment by driver characteristic[a]

[a] Sample runs from 1992–2015. Drivers are measured per 100,000 population aged 16 and over. Employment rates are calculated as the number employed divided by the regional working aged population (aged 16–64). Semi-elasticities are shown with 95% confidence intervals. Robust standard errors were clustered at the GOR-quarter level. Each semi-elasticity represents a separate regression. Coefficients and standard errors are provided in Table A.2.4 in the appendix.

Thus, our results show the overall procyclical relationship persists when disaggregating by driver age and sex, with the largest effect for drivers of unknown sex and age but there is no significant effect for drivers aged under 18 years.

2.6 Robustness of main results

In this section we explore the robustness of our results for total accidents to different specifications of the model and the dependent variable (table 2.8).

Non-linear model

Several studies (see, for example, Chen, 2014; W. N. Evans & Moore, 2012; Gerdtham & Ruhm, 2006; Ruhm, 2000) model the dependent variable in logarithmic form, providing semi-elasticities directly as coefficients. One disadvantage of this approach is that sample sizes can vary when the dependent variable is zero (you cannot take the log of zero). In estimating our model for total accidents in this form, we obtain qualitatively similar results (1.9% effect) to the linear (levels) model (2.2% effect): a significant procyclical relationship with employment. Earlier research (e.g. Ruhm, 2000) finds comparable effects using linear versus log-linear model specifications.

Lagged employment

There may be a lag in becoming aware of movements in the regional unemployment rate as the rate is not known and publicised until after the actual rate is measured, and attention tends to focus on the national rate. Gonzalez and Quast (2011), Lin (2009) and Ruhm (2000) investigated the effects of lags of unemployment on road fatalities and found the contemporaneous semi-elasticity was slightly lower when lags were included, implying the effect of a change in the unemployment rate is distributed over time. In our analysis, contemporaneous and lagged employment could represent short and medium term effects, with short run expansions typically associated with more intensive use of existing inputs (worsening health) (Gerdtham & Ruhm, 2006). When we use lagged employment we find the semi-elasticity is slightly smaller (2.1% compared to 2.2%) but still significant. This suggests there might be some small adjustment process in behaviour when economic conditions change.

Unemployment

Unemployment can be used as another measure of economic activity. When unemployment is used, we find similar results to the levels model (2.2% versus -2.4%, where we expect such an opposite sign when using unemployment): a procyclical relationship. Slightly different semi-elasticities are to be expected as unemployment rates do not include the effects of individuals moving in and out of the labour force.

Global Financial Crisis

The GFC was a period of immense change in the economy and this is reflected in large changes in employment. In contrast with the recovery after the 1991 recession, much of the increase in employment was in part-time and casual jobs (Coulter, 2016). During the downturn, accidents might have increased (or showed smaller than usual decreases) due to changes in behaviour or other circumstances, such as cognitive distraction stemming from stress, anxiety, frustration, sleep disruption and increased alcohol consumption as a result of increased economic uncertainty (Vandoros, Avendano, & Kawachi, 2018). Changes in behaviour might have resulted from changes in individuals' risk preferences during the uncertain times associated with the GFC.[26] At the same time, while employment growth might be associated with increases in the volume of commuting traffic and therefore potentially accidents, restricted hours of work might also have led to a lower than expected increase in accidents through the mechanisms of relatively less work-related tiredness and inattention, although these might have been offset to some degree by job-related stress. With the growth in hours worked being less than the growth in employment, income effects are likely to be muted during the recovery, for example, reducing individuals' capacity to upgrade to newer, safer vehicles. These changes might therefore have affected the relationship between employment and accidents.[27]

To investigate the potential change in this relationship, the sample period is split into pre-GFC (1992q1–2008q3) and GFC (2008q4–2015q4) sub periods. The GFC began in the final quarter of 2008.[28,29] For total accidents there is a procyclical relationship pre-GFC but there is no significant relationship during the GFC. These results suggest there may have been offsetting effects of traffic volumes and stress behaviour arising from uncertainty during the GFC. Alternatively, as the GFC period covers only about 7 years, this might not yield sufficient observations to identify an effect. It is difficult to compare these results with estimates from the overall model, as semi-elasticities are calculated with reference to the mean accident rate over the sample and this differs in the two sub-periods.

[26] According to Cassar, Healy, and von Kessler (2017), there is some evidence that individual experiences such as external shocks can change risk preferences and risky behaviour. For example, in their study of risk preferences before and after an earthquake in Japan, Hanaoka, Shigeoka, and Watanabe (2015) found men became more risk tolerant and increased gambling after the natural disaster.

[27] Ruhm (2015) provides evidence of a weakening procyclical relationship between economic conditions and fatalities from traffic accidents over the period 1976–2010.

[28] According to Jofre-Bonet, Serra-Sastre, and Vandoros (2018), in England the Great Recession began in December 2007 when GDP growth was hit. However, the GFC actually hit in late 2008 when the government unveiled its plan to part nationalise banks and inject money into the money markets (see https://www.theguardian.com/business/2011/aug/07/global-financial-crisis-key-stages and https://www.telegraph.co.uk/finance/financialcrisis/8592990/Timeline-of-world-financial-crisis.html).

[29] Although we can identify the beginning of the GFC period, there may well be lags in behavioural responses as individuals adjusted to changed economic and financial circumstances. Indeed, the length of such lags may vary according to different behaviours.

Table 2.8: Semi-elasticities for different model specifications for overall accidents[a]

Dependent variable specification	Measure of economic activity	Sample	Semi-elasticity
Level	Employment_t	Full	0.022***
Ln	Employment_t	Full	0.019***
Level	Employment_{t-1}	Full	0.021***
Level	Unemployment_t	Full	-0.024***
Level	Employment_t	Pre-GFC	0.013***
Level	Employment_t	Post-GFC	-0.004

[a]Sample runs from 1992–2015, except for pre-GFC (1992–2008q3) and post-GFC (2008q4–2015) sub periods. Dependent variables based on per capita measurements (per 100,000 population for each GOR and quarter). Robust standard errors were clustered at the GOR-quarter level. Each cell represents a separate regression. Coefficients and standard errors are provided in Table A.2.5 in the appendix. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Accident severity

Rather than separately consider the effects of changes in the economy on accidents and fatalities, we can take a step beyond the existing literature and get some idea of how accident severity responds by examining fatalities per accident or severe (serious or fatal) casualties per accident. These concepts capture what could be termed ‘casualty intensity’. Such measures would show any wedge between the number of accidents and the number of casualties of a fatal or serious nature. Note that accidents can be treated as probabilistically independent events, but since accidents can have multiple fatalities, the latter are not independent (Fridstrøm et al., 1995).

Fatalities per accident shows no significant relationship with the economic cycle (table 2.9). This could reflect stability in risky behaviours as passenger numbers increase with improvements in economic circumstances. Casualties killed or seriously injured per accident shows no significant relationship with employment. Accident severity is not typically considered in the literature focussing on effects of macroeconomic change, so this analysis is new. Further work is required to explore these relationships in more detail and this is the subject of chapter 3.

Table 2.9: Effects of employment on accident severity[a]

	Coefficient	SE
Fatalities per accident		
Employment rate	0.0001	(0.0001)
Killed or seriously injured per accident		
Employment rate	-0.0005	(0.0012)

[a]Sample runs from 1992–2015. Dependent variable is fatalities per accident and killed or seriously injured per accident and the mean (across GORs and time) is 0.016 and 0.185, respectively. Robust standard errors, clustered at the GOR-quarter level, are shown in parentheses. Each row represents a separate regression. *** p < 0.01, ** p < 0.05, * p < 0.1.

2.7 Conclusions

A major area of research in health economics has been the effects of changes in the economy on overall mortality and various causes of death. Until the most recent work of Ruhm (2015), most studies showed a procyclical relationship overall and for most causes of death. However, all studies agree the relationship for road accidents is procyclical. This chapter has contributed to our understanding of how macroeconomic conditions affect health by examining the relationship between the economic cycle and road accidents in Britain. Using data on the universe of road accidents reported to police in Britain since 1992, we have looked at both the number of accidents and fatalities as well as examining accidents, drivers and fatalities disaggregated by type to understand the mechanisms that drive the relationship between macroeconomic conditions and accidents and fatalities.

Overall, in modelling the relationship with employment at the GOR level, we find strong evidence of a procyclical pattern in accidents and fatalities and this pattern persists when we disaggregate by accident and driver characteristics. In the literature linking macroeconomic conditions and fatalities, there is an effect of unemployment of between -1 and -3%, depending on the time period considered and the country/countries studied. For example, effects for the US have been about -3% in samples prior to 2000 and -1 to -2% for samples including later years. The effect for Asia-Pacific countries has been largest at -3.4%, followed by OECD countries (-2.1%), Spain (-2%) and Germany (-1%). Consistent with the literature, at the aggregate level we find an employment effect size in the order of 2% for both fatalities and accidents. This means that a one percentage point increase in the employment rate is associated with a 2% increase in accidents and fatalities. Disaggregating the totals and considering driver characteristics, we find effects typically vary between 1 and 3% but there are some stronger and some weaker relationships. The strongest results are found for accidents involving motorcycles and HGVs, accidents occurring at night and accidents in unknown weather conditions. The latter are most likely the result of accidents reported to police after the fact. Strong results are also found for drivers of unknown age and sex. These are also likely to be from accidents reported later. Fatalities involving motorcycles, on motorways and A(M) roads and occurring at night also show strong relationships with the economic cycle. These findings support our research hypotheses.

There is no a priori preferred model specification in the literature. We have adopted a main specification and then explored the robustness of our results with reference to several alternatives. Most of our estimates are robust to these alternative specifications. Results for the model with lagged employment show a small difference, indicating there may be some period of adjustment in behaviours. Estimates for the period of the GFC are not significant but this could be due to the restricted sample period. Also, results for accidents should be interpreted in light of potential underreporting that may be associated with the business cycle.

Although there are multiple mechanisms at work linking macroeconomic conditions to accidents and fatalities, further research is needed to directly test those mechanisms. In this analysis we are unable to disentangle the effects of factors underlying those mechanisms. In any case, 'mechanisms for the previously observed procyclical variation in mortality remain poorly understood' (Ruhm, 2015, p. 26).

It is important to understand and respond to factors influencing accidents and their severity if we are to avoid the health consequences of major increases in road accidents and fatalities as the economy recovers following downturns. As we have seen, a 1 percentage point increase in the employment rate is associated with a 2.2% increase in accidents and a 2.2% increase in fatalities. At the end of our sample in 2015, this equates to an additional 785 accidents and 11 fatalities for the quarter. With an average cost in 2015 of £76,000 per accident and £2m per fatality, these figures represent an additional cost of £60m associated with all accidents and £20m associated with fatalities (although the two costs are not mutually exclusive). Were the increase in employment rates sustained over a year, these figures would rise to £240m and £80m, respectively. In understanding the factors at work, we can target areas for potential interventions. For example, investment in road safety campaigns and initiatives (such as advertising about the effects of fatigue or penalties for drink driving or speeding) could help reduce accidents and their severity, thereby reducing the burden on the health system.

By using an all-encompassing dataset on road accidents in British regions over some 23 years (including the economically turbulent period associated with the GFC) and estimating a variety of model specifications, this chapter provides a unique empirical contribution to the literature on economic activity and health in relation to road accidents and fatalities. Using quarterly longitudinal data and panel techniques to control for both region- and quarter-specific effects, and by breaking down totals by accident and driver characteristics we are able to see that overall results do mask some heterogeneity in the strength of the relationships with economic activity. Results indicate there may be several behavioural mechanisms at work.

Appendix

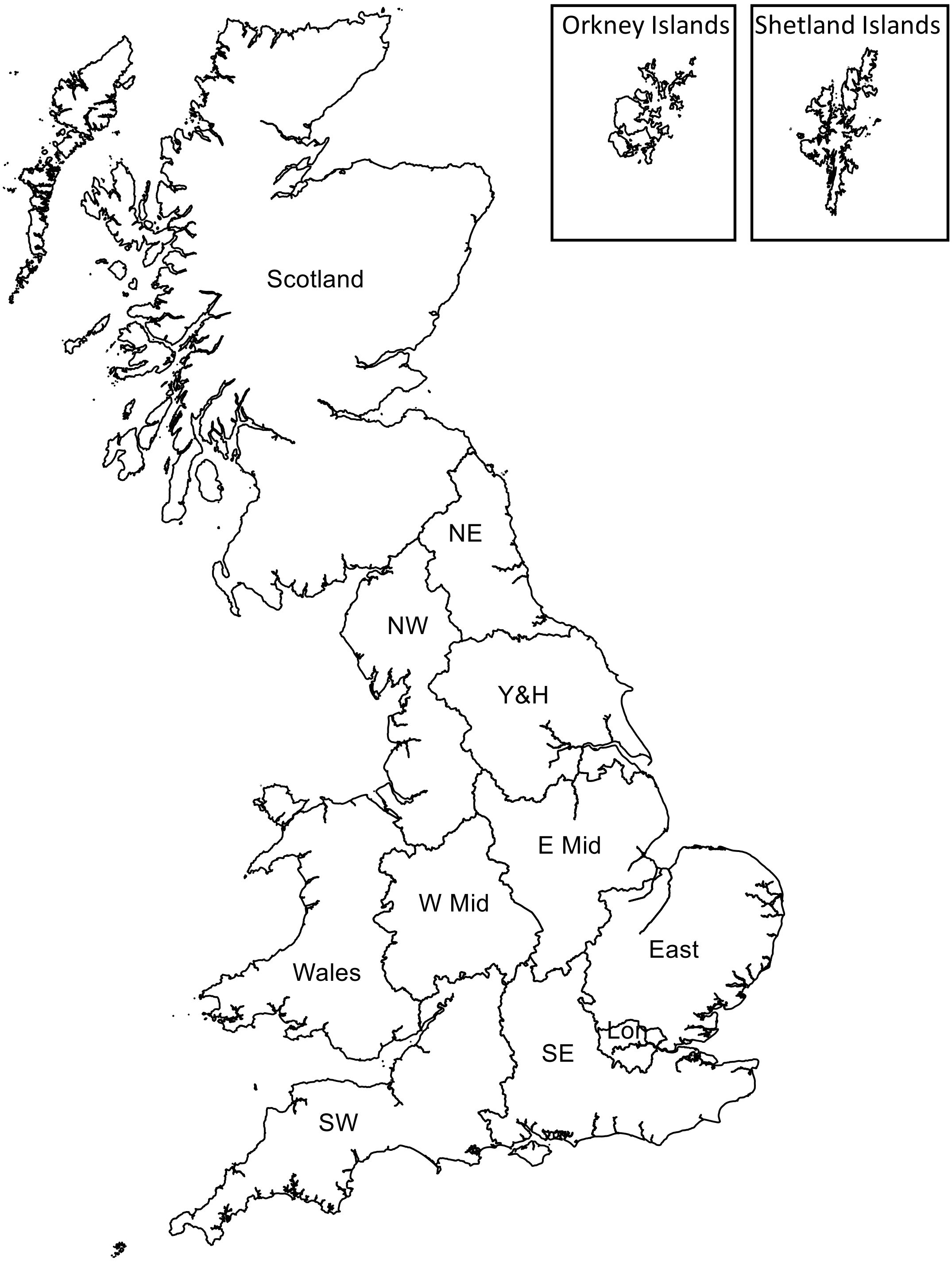

Figure A.2.1: British regions[a]

[a] The 11 regions comprise East of England, East Midlands, London, North East England, North West England, South East England, South West England, West Midlands, Yorkshire and the Humber, Wales and Scotland (incorporating the Orkney and Shetland Islands).

Table A.2.1: Vehicle types and aggregated categories

Stats19 vehicle type	Aggregated vehicle category
-1 NULL or Invalid value	Other/unknown vehicle
1 Pedal cycle	Bicycle
2 Motorcycle 50cc and under	Motorcycle
3 M/cycle over 50 and up to 125cc (from 1999)	Motorcycle
4 Motorcycle over 125cc and up to 500cc (from 2005)	Motorcycle
5 Motorcycle over 500cc (from 2005)	Motorcycle
8 Taxi / Private hire car (from 2005)	Car
9 Car (from 2005)	Car
10 Minibus (8 - 16 passenger seats) (from 1999)	Other/unknown vehicle
11 Bus or coach (17 or more pass seats)	Bus
14 Other motor vehicle	Other/unknown vehicle
15 Other non-motor vehicle	Other/unknown vehicle
16 Ridden horse (from 1999)	Other/unknown vehicle
17 Agricultural vehicle (from 1999)	Other/unknown vehicle
18 Tram (from 1999)	Other/unknown vehicle
19 Van / Goods 3.5 tonnes mgw or under	Goods
20 Goods over 3.5t. and under 7.5t. (from 1999)	Goods
21 Goods 7.5 tonnes mgw and over (from 1999)	Goods
22 Mobility scooter (from 2011)	Motorcycle
23 Electric motorcycle (from 2011)	Motorcycle
90 Other vehicle	Other/unknown vehicle
97 Motorcycle - unknown cc (from 2011)	Motorcycle
98 Goods vehicle - unknown weight (self rep only)	Goods
99 Undefined	Other/unknown vehicle
103 Motorcycle - Scooter (1979-1998)	Motorcycle
104 Motorcycle (1979-1998)	Motorcycle
105 Motorcycle - Combination (1979-1998)	Motorcycle
106 Motorcycle over 125cc (1999-2004)	Motorcycle
108 Taxi (excluding private hire cars) (1979-2004)	Car
109 Car (including private hire cars) (1979-2004)	Car
110 Minibus/Motor caravan (1979-1998)	Other/unknown vehicle
113 Goods over 3.5 tonnes (1979-1998)	Goods

Table A.2.2: Data processing steps

Stats19 data (1985–2015)
Process vehicles primary data
Rename variables for consistency across years where required
Generate binary variables that can be aggregated later to calculate the number of observations in each disaggregated category
Hit-and-run and no-hit-run, missing treated as no-hit-run
Male driver, female driver and unknown sex driver
Age of driver: under 18, 18–24, 25–49, 50–64, 65+, unknown age
Vehicle types as per table A.2.1: bicycle, Motorcycle, car, bus, goods, other vehicle
All generated vehicle variables aggregated to accident level for merging with accident level data later.
Process casualties primary data
Rename variables for consistency across years where required
Generate binary variable that can be aggregated later to calculate the number of fatalities
Fatalities aggregated to accident level for merging with accident level data later.
Process contributory factors primary data
Generate binary variables for alcohol and drugs that can be aggregated later to calculate the number of accidents involving each contributory factor.
Aggregate alcohol and drugs variables to accident level for merging with accident level data later.
Process accidents primary data
Rename variables for consistency across years where required
Generate binary variables that can be aggregated later to calculate the number of observations in each disaggregated category
Road type
Accident severity
Weather conditions
Light conditions - aggregated to day/night
Time and day – aggregated to weekday peak, weekday off-peak and weekend
Merge derived accident, vehicle, casualty and contributory factors data
Calculate number of fatalities involved in accidents involving alcohol
Calculate number of fatalities involved in accidents involving drugs
Generate number of fatalities per accident by accident characteristics
Using vehicle level indicator of hit and run, generate binary indicator for accidents and fatalities that were hit and run and those not hit and run.
Generate number of fatalities in accidents involving a vehicle of each type
Generate binary indicator of whether an accident involved at least one vehicle for each type of vehicle
Aggregation of merged data to Local Authority, month and year level
Keep only variables required for analysis
Consolidate data for analysis
Append merged data for each year

Table A.2.2 *(Continued)*

Regional processing
Map Local Authorities to Counties
Map Counties to GORs
Aggregation of consolidated data to GOR, month and year level
Keep only variables required for analysis
Aggregation of monthly data to quarterly level
Save data file for future merging with economic data
LFS data (1992:2–2017:2)
Process each quarterly data file
Generate year and quarter indicator
Generate labour force status indicator from disaggregate categories
Aggregate regions to GOR level to match Stats19
Save variables for analysis: GOR, sex age labour force status, person weight
Consolidate data for analysis
Append merged data for each quarter
Calculate weighted variables for analysis
Labour force status (employed, unemployed and not in the labour force) for individuals aged 16–64
Population aged 16–64, 16 and over, 18–24, 25–49, 50–64, 65 and over, males, females
Aggregate from individual level to GOR level by year and quarter
Calculate (population weighted) labour force rates
Employment to population rate 16–64, unemployment rate 16–64
Rename variables where required for consistency with Stats19 variables
Keep only variables required for analysis
Merged Stats19 and LFS data
Keep only matched records
Generate additional variables for analysis
Sequence of quarters
For accidents and fatalities, generate adverse weather (other than fine, no winds) and other/unknown weather
For accidents and fatalities, aggregate motorways and A(M) roads
Calculate per capita accident, vehicle and fatality variables
Divide by 100,000 population (aged 16 and over) for each GOR, quarter and year
Calculate vehicle driver age divided by relevant population (18–24, 25–49, 50–64, 65 and over, male, female) for sensitivity testing
Calculate casualty intensity variables for analysis — Fatalities per accident, killed or seriously injured per accident
Generate all analysis variables in logarithms for modelling
Generate regional time trends
Generate series of GOR-quarters for clustering standard errors
Generate lags of regional employment and unemployment rates

Regional employment, accidents and fatalities

Figure A.2.2: shows per capita accidents, per capita fatalities and the local employment to population ratio for each of the 11 regions studied. Although accidents and fatalities show a downward trend, there is evidence of seasonal variation and some short term increases. Effects of the GFC on employment are evident in each region circa 2008. For most regions it appears there is a procyclical relationship with accidents and fatalities around the time of the GFC with accidents and fatalities levelling off or increasing around that time (there appears to be a weaker relationship for Scotland).

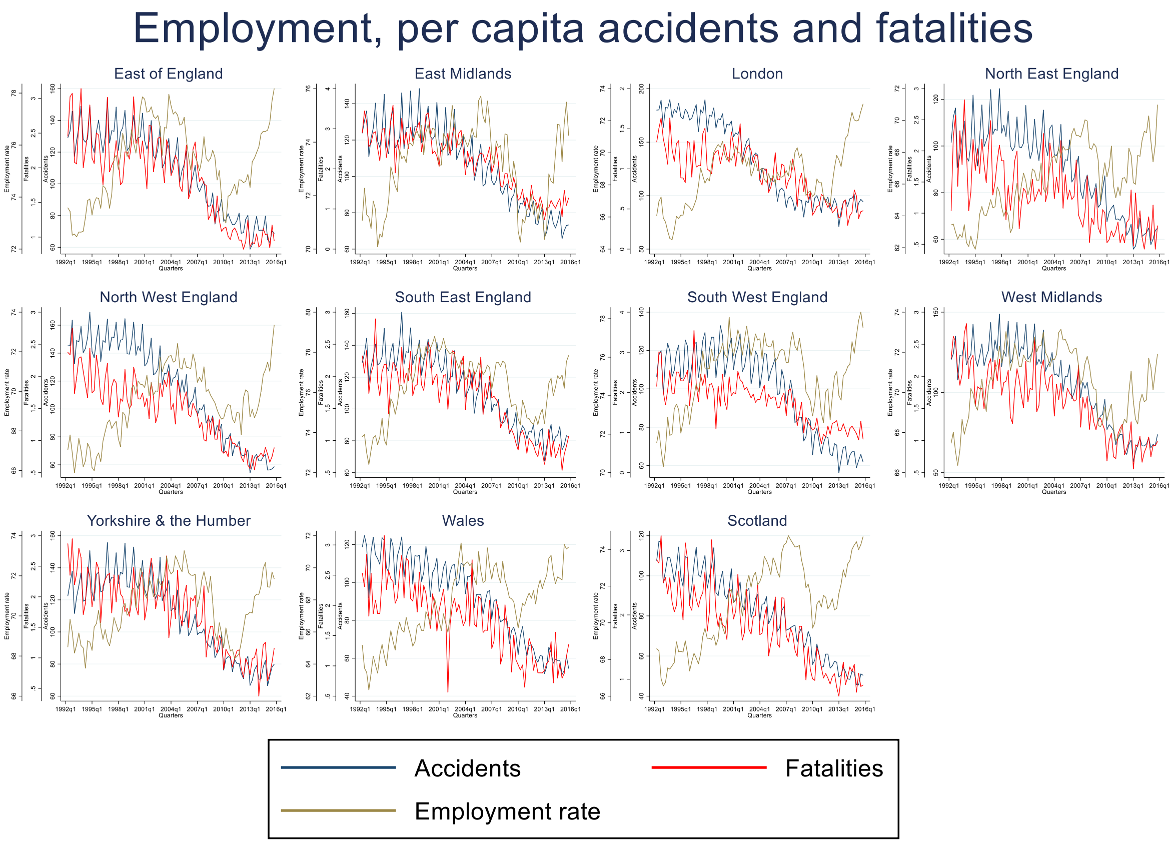

Figure A.2.2: Accidents, fatalities and employment by GOR, 1992–2015[a]

[a] Accidents and fatalities are measured per 100,000 population aged 16 and over. Employment rates are calculated as the number employed divided by the regional working aged population (aged 16–64).

Linear modelling results

Our main results consider linear relationships between employment and accidents, fatalities and driver characteristics. In the chapter we present semi-elasticities for these effects. In Table A.2.3 and Table A.2.4 we include coefficients and standard errors underpinning the results in the chapter.

Table A.2.3: Fixed effects linear modelling results for accidents and fatalities[a]

	Accidents			Fatalities		
		Employment/population			Employment/population	
	Mean	Coefficient	SE	Mean	Coefficient	SE
Total	104.83	2.261***	(0.577)	1.64	0.037***	(0.012)
Severity						
Fatal	1.50	0.040***	(0.010)			
Serious	15.26	0.304***	(0.045)			
Slight	88.07	1.917***	(0.567)			
Vehicle involvement in accident						
Bicycle	10.36	0.175**	(0.075)	0.08	0.0002	(0.002)
Motorcycle	12.04	0.367***	(0.124)	0.29	0.009**	(0.004)
Car	93.30	1.964***	(0.517)	1.33	0.030**	(0.011)
Bus	4.94	0.041	(0.028)	0.07	0.001	(0.002)
Goods	13.35	0.444***	(0.074)	0.38	0.007	(0.005)
Other vehicle	2.61	0.042*	(0.022)	0.06	0.003	(0.002)
Hit-and-run						
Yes	10.24	0.164**	(0.063)	0.06	0.003	(0.002)
No	96.26	2.029***	(0.520)	1.61	0.036***	(0.012)
Road type						
Motorway/A(M)	3.75	0.101***	(0.027)	0.08	0.006**	(0.003)
A	47.33	1.293***	(0.321)	0.95	0.019*	(0.010)
B	13.55	0.223***	(0.074)	0.23	0.002	(0.004)
C	9.31	0.210**	(0.097)	0.13	0.003	(0.003)
Unclassified	30.89	0.433***	(0.144)	0.25	0.007**	(0.003)

Table A.2.3 (*Continued*)

	Accidents			Fatalities		
		Employment/population			Employment/population	
	Mean	Coefficient	SE	Mean	Coefficient	SE
Light conditions, time and day						
Daytime	76.54	1.385***	(0.427)	0.95	0.007	(0.009)
Night	28.27	0.894***	(0.212)	0.69	0.030***	(0.008)
Weekday peak	31.38	0.756***	(0.175)	0.32	0.003	(0.006)
Weekday off peak	47.43	0.981***	(0.282)	0.78	0.019**	(0.008)
Weekend	26.01	0.522***	(0.134)	0.53	0.015**	(0.006)
Contributory factor						
Alcohol	3.19	-0.028	(0.043)	0.10	-0.0002	(0.005)
Drugs	0.36	-0.003	(0.010)	0.03	0.002	(0.002)
Weather						
Fine no wind	82.40	1.829***	(0.442)	1.34	0.031***	(0.010)
Adverse weather	18.85	0.218**	(0.107)	0.26	0.003	(0.004)
Other/unknown weather	3.58	0.213***	(0.074)	0.04	0.002	(0.001)

[a]Sample runs from 1992–2015, except for hit-and-run (1992–2014) and contributory factors (2005–2015). Dependent variables are measured in levels per 100,000 population (for each GOR and quarter) and the overall mean (across GORs and time) is shown. Robust standard errors, clustered at the GOR-quarter level, are shown in parentheses. Each cell represents a separate regression. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.2.4: Fixed effects linear modelling results for vehicles[a]

		Employment/population	
	Mean	Coefficient	SE
All drivers	191.13	4.025***	(0.998)
Driver sex			
Male	128.72	2.530***	(0.634)
Female	52.16	0.933***	(0.303)
Unknown	10.25	0.562***	(0.096)
Driver age			
Under 18	7.43	0.084	(0.066)
18–24	33.07	0.732***	(0.232)
25–49	95.87	1.793***	(0.604)
50–64	26.57	0.748***	(0.146)
65 or over	10.36	0.120***	(0.033)
Unknown	17.83	0.548***	(0.151)

[a]Sample runs from 1992–2015. Dependent variables are measured in levels per 100,000 population (for each GOR and quarter) and the overall mean (across GORs and time) is shown. Robust standard errors, clustered at the GOR-quarter level, are shown in parentheses. Each cell represents a separate regression. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Additional robustness results

Here we provide coefficients and standard errors associated with the semi-elasticities presented in the chapter.

Table A.2.5: Estimates for economic activity using different model specifications for overall accidents[a]

Dependent variable specification	Measure of economic activity	Sample	Coefficient	SE
Level	$Employment_t$	Full	2.261***	(0.577)
Ln	$Employment_t$	Full	0.019***	(0.005)
Level	$Employment_{t-1}$	Full	2.161***	(0.631)
Level	$Unemployment_t$	Full	-2.548***	(0.396)
Level	$Employment_t$	Pre-GFC	1.551***	(0.361)
Level	$Employment_t$	Post-GFC	-0.290	(0.234)

[a]Sample runs from 1992–2015, except for pre-GFC (1992-2008q3) and post-GFC (2008q4-2015) sub periods. Dependent variables based on per capita measurements (per 100,000 population for each GOR and quarter). Robust standard errors are shown in parentheses and were clustered at the GOR-quarter level. Each cell represents a separate regression. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

References

Alonso, F., Esteban, C., Montoro, L., & Tortosa, F. (2014). Psychotropic drugs and driving: prevalence and types. *Annals of General Psychiatry, 13*(1), 14. doi:10.1186/1744-859X-13-14

Amoros, E., Martin, J. L., & Laumon, B. (2003). Comparison of road crashes incidence and severity between some French counties. *Accident Analysis & Prevention, 35*(4), 537-547. doi:https://doi.org/10.1016/S0001-4575(02)00031-3

Anderson, T. K. (2010). Using geodemographics to measure and explain social and environment differences in road traffic accident risk. *Environment and Planning A, 42*(9), 2186-2200. doi:10.1068/a43157

Ariizumi, H., & Schirle, T. (2012). Are recessions really good for your health? Evidence from Canada. *Social Science & Medicine, 74*(8), 1224-1231. doi:https://doi.org/10.1016/j.socscimed.2011.12.038

Bazargan-Hejazi, S., Teruya, S., Pan, D., Lin, J., Gordon, D., Krochalk, P. C., & Bazargan, M. (2017). The theory of planned behavior (TPB) and texting while driving behavior in college students. *Traffic Injury Prevention, 18*(1), 56-62. doi:10.1080/15389588.2016.1172703

Behnood, A., & Mannering, F. L. (2015). The temporal stability of factors affecting driver-injury severities in single-vehicle crashes: some empirical evidence. *Analytic Methods in Accident Research, 8*, 7-32. doi:https://doi.org/10.1016/j.amar.2015.08.001

Beland, L.-P., & Brent, D. A. (2018). Traffic and crime. *Journal of Public Economics, 160*, 96-116. doi:https://doi.org/10.1016/j.jpubeco.2018.03.002

Bellinger, D. B., Budde, B. M., Machida, M., Richardson, G. B., & Berg, W. P. (2009). The effect of cellular telephone conversation and music listening on response time in braking. *Transportation Research Part F: Traffic Psychology and Behaviour, 12*(6), 441-451. doi:https://doi.org/10.1016/j.trf.2009.08.007

Bone, S. A., & Mowen, J. C. (2006). Identifying the traits of aggressive and distracted drivers: a hierarchical trait model approach. *Journal of Consumer Behaviour, 5*(5), 454-464. doi:https://doi.org/10.1002/cb.193

Buchmueller, T., Grignon, M., & Jusot, F. (2006). *Unemployment and mortality in France, 1982-2002* Center for Health Economics and Policy Analysis Working Paper 07-04. McMaster University.

Cameron, A. C., & Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources, 50*(2), 317-372.

Cassar, A., Healy, A., & von Kessler, C. (2017). Trust, risk, and time preferences after a natural disaster: experimental evidence from Thailand. *World Development, 94*, 90-105. doi:https://doi.org/10.1016/j.worlddev.2016.12.042

Charles, K. K., & DeCicca, P. (2008). Local labor market fluctuations and health: is there a connection and for whom? *Journal of Health Economics, 27*(6), 1532-1550. doi:https://doi.org/10.1016/j.jhealeco.2008.06.004

Chen, G. (2014). Association between economic fluctuations and road mortality in OECD countries. *European Journal of Public Health, 24*(4), 612-614. doi:10.1093/eurpub/cku014

Cotti, C., & Tefft, N. (2011). Decomposing the relationship between macroeconomic conditions and fatal car crashes during the great recession: alcohol- and non-alcohol-related accidents. In *The B.E. Journal of Economic Analysis & Policy* (Vol. 11).

Coulter, S. (2016). Chapter 6: The UK labour market and the 'great recession'. In M. Myant, S. Theodoropoulou, & A. Piasna (Eds.), *Unemployment, Internal Devaluation and Labour*

Market Deregulation in Europe (pp. 197-227). Brussels: European Trade Union Institute.
Edwards, R. (2008). Who is hurt by procyclical mortality? *Social Science & Medicine, 67*(12), 2051-2058. doi:http://dx.doi.org/10.1016/j.socscimed.2008.09.032
Evans, W., & Graham, J. D. (1988). Traffic safety and the business cycle. *Alcohol, Drugs, and Driving, 4*(1), 31-38.
Evans, W. N., & Moore, T. J. (2012). Liquidity, economic activity, and mortality. *Review of Economics & Statistics, 94*(2), 400-418.
French, M. T., & Gumus, G. (2014). Macroeconomic fluctuations and motorcycle fatalities in the U.S. *Social Science & Medicine, 104*, 187-193. doi:http://dx.doi.org/10.1016/j.socscimed.2013.12.019
French, M. T., & Gumus, G. (2015). *Hit-and-run or hit-and-stay: do stricter BAC limits encourage drivers to flee the crash scene?* . Fall Conference of the Association for Public Policy Analysis and Management. Miami, FL. Retrieved from https://www.bc.edu/content/dam/files/schools/cas_sites/economics/pdf/Seminars/SemF2015/Hit-and-run%20manuscript,%2027%20July%202015.pdf
Fridstrøm, L., Ifver, J., Ingebrigtsen, S., Kulmala, R., & Thomsen, L. K. (1995). Measuring the contribution of randomness, exposure, weather, and daylight to the variation in road accident counts. *Accident Analysis & Prevention, 27*(1), 1-20. doi:https://doi.org/10.1016/0001-4575(94)E0023-E
Fuchs, J., & Weber, E. (2013). A new look at the discouragement and the added worker hypotheses: applying a trend–cycle decomposition to unemployment. *Applied Economics Letters, 20*(15), 1374-1378. doi:10.1080/13504851.2013.812777
García-ferrer, A., Bujosa, M., de Juan, A., & Sánchez-Mangas, R. (2019). *The relationship between traffic accidents and real economic activity revisited: old targets and new policy implications*. Unpublished manuscript. Universidad Autónoma de Madrid. Madrid, Spain.
García-ferrer, A., de Juan, A., & Poncela, P. (2007). The relationship between road traffic accidents and real economic activity in Spain: common cycles and health issues. *Health Economics, 16*(6), 603-626. doi:10.1002/hec.1186
Gerdtham, U.-G., & Johannesson, M. (2005). Business cycles and mortality: results from Swedish microdata. *Social Science & Medicine, 60*(1), 205-218. doi:https://doi.org/10.1016/j.socscimed.2004.05.004
Gerdtham, U.-G., & Ruhm, C. J. (2006). Deaths rise in good economic times: evidence from the OECD. *Economics & Human Biology, 4*(3), 298-316. doi:http://dx.doi.org/10.1016/j.ehb.2006.04.001
Gonzalez, F., & Quast, T. (2011). Macroeconomic changes and mortality in Mexico. *Empirical Economics, 40*(2), 305-319. doi:10.1007/s00181-010-0360-0
Green, C. P., Heywood, J. S., & Navarro, M. (2014). Did liberalising bar hours decrease traffic accidents? *Journal of Health Economics, 35*, 189-198. doi:http://dx.doi.org/10.1016/j.jhealeco.2014.03.007
Haaland, V. F., & Telle, K. (2015). Pro-cyclical mortality across socioeconomic groups and health status. *Journal of Health Economics, 39*, 248-258. doi:http://dx.doi.org/10.1016/j.jhealeco.2014.08.005
Hanaoka, C., Shigeoka, H., & Watanabe, Y. (2015). *Do risk preferences change? Evidence from panel data before and after the great east Japan earthquake*. NBER Working Paper Series. NBER. Cambridge. Retrieved from http://www.nber.org/papers/w21400
Hanewald, K. (2011). Explaining mortality dynamics. *North American Actuarial Journal, 15*(2), 290-314. doi:10.1080/10920277.2011.10597622

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. doi:https://doi.org/10.1016/j.socscimed.2016.02.016

Hollingsworth, A., Ruhm, C. J., & Simon, K. (2017). Macroeconomic conditions and opioid abuse. *Journal of Health Economics, 56*(Supplement C), 222-233. doi:https://doi.org/10.1016/j.jhealeco.2017.07.009

Jofre-Bonet, M., Serra-Sastre, V., & Vandoros, S. (2018). The impact of the great recession on health-related risk factors, behaviour and outcomes in England. *Social Science & Medicine, 197*, 213-225. doi:https://doi.org/10.1016/j.socscimed.2017.12.010

Lam, J.-P., & Piérard, E. (2017). The time-varying relationship between mortality and business cycles in the USA. *Health Economics, 26*(2), 164-183. doi:10.1002/hec.3285

Lin, S.-J. (2009). Economic fluctuations and health outcome: a panel analysis of Asia-Pacific countries. *Applied Economics, 41*(4), 519-530. doi:10.1080/00036840701720754

Lindo, J. M. (2013). *Aggregation and the estimated effects of local economic conditions on health*. NBER Working Paper 19042. NBER. Cambridge.

Maheshri, V., & Winston, C. (2016). Did the great recession keep bad drivers off the road? *Journal of Risk and Uncertainty, 52*. doi:10.1007/s11166-016-9239-6

Mais, D., Lloyd, D., & Davies, J. (2016). Modelling weather effects on road casualty statistics. *Significance, February*, 28-31. Accessed

Massie, D. L., Campbell, K. L., & Williams, A. F. (1995). Traffic accident involvement rates by driver age and gender. *Accident Analysis & Prevention, 27*(1), 73-87. doi:https://doi.org/10.1016/0001-4575(94)00050-V

Miller, D. L., Page, M. E., Stevens, A. H., & Filipski, M. (2009). Why are recessions good for your health? *The American Economic Review, 99*(2), 122-127.

Muazzam, S., & Nasrullah, M. (2011). Macro determinants of cause-specific injury mortality in the OECD countries: an exploration of the importance of GDP and unemployment. *Journal of Community Health, 36*(4), 574-582. doi:10.1007/s10900-010-9343-5

Neumayer, E. (2004). Recessions lower (some) mortality rates: evidence from Germany. *Social Science & Medicine, 58*(6), 1037-1047. doi:http://dx.doi.org/10.1016/S0277-9536(03)00276-4

Noland, R. B. (2003). Traffic fatalities and injuries: the effect of changes in infrastructure and other trends. *Accident Analysis & Prevention, 35*(4), 599-611. doi:https://doi.org/10.1016/S0001-4575(02)00040-4

OECD/ITF. (2015). *Why does road safety improve when economic times are hard?* Research Report. OECD/ITF. Paris.

Partyka, S. C. (1984). Simple models of fatality trends using employment and population data. *Accident Analysis & Prevention, 16*(3), 211-222. doi:http://dx.doi.org/10.1016/0001-4575(84)90015-0

Partyka, S. C. (1991). Simple models of fatality trends revisited seven years later. *Accident Analysis & Prevention, 23*(5), 423-430. doi:http://dx.doi.org/10.1016/0001-4575(91)90061-9

Reinfurt, D. W., Stewart, J. R., & Weaver, N. L. (1991). The economy as a factor in motor vehicle fatalities, suicides, and homicides. *Accident Analysis & Prevention, 23*(5), 453-462. doi:http://dx.doi.org/10.1016/0001-4575(91)90065-D

Reinhart, C. M., & Rogoff, K. S. (2009). The aftermath of financial crises. *American Economic Review, 99*(2), 466-472.

Ruhm, C. J. (1995). Economic conditions and alcohol problems. *Journal of Health Economics, 14*(5), 583-603. doi:https://doi.org/10.1016/0167-6296(95)00024-0

Ruhm, C. J. (2000). Are recessions good for your health? *The Quarterly Journal of Economics, 115*(2), 617-650. doi:10.1162/003355300554872

Ruhm, C. J. (2003). Good times make you sick. *Journal of Health Economics, 22*(4), 637-658. doi:http://dx.doi.org/10.1016/S0167-6296(03)00041-9

Ruhm, C. J. (2006). Macroeconomic conditions, health and mortality. In A. M. Jones (Ed.), *The Elgar Companion to Health Economics* (pp. 5-16). Gloucestershire: Edward Elgar.

Ruhm, C. J. (2015). Recessions, healthy no more? *Journal of Health Economics, 42*, 17-28. doi:http://dx.doi.org/10.1016/j.jhealeco.2015.03.004

Ruhm, C. J. (2016). Health effects of economic crises. *Health Economics, 25*(S2), 6-24. doi:10.1002/hec.3373

Scott, P. P. (1986). Modelling time-series of British road accident data. *Accident Analysis & Prevention, 18*(2), 109-117. doi:http://dx.doi.org/10.1016/0001-4575(86)90055-2

Scuffham, P. A. (2003). Economic factors and traffic crashes in New Zealand. *Applied Economics, 35*(2), 179-188. doi:10.1080/0003684022000017566

Steinbach, R., Edwards, P., & Grundy, C. (2013). The road most travelled: the geographic distribution of road traffic injuries in England. *International Journal of Health Geographics, 12*(1), 30. doi:10.1186/1476-072X-12-30

Stevens, A. H., Miller, D. L., Page, M. E., & Filipski, M. (2015). The best of times, the worst of times: understanding pro-cyclical mortality. *American Economic Journal: Economic Policy, 7*(4), 279-311. doi:10.1257/pol.20130057

Stuckler, D., Basu, S., Suhrcke, M., Coutts, A., & McKee, M. (2009). The public health effect of economic crises and alternative policy responses in Europe: an empirical analysis. *The Lancet, 374*(9686), 315-323. doi:https://doi.org/10.1016/S0140-6736(09)61124-7

Tapia Granados, J. A. (2005a). Increasing mortality during the expansions of the US economy, 1900–1996. *International Journal of Epidemiology, 34*(6), 1194-1202. doi:10.1093/ije/dyi141

Tapia Granados, J. A. (2005b). Recessions and mortality in Spain, 1980-1997. *European Journal of Population, 21*(4), 393-422.

Tapia Granados, J. A. (2008). Macroeconomic fluctuations and mortality in postwar Japan. *Demography, 45*(2), 323-343.

Traynor, T. L. (2008). Regional economic conditions and crash fatality rates – a cross-county analysis. *Journal of Safety Research, 39*(1), 33-39. doi:http://dx.doi.org/10.1016/j.jsr.2007.10.008

UK Department for Transport. (2013). *Reported road casualties in Great Britain: guide to the statistics and data sources*. Department for Transport. London.

UK Department for Transport. (2014). *Reported road casualties in Great Britain: 2013 annual report*. Department for Transport. London.

UK Department for Transport. (2016). *Reported road casualties Great Britain 2015: annual report*. Department for Transport. London.

UK Department of the Environment, Transport and the Regions. (2001). *Road accident data - GB - variables and values and export record layouts*. Department of the Environment, Transport and the Regions. London.

UK Office of National Statistics. (2016). *Labour Force Survey user guide volume 1 - LFS background and methodology 2016*. Office of National Statistics. London.

UK Office of National Statistics. (n.d.). *Reported road casualties - data accessibility project - final report*. Office of National Statistics. London.

Vandoros, S., Avendano, M., & Kawachi, I. (2018). The short-term impact of economic uncertainty on motor vehicle collisions. *Preventive Medicine, 111*, 87-93. doi:https://doi.org/10.1016/j.ypmed.2018.02.005

Wagenaar, A. C. (1984). Effects of macroeconomic conditions on the incidence of motor vehicle accidents. *Accident Analysis & Prevention, 16*(3), 191-205. doi:http://dx.doi.org/10.1016/0001-4575(84)90013-7

Wegman, F., Allsop, R., Antoniou, C., Bergel-Hayat, R., Elvik, R., Lassarre, S., . . . Wijnen, W. (2017). How did the economic recession (2008–2010) influence traffic fatalities in OECD-countries? *Accident Analysis & Prevention*, *102*(Supplement C), 51-59. doi:https://doi.org/10.1016/j.aap.2017.01.022

Chapter 3 The economy and road accident severity in Britain

3.1 Introduction

The link between economic activity and health is well established, as evidenced by a substantial literature (see, for example, Gerdtham & Ruhm, 2006; Hollingsworth, Ruhm, & Simon, 2017; Miller, Page, Stevens, & Filipski, 2009; Neumayer, 2004; Ruhm, 2000, 2015, 2019). However, the evidence is mixed, with some studies finding the relationship is procyclical and others countercyclical across a range of health conditions and for mortality from specific causes. However, one finding for which there is more consensus is the procyclical relationship between the economy and road accidents, with accidents and fatalities rising when the economy expands. One of the main explanations is that this is simply because there is more traffic on the road (cars, vans, lorries, taxis, etc.) (French & Gumus, 2014; OECD/ITF, 2015; UK Department for Transport, 2016; Wagenaar, 1984). Our own study of this relationship in chapter 2 showed a similar procyclical relationship for regions across Britain, with a 1 percentage point increase in employment resulting in a 2% increase in accidents and fatalities.

However, changes in the local economy could have affected numbers of accidents and fatalities without any change in individual driver behaviour — it could have been caused purely by a change in the number of vehicles and therefore drivers. Although having more vehicles on the roads increases the likelihood of accidents, at certain times and under certain conditions an increase in congestion may occur. This would limit speeds and reduce accident severity. As the focus of our previous analysis tended to be on physical characteristics of accidents, such as road types and weather, it is not clear from that analysis whether behaviour has a role to play.

Few studies have examined if the severity of specific road accidents is also procyclical, and if there is a heterogeneous relationship across accident characteristics and driver/vehicle characteristics. A priori we can think of hypotheses as to why the relationship might be procyclical or countercyclical. For example, economic expansions increase the value of time and could lead individuals to speed and increase accident severity. However, during peak times and at weekends there could be congestion on the roads that would reduce driving speeds and therefore severity. So, the actual relationship is an empirical question.

Using unique individual driver-level data on some 8.6 million accidents and a novel empirical approach that relates to the business cycle/health literature, this chapter more broadly asks whether there is a link between the economy and accident severity and if that relationship is due to traffic volumes and congestion and/or whether a change in driving behaviour is part of the explanation. If there are behavioural underpinnings, we ask what are the characteristics of individuals who change their behaviour, how do they change their behaviour and what are their accident severity outcomes?

It is found in the literature that (health) behavioural responses vary according to gender, life stage and socioeconomic status (SES) (Cawley & Ruhm, 2011). Our empirical strategy allows us to analyse the effects of changes in economic activity on accident outcomes for particular subgroups to identify the likely behavioural mechanisms at work. For example, we consider slight accidents which are likely due to road conditions versus more severe accidents which are likely due to factors such as speeding, alcohol and drugs.

This is one of a handful of studies of the relationship between accident severity and economic activity (see, for example, Gerdtham & Johannesson, 2005; Noland, 2003) and is the first known direct study of individual accident severity and the economy for Britain. Uniquely, we use car types as a proxy for driver behaviour and SES, as some types of cars appeal to drivers with distinct behaviours (more or less risky) and premium and luxury cars are considerably more expensive to purchase. With such high costs (particularly to individuals and the health care system) associated with the more severe accidents, it is important to understand how economic activity affects individual accident severity. Understanding who is affected, and how, is required in order that governments can design targeted policies that reduce harm and save lives. This chapter complements the macroeconomic literature relating accidents to the economic cycle and provides essential information for policy makers in order to mitigate the impacts of the cycle on health. It therefore provides a foundation for evidence-based policy responses to improve the health of the nation and lessen the economic and emotional burden of accidents.

3.2 Background and literature review

According to the World Health Organization, more than 1.2 million people die and up to 50 million people are injured in road accidents each year and such accidents result in global losses in the order of 3% of GDP (World Health Organization, 2015). In fact, in 2012 road accidents were the 10th leading cause of death globally, and have subsequently moved into 8th position in 2016 (World Health Organization, 2018). In Britain, the rate of accidents was declining but has levelled off since 2010 (World Health Organization, 2018). Since at least 2000, the decline in fatalities has outstripped the decline in less serious casualties (Lloyd, Wallbank, & Broughton, 2015), resulting in a decline in accident severity. With established links between numbers of accidents and economic performance, there may well be a further link in terms of accident severity, providing a way to target reducing severity and consequently reducing accident costs to society and individuals.

Many studies explore the link between numbers of road accidents and economic performance but very few consider accident severity. Investigating the relationship between business cycles and individual mortality for Sweden from 1981 to 1996, Gerdtham and Johannesson (2005) found the probability of death from other external causes (including road accidents) reduced as unemployment increased, suggesting severity may be procyclical (that is, severity increases as the economy expands; although small sample sizes indicated limited testing power and the results were not statistically significant). Noland (2003) found a larger effect of changes in per capita income on fatalities than injuries in the US, indicating severity is likely to increase as the economy adjusts.

There are two potential mechanisms linking economic activity and accident outcomes, namely traffic volumes/congestion and driver behaviour (He, 2016).[1] In recessions, traffic volumes (hence congestion) decline as fewer individuals commute or make leisure trips and road freight is reduced (He, 2016; Vogiatzis & Kopelias, 2015). The accident rate usually depends on traffic volume (Wegman et al., 2017; Yannis, Theofilatos, Ziakopoulos, & Chaziris, 2014) as road congestion can change accident risk (A. H. Stevens, Miller, Page, & Filipski, 2015) through lowering vehicle travelling speeds (Fridstrøm, Ifver, Ingebrigtsen, Kulmala, & Thomsen, 1995; Fridstrøm & Ingebrigtsen, 1991). Therefore, we might expect average severity of accidents to decrease with increases in traffic volume.

Beyond traffic volumes and congestion, driver behaviour may also link economic activity and accident severity. Using logit models with survey data for the US, Norris, Matthews, and Riad

[1] There could also be a change in composition of drivers/vehicles, however without data on all drivers we cannot identify such selection effects using accidents and it is not clear what the effects might be.

(2000) found significantly lower severity if individuals were employed or economically secure and they argue that this might indicate fatigue, distraction or irritability associated with stress.

It seems logical that accident severity may respond to the economic cycle through changes in drivers' risky behaviour as the economy adjusts. Traditionally, analysis of risky decision making has relied on expected utility theory, in which individuals compare benefits and costs associated with a risky activity. If the benefits exceed the costs, the individual will engage in the risky behaviour (Gruber, 2001). In terms of road safety, 'drivers and road users in general will change their behaviour if they see an economic benefit (for example through speed choice) or perhaps also if they can understand the risks involved' (Lloyd, Reeves, Broughton, & Scoons, 2013, p. 72).

Risk preferences reflect the curvature of the utility function and affect perceived benefits and costs. Evidence indicates risk preferences vary between individuals: females, older people and individuals on lower incomes are more risk averse (Cahlíková & Cingl, 2017; Dohmen et al., 2011; Hartog, Ferrer-i-Carbonell, & Jonker, 2002; Sahm, 2012). In particular, Dohmen, Falk, Golsteyn, Huffman, and Sunde (2017) find females are more risk averse and that for both sexes risk aversion increases until about age 65 and then levels off. Schurer (2015) documents that risk tolerance (in effect, the opposite of risk aversion) declines for all socioeconomic groups up to age 45, but then risk tolerance stabilises or increases for high SES individuals but keeps declining for low SES individuals.

'Individual risk preferences appear to be persistent and moderately stable over time, but their degree of stability is too low to be reconciled with the assumption of perfect stability in neoclassical economic theory' (Schildberg-Hörisch, 2018, p. 148). Experimental evidence shows stress increases risk aversion in men and women (although the result for women is not statistically significant) (Cahlíková & Cingl, 2017). Individuals become more risk averse in response to a natural disaster (Cassar, Healy, & von Kessler, 2017; Said, Afzal, & Turner, 2015)[2], major financial crisis (Guiso, Sapienza, & Zingales, 2018) and war (Y.-I. Kim & Lee, 2014).

[2] Although Hanaoka, Shigeoka, and Watanabe (2015) find increasing preference for risk after the Great East Japan Earthquake, and there is evidence of risk seeking after floods (Page, Savage, & Torgler, 2014).

Risk preferences also vary with economic conditions: economic downturns are associated with increased risk aversion (Bucciol & Miniaci, 2018; Dohmen et al., 2017; Sahm, 2007, 2012; Schildberg-Hörisch, 2018). For large negative economic shocks such as the Global Financial Crisis (GFC), the evidence shows an increase in risk aversion (Schildberg-Hörisch, 2018). Risk preferences are likely to affect risky driving behaviour and driver behaviour is more important than 'vehicle, environmental or geometric factors.' (Cardamone, Eboli, Forciniti, & Mazzulla, 2017, p. 13) in explaining the number of accidents. Driving behaviours are many and varied and can also influence accident severity. Behaviours may be affected by driving experience, socioeconomic characteristics and a driver's psychological state (Cardamone et al., 2017). This suggests recessions may be linked to reduced accident severity.

Driving style (or behaviours) embodies the way people choose to drive and their driving habits they have built up over time (Elander, West, & French, 1993). Key aspects of style include driving speed, overtaking behaviour, distance (tailgating) and decisions affecting traffic violations including drink/drug driving and use of a hand-held mobile phone (Cardamone et al., 2017).[3] These behaviours are likely to be affected by attitudes, beliefs, needs and values (Elander et al., 1993). For example, drivers may have different attitudes to driving and potential accident involvement, and/or different beliefs about what constitutes good/bad driving and where their own level of skill places them on this scale (Elander et al., 1993).

Studies in road safety have shown that fatalities tend to decline during economic recessions and recent work has attributed this to 'fundamental shifts in driver exposure with more crash-prone drivers driving less and safer drivers driving more' (Behnood & Mannering, 2016, p. 14) (see also Bertoli, Grembi, and Vall Castellò (2018)). According to OECD/ITF (2015), 'economic recessions may be associated with more cautious road user behaviour, such as less drinking and driving, lower speed, fewer holiday trips on unfamiliar roads, etc' (p. 127) when drivers are uncertain about their financial prospects, and this would reduce extreme behaviours and lead to reduced accident severity. Lloyd et al. (2015) investigated road fatalities in Britain during the recession from 2007 to 2010 and found a faster decline in fatalities than injuries, which suggests a reduction in accident severity had occurred.

[3] Many types of traffic violation have been shown to correlate with accident severity (Ayuso, Guillén, & Alcañiz, 2010).

As the economy expands, we might expect to see increased severity due to behaviours stemming from time pressures, fatigue and income effects. ‘Reduced income and work hours may lead to changes in actual driving behaviour such as slower, less reckless driving if drivers are less willing to pay for speeding tickets or have a lower opportunity cost of time’ (Cotti & Tefft, 2011, p. 5). However, if vehicle maintenance behaviour is procyclical (reducing with economic contractions as people have less income), we might expect accidents to be more severe in recessions. If individuals upgrade vehicles to newer, safer models when the economy is performing well, there may be risk compensatory behaviour such as attempting to speed, which is also consistent with an increased value of time when hours worked are likely to be increasing. The effects on accident severity are then likely to be determined by accident outcomes of other road users (as effects on drivers are minimal).

In summary, the available literature shows no consensus on the relationship between economic conditions and accident severity. It appears there may be several factors at play — potentially working in opposite directions — and what the overall effect is will be an empirical question and may even change over time. To better understand these influences, we now consider accident characteristics (which might help explain the role of traffic volumes and congestion on accident severity) and driver characteristics (which are associated with certain behaviours linked to severity).

3.2.1 Accident characteristics associated with accident severity

It seems that traffic volumes respond positively to the economic cycle and many studies show increases in traffic volume reduce speed and accident severity (Christoforou, Cohen, & Karlaftis, 2010; Martin, 2002; Quddus, Wang, & Ison, 2010; Xu, Tarko, Wang, & Liu, 2013; Yannis et al., 2014; Zeng et al., 2019). Although, some argue the effect of congestion on accident severity is not clear (Theofilatos & Yannis, 2014). It could be that the effects of traffic volumes might vary by road type: for example, severity tends to be worse on rural roads (Amoros, Martin, & Laumon, 2003) and these roads are likely to carry lower traffic volumes. Alternatively, the effects in these studies could be capturing something else. For example, congestion had an increasing or no effect on accident severity for the M25 London orbital motorway (Quddus et al., 2010; Wang, Quddus, & Ison, 2013). However, Wang et al. (2013) argue this might be due to worse driving behaviour associated with congestion. According to Noland and Quddus (2005), congestion may have little effect on severity in urban settings. During economic expansions, there will be more freight activity bringing more heavy goods vehicles (HGVs) and motorcycles onto the roads. While congestion would limit speeds and reduce accident severity, the change in vehicle mix on the roads favouring HGVs and motorcycles would lead to higher impact accidents (through both vehicle mass and rider vulnerability) and increase severity. These different mechanisms imply the relationship is an empirical issue and it is not clear what we expect to find. Indeed, the overall result will be the net effect of potentially countervailing forces.

Under certain conditions there could be more congestion associated with economic growth that reduces traffic speeds. For example, traffic volumes are higher during the day (particularly during peak hours) and additional traffic could actually reduce speeds, whereas traffic levels are lower at night and increases in volume may not be sufficient to induce congestion-related speed reductions. Indeed, severity levels are also higher at night due to lower traffic volumes (Martin, 2002). Congestion may also be important for motorways rather than urban roads (Noland & Quddus, 2005), leading to reduced severity on motorways but not minor B roads. One study indicates accident severity does not differ between weekdays and weekends (Martin, 2002) although this result only applied to motorways and did not take into account potential differences between peak and off-peak times of the day. Comparing peak and off peak times, Shefer and Rietveld (1997) found reduced fatality rates in morning peak hours on highways.

Although not directly analysing severity, the study by He (2016) indicates fatalities for accidents involving HGVs (large trucks) decline with unemployment (whereas there was no significant effect when HGVs were not involved). This would be consistent with a lower volume of HGV traffic during recessions affecting the mix of vehicles on the roads.

To the extent that motorcycling involves small goods deliveries, we may expect average accident severity to increase with economic activity due to the vulnerability of these riders. Moreover, as motorcycling is largely a recreational activity, we would expect fewer motorcycle accidents during economic contractions (French & Gumus, 2014) and this would reduce average severity.

3.2.2 Driver and vehicle characteristics and behaviour

Accident severity also depends on behaviours that can be associated with driver age, sex and income (Cardamone et al., 2017) and these behaviours can vary across the economic cycle. We now outline the main behaviours across these groups, noting there may be some offsetting effects of different behaviours.

3.2.2.1 Driver sex

Evidence from a variety of countries indicates sensation seeking is associated with risky driving behaviours (such as drink driving and speeding) and accidents, and is higher in men than women (Jonah, 1997). Males, in particular, are more likely to underestimate dangers and overestimate their driving skills (Roidl, Siebert, Oehl, & Höger, 2013) and are therefore more likely to speed, drive under the influence of alcohol and drive in a generally more risky manner (Massie, Campbell, & Williams, 1995). There is some evidence that, although females may have higher trait driving anger (Albentosa, Stephens, & Sullman, 2018), male drivers are more likely to suffer from physical aggressive expression and total aggressive expression (Deffenbacher, Lynch, Oetting, & Swaim, 2002) and this would be consistent with 'road rage'. Indeed, Asbridge, Smart, and Mann (2003) found road rage offending was more likely to be associated with males than females. Females are also more likely to adopt anxious or careful driving styles (Taubman-Ben-Ari & Yehiel, 2012), although these effects could be offset as females can be more likely to get distracted (Massie et al., 1995).

While both sexes use drugs and drive, males are more likely to have used cannabinols and females depressants, narcotics and other drugs (Romano & Pollini, 2013), potentially affecting accidents in different ways.

3.2.2.2 Driver age

Young people are more likely to drive in a reckless or angry manner (Sullman, 2015; Taubman-Ben-Ari & Yehiel, 2012). Indeed, risk compensation, speeding, alcohol, drugs, distraction, anger/aggression and fatigue are common elements mostly associated with young, male drivers (Massie et al., 1995). A study of young drivers in New South Wales showed such risky driving behaviours tend to be associated with lower perceived accident risks but higher actual accident risk (Ivers et al., 2009).

Younger drivers have higher rates of drink driving (Jonah, 1997) and have higher levels of impairment than older drivers with the same blood alcohol reading (Vaez & Laflamme, 2005). Younger drivers also have less experience and tend to be involved in accidents in which driver error is at fault. They also take more risks than older drivers (Dee & Evans, 2001; J.-K. Kim, Ulfarsson, Kim, & Shankar, 2013) and can also be subject to distractions stemming from, for example, social factors (Hurts, Angell, & Perez, 2011). In fact, 'loud music can act as a distraction, and research suggests that listening attentively to the radio can worsen driving performance, particularly lane keeping, as much as a mobile phone conversation' (Ivers et al., 2009, p. 1641). In-vehicle distraction can result from younger drivers being more confident with new technologies leading inexperienced drivers to overestimate their ability to multi-task while driving (Neyens & Boyle, 2008). Aggressive driving increases accident severity and tends to be associated with youth and alcohol involvement (Paleti, Eluru, & Bhat, 2010). Asbridge et al. (2003) found road rage was mostly associated with individuals aged 18–29 although it was not uncommon across most age groups except those aged 65 or over.

Risky behaviour declines with age from its peak at about age 16 (Hayley, Ridder, Stough, Ford, & Downey, 2017; Jonah, 1997). The tendency to speed declines with age (Choudhary & Velaga, 2017; Hakamies-Blomqvist, Sirén, & Davidse, 2004; Jonah, 1997) and this might be because younger (male) drivers are more confident in their driving ability and perceive their driving as less risky (Massie et al., 1995). As individuals age, there is a decline in their sensory, motor and cognitive skills, leaving them more vulnerable to the effects of driver distraction (Hurts et al., 2011). In fact, 'older drivers have more difficulty in filtering out irrelevant stimuli' (Clarke, Ward, Bartle, & Truman, 2010, p. 1018). However, there may also be compensatory behaviour as older individuals choose not to interact with some in-vehicle devices such as mobile phones (Neyens & Boyle, 2008; Young & Regan, 2007), to drive more slowly or stick to familiar routes (Hurts et al., 2011).[4] Over the life course, drug use varies as cannabinols and stimulants are most likely to be used by drivers aged 20 or under, narcotics and depressants most likely to be used by drivers aged 35–64 and 65 or over, and other drugs are most likely to be used by drivers aged 65 or over (Romano & Pollini, 2013).

Older drivers (aged 70+) have higher blameworthiness and more fatigue-related accidents (Clarke et al., 2010). However, 'speeding and tail-gating are less common among older drivers' (Hakamies-Blomqvist et al., 2004, p. 78). This might be because younger (male) drivers are more confident in their driving ability and perceive their driving as less risky (Massie et al., 1995). Older individuals are more likely to be driving older cars (J.-K. Kim et al., 2013), which

[4] Driver distraction may be more prevalent due to 'increasing availability of sophisticated equipment, such as entertainment systems, telephones and navigation systems, which can be operated within the vehicle' (A. Stevens & Minton, 2001, p. 539). Driver age and driving experience can affect distraction levels from in-vehicle devices, with old and novice drivers more at risk (Young & Regan, 2007).

with fewer safety features means they are likely to have more severe accidents. Those who drive older cars may also behave differently from those driving newer cars (Broughton, 2008)

Evidence on the detailed effects of distraction and inattention on accident severity is mixed and varies by distraction source and age of the driver, although there is consensus that severity increases with these factors (see, for example, Behnood & Mannering, 2015; Elvik, 2011; Ferdinand et al., 2014; Neyens & Boyle, 2008).

Changes in the economy can affect accident severity through the composition of drivers and therefore prevalent behaviours. ‘Younger people, who are more affected by an employment crisis and are generally riskier drivers, are more likely to withdraw from the pool of potential drivers’ (Bertoli et al., 2018, p. 274), which would reduce severity. If economic expansions are associated with longer working hours, stress due to time pressures and inadequate/poor quality sleep, this could lead to driver fatigue (Peden et al., 2004) and raise accident severity.

3.2.2.3 Driver SES

There is some evidence that high SES is associated with risky driving behaviours (Atombo, Wu, Tettehfio, & Agbo, 2017; Piff, Stancato, Côté, Mendoza-Denton, & Keltner, 2012) and road accident fatalities (Hosking, Ameratunga, Exeter, Stewart, & Bell, 2013). Machado-León, de Oña, de Oña, Eboli, and Mazzulla (2016) found high income drivers were more likely to factor speeding and tailgating into their risk perceptions, although this may not fully translate into driving behaviours. A positive link with income would suggest risky driving is procyclical.

To some extent, car type (vehicle makes) can be used to proxy driver SES, as wealthier drivers are more likely to have more expensive cars (premium or luxury rather than ‘standard’). For example, Lansley (2016) found an association between type of car ownership and social standing: car types that were seen as more expensive (luxury, executive and sports, rather than mini and family cars) were more common in high socioeconomic neighbourhoods in Britain. This would suggest drivers of standard cars are likely to be of low SES and are likely to have less severe accidents, although if safety features are correlated with car price, we may expect the opposite. Failing to yield to pedestrians at intersections may be associated with accidents and there is some evidence that this behaviour is linked to the cost of cars (Coughenour, Abelar, Pharr, Chien, & Singh, 2020). Vehicle maintenance can be particularly expensive for low SES drivers, and poor maintenance during recessions would be associated with more severe accidents. It is therefore not clear a priori what effects we can expect overall.

Overall, based on the literature, we expect less severe accidents associated with increased traffic volumes and congestion when the economy is performing well. However, more severe accidents become likely due to the higher risk preferences of young male drivers in response to economic expansions as they increase their general risk tolerance and are prone to speeding and drink driving. Smaller procyclical effects on severity may be associated with female drivers as they have less attachment to the labour market. If car type is correlated with driver SES, we might expect procyclical severity for drivers of luxury cars as risky behaviours are more likely from those with higher incomes (poorer people are more risk averse). It will be difficult to identify a single effect, so we need to look at overall results and results by characteristic to see what might be happening in terms of some behaviours.

3.3 Data

This analysis uses the British Stats19 accident data — an administrative database of the number and characteristics of all personal injury accidents reported to the police in England, Scotland and Wales. All vehicle types are included in the data — not just cars. The data are publicly available from www.data.gov.uk/dataset/road-accidents-safety-data. Stats19 is the best available, comprehensive source of information on road accidents in Britain and is likely among the best data sources on accidents globally. Data are collected either at the accident scene or as reported after the fact. Accident severity is classed according to the most serious casualty and is categorised as fatal, serious or slight. Fatalities represent deaths from the accident occurring within 30 days. Most serious injuries require hospitalisation and the remainder are considered slight injuries. A full list of conditions which are considered serious injuries is given in UK Department for Transport (2016). More details on this dataset are provided in chapter 2, section 2.3.

In addition to characteristics of the accident, Stats19 records the age and sex of all drivers involved in the accidents, allowing us to model outcomes at the vehicle level. For our analysis, we want to link accident outcomes to risky driving behaviour by different demographic groups so we categorise drivers by sex and age group (all males, males 18–24, males 25–64, males 65 or over, all females, females 18–24, females 25–64 and females 65 or over).[5] These data are available for our full sample from 1992 to 2015. Vehicle makes, models and year of first registration are separately collected from vehicle registrations data between 2002 and 2015, limiting some of our analysis to this period. These variables are used to proxy driver SES and vehicle safety features, as some vehicles (defined by a combination of makes, models and registration years) are more expensive and have greater safety features than others.

The data are subject to some limitations. Severity is determined by police and necessarily involves some judgement, especially since medical conditions can change and may not be fully apparent at the time of the accident. There is potentially significant underreporting of the less severe accidents (Mannering & Bhat, 2014; Savolainen, Mannering, Lord, & Quddus, 2011). In comparisons with hospital, police and insurance data, it has been found that underreporting may be as high as 30 per cent for severe injury accidents and 75 per cent for slight accidents, whereas underreporting of fatal accidents tends to be about zero (Savolainen et al., 2011). This underreporting occurs because individuals can be loath to deal with insurance claims and police lest they incur large excess payments or infringement notices. Underreporting may also occur because individuals differ in what they consider to be a reportable accident (Elander et al., 1993). In fact, in the UK underreporting is likely to occur because the drivers need only exchange their details and there is no legal duty to report an accident even if there is an injury (UK Department for Transport, 2013). Moreover, some accidents that should be reported to police are not, because the driver may not know the legal requirements or may not want to report the accident (for example if he/she has been drinking alcohol or is uninsured) (UK Department for Transport, 2013). Underreporting of less severe accidents will bias upward the average severity of all reported accidents, although this would only affect our results if the extent of underreporting is associated with economic activity.[6]

For our measure of economic activity we use the employment to population ratio from the UK Labour Force Survey (UK Office of National Statistics, 2016) as this measure accounts for

[5] Individuals aged 17 may apply for a driving licence. However, since in 2012 only 10% did so, we begin our adult driver age band at 18 (UK Department for Transport, 2014).

[6] Economic activity may have different effects on underreporting of less serious accidents. For example, in recessions individuals may fail to report if this affects the excess on insurance, which is less affordable. However, in expansions individuals may fail to report if they are under strict time pressures. This makes the aggregate relationship unclear a priori.

added and discouraged workers as the economy adjusts (Fuchs & Weber, 2013). For each accident we know the date and location so we can use the employment rate from the same region and quarter.

From 1992 to 2015 there were 8.6 million vehicles involved in accidents in Britain, with 85.3% involved in slight accidents, 13.3% in serious accidents and 1.4% in fatal accidents. Fatal accidents are relatively rare, so in the accidents literature are often combined with serious accidents into a new category — killed or seriously injured (KSI) — for analysis (see, for example, Behnood & Mannering, 2015). In this chapter, we measure individual accident severity as a binary variable KSI: serious or fatal accidents in which someone is killed or seriously injured versus slight accidents. Accident severity varies considerably by region. Average accident severity over the sample period is highest in Scotland with 20% of accidents being fatal or serious, although Scotland has about 6% of accidents (figure 3.1). Accident severity is lowest in North East England with 12.7% of accidents being serious or fatal (although the region only accounts for 3.7% of accidents). London also has a low severity rate of 12.7% despite having the highest number of accidents (15%). These differences might reflect more widespread use of low speed zones or traffic calming measures in these areas in London.

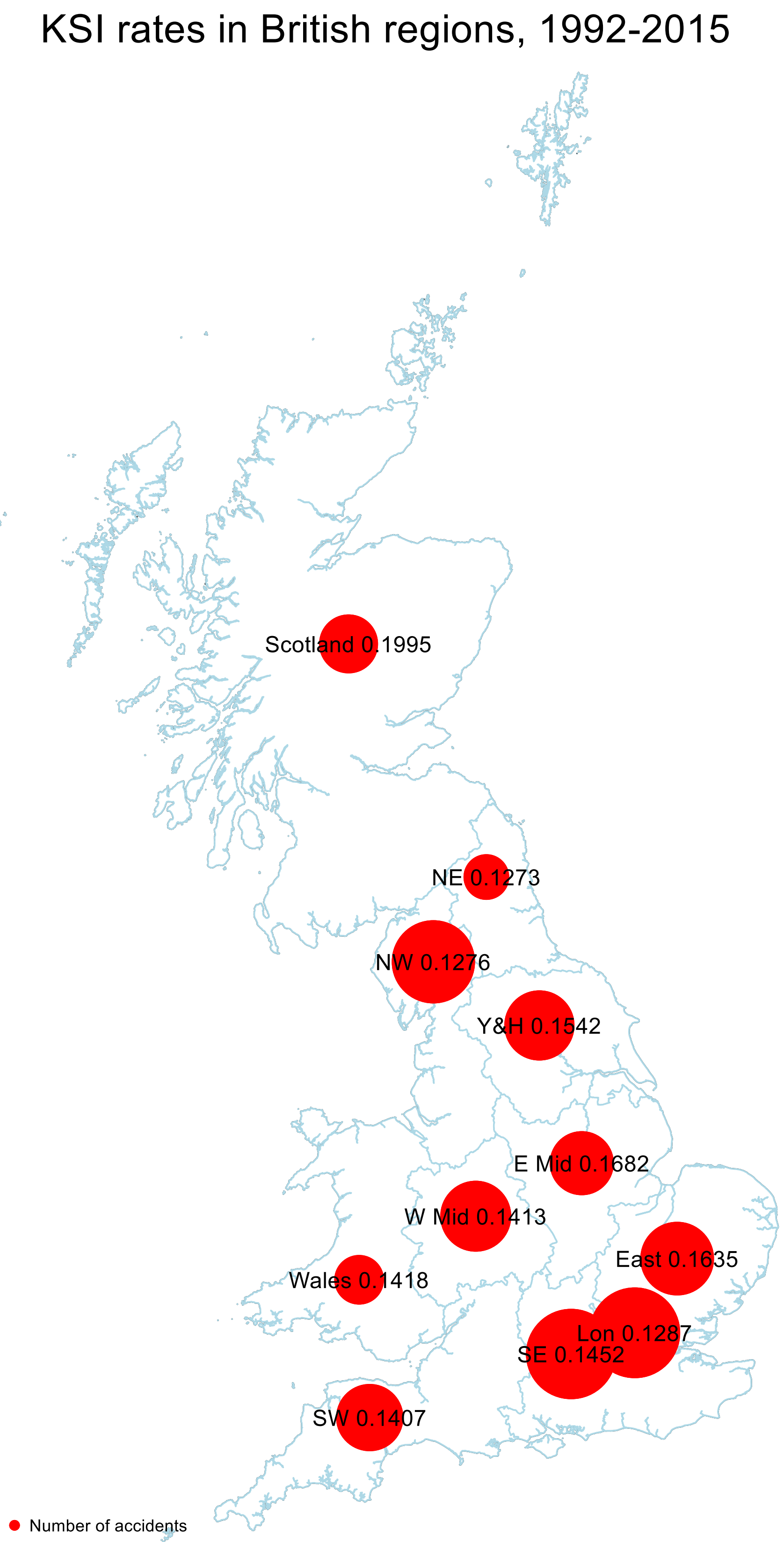

Figure 3.1: Average accident severity (KSI, proportion fatal or serious) by region 1992–2015

[a]The severity rate compares fatal and serious accidents with slight accidents. Rates are on a zero–one scale. Numbers of accidents range from 314,763 in North East England to 1,293,458 in London.

More broadly, variation between regions may reflect differences in road types and conditions, policing effects, geography, congestion and other factors affecting driver behaviours such as economic conditions. Some regions have shown a distinct downward trend (East of England, East Midlands, London and Scotland) while others have shown a levelling off (North East England, Yorkshire and the Humber) and the remainder have shown an increase over at least the end of the sample period. London has had a pronounced downward trend over the sample (figure 3.2). This downward trend is consistent with a background downward trend in numbers of casualties and the implementation of an increasing number of 20 mph zones in London (Grundy, Steinbach, Edwards, Wilkinson, & Green, 2008). There has also been an increase in congestion since at least 2008 (see https://www.tomtom.com/en_gb/trafficindex/city/london) which would be expected to lower speeds and reduce accident severity.

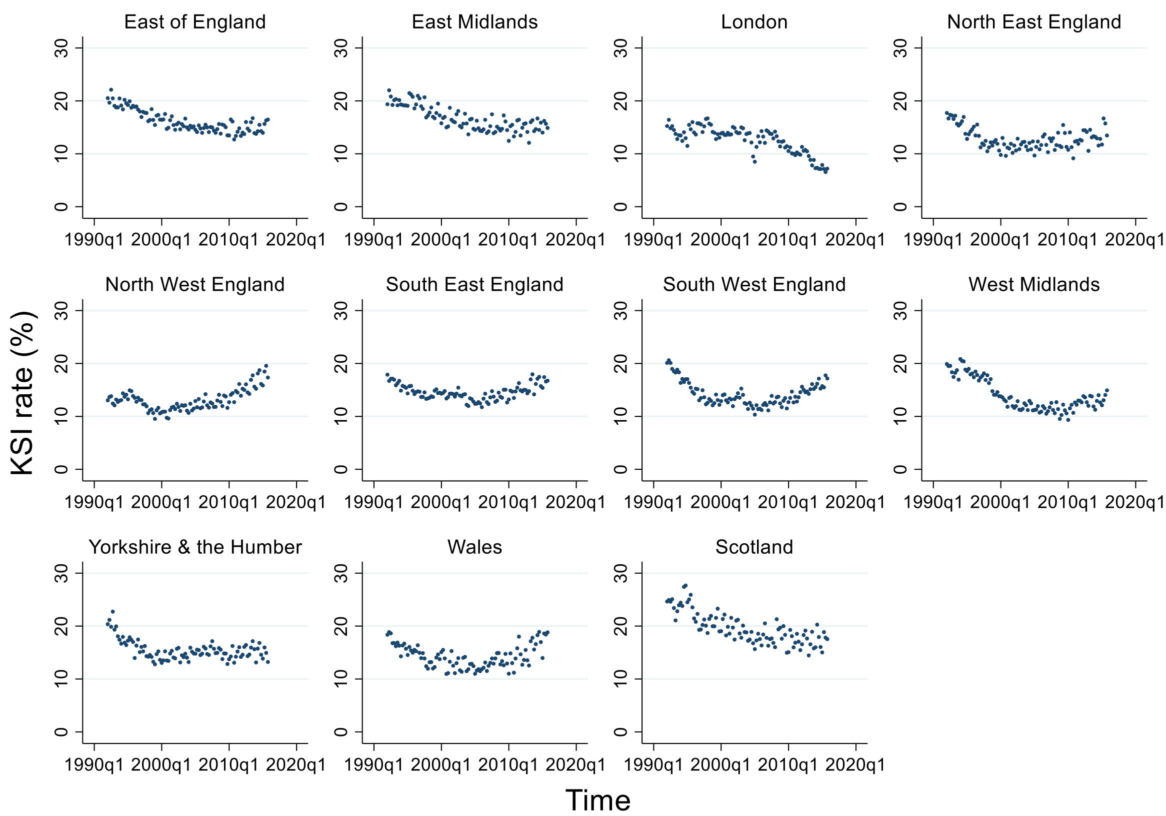

Figure 3.2: KSI rate (per cent fatal or serious accidents) over time, by region 1992–2015 quarterly[a]

As expected, accident severity varies by accident characteristic (table 3.1). For example, severity is higher in darkness (18% KSI), at night (21% KSI) relative to peak hours, on B roads (16% KSI) relative to motorways and A(M) roads and this is consistent with a congestion story.

Severity is also relatively high when motorcycles are involved (28% KSI) and this is consistent with known vulnerability of motorcycle riders.[7]

Table 3.1: Accident severity descriptive statistics by accident characteristic, 1992–2015[a]

	mean	sd	n
Light conditions			
Daylight	0.1364	0.3433	6,375,703
Dark	0.1759	0.3807	2,218,979
Time of day			
Night	0.2108	0.4079	1,754,041
Morning peak (Mon-Fri)	0.1222	0.3275	914,511
Afternoon peak (Mon-Fri)	0.1372	0.3441	1,674,603
Road type			
Motorway/A(M) road	0.1295	0.3357	401,105
B road	0.1614	0.3679	1,061,799
Vehicle involvement			
Bicycle	0.1592	0.3659	489,347
Motorcycle	0.2754	0.4467	585,773
Car	0.1313	0.3378	6,515,321
Bus	0.1302	0.3365	225,917
Goods	0.1732	0.3785	662,614
Other vehicle	0.1828	0.3865	116,568

[a]All accidents. Severity compares fatal and serious accidents (KSI) with slight accidents. Night hours are 8pm–4am every day. Morning peak hours are 7–9am and afternoon peak hours are 4–7pm Monday–Friday. Vehicle involvement indicates one or more of those vehicles were involved in the accident. Categories may therefore overlap.

In terms of the macroeconomic cycle, we showed in chapter 2 that accident numbers respond to economic activity in a procyclical manner (accidents rise with economic expansions). However, bivariate plots indicate there may also be a relationship with (average) accident severity. In terms of KSI accidents, in most regions the rate is decreasing as economic activity (represented by employment rates) increases (figure 3.3). In London, the trend is very pronounced and indeed large reductions in severity and increases in already high employment rates from 2012 result in what appear to be outliers when employment is above 70%.

[7] For example, motorcycle riders are estimated to be about 30 times more likely to be killed than car occupants in an accident (Huggins, 2013).

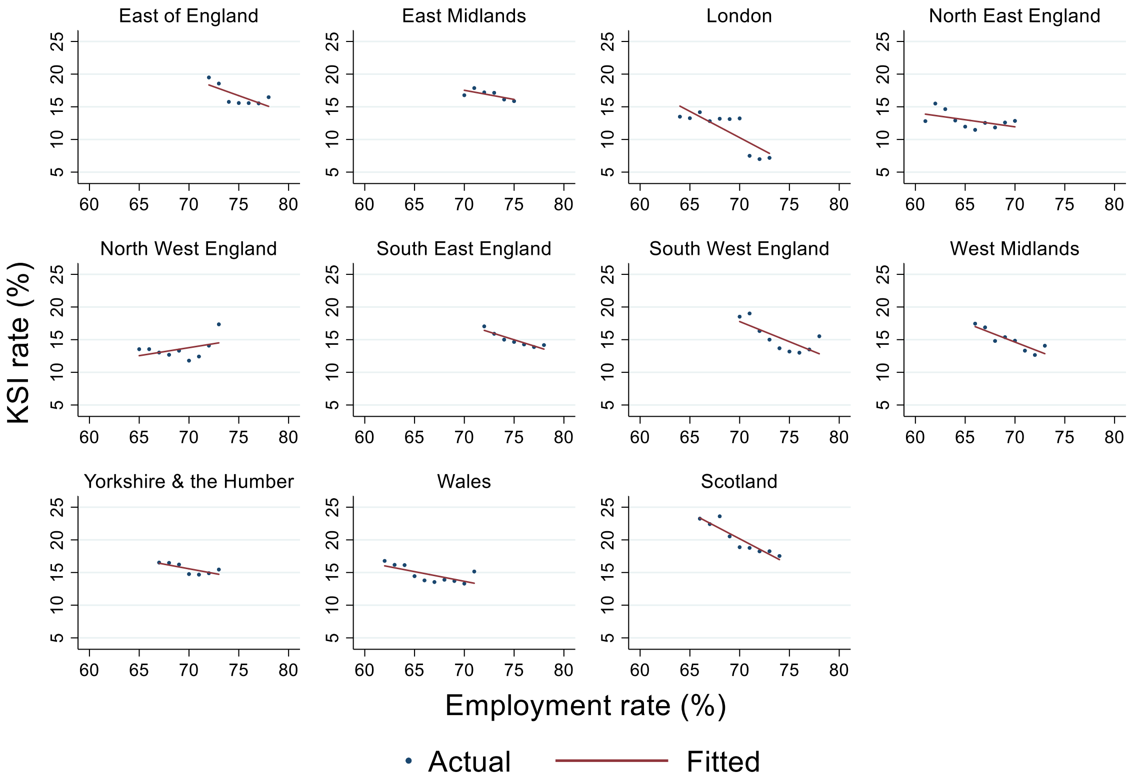

Figure 3.3: Average accident severity (KSI, per cent fatal or serious) by employment rate, by region 1992–2015

Importantly, the age composition of vehicles in the UK has changed over the study period (figure 3.4), although we do not have figures before 2002. This is likely to reflect increased longevity and lower replacement rates of older vehicles. Although an older fleet implies average vehicle safety is likely to have decreased over time, safety trends for new vehicles are likely to be increasing (new cars today are safer than new cars of yesterday), so the effects are likely to be muted. The average age of vehicles involved in injury accidents has mirrored the age of vehicles in the fleet, increasing since about 2005. This could reflect the interaction of driver behaviours and vehicle (lack of) safety features. A brief history of car safety features in the UK is provided at: https://www.autoexpress.co.uk/car-news/90221/the-evolution-of-car-safety-a-history. Key features include electronic stability control/traction control, adaptive cruise control, airbags, anti-lock brake system (ABS), blind spot monitoring, autonomous braking and features designed to protect pedestrians such as pop-up bonnets and the pedestrian detection system.[8,9]

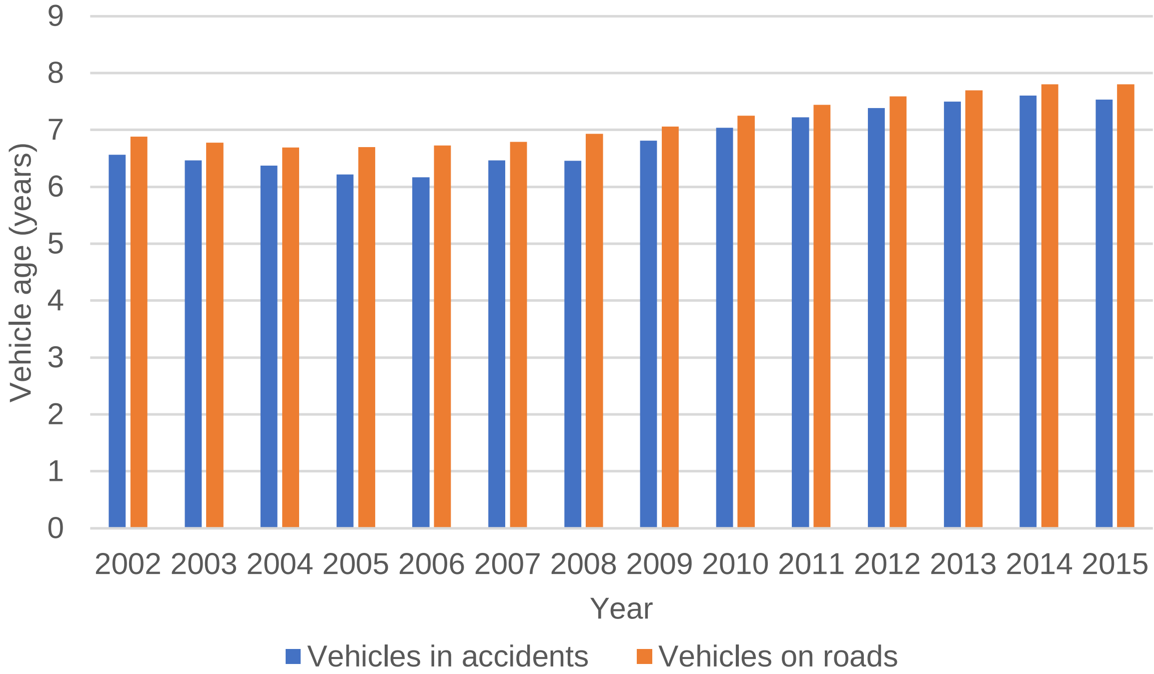

Figure 3.4: Average age of all vehicles in accidents in Britain and on UK roads, 2002–2015

Source: Stats19 and Statista (2019).

For multiple vehicle accidents our data do not identify which driver was at fault, so it is difficult to associate severity with behaviours. However, we can overcome this limitation by focussing on single car accidents, as this allows us to link severity and hypothesised behaviours for a

[8] Timings for a selection of some key vehicle safety features is as follows. 1994: Although driver airbags were introduced in the 1970s, the side impact airbag was introduced. 1995: electronic stability control introduced. 1999: introduction of adaptive cruise control. Most new cars had airbags (although they were not compulsory). 2004: Introduced in 1966, the anti-lock brake system (ABS) became compulsory for new cars. Blind spot information system introduced. 2005: Introduction of the pop-up bonnet designed to reduce pedestrian injuries. 2007: Blind spot monitoring was introduced. 2008: autonomous braking introduced. 2010: pedestrian detection system introduced. 2011: autonomous braking made compulsory for new cars. 2014 electronic stability control became mandatory on all new cars.

[9] Some key UK safety initiatives to emerge during our sample period include the introduction of speed cameras and of 60mph speed limiters on HGVs in 1992, consolidation of seat belt wearing regulations in 1993, lowering of speed limiters on buses and HGVs in 1994, the introduction of an offence for using a hand-held mobile phone while driving in 2003, increases in penalties for careless and inconsiderate driving, mobile phone use and not wearing a seatbelt in 2013, and new drug driving laws were introduced in 2015 (UK Department for Transport, 2015).

more homogeneous group of drivers, although the composition of accidents is likely to be different. Males have more severe accidents than females, with severity rates of 24% for males and 19% for females (table 3.2). Interestingly, young male and old female drivers are more likely to have severe accidents (24–25% KSI). This is likely due to a combination of behavioural factors, vehicle age/safety features and availability of emergency treatment at the accident scene.

Table 3.2: Single car accident severity descriptive statistics by driver characteristic, 1992–2015[a]

	mean	sd	n
Males			
All	0.2352	0.4241	707,271
18–24	0.2510	0.4336	183,011
25–64	0.2336	0.4231	417,314
65 or over	0.2355	0.4243	49,651
Females			
All	0.1925	0.3943	320,877
18–24	0.1903	0.3925	74,777
25–64	0.1929	0.3946	211,060
65 or over	0.2354	0.4243	18,614

[a]Single car accidents only. Severity compares fatal and serious accidents (KSI) with slight accidents.

A unique feature of our data is the detailed information about vehicle makes, models and registration years. There are 189,157 vehicle types in the data, based on make, model and year of first registration, of which 155,637 are cars. The information is very detailed, so we can distinguish accident outcomes for, say, a 2003 Ford Fiesta Classic compared to a 2001 Volkswagen Golf GL or a 2007 Audi A4.

From the 193 car makes in the data, we have identified a selection as standard, premium and luxury (table 3.3). We have selected Ford, Nissan, Toyota and Vauxhall to represent standard cars. Premium cars are represented by Audi, BMW, Jaguar, Lexus and Mercedes. The selected luxury cars are Aston Martin, Bentley, Ferrari, Lamborghini, Lotus, Maserati, Porsche and Rolls Royce. Together these makes of car represent 47.7% of cars involved in single car accidents. The categories broadly follow price brackets.[10] Luxury cars are, on average, the least

[10] There is subjectivity involved in classifying these types of car. Here we have picked a small subset of makes of car for illustrative purposes — the list is far from exhaustive. We seek to convey the broad appeal of particular makes/brands of car to certain types of drivers to see whether there are different safety outcomes over the economic cycle. There may be certain models of car make that fit a different ‘type’ (such as high performance Fords) but we necessarily abstract from such details.

safe in accidents with KSI rates of about 23%, which points towards driver behaviour as being important. Data are also available on whether alcohol or drugs were deemed to contribute to the accident. We can see that accidents involving alcohol are fairly severe (KSI rate 28%) and drugs even more so (KSI 40%), although the number of accidents involving drugs is small.

Table 3.3: Single car accident severity descriptive statistics by selected car type and behavioural factor, 2002–2015[a]

	mean	sd	n
Car type			
Standard	0.2060	0.4044	170,498
Premium	0.2166	0.4119	34,481
Luxury	0.2279	0.4197	1,325
Contributory factor			
Alcohol	0.2834	0.4507	27,188
Drugs	0.3957	0.4891	2,575

[a]Single car accidents only. Severity compares fatal and serious accidents (KSI) with slight accidents. Standard cars are Ford, Nissan, Toyota and Vauxhall. Premium cars are Audi, BMW, Jaguar, Lexus and Mercedes. Luxury cars are Aston Martin, Bentley, Ferrari, Lamborghini, Lotus, Maserati, Porsche and Rolls Royce. All models and registration years are included.

3.4 Empirical strategy

Our aim is to conduct a micro analysis to investigate the links between changes in the economy and road accident severity. Based on the aggregate procyclical relationship between economic activity and numbers of accidents found in chapter 2 and the limited literature linking behaviours to economic activity and accidents to behaviours, we hypothesise:

H1 there will be a relationship between employment and accident severity.

We begin by using the same identification strategy as in chapter 2. We account for time and Government Office Region-specific (GOR) variations in the data and focus on the effects of the regional economic cycle on accident severity. Time dummies capture nationwide movements in such factors as (national) economic conditions, time-varying national policies, vehicle safety standards and seasonality, which may be correlated with observed characteristics. GOR dummies account for factors that vary by region, such as policing effects, road topography and region geography. Factors that vary by time and region — such as congestion — are not captured by the dummies and, since suitable data are not available, these effects cannot be directly controlled for. Importantly, however, our data relates to accidents that have happened, so our specification conditions on accidents occurring and therefore implicitly controls for factors that influence whether an accident happens, such as traffic volumes and/or congestion. That is, accidents are linked to some measure of exposure such as traffic volumes. As the overwhelming majority of accidents are slight, the size of our base category (slight accidents) should be proportional to traffic volumes. However, severity is linked to congestion which relates to flows rather than volumes.[11]

The model uses within-GOR variations in accident severity to identify the effect of economic change, while controlling for confounding effects associated with time and space. Thus the impact of regional economic conditions is identified by within-GOR variations in severity relative to other GORs.

With a full working sample of about 8.6 million vehicles, and 14.7% being involved in severe accidents (KSI=1), our basic model is specified as:

$$KSI_{irt} = \sum_{j=1}^{95} \beta_{11,j} qtr_{ij} + \beta_{12} E_{rt} + \alpha_{1r} + \varepsilon_{1irt}$$

$$(i=1, \dots, n_{rt};\ r=1, \dots, 11;\ t=1992{:}2, \dots, 2015{:}4) \quad (1)$$

where KSI_{irt} is severity for accident occurrence *i* in region *r* at quarter *t*. Our measure of severity equals zero if the accident is slight and one if the accident is serious or fatal (i.e. KSI).

We include a dummy for the quarter and year when accident s occurs (qtr_{sj}).[12] E_{rt} is the region-specific employment rate in quarter *t*. Region dummy variables are given by α_{1r}, and ε_{1srt} is the error term. Region dummies account for factors influencing accident severity that vary between regions, such as fixed infrastructure, the geography of the area (some aspects of road types such as curves and widths can affect vision and overtaking and therefore accident severity). The number of individual accidents in the region-quarter is given by n_{rt}.

In chapter 2, we included a linear regional time trend to account for factors changing over time by region, such as differing population growth (which is likely to affect traffic volumes and

[11] The congestion mechanism is investigated later by comparing accident outcomes at different times and on different road types.

[12] In our modelling, quarter-year dummies account for the seasonality associated with weather and road conditions. What remains is behaviour associated with driver age, sex and SES (proxied by car type).

congestion) and changes in road safety expenditure or policing that might affect accident severity. We thus include region-specific time trends in our second specification as:

$$KSI_{irt} = \sum_{j=1}^{95} \beta_{21,j} qtr_{ij} + \beta_{22} E_{rt} + \beta_{23,r} trend_{rt} + \alpha_{2r} + \varepsilon_{2irt}$$

$$(i=1, \dots, n_{rt};\ r=1, \dots, 11;\ t=1992{:}2, \dots, 2015{:}4) \quad (2)$$

To investigate whether the relationship between accident severity and economic conditions has been changing over time we also estimate both models (1) and (2) over subsample periods. We begin by considering the period 1992–2001 when employment was steadily increasing to gauge the effect of expansions (see figure 2.1 in chapter 2). Over this period, several car safety features were introduced (including side impact airbags and electronic stability control) or extended throughout the new car fleet (driver and passenger airbags) and HGV and bus speed limiter reductions in 1994 presumably reduced accident severity. We then examine the relationship from 2002 to 2008 as the period leading up to the GFC. During this time, anti-lock braking systems became compulsory on new cars and the pop-up bonnet was created to improve pedestrian safety in accidents involving new cars. Hand-held mobile phone laws also came into effect. As new car sales and HGV use are associated with the economic cycle, these safety initiatives are likely to have changed the relationship between economic activity and accident severity. We also focus on the period from 2009 to 2015 (post-GFC) which was associated with more variation in economic conditions than previously and saw the introduction of further car safety features (such as autonomous braking) and increases in penalties for errant driving behaviours such as careless driving, mobile phone use, drug use and failure to wear a seatbelt.

We can further tighten the identification strategy by including vehicle fixed effects (defined by make, model and year of first registration) although this limits our sample. We re-estimate model (1) over the available subsample periods (2002–2008, 2009–2015) with vehicle fixed effects (we do likewise with model 2). This allows us to remove vehicle-type variations from the data, so we now compare vehicles of the same type in the same region to identify the effects of changes in the regional economy on accident severity. These model variants are specified as:

$$KSI_{irt} = \sum_{j=1}^{95} \beta_{31,j} qtr_{ij} + \beta_{32} E_{rt} + \alpha_{3r} + \delta_{3i} + \varepsilon_{3irt}$$

(i=1, … , n_{rt}; r=1, … , 11; t=2002:1, … , 2015:4) (3)

and

$$KSI_{irt} = \sum_{j=1}^{95} \beta_{41,j} qtr_{ij} + \beta_{42} E_{rt} + \beta_{43,r} trend_{rt} + \alpha_{4r} + \delta_{4i} + \varepsilon_{4irt}$$

(i=1, … , n_{rt}; r=1, … , 11; t=2002:1, … , 2015:4) (4)

There are some 189,000 vehicle-type fixed effects in this sample, given by δ_i. They capture differences in tastes and preferences of drivers and vehicle quality. For example, an individual may prefer to drive a particular make of vehicle — such as a 2007 Volvo S60 luxury T5 — as it is reputed to have better safety features in case of an accident and this will affect accident severity. We are accounting for broad tastes and preferences and vehicle safety features, so what remains relates to changes in behaviour and congestion as the economy adjusts. In these fixed effects models, standard errors are clustered by vehicle type to account for heterogeneity within types of vehicles (such as driver behaviours and vehicle-specific safety features). The introduction of vehicle fixed effects represents a novel contribution to the literature.

We also hypothesise:

- H2 a weaker accident severity relationship under certain conditions associated with congestion (daytime, peak hour, dry weather, local roads, goods vehicles/motorcycles (deliveries/freight)).

In this analysis, we estimate model (1) on all accidents for the full sample period and sub periods for various splits of the sample according to accident characteristics to see if there is a procyclical relationship between severity and employment under varying conditions. Corresponding results for model (2) are given in the appendix. A countercyclical relationship suggests increases in employment are associated with more traffic, congestion, lower speeds and lower severity. i.e. not risky behaviour. A procyclical relationship suggests risky behaviour. At this stage we analyse all vehicles involved in accidents, although for multi-vehicle accidents we cannot identify which driver was ‘at fault’.

Finally, we investigate driver/vehicle characteristics and hypothesise:

H3 there is a stronger relationship for certain types of driver associated with risky behaviour (males/young males, luxury car drivers relative to standard car drivers, when alcohol/drugs are involved).

Here we want to identify individual driver behaviour as far as possible, so we focus on single car accidents rather than accidents involving all vehicle types. Our estimation sample comprises some 1.6 million cars involved in single vehicle injury accidents from 1992 to 2015. Our investigation of selected car types involves some 207,000 single car accidents over the shorter period 2002–2015.[13]

By analysing subgroups identified by driver demographics, car types and alcohol/drug involvement, this modelling strategy allows us to better identify what type of driver is engaging in some of the risky behaviours linking economic activity to more serious accidents. For example, we will compare slight accidents which are more likely due to road conditions with severe accidents which are likely due to risky behaviours (such as alcohol consumption, drug taking, speeding and driving recklessly) and potentially change as the economy adjusts. Drivers of low SES driving 'standard' vehicles may be subject to larger income effects and therefore larger behavioural changes (such as drinking excessive alcohol) as economic conditions change, and these behavioural changes are associated with increased accident severity.

With millions of observations for our main models, and an extensive fixed effects specification, we estimate linear probability models rather than binary probit models, as estimation of marginal effects for the probit model is computationally intensive.

All analysis was carried out using Stata15.

3.5 Results

Links between accident severity and economic conditions (employment) are explored for a model with and without region-specific trends (table 3.4). In addition to estimates for the full

[13] These single car accidents associated with identified car types account for 47% of single car accidents that occurred over this shorter sample period.

sample, we provide results for three subperiods: 1992–2001 when employment is steadily rising, 2002–2008 when it is fairly stable and 2009–2015 when employment cycles post-GFC.

Overall, we find a countercyclical relationship between severity and employment, which is significant if we include region-specific trends (although we may be overcontrolling when including time trends). For the full sample period there are about 8.6 million vehicles involved in accidents across Britain, of which some 1.2 million are serious or fatal (KSI). On average, this equates to just over 13,000 vehicles involved in KSI accidents per quarter. For the model with no trends, a 1 percentage point increase in the employment rate is estimated to result in about 5 fewer vehicles involved in serious or fatal accidents over a quarter across Britain (a decrease of 0.00005 in the KSI rate). If we include region-specific trends, that figure increases to 84 fewer vehicles (0.0009 reduction in the KSI rate).

However, the relationship seems to be changing over time with a significant procyclical effect pre-GFC but not thereafter. From 1992 to 2001, a 1 percentage point increase in employment rates is associated with 422 additional vehicles in KSI accidents (289 if trends are included) in Britain over a quarter. The number falls to 289 if trends are included in the model. From 2002 to 2008, there is a similar story: 191 additional vehicles in KSI accidents (236 with trends) in a quarter. Over the period 2009–2015, we estimate a 1 percentage point increase in the employment rate reduced the KSI rate by 0.0063 (0.0001 if trends were included) and this equates to 426 fewer vehicles in KSI accidents (but 8 more vehicles if trends are included).[14]

If we add vehicle fixed effects to more tightly control for variation (i.e. comparing accident outcomes for the same make, model and registration year of vehicle in the same region when employment is high versus when it is low), we see little difference in the results (and note that we can only estimate over the period 2002–2015 due to data availability). Between 2002 and 2008 the KSI rate was estimated to fall by 0.0059 (increase by 0.0001 if trends were included) for a 1 percentage point increase in the employment rate. Since vehicle fixed effects have so little effect, we revert back to the pooled OLS specification for the remainder of our analysis.

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[14] A countercyclical relationship overall but procyclical relationship for the subperiods may initially seem counterintuitive. However, the size of the procyclical effect is declining over time and this leads to a small countercyclical effect over the full sample.

Coming back to the sub-sample results, our findings could be consistent with the risky behaviour story prevailing before the GFC and congestion driving the results post-GFC. We now turn to further investigation of these effects.

Table 3.4: Severity modelling results for overall and subsample periods with and without region-specific trends[a]

Sample	No trends	Trends	No trends	Trends
1992–2015	-5.41e-05	-0.0009***		
	(0.0001)	(0.0002)		
1992–2001	0.0040***	0.0027***		
	(0.0003)	(0.0003)		
2002–2008	0.0021***	0.0026***	0.0021***	0.0026***
	(0.0003)	(0.0004)	(0.0004)	(0.0005)
2009–2015	-0.0063***	0.0001	-0.0059***	0.0001
	(0.0004)	(0.0005)	(0.0004)	(0.0005)
Qtr dummies	✓	✓	✓	✓
GOR dummies	✓	✓	✓	✓
Vehicle fixed effects			✓	✓
Robust SE	✓	✓		
Clustered (vehicle) SE			✓	✓

[a]Severity compares fatal and serious accidents (KSI) with slight accidents. Trends are region-specific. Applicable standard errors shown in parentheses. Clustered standard errors are clustered by vehicle make, model and year of first registration. Vehicles include cars and all other vehicle types. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.5.1 Accident characteristics

Noting that the relationship changes before and after the GFC, we focus on the time subsamples rather than results for the total time available and investigate the effects of changes in employment for accidents with particular characteristics (table 3.5 and figure 3.5). Broadly speaking, we tend to see a procyclical relationship before the GFC but not after.

There are larger employment coefficients for accidents occurring in the dark and smaller coefficients during daylight. The KSI rate during the dark increases by 0.006 (a 3% effect) for a 1 percentage point increase in the employment rate before 2002, and there is a slightly smaller coefficient and percentage effect from 2002 to 2008. However, differences in the underlying KSI rate mean these effects equate to an average of 154 additional vehicles in KSI accidents in darkness in the early period (but 252 during daylight) and 59 additional vehicles in darkness for a quarter between 2002 and 2008 (and 123 in daylight). So the effect on numbers of serious or fatal accidents is greater in daylight. As employment increases there is a smaller effect on the KSI rate during daylight, suggesting risky behaviour is tempered by congestion limits being reached during the day. Post-GFC, severity declines with employment: by 0.008 (5.1%) during darkness and 0.006 (4.3%) during daylight. The larger reduction during darkness would be consistent with relatively more risky behaviour during daylight hours constraining the reduction.

As there can be a difference between light conditions at certain times of the day between summer and winter, we also consider times and days. Again for overnight (8pm–4am) and peak hours (Monday–Friday 7–9am and 4–7pm) we see the same procyclical relationship pre-GFC and a countercyclical relationship thereafter. For a 1 percentage point increase in the employment rate, we estimate the nightly KSI rate increases by 0.005 (2%) for the 1992–2001 sample period and 0.004 (1.9%) for the 2002–2008 sample period. Coefficient estimates are somewhat smaller during peak hours (0.004 morning peak, 1992–2001; 0.003 morning peak, 2002–2008; 0.003 afternoon peak, 1992–2001; 0.001 afternoon peak 2002–2008), and the effects on numbers of vehicles in KSI accidents are also smaller during peaks (averaging 49 vehicles in the morning peak and 66 in the afternoon per quarter over 1992–2001 and 28 and 21 vehicles over 2002–2008 for morning and afternoon peaks, respectively) relative to overnight (76 vehicles for a quarter between 1992 and 2001 and 54 vehicles between 2002 and 2008). After the GFC we see the largest decline in the severity rate overnight (-0.010) relative to morning peak (-0.007) and afternoon peak (-0.005). In levels, this equates to 93 fewer vehicles in KSI accidents at night and 54 fewer vehicles in morning peaks and 69 fewer in the afternoon peak as employment rises by 1 percentage point. The strongest relationship at night pre-GFC is consistent with a relative lack of congestion allowing faster speeds during those hours (i.e. congestion during the peak times limits increase in severity). But post-GFC, as employment goes up, severity goes down the most at night, suggesting much lower speeds at night.

In terms of road type, we compare motorways/A(M) roads and local B roads as they are expected to have different traffic patterns. We see the same procyclical relationship pre-GFC but not post-GFC for B roads. Before the GFC, for the two sample periods we see coefficients of 0.004 and 0.0003 that equate to effects of 2.8% and 0.2% for B roads (associated with a 1 percentage point increase in the employment rate). After the GFC the coefficient becomes negative (-0.006) with an effect of -3.9%. This equates to 63 additional vehicles in KSI accidents on B roads in a quarter between 1992 and 2001, 4 additional vehicles between 2002 and 2008 but 51 fewer vehicles in a quarter from 2009 to 2015. Interestingly, in contrast to our other results, post-GFC there remains a procyclical relationship for motorways: severity increases with employment for accidents on motorways post-GFC. We see for example that the coefficient is 0.013 in the early sample, 0.001 in the middle sample and 0.006 post-GFC (equating to 61 additional vehicles in KSI accidents in the early sample, 6 leading up to the GFC and 19 vehicles in KSI accidents after the GFC as employment rises by 1 percentage point in a quarter). This is consistent with an increase in risky driving behaviour by motorists. Perhaps there is also congestion on B roads post-GFC.

Accidents involving each vehicle type show similar patterns: procyclical relationships (mostly with some significance) before the GFC but relatively strong and highly significant countercyclical relationships post-GFC, consistent with congestion reducing speeds. Pre-GFC, the largest effects are for cars and goods vehicles (0.004 (2.9%) and 0.006 (3.3%), respectively in 1992–2001, and 0.002 (1.4%) and 0.002 (1.4%) in 2002–2008). This equates to 335 additional cars and 52 additional good vehicles in KSI accidents in a quarter between 1992 and 2001 and 115 additional cars and 15 additional goods vehicles between 2002 and 2008, although there are also expected to be an additional 26 bicycles in KSI accidents in a quarter between 2002 and 2008 as employment rises by 1 percentage point. The largest reductions in severity rates post-GFC are for accidents involving buses, motorcycles or bicycles. There are smaller reductions for accidents involving cars, goods vehicles or 'other' vehicles. However, in terms of numbers of accidents, post-GFC we expect to see 260 fewer cars in KSI accidents and 60 fewer motorcycles, 48 fewer bicycles and 29 fewer good vehicles in such accidents as employment increases. Percentage effects suggest there is congestion post-GFC that is having the largest effect on severity rates for buses.

Accounting for region-specific trends makes little difference to the results (Table A.3.2): we broadly see a procyclical relationship before the GFC but not thereafter.

Table 3.5: Severity modelling results for overall and subsample periods by accident characteristic[a]

	1992–2015			1992–2002			2002–2008			2009–2015		
	Coefficient	SE	n	Coefficient	SE	n	Coefficient	SE	n	Coefficient	SE	n
Light conditions												
Daylight	4.42e-05	(0.0002)	6,375,703	0.0032***	(0.0003)	3,075,550	0.0018***	(0.0004)	1,876,851	-0.0057***	(0.0004)	1,423,302
Dark	-0.0002	(0.0003)	2,218,979	0.0056***	(0.0006)	1,076,670	0.0025***	(0.0007)	664,206	-0.0081***	(0.0008)	478,103
Time of day												
Night (8pm-4am)	-0.0009**	(0.0004)	1,293,322	0.0047***	(0.0008)	638,795	0.0039***	(0.0009)	393,535	-0.0100***	(0.0011)	260,992
Morning peak (Mon-Fri)	0.0003	(0.0004)	914,511	0.0044***	(0.0008)	435,950	0.0029***	(0.0009)	269,369	-0.0072***	(0.0011)	209,192
Afternoon peak (Mon-Fri)	-0.0004	(0.0003)	1,674,603	0.0032***	(0.0006)	798,916	0.0012*	(0.0007)	493,350	-0.0051***	(0.0008)	382,337
Road type												
Motorway /A(M) road	0.0063***	(0.0007)	401,105	0.0132***	(0.0014)	178,842	0.0012	(0.0015)	131,364	0.0058***	(0.0018)	90,899
B road	4.18e-05	(0.0004)	1,061,799	0.0048***	(0.0008)	510,945	0.0003	(0.0009)	314,051	-0.0061***	(0.0011)	236,803
Vehicle involvement												
Bicycle	-0.0028***	(0.0006)	489,347	0.0010	(0.0012)	233,736	0.0059***	(0.0016)	119,142	-0.0099***	(0.0015)	136,469
Motorcycle	-0.0055***	(0.0007)	585,773	-0.0016	(0.0014)	257,942	0.0022	(0.0016)	182,884	-0.0115***	(0.0017)	144,947
Car	0.0002	(0.0001)	6,515,321	0.0041***	(0.0003)	3,166,809	0.0017***	(0.0003)	1,940,957	-0.0052***	(0.0004)	1,407,555
Bus	-0.0020***	(0.0008)	225,917	0.0038**	(0.0015)	111,355	0.0018	(0.0018)	68,348	-0.0140***	(0.0023)	46,214
Goods	0.0017***	(0.0005)	662,614	0.0062***	(0.0011)	327,417	0.0022*	(0.0012)	193,234	-0.0058***	(0.0014)	141,963
Other vehicle	-0.0017	(0.0013)	116,568	0.0012	(0.0027)	55,819	0.0024	(0.0028)	36,492	-0.0077**	(0.0039)	24,257

[a]All accidents. Severity compares fatal and serious accidents (KSI) with slight accidents. Pooled OLS models contain quarter and region dummies. Robust standard errors shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

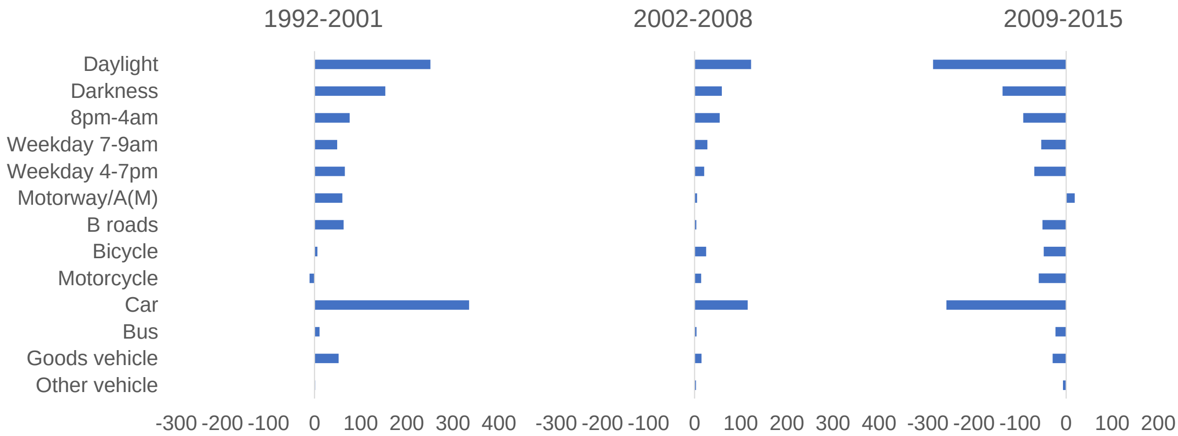

Figure 3.5: Changes in numbers of drivers in KSI accidents by accident characteristic and subsample period[a]

[a]All accidents. Effects are for a 1 percentage point rise in the employment rate, per region per quarter.

3.5.2 Driver and vehicle characteristics and behaviour

To get a better idea of the influence of driver behaviour, we focus here on single car accidents as this is the only way to associate 'at fault' driver behaviour with accident outcomes. With potentially different risky behaviour profiles, we split our results by age and sex, car type and behavioural factor (alcohol and drugs) (table 3.6 and figure 3.6).

For both sexes we see a procyclical relationship (that weakens for females) pre-GFC and a countercyclical relationship post-GFC. For males, a 1 percentage point increase in the employment rate increases the KSI rate by 0.003 (1.3%) in 1992–2001, by 0.004 (1.8%) in 2002–2008 but reduces it by 0.009 (3.9%) in 2009–2015. This increases the number of vehicles driven by males and involved in KSI accidents by 30 in a quarter during 1992–2001, by 29 in 2002–2008 but reducing such numbers of vehicles by 43 in a quarter during 2009–2015. Although we see larger coefficients for females over most of this time, the percentage effects are smaller from 2002 onwards. There are larger increases in vehicles driven by males and involved in KSI accidents than those driven by females pre-GFC, but the larger reductions post-GFC are for vehicles driven by males.

Pre-GFC, there is a procyclical relationship between employment and accident severity for most age–sex groups and a countercyclical relationship thereafter. Strongest results are observed for 18–24 year old males, consistent with known risky behaviours undertaken by these individuals (coefficients of about 0.005 pre GFC and -0.008 post-GFC equate to effects of 2.6 and -4.4%, which then average 11 additional vehicles in KSI accidents pre-GFC and 9 fewer accidents post-GFC). However, although there are smaller effects on the severity rate for males aged 25–64, they imply about 11 more KSI accidents pre-GFC and 22 fewer accidents post-GFC. Results are mostly not significant for individuals aged 65 or over who are likely retired from the labour force. Results post-GFC would be consistent with less risky behaviour/more traffic congestion lowering speeds, apart from the relatively small reduction for females aged 18–24 for whom there may be some risky driving behaviour partially offsetting this effect.

We use car type as a proxy for driver SES and analyse accident severity for a selection of car makes. We classify makes as standard (Ford, Nissan, Toyota and Vauxhall), premium (Audi, BMW, Jaguar, Lexus and Mercedes) and luxury (Aston Martin, Bentley, Ferrari, Lamborghini, Lotus, Maserati, Porsche and Rolls Royce) with all models and registration years included. These data are only available from 2002.

Pre-GFC there is limited evidence of a procyclical relationship with severity for standard cars and nothing significant for the other makes of car. However, post-GFC there is a significant countercyclical relationship for standard and premium cars. This suggests a reduction in risky driving behaviour for these drivers. Although based on very small numbers of accidents and not statistically significant, there might be a procyclical relationship for luxury cars post-GFC. The major effect on numbers of KSI accidents is for standard cars, with a 1 percentage point increase in employment rates associated with 12 additional KSI accidents for standard makes of car in a quarter pre-GFC (a coefficient of 0.004) and 17 fewer KSI accidents for these cars thereafter (coefficient of -0.006). Although there is a larger coefficient on luxury cars, they are involved in so few accidents that the effect on numbers of KSI accidents is negligible (less than one vehicle in a quarter).

There are no significant effects for single car accidents involving alcohol or drugs pre/post GFC. This suggests there may be offsetting effects in terms of more risky behaviour but to a lesser extent driving at uncongested times. Across all driver types we see similar effects when we include region-specific trends (Table A.3.3), namely procyclical relationships pre-GFC but not thereafter.

Table 3.6: Severity modelling results for overall and subsample periods by driver and vehicle characteristic and behaviour[a]

	Full sample[b]			1992–2002			2002–2008			2009–2015		
	Coefficient	SE	n	Coefficient	SE	n	Coefficient	SE	n	Coefficient	SE	n
Males												
All	-0.0009*	(0.0006)	707,271	0.0032***	(0.0011)	366,200	0.0040***	(0.0013)	201,931	-0.0086***	(0.0017)	139,140
18–24	0.0006	(0.0011)	183,011	0.0056***	(0.0022)	96,480	0.0045*	(0.0027)	54,815	-0.0079**	(0.0037)	31,716
25–64	-0.0016**	(0.0007)	417,314	0.0018	(0.0014)	220,969	0.0031*	(0.0017)	114,658	-0.0075***	(0.0022)	81,687
65 or over	-0.0037*	(0.0021)	49,651	-0.0005	(0.0046)	21,361	0.0054	(0.0050)	14,139	-0.0141***	(0.0054)	14,151
Females												
All	-0.0019**	(0.0008)	320,877	0.0054***	(0.0016)	152,066	0.0010	(0.0018)	93,740	-0.0072***	(0.0022)	75,071
18–24	-0.0011	(0.0016)	74,777	0.0063*	(0.0034)	35,243	0.0019	(0.0035)	22,334	-0.0022	(0.0046)	17,200
25–64	-0.0019**	(0.0009)	211,060	0.0053***	(0.0019)	103,099	0.0002	(0.0022)	60,882	-0.0082***	(0.0027)	47,079
65 or over	-0.0076**	(0.0035)	18,614	0.0100	(0.0084)	6,887	0.0020	(0.0085)	5,296	-0.0089	(0.0082)	6,431
Car type												
Standard	-0.0050***	(0.0013)	170,498				0.0036*	(0.0019)	96,009	-0.0064***	(0.0023)	74,489
Premium	-0.0150***	(0.0027)	34,481				-0.0020	(0.0048)	16,184	-0.0133***	(0.0045)	18,297
Luxury	0.0076	(0.0153)	1,325				0.0198	(0.0252)	761	0.0240	(0.0278)	564
Alcohol	0.0045	(0.0042)	27,188				0.0027	(0.0074)	12,498	0.0069	(0.0061)	14,690
Drugs	-0.0064	(0.0150)	2,575				0.0132	(0.0288)	977	-0.0098	(0.0201)	1,598

[a]Single car accidents only. [b]Full sample is 1992–2015 for driver age and gender, but 2002–2015 for car types and alcohol /drugs. Severity compares fatal and serious accidents (KSI) with slight accidents. Pooled OLS models contain quarter and region dummies. Robust standard errors shown in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

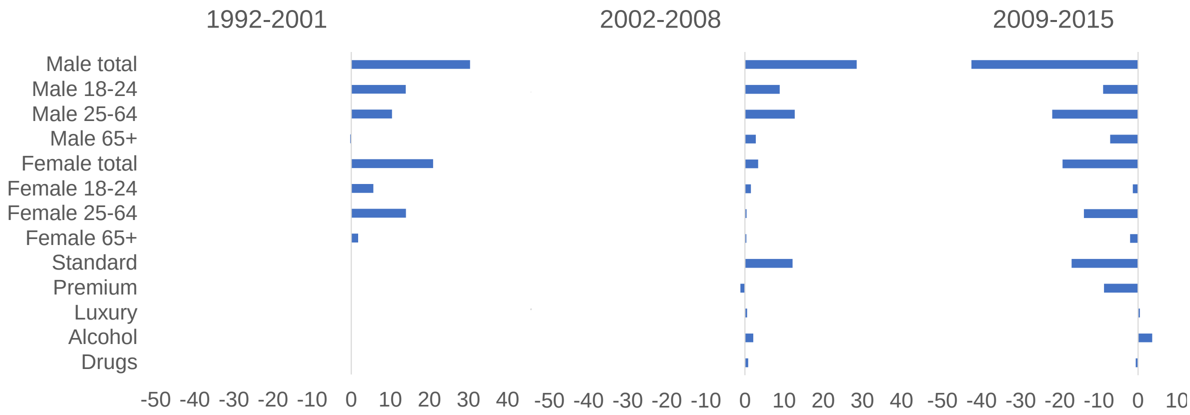

Figure 3.6: Changes in numbers of drivers in KSI accidents by driver and vehicle characteristic and subsample period[a]

[a]Single car accidents only. Estimates for car type and alcohol/drugs not available for 1992–2001 due to sample limitations. Effects are for a 1 percentage point rise in the employment rate, per region per quarter.

3.6 Conclusions

The literature has already made the link between the economic cycle and numbers of accidents and there is consensus that the relationship is procyclical. In chapter 2, we provide evidence that this relationship holds in Britain. In good times, road accidents place a larger burden on the health system, and reducing that burden relies on understanding the mechanisms that link economic activity and accidents. In particular, the most severe accidents weigh most heavily on individuals and the health system and it is therefore important to understand how we might reduce this burden.

Using data on all 8.6 million injury accidents reported to police in Britain over the period 1992–2015, this chapter considers the relationship between regional economic activity and accident severity at the individual driver level. The link between changes in the economy and accident severity may occur through two channels. Economic expansions lead to more traffic on the roads at certain times, which can increase congestion. This would lead to lower driving speeds, potentially reducing accident severity. However, at the same time, economic expansions may induce more risky driving through changes in risk preferences, time pressures and income effects. Investigation of driver demographics gives some idea of likely behaviours contributing to accident severity as the economy adjusts. Severity of accidents involving particular types of cars gives some idea of the effects of driver SES. Identifying outcomes of accidents involving alcohol or drugs speaks more directly to driver behaviour.

Allowing for variations across time and British regions, overall we find a relationship that changes over time: economic expansions (captured by rising regional employment rates) are associated with increased severity pre-GFC but not post-GFC (when there was considerable variation in economic conditions and increases in penalties for some driving behaviours, such as careless driving and mobile phone use while driving). This suggests there is a prevalence of risky driving before the GFC but that effects of traffic volumes and congestion take over thereafter. What we see is a net effect and we note that even within behaviours there are some 'pluses and minuses'. There may also be other factors affecting the relationship such as particular safety interventions, driver education (changing attitudes to risk), changing road technology and emergency service expenditure, but we have no data to investigate these effects. To control for these factors, we estimate a model with region and time dummies, and in some cases region-specific time trends and vehicle type fixed effects.

Serious and fatal accidents place an enormous burden on the health sector and the individuals involved in such accidents. By understanding behaviours contributing to accident severity, we are able to better target potential interventions to improve road safety. For example, education campaigns on the dangers of drink and drug driving, fatigue or distraction targeted to particular demographic groups could reduce accident severity when the economy is expanding. Similarly, additional enforcement activity in good economic times could lessen the desire for both legal and illegal behaviours and also reduce accidents.

This chapter provides a novel analysis of individual accident data to shed new light on the relationship between economic conditions and accident severity. We believe that this provides the most detailed such analysis to date for Britain. This research complements the existing literature linking accidents and the economic cycle. In order to improve the health of the nation and lessen the economic and emotional burden of accidents, we need to understand the pathways through which we can affect health as the economy adjusts. A driver-level analysis goes some way to identifying the behaviours associated with accident severity. With such high costs (from a policy perspective, particularly the costs to the health care system associated with the more severe accidents), it is important to understand how economic activity affects behavioural factors that contribute to individual accident severity.

Appendix

Table A.3.1: Data processing steps

Stats19 data (1985–2015)
Process vehicles primary data
Rename variables for consistency across years where required
Aggregate vehicle types for consistency across years
Bicycle, Motorcycle, Car, Bus, Goods vehicle, Other vehicle
Consolidate data for analysis
Append vehicles data for each year
Process accidents primary data
Rename variables for consistency across years where required
Map Local Authorities to Counties
Map Counties to GORs
LFS data (1992:2–2017:2)
Process each quarterly data file
Generate year and quarter indicator
Generate labour force status indicator from disaggregate categories
Aggregate regions to GOR level to match Stats19
Save variables for analysis: GOR, sex age labour force status, person weight
Consolidate data for analysis
Append merged data for each quarter
Calculate weighted variables for analysis
Labour force status (employed, unemployed and not in the labour force) for individuals aged 16–64
Aggregate from individual level to GOR level by year and quarter
Calculate (population weighted) labour force rates
Employment to population rate 16–64
Rename variables where required for consistency with Stats19 variables
Keep only variables required for analysis
Merge accident, contributory factors data and LFS data
Keep matched data
Append accidents data for each year
Generate severity indicator
Merge accident and vehicles data
Generate variables for numbers of vehicles by type
Merge sensitive data on vehicle make/model/age (2002–2015 only)
Generate vehicle type (make, model, year) indicator
Generate single vehicle indicator

Table A.3.2: Severity modelling results for overall and subsample periods by accident characteristic[a]

	1992–2015			1992–2002			2002–2008			2009–2015		
	Coefficient	SE	n	Coefficient	SE	n	Coefficient	SE	n	Coefficient	SE	n
Light conditions												
Daylight	-0.0011***	(0.0002)	6,375,703	0.0019***	(0.0004)	3,075,550	0.0022***	(0.0004)	1,876,851	9.40e-05	(0.0005)	1,423,302
Dark	-0.0006	(0.0003)	2,218,979	0.0046***	(0.0006)	1,076,670	0.0032***	(0.0008)	664,206	0.0001	(0.0010)	478,103
Time of day												
Night (8pm-4am)	-0.0013***	(0.0005)	1,293,322	0.0039***	(0.0009)	638,795	0.0046***	(0.0011)	393,535	-0.0018	(0.0014)	260,992
Morning peak (Mon-Fri)	-0.0009*	(0.0005)	914,511	0.0024***	(0.0009)	435,950	0.0037***	(0.0011)	269,369	0.0003	(0.0013)	209,192
Afternoon peak (Mon-Fri)	-0.0014***	(0.0004)	1,674,603	0.0017**	(0.0007)	798,916	0.0005	(0.0008)	493,350	7.47e-05	(0.0010)	382,337
Road type												
Motorway/ A(M) road	0.0073***	(0.0008)	401,105	0.0090***	(0.0015)	178,842	0.0031*	(0.0017)	131,364	0.0099***	(0.0020)	90,899
B road	-0.0008*	(0.0005)	1,061,799	0.0047***	(0.0009)	510,945	0.0008	(0.0012)	314,051	-0.0009	(0.0013)	236,803
Vehicle involvement												
Bicycle	-0.0033***	(0.0007)	489,347	0.0013	(0.0013)	233,736	0.0061***	(0.0019)	119,142	0.0004	(0.0019)	136,469
Motorcycle	-0.0073***	(0.0008)	585,773	0.0003	(0.0016)	257,942	0.0016	(0.0019)	182,884	-0.0027	(0.0022)	144,947
Car	-0.0003	(0.0002)	6,515,321	0.0027***	(0.0003)	3,166,809	0.0023***	(0.0004)	1,940,957	0.0002	(0.0005)	1,407,555
Bus	-0.0035***	(0.0009)	225,917	0.0020	(0.0017)	111,355	0.0017	(0.0022)	68,348	-0.0018	(0.0029)	46,214
Goods	0.0002	(0.0006)	662,614	0.0038***	(0.0012)	327,417	0.0039***	(0.0015)	193,234	-0.0002	(0.0017)	141,963
Other vehicle	-0.0010	(0.0016)	116,568	0.0029	(0.0030)	55,819	-0.0005	(0.0035)	36,492	-1.36e-05	(0.0044)	24,257

[a]All accidents. Severity compares fatal and serious accidents (KSI) with slight accidents. Pooled OLS models contain quarter and region dummies and region-specific time trends. Robust standard errors shown in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table A.3.3: Severity modelling results for overall and subsample periods by driver and vehicle characteristic and behaviour[a]

	Full sample[b]			1992–2002			2002–2008			2009–2015		
	Coefficient	SE	n	Coefficient	SE	n	Coefficient	SE	n	Coefficient	SE	n
Males												
All	-0.0009	(0.0007)	707,271	0.0046***	(0.0012)	366,200	0.0049***	(0.0017)	201,931	-0.0013	(0.0020)	139,140
18–24	0.0024*	(0.0014)	183,011	0.0072***	(0.0025)	96,480	0.0013	(0.0034)	54,815	-0.0026	(0.0042)	31,716
25–64	-0.0016*	(0.0009)	417,314	0.0032**	(0.0016)	220,969	0.0059***	(0.0022)	114,658	-0.0004	(0.0026)	81,687
65 or over	-0.0047*	(0.0026)	49,651	0.0003	(0.0051)	21,361	0.0096	(0.0062)	14,139	-0.0047	(0.0062)	14,151
Females												
All	-0.0010	(0.0010)	320,877	0.0066***	(0.0018)	152,066	0.0008	(0.0022)	93,740	-0.0009	(0.0025)	75,071
18–24	0.0015	(0.0020)	74,777	0.0069*	(0.0039)	35,243	-0.0023	(0.0046)	22,334	0.0052	(0.0051)	17,200
25–64	-0.0010	(0.0012)	211,060	0.0060***	(0.0022)	103,099	0.0013	(0.0028)	60,882	-0.0023	(0.0032)	47,079
65 or over	-0.0071	(0.0044)	18,614	0.0148	(0.0095)	6,887	0.0020	(0.0104)	5,296	-0.0044	(0.0095)	6,431
Car type												
Standard	0.0018	(0.0016)	170,498				0.0044*	(0.0024)	96,009	0.0019	(0.0026)	74,489
Premium	-0.0057	(0.0037)	34,481				0.0026	(0.0059)	16,184	-0.0052	(0.0057)	18,297
Luxury	0.0345*	(0.0204)	1,325				0.0104	(0.0308)	761	0.0541	(0.0348)	564
Alcohol	0.0075	(0.0048)	27,188				-0.0072	(0.0097)	12,498	0.0094	(0.0066)	14,690
Drugs	0.0040	(0.0171)	2,575				0.0172	(0.0385)	977	-0.0136	(0.0216)	1,598

[a]Single car accidents only. [b]Full sample is 1992–2015 for driver age and gender, but 2002–2015 for car types and alcohol /drugs. Severity compares fatal and serious accidents (KSI) with slight accidents. Pooled OLS models contain quarter and region dummies and region-specific time trends. Robust standard errors shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

References

Albentosa, J., Stephens, A. N., & Sullman, M. J. M. (2018). Driver anger in France: The relationships between sex, gender roles, trait and state driving anger and appraisals made while driving. *Transportation Research Part F: Traffic Psychology and Behaviour*, *52*, 127-137. doi:https://doi.org/10.1016/j.trf.2017.11.019

Amoros, E., Martin, J. L., & Laumon, B. (2003). Comparison of road crashes incidence and severity between some French counties. *Accident Analysis & Prevention*, *35*(4), 537-547. doi:https://doi.org/10.1016/S0001-4575(02)00031-3

Asbridge, M., Smart, R. G., & Mann, R. E. (2003). The "homogamy" of road rage: understanding the relationship between victimization and offending among aggressive and violent motorists. *Violence and Victims*, *18*(5), 517-531.

Atombo, C., Wu, C., Tettehfio, E. O., & Agbo, A. A. (2017). Personality, socioeconomic status, attitude, intention and risky driving behavior. *Cogent Psychology*, *4*(1), 1376424. doi:10.1080/23311908.2017.1376424

Ayuso, M., Guillén, M., & Alcañiz, M. (2010). The impact of traffic violations on the estimated cost of traffic accidents with victims. *Accident Analysis & Prevention*, *42*(2), 709-717. doi:https://doi.org/10.1016/j.aap.2009.10.020

Behnood, A., & Mannering, F. L. (2015). The temporal stability of factors affecting driver-injury severities in single-vehicle crashes: some empirical evidence. *Analytic Methods in Accident Research*, *8*, 7-32. doi:https://doi.org/10.1016/j.amar.2015.08.001

Behnood, A., & Mannering, F. L. (2016). An empirical assessment of the effects of economic recessions on pedestrian-injury crashes using mixed and latent-class models. *Analytic Methods in Accident Research*, *12*, 1-17. doi:https://doi.org/10.1016/j.amar.2016.07.002

Bertoli, P., Grembi, V., & Vall Castellò, J. (2018). Not all silver lining? The great recession and road traffic accidents. *Regional Science and Urban Economics*, *70*, 274-288. doi:https://doi.org/10.1016/j.regsciurbeco.2018.04.001

Broughton, J. (2008). Car driver casualty rates in Great Britain by type of car. *Accident analysis and prevention*, *40*(4), 1543-1552.

Bucciol, A., & Miniaci, R. (2018). Financial Risk Propensity, Business Cycles and Perceived Risk Exposure. *Oxford Bulletin of Economics and Statistics*, *80*(1), 160-183. doi:10.1111/obes.12193

Cahlíková, J., & Cingl, L. (2017). Risk preferences under acute stress. *Experimental Economics*, *20*(1), 209-236. doi:10.1007/s10683-016-9482-3

Cardamone, A. S., Eboli, L., Forciniti, C., & Mazzulla, G. (2017). How usual behaviour can affect perceived drivers' psychological state while driving. *Transport*, *32*(1), 13-22. doi:10.3846/16484142.2015.1059885

Cassar, A., Healy, A., & von Kessler, C. (2017). Trust, risk, and time preferences after a natural disaster: experimental evidence from Thailand. *World Development*, *94*, 90-105. doi:https://doi.org/10.1016/j.worlddev.2016.12.042

Cawley, J., & Ruhm, C. J. (2011). Chapter three - the economics of risky health behaviors. In M. V. Pauly, T. G. McGuire, & P. P. Barros (Eds.), *Handbook of Health Economics* (Vol. 2, pp. 95-199): Elsevier.

Choudhary, P., & Velaga, N. R. (2017). Mobile phone use during driving: Effects on speed and effectiveness of driver compensatory behaviour. *Accident Analysis & Prevention*, *106*, 370-378. doi:https://doi.org/10.1016/j.aap.2017.06.021

Christoforou, Z., Cohen, S., & Karlaftis, M. G. (2010). Vehicle occupant injury severity on highways: an empirical investigation. *Accident Analysis & Prevention*, *42*(6), 1606-1620. doi:https://doi.org/10.1016/j.aap.2010.03.019

Clarke, D. D., Ward, P., Bartle, C., & Truman, W. (2010). Older drivers' road traffic crashes in the UK. *Accident Analysis & Prevention, 42*(4), 1018-1024. doi:http://dx.doi.org/10.1016/j.aap.2009.12.005

Cotti, C., & Tefft, N. (2011). Decomposing the relationship between macroeconomic conditions and fatal car crashes during the great recession: alcohol- and non-alcohol-related accidents. In *The B.E. Journal of Economic Analysis & Policy* (Vol. 11).

Coughenour, C., Abelar, J., Pharr, J., Chien, L.-C., & Singh, A. (2020). Estimated car cost as a predictor of driver yielding behaviors for pedestrians. *Journal of Transport & Health, 16*, 100831. doi:https://doi.org/10.1016/j.jth.2020.100831

Dee, T. S., & Evans, W. N. (2001). Teens and traffic safety. In J. Gruber (Ed.), *Risky behaviour among youths: an economic analysis* (pp. 121-166). Chicago: University of Chicago Press.

Deffenbacher, J. L., Lynch, R. S., Oetting, E. R., & Swaim, R. C. (2002). The Driving Anger Expression Inventory: a measure of how people express their anger on the road. *Behaviour Research and Therapy, 40*(6), 717-737. doi:https://doi.org/10.1016/S0005-7967(01)00063-8

Dohmen, T., Falk, A., Golsteyn, B. H. H., Huffman, D., & Sunde, U. (2017). Risk Attitudes Across The Life Course. *Economic Journal, 127*(605), F95-F116. doi:10.1111/ecoj.12322

Dohmen, T., Huffman, D., Schupp, J., Falk, A., Sunde, U., & Wagner, G. G. (2011). Individual risk attitudes: measurement, determinants, and behavioral consequences. *Journal of the European Economic Association, 9*(3), 522-550.

Elander, J., West, R., & French, D. (1993). Behavioral correlates of individual differences in road-traffc crash risk: an examination of methods and findings. *Psychological Bulletin, 113*(2), 279-294.

Elvik, R. (2011). Effects of mobile phone use on accident risk: problems of meta-analysis when studies are few and bad. *Transportation Research Record, 2236*(1), 20-26. doi:10.3141/2236-03

Ferdinand, A. O., Menachemi, N., Sen, B., Blackburn, J. L., Morrisey, M., & Nelson, L. (2014). Impact of texting laws on motor vehicular fatalities in the United States. *American Journal of Public Health, 104*(8), 1370-1377. doi:10.2105/AJPH.2014.301894

French, M. T., & Gumus, G. (2014). Macroeconomic fluctuations and motorcycle fatalities in the U.S. *Social Science & Medicine, 104*, 187-193. doi:http://dx.doi.org/10.1016/j.socscimed.2013.12.019

Fridstrøm, L., Ifver, J., Ingebrigtsen, S., Kulmala, R., & Thomsen, L. K. (1995). Measuring the contribution of randomness, exposure, weather, and daylight to the variation in road accident counts. *Accident Analysis & Prevention, 27*(1), 1-20. doi:https://doi.org/10.1016/0001-4575(94)E0023-E

Fridstrøm, L., & Ingebrigtsen, S. (1991). An aggregate accident model based on pooled, regional time-series data. *Accident Analysis & Prevention, 23*(5), 363-378. doi:https://doi.org/10.1016/0001-4575(91)90057-C

Fuchs, J., & Weber, E. (2013). A new look at the discouragement and the added worker hypotheses: applying a trend–cycle decomposition to unemployment. *Applied Economics Letters, 20*(15), 1374-1378. doi:10.1080/13504851.2013.812777

Gerdtham, U.-G., & Johannesson, M. (2005). Business cycles and mortality: results from Swedish microdata. *Social Science & Medicine, 60*(1), 205-218. doi:https://doi.org/10.1016/j.socscimed.2004.05.004

Gerdtham, U.-G., & Ruhm, C. J. (2006). Deaths rise in good economic times: evidence from the OECD. *Economics & Human Biology, 4*(3), 298-316. doi:http://dx.doi.org/10.1016/j.ehb.2006.04.001

Gruber, J. (2001). Risky behaviour among youths: an economic analysis. In J. Gruber (Ed.), *Risky behaviour among youths: an economic analysis* (pp. 1-28). Chicago: University of Chicago Press.
Grundy, C., Steinbach, R., Edwards, P., Wilkinson, P., & Green, J. (2008). *20 mph zones and road safety in London: a report to the London Road Safety Unit*. London School of Hygiene & Tropical Medicine. London.
Guiso, L., Sapienza, P., & Zingales, L. (2018). Time varying risk aversion. *Journal of Financial Economics, 128*(3), 403-421. doi:https://doi.org/10.1016/j.jfineco.2018.02.007
Hakamies-Blomqvist, L. i., Sirén, A., & Davidse, R. (2004). *Older drivers: a review*. VTI Rapport 497A. Swedish National Road and Transport Research Institute. Linköping. Retrieved from http://vti.diva-portal.org/smash/get/diva2:675241/FULLTEXT01.pdf
Hanaoka, C., Shigeoka, H., & Watanabe, Y. (2015). *Do risk preferences change? Evidence from panel data before and after the great east Japan earthquake*. NBER Working Paper Series. NBER. Cambridge. Retrieved from http://www.nber.org/papers/w21400
Hartog, J., Ferrer-i-Carbonell, A., & Jonker, N. (2002). Linking Measured Risk Aversion to Individual Characteristics. *Kyklos, 55*(1), 3-26. doi:10.1111/1467-6435.00175
Hayley, A. C., Ridder, B. d., Stough, C., Ford, T. C., & Downey, L. A. (2017). Emotional intelligence and risky driving behaviour in adults. *Transportation Research Part F: Traffic Psychology and Behaviour, 49*, 124-131. doi:https://doi.org/10.1016/j.trf.2017.06.009
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. doi:https://doi.org/10.1016/j.socscimed.2016.02.016
Hollingsworth, A., Ruhm, C. J., & Simon, K. (2017). Macroeconomic conditions and opioid abuse. *Journal of Health Economics, 56*(Supplement C), 222-233. doi:https://doi.org/10.1016/j.jhealeco.2017.07.009
Hosking, J., Ameratunga, S., Exeter, D., Stewart, J., & Bell, A. (2013). Ethnic, socioeconomic and geographical inequalities in road traffic injury rates in the Auckland region. *Australian and New Zealand Journal of Public Health, 37*(2), 162-167. doi:10.1111/1753-6405.12034
Huggins, R. (2013). Using speeding detections and numbers of fatalities to estimate relative risk of a fatality for motorcyclists and car drivers. *Accident Analysis & Prevention, 59*, 296-300. doi:https://doi.org/10.1016/j.aap.2013.06.020
Hurts, K., Angell, L. S., & Perez, M. A. (2011). The distracted driver: mechanisms, models, and measurement. *Reviews of Human Factors and Ergonomics, 7*(1), 3-57. doi:10.1177/1557234X11410387
Ivers, R., Senserrick, T., Boufous, S., Stevenson, M., Chen, H.-Y., Woodward, M., & Norton, R. (2009). Novice drivers' risky driving behavior, risk perception, and crash risk: findings from the DRIVE study. *American Journal of Public Health, 99*(9), 1638-1644.
Jonah, B. A. (1997). Sensation seeking and risky driving: a review and synthesis of the literature. *Accident Analysis & Prevention, 29*(5), 651-665. doi:https://doi.org/10.1016/S0001-4575(97)00017-1
Kim, J.-K., Ulfarsson, G. F., Kim, S., & Shankar, V. N. (2013). Driver-injury severity in single-vehicle crashes in California: a mixed logit analysis of heterogeneity due to age and gender. *Accident Analysis & Prevention, 50*, 1073-1081. doi:https://doi.org/10.1016/j.aap.2012.08.011
Kim, Y.-I., & Lee, J. (2014). The long-run impact of a traumatic experience on risk aversion. *Journal of Economic Behavior & Organization, 108*, 174-186. doi:https://doi.org/10.1016/j.jebo.2014.09.009

Lansley, G. (2016). Cars and socio-economics: understanding neighbourhood variations in car characteristics from administrative data. *Regional Studies, Regional Science, 3*(1), 264-285. doi:10.1080/21681376.2016.1177466

Lloyd, L., Reeves, C., Broughton, J., & Scoons, J. (2013). *Investigating the reduction in fatal accidents in Great Britain from 2007-2010*. Published Project Report PPR663. Transport Research Laboratory. Wokingham.

Lloyd, L., Wallbank, C., & Broughton, J. (2015). A collection of evidence for the impact of the economic recession on road fatalities in Great Britain. *Accident Analysis & Prevention, 80*(Supplement C), 274-285. doi:https://doi.org/10.1016/j.aap.2015.03.026

Machado-León, J. L., de Oña, J., de Oña, R., Eboli, L., & Mazzulla, G. (2016). Socio-economic and driving experience factors affecting drivers' perceptions of traffic crash risk. *Transportation Research Part F: Traffic Psychology and Behaviour, 37*, 41-51. doi:https://doi.org/10.1016/j.trf.2015.11.010

Mannering, F. L., & Bhat, C. R. (2014). Analytic methods in accident research: methodological frontier and future directions. *Analytic Methods in Accident Research, 1*, 1-22. doi:https://doi.org/10.1016/j.amar.2013.09.001

Martin, J.-L. (2002). Relationship between crash rate and hourly traffic flow on interurban motorways. *Accident Analysis & Prevention, 34*(5), 619-629. doi:https://doi.org/10.1016/S0001-4575(01)00061-6

Massie, D. L., Campbell, K. L., & Williams, A. F. (1995). Traffic accident involvement rates by driver age and gender. *Accident Analysis & Prevention, 27*(1), 73-87. doi:https://doi.org/10.1016/0001-4575(94)00050-V

Miller, D. L., Page, M. E., Stevens, A. H., & Filipski, M. (2009). Why are recessions good for your health? *The American Economic Review, 99*(2), 122-127.

Neumayer, E. (2004). Recessions lower (some) mortality rates: evidence from Germany. *Social Science & Medicine, 58*(6), 1037-1047. doi:http://dx.doi.org/10.1016/S0277-9536(03)00276-4

Neyens, D. M., & Boyle, L. N. (2008). The influence of driver distraction on the severity of injuries sustained by teenage drivers and their passengers. *Accident Analysis & Prevention, 40*(1), 254-259. doi:https://doi.org/10.1016/j.aap.2007.06.005

Noland, R. B. (2003). Traffic fatalities and injuries: the effect of changes in infrastructure and other trends. *Accident Analysis & Prevention, 35*(4), 599-611. doi:https://doi.org/10.1016/S0001-4575(02)00040-4

Noland, R. B., & Quddus, M. A. (2005). Congestion and safety: A spatial analysis of London. *Transportation Research Part A: Policy and Practice, 39*(7), 737-754. doi:https://doi.org/10.1016/j.tra.2005.02.022

Norris, F. H., Matthews, B. A., & Riad, J. K. (2000). Characterological, situational, and behavioral risk factors for motor vehicle accidents: a prospective examination. *Accident Analysis & Prevention, 32*(4), 505-515. doi:https://doi.org/10.1016/S0001-4575(99)00068-8

OECD/ITF. (2015). *Why does road safety improve when economic times are hard?* Research Report. OECD/ITF. Paris.

Page, L., Savage, D. A., & Torgler, B. (2014). Variation in risk seeking behaviour following large losses: a natural experiment. *European Economic Review, 71*, 121-131. doi:https://doi.org/10.1016/j.euroecorev.2014.04.009

Paleti, R., Eluru, N., & Bhat, C. R. (2010). Examining the influence of aggressive driving behavior on driver injury severity in traffic crashes. *Accident Analysis & Prevention, 42*(6), 1839-1854. doi:https://doi.org/10.1016/j.aap.2010.05.005

Peden, M., Scurfield, R., Sleet, D., Mohan, D., Hyder, A. A., Jarawan, E., & Mathers, C. (2004). *World report on road traffic injury prevention*. World Health Organization. Geneva.

Piff, P. K., Stancato, D. M., Côté, S., Mendoza-Denton, R., & Keltner, D. (2012). Higher social class predicts increased unethical behavior. *Proceedings of the National Academy of Sciences, 109*(11), 4086. doi:10.1073/pnas.1118373109

Quddus, M. A., Wang, C., & Ison, S. G. (2010). Road traffic congestion and crash severity: econometric analysis using ordered response models. *Journal of Transportation Engineering, 136*(5), 424-435. doi:10.1061/(ASCE)TE.1943-5436.0000044

Roidl, E., Siebert, F. W., Oehl, M., & Höger, R. (2013). Introducing a multivariate model for predicting driving performance: the role of driving anger and personal characteristics. *Journal of Safety Research, 47*, 47-56. doi:https://doi.org/10.1016/j.jsr.2013.08.002

Romano, E., & Pollini, R. A. (2013). Patterns of drug use in fatal crashes. *Addiction, 108*(8), 1428-1438.

Ruhm, C. J. (2000). Are recessions good for your health? *The Quarterly Journal of Economics, 115*(2), 617-650. doi:10.1162/003355300554872

Ruhm, C. J. (2015). Recessions, healthy no more? *Journal of Health Economics, 42*, 17-28. doi:http://dx.doi.org/10.1016/j.jhealeco.2015.03.004

Ruhm, C. J. (2019). Drivers of the fatal drug epidemic. *Journal of Health Economics, 64*, 25-42. doi:https://doi.org/10.1016/j.jhealeco.2019.01.001

Sahm, C. R. (2007). *How much does risk tolerance change?* Finance and Economics Discussion Series 2007-66. Divisions of Research & Statistics and Monetary Affairs, Federal Reserve Board. Washington, D.C.

Sahm, C. R. (2012). How Much Does Risk Tolerance Change? *Quarterly Journal of Finance, 02*(04), 1250020. doi:10.1142/S2010139212500206

Said, F., Afzal, U., & Turner, G. (2015). Risk taking and risk learning after a rare event: evidence from a field experiment in Pakistan. *Journal of Economic Behavior & Organization, 118*, 167-183. doi:https://doi.org/10.1016/j.jebo.2015.03.001

Savolainen, P. T., Mannering, F. L., Lord, D., & Quddus, M. A. (2011). The statistical analysis of highway crash-injury severities: a review and assessment of methodological alternatives. *Accident Analysis & Prevention, 43*(5), 1666-1676. doi:https://doi.org/10.1016/j.aap.2011.03.025

Schildberg-Hörisch, H. (2018). Are risk preferences stable? *Journal of Economic Perspectives, 32*(2), 135-154.

Schurer, S. (2015). Lifecycle patterns in the socioeconomic gradient of risk preferences. *Journal of Economic Behavior & Organization, 119*, 482-495. doi:https://doi.org/10.1016/j.jebo.2015.09.024

Shefer, D., & Rietveld, P. (1997). Congestion and Safety on Highways: Towards an Analytical Model. *Urban Studies (Routledge), 34*(4), 679-692. doi:10.1080/0042098975970

Statista. (2019). Average age of cars on the road in the United Kingdom. Retrieved from https://www.statista.com/statistics/299951/average-age-of-cars-on-the-road-in-the-united-kingdom/. Accessed.

Stevens, A., & Minton, R. (2001). In-vehicle distraction and fatal accidents in England and Wales. *Accident Analysis & Prevention, 33*(4), 539-545. doi:https://doi.org/10.1016/S0001-4575(00)00068-3

Stevens, A. H., Miller, D. L., Page, M. E., & Filipski, M. (2015). The best of times, the worst of times: understanding pro-cyclical mortality. *American Economic Journal: Economic Policy, 7*(4), 279-311. doi:10.1257/pol.20130057

Sullman, M. J. M. (2015). The expression of anger on the road. *Safety Science, 72*, 153-159. doi:https://doi.org/10.1016/j.ssci.2014.08.013

Taubman-Ben-Ari, O., & Yehiel, D. (2012). Driving styles and their associations with personality and motivation. *Accident Analysis & Prevention, 45*, 416-422. doi:https://doi.org/10.1016/j.aap.2011.08.007

Theofilatos, A., & Yannis, G. (2014). A review of the effect of traffic and weather characteristics on road safety. *Accident Analysis & Prevention, 72*, 244-256. doi:https://doi.org/10.1016/j.aap.2014.06.017

UK Department for Transport. (2013). *Reported road casualties in Great Britain: guide to the statistics and data sources*. Department for Transport. London.

UK Department for Transport. (2014). *Facts on young drivers*. Department for Transport. London.

UK Department for Transport. (2015). *Reported road casualties Great Britain 2014 annual Report*. Department for Transport. London.

UK Department for Transport. (2016). *Reported road casualties Great Britain 2015: annual report*. Department for Transport. London.

UK Office of National Statistics. (2016). *Labour Force Survey user guide volume 1 - LFS background and methodology 2016*. Office of National Statistics. London.

Vaez, M., & Laflamme, L. (2005). Impaired driving and motor vehicle crashes among Swedish youth: an investigation into drivers' sociodemographic characteristics. *Accident Analysis & Prevention, 37*(4), 605-611. doi:https://doi.org/10.1016/j.aap.2005.03.001

Vogiatzis, K., & Kopelias, P. (2015). Benefits and limitations toward a sustainable road environment during the years of economic recession. *International Journal of Sustainable Development and Planning, 10*(5), 701-712. doi:https://doi.org/10.2495/SDP-V10-N5-701-712

Wagenaar, A. C. (1984). Effects of macroeconomic conditions on the incidence of motor vehicle accidents. *Accident Analysis & Prevention, 16*(3), 191-205. doi:http://dx.doi.org/10.1016/0001-4575(84)90013-7

Wang, C., Quddus, M., & Ison, S. (2013). A spatio-temporal analysis of the impact of congestion on traffic safety on major roads in the UK. *Transportmetrica A: Transport Science, 9*(2), 124-148. doi:10.1080/18128602.2010.538871

Wegman, F., Allsop, R., Antoniou, C., Bergel-Hayat, R., Elvik, R., Lassarre, S., . . . Wijnen, W. (2017). How did the economic recession (2008–2010) influence traffic fatalities in OECD-countries? *Accident Analysis & Prevention, 102*(Supplement C), 51-59. doi:https://doi.org/10.1016/j.aap.2017.01.022

World Health Organization. (2015). *Global status report on road safety 2015*. WHO. Geneva.

World Health Organization. (2018). *Global status report on road safety 2018*. WHO. Geneva.

Xu, C., Tarko, A. P., Wang, W., & Liu, P. (2013). Predicting crash likelihood and severity on freeways with real-time loop detector data. *Accident Analysis & Prevention, 57*, 30-39. doi:https://doi.org/10.1016/j.aap.2013.03.035

Yannis, G., Theofilatos, A., Ziakopoulos, A., & Chaziris, A. (2014). Investigation of road accident severity. *Traffic Engineering & Control, 55*, 31-35. Retrieved from http://link.galegroup.com/apps/doc/A377576494/AONE?u=monash&sid=AONE&xid=d8d188e2. Accessed 2019/2/25/.

Young, K., & Regan, M. (2007). Driver distraction: a review of the literature. In I. J. Faulks, M. Regan, M. Stevenson, J. Brown, A. Porter, & J. D. Irwin (Eds.), *Distracted driving* (pp. 379-405). Sydney: Australasian College of Road Safety.

Zeng, Q., Gu, W., Zhang, X., Wen, H., Lee, J., & Hao, W. (2019). Analyzing freeway crash severity using a Bayesian spatial generalized ordered logit model with conditional autoregressive priors. *Accident Analysis & Prevention, 127*, 87-95. doi:https://doi.org/10.1016/j.aap.2019.02.029

Chapter 4 Stock market returns and road accidents in Britain

4.1 Introduction

Stock market fluctuations are typically studied in the context of financial gains and losses. However, in the wake of the Global Financial Crisis (GFC) there has been growing interest in the relationship between stock markets and wellbeing, physical and mental health conditions. Most papers find health decreases as stock market performance weakens (see, for example, Chen, Chen, Liu, and Lin (2012) (who look at strokes), Fiuzat, Shaw, Thomas, Felker, and O'Connor (2010) (who consider heart attacks), and C.-L. Lin, Liu, and Chen (2017) (who examine attempted suicide)).

One aspect of health that has received little attention in this literature is the impact of the stock market on road accidents. According to Becker (2007), exogenous (perhaps anticipated) events, such as the prospect of advances in medical knowledge or new drugs being developed in the future, can affect individual attitudes about the future and therefore can affect their behaviour (see Cotti, Dunn, & Tefft, 2015). By extension, anticipated changes in income or wealth through changes in the stock market could also affect driving behaviour. Stock market fluctuations could impact on road accidents through multiple pathways. In particular, we would expect to see effects through health behaviours (such as alcohol consumption) and psychological factors (such as driver distraction). Furthermore, stock market crashes are well publicised and have become an important financial indicator such that even people without direct involvement in these markets may still be impacted.[1]

There are a number of key pathways by which the stock market can impact on road accidents. Stock market movements are a real-time indicator ('news') of how the economy is performing. Such movements also impact on emotions (H. Lin et al., 2013; Ma, Chen, Jiang, Song, & Kan, 2011). Changes in the stock market affect both stock holders and non-stock holders through wealth channels and uncertainty (Angrisani & Lee, 2016). Evidence suggests most individuals

[1] There are also additional welfare implications from negative spillovers as some individuals who are involved in the stock market might collide with individuals who have no involvement with the stock market given that most accidents involve more than one vehicle.

are aware of economic uncertainty (Kalcheva, McLemore, & Sias, 2017) and changes in the stock market can lead to short-run anxiety about future prospects (Frijters, Johnston, Shields, & Sinha, 2015), even for non-stock holders.

Psychological distress caused by daily stock market fluctuations (such as negative shocks) could affect driving performance through judgement errors and lapses in concentration (Giulietti, Tonin, & Vlassopoulos, 2020). Although research indicates changes in the stock market can affect physiological aspects of health, these types of health conditions are less likely to affect road accidents. It is possible that negative stock market returns lead to risk seeking driving behaviour and affect health through involvement in road accidents, although not all drivers invest in the stock market to the same extent (Giulietti et al., 2020). Inexperienced investors may be particularly vulnerable to changes in the stock market through overreaction to adverse returns in their portfolios and therefore at higher risk of accidents (Giulietti et al., 2020). Notwithstanding seasonal effects, under the efficient markets hypothesis, stock prices incorporate all currently available information about firms and their performance and hence are highly variable and largely unpredictable (Ratcliffe & Taylor, 2015). This implies large changes in the stock market represent an exogenous shock to individuals which may causally affect their driving behaviour.

In terms of road accidents, there are only two papers to date that consider the relationship with the stock market (Cotti et al., 2015; Giulietti et al., 2020), both of which use US data. Those papers tend to find that declines in the stock market are significantly associated with increased fatal road accidents. This chapter complements and extends that literature by providing an original and detailed investigation into the relationship between stock market movements and road accidents in Britain. In particular, we test whether there is an asymmetry that positive and negative stock market returns have a differential effect. This is based on a hypothesis that both positive and negative stock market returns lead to driver distraction and accidents at the region level and thus we contribute to the international literature on the relationship between road accidents and the stock market. Our data covers three decades and comprises daily observations on every road accident reported to police. We adopt a tightly identified model that considers movements in accidents within a month and region within Britain using daily data and allows for a more nuanced approach. Importantly, the tightly specified models are able to control for potentially confounding factors on which we have no data (such as traffic volumes and congestion). One of our main model specifications allows for asymmetric effects of (continuous) positive and negative returns, which provide an extension over the categorical measures of returns adopted by Giulietti et al. (2020) that we also use. Using daily variations within the same month, and controlling for regional fixed effects, also improves on the approach adopted in the extant literature. Using daily data also represents an improvement over the monthly data used by Cotti et al. (2015) and our application to all road accidents extends our coverage beyond just fatal car accidents studied in the literature to date. We also consider driver and accident characteristics to better understand our results.

As previously mentioned, we believe that this chapter represents the first attempt to consider the relationship between movements in a stock market index and health stemming from road accidents in British regions. Britain provides a salient context for this study because it is one of the largest financial hubs and was hit particularly hard by the GFC (Jofre-Bonet, Serra-Sastre, & Vandoros, 2018). We use the UK's headline stock index — the FTSE100 — as the measure of the stock market given that this index is the most widely reported. Large movements in the stock market over the 30 year period, including the GFC, allow us to investigate the short run relationship with road accidents over a long period. While the stock market is often a leading indicator of employment, this investigation adds to the analysis in chapters 2 and 3 by considering variations at a daily rather than quarterly level and allows for added effects related to stock market involvement rather than general employment trends.

The relationship between stock market movements and road accidents and fatalities is important to individual health and hence to 'government agencies, insurance companies, the police and other parties seeking to understand and predict road safety outcomes' (Burke & Teame, 2018, p. 150) and deliver better health outcomes for their citizens. In Britain in 2015, the average value of traffic accident prevention was approximately £76,000, comprising £2m for fatal accidents, £230,000 for serious and £24,000 for slight accidents. These costs comprise loss of output, ambulance and hospital treatment costs and human costs (willingness to pay) (UK Department for Transport, 2016b). It is therefore important to examine and understand aspects of our world that impact on driving behaviours. Here we focus on the extemporaneous relationship between stock market movements and road accidents in order to ensure public safety and better health outcomes. In terms of a policy response, awareness campaigns focussing on the impacts of mental and emotional shocks on driving behaviour could mitigate the effects of adverse stock market events on health outcomes (Giulietti et al., 2020).

4.2 Background and literature review

Studies of the stock market and health are relatively recent. These investigations of health have focussed on a variety of physical, behavioural (drinking alcohol and smoking) and mental health conditions, in addition to wellbeing (life satisfaction) more generally.

Evidence on the link between stock market performance and overall mortality is mixed. For the US, over the period 1994–2014, Pool et al. (2018) found large negative wealth shocks were associated with increased risk of overall mortality for older individuals. However, using a shorter timeframe from 2005 to 2008 and daily data, Schwartz, Pezzullo, McDonald, Poole, and Kloner (2012) found no significant effect on mortality and the authors attributed this lack of effect to investors' use of financial advisors to manage their portfolios and investors' reliance on monthly stock market reports. Yap et al. (2016) studied the Singapore stock market from 2001 to 2012 and found there was no effect on overall mortality.

Several studies have investigated the effects of the stock market on cardiac deaths. Studies of China and Taiwan found both increases and decreases in the stock market were associated with increased cardiac deaths (H. Lin et al., 2013; Ma et al., 2011). For China the results were attributed to the fact that Chinese investors gamble with investments and have unrealistic expectations of likely returns (Ma et al., 2011). However, a lack of hands-on involvement in the stock market during the GFC might have led to the lack of a significant effect on cardiac mortality for the US (Schwartz, Pezzullo, et al., 2012).

Using US Health and Retirement Survey data and Standard and Poor's 500 (S&P500) data from 1998 to 2011, Schwandt (2018) investigated the effects of changes in stock wealth stemming from changes in the stock market on a physical health index and self-reported health, finding a 10% reduction in stock wealth led to a 2% reduction in a standard deviation in these health measures. A similar effect was found for survival rates. However, this result only applies to stock holders and will not capture information effects on non-stock holders.

Some authors have found an association between stock market performance and heart attacks. In a review of the literature, Schwartz, French, et al. (2012) claimed that acute myocardial infarction could be triggered by anxiety and acute mental stress and stock market volatility. Using monthly US data over the period around the GFC, Fiuzat et al. (2010) found increased rates of acute myocardial infarction (heart attacks) among patients suspected of having ischemic heart disease, associated with NASDAQ declines. However, using the Dow Jones

Industrial Average over a similar time period, Li et al. (2014) found no significant relationship with hospital admissions due to acute myocardial infarction. Yap et al. (2016) used Singaporean data from 2001 to 2012 and found a greater weekly percentage change in the stock market was associated with *fewer* acute myocardial infarctions but more heart failure admissions.

Angrisani and Lee (2016) investigated the relationship between the US stock market's S&P500 and hypertension around the 2008 recession for older individuals. Using annual survey data from 2004 to 2010 and biomarker data from 2006 and 2010, their results showed no significant association overall for the self reported survey measures of hypertension but a significant negative association using biomarkers data for males and low educated individuals.

Chen et al. (2012) found low stock market levels and reductions in the index were associated with increased (inpatient) hospitalisation due to strokes in Taiwan over the period 2001–2007. The effects were largest and significant for the older age groups. The authors speculate that these results might be due to older individuals having no labour income and being reliant on financial investments such as pension funds. However, using data from Singapore, Yap et al. (2016) found limited evidence of stock market changes being associated with *fewer* strokes, although at best the statistical significance was marginal.

While there are therefore several studies of major health conditions and the stock market, for our purposes they might be of limited relevance, as 'available data and literature suggest that … natural driver deaths are relatively minor components of total road traffic fatalities' (Routley, Staines, Brennan, Haworth, & Ozanne-Smith, 2003, p. 45). Indeed, 'a British study … found 0.2% of all traffic related hospital presentations … died of natural causes' (Routley et al., 2003, p. 17), although there remains the possibility of some underreporting due to inconclusive post-mortem examinations.

Movements in the stock market are also associated with suicide. Evidence indicates that the 2008 recession was associated with increased suicides in Europe, the US and the UK, with regional differences found (Haw, Hawton, Gunnell, & Platt, 2014). There was a significant relationship between bankruptcy and suicide although not strong evidence of a relationship with debt. C.-L. Lin et al. (2017) examined the relationship between (trading) daily stock price movements and hospitalisations associated with attempted suicide in Taiwan and a significant relationship was found between low stock market performance and attempted suicide. Stock market fluctuations can reflect economic uncertainty and Vandoros, Avendano, and Kawachi (2019) found a positive short-term relationship between uncertainty and suicides.

In some cases, suicide and road accidents coincide so findings from this literature might be relevant to our study. However, 'literature shows suicides by motor vehicle crash to be a small proportion of the total road toll with estimates of between 1% and 7% of all motor vehicle crash fatalities.' (Routley et al., 2003, p. xii). For example, Australian data indicate some 126 cases of deliberate motor vehicle accidents between 1990 and 2001, representing about 0.8% of road accident fatalities (Routley et al., 2003). Even accounting for some underreporting due to a reluctance to classify these fatalities as suicide (due to lack of a suicide note and/or apathy and ignorance and/or to spare the deceased's family additional pain and suffering), the numbers are still likely to be small. Finally, there might also be attempted suicides to consider. However, even though 'there are at least 10 times as many persons engage in non-fatal suicidal behaviour as those who complete suicide' (Routley et al., 2003, p. 23-24), the numbers remain small.

While less extreme than suicide, mental health can also be affected by movements in the stock market. Mental health may be captured objectively using hospital admission or doctor visit data, or subjective survey measures.

Using survey measures of mental health for older people in the US, Schwandt (2018) examined responses to changes in values of stock wealth as the market adjusted. A 10% reduction in such wealth was associated with a 3% reduction in a standard deviation in the mental health index. This result is important as the sample period included the GFC, when the market was particularly volatile. However, the analysis is silent on the effects of movements in the stock market on mental health of younger people and non-stock holders.

Chen, Lin, Liu, and Chen (2016) found a significant negative relationship between stock market performance and neurotic disorder doctor visits in Taiwan. Similarly, Engelberg and Parsons (2016) found a significant negative relationship between hospital admissions (for psychological conditions) and returns in California between 1983 and 2011. C.-L. Lin, Chen, and Liu (2015) used daily data from 1998 to 2009 and found a negative relationship between stock prices, daily stock price falls and consecutive day stock price falls and mental disorder hospitalisation for Taiwan. Larger negative effects on all three stock market measures were found for males than for females.

Focussing on the October 2008 stock market crash, McInerney, Mellor, and Nicholas (2013) compared cross wave (2006 and 2008) changes in mental health and wealth for individuals interviewed in the US before and after the crash. There was no significant effect of the stock market crash on clinical measures of depression, but the crash increased the likelihood of feeling depressed (worsened subjective measures of mental health) and increased the likelihood of taking antidepressants for those with large stock holdings.

Using annual British data from 1991 to 2008, Ratcliffe and Taylor (2015) modelled the effects of stock market activity (percentage change in FTSE) on mental health and found evidence that increases in low frequency stock prices were associated with better mental health but increases in uncertainty were associated with worse mental health. The authors speculated that the reason for no effect with high frequency stock prices was that 'day-to-day activity in the stock market may go unnoticed by those without a keen interest in stock prices unless representing very unusual activity. For example, usually very sharp increases/declines or sustained positive/negative outcomes generates intense media scrutiny' (Ratcliffe & Taylor, 2015, p. 833). Although the effect was smaller, there was evidence that changes in the stock market affect mental health of non-stock holders.

Cotti et al. (2015) examined monthly movements in stock prices and crash indicators (1987 and 2008/09) for US states from 1984 to 2010 and found reductions in the Dow Jones Industrial Average and stock market crashes were associated with reduced mental health. Stock market returns less than -10% were also significantly associated with increased poor mental health days.

Frijters et al. (2015) modelled individual wellbeing and stock market prices for Australia and found stock market increases were positively related to life satisfaction for males and for those with greater exposure to the stock market. The authors found the strongest results using a one month average stock market index and concluded one week represents small changes that go unnoticed and that 3 months aggregates lots of changes that have been adjusted to or forgotten. When split by males and females, the results were only significant for males. Interestingly, the authors also included the Dow Jones Industrial Average and found only the local (Australian) index had a significant effect.

There may also be a relationship between stock market movements and health behaviours such as drinking alcohol. Kalcheva et al. (2017) found a significant positive relationship between stock market uncertainty (measured by the Chicago Board of Trade Volatility Index (VIX)) and unhealthy behaviours — such as alcohol consumption and binge drinking — over the period 1990–2015.

Adverse stock market movements could lead to anger as well as disappointment. There is some evidence that drivers with higher levels of anger have more losses of concentration while driving (Deffenbacher, Deffenbacher, Lynch, & Richards, 2003). These lapses are also associated with more risky driving behaviours and could therefore increase the chances of accidents occurring. Qualitative research indicates motorcycle riders' 'concentration may suffer under certain circumstances' and that stress can be a distractor for professional drivers (UK Department for Transport, 2009, p. 229). Research also suggests that, for novice drivers, listening attentively to the radio can adversely affect driving in a similar way to using a mobile phone (Ivers et al., 2009) and extreme emotions can lead to distraction and reduce cognitive function among young drivers (McNally & Bradley, 2014). Driver distraction (mind wandering) has also been associated with road accidents and, in particular, responsibility for such accidents as mind wandering could lead to overlooking hazards and making driving errors (Galéra et al., 2012). Changes in the stock market could lead to economic uncertainty, which affects negative emotions and leads to reduced concentration and ultimately more road accidents (Norris, Matthews, & Riad, 2000; Vandoros, Avendano, & Kawachi, 2018; Vandoros, Kavetsos, & Dolan, 2014).

There is limited literature on the relationship between stock market performance and road accidents and what there is suggests that there is likely to be a negative relationship between the two. Vandoros et al. (2014) studied the effect of announced austerity measures on road accidents in 2010/11 in Greece. These austerity measures are likely to also lower stock market performance, so this study remains relevant. The authors found that total and non-fatal accidents increased in the two days following the announcements although there was no significant effect for fatal accidents.

Stock market volatility may be reflected partly in economic uncertainty indicators. Vandoros et al. (2018) considered the relationship between road accidents (all motor vehicles) in Britain and the Economic Policy Uncertainty Index (EPU) over the period 2005–2015 using daily data. These authors found a highly significant elasticity of 0.008. Although this seems small, there is a great deal of variability in the EPU, with a standard deviation of 159 over their sample period. This implies a one standard deviation increase in the EPU would increase road accidents by 1.3%.

There is evidence that stock market returns and consumer confidence are correlated (see, for example, Jansen & Nahuis, 2003). Using monthly data from 1998 to 2017, Burke and Teame (2018) found no significant relationship between road fatalities and consumer confidence in Australia, implying by extrapolation that there is no relationship with the stock market.

More directly relevant to our purpose are the studies considering fatal car accidents and the stock market. Cotti et al. (2015) looked at monthly movements in stock prices and market crash indicators (1987 and 2008/09) for US states from 1984 to 2010 and found reductions in the Dow Jones Industrial Average and stock market crashes were associated with increases in fatal car accidents involving alcohol. Estimates suggest the 2008/09 stock market crash was associated with a 5.9% increase in alcohol related fatal car accidents. Also, based on levels, a 10% reduction in the Dow Jones Industrial Average was associated with a 1.3% increase in such accidents, and months with a greater than 10% reduction in returns showed a 5.3% increase in accidents.

In a similar vein, Giulietti et al. (2020) investigated the relationship between the stock market and fatal car accidents in the US between 1990 and 2015. They found a one standard deviation reduction in stock market returns (measured by the S&P500) was associated with a significant 0.6% increase in the number of fatal accidents nationally. The authors argue that their results are consistent with emotions immediately responding to poor stock market performance. They also found the effect on accidents was asymmetric in that only the lowest tercile of returns (negative) had a significant coefficient. To investigate heterogeneity, Giulietti et al. (2020) also estimated the effect of returns on groups of drivers with differential attachment to the stock market — with low attachment proxied by drivers aged 25 years or under, living in areas with lower incomes and those driving car makes associated with lower stock market exposure (based on survey data). If there is a causal relationship between accidents and returns, we expect the effects to be weaker for those with less involvement in the stock market, and that is what the authors found. Using accident contributory factors, the authors attributed the effects of changes in returns to reckless driving and drink driving but found no effect for distraction or speed.

Many methods are used to study the effects of the stock market on health, from cross-tabs and correlations (see, for example, Jansen & Nahuis, 2003; Li et al., 2014), and time series methods (see, for example, Engelberg & Parsons, 2016; Fiuzat et al., 2010) to fixed effects panel estimation (see, for example, Cotti et al., 2015; Giulietti et al., 2020; Ratcliffe & Taylor, 2015). Among these methods and given appropriate data, fixed effects estimation is preferred as it allows for variations in outcomes between regions and over time to be accounted for. It is also the dominant estimation technique in the relevant literature (included in table 4.1).

Measures of the stock market include indicators of major change (announcements, recession indicators: Haw et al. (2014), McInerney et al. (2013), Vandoros et al. (2014)), survey based information (wealth shocks: Pool et al. (2018), Schwandt (2018)), general indexes (consumer confidence and volatility indexes: Burke and Teame (2018), Jansen and Nahuis (2003), Kalcheva et al. (2017)). However, the majority of studies use direct measures of stock prices (see, for example, Cotti et al., 2015; Frijters et al., 2015; Giulietti et al., 2020; Ratcliffe & Taylor, 2015).

Table 4.1: Studies of the relationship between the stock market and health

Study	Data	Time	Methods	Result	Dependent variable	Other control variables	Stock market measure
Angrisani & Lee (2016)	US	2004-2010	Linear probability FE model	Effect of S&P500 on hypertension status (0,1) -0.006 and worsening hypertension (0,1) -0.009 but neither significant	Change or worsening in hypertension status	Change in: house prices, unemp rate, stock prices, age, marital status, household size; interview season, year and state FE.	Stock prices
Burke & Teame (2018)	Australia	1998-2017	IV estimation	Coefficient -0.002 marginally significant, average reduction in confidence over the sample leading to 0.5% more deaths.	Log fatalities	Unemployment, petrol prices, time trend, month dummies	Consumer confidence index
Chen et al (2012)	Taiwan	2001-2007	Autoregression	Stroke numbers increase with reductions in the TAIEX, elasticity approx. -0.1.	Hospitalisations due to strokes	TAIEX level, change, change^2, SARS dummy, time trend, day of week dummies, month dummies, lag hospitalisations	Stock prices
Chen et al (2016)	Taiwan	2006-2011	Integer valued autoregressive model	Daily (percentage) increase significantly associated with 0.53 reduction in number of doctor visits.	Number of doctor visits	Day, month and year dummies	Stock prices
Cotti et al (2015)	US	1984-2010	FE model, with OLS and variants for robustness	5.92% increase in fatal alcohol accidents stems from GFC crash; 10% reduction in DJIA associated with 1.3% increase in alcohol related fatal accidents.	Various, includes number of alcohol related fatal accidents	unemployment, per capita income, year, month, state FE, state time trends	Stock prices
Engelberg & Parsons (2016)	California	1983-2011	Time series regression	1 SD reduction in returns leads to 9.68% increase in hospitalisations, with larger effects for mental health conditions.	Log hospital admissions on trading days	Year, month and day and key holiday dummies	Stock prices
Fiuzat et al (2010)	US	2006-2009	Time series analysis	10 ppt decrease in NASDAQ associated with 2.7ppt increase in AMI rates	Acute Myocardial Infarction (AMI) rates	Seasonal dummies	Stock prices
Frijters et al (2015)	Australia	2001-2012	FE modelling for overall life satisfaction, and 6 domains of wellbeing	100 pt reduction in All Ords index associated with reduced life satisfaction (0.016 on a 0-10 scale). Similar relationships found for other satisfaction domains.	Satisfaction: life, financial, emp, health; mental health score; chronic health conditions.	Age, marital status, no. children, education, immigrant/LOTE, state unemployment rate, interview day and month dummies.	Stock prices
Giulietti et al (2020)	US	1990-2015	FE national model	1 SD reduction in returns associated with 0.23 (0.6%) additional fatal accidents	Number of fatal accidents	Linear and quadratic time trend, holiday FE, rainfall, wind direction and speed, CO2 emissions, VIX volatility index.	Stock prices
Kalcheva et al (2017)	US	1990-2015	FE model, OLS (aggregate state-level and individual level) and logistic (individual level)	1 SD higher expected volatility associated with 4.6%SD higher level of drinking, 10.2%SD higher level of number of drinks consumed, 7.2% SD higher level of binge drinking, 2.4% SD higher BMI, 4.4% SD higher fraction of population overweight, 2.4% SD higher fraction of population obese and 2.9% SD higher smoking level.	Drink (Y/N), number of drinks, binge drinking, BMI, smoking	Market returns, state FE; state level: time trends, unemp, income, demographics (age, gender, employed, marital status, race, education)	Volatility index
Li et al (2014)	US	2006-2012	Spearman rank correlations (bivariate)	Correlations negative but not significant	Numbers of AMI	N/A	Stock prices
Lin et al (2013)	China	2006-2010	Distributed lag non-linear model (GLM with Poisson model)	Relative risk showed higher risk of mortality when the market goes down or up, but not immediately. For example, in Taishan after 10 days, expect a 0.5% increase in risk of death for an approx. 1 SD change in the stock exchange index.	Log daily cardiovascular mortality	Day of week, public holidays, temperature, relative humidity, air pollution (4 gases)	Stock prices

Table 4.1 (continued)

Study	Data	Time	Methods	Result	Dependent variable	Other control variables	Stock market measure
Lin et al (2015)	Taiwan	1998-2009	Integer valued autoregressive model	A 1000 pt drop in the index increases hospitalisations by 4.7%. A 1% drop in the index increases admissions by 0.36%. An extra day falling is associated with an increase in admissions of 0.32% on that day.	Number of hospital admissions	Month and year dummies	Stock prices
Lin et al (2017)	Taiwan	1998-2012	Integer valued autoregressive model	A 1000 pt reduction in the stock market index is associated with a 2.11% increase in daily hospitalisations due to suicide attempts and the result is significant.	Hospitalisations due to attempted suicide	Stock market level (and lags, divided by 1000), daily percentage change (and lag), days in a run (up or down), monthly unemployment rate, day of week, annual linear and quadratic time trend	Stock prices
Ma et al (2011)	China	2006-2008	GLM with Poisson regression	A 100 pt change in index (in either direction) is associated with a 5.2% increase in coronary heart disease (CHD) deaths; in % change model, elasticity of 0.0187	CHD deaths	Long term seasonality, day of the week, index closing value, weather, air pollution	Stock prices
McInerney et al (2013)	US	2006, 2008	Pooled OLS	No significant effects on clinical measures of mental health but for those with high stock levels there was a 35% increase in antidepressant use and a 50% increase in probability of feeling depressed post-crash.	Change in clinical and subjective mental health and antidepressant use	Household characteristics such as (changes in) income, education, age, marital status and employment	GFC indicator
Ratcliffe & Taylor (2015)	UK	1991-2008	FE	Only significant effect (positive) at 26 and 52 weeks (100 pt rise in FTSE increases mental health by 0.7 on a 37 point scale).	Mental wellbeing score	Age, household composition, education, region of residence	Stock prices
Schwandt (2018)	US	1998-2011	First difference model	2-3% change in SD of health outcome measure for 10% change in wealth	Change in physical and mental health outcomes and survival rates	Age, gender, cohort, race, region, degree, lagged marital status	Predicted changes in stock wealth stemming from stock market changes
Schwartz et al (2012)	US	2005-2008	Graphical analysis	N/A	Seasonally adjusted death rates for all causes, circulatory, AMI and ischemic heart disease	N/A	GFC indicator
Vandoros et al (2014)	Greece	2010-2011	OLS	Semi-elasticity 0.09 on day 1 and 0.08 on day 2 for total accidents	Log accidents	Petrol prices, unemployment, holidays, strikes, daylight saving time, day of week and seasonal effects	Announcements of austerity measures
Vandoros et al (2018)	Britain	2005-2015	GARCH model	0.008% increase in acc for 1% increase in uncertainty. 1 SD increase in uncertainty leads to 1.3% increase in acc.	Log number of road accidents (all vehicles)	Month and day of the week, monthly unemployment rates and weekly unleaded petrol prices	Economic policy uncertainty index
Yap et al (2016)	Singapore	2001-2012	GLM with Poisson regression	Small effects of volatility on congestive heart failure rates but not for overall or cardiovascular mortality, AMI or stroke.	Hospital admissions and mortality	Air pollutants and calendar year	Stock prices

While there is a growing literature on the effects of the stock market on health, there are only a couple of papers that extend the definition of health to road accidents. These two main papers suggest there is a weak relationship but that it is there. To the extent that not everyone has a direct (or indirect) involvement in the stock market we would expect the relationship to be weak and perhaps only significant at the extremes of market movements.

4.2.1 Mechanisms

Changes in the stock market affect stock holders directly through changes in portfolio values (Engelberg & Parsons, 2016). Effects for stock holders might be more muted than expected if stocks are managed through financial advisors and evaluations of market performance are limited to reading personal financial statements (H. Lin et al., 2013).

Stock market losses may result in major losses in wealth/savings (Haw et al., 2014). Sudden wealth losses might negatively affect health due to loss aversion (Chen et al., 2016). Individuals of different ages might be affected to a greater or lesser extent according to the time horizon left to recoup losses from labour income or from offsetting movements in the stock market (Chen et al., 2016). Younger individuals are less likely to be directly involved in the stock market than older individuals, suggesting that the adjustment mechanisms vary by age. People from lower socioeconomic status (SES) groups 'are more vulnerable to financial turmoil' (Chen et al., 2016, p. 614) and are likely to have lower levels of financial literacy which might make them view losses as 'real' rather than paper (Cotti et al., 2015).

Psychological distress — including anxiety, worry and stress — resulting from large changes in one's financial position could distract individuals, reducing their concentration while driving and leading to erroneous and dangerous driving behaviours and accidents (Giulietti et al., 2020; Vandoros et al., 2014). 'Stress about one's finances also increases the likelihood of having a serious accident' (Vandoros et al., 2014, p. 557). In a similar vein, McInerney et al. (2013) found increased treatment for depression among individuals with large stock holdings as a result of the 2008 stock market crash. To the extent that depression medication can affect mental alertness, this mechanism could increase the likelihood of accidents and fatalities. Apart from a link between distraction and road accidents, emotional stress may also lead to risky behaviours such as binge drinking (Yap et al., 2016) which may affect numbers of road accidents. Linking with the stock market, a study by Cotti et al. (2015) showed an increase in binge drinking and alcohol related traffic fatalities during the 2008/09 financial crisis.

Evidence shows effects of the stock market occur within the same day for psychological conditions, 'suggesting that anticipation over future consumption directly influences instantaneous utility' (Engelberg & Parsons, 2016, p. 1227). In the face of a stock market crash, present bias means individuals might 'substitute towards consuming immediately pleasurable goods [such as alcohol] to alleviate worse well-being that arises in the face of a bleaker future' (Cotti et al., 2015, p. 819). Rational addiction might also be relevant as lower expected future utility due to a stock market crash might increase present consumption of addictive goods such as alcohol (Cotti et al., 2015). This would then potentially increase the likelihood of road accidents and fatalities.

Kalcheva et al. (2017) hypothesise that 'stress due to high economic uncertainty increases temporal discounting leading to decreased impulse control and an associated increase in unhealthy decisions' (p. 1). For example, economic uncertainty increases stress and the immediate utility of drinking alcohol and decreases the utility from not drinking in the future. That is, there is a 'tradeoff between immediate gratification and the "present value" of not engaging in the behaviour' (Kalcheva et al., 2017, p. 2).

In the past, drivers may have responded to radio news on the drive home from work or newspaper reports affecting the drive to work on the following day. In more recent times, driver distraction could be due to the increased use of smartphones (see, for example, Burke & Teame, 2018). Such phones might be used by those with high stock market involvement to monitor their investments.

Based on the limited empirical evidence on road accidents, we hypothesise that worse performance of the stock market leads to changes in health conditions (such as anxiety and stress (Schwartz, Pezzullo, et al., 2012), which might lead to driver fatigue and distraction) and health behaviours (such as drinking alcohol) which then lead to changes in driver behaviours that lead to more accidents. Although research indicates changes in wealth (anticipated or otherwise) can affect physiological aspects of health (Pool et al., 2018), these types of health conditions are less likely to affect road accidents.

In thinking about market movements, individuals might respond differently to gains than losses (McInerney et al., 2013), so we will examine both positive and negative changes in the stock market. Although there is limited literature for the US on the link between stock market movements and road accidents, we might expect smaller effects for British regions as there has been a lower involvement in the stock market during our observation period. For example, based on survey data, participation in the US stock market was estimated at 48 per cent in 1998 and 40 per cent in 1999 whereas participation in the UK stock market was estimated at 34 per cent in 1998 and 26 per cent in 1999 (Banks, Blundell, & Smith, 2002; Guiso, Haliassos, Jappelli, & Claessens, 2003).

The overall relationship between accidents and the stock market might mask some heterogeneity in responses according to particular characteristics of the accident, and driver/vehicle. In particular, there might be different mechanisms determining the relationship. For example, younger drivers might respond less strongly to negative movements in the stock market as they have more time available to recover from stock market losses before they need the associated wealth (Deaton, 2012). Alternatively, younger people might respond more strongly to market reductions if investments represent a larger share of their wealth. There might be a stronger relationship with the stock market for men than women as men are more likely to work and to be the primary earner, and women are less likely to be responsible for household financial decisions, which might manifest as less response to financial shocks for women (Frijters et al., 2015).

There might also be some differences in the behavioural mechanisms affecting responses to changes in the stock market. For example, there could be increased alcohol related accidents on the back of celebratory drinking as the market rises but there could be more accidents due to driver error as a result of stress when the market declines. That is, both changes in the market result in increased accidents but for different reasons.

We might also anticipate larger impacts on more serious accidents as a result of cascading effects on accident severity whereby changes in the stock market result in ‘near misses’ becoming slight accidents, slight accidents becoming serious accidents and perhaps even serious accidents becoming fatal accidents, although with smaller numbers of more serious accidents, the effects are still likely to decrease with severity. On the other hand, risk compensation behaviour might mean average accident severity declines with movements in the stock market. For example, distracted drivers may (unwittingly) reduce their speed (Hurts, Angell, & Perez, 2011).

4.3 Data

Our analysis focusses on the stock market and road accidents in Britain. For each of these two key variables we provide some background on the local context and describe the data used.

4.3.1 Stock market

There is scant information about the British population's participation in the stock market and publicly available information is somewhat dated (Banks & Smith, 2000). Based on UK Family Expenditure Survey data, the rate of UK household direct share ownership was about 9% in 1985 and rose to 23% in 1988 and remained fairly stable until at least 1996 (Banks, Blundell, & Smith, 2003). In 1998 about 34% of the UK population had direct and/or indirect shareholdings (Guiso et al., 2003). British Household Panel Survey data from 1995, 2000 and 2005 indicate stock market participation has remained low, with estimates of minimal participation averaging about 21% across the three waves. There is also evidence that most individuals did not tend to change their stock market participation status across the waves (Changwony, Campbell, & Tabner, 2015). The rapid increase in the late 1980s is partly attributed to the UK government introducing tax-favoured employee share ownership schemes alongside floating public utilities like British Telecom and British Gas in the mid-1980s in an effort to encourage a 'share-owning democracy' (Banks et al., 2003, p. 260). During the mid-1980s, the increase in share ownership also likely resulted in a change in the composition of share owners (Attanasio, Banks, & Tanner, 2002). In 1997/98 ownership of risky assets (which include shares) varied by age, with a 'hump' shape peaking at age 55–59 (Banks & Smith, 2000) and the average age of shareholders was 51.7 years (Attanasio et al., 2002). The lower rates of shareholding at older ages could be the result of drawing down on risky assets or it could be a cohort effect in that these older individuals always held lower levels of such assets (Banks & Smith, 2000). It is likely that share ownership has risen since the mid-2000s although it is not clear by how much. It is also not clear what has happened to share market participation since the GFC.

This analysis represents the first attempt to model the effects of stock market movements on road accidents in Britain. In assessing the impact of stock market movements on accidents we refer to the local stock market. Stock market data comprise the UK Financial Times Stock Exchange 100 Index (FTSE100). This series was extracted from the Datastream database (Datastream International, 2018, available from Datastream International) for the full sample period and the series comprises the daily closing price of the Index. In investigating the relationship of accidents to stock market returns we use London FTSE100 data as it is likely to be uppermost in the minds of individuals (relative to other market measures locally and internationally) in Britain.

Stock market movements only occur on trading days (which excludes weekends and public holidays), whereas accidents occur every day. Over the 31 years of our observation window, each year there are 104 non-trading days that are weekends and approximately 8-10 weekday public holidays (mostly Mondays). To include accidents on non-trading days in the analysis, we set the FTSE100 return on non-trading days to the return on the previous trading day. So, for example, the FTSE100 return on a Saturday, Sunday or public holiday is the same as the preceding trading day. This implies there are no zero returns on non-trading days.

There are various options for how to incorporate the stock market in our modelling. The level of the FTSE100 is non-stationary and contains a unit root in the series, which makes the relationship with accidents (which are stationary) potentially meaningless. The same is true of the logarithm of the FTSE100. Given that the FTSE100 series trends upwards, changes in the level will have an exploding variance through time which violates our regression assumptions. As is commonly used in time-series modelling of stock market variability we use returns at the market close (the difference in log FTSE – or the growth form of the FTSE), calculated as:

$$100*(\ln FTSEt - \ln FTSEt\text{-}1) \quad (1)$$

where FTSE is the level of the index. Timing our observations at market close means all the day's information has been incorporated into stock prices.

4.3.2 Accidents and vehicles

Prior to a detailed discussion of the data we will use, here we provide some background information on the British context in relation to vehicle licensing, ownership and use.

Vehicles on the roads are dominated by cars. In Britain, at the end of 2017 the registered vehicle fleet comprised 31.2 million cars, 3.9 million light goods vehicles, 500,000 heavy goods vehicles, 1.2 million motorcycles and 158,000 buses and coaches (UK Department for Transport, 2018). Some of these car drivers are inexperienced. In 2014/15 there were some 718,710 individuals who passed their practical driving (car) test, of which 36.8% were aged 17 or 18 (Table DRT0203, see: https://www.gov.uk/government/statistical-data-sets/driving-test-statistics-drt).

Licence holding in England has been increasing over the long term. In the mid-1970s, there were 48% of individuals aged 17 or over with a full car driving licence whereas that rate rose to 74% in 2015 (UK Department for Transport, 2016a). The sharpest increase has been for women (29% in 1975/76 and 68% in 2015) and older individuals (60–69 year olds went from 35% in 1975/76 to 81% in 2015; those aged 70 or over went from 15% to 64% over the same period) (Table NTS0201, see: https://www.gov.uk/government/statistical-data-sets/nts02-driving-licence-holders#table-nts0201). However, the rate of licence holding among youth aged 17–20 is still quite low at 30%, compared with about 65% for those aged 21–29 (UK Department for Transport, 2016a).

Car ownership is becoming more common in England, with the share of households with no access to a car falling from 38% in 1985/86 to 25% in 2015 and the share of households with access to two or more cars rising from 17% in 1985/86 to 33% in 2015 (UK Department for Transport, 2016a). There are also variations by SES as almost half of the households in the lowest income quintile have no access to a car whereas only 10% of the highest income quintile have no access to a car and over 50% of those in the highest income quintile have access to two or more cars (UK Department for Transport, 2016c). In 2014, 64% of personal trips were made by car and 78% of distance travelled for personal trips was by car (UK Department for Transport, 2016c).

There has also been an increase in light goods vehicle (van) traffic in recent years (some 38% since 2000) as a result of more favourable taxation rules and the increase in internet shopping and home deliveries (UK Department for Transport, 2016c). About half of the registered vans in 2008 were primarily used to transport equipment, and another 21% were used for delivery or collection of goods (UK Department for Transport, 2016c).

Data on accidents and fatalities comes from the British Stats19 administrative data on all accidents reported to police in Britain (Department for Transport, 2016, Police reported personal-injury road accident data (Stats19), available at: www.data.gov.uk/dataset/road-accidents-safety-data). Stats19 includes information about every accident involving personal injury and at least one vehicle that has been reported to police within 30 days of occurrence. Data may be collected at the scene of the accident or be reported later by those involved in the accident or other members of the public. These data represent the best available information on accidents. Nearly all accidents involving fatalities are reported to police. However, there is still some underreporting of accidents not involving fatalities (UK Department for Transport, 2016b).

Accidents are determined as fatal, serious or slight according to the most severe casualty. Fatalities involve death within 30 days of the accident; most serious casualties involve injuries requiring hospital treatment and the remainder are considered slight casualties. Accident severity is classified by police rather than medical personnel and involves some judgement — particularly as the severity of some injuries might not be apparent at the time of the accident. Further details of these data are available in section 2.3.

As the Stats19 data are, in effect, a census, we can construct a daily series that extends back from 2015 to 1985 — over 30 years, providing data on over 11,000 days. Daily accidents are further split by British Government Office Regions (GORs), yielding some 124,000 observations for analysis.[2] GORs are used as a large proportion of journeys — such as those involving motorways — are likely to cross boundaries for smaller areas, potentially confounding regional effects.

Longitudinal modelling typically shows an association between stock market movements and suicide, with suicides rising when the market declines (Agrrawal, Waggle, & Sandweiss, 2017). Although some road accidents are the result of driver suicide, these are mostly not captured by our data (indeed, where the accidents can be attributed to suicide, they are explicitly excluded from the source data). However, accidents associated with attempted suicide remain in the data (although they cannot be separately identified).

4.3.3 Descriptive statistics

The distribution of returns is symmetric about zero with a mean of 0.04, standard deviation of 1.09 and skewness of -0.43. The distribution has ‘fat tails’, with kurtosis of 12.20. This means the models might struggle to fit returns in the tails. Figure 4.1 shows there is substantial volatility in returns, particularly at the time of the 1987 stock market crash and the 2008 GFC, although there are other periods when returns fluctuate quite markedly.

[2] GORs are East of England, East Midlands, London, North East England, North West England, South East England, South West England, West Midlands, Yorkshire & the Humber, Wales, and Scotland.

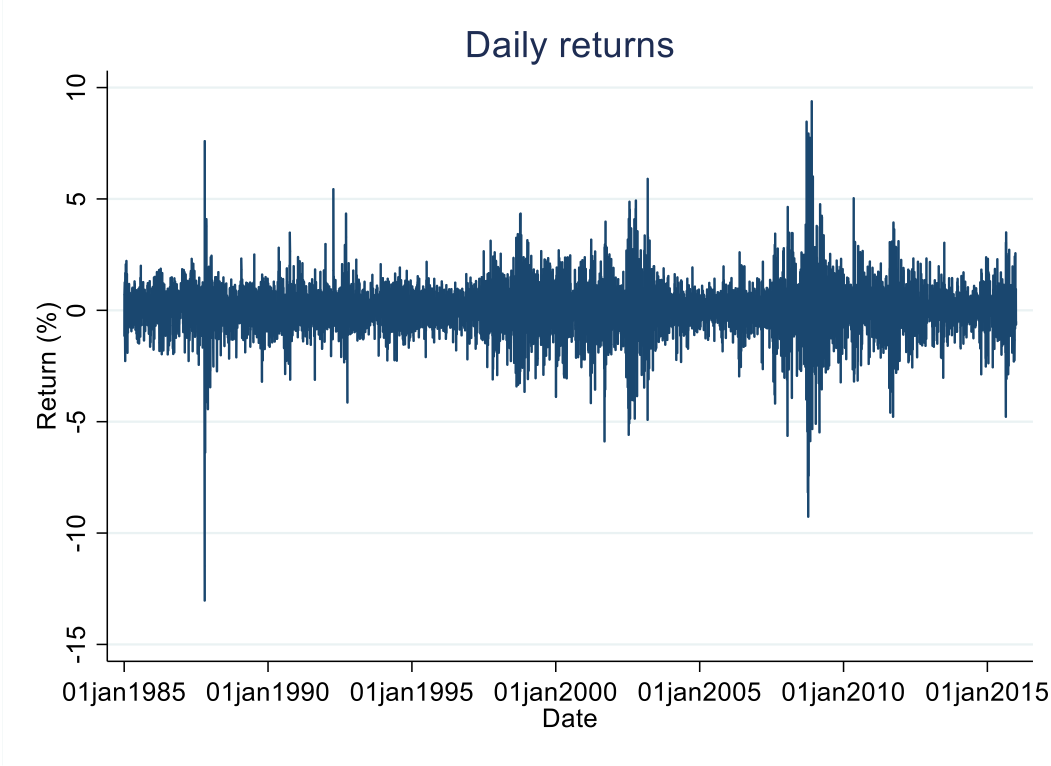

Figure 4.1: Daily returns, weekday sample 1985–2015

There are 7821 daily observations on returns from Monday to Friday (trading days) over the sample period and, although the range is from -14 to 9%, the bulk of the observations (about 95%) are in the range -2 to 2%. The distribution is shown in figure 4.2 and a summary is shown in table 4.2.

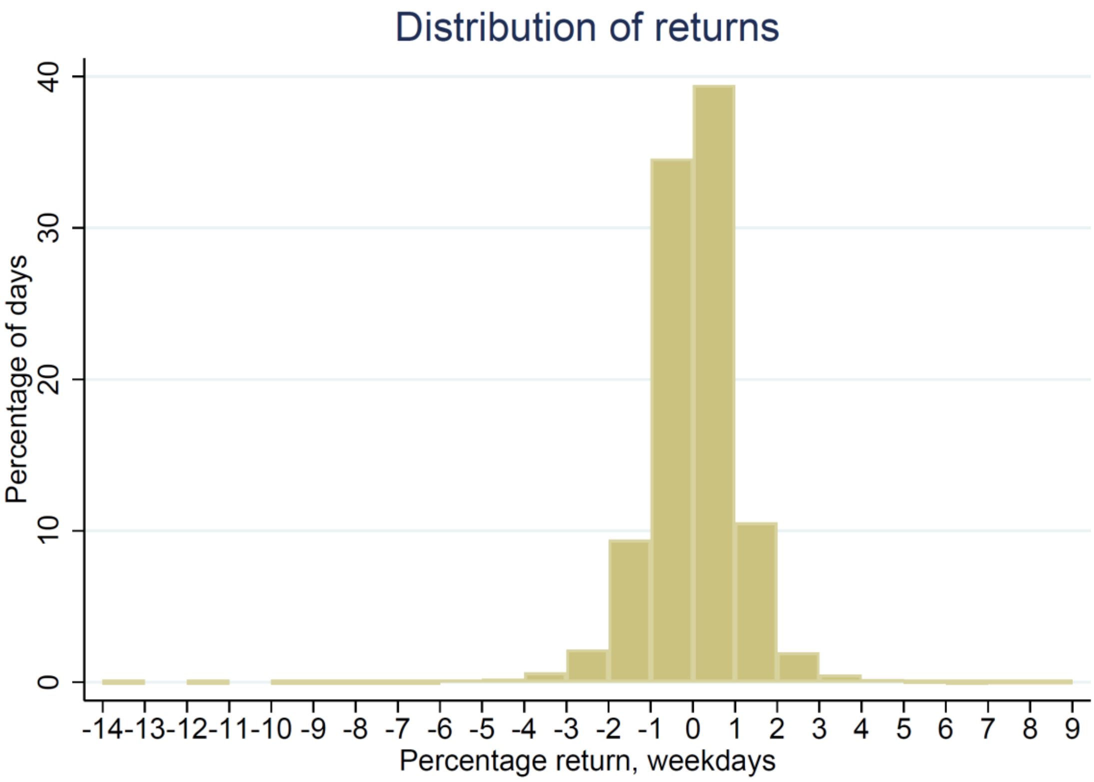

Figure 4.2: Distribution of returns, weekday sample 1985–2015

Table 4.2: Summary of returns, weekdays only, 1985–2015

Return	No. weekdays
Less than -2%	252
-2 to -1%	735
-1 to 0%	2,734
0 to 1%	3,082
1 to 2%	808
Greater than 2%	210
Total	7821

In our analysis, each week is divided into 7 ‘periods’, with 5 periods during the weekdays and 2 on weekends. Descriptive statistics for the average number of accidents per region per period (‘day’) are given in table 4.3. The overall sample includes approximately 6.5 million accidents. Two further samples explore times when the market is closed. The weekday sample includes accidents occurring on weekdays at times when the market is closed and the weekend sample includes all accidents over the weekend. Further explanation of the construction of these periods is described in section 4.4 (particularly figures 4.5, 4.6 and 4.7). Overall there are about 52 accidents per region per 24 hour period, although there is substantial variation with a standard deviation of 27. During weekday periods when the market has closed there are about 24 accidents per region per period and again there is substantial variation. Consistent with weekends being more dangerous for accidents, weekends have more accidents than weekdays with over 45 accidents per region per period.

Table 4.3: Descriptive statistics for number of accidents, 1985–2015[a]

Sample	Mean	SD	Number of region-periods
Accidents			
Overall	52.18	27.26	124,509
Weekday	24.43	14.01	88,913
Weekend	45.02	23.28	35,574
Fatal accidents			
Overall	0.79	0.98	124,509
Weekday	0.48	0.81	88,913
Weekend	0.89	1.13	35,574

[a]Numbers per region per period (day). Number of region-periods is the full estimation sample of region-periods. Overall sample represents all times on all days. Weekday sample represents weekdays at times when the market has closed. Weekend samples run from 5pm Friday to 8am Monday. Further details of these sample splits are provided in section 4.4.

Table 4.4 presents descriptive statistics for accident subsamples defined by accident and driver/vehicle characteristics. On average (across region-periods), most accidents and fatal accidents occur on A roads, followed by Unclassified roads. Most accidents occur during daylight, although there is little difference between the incidence of overall and fatal accidents at night. Fine weather coincides with most accidents and fatal accidents. Alcohol is a factor in more accidents than are drugs. The majority of drivers involved in accidents are male, although the proportion is much higher among fatal accidents. Having a driver aged 25–49 years is most common for accidents and fatal accidents, although per year of age the 18–24 year olds account for more accidents and fatal accidents. Relatively few accidents involve a hit-and-run vehicle. The overwhelming majority of accidents involve cars, which probably relates to the fleet composition.

Table 4.4: Descriptive statistics for accidents by characteristic[a]

	Overall accidents		Fatal accidents	
Sample	Mean	SD	Mean	SD
Road type				
Motorways and A(M) roads	1.78	2.04	0.04	0.20
A roads	24.21	15.74	0.46	0.72
B roads	6.59	3.95	0.11	0.33
C roads	4.56	4.04	0.06	0.25
Unclassified roads	15.04	8.13	0.13	0.37
Light conditions				
Daylight	37.71	21.47	0.46	0.72
Night	14.46	12.31	0.33	0.62
Weather conditions				
Fine weather	41.09	23.67	0.64	0.88
Adverse weather	9.39	13.07	0.13	0.40
Contributory factor				
Alcohol involvement	1.46	1.62	0.04	0.21
Drug involvement	0.16	0.42	0.01	0.11
Driver involvement				
Driver sex				
Male	44.23	23.68	0.72	0.93
Female	20.68	11.67	0.19	0.44
Driver age				
Age 1–17	4.11	3.46	0.04	0.21
Age 18–24	16.25	9.92	0.25	0.53
Age 25–49	34.82	19.19	0.50	0.75
Age 50–64	11.29	6.21	0.19	0.44
Age 65 or over	4.56	3.03	0.10	0.32
Vehicle involvement				
Hit-and-run vehicle	4.81	3.54	0.03	0.18
No-hit-and-run vehicle	47.95	25.10	0.77	0.96
Vehicle type involvement				
Bicycle	5.43	4.44	0.04	0.21
Motorcycle	7.15	6.37	0.14	0.39
Car	45.65	23.46	0.62	0.85
Bus	2.48	2.58	0.03	0.18
Goods vehicle	6.88	5.20	0.19	0.45
Other vehicle	1.24	1.27	0.03	0.17

[a]Numbers per region per period (day). In most cases, for the full sample, the number of region-periods is 124,509 (1985–2015). Exceptions are alcohol and drugs (region-periods=44,176, 2005–2015) and hit-and-run, no-hit-and-run (region-periods=120,494, 1985–2014).

Figure 4.3 shows the relationship between total number of accidents per day and stock market returns. The polynomial fit is mostly quite flat apart from that associated with extreme negative returns. There is regional variation in the levels and patterns for each region (see Figure A.4.1 in appendix).

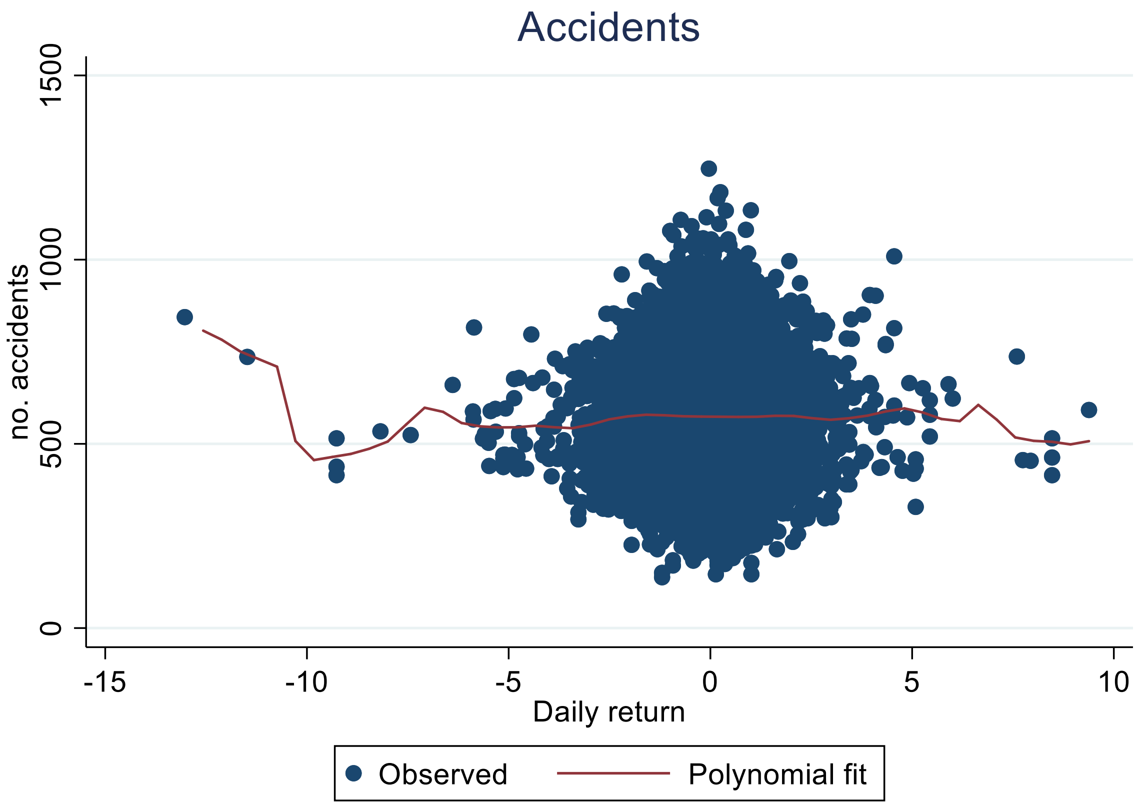

Figure 4.3: Total accidents, 1985–2015

Figure 4.4 shows the number of fatal accidents in Britain. The highest numbers of fatal accidents occur when returns are close to zero and the polynomial fit is flat over most of the range. There is some variation in the trends by region (see Figure A.4.2 in appendix).

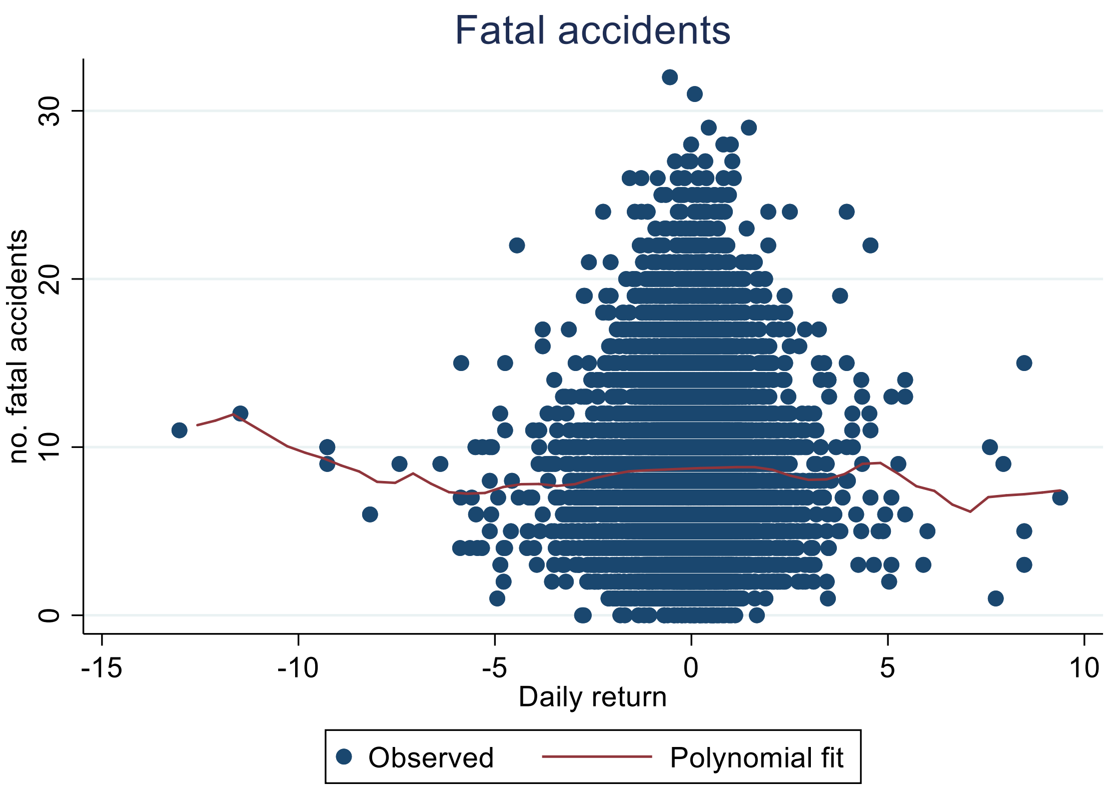

Figure 4.4: Fatal accidents, 1985–2015

There are variations in the number of accidents by road type. Motorways and A(M) roads tend to have the least number of accidents, which is interesting given they have the largest traffic volumes and speeds. The largest number of accidents are on A roads, followed by Unclassified roads, which have the largest road network. Figure A.4.3–Figure A.4.8 show there are regional variations in the relationship between returns and accidents by road type.

4.4 Empirical strategy

The model for the relationship between accidents and returns for the overall sample is shown in figure 4.5. Accidents are aggregated into 7 time periods across the week, with each period beginning at 5pm after the close of market (for consistency with the weekdays, we define weekend periods to begin at 5pm). For each period, accidents are related to the most recent measure of returns based on daily closing prices (R). So, for example, accidents occurring from 5pm Tuesday through 4:59pm Wednesday (period 2) are related to Tuesday's return (which in itself is the log difference between Monday and Tuesday's closing price for the FTSE100).

Weekend returns carry over from Fridays, so all accidents from 5pm Friday until 4:59pm Monday (periods 5, 6 and 7) are related to Friday's return. Returns for non-trading weekdays are recorded as the previous trading day return.

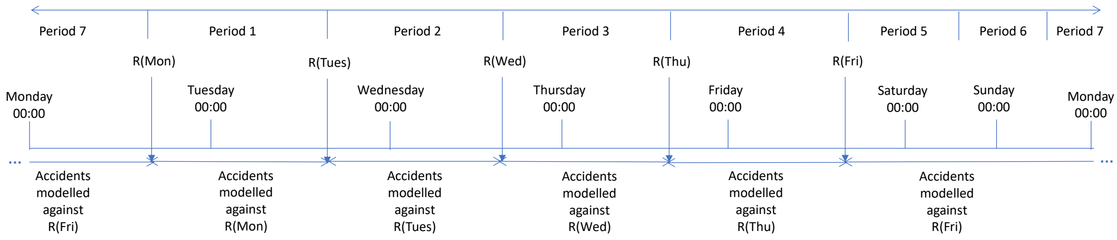

Figure 4.5: Overall model

Figure 4.6 shows the stylised relationship between accidents and returns for the weekday sample. For this sample, only accidents occurring when the market is closed (5pm–7:59am) during weekdays are included. The sample begins after market closing on a Monday. Accidents occurring from 5pm Monday until 7:59am Tuesday (when the market opens) are labelled period 1 accidents and are related to Monday's return (which comprises the log difference in the FTSE100 between Monday and the previous Friday). We relate Friday's return to accidents occurring between Friday 5pm and Saturday 7:59am (period 5).

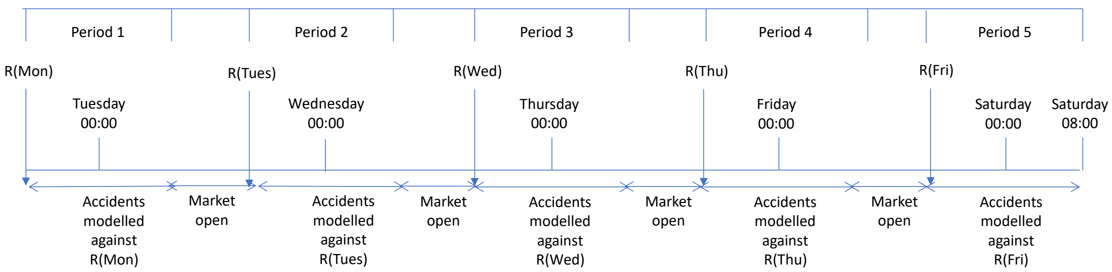

Figure 4.6: Weekday model

The relationship between returns and accidents for the weekend sample is shown in figure 4.7. Again, this sample captures accidents occurring when the market is closed. Accidents are included if they occur between 8am on Saturday and 7:59am on Monday. That is, we take the weekend to begin from the end of the weekday sample (period 6). Periods are defined as 8am–7:59am on the following day. Accidents in these two periods are related to the return from Friday.

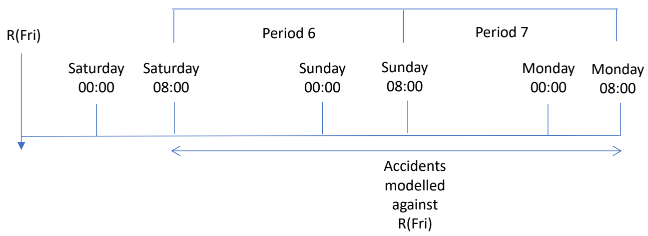

Figure 4.7: Weekend model

Based on limited available literature, we hypothesise:

H1 there will be an increase in total accidents and fatal accidents with negative returns,

H2 there will be a stronger relationship on weekdays after the stock market has closed (a recency effect), and

H3 there will be some heterogeneity in responses according to accident and driver characteristics.

The specification for our models is:

$$lnA_{rt} = \beta_0 + \beta_1 R_{t-1}^{+} + \beta_2 R_{t-1}^{-} + \sum_{i=2}^{7} \beta_{4i} period_{it} + \sum_{j=2}^{372} \beta_{5j} GORmonth_{jt} + \varepsilon_{rt}$$

r=1, … , 11; t=1/1/1985, … , 31/12/2015 (2)

where lnA_{rt} is the natural logarithm of the number of accidents in region *r* in period *t*, R_{t-1} is the lagged return (from the end of the previous period) with R_{t-1}^{+} a continuous measure of positive returns and R_{t-1}^{-} a measure of negative returns. We include a dummy for each period ($period_{it}$), for each region and month in the observation window ($GORmonth_{jt}$) — which acts like a region–time fixed effect — and ε_{rt} is the normal error term for each GOR and time period. Specifications for the weekday and weekend models have fewer period fixed effects according to the fewer periods included but are otherwise the same. We use logarithms for the dependent variable as we believe changes in returns may have a proportional effect on accidents (although we also investigate effects on numbers of accidents in the appendix).

We also estimate equation (2) for fatal accidents. However, there are some days in some regions where there are no fatal accidents. Rather than drop these observations from our sample (as you cannot take the log of zero), we use the inverse hyperbolic sine transformation (asinh) for the dependent variable (Burbidge, Magee, & Robb, 1988; MacKinnon & Magee, 1990). This transformation takes the form

$$y^{*} = ln\left(y + \sqrt{y^{2} + 1}\right) \tag{3}$$

and the dependent variable is the inverse hyperbolic sine of the number of fatal accidents. The additional term in the logarithmic expression allows us to include the zero observations in our estimation, and ‘except for small values of y, asinh(y) = log(2) + log(y)’ (Bahar & Rapoport, 2018, p. F280).[3] Coefficient interpretation is the same as for a logarithmic model, namely that the coefficient shows the percentage change in the outcome variable for a unit change in, say, returns (Clemens & Tiongson, 2017). For comparison with the literature, we also estimate our models for accidents and fatalities using a continuous measure of returns.

Using a fixed effects panel regression means the effects of the stock market are identified by variation within regions within periods in the number of accidents, according to the fixed effects. The region–month fixed effects capture aspects such as region-specific road safety campaigns. Period (day) fixed effects are likely to capture traffic volumes and congestion.[4]

In understanding the relationship between returns and accidents there are many potential confounding factors that are hard to measure or get data on. In our analysis we account for these factors using a fixed effects model with tight identification: within period within region variation. Our approach means we might be losing some valid variation, but the tighter identification does provide great confidence that we are truly capturing the effects of changes in returns on numbers of accidents.

The two most comparable and relevant papers that investigate the relationship between traffic accidents and the stock market also use a fixed effects model, although they treat returns differently. Cotti et al. (2015) have three models which specify returns in terms of a 2008/09 stock market crash indicator variable, a log average monthly closing price of the Dow Jones

[3] Therefore, for values of one and above, there should be a small, almost constant upward shift in the inverse hyperbolic sine function compared with the logarithmic function.

[4] Period fixed effects will also capture these effects for the weekdays when the market is closed, such as bank holidays.

Index, and an indicator for when the monthly return was less than -10%. Giulietti et al. (2020) use the daily stock market return (S&P500) but it enters as a continuous variable, so the estimated effect is linear with no discontinuity. Those authors also adopt an asymmetric effects specification in which they use dummies for categories of positive and negative returns. In our model we also wish to allow for the possibility that there might be asymmetric effects of returns in terms of the sign and size of coefficients for positive and negative returns. Our modelling approach is more flexible than the approaches used in the extant literature, whilst allowing for the possibility that accidents might only respond to negative movements in the share market. To investigate the robustness of our main results, we also consider returns in categorical form. In modelling daily accidents we use natural logarithms as the dependent variable because there is little difference between levels and logarithms in terms of linearity and there are no regions with zero accidents on any days. Moreover, the logarithmic specification allows us to interpret the coefficients as elasticities. For fatal accidents we use the inverse hyperbolic sine transformation to account for zeros. Returns are based on closing prices and are therefore lagged to ensure they occur before the accidents in a given period. We estimate heteroscedasticity-robust standard errors rather than clustered standard errors, as it is not clear at which level they should be clustered.

All estimation was carried out using Stata15.

4.5 Results

Results for the estimated models for three sample specifications for accidents and fatal accidents are presented in table 4.5. For the full sample we see a 1% increase in positive returns leads to a 0.5% increase in accidents and a 1% decrease in negative returns leads to a 0.7% increase in accidents. That is, accidents respond to the absolute value of the percentage change in returns and the function follows a V-shape. A similar but weaker pattern emerges for the weekday model, as a 1% increase in positive returns leads to a 0.2% increase in accidents (although this result is not statistically significant) and a 1% decrease in negative returns leads to a 0.6% increase in accidents. Again the same pattern appears on weekends but the effects are stronger: a 1% increase in positive returns leads to a 0.9% increase in accidents and a 1% decrease in negative returns leads to a 0.6% increase in accidents. These results would be consistent with the hypothesis of changes in returns (positive or negative) leading to cognitive distraction, and distraction is known to be associated with accidents (Galéra et al., 2012; Young & Regan, 2007). The relatively small effect is consistent with low involvement in the stock market and might also result from most changes in returns being small enough that they go unnoticed (Frijters et al., 2015).[5] Adopting a continuous measure of returns, there is a negative relationship that is significant for the weekday sample: as returns increase by 1%, accidents decrease by 0.2%. This is a slightly smaller effect than was found by Giulietti et al. (2020) (0.6%), although their results relate to fatal accidents. Our results are smaller again and not significant for the full sample or the weekend sample.

For fatal accidents there are some days in some regions with zeros. Rather than drop those observations from our estimation sample, we use the inverse hyperbolic sine transformation. Coefficient interpretation is the same as for a logarithmic model. It seems there is a significant negative effect for negative returns in that as we get larger negative returns we get *fewer* fatal accidents. The same pattern is observed for our weekday sample. For the weekend sample there are no statistically significant effects. This negative relationship is consistent with some literature that finds inattention (rather than the broader concept of distraction) is associated with reduced accident severity (Donmez & Liu, 2015; Neyens & Boyle, 2008), which might be sufficient to convert what would have been fatal accidents into less severe accidents. For comparison with the literature, we also report results for the continuous measure of returns. Here we see a positive and significant relationship on weekdays but no significant effects for the full sample or the weekend sample. On weekdays as returns increase by 1%, fatal accidents increase by 0.4%. This stands in contrast to Giulietti et al. (2020), who found the opposite relationship for the US.

[5] The finance industry is concentrated in London, and it may appear that this drives our results. However, this should not be the case as we have a fixed effect for London included in the model.

Table 4.5: Modelling results, 1985–2015[a]

	Full sample	Weekdays	Weekends
Accidents			
Positive returns	0.005***	0.002	0.009***
	(0.001)	(0.002)	(0.003)
Negative returns	0.007***	0.006***	0.006*
	(0.001)	(0.002)	(0.003)
Continuous returns	-0.001	-0.002**	0.002
	(0.001)	(0.001)	(0.001)
Fatal accidents			
Positive returns	-0.002	0.001	0.001
	(0.003)	(0.003)	(0.007)
Negative returns	-0.006**	-0.006**	0.004
	(0.003)	(0.003)	(0.006)
Continuous returns	0.002	0.004**	-0.002
	(0.002)	(0.001)	(0.003)
Period fixed effects	✓	✓	✓
GOR-month fixed effects	✓	✓	✓
Number of region-periods	124,509	88,935	35,574

[a]Each column is a separate regression using positive and negative returns or continuous returns for the sample identified. Accidents are modelled using logarithms. Fatal accidents are modelled using the inverse hyperbolic sine transformation. Coefficient interpretation is the same between the two models. Daily returns are as specified in the stylised models in figures 4.5–4.7. The full sample covers all hours in all 7 time periods, with each period beginning at 5pm. The weekday sample relates to weekdays and covers periods 1–5 with each period beginning at 5pm and ending at 8am. The weekend sample relates to weekends and covers periods 6 and 7, with each period beginning at 8am to avoid overlap with the weekday model. For weekend periods, the relevant return is from the Friday. For non-trading days, we use the latest available trading day return. Robust standard errors shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Further results are given in the appendix. Coefficients for the levels form of the models are given in Table A.4.2 in the appendix. Most results are qualitatively the same in terms of signs and significance. The GFC represented a period of increased volatility in returns and may have led to a change in the relationship with accidents. Indeed, we find a slightly stronger relationship post-GFC for overall accidents. However, the significant relationship between fatal accidents and negative returns becomes insignificant post-GFC (see Table A.4.8 in appendix). Modelling returns over 7-day periods shows weaker results for accidents and no significant effects for fatal accidents (see Table A.4.10 in appendix).

4.5.1 Disaggregated modelling results

To better understand the results, here we break down the full sample (all days of the week) from table 4.5 by various characteristics of accidents (table 4.6) and the vehicles/drivers involved (table 4.7). Characteristics are included in order to observe the effects of the stock market in relation to road and climactic conditions (which could represent driving choices), vehicle types and driver characteristics (which could represent potentially different driving behaviour risks).

All measures are at the accident level, so, for example, male driver involvement in table 4.7 indicates that at least one male driver was involved in the accident; there might or might not be a female involved in those accidents. For vehicle and driver characteristics it is not known if the specified vehicle/driver is 'at fault'. Each 'line' is a separate regression on a subset of accidents and includes period (day) and GOR-month fixed effects and we estimate robust standard errors. In each model the dependent variable uses the inverse hyperbolic sine transformation so as to include days/regions where there are zero accidents and zero fatal accidents of a particular type. Therefore sample sizes are the same.[6] Most of the results are similar to the full sample results from table 4.5.

Overall there is a symmetric effect of returns on accidents, in that both positive and negative returns increase accidents. This result is robust to variations in the sample definition — therefore it is not the result of an aggregation bias. This finding is consistent with the hypothesis that stock market news — be it good or bad — results in driver distraction, and driver distraction is a major contributor to accidents (Young & Regan, 2007).[7] In essence, changes in the stock market induce positive or negative moods which 'load up' cognitive resources and decrease capacity to attend to tasks (Mitchell & Phillips, 2007). The effects are typically small because stock market involvement in the middle of our observation period is some 34% (see Guiso et al., 2003).[8] Adopting a continuous measure of returns, we find significant negative effects of a 1% increase in returns for a few types of accident — on motorways/A(M) roads (-0.4%), on B roads (-0.3%), in daylight (-0.1%) and in adverse weather conditions (-1.2%). Similarly, significant negative effects are found for accidents involving bicycles (-0.4%), motorcycles (-0.4%) and goods vehicles (-0.5%). Although not strictly comparable, Cotti et al. (2015) find a more than 10% decrease in monthly returns leads to a 5.25% increase in alcohol-related accidents in the US. However, we find no such effect — indeed although not statistically

[6] Within 'families' of outcomes (i.e. groups of sample splits), we also calculated family-wise p values using the Westfall and Young (1993) procedure with 5,000 bootstraps to account for multiple hypothesis tests using the wyoung Stata command written by Jones, Molitor, and Reif (2018). Most of the significance levels were similar to those using unadjusted p values.

[7] The increase in accidents would also be consistent with a change in risk preferences, with individuals preferring to take on more risk (say, a more cavalier attitude to driving) as the stock market moves. However, this is not something that we can measure in this study.

[8] Larger effects are estimated for drivers aged 50–64 and they are likely to have a larger interest in the stock market.

significant, our equivalent coefficient on accidents involving alcohol would be relatively large and positive (about 7%).

For fatal accidents, most of the significant effects for negative returns are negative — as with the overall fatal accidents result, negative returns decrease fatal accidents of most types. The exception is drugs-involved fatal accidents which are positive and significant. That is, as returns decline, fatal accidents involving drugs increase. There are very few significant effects associated with positive returns and they tend to work to reduce fatal accidents. Again, this result is consistent with the hypothesis of driver inattention reducing fatal accidents (Young & Regan, 2007). Considering continuous returns, we find positive effects on Unclassified roads (0.2%) and during fine weather (0.4%) but negative effects in adverse weather (-0.2%). Driver age also has some influence, with effects of 0.3% for when drivers aged 18–24 are involved and -0.2% when drivers aged 50–64 are involved. Modelling results in levels are included in Table A.4.3 and Table A.4.4 in the appendix and give qualitatively similar results.

Table 4.6: Modelling results for accidents and fatal accidents by accident characteristic sample[a]

	Accidents			Fatal accidents		
Sample	Negative returns	Positive returns	Continuous returns	Negative returns	Positive returns	Continuous returns
Overall model	*0.007****	*0.005****	*-0.001*	*-0.006***	*-0.002*	*0.002*
	(0.001)	*(0.001)*	*(0.001)*	*(0.003)*	*(0.003)*	*(0.002)*
Road type						
Motorways and A(M) roads	0.005*	-0.002	-0.004**	-0.000	-0.001	-0.0003
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.0004)
A roads	0.003*	0.004**	0.001	-0.000	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)
B roads	0.012***	0.006**	-0.003**	-0.002	-0.002*	-0.0003
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
C roads	0.007**	0.004	-0.002	-0.002*	-0.001	0.0001
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Unclassified roads	0.008***	0.007***	-0.001	-0.003**	0.0005	0.002**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Light conditions						
Daylight	0.008***	0.006***	-0.001*	-0.006**	-0.004*	0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Night	0.006***	0.008***	0.001	-0.001	0.002	0.002
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Weather conditions						
Fine weather	0.009***	0.012***	0.001	-0.006**	0.002	0.004**
	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)	(0.001)
Adverse weather	-0.002	-0.027***	-0.012***	-0.000	-0.004**	-0.002**
	(0.007)	(0.007)	(0.004)	(0.002)	(0.002)	(0.001)
Contributory factor						
Alcohol involvement	0.001	0.007	0.003	0.004***	0.003*	-0.001
	(0.005)	(0.005)	(0.002)	(0.001)	(0.001)	(0.001)
Drug involvement	0.005*	0.004	-0.001	-0.000	-0.001	-0.0003
	(0.003)	(0.003)	(0.001)	(0.0008)	(0.001)	(0.0004)

[a]Each row is a separate regression using positive and negative returns or continuous returns for the sample identified. Accidents and fatal accidents are modelled using the inverse hyperbolic sine transformation. Coefficient interpretation is the same as a logarithmic model. Models contain period and GOR-month fixed effects. Each observation represents daily accidents over a 24 hour period beginning at 5pm. Weekdays and weekends are included. For weekend periods, the relevant return is from the Friday. For non-trading days, we use the latest available trading day return. Sample runs from 1985–2015 except for contributory factors which run from 2005–2015. Robust standard errors shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.7: Modelling results for accidents and fatal accidents by driver/vehicle characteristic sample[a]

Sample	Accidents			Fatal accidents		
	Negative returns	Positive returns	Continuous returns	Negative returns	Positive returns	Continuous returns
Driver involvement						
Driver sex						
Male	0.006***	0.005***	-0.001	-0.006**	-0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)
Female	0.009***	0.007***	-0.001	-0.002	-0.004**	-0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Driver age						
Age 1–17	0.007**	0.004	-0.002	-0.001	-0.000	0.0002
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.0005)
Age 18–24	0.005***	0.005**	-0.0003	-0.004**	0.001	0.003**
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Age 25–49	0.006***	0.004***	-0.001	-0.000	-0.002	-0.001
	(0.001)	(0.002)	(0.001)	(0.003)	(0.003)	(0.001)
Age 50–64	0.011***	0.008***	-0.002	0.000	-0.003*	-0.002*
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Age 65 or over	0.007**	0.002	-0.002	0.000	0.000	-1.11e-05
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Vehicle involvement						
Hit-and-run vehicle	0.007**	0.007**	3.19e-05	-0.000	0.000	0.0001
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.0004)
No-hit-and-run vehicle	0.005***	0.004***	-0.001	-0.006**	-0.003	0.001
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)
Vehicle type involvement						
Bicycle	0.017***	0.010***	-0.004**	-0.001	-0.000	0.0004
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.0005)
Motorcycle	0.014***	0.006**	-0.004**	-0.002	-0.001	0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
Car	0.006***	0.005***	-0.001	-0.005*	-0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)
Bus	0.007**	0.003	-0.002	0.000	0.001	0.001
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.0004)
Goods vehicle	0.017***	0.007**	-0.005***	-0.001	-0.002	-0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
Other vehicle	0.004	0.004	-3.33e-05	-0.002***	-0.002***	-1.13e-05
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.0004)

[a]Each row is a separate regression using positive and negative returns or continuous returns for the sample identified. Accidents and fatal accidents are modelled using the inverse hyperbolic sine transformation. Coefficient interpretation is the same as a logarithmic model. Models contain period and GOR-month fixed effects. Each observation represents daily accidents over a 24 hour period beginning at 5pm. Weekdays and weekends are included. For weekend periods, the relevant return is from the Friday. For non-trading days, we use the latest available trading day return. Sample runs from 1985–2015 except for hit-and-run/no-hit-and-run which run from 1985–2014. Individuals aged under 18 are few and mostly bicycle riders. Robust standard errors shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

There might also be a wealth effect if accidents in wealthier areas show a different response to returns, relative to poorer areas. In this analysis we investigate the relationship of accidents to returns at county level (and assume accidents occur in the same area as the driver resides). We choose county level to reduce income variability within areas. Using Office of National Statistics (ONS) data on mean gross disposable income per capita at Nomenclature of Territorial Units for Statistics (NUTS) 3 level, we aggregate to county level and identify the counties in the top and bottom income deciles (Table A.4.5). The top income decile comprises Surrey incl. Met Police District, Greater London/London, Hertfordshire incl. Met Police District, Buckinghamshire and Oxfordshire. The mean income ranges from about £23,000 to £28,000. The bottom income decile comprises South Wales, Durham (excl. Cleveland), Cleveland, Tyne & Wear, South Yorkshire and West Midlands. The mean income ranges from about £14,000 to £15,000.

Having identified the counties in the top and bottom income deciles, we then estimate the overall model for these two groups separately using the inverse hyperbolic sine transformation to allow for some counties in some regions having zero accidents on some days (table 4.8). These results indicate the stock market has the largest effect on the poorer counties and that both positive and negative returns increase accidents. There is also a somewhat smaller positive effect from positive returns in top decile counties, indicating accidents in wealthier counties increase in response to 'good news' from the stock market. Although those in the bottom income decile are less likely to own shares, this result is consistent with a 1% change in returns having a larger income effect for the poor than the rich. These results are also consistent with the hypothesis that wealthier investors are more informed about what movements in the stock market mean in terms of paper losses and they are potentially more used to (at least small) movements in the stock market (Cotti et al., 2015). Considering continuous returns, there is a small and insignificant relationship with accidents in both top and bottom income decile counties. For fatal accidents there is no statistically significant relationship with returns (positive, negative or continuous) in either the top or the bottom decile counties. This suggests the response to returns comes in the form of less severe accidents due to minor distractions. It might also be the case that there is insufficient variation in the number of fatal accidents at county level to identify an effect. Results for levels models are shown in Table A.4.6 in the appendix and are qualitatively the same in terms of coefficient signs and significance in most cases.

Table 4.8: Modelling results for accidents and fatalities by counties in the top and bottom income deciles, 1985–2015[a]

Sample	Accidents			Fatal accidents		
	Negative returns	Positive returns	Continuous returns	Negative returns	Positive returns	Continuous returns
Top decile	0.002	0.007**	0.003	-0.002	0.000	0.001
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)
Bottom decile	0.008***	0.009**	2.60e-05	-0.001	-0.001	0.0001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)

[a]Each row is a separate regression using positive and negative returns or continuous returns for the sample identified. Accidents and fatal accidents are modelled using the inverse hyperbolic sine transformation. Coefficient interpretation is the same as a logarithmic model. Models contain period and county-month fixed effects. Each observation represents daily accidents over a 24 hour period beginning at 5pm. Weekdays and weekends are included. For weekend periods, the relevant return is from the Friday. For non-trading days, we use the latest available trading day return. Robust standard errors shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.6 Robustness checks

The relationship between accidents and the stock market might be sensitive to the specification of returns. In this section we investigate the robustness of results to a change in the way returns are incorporated in the models for accidents and fatal accidents.

4.6.1 Categorical returns

For each main model estimated previously (see equation 2) we vary the treatment of returns by specifying returns using dummy variable indicators for whether the return was less than -2%, between -2% and -1%, between -1% and 1%, between 1% and 2%, and greater than 2%, with -1 to 1% as the reference category. We use 2% (and -2%) as cut points as this is very close to two standard deviations in returns, which is what the literature tends to use to define large changes (see, for example, Ratcliffe & Taylor, 2015). For ease of exposition, we refer to changes in the range 1 to 2% (and -2 to -1%) as moderate returns and in the range -1 to 1% as small returns. As per the main models, period and GOR-month fixed effects are included and we estimate robust standard errors. The models are estimated on the full sample, weekdays and weekends (table 4.9) using logarithms for total accidents and the inverse hyperbolic sine transformation for fatal accidents so the sample sizes are the same.

For the categorical returns models we see that the full sample shows a V-shape in returns similar to the main model with asymmetric returns. That is, relative to returns in the range -1 to 1%, a large return of greater than 2% increases accidents by 2.0%. A moderate return in the range 1 to 2% has a positive but insignificant effect. Moderate reductions in returns (in the range -2 to -1%) are associated with a 1.4% increase in accidents and the coefficient on large negative returns (less than -2%) is not significant. The pattern of coefficients is consistent with changes in returns leading to driver distraction and resulting in additional accidents. For the weekday sample, we see that there is also a V-shape, although only the coefficient on returns of -2 to -1% is highly significant. On weekends there is broadly a V-shape in the pattern of coefficients (although the coefficient on large negative returns is negative and marginally significant). For fatal accidents the picture is somewhat different, as almost none of the coefficients are significant. Again, results for levels models are provided in Table A.4.7 in the appendix and show qualitatively similar results in most cases.

Table 4.9: Categorical and continuous positive and negative returns modelling results, 1985–2015[a]

	Full sample		Weekdays		Weekends	
	(1)	(2)	(3)	(4)	(5)	(6)
Accidents						
R ≥2%	0.020***		0.013*		0.019*	
	(0.005)		(0.008)		(0.010)	
1≤R<2%	0.003		-0.004		0.011**	
	(0.003)		(0.004)		(0.005)	
-2≤R<-1%	0.014***		0.016***		0.015***	
	(0.003)		(0.004)		(0.005)	
R<-2%	-0.002		-0.001		-0.020**	
	(0.005)		(0.007)		(0.009)	
Positive returns		0.005***		0.002		0.009***
		(0.001)		(0.002)		(0.003)
Negative returns		0.007***		0.006***		0.006*
		(0.001)		(0.002)		(0.003)
Fatal accidents						
R ≥2%	-0.002		0.009		-0.024	
	(0.011)		(0.011)		(0.024)	
1≤R<2%	0.002		0.001		0.000	
	(0.006)		(0.006)		(0.012)	
-2≤R<-1%	-0.007		-0.011*		0.001	
	(0.006)		(0.006)		(0.013)	
R<-2%	-0.014		-0.013		0.003	
	(0.010)		(0.009)		(0.021)	
Positive returns		-0.002		0.001		0.001
		(0.003)		(0.003)		(0.007)
Negative returns		-0.006**		-0.006**		0.004
		(0.003)		(0.003)		(0.006)
Period fixed effects	✓	✓	✓	✓	✓	✓
GOR-month fixed effects	✓	✓	✓	✓	✓	✓
Number of region-periods	124,509	124,509	88,935	88,935	35,574	35,574

[a]Each column is a separate regression using categorical returns or positive and negative returns for the sample identified. Accidents are modelled using logarithms. Fatal accidents are modelled using the inverse hyperbolic sine transformation. Coefficient interpretation is the same between the two models. R denotes daily returns as specified in the stylised models in figures 4.5–4.7. Models 1 and 2 cover all hours in all 7 time periods, with each period beginning at 5pm. Models 3 and 4 relate to weekdays and cover periods 1–5 with each period beginning at 5pm and ending at 8am. Models 5 and 6 relate to weekends and cover periods 6 and 7, with each period beginning at 8am to avoid overlap with the weekday models. For weekend periods, the relevant return is from the Friday. For non-trading days, we use the latest available trading day return. Models 1, 3 and 5 include returns as dummy variables. The reference category for these models is -1%≤R<1%. Models 2, 4 and 6 include returns as continuous positive or negative variables. Robust standard errors shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.7 Conclusions

Over the past 20 years, several papers have investigated the effects of the stock market and various health conditions, with most papers finding health worsens when the stock market drops. This chapter complements and extends this literature, by investigating the effects of both positive and negative stock market returns on overall and fatal road accidents for all types of vehicle at the region level for Britain. We use daily data on accidents and FTSE100 returns spanning some 30 years. Our tight fixed effects model specification considers movements in accidents within a month and region within Britain and allows for a nuanced approach in which the tightly specified models control for confounding factors on which we have no data (such as traffic volumes and congestion).

There is no consensus in the literature on model specification. Rather, two related papers compare various specifications. In this vein, we adopt a main specification and explore several alternatives. To date, the two papers that have considered the relationship between fatal road accidents in the US and stock market performance have both found fatal accidents increase when the market weakens. When we analyse the effect of a continuous measure of returns on total accidents, we find no significant effect for the full sample but a significant negative effect on weekdays (but with a smaller coefficient than Cotti et al. (2015) and Giulietti et al. (2020) found for fatal accidents in the US). However, a more comparable sample relates to fatal accidents and we find the opposite effect to that in the literature — a significant positive effect on weekdays.

In response to positive and negative returns, we find a reasonably robust V-shape for overall accidents — positive and negative returns increase accidents — and this relationship is also found when we break down overall accidents by characteristics. Thus, we find support for our main hypothesis (and consistency with the limited literature), but we also find an additional somewhat unexpected effect of positive returns on overall accidents. For fatal accidents we get a negative effect for negative returns — fatal accidents decline as returns go down overall and on weekdays, in contrast to our hypothesis and the literature. As we disaggregate the sample by fatal accident characteristics, most of the significant effects are also negative with fatal accidents declining as returns decrease and there is some heterogeneity, supporting our hypothesis. However, accidents involving drugs show increased fatal accidents as returns decline. In contrast to our hypothesis, we do not find a stronger relationship on weekdays as we might expect if there is a recency effect and, in fact, there is a much weaker relationship with positive returns on weekdays for overall accidents. There is also no significant strengthening of the relationships for fatal accidents on weekdays.

In terms of counties, the rich respond positively to positive returns and the poor counties show the familiar V-shape relative to returns, consistent with a given change in return having a larger effect on areas with relatively small incomes. There are no significant effects for the rich and poor counties in relation to fatal accidents. However, this could be due to insufficient variation in road accidents at this level.

These results might suggest a substitution effect in accidents — as returns go down people try to drive more conservatively and have fewer fatal accidents but inattention leads to more minor accidents, so overall accident severity declines. The results also imply that as returns go up fatal accident numbers are unaffected.

Our results are not without parallel. Although considering consumer confidence rather than the stock market per se, Burke and Teame (2018) found no effect on road fatalities in Australia. Economic uncertainty may be correlated with stock market movements, and this would make the results of Vandoros et al. (2018) relevant. In their paper, greater uncertainty was linked to increases in road accidents. If positive and negative stock market movements are associated with uncertainty, this may go some way to corroborating our finding of a V-shape for overall accidents. Broader health literature on the effects of the stock market may also support our findings of both positive and negative changes worsening health (increasing accidents). For example, both H. Lin et al. (2013) and Ma et al. (2011) found changes in the stock market increased mortality in China around the time of the GFC.

In terms of a policy response, awareness campaigns focussing on the impacts of mental and emotional shocks on driving behaviour, particularly driver distraction and inattention, could mitigate the effects of more extreme positive and negative stock market movements.

Appendix

Table A.4.1: Data processing steps

Stats19 data (1985-2015)
GOR level — extract vehicle and accident characteristics
Rename variables for consistency across years where required
Generate binary variables that can be aggregated later to calculate the number of observations in each disaggregated category
All generated vehicle variables aggregated to accident level for merging with accident level data later.
Generate GOR indicator
Generate indicators for market open hours, market closed (weekday) hours and market closed (weekend) hours
Create separate dataset for overall sample, weekday sample and weekend sample by aggregating combinations of hours
Fill variables for missing days (no accidents) with zeros
Merge contributory factors data (alcohol and drugs)
County level — Extract overall and fatal accidents data
Rename variables for consistency across years where required
Generate county indicator
Combine market open hours, market closed (weekday) hours and market closed (weekend) hours into periods
Generate indicators for periods (days)
Create dataset for overall sample
Fill variables for missing days (no accidents) with zeros
Merge county income data for deciles
Calculate per capita income measures for each county and identify deciles
FTSE data (1985-2015)
Extract FTSE100 data
Merge with accidents data (4 files)
Merged Stats19 and FTSE data (3 datasets at GOR level, 1 dataset at county level, each operated on in the same way as below)
Generate day sequence and GOR-month-sequence variable
Generate daily returns variables and categorical analogue, based on current and previous trading day FTSE levels
Generate 7 day returns variables, assuming FTSE levels carry over on non-trading days

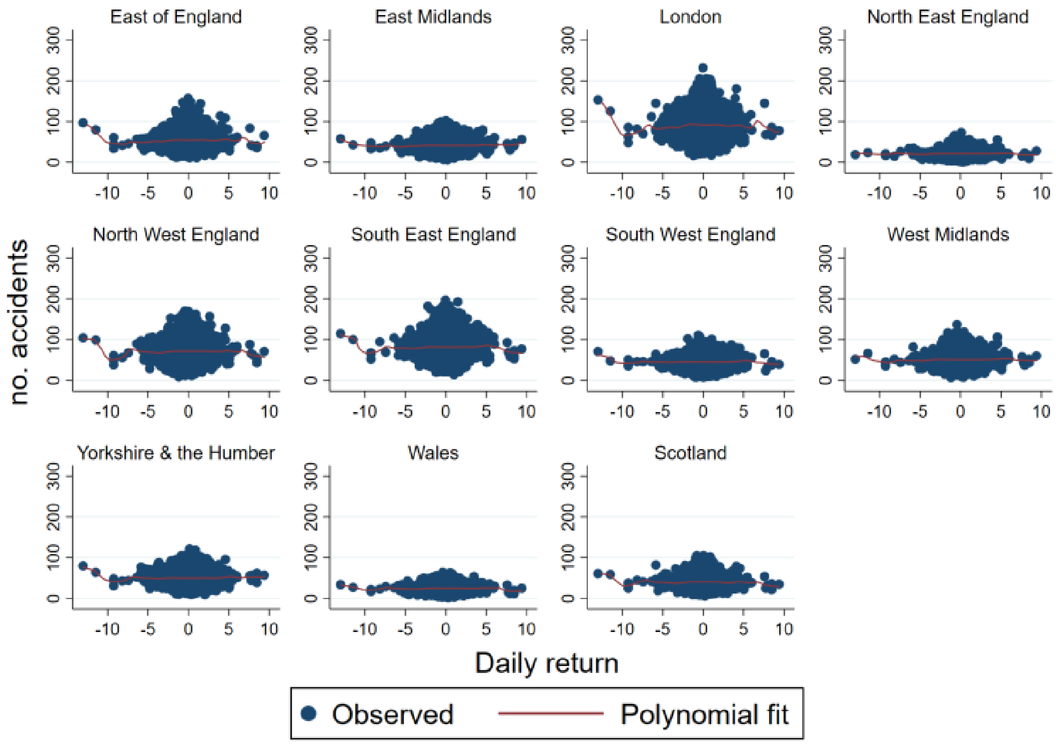

Figure A.4.1: Accidents by region, 1985–2015

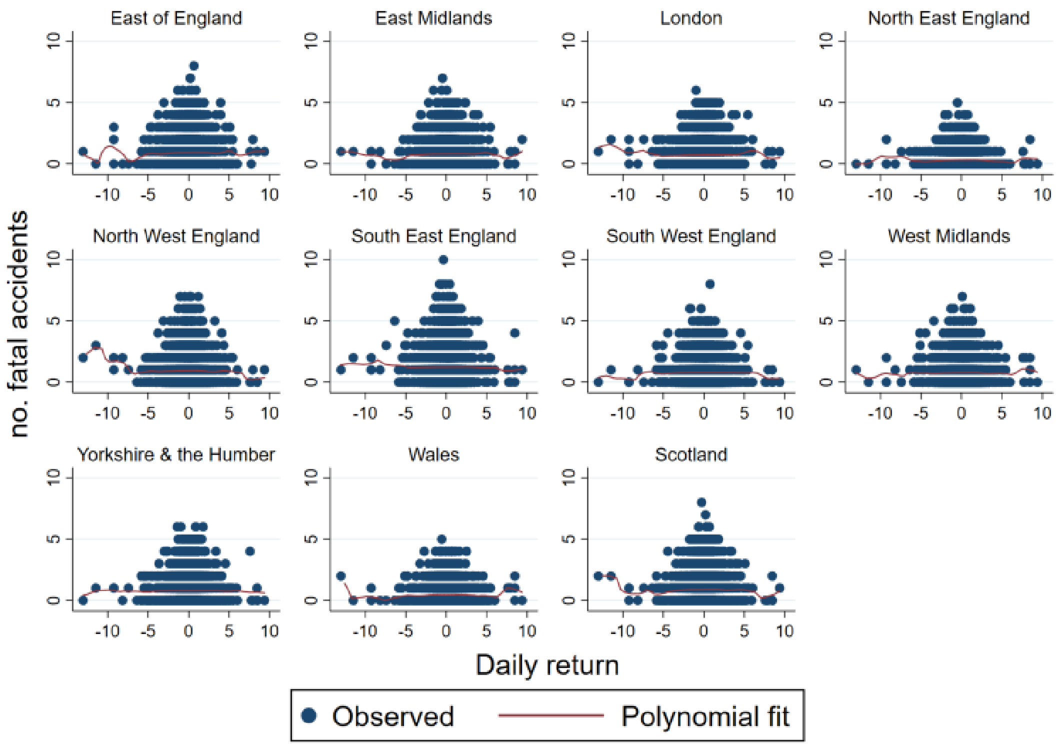

Figure A.4.2: Fatal accidents by region, 1985–2015

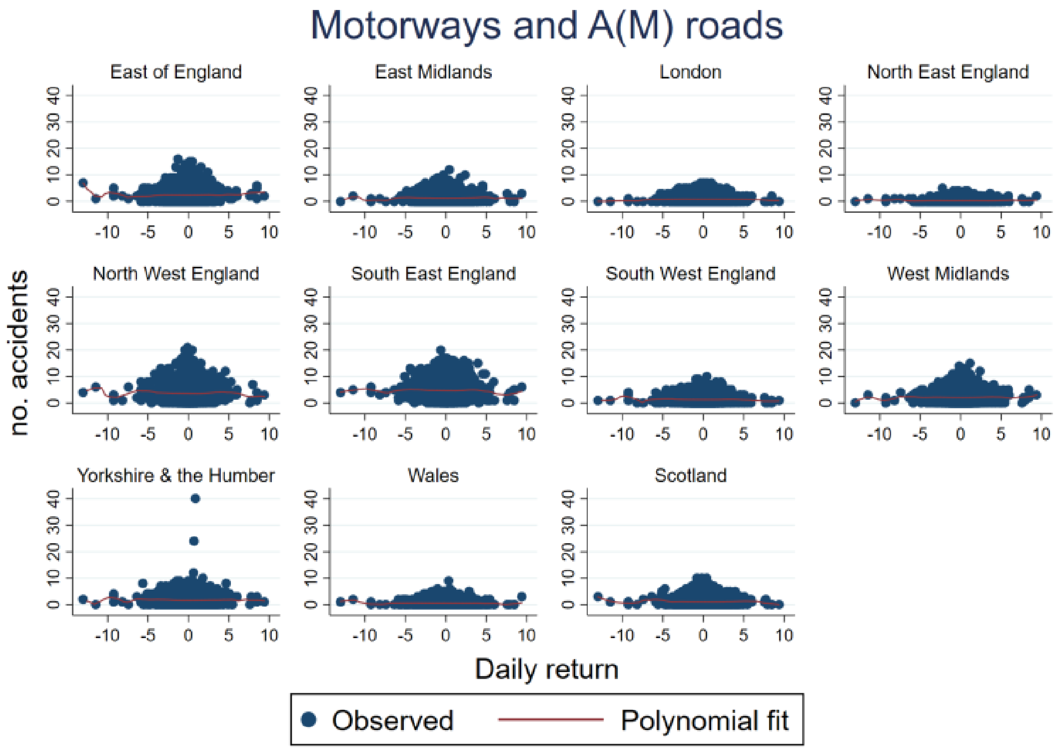

Figure A.4.3: Accidents on motorways and A(M) roads by region, 1985–2015

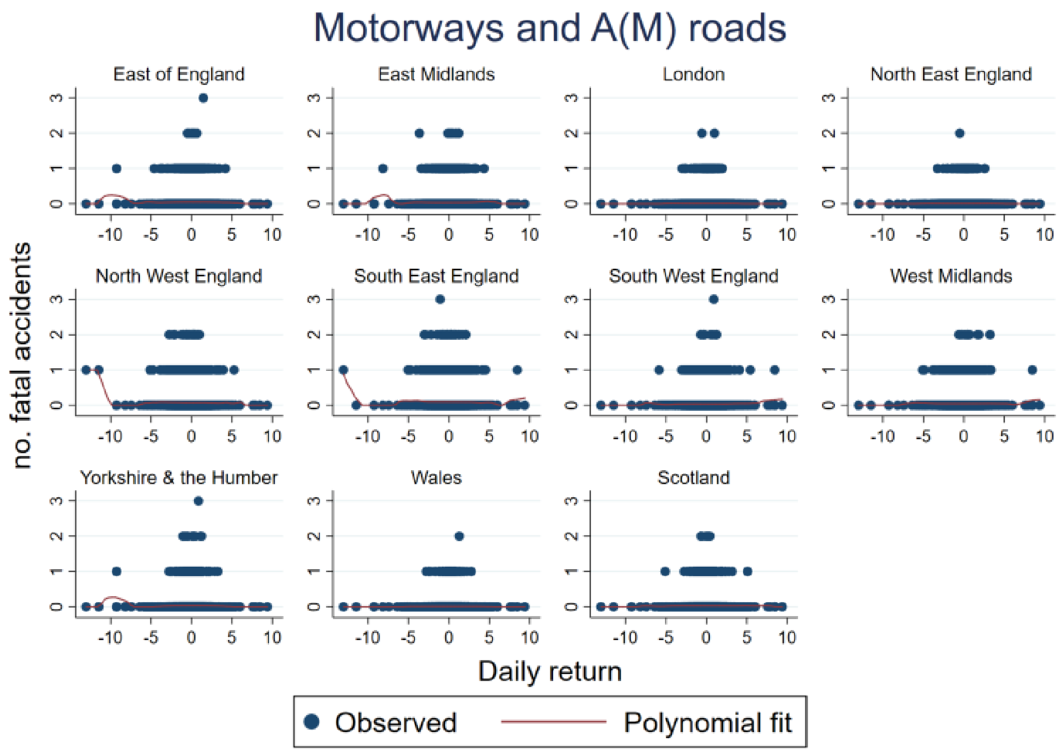

Figure A.4.4: Fatal accidents on motorways and A(M) roads by region, 1985–2015

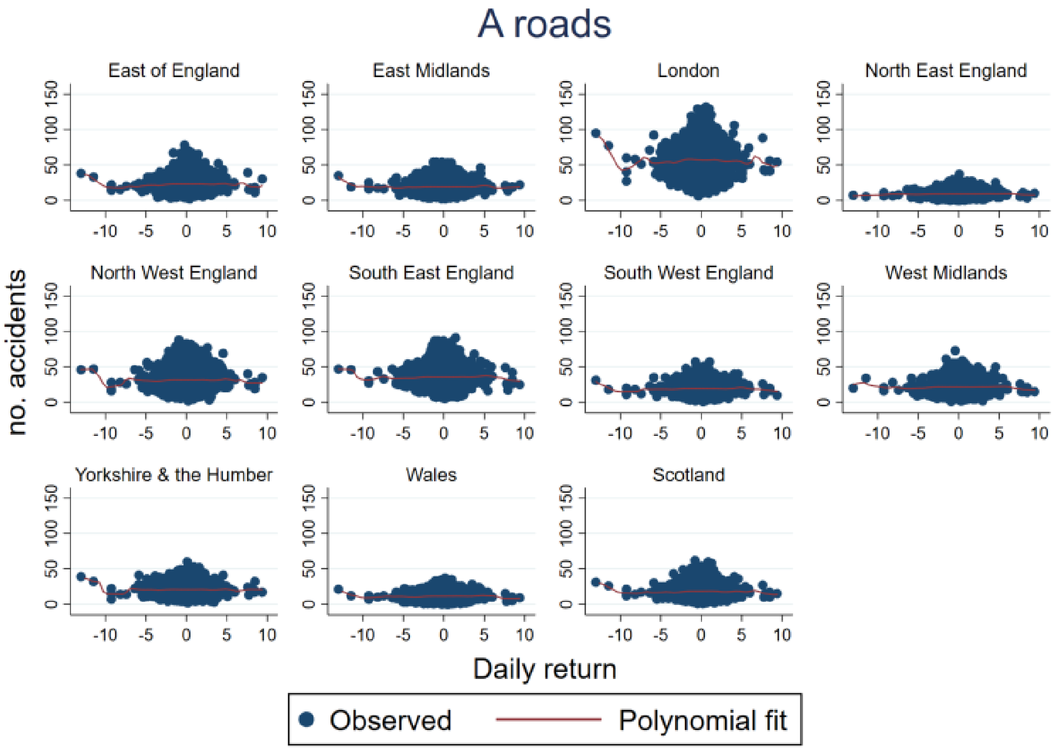

Figure A.4.5: Accidents on A roads by region, 1985–2015

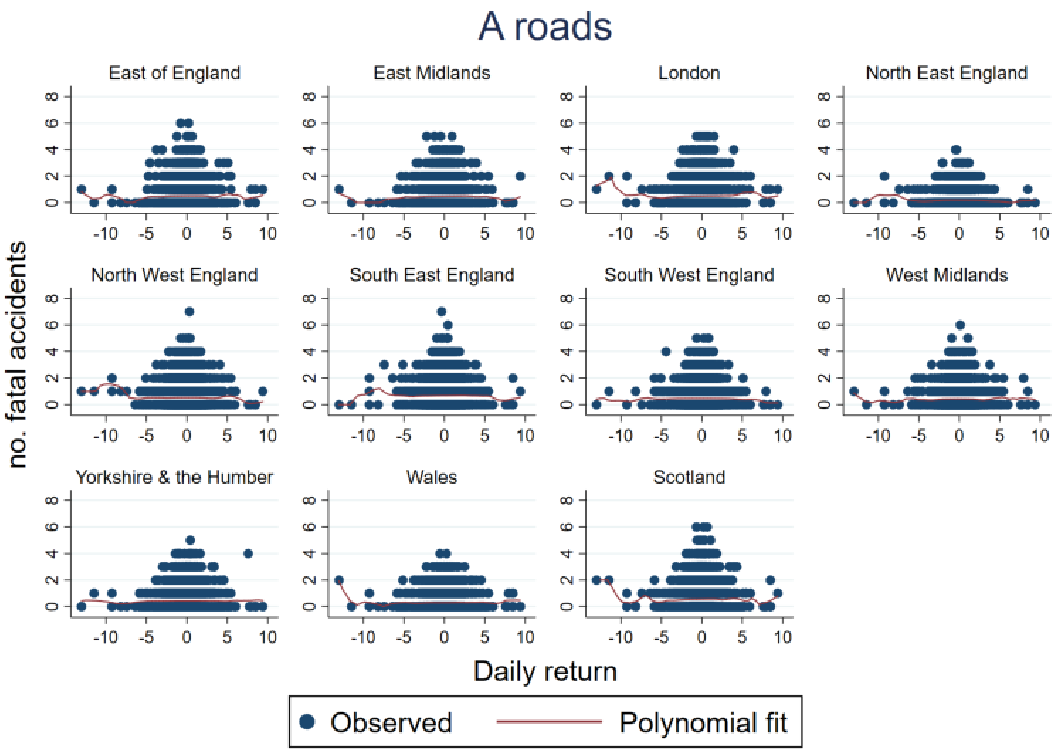

Figure A.4.6: Fatal accidents on A roads by region, 1985–2015

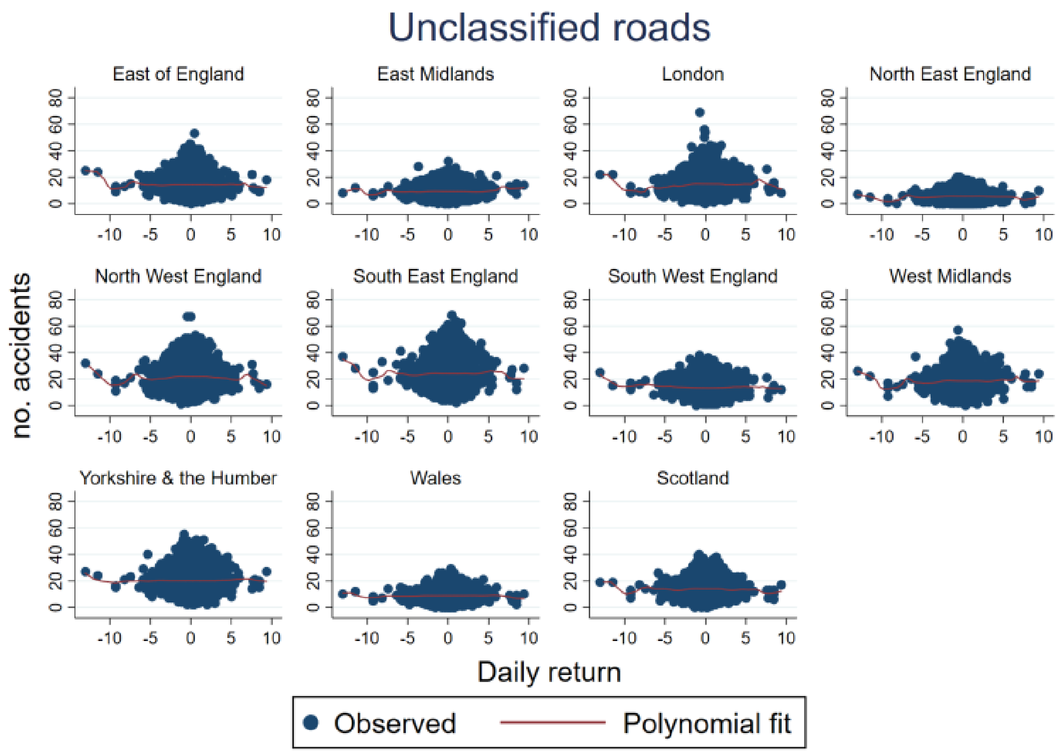

Figure A.4.7: Accidents on Unclassified roads by region, 1985–2015

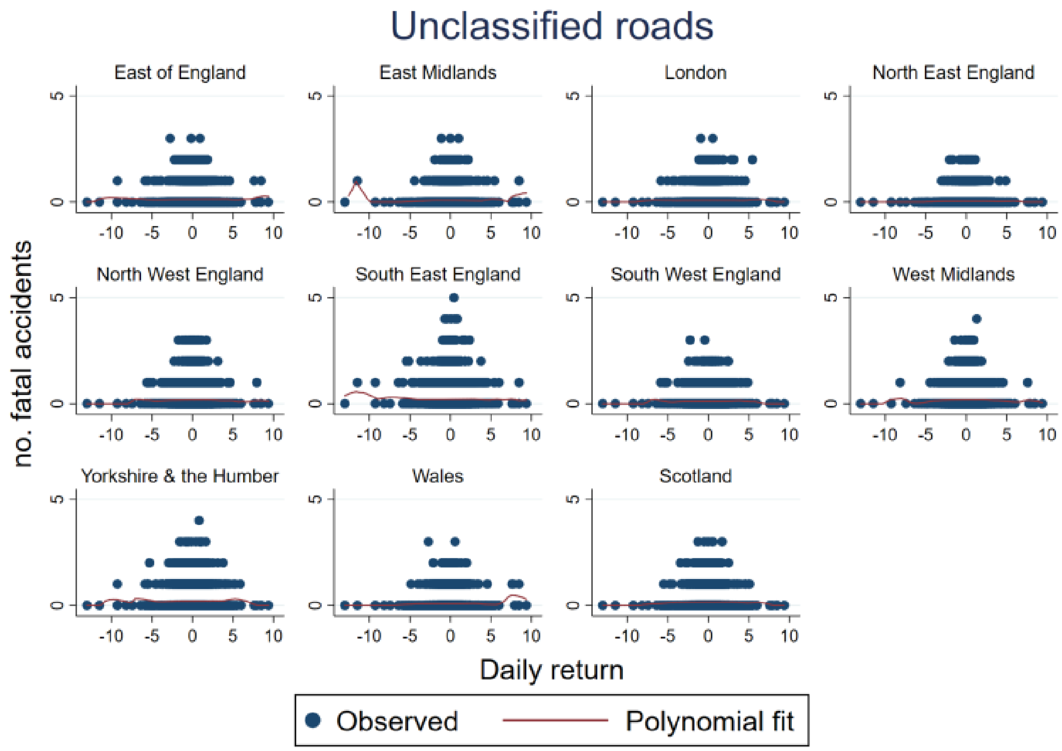

Figure A.4.8: Fatal accidents on Unclassified roads by region, 1985–2015

Levels of accidents and fatalities

In the chapter we use logarithms and inverse hyperbolic sines for the dependent variables as we believe changes in returns have a proportional effect on accidents and we can interpret the coefficients as elasticities. However, we may believe the relationship between accidents and returns is linear in levels, so here we also provide such results in Table A.4.2 – Table A.4.6. Most results are qualitatively the same in terms of signs and significance.

Table A.4.7 presents results for levels models in terms of categorical and positive and negative measures of returns and shows qualitatively similar results in most cases.

Table A.4.2: Modelling results, levels models 1985–2015[a]

	Full sample	Weekdays	Weekends
Accidents			
Positive returns	0.167**	-0.001	0.496***
	(0.066)	(0.041)	(0.119)
Negative returns	0.166***	0.014	0.272**
	(0.063)	(0.041)	(0.116)
Continuous returns	-0.002	-0.008	0.117**
	(0.033)	(0.022)	(0.058)
Fatal accidents			
Positive returns	-0.002	0.002	0.002
	(0.004)	(0.004)	(0.010)
Negative returns	-0.008*	-0.007*	0.005
	(0.004)	(0.004)	(0.010)
Continuous returns	0.003	0.004**	-0.001
	(0.002)	(0.002)	(0.005)
Period fixed effects	✓	✓	✓
GOR-month fixed effects	✓	✓	✓
Number of region-periods	124,509	88,935	35,574

[a]Each column is a separate regression using positive and negative returns or continuous returns for the sample identified. Accidents and fatal accidents are modelled in levels. Daily returns are as specified in the stylised models in figures 4.5–4.7. The full sample covers all hours in all 7 time periods, with each period beginning at 5pm. The weekday sample relates to weekdays and covers periods 1–5 with each period beginning at 5pm and ending at 8am. The weekend sample relates to weekends and covers periods 6 and 7, with each period beginning at 8am to avoid overlap with the weekday model. For weekend periods, the relevant return is from the Friday. For non-trading days, we use the latest available trading day return. Robust standard errors shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4.3: Modelling results for levels of accidents and fatal accidents by accident characteristic sample[a]

Sample	Accidents			Fatal accidents		
	Negative returns	Positive returns	Continuous returns	Negative returns	Positive returns	Continuous returns
Overall model	*0.166****	*0.167***	*-0.002*	*-0.008**	*-0.002*	*0.003*
	(0.063)	*(0.066)*	*(0.033)*	*(0.004)*	*(0.004)*	*(0.002)*
Road type						
Motorways and A(M) roads	0.008	-0.005	-0.006*	-0.000	-0.001	-0.0004
	(0.008)	(0.008)	(0.004)	(0.001)	(0.001)	(0.001)
A roads	0.045	0.047	3.63e-05	-0.000	0.002	0.001
	(0.035)	(0.036)	(0.019)	(0.003)	(0.003)	(0.002)
B roads	0.039**	0.034**	-0.003	-0.002	-0.003*	-0.0003
	(0.015)	(0.015)	(0.008)	(0.002)	(0.002)	(0.001)
C roads	0.017	0.020	0.001	-0.002*	-0.002	0.0002
	(0.012)	(0.012)	(0.007)	(0.001)	(0.001)	(0.001)
Unclassified roads	0.057**	0.072***	0.006	-0.004**	0.001	0.002**
	(0.024)	(0.025)	(0.013)	(0.002)	(0.002)	(0.001)
Light conditions						
Daylight	0.084*	0.038	-0.024	-0.007**	-0.006*	0.001
	(0.049)	(0.053)	(0.026)	(0.003)	(0.003)	(0.002)
Night	0.082***	0.130***	0.022	-0.001	0.003	0.002
	(0.031)	(0.031)	(0.016)	(0.003)	(0.003)	(0.002)
Weather conditions						
Fine weather	0.285***	0.393***	0.048	-0.008**	0.003	0.006**
	(0.061)	(0.065)	(0.034)	(0.004)	(0.004)	(0.002)
Adverse weather	-0.106*	-0.243***	-0.065*	-0.000	-0.005***	-0.003**
	(0.061)	(0.064)	(0.035)	(0.002)	(0.002)	(0.001)
Contributory factor						
Alcohol involvement	-0.000	0.013	0.006	0.005***	0.003*	-0.001
	(0.010)	(0.010)	(0.005)	(0.002)	(0.002)	(0.001)
Drug involvement	0.007*	0.005	-0.001	-0.000	-0.001	-0.0003
	(0.004)	(0.003)	(0.002)	(0.001)	(0.001)	(0.0005)

[a]Each row is a separate regression using positive and negative returns or continuous returns for the sample identified. Accidents and fatal accidents are modelled using levels. Models contain period and GOR-month fixed effects. Each observation represents daily accidents over a 24 hour period beginning at 5pm. Weekdays and weekends are included. For weekend periods, the relevant return is from the Friday. For non-trading days, we use the latest available trading day return. Sample runs from 1985–2015 except for contributory factors which run from 2005–2015. Robust standard errors shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4.4: Modelling results for levels of accidents and fatal accidents by driver/vehicle characteristic sample[a]

	Accidents			Fatal accidents		
Sample	Negative returns	Positive returns	Continuous returns	Negative returns	Positive returns	Continuous returns
Driver involvement						
Driver sex						
Male	0.126**	0.146***	0.007	-0.008*	-0.001	0.003
	(0.054)	(0.056)	(0.029)	(0.004)	(0.004)	(0.002)
Female	0.089***	0.076**	-0.008	-0.003	-0.005**	-0.001
	(0.034)	(0.038)	(0.018)	(0.002)	(0.002)	(0.001)
Driver age						
Age 1-17	0.023**	0.004	-0.010*	-0.001	-0.000	0.0002
	(0.011)	(0.011)	(0.006)	(0.001)	(0.001)	(0.001)
Age 18-24	0.006	0.042	0.018	-0.005**	0.001	0.003**
	(0.026)	(0.027)	(0.014)	(0.002)	(0.002)	(0.001)
Age 25-49	0.098**	0.092*	-0.005	-0.000	-0.002	-0.001
	(0.048)	(0.050)	(0.026)	(0.003)	(0.003)	(0.002)
Age 50-64	0.066***	0.050**	-0.009	0.000	-0.004*	-0.002*
	(0.021)	(0.022)	(0.011)	(0.002)	(0.002)	(0.001)
Age 65 or over	0.030**	0.009	-0.011*	0.000	0.000	4.85e-05
	(0.012)	(0.012)	(0.006)	(0.002)	(0.002)	(0.001)
Vehicle involvement						
Hit-and-run vehicle	0.020	0.036***	0.007	-0.000	0.000	0.0001
	(0.013)	(0.013)	(0.007)	(0.001)	(0.001)	(0.0005)
No-hit-and-run vehicle	0.107*	0.119*	0.004	-0.008*	-0.004	0.002
	(0.060)	(0.064)	(0.032)	(0.004)	(0.004)	(0.002)
Vehicle type involvement						
Bicycle	0.066***	0.035**	-0.016**	-0.001	-0.000	0.0005
	(0.014)	(0.014)	(0.007)	(0.001)	(0.001)	(0.001)
Motorcycle	0.058***	0.031*	-0.014	-0.003	-0.001	0.001
	(0.019)	(0.018)	(0.009)	(0.002)	(0.002)	(0.001)
Car	0.117**	0.151**	0.015	-0.006*	-0.003	0.002
	(0.057)	(0.061)	(0.031)	(0.004)	(0.004)	(0.002)
Bus	0.013	0.004	-0.005	-0.000	0.001	0.001
	(0.009)	(0.009)	(0.005)	(0.001)	(0.001)	(0.001)
Goods vehicle	0.051***	0.002	-0.025***	-0.001	-0.002	-0.0005
	(0.017)	(0.017)	(0.009)	(0.002)	(0.002)	(0.001)
Other vehicle	0.004	0.006	0.001	-0.002***	-0.002***	-1.60e-05
	(0.006)	(0.006)	(0.003)	(0.001)	(0.001)	(0.0004)

[a]Each row is a separate regression using positive and negative returns or continuous returns for the sample identified. Accidents and fatal accidents are modelled using levels. Models contain period and GOR-month fixed effects. Each observation represents daily accidents over a 24 hour period beginning at 5pm. Weekdays and weekends are included. For weekend periods, the relevant return is from the Friday. For non-trading days, we use the latest available trading day return. Sample runs from 1985–2015 except for hit-and-run/no-hit-and-run which run from 1985–2014. Robust standard errors shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4.5: Mean income for counties in the top and bottom decile, 2015[a]

County	Mean income £
Top decile	
Surrey incl. Met Police District	28,212
Greater London/London	26,864
Hertfordshire incl. Met Police District	24,245
Buckinghamshire	24,237
Oxfordshire	23,284
Bottom decile	
South Wales	15,388
Durham (excl. Cleveland)	15,361
Cleveland	15,304
Tyne & Wear	15,260
South Yorkshire	15,167
West Midlands	14,695

[a]Income is gross disposable income per capita.

Table A.4.6: Modelling results for levels of accidents and fatalities by counties in the top and bottom income deciles, 1985–2015[a]

	Accidents			Fatal accidents		
Sample	Negative returns	Positive returns	Continuous returns	Negative returns	Positive returns	Continuous returns
Top decile	0.079	0.066	-0.008	-0.003	0.001	0.002
	(0.062)	(0.067)	(0.033)	(0.004)	(0.004)	(0.002)
Bottom decile	0.073***	0.076**	0.0002	-0.001	-0.001	0.0001
	(0.027)	(0.031)	(0.015)	(0.002)	(0.002)	(0.001)

[a]Each row is a separate regression using positive and negative returns or continuous returns for the sample identified. Accidents and fatal accidents are modelled using levels. Models contain period and county-month fixed effects. Each observation represents daily accidents over a 24 hour period beginning at 5pm. Weekdays and weekends are included. For weekend periods, the relevant return is from the Friday. For non-trading days, we use the latest available trading day return. Robust standard errors shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4.7: Categorical and continuous positive and negative returns modelling results in levels, 1985–2015[a]

	Full sample		Weekdays		Weekends	
	(1)	(2)	(3)	(4)	(5)	(6)
Accidents						
R ≥2%	0.929***		0.190		1.291***	
	(0.250)		(0.150)		(0.453)	
1≤R<2%	0.037		-0.092		0.725***	
	(0.127)		(0.080)		(0.214)	
-2≤R<-1%	0.560***		0.177**		0.683***	
	(0.124)		(0.082)		(0.226)	
R<-2%	-0.607***		-0.306**		-0.899**	
	(0.232)		(0.141)		(0.378)	
Positive returns		0.167**		-0.001		0.496***
		(0.066)		(0.041)		(0.119)
Negative returns		0.166***		0.014		0.272**
		(0.063)		(0.041)		(0.116)
Fatal accidents						
R ≥2%	0.001		0.014		-0.021	
	(0.016)		(0.014)		(0.038)	
1≤R<2%	0.002		0.001		0.003	
	(0.009)		(0.008)		(0.018)	
-2≤R<-1%	-0.009		-0.013*		0.001	
	(0.009)		(0.008)		(0.019)	
R<-2%	-0.019		-0.014		-0.001	
	(0.015)		(0.013)		(0.031)	
Positive returns		-0.002		0.002		0.002
		(0.004)		(0.004)		(0.010)
Negative returns		-0.008*		-0.007*		0.005
		(0.004)		(0.004)		(0.010)
Period fixed effects	✓	✓	✓	✓	✓	✓
GOR-month fixed effects	✓	✓	✓	✓	✓	✓
Number of region-periods	124,509	124,509	88,935	88,935	35,574	35,574

[a]Each column is a separate regression using categorical returns or continuous returns for the sample identified. Accidents and fatal accidents are modelled using levels. R denotes daily returns as specified in the stylised models in figures 4.5–4.7. Models 1 and 2 cover all hours in all 7 time periods, with each period beginning at 5pm. Models 3 and 4 relate to weekdays and cover periods 1–5 with each period beginning at 5pm and ending at 8am. Models 5 and 6 relate to weekends and cover periods 6 and 7, with each period beginning at 8am to avoid overlap with the weekday models. For weekend periods, the relevant return is from the Friday. For non-trading days, we use the latest available trading day return. Models 1, 3 and 5 include returns as dummy variables. The reference category for these models is -1%≤R<1%. Models 2, 4 and 6 include returns as continuous positive or negative variables. Robust standard errors shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Pre- and post-Global Financial Crisis

During the GFC, people became much more aware of the stock market (Deaton, 2012). Stock market volatility also increased after the GFC, and hence there might have been a change in the relationship with road accidents. In order to investigate this possibility, we re-ran the main model (all periods) on a subset of observations before and after the GFC. The period of the GFC was one of particularly volatile movements in returns, so we exclude this period from our analysis. The pre-GFC period runs from 1985 to 2007 and the post-GFC period runs from 2009 to 2015. The results show positive and negative returns have a direct (positive) relationship with road accidents in both periods (Table A.4.8). Pre-GFC there are symmetric effects of similar size, leading to an almost zero effect of the continuous measure of returns. However, post-GFC the larger effect is for negative returns and shows a negative relationship with continuous returns (as returns increase, accidents decrease — although the differences are not statistically significant as the 95% confidence intervals are overlapping). Overlapping confidence intervals also indicate there is no significant difference in the relationship with returns pre- and post-GFC.

For fatal accidents the only significant effect is for negative returns pre-GFC, for which accidents decrease. This again suggests the effects of driver inattention could manifest as more slight accidents rather than severe (fatal) accidents. Perhaps overall people are driving more conservatively to avoid serious accidents but inattention leads to less severe accidents. For the continuous measure of returns, there is no significant effect on fatal accidents before or after the GFC. For comparison, results for levels models are included in Table A.4.9 and show qualitatively similar results.

Table A.4.8: Pre- and post-Global Financial Crisis modelling results[a]

	Accidents		Fatal accidents	
	Pre-GFC	Post-GFC	Pre-GFC	Post-GFC
Positive returns	0.004**	0.007**	-0.003	0.000
	(0.002)	(0.003)	(0.004)	(0.006)
Negative returns	0.004**	0.013***	-0.008**	-0.005
	(0.002)	(0.003)	(0.004)	(0.005)
Continuous returns	-2.05e-05	-0.003**	0.002	0.003
	(0.001)	(0.001)	(0.002)	(0.003)
Period fixed effects	✓	✓	✓	✓
GOR-month fixed effects	✓	✓	✓	✓
Number of region-periods	92,367	28,116	92,367	28,116

[a]Each column is a separate regression using positive and negative returns or continuous returns for the sample identified. Accidents are modelled using logarithms. Fatal accidents are modelled using the inverse hyperbolic sine transformation. Coefficient interpretation is the same between the two models. Pre-GFC period runs from 1/1/1985 to 31/12/2007. Post-GFC period runs from 1/1/2009 to 31/12/2015. Each observation represents daily accidents over a 24 hour period beginning at 5pm. Weekdays and weekends are included. For weekend periods, the relevant return is from the Friday. For non-trading days, we use the latest available trading day return. Robust standard errors shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4.9: Pre- and post-Global Financial Crisis levels modelling results[a]

	Accidents		Fatal accidents	
	Pre-GFC	Post-GFC	Pre-GFC	Post-GFC
Positive returns	0.138	0.223**	-0.003	-0.002
	(0.091)	(0.102)	(0.006)	(0.008)
Negative returns	0.071	0.418***	-0.011*	-0.008
	(0.084)	(0.108)	(0.006)	(0.007)
Continuous returns	0.032	-0.105*	0.004	0.003
	(0.047)	(0.056)	(0.003)	(0.004)
Period fixed effects	✓	✓	✓	✓
GOR-month fixed effects	✓	✓	✓	✓
Number of region-periods	92,367	28,116	92,367	28,116

[a]Each column is a separate regression using positive and negative returns or continuous returns for the sample identified. Accidents and fatal accidents are modelled using levels. Pre-GFC period runs from 1/1/1985 to 31/12/2007. Post-GFC period runs from 1/1/2009 to 31/12/2015. Each observation represents daily accidents over a 24 hour period beginning at 5pm. Weekdays and weekends are included. For weekend periods, the relevant return is from the Friday. For non-trading days, we use the latest available trading day return. Robust standard errors shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Extended returns

Thus far we have investigated daily returns as the measure of the stock market. It may be that individuals are responding to longer term changes, so here we examine the effects of using returns measured over 7 days (Table A.4.10). Again the models are specified as per equation 2.

For the full sample model, incorporating 7 day returns has meant that now a positive return leads to a small decrease in accidents (in the order of 0.1%) whereas a negative return over a week leads to significantly more accidents (although the magnitude is small). On weekdays there remains the V-shape in accidents that we saw with single day returns (although only the coefficient on negative returns is statistically significant). The relationship is about the same when we use 7 day returns as 1 day returns. For weekends there is now a different relationship with returns as a positive return over 7 days now leads to a statistically significant reduction in accidents of 0.4% per 1% increase in returns.

Results are driven by extreme positive returns over 7 days for the full sample and weekends and extreme negative returns for weekdays. These represent the effects of cumulative daily increases over a week. The explanation might relate to the time available to assimilate changes in returns. This might lead to less cognitive distraction and accidents over the full sample and at weekends when the market is going up (but more distraction and accidents during weekdays when weekly returns are negative). Cumulative negative returns lead to more distractions, particularly on weekdays.

The same broad pattern of coefficients can be seen for fatal accidents although they are not significant. Compared to single day returns, the significant negative effect of negative returns is now positive and insignificant with 7 day returns, indicating the effect has all but disappeared. Results for the levels models (Table A.4.11) show qualitatively similar results.

Table A.4.10: Asymmetric 7 day returns logarithmic modelling results, 1985–2015[a]

	Full sample	Weekdays	Weekends
Accidents			
Positive returns	-0.001*	0.001	-0.004***
	(0.001)	(0.001)	(0.002)
Negative returns	0.002***	0.004***	0.0002
	(0.001)	(0.001)	(0.001)
Fatal accidents			
Positive returns	-0.001	0.001	-0.004
	(0.002)	(0.001)	(0.003)
Negative returns	0.001	0.001	0.002
	(0.001)	(0.001)	(0.003)
Period fixed effects	✓	✓	✓
GOR-month fixed effects	✓	✓	✓
Number of region-periods	124,454	88,880	35,552

[a]Accidents are modelled using logarithms. Fatal accidents are modelled using the inverse hyperbolic sine transformation. Coefficient interpretation is the same between the two models. Daily returns are as specified in the stylised models in figures 4.5–4.7, although the return is now calculated as 100*(ln FTSEt – ln FTSEt-7) where FTSE is the level of the index. The full sample covers all hours in all 7 time periods, with each period beginning at 5pm. The weekday sample relates to weekdays and covers periods 1–5 with each period beginning at 5pm and ending at 8am. The weekend sample relates to weekends and covers periods 6 and 7, with each period beginning at 8am to avoid overlap with the weekday model. For weekend periods, the relevant return is from the Friday. For non-trading days, we use the latest available trading day return. Robust standard errors shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.4.11: Asymmetric 7 day returns levels modelling results, 1985–2015[a]

	Full sample	Weekdays	Weekends
Accidents			
Positive returns	-0.052	0.014	-0.159***
	(0.038)	(0.022)	(0.054)
Negative returns	0.048	0.041*	-0.062
	(0.039)	(0.022)	(0.047)
Fatal accidents			
Positive returns	-0.002	0.002	-0.005
	(0.002)	(0.002)	(0.005)
Negative returns	0.001	0.001	0.002
	(0.002)	(0.002)	(0.005)
Period fixed effects	✓	✓	✓
GOR-month fixed effects	✓	✓	✓
Number of region-periods	124,454	88,902	35,552

[a]Accidents and fatal accidents are modelled using levels. Daily returns are as specified in the stylised models in figures 4.5–4.7, although the return is now calculated as 100*(ln FTSEt – ln FTSEt-7) where FTSE is the level of the index. The full sample covers all hours in all 7 time periods, with each period beginning at 5pm. The weekday sample relates to weekdays and covers periods 1–5 with each period beginning at 5pm and ending at 8am. The weekend sample relates to weekends and covers periods 6 and 7, with each period beginning at 8am to avoid overlap with the weekday model. For weekend periods, the relevant return is from the Friday. For non-trading days, we use the latest available trading day return. Robust standard errors shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

References

Agrrawal, P., Waggle, D., & Sandweiss, D. H. (2017). Suicides as a response to adverse market sentiment (1980-2016). *PLoS ONE, 12*(11), e0186913. doi:https://doi.org/10.1371/journal.pone.0186913

Angrisani, M., & Lee, J. (2016). Health effects of short-term fluctuations in macroeconomic conditions: the case of hypertension for older Americans. *Health Economics, 25*(S2), 113-125. doi:10.1002/hec.3374

Attanasio, O. P., Banks, J., & Tanner, S. (2002). Asset holding and consumption volatility. *Journal of Political Economy, 110*(4), 771-792. doi:10.1086/340774

Bahar, D., & Rapoport, H. (2018). Migration, knowledge diffusion and the comparative advantage of nations. *The Economic Journal, 128*(612), F273-F305. doi:10.1111/ecoj.12450

Banks, J., Blundell, R., & Smith, J. P. (2002). *Wealth portfolios in the UK and the US*. NBER Working Paper 9128. NBER. Cambridge.

Banks, J., Blundell, R., & Smith, J. P. (2003). Understanding differences in household financial wealth between the United States and Great Britain. *The Journal of Human Resources*, *38*(2), 241-279. doi:10.2307/1558745

Banks, J., & Smith, S. (2000). *UK household portfolios*. Working Paper 00/14. Institute for Fiscal Studies. London.

Becker, G. S. (2007). Health as human capital: synthesis and extensions. *Oxford Economic Papers, 59*(3), 379-410.

Burbidge, J. B., Magee, L., & Robb, A. L. (1988). Alternative transformations to handle extreme values of the dependent variable. *Journal of the American Statistical Association, 83*(401), 123-127. doi:10.2307/2288929

Burke, P. J., & Teame, A. (2018). Fuel prices and road deaths in Australia. *Economic Papers: A journal of applied economics and policy, 37*(2), 146-161. doi:10.1111/1759-3441.12207

Changwony, F. K., Campbell, K., & Tabner, I. T. (2015). Social engagement and stock market participation. *Review of Finance, 19*(1), 317-366. doi:10.1093/rof/rft059

Chen, C.-C., Chen, C.-S., Liu, T.-C., & Lin, Y.-T. (2012). Stock or stroke? Stock market movement and stroke incidence in Taiwan. *Social Science & Medicine, 75*(11), 1974-1980. doi:https://doi.org/10.1016/j.socscimed.2012.07.008

Chen, C.-C., Lin, Y.-T., Liu, T.-C., & Chen, C.-S. (2016). Economic stress and mental health: the relationship between the stock market and neurotic disorder doctor visits. *Stress and Health, 32*(5), 607-615. doi:10.1002/smi.2677

Clemens, M. A., & Tiongson, E. R. (2017). Split decisions: household finance when a policy discontinuity allocates overseas work. *The Review of Economics and Statistics, 99*(3), 531-543. doi:10.1162/REST_a_00657

Cotti, C., Dunn, R., A., & Tefft, N. (2015). The Dow is killing me: risky health behaviors and the stock market. *Health Economics*, *24*(7), 803-821. doi:10.1002/hec.3062

Deaton, A. (2012). The financial crisis and the well-being of Americans: 2011 OEP Hicks Lecture. *Oxford Economic Papers, 64*(1), 1-26.

Deffenbacher, J. L., Deffenbacher, D. M., Lynch, R. S., & Richards, T. L. (2003). Anger, aggression, and risky behavior: a comparison of high and low anger drivers. *Behaviour Research and Therapy, 41*(6), 701-718. doi:https://doi.org/10.1016/S0005-7967(02)00046-3

Donmez, B., & Liu, Z. (2015). Associations of distraction involvement and age with driver injury severities. *Journal of Safety Research, 52*, 23-28. doi:https://doi.org/10.1016/j.jsr.2014.12.001

Engelberg, J., & Parsons, C., A. (2016). Worrying about the stock market: evidence from hospital admissions. *The Journal of Finance, 71*(3), 1227-1250. doi:10.1111/jofi.12386

Fiuzat, M., Shaw, L. K., Thomas, L., Felker, G. M., & O'Connor, C. M. (2010). United States stock market performance and acute myocardial infarction rates in 2008–2009 (from the Duke databank for cardiovascular disease). *The American Journal of Cardiology, 106*(11), 1545-1549. doi:https://doi.org/10.1016/j.amjcard.2010.07.027

Frijters, P., Johnston, D. W., Shields, M. A., & Sinha, K. (2015). A lifecycle perspective of stock market performance and wellbeing. *Journal of Economic Behavior & Organization, 112*, 237-250. doi:https://doi.org/10.1016/j.jebo.2015.02.004

Galéra, C., Orriols, L., M'Bailara, K., Laborey, M., Contrand, B., Ribéreau-Gayon, R., . . . Lagarde, E. (2012). Mind wandering and driving: responsibility case-control study. *BMJ : British Medical Journal, 345*, e8105. doi:10.1136/bmj.e8105

Giulietti, C., Tonin, M., & Vlassopoulos, M. (2020). When the market drives you crazy: Stock market returns and fatal car accidents. *Journal of Health Economics, 70*, 102245. doi:https://doi.org/10.1016/j.jhealeco.2019.102245

Guiso, L., Haliassos, M., Jappelli, T., & Claessens, S. (2003). Household stockholding in Europe: where do we stand and where do we go? *Economic Policy, 18*(36), 125-170.

Haw, C., Hawton, K., Gunnell, D., & Platt, S. (2014). Economic recession and suicidal behaviour: possible mechanisms and ameliorating factors. *International Journal of Social Psychiatry, 61*(1), 73-81. doi:10.1177/0020764014536545

Hurts, K., Angell, L. S., & Perez, M. A. (2011). The distracted driver: mechanisms, models, and measurement. *Reviews of Human Factors and Ergonomics, 7*(1), 3-57. doi:10.1177/1557234X11410387

Ivers, R., Senserrick, T., Boufous, S., Stevenson, M., Chen, H.-Y., Woodward, M., & Norton, R. (2009). Novice drivers' risky driving behavior, risk perception, and crash risk: findings from the DRIVE study. *American Journal of Public Health, 99*(9), 1638-1644.

Jansen, W. J., & Nahuis, N. J. (2003). The stock market and consumer confidence: European evidence. *Economics Letters, 79*(1), 89-98. doi:https://doi.org/10.1016/S0165-1765(02)00292-6

Jofre-Bonet, M., Serra-Sastre, V., & Vandoros, S. (2018). The impact of the great recession on health-related risk factors, behaviour and outcomes in England. *Social Science & Medicine, 197*, 213-225. doi:https://doi.org/10.1016/j.socscimed.2017.12.010

Jones, D., Molitor, D., & Reif, J. (2018). *What do workplace wellness programs do? Evidence from the Illinois Workplace Wellness Study*. NBER Working Paper 24229. NBER. Cambridge.

Kalcheva, I., McLemore, P., & Sias, R. (2017). *Stock market uncertainty and unhealthy choices*. Mimeo. The A. Gary Anderson Graduate School of Management, University of California, Riverside.

Li, Y., Rukshin, I., Pan, F., Sen, S., Islam, M., Yousif, A., & Rukshin, V. (2014). The impact of the 2008-2009 economic recession on acute myocardial infarction occurrences in various socioeconomic areas of Raritan Bay region, New Jersey. *North American Journal of Medical Science, 6*(5), 215-218. doi:10.4103/1947-2714.132938

Lin, C.-L., Chen, C.-S., & Liu, T.-C. (2015). Do stock prices drive people crazy? *Health Policy and Planning, 30*(2), 206-214. doi:10.1093/heapol/czu007

Lin, C.-L., Liu, T.-C., & Chen, C.-S. (2017). The association between attempted suicide and stock price movements: evidence from Taiwan. *Psychiatry Research, 254*, 323-331. doi:https://doi.org/10.1016/j.psychres.2017.05.004

Lin, H., Zhang, Y., Xu, Y., Liu, T., Xiao, J., Luo, Y., . . . Ma, W. (2013). Large daily stock variation Is associated with cardiovascular mortality in two cities of Guangdong, China. *PLoS ONE*, *8*(7), e68417. doi:https://doi.org/10.1371/journal.pone.0068417

Ma, W., Chen, H., Jiang, L., Song, G., & Kan, H. (2011). Stock volatility as a risk factor for coronary heart disease death. *European Heart Journal*, *32*(8), 1006-1011. doi:10.1093/eurheartj/ehq495

MacKinnon, J. G., & Magee, L. (1990). Transforming the dependent variable in regression models. *International Economic Review*, *31*(2), 315-339. doi:10.2307/2526842

McInerney, M., Mellor, J. M., & Nicholas, L. H. (2013). Recession depression: mental health effects of the 2008 stock market crash. *Journal of Health Economics, 32*(6), 1090-1104. doi:https://doi.org/10.1016/j.jhealeco.2013.09.002

McNally, B., & Bradley, G. L. (2014). Re-conceptualising the reckless driving behaviour of young drivers. *Accident Analysis & Prevention*, *70*, 245-257. doi:https://doi.org/10.1016/j.aap.2014.04.014

Mitchell, R. L. C., & Phillips, L. H. (2007). The psychological, neurochemical and functional neuroanatomical mediators of the effects of positive and negative mood on executive functions. *Neuropsychologia*, *45*(4), 617-629. doi:https://doi.org/10.1016/j.neuropsychologia.2006.06.030

Neyens, D. M., & Boyle, L. N. (2008). The influence of driver distraction on the severity of injuries sustained by teenage drivers and their passengers. *Accident Analysis & Prevention, 40*(1), 254-259. doi:https://doi.org/10.1016/j.aap.2007.06.005

Norris, F. H., Matthews, B. A., & Riad, J. K. (2000). Characterological, situational, and behavioral risk factors for motor vehicle accidents: a prospective examination. *Accident Analysis & Prevention*, *32*(4), 505-515. doi:https://doi.org/10.1016/S0001-4575(99)00068-8

Pool, L. R., Burgard, S. A., Needham, B. L., Elliott, M. R., Langa, K. M., & Mendes de Leon, C. F. (2018). Association of a negative wealth shock with all-cause mortality in middle-aged and older adults in the United States. *JAMA, 319*(13), 1341-1350. doi:10.1001/jama.2018.2055

Ratcliffe, A., & Taylor, K. (2015). Who cares about stock market booms and busts? Evidence from data on mental health. *Oxford Economic Papers*, *67*(3), 826-845. doi:10.1093/oep/gpv030

Routley, V., Staines, C., Brennan, C., Haworth, N., & Ozanne-Smith, J. (2003). *Suicide and natural deaths in road traffic - review*. Monash University Accident Research Centre Report No. 216. MUARC. Melbourne.

Schwandt, H. (2018). Wealth shocks and health outcomes: evidence from stock market fluctuations. *American Economic Journal: Applied Economics*, *10*(4), 349-377.

Schwartz, B. G., French, W. J., Mayeda, G. S., Burstein, S., Economides, C., Bhandari, A. K., . . . Kloner, R. A. (2012). Emotional stressors trigger cardiovascular events. *International Journal of Clinical Practice*, *66*(7), 631-639. doi:10.1111/j.1742-1241.2012.02920.x

Schwartz, B. G., Pezzullo, J. C., McDonald, S. A., Poole, W. K., & Kloner, R. A. (2012). How the 2008 stock market crash and seasons affect total and cardiac deaths in Los Angeles County. *The American Journal of Cardiology*, *109*(10), 1445-1448. doi:https://doi.org/10.1016/j.amjcard.2012.01.354

UK Department for Transport. (2009). *Behavioural research in road safety 2007: seventeenth seminar*. Department for Transport. London.

UK Department for Transport. (2016a). *National Travel Survey: England 2015, statistical release 8 September 2016*. Department for Transport. London.

UK Department for Transport. (2016b). *Reported road casualties Great Britain 2015: annual report*. Department for Transport. London.

UK Department for Transport. (2016c). *Road use statistics Great Britain 2016*. Department for Transport. London.

UK Department for Transport. (2018). *Vehicle licensing statistics: annual 2017 (revised)*. Department for Transport. London.

Vandoros, S., Avendano, M., & Kawachi, I. (2018). The short-term impact of economic uncertainty on motor vehicle collisions. *Preventive Medicine, 111*, 87-93. doi:https://doi.org/10.1016/j.ypmed.2018.02.005

Vandoros, S., Avendano, M., & Kawachi, I. (2019). The association between economic uncertainty and suicide in the short-run. *Social Science & Medicine, 220*, 403-410. doi:https://doi.org/10.1016/j.socscimed.2018.11.035

Vandoros, S., Kavetsos, G., & Dolan, P. (2014). Greasy roads: the impact of bad financial news on road traffic accidents. *Risk Analysis, 34*(3), 556-566. doi:10.1111/risa.12123

Westfall, P. H., & Young, S. S. (1993). *Resampling-based multiple testing: examples and methods for p-value adjustment*. New York: John Wiley & Sons.

Yap, J., Earnest, A., Lee, V., Sng, G., Lam, C., & Yeo, K. K. (2016). Impact of stock market volatility on mortality and cardiovascular events. *International Journal of Cardiology, 223*, 318-319. doi:https://doi.org/10.1016/j.ijcard.2016.08.206

Young, K., & Regan, M. (2007). Driver distraction: a review of the literature. In I. J. Faulks, M. Regan, M. Stevenson, J. Brown, A. Porter, & J. D. Irwin (Eds.), *Distracted driving* (pp. 379-405). Sydney: Australasian College of Road Safety.

Chapter 5: Penalties and behaviour: road accidents and the introduction of harsher driving penalties in Britain

5.1 Introduction

Policy makers often use penalties as a means to impact behaviours. These penalties work to internalise the social costs associated with individuals' actions, prompting some individuals to modify their behaviour (Pigou, 1932). 'The goal of enforcement … is to achieve that degree of compliance with the rule of prescribed (or proscribed) behaviour that the society believes it can afford' (Stigler, 1970, p. 526). One aspect of enforcement is the penalty for committing an offence. While much economic analysis of penalties relates to indictable (more serious) offences (Bar-Ilan & Sacerdote, 2004), some motor vehicle offences can also lead to significant harm when individuals are injured or die. Driver behaviour affecting traffic violations is more important than other factors in explaining numbers of accidents and their severity (Cardamone, Eboli, Forciniti, & Mazzulla, 2017). It is for these reasons that a common application of economic theory is in the context of road safety enforcement relating to driver behaviour.

Despite a large literature, including papers in leading economics journals, there remains considerable uncertainty about the best size and structure of incentives needed to further reduce serious accidents and fatalities (see, for example, Bourgeon & Picard, 2007; De Paola, Scoppa, & Falcone, 2013; Hansen, 2015; Kantorowicz-Reznichenko, 2015; Montag, 2014). Some recent examples focus on the link between general enforcement (which increases expected penalties) and fatalities (DeAngelo & Hansen, 2014), penalty points systems and risky driver behaviour (De Paola et al., 2013; Gras, Font-Mayolas, Planes, & Sullman, 2014), traffic cameras and accidents (Gallagher & Fisher, 2020), texting/mobile phone use bans and accidents (Abouk & Adams, 2013; Burger, Kaffine, & Yu, 2014; Ferdinand et al., 2014; Rocco & Sampaio, 2016), drug driving laws and fatalities (Anderson & Rees, 2015), licence suspensions and speeding recidivism (Gehrsitz, 2017) and speeding and fines (Traxler, Westermaier, & Wohlschlegel, 2018).

One key aspect of driving behaviour involves decisions affecting traffic violations, such as use of a mobile phone while driving and exceeding the speed limit (speeding). Being distracted by a mobile phone while driving can have serious consequences for accidents, increasing the risk of an accident by four times (World Health Organization, 2018). Experiments have shown that talking on a mobile phone reduces reaction time for drivers (Farmer, Braitman, & Lund, 2010).[1] Based on survey data, US drivers claimed to spend 6.7% of driving time talking on mobile phones, although actual rates may be much higher (Farmer et al., 2010). In that study it was estimated that some 19% of fatal accidents could have been avoided if there were no drivers talking on mobile phones. In a meta-analysis, Elvik (2011) found accident risk to be about three times higher when mobiles were used by drivers and McEvoy, Stevenson, and Woodward (2007) and Redelmeier and Tibshirani (1997) found a fourfold increase in accident risk. Klauer et al. (2014) found a more than twofold increase in accident risk among experienced drivers dialling a mobile phone but an eightfold increase among novice drivers. In recent years, driver distraction may be more prevalent due to increasing use of mobile phones (Stevens & Minton, 2001). Although using a mobile phone while driving has been found to increase accident severity (mostly significantly) (Donmez & Liu, 2015), enforcement remains difficult as drivers may put down their phone before police arrive on the scene (UK Department for Transport, 2016a).

Another important factor in accidents is speed. A common phrase in the road safety literature is 'speed kills', as, when driving, there is a trade-off between speed and safety.[2] According to Elvik (2005), 'speed is likely to be the single most important determinant of fatalities' (p. 69). The relationship between speed and accident severity can be traced back to the power model of Nilsson (2004), in which (for example) the change in numbers of fatal accidents is determined by the fourth power of the change in mean speed (see, for example, Elvik, 2012). Perhaps a better representation is of the positive (logistic) relationship between impact speed and the probability of death (Elvik, 2012). Effective speed management is an important component in an overall road safety strategy (World Health Organization, 2018). To increase road safety, speed limits are imposed by government and enforced by police. Speed limits on particular roads are determined with reference to local factors such as traffic mix (including the extent of vulnerable road users), safety history (black spots), and road characteristics such as directional divisions, median strips and guard rails (Brubacher, Chan, Erdelyi, Lovegrove, & Faghihi, 2018; United Nations Road Safety Collaboration, 2008). In high income countries

[1] Conversely, Papadimitriou, Argyropoulou, Tselentis, and Yannis (2019) find mobile phone use is negatively correlated with speed, indicating there is compensatory behaviour at play.

[2] In this chapter we focus on accident severity in relation to average speed rather than speed variance, although both have been shown to affect severity (Rodriguez, 1990).

average speed limits tend to be 30–50km/h on urban roads, 70–100 km/h on main highways or rural roads and 90–130 km/h on motorways (United Nations Road Safety Collaboration, 2008).

One way of potentially reducing these accident numbers is to control driver behaviour, but introducing laws governing mobile phone use and setting speed limits does not guarantee compliance. Individuals may use a mobile phone for convenience and may drive fast in order to save time or for the thrill of driving fast (or simply because they are unaware of the speed limit on a particular road). A system of penalties for drivers caught using mobiles or exceeding the speed limit is therefore required to induce would-be offenders to obey the laws and to penalise violations. This can be achieved to a greater or lesser extent by changing incentives through introducing harsher penalties for errant driving behaviours. In 2017 there were two such interventions targeted at drivers using a mobile phone and speeding. The first intervention (applied throughout Britain) took place on 1 March and involved increasing the fine from ₤100 to ₤200 and doubling penalty points from 3 to 6 for drivers caught using a hand-held mobile phone. The second intervention only applied to drivers in England and Wales and involved increasing the fine for excessive speeding from 100% to 150% of weekly income.

On 1 December 2003, a law was introduced prohibiting the use of hand-held mobile phones while driving in Britain (UK Department for Transport, 2018a). Initially the penalty was a ₤30 fine. Subsequently there was an increase to ₤60 and three penalty points introduced in 2007 and the fine increased to ₤100 in 2013 (UK Department for Transport, 2016a). However, it has been noted that the fine increase alone was not sufficient to significantly affect numbers of drivers using mobile phones and that only the introduction of penalty points in 2007 saw a significant decline in offences (UK Department for Transport, 2016a). The efficacy of these mobile penalties remains in doubt, as in 2016, there were still 11,961 offenders found guilty of using a hand-held mobile phone while driving (UK Ministry of Justice, 2018) and 2,153,420 findings of guilt/fixed penalty notices or written warnings issued for speeding in England and Wales (UK Department for Transport, 2018b).

The 2017 Seatbelt and Mobile Phone Use Survey of Great Britain estimated on weekdays about 0.6% of drivers in England and Wales and 2% of drivers in Scotland used hand-held mobile phones while the vehicle was in motion and 2.2% of drivers in England and Wales and 2.5% of drivers in Scotland used mobiles while stationary (UK Department for Transport, 2019a). On weekends, such behaviour was more prevalent as 1.9% of drivers in England and Wales and 0.5% of drivers in Scotland were using mobiles while in motion. To address this problem, on 1 March 2017 the British Government doubled the penalties for using hand-held mobile phones while driving to a £200 fine and six penalty points (UK Department for Transport, 2018a).

As background to the second intervention, since at least 2008 England and Wales have had income-based fines for speeding (Sentencing Guidelines Council, 2008), with lower rates for the less serious speeding offences. For many drivers, these fines are not sufficient to eliminate all speeding behaviour. In 2017 there were 2.2m speed limit offences committed in England and Wales and these offences comprised findings of guilt at all courts, fixed penalty notices and written warnings issued to drivers (UK Department for Transport, 2018a). In recognition of the increasing harm associated with the most serious cases of speeding, on 24 April 2017, the Sentencing Council introduced a higher penalty for the most serious category of speeding in England and Wales, increasing these fines from 100% to 150% of an offender's weekly income (Sentencing Guidelines Council, 2017a).

Although analyses of such interventions mostly consider the effects on numbers of offences committed, the interventions are essentially designed to improve road safety. Therefore, in this chapter we focus on identifying the effects on numbers of fatal or serious accidents, which is important as this is what the imposition of penalties is ultimately designed to reduce.

In Britain in 2016 there were 100,296 injury accidents (of which 18,936 were classified as fatal or serious) for which a police officer attended the scene and at least one accident contributory factor was recorded (UK Department for Transport, 2017). Among serious or fatal accidents, about 1% were associated with using a mobile phone while driving and some 8 per cent were associated with speeding.[3] Mobile phone use while driving was reported as a contributory factor in 0.5% of all accidents and 0.62% of fatal or serious accidents (UK Department for Transport, 2018a). There was little difference in mobile-phone-related accidents across road types, suggesting mobile phone use rates may be fairly uniform. There was a higher rate of mobile phone involvement in accidents in England and Wales (0.48%) than in Scotland (0.16%) and within England this rate was highest for the East of England (0.77%) and the West

[3] Use of the mobile phone as a contributory factor in accidents may actually be higher than reported by police, as 'most distracting behaviour probably is not recorded, no matter how serious the crash' (Farmer et al., 2010, p. 466). That is, it can be difficult to assess the involvement of mobile phone use in accidents as this behaviour can be difficult to detect (World Health Organization, 2018).

Midlands (0.69%) (UK Department for Transport, 2018a). Across Britain in 2017, exceeding the speed limit was reported as a contributory factor in 5% of injury accidents, with 5% of slight, 7% of serious and 14% of fatal accidents reported to involve speeding violations (UK Department for Transport, 2018a). Speeding and accidents also vary by road type. Exceeding the speed limit was a factor in 3% of accidents on motorways but 5–6% of accidents on other road types (UK Department for Transport, 2018a). This suggests drivers are more likely to speed on roads with lower speed limits. There are also differences in the extent of involvement of speeding in accidents between vehicle types. Some 5% of motorcycles and 3% of cars involved in accidents had speeding as a contributory factor, whereas only 1–2% of goods vehicles had speeding attributed to the accident (UK Department for Transport, 2018a). In England and Wales, exceeding the speed limit was attributed to a slightly higher share of accidents (5%) than in Scotland (3%) and there was some regional variation with 10% of accidents in the West Midlands and 3% in Yorkshire and the Humber involving speeding (UK Department for Transport, 2018a).

The average value of road accident prevention was approximately £90,000 per accident in Britain in 2017. These costs varied by accident severity: £2.1m for fatal accidents, £244,000 for serious and £25,000 for slight accidents (UK Department for Transport, 2018a). The total value of all injury accidents was approximately £11.8b. Notwithstanding costs associated with loss of output (about £2b), very large human, medical and ambulance costs in the order of £9b leave a large burden on the healthcare system that could be reduced by successful accident prevention efforts.

Using British Stats19 data on the universe of accidents, we investigate the effects of the 2017 interventions on numbers of serious or fatal accidents. We focus on these accidents as they account for the bulk of casualty- and accident-related costs (some 77% or £9b out of the total of £11.8b in 2017) (UK Department for Transport, 2018a). After accounting for longer term trends and seasonal/day of the week effects, we use Regression Discontinuity in Time (RDiT) analysis to see what happened in the affected countries before and after the interventions and we use Difference-in-Difference (DiD) analysis to compare areas or groups affected by an intervention with areas or groups unaffected to identify ‘treatment’ effects.

To our knowledge this is the first attempt to comprehensively examine the effects of these two road safety interventions on numbers of serious or fatal accidents. In this respect, our research question is unique as we focus on health outcomes rather than general ‘road safety’ as an outcome of policy. Moreover, 'there remains a dearth of evidence on the effectiveness of interventions to reduce distracted driving' (World Health Organization, 2018, p. 45) and with our analysis of the mobile phone intervention we seek to partially fill this gap. Our investigation sheds light on the link between penalties and road accidents, which, to date, has been missing from the literature. These results are critical for policymakers to determine the effectiveness of specific interventions (do they save lives or just raise revenue?) and the likely success of future endeavours.

5.2 Background and literature review

The economic analysis of crime began with the work of Becker (1968). In that work, Becker argued that individuals maximise utility by comparing the expected gains and losses associated with offending. Expected penalties would have two components: the actual penalty (often a fine) and the probability of conviction. Becker argued that the expected penalty should equal the expected marginal harm plus the cost of apprehension and conviction. Equality with expected harm implies the penalty is act based rather than harm based (Polinsky & Shavell, 2000). Of course, if it is costly to impose the penalty, that cost must also be included in calculating the optimal penalty (Polinsky & Shavell, 2000). Such a penalty assumes individuals are risk neutral. For risk averse individuals the optimal penalty could be lower (Polinsky & Shavell, 2000).

5.2.1 Economic theory of penalties

In relation to crime, individual behaviour is partly determined by decisions about whether to offend. One way to demonstrate how this decision is made is by considering a function that captures utility (benefits of offending) net of costs (figure 5.1). In choosing whether to violate a law, individuals will seek to maximise such a function (the orange line). Penalties will lower such a curve at the point where the penalty engages (the yellow line), leading some types of individuals, such as those on the left of figure 5.1, to reduce their 'desire to offend' to a level consistent with the highest point on this function (at the 'notch' or discontinuity) resulting in complying with the law. Other types of individuals such as those on the right may have a higher preference for the offensive behaviour and the penalty has no effect on the utility maximising behaviour. Implicit in this analysis is the probability of detection of offensive behaviour and subsequent enforcement of the penalty. The distinct 'notch' in expected utility at the point at which the penalty comes into play represents the expected penalty, that is, the penalty multiplied by the individual's belief about the probability of detection. A high probability of detection will increase the size of the 'notch'. If the penalty is severe enough, it is possible to induce all individuals to obey the law (Rodriguez, 1990). Over time, individuals may adjust downwards their beliefs about the probability of detection, moving the expected utility curve back towards the original orange curve and resulting in changes in behaviour back towards pre-penalty levels.

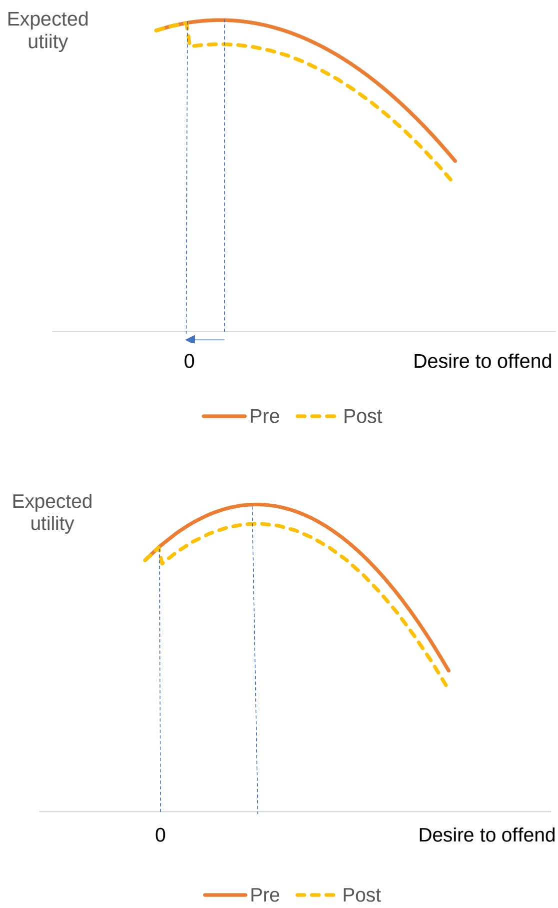

Figure 5.1: Adjusted utility function for two types of individuals, pre- and post-penalty implementation

Perhaps a more transparent way to demonstrate the effect of a penalty on behaviour is to separately consider the marginal benefits and marginal costs that an individual equates to determine the optimum behaviour. A given increase in the desire to offend represents a larger proportion at low levels, so the marginal benefit of offending is downward sloping. Marginal costs are upward sloping as there is a positive relationship between offending and expected harm caused. To the extent that there are externalities from the offensive behaviour, the marginal social benefit (cost) and marginal private benefit (cost) will differ. For simplicity we assume in figure 5.2 that the marginal social cost equals the marginal private cost and in figure 5.3 that marginal social benefit equals marginal private benefit. The socially optimum behaviour occurs where the marginal social benefit equals the marginal social cost, although in this scenario individuals do not factor in the externalities and their desire to offend is determined by the equating of marginal private benefits and marginal private costs.

In figure 5.2 we present the (expected) penalty as a reduction in benefits, whereas in figure 5.3 we present the penalty as an increase in costs. In both cases, the penalty (incorporated in the orange line) brings social (blue) and private (red) valuations more in line and these individuals will choose to comply with the law. Again, individuals may lower their beliefs about the probability of detection over time and revert to pre-penalty behaviours.

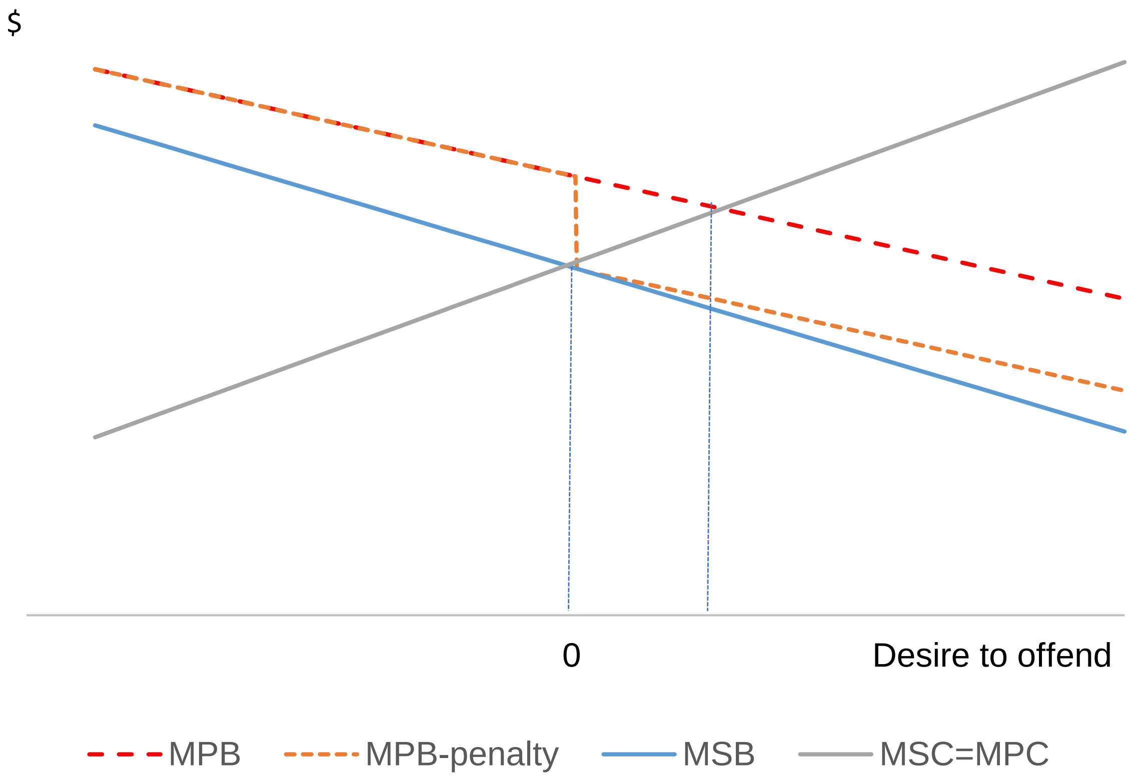

Figure 5.2: Equilibrium behaviour pre- and post-penalty implementation, change in marginal private benefits

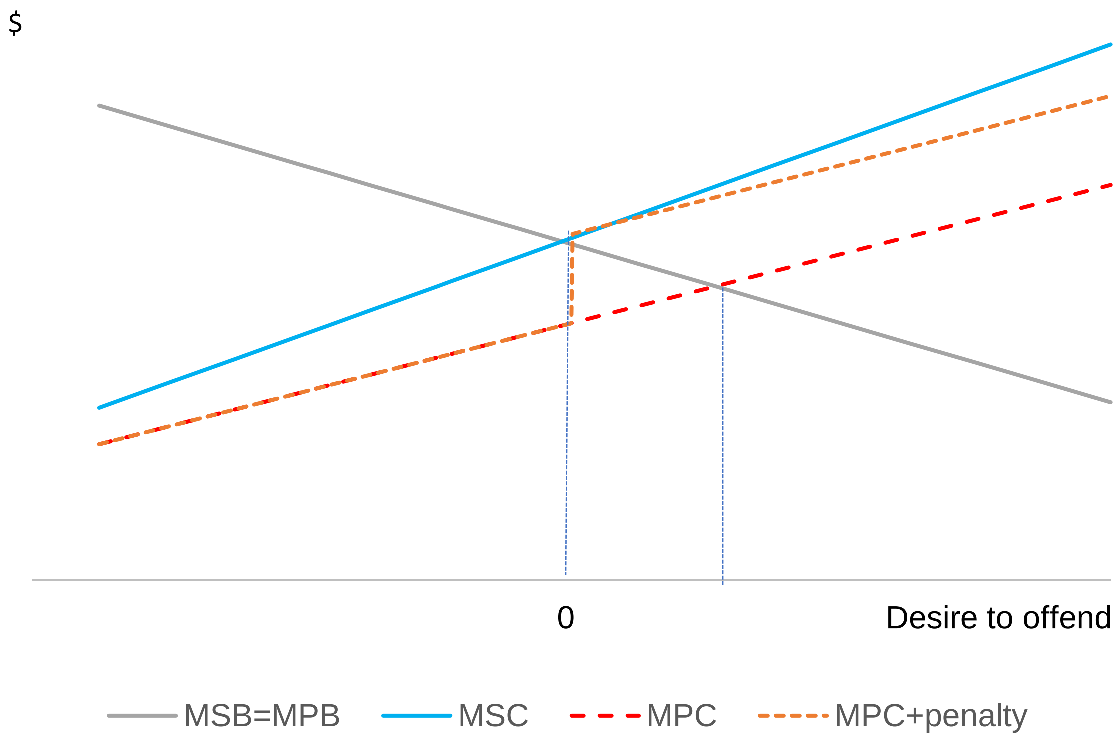

Figure 5.3: Equilibrium behaviour pre- and post-penalty implementation, change in marginal private costs

As before, there may be some individuals with very high valuations of benefits and/or very low valuations of costs for whom the penalty is not sufficient to generate an equilibrium at the socially optimal outcome (compliance).

In economic terms, driving offences can be thought of as an externality of driving. The externality arises because, in making decisions, individual drivers do not take into account the consequences of their driving behaviour for other road users (such as accidents involving other vehicles, cyclists or pedestrians). The rationale for penalties is to influence driving behaviour, reducing individuals' preferences for offensive behaviour such that they behave in socially optimal (safe) ways. This works by lowering utility and therefore the marginal private benefit from offending or by directly raising the marginal private costs of offending. Either way, the incentive to offend is reduced.

In the case of mobile phone use while driving, benefits are usually defined by convenience. For speeding, benefits would typically be measured in terms of time saved. Other motivations include impressing others, expressing independence/defiance, inadvertence, social acceptability and the sheer pleasure of driving fast (Corbett, 2010). In both cases, expected losses (costs) would include expected penalties and other costs associated with vehicle damage and personal injury caused by road accidents. Social costs would include cost of emergency services when there are accidents, additional travel time for other drivers due to congestion, and workplace disruptions and costs associated with legal proceedings (Bourgeon & Picard, 2007). For driving offences, penalties may be monetary (fines[4]) or non-monetary (penalty points leading to eventual licence suspension or withdrawal). The idea behind such non-monetary penalties is to 'incapacitate' offending drivers and keep them off the roads. Penalty points have the added psychic costs associated with stigma if they result in licence suspension.

Rather than having a fine as a set monetary amount, it can be set in relation to an offender's income. Income-based fines are often referred to as unit, day or structured fines. This type of fine has been introduced in several countries, beginning with Finland in 1921 (Hillsman, 1990) and most recently in Switzerland in 2007 (Kantorowicz-Reznichenko, 2015). Fines are based on offence seriousness and offender's financial resources. Seriousness is accounted for by allocating a number of days or units to the penalty, with more days reflecting more severe offenses. Financial resources are the offender's income (usually daily) and, in some countries, wealth. The fine is then the product of the two.

While the marginal harm is not related to the offender's income or wealth, the cost of conviction may vary with income as richer individuals are able to afford better legal representation which may lead to longer and more complex hearings. This would imply that the penalty should also vary with income. Moreover, individuals respond to expected losses which comprise the penalty and the probability of conviction. As the probability of conviction can vary with income (again, because of affordability of legal representation), so too should the penalty so the expected penalty for all individuals is equal.

In the case of monetary penalties, the idea of wealth-determined fines goes back to Bentham, who in 1931 stated 'pecuniary punishments should always be regulated by the fortune of the offender' (Becker, 1968, p. 195). It has also been addressed by Polinsky and Shavell (1984, 1991), who argue that the optimal fine should (for all but the most wealthy) equal an

[4] Monetary penalties can also include increases in insurance premiums, although this is not something we focus on.

individual's wealth when the probability of conviction varies. The theoretical model of Garoupa (1998) also suggests an optimal fine for individuals with differing levels of income would increase with income. However, for the most wealthy individuals the fine should be less than their income to avoid the overdeterrence problem (Kantorowicz-Reznichenko, 2015).

The idea behind this type of fine is that, for a given offence, offenders get an equivalent rather than identical penalty, and more serious offences attract higher penalties. Thus the penalty takes into consideration the principles of equity and proportionality (Raine & Dunstan, 2009).

5.2.2 Penalty points, mobile phone use and accidents

Accident contributory factor data bears out the relationship between driver behaviour and accidents and their severity. Penalties are used to incentivise optimal behaviour. Various studies have considered the efficacy of different penalties for particular driving behaviours. De Paola et al. (2013) investigated the introduction of a penalty points system in Italy for various driving offences and found a smaller reduction for offences that were already punished under the previous penalty system. Gras et al. (2014) examined the impacts of the introduction of a penalty points system in Spain in 2006 and found about 9% fewer individuals used a mobile phone while driving after the system was introduced. This was partly attributed to the penalty and partly to increased enforcement. Moreover, there was a higher probability of accident involvement among those individuals using mobile phones while driving. In a study of the introduction of California's hand-held mobile phone ban, Burger et al. (2014) found no evidence of reduced numbers of accidents, perhaps due to drivers substituting to hands-free mode or not responding to the penalties (indeed, the authors point out that if lack of compliance is the cause then increasing fines may work). Although numbers remained stable, it might also be that accident *severity* declined.

Mobile phone use contributes to road accidents through driver distraction (McEvoy et al., 2007; Redelmeier & Tibshirani, 1997), which can reduce reaction times among other things (Farmer et al., 2010). Distractions take multiple forms, such as cognitive (conversation to task related), visual (looking at the phone), auditory (listening to the phone) and manual (holding the phone or dialling/texting) (McEvoy et al., 2007).

Research linking mobile use and accidents dates back at least to the late 1990s (see, for example, Violanti & Marshall, 1996). Experiments with driving simulators indicates phone use affects some aspects of driving performance (Redelmeier & Tibshirani, 1997). Accidents can be associated with ‘harsh events’ such as accelerations, braking and cornering that are associated with mobile use (Papadimitriou et al., 2019). Research typically shows use of a mobile phone increases serious accident risk by 3–4 times (Elvik, 2011; Ferdinand et al., 2014; McEvoy et al., 2007; Redelmeier & Tibshirani, 1997), and texting increases the risk by about 23 times (World Health Organization, 2018). Studies use police reports of accidents or survey data, with mobile use variously determined by billing records, in-car cameras, police reports (such as contributory factors) and survey data (Elvik, 2011).

5.2.3 Fines, speeding and accidents

Traxler et al. (2018) investigated driver responses to increases in speeding penalties introduced in 2009 in Germany. The change involved an increase in a step-wise (or notched) penalty scheme. They used data on measured speed and speeding fines collected for the Autobahn and found ‘bunching’ in both variables at speeds where the discontinuity in penalties (as speed increases) changed. In particular, after the reform they found a 25% reduction in the (admittedly small) share of speeding drivers driving 20 or more kilometres over the speed limit and an increase in speeding tickets just below this cut-off. This indicates that when the relativity in fines changed, some drivers tended to lower their speed just enough to fall into the lower penalty category. This change in behaviour caused a bunching or spike in the distribution of fines at that point. In the context of a laboratory experiment, DeAngelo and Charness (2012) also found individuals were less likely to speed in response to increases in the expected cost of speeding.

Individuals can disobey red lights for similar reasons to speeding, making these findings relevant. Bar-Ilan and Sacerdote (2004) found red-light running decreased with an increase in the fine, particularly for younger drivers and for those with older vehicles (although the fine level is fixed for all offenders).

Interestingly, Gehrsitz (2017) investigated the effects of temporary licence suspensions in Germany and found major traffic offence (such as speeding and texting while driving) recidivism was reduced by 20% in response to the penalty.

Increases in speed result in longer distances travelled for a given reaction time and longer braking distances. This increases the energy that must be absorbed in an accident and increases severity of the outcome (United Nations Road Safety Collaboration, 2008). Speed therefore increases the probability of being involved in an accident (Aarts & van Schagen, 2006; Wang, Quddus, & Ison, 2013) and increases the severity of such accidents (Elvik, 2005; Elvik, Vadeby, Hels, & van Schagen, 2019).[5] All else equal, higher driving speeds correspond to higher impact speed and greater injury severity (Hussain, Feng, Grzebieta, Brijs, & Olivier, 2019; Yannis, Theofilatos, Ziakopoulos, & Chaziris, 2014). This relationship is usually termed the 'power model', as accident severity is linked to a power function of vehicle speed, and was introduced into the literature by Nilsson (1982). This relationship is discussed in the appendix (see Figure A.5.1).

There are many studies demonstrating the link between speed and accidents and their severity. Elvik (2005) conducted a meta analysis of 98 studies of speed and road safety and found a strong positive relationship between the two. In a later investigation, meta analysis of 21 studies revealed this relationship has become even stronger in recent times (Elvik et al., 2019). Castillo-Manzano, Castro-Nuño, López-Valpuesta, and Vassallo (2019) conducted a meta analysis of 17 studies from 1990–2016 of the relationship between increased speed limits and fatalities in the US and also found a positive relationship.

It is difficult to compare the power model for different road types, as engineering measures have been designed to improve safety on higher speed roads such as motorways relative to lower speed roads (Brubacher et al., 2018). Nevertheless, the broad relationship has been found for cars (Dissanayake, 2004; O'Donnell & Connor, 1996), buses (Kaplan & Prato, 2012) and trucks (Peng & Boyle, 2012). Pedestrians are particularly vulnerable and constitute the largest group of road users involved in fatal accidents (Hussain et al., 2019). Pedestrians are less protected than drivers and meta analysis has shown a 1km/h increase in speed increases the probability of a pedestrian fatality by an average of 11% (Hussain et al., 2019).

Rather than modelling the severity of all accidents, some studies focus specifically on the number of fatal accidents and find a positive relationship with speed. For example, using an interrupted time series approach, Brubacher et al. (2018) found an increase in speed limits in British Columbia led to a 118% increase in average monthly fatal accidents on rural highways affected by the change in speed limit from 110km/h to 120km/h.

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[5] Effects on accident severity may vary according to the measure of speed adopted (actual speed, speed limit or speed variation) (Wang et al., 2013).

Most studies evaluate the effects of speed using variations in posted speed limits to see the effect on accidents and severity. Another way to gauge the effects of speed it to see how drivers respond to changes in the incentives to drive above the speed limit. Fines represent a disincentive to speed and can affect driving behaviour and therefore accident outcomes.

5.3 Road safety interventions

In an effort to improve road safety in Britain, two penalty interventions were implemented in 2017. Both involved increasing existing penalties for driving offences, the first for use of a hand-held mobile phone while driving and the second for 'excessive' speeding (more than 20–30 mph over the limit).

5.3.1 Mobile phone use

Since 2013 the penalty for using a hand-held mobile phone while driving has been a flat £100 fine and three penalty points (UK Department for Transport, 2016a). In spite of this, after the 2013 fine increase, there was no ongoing reduction in mobile phone use (UK Department for Transport, 2016a).

In an effort to reduce distracted driving (which has a worse effect on driving than being over the drink-drive limit (UK Department for Transport, 2016a)), on 1 March 2017 the UK Department for Transport doubled the penalty for using a hand-held mobile phone while driving to £200 and six penalty points. Drivers caught twice or accruing 12 penalty points faced going to court, disqualification and fines of up to £1000. In addition, newly qualified drivers (within two years of gaining a licence) could have their licence revoked and truck or bus drivers could be suspended. The new penalties were designed to reflect the seriousness of the offence, to treat all drivers equally and to increase the deterrent effect (UK Department for Transport, 2016a).

5.3.2 Speeding

England and Wales have had formal income-based fines for speeding since at least 2008, but there are alternative penalties for some less serious offences.[6] Police have some discretion in enforcement action. For example, depending on the circumstances they could issue a summons, issue a fixed penalty notice, offer a speed awareness course (at the offender's cost), issue a caution, warning or even take no action (Association of Chief Police Officers, 2013). However, 'driving at any speed over the limit is an offence and the police are not restricted and may prosecute' (Association of Chief Police Officers, 2013, p. 7). Table 5.1 shows how some of the enforcement activities can change with the severity of the offence. Police are able to issue fixed penalty notices comprising a £100 fine and 3 demerit points (if the offender pleads guilty) though these are unlikely to apply to the more serious speeding offences on which we will focus. Moreover, if an offender has 9 or more penalty points on his or her licence, the police cannot issue a fixed penalty notice and the offender has to go to court (Robbins, 2018).

Table 5.1: Speed enforcement guidelines for England and Wales, mph

Limit	Device tolerance	Fixed penalty when education is not appropriate	Speed awareness if appropriate		Summons in all other cases and above
			From	To	
20	22	24	24	31	35
30	32	35	35	42	50
40	42	46	46	53	66
50	52	57	57	64	76
60	62	68	68	75	86
70	73	79	79	86	96

Source: Association of Chief Police Officers (2013, p. 8).

Speeding penalties imposed by courts are governed by Sentencing Council Guidelines (table 5.2). Fines are set in bands according to percentages of income and between bands the amount of the fine varies to reflect the seriousness of the offence. Within a band there is scope to vary the fine rate. In addition to having a range from which to set the fine and some variation in demerit points/disqualification durations, there is further leeway in sanctions, as courts consider aggravating (increasing seriousness) and mitigating (reducing seriousness) factors and

[6] The Criminal Justice Act 2003 introduced a statutory duty for magistrates to take account of an offender's financial position and offence seriousness in setting fines, although there were no specific rules on how to accomplish this and adherence to this method of fine setting was not mandatory (Raine & Dunstan, 2009).

adjust the sentence accordingly. Aggravating factors can include previous convictions, road and weather conditions, vehicle type (e.g. goods vehicles), location (near schools) and traffic/pedestrian density in the area. Mitigating factors are having no previous convictions, being of good character and establishment of a genuine emergency (Sentencing Guidelines Council, 2017a). There may also be reductions in fines for guilty pleas.

Notwithstanding income-based fines, the maximum fine that can be imposed is £2500 if the offence occurred on a motorway and £1000 if the offence occurred on another road type. These maxima ensure the fine is proportionate to the seriousness of the offence.

Income based fines are designed to have an equal impact on the offender regardless of his or her financial circumstances and they have been designed to impose hardship but not to force the offender below a subsistence level of income available for reasonable living expenses. In determining the amount of a fine, the court makes reference to an offender's relevant weekly income.[7] Where an offender is in employment (including self-employment) and earns more than £120 per week after deductions for tax and national insurance (or equivalent if self-employed), relevant weekly income is actual income.[8] If such actual income is less than £120 or if the offender's only source of income is state benefit (with or without relatively low income permitted under such schemes), relevant weekly income is deemed to be £120. If an offender provides insufficient reliable information, the court can make its own determination about relevant weekly income. If there is no information about an offender's financial position, the court deems relevant weekly income to be £440 (a figure based on projected national median gross personal income). In some cases, the court may also take into account an offender's (or household's) broader financial circumstances (Sentencing Guidelines Council, 2017a).

Although further analysis would be required to determine whether the levels are optimal from a social perspective, the design of the system mimics the optimal fine structure suggested by economic theory.

[7] Under the Criminal Justice Act 2003, the financial circumstances order compels offenders to inform the court of their financial circumstances (UK Ministry of Justice, 2011).

[8] In 2015 when this limit was first applied, £120 was halfway between the base rate for jobseeker's allowance and net weekly income associated with an adult on the minimum wage working 30 hours per week (Sentencing Guidelines Council, 2008).

Table 5.2: Major speeding penalties in England and Wales, 2008

Speed limit		Recorded speed	
20	21 – 30	31 – 40	41 – 50
30	31 – 40	41 – 50	51 – 60
40	41 – 55	56 – 65	66 – 75
50	51 – 65	66 – 75	76 – 85
60	61 – 80	81 – 90	91 – 100
70	71 – 90	91 – 100	101 – 110
Starting point	50% of relevant weekly income	100% of relevant weekly income	100% of relevant weekly income
Range	25 – 75% of relevant weekly income	75 – 125% of relevant weekly income	75 – 125% of relevant weekly income
Maximum	£1000 on non-motorway and £2500 on motorway	£1000 on non-motorway and £2500 on motorway	£1000 on non-motorway and £2500 on motorway
Points/disqualification	3 points	4 – 6 points OR Disqualify 7 – 28 days	6 points OR Disqualify 7 – 56 days

Source: Based on Sentencing Guidelines Council (2008).

Different levels of speeding are associated with different levels of (expected) harm, according to the probability of an accident occurring and accident severity. Therefore the principle of marginal deterrence becomes relevant in setting fines. This principle, originally proposed by Stigler (1970), suggests penalties should increase with offence seriousness in order to deter individuals from committing more serious offences (Butler, Drahozal, & Shepherd, 2014; Polinsky & Shavell, 2000; Pyle, 1995).[9] For less serious speed offences, lower fines would induce a switch from more serious offences and the harm caused is likely to be lower overall (for example as fatalities become serious or slight injuries when speed declines). This substitution would increase social welfare (Butler et al., 2014).

On 24 April 2017, the Sentencing Guidelines Council issued new sentencing guidelines for magistrates courts in England and Wales. Consistent with the principle of marginal deterrence, the effect of the new guidelines was to increase fines for the most serious speeding offences from 100% to 150% of relevant weekly income, with the range of fines also increased (table 5.3). The idea behind the change was to ‘take into account the increase in potential harm that can result as speed above the limit increases’ and to ‘ensure that there is a clear increase in fine level as the seriousness of offending increases’ (Sentencing Guidelines Council, 2017b, p. 1). Maximum fines remained at £2500 for offences committed on motorways and £1000 for those

[9] The principle of proportionality works in a similar manner, as it also involves a relationship between the crime and penalty: ‘let the punishment fit the crime’. However, it is not clear from whose viewpoint (offender, society or victim) the damage (or gain) from the crime should be measured (Ginter, 1999).

on non-motorways and penalty points and disqualification remained unchanged from 2008 settings. The change was announced on 24 January 2017 in a press release from the Sentencing Guidelines Council (Sentencing Guidelines Council, 2017b).[10]

Table 5.3: Change in speeding penalties in England and Wales, 2008–2017

Speed limit	Recorded speed 2008	Recorded speed 2017
20	41 – 50	41 and above
30	51 – 60	51 and above
40	66 – 75	66 and above
50	76 – 85	76 and above
60	91 – 100	91 and above
70	101 – 110	101 and above
Starting point	100% of relevant weekly income	150% of relevant weekly income
Range	75 – 125% of relevant weekly income	125 – 175% of relevant weekly income
Maximum	£1000 on non-motorway and £2500 on motorway	£1000 on non-motorway and £2500 on motorway
Points/disqualification	6 points OR Disqualify 7 – 56 days	6 points OR Disqualify 7 – 56 days

Source: Based on Sentencing Guidelines Council (2008, 2017a).

Figure 5.4 shows how the old and new fines worked for the most serious category of speeding. For individuals on the median full-time employee income (approx. £28,000 per annum gross or £427 net per week), their fine increased from £427 to £641. For individuals working full time and earning income at the 90th percentile (£57,000 gross per annum or £779 net per week), their fine increased from £779 to either £1169 if the offence occurred on a motorway or £1000 if the offence occurred on a non-motorway.[11]

[10] According to Pina-Sánchez et al. (2019), the Sentencing Council deliberately announces changes to guidelines before they come into force so sentencers can 'familiarize themselves with their content' (p. 987).

[11] These income figures are based on data for England and Wales from the UK Annual Survey of Hours and Earnings for 2017 (see: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/bulletins/annualsurveyofhoursandearnings/2017provisionaland2016revisedresults#regional-earnings) and net earnings figures were then obtained from https://www.netsalarycalculator.co.uk/2016-2017-net-salary-calculator-gross-to-net-pay/, accessed 8/10/2019.

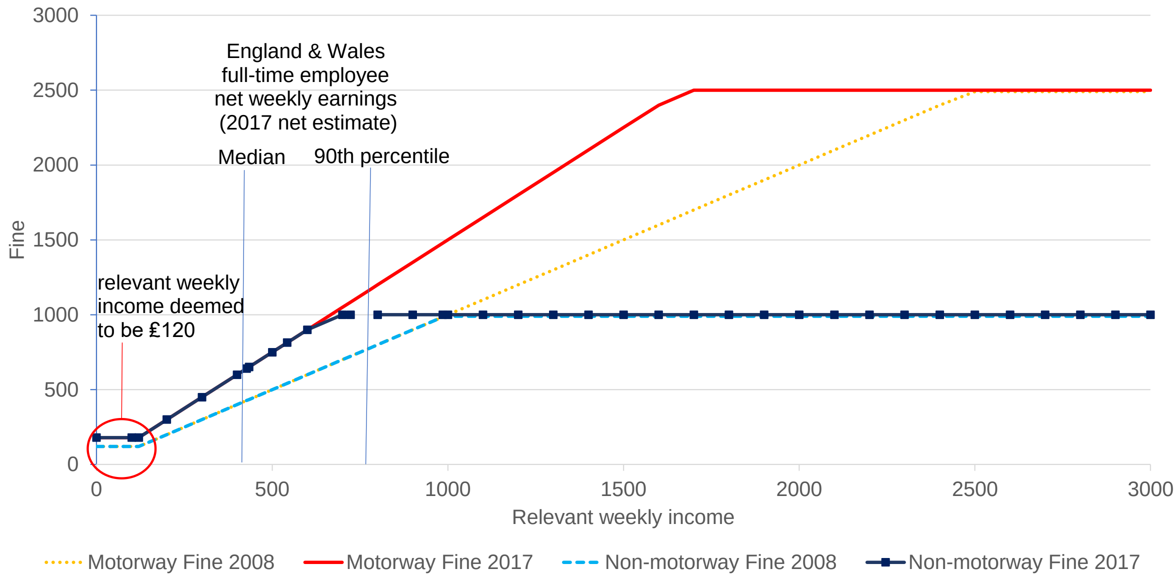

Figure 5.4: Most serious speeding offence fine regimes, 2008 and 2017

5.4 Data

Accident data comes from the British Stats19 database, which records details of every personal injury road accident involving at least one vehicle (of any type) and reported to police in Britain. The data are publicly available and can be downloaded from www.data.gov.uk/dataset/road-accidents-safety-data. Despite some known underreporting (particularly for less severe accidents), Stats19 remains a comprehensive source of data on the number and characteristics of road accidents reported by police, individuals involved in the accident or other members of the public (UK Department for Transport, 2016b). Accident severity is determined by the most serious casualty in the accident and is classified as fatal (death within 30 days), serious (injuries typically requiring hospitalisation) and slight (most other injuries). UK Department for Transport (2016b) provides a full list of conditions that are classified as serious injuries. Severity may include some measurement error as it is determined by police at the scene and the extent of some injuries may not be apparent to them at the time — indeed, identification of an accident as fatal might not occur until up to 30 days after the fact (UK Department for Transport, 2013). In our analysis we focus on serious or slight accidents as they account for over three-quarters of the total costs of injury accidents (UK Department for Transport, 2018a). Further details about the dataset are available in chapter 2 (section 2.3). Stats19 is provided at the individual accident level and includes information about geographic location. We aggregate to daily observations for each Local Authority (LA) in England and Wales (and in some cases Scotland) for our analysis. As part of the extended Stats19 dataset, information is recorded on up to 6 of some 77 contributory factors (UK Department for Transport, 2009), but these data were not made available for our analysis period.

Weather data were included to account for any unusual weather events at the time of the interventions. Data came from the UK Met Office Integrated Data Archive System (MIDAS) Land and Marine Surface Stations data provided by the Centre for Environmental Data Analysis (CEDA) (UK Met Office, 2018). Weather data comprise daily precipitation, maximum and minimum temperatures for each station.[12] There were 2635 stations recording rainfall and 449 stations recording temperature in the UK in 2018. Data processing steps are reported in Table A.5.1 in the appendix.

Considering the time around the interventions (specifically 365 days either side of the speed intervention), in both England/Wales and Scotland there is a substantive number of LA-days with no serious or fatal accidents (table 5.4).

Table 5.4: Distribution of daily serious or fatal accidents at Local Authority level for England, Wales and Scotland[a]

	England & Wales		Scotland	
Number of serious or fatal accidents	Freq.	Percent	Freq.	Percent
0	215,041	84.53	20,667	88.35
1	34,644	13.62	2,470	10.56
2	4,092	1.61	227	0.97
3	514	0.2	25	0.11
4	81	0.03	2	0.01
5	11	0	1	0
6	5	0	0	0
Total	254,388	100	23,392	100

[a]Sample comprises 365 days before and after the speeding intervention (centred at 24 April 2017).

[12] Not all stations are open/take readings every day of the sample period and some stations may measure temperature or precipitation but not both. There are a variety of other reasons for missing weather data. If the station uses manual observations, the person making the observations may not have been available. Also, equipment may have been faulty, or quality control procedures may mean data has been deleted due to problems with instruments or data corruption.

There are small variations in the mean numbers of serious or fatal accidents at various times around the two interventions (table 5.5). For England and Wales, numbers of accidents after the speeding intervention are significantly higher (at the 10% level of significance) but the numbers of accidents in Scottish LAs is not significantly different for the three time periods. As there may be other factors than the interventions influencing accidents at these times, we use an econometric model to account for these factors to estimate the true effect of the reforms.

Table 5.5: Summary statistics on daily serious or fatal accidents at Local Authority level for England, Wales and Scotland[a]

Country and time	Obs	Mean	SE	Std. Dev.	Min	Max
England & Wales						
1 Mar 2016-28 Feb 2017	127,020	0.172	0.001	0.434	0	6
1 Mar 2017-23 Apr 2017	18,792	0.169	0.003	0.431	0	4
24 Apr 2017-23 Apr 2018	127,368	0.177	0.001	0.444	0	6
Scotland						
1 Mar 2016-28 Feb 2017	11,680	0.135	0.004	0.386	0	5
1 Mar 2017-23 Apr 2017	1,728	0.122	0.009	0.357	0	3
24 Apr 2017-23 Apr 2018	11,712	0.122	0.003	0.361	0	3

[a]Samples are split between the year prior to the mobiles intervention, the time between the two interventions and the year after the speeding intervention.

5.5 Empirical strategy

Our treatments comprise the introduction on 1 March 2017 of a doubling of fines and penalty points for using a mobile phone while driving in England, Wales or Scotland and the introduction on 24 April 2017 of 50% larger fines for the most serious category of speeding in England and Wales. We hypothesise that these increases in penalties induce fewer serious or fatal accidents as:

H1 there will be less use of mobile phones in response to higher penalties, reducing driver distraction and leading to fewer serious or fatal accidents, and

H2 there will be less excessive speeding on the part of motorists in order to avoid the harsher fine, and driving at lower speeds reduces the number of serious or fatal accidents.

In order to tightly identify the effects of the increase in speeding fines, our modelling strategy involves a two-step process similar to that used by Castriota and Tonin (2019), De Paola et al. (2013) and Hausman and Rapson (2018). The first step involves estimating and removing long term effects of trend, seasonal, public holiday and weather factors from the raw data to create an adjusted series. The second step involves either a Regression Discontinuity in Time (RDiT) or Difference-in Difference (DiD) analysis of the intervention. DiD differs from RDiT in that the former makes use of a control group from which to compare results before and after the treatment. As the increased speeding fine relates to the most serious cases of speeding, we focus on accidents in which someone is seriously injured or killed.[13] We refer to such accidents as KSI (killed or seriously injured casualties).

This two-step RDiT approach — termed the augmented local linear approach by Hausman and Rapson (2018) — improves on the usual one-step approach (in which trend, seasonal, holiday, weather and treatment effects would be estimated from a single model), as the former accounts for longer term trend, seasonal/holiday and weather effects over 10 years rather than short term effects estimated over a much shorter period under the one-step approach. This allows for more precise estimates of these controls. The two-step DiD approach involves an analogous procedure and we believe is new to the accident literature.

5.5.1 Data adjustment

Accident numbers vary around trend, seasonal, day of week and public holiday effects associated with traffic volumes, vehicle and environmental safety features and some aspects of driver behaviour (resulting from say fatigue or time pressure on different types of days). Numbers also vary with weather conditions such as temperature and rainfall (affecting driving speeds and stopping distances and general road conditions). These factors are likely to be long term phenomena, so we estimate their effects over a 10 year period. For illustrative purposes, figure 5.5 shows serious or fatal accident numbers for England and Wales combined, with long term (national) trend, monthly seasonal and public holiday effects overlaid on the raw data.[14] Based on this picture, we expect numbers of serious or fatal accidents to increase significantly after the policy intervention due to seasonality/public holidays. It is therefore essential that these effects (together with day of the week effects) be removed from the data in order to identify the effects of the two penalty increases. Numbers of more serious accidents can also

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[13] For comparative purposes we also estimate the effects of the interventions on all injury accidents and present results in the appendix.

[14] For simplicity, weekday effects are not shown.

vary with weather conditions, so we want to ensure any estimated effects of the policies are not confounded by particularly good or bad weather conditions immediately after the interventions.

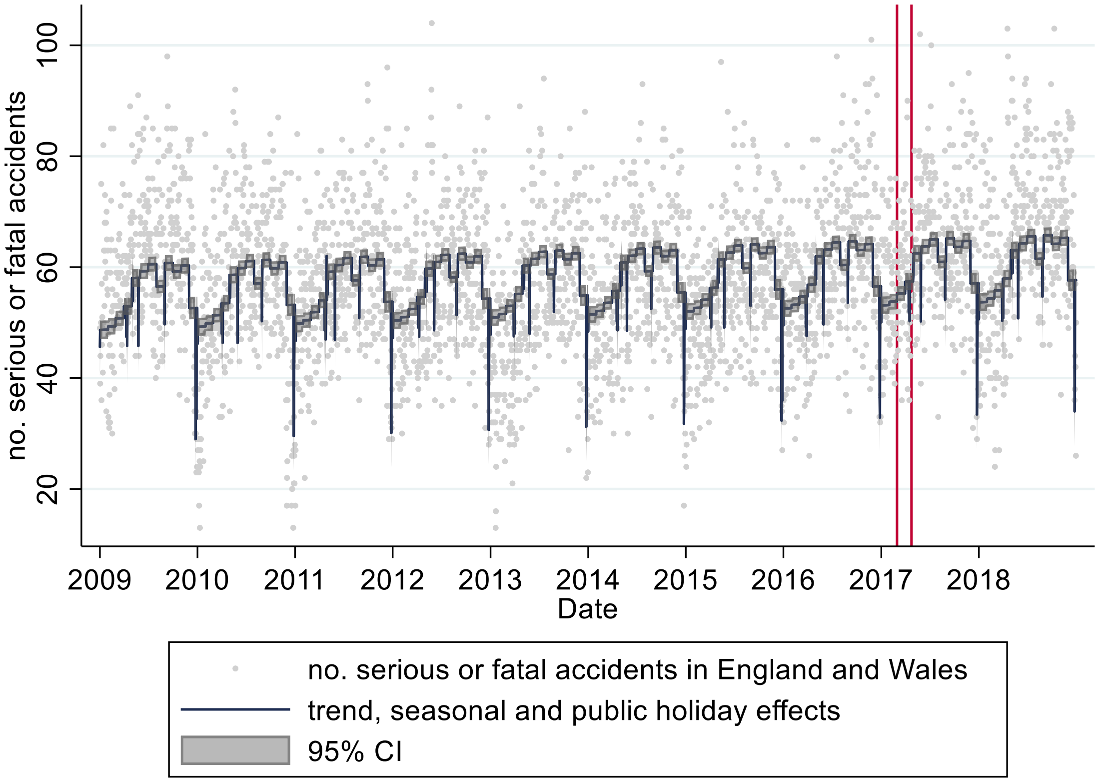

Figure 5.5: Serious or fatal accidents and long term (national) trend, seasonal and public holiday effects, England and Wales[a]

[a]Effects are estimated from a regression model incorporating a national trend, seasonal and public holiday dummies over the period 1/1/2009 to 31/12/2018. The dates of the two interventions are indicated by the red lines.

There are differences between geographic areas, so we define our first step model at the LA level and estimate using a one way (LA) fixed effects specification including weather variables (including weather and fixed effects in this step is recommended by Hausman and Rapson (2018)). Thus our first-step model is:

$$ksi_{it} = \beta_{1,i}Trend_{it} + \sum_{k=2}^{12}\beta_{2,\mathrm{k}}month_{kt} + \sum_{l=2}^{7}\beta_{3,\mathrm{l}}day_{lt}$$

$$+\beta_4 NY_t + \beta_5 GF_t + \beta_6 EM_t + \beta_7 MH_t + \beta_8 SBH_t + \beta_9 ABH_t + \beta_{10} XD_t + \beta_{11} BD_t$$

$$+\beta_{12} RW_t + \beta_{13} DJ_t + \beta_{14} max\_temp_{it} + \beta_{15} min\_temp_{it} + \beta_{16} prcp_{it} + \alpha_i + \varepsilon_{it}$$

(i=1, …, 380; t=1/1/2009, …, 31/12/2018) (1)

where ksi_{it} is the number serious or fatal accidents in which someone is killed or seriously injured in LA *i* (within England, Wales and Scotland) on day *t*, Trend_{it} is an LA-specific time trend for England, Wales and Scotland, month_{kt} is a set of monthly dummies, day_{lt} is a set of day of the week dummies, NY is a dummy for New Year's Day or its substitute holiday, GF is a dummy for Good Friday, EM is a dummy for Easter Monday, MH is a dummy for the May bank holiday, SBH is a dummy for the Spring bank holiday (in May), ABH is a dummy for the August bank holiday, XD is a dummy for Christmas day (or its substitute), BD is a dummy for Boxing day (or its substitute), RW is a dummy for the day of the Royal Wedding in 2011 and DJ is a dummy for the Diamond Jubilee in 2012.[15] $\mathrm{Max\_temp}_{it}$ and $\mathrm{min\_temp}_{it}$ are daily maximum and minimum air temperature (Celsius) in each LA, prcp_{it} is daily precipitation (mm) in each LA and α_i are LA fixed effects.[16] In some analyses we restrict attention to the 348 LAs in England and Wales. Estimated standard errors are robust to heteroscedasticity.

Typically, our 10 year estimation sample for this step runs from 1/1/2009 to 31/12/2018.[17] Having estimated equation (1), we then remove these effects from the raw data in preparation for step two (RDiT or DiD).

5.5.2 Regression Discontinuity in Time (RDiT)

One way to identify the causal effect of the policy change on accidents is to employ an RDiT approach in step two. RDiT is a variant of Regression Discontinuity Design — a technique that has been used since the 1960s (Imbens & Wooldridge, 2009) — in which time is the running

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[15] A full list of public holiday dates is given in the appendix (Table A.5.2).

[16] Weather measurements relate to the station nearest the centroid of the LA area that was open on the day and had recorded measurements. The nearest weather station was identified using Stata's geonear user written command. Average distances from centroids to temperature stations were 7.14 miles (ranging from 0.27 miles to 26.75 miles) and to rainfall stations were 3.15 miles (ranging from 0.23 miles to 33.90 miles).

[17] IMD data are only available from 1 Jan 2016, so this limits our sample period for step one when we investigate heterogeneity by driver income.

variable and treatment begins at a particular known point in time, introducing a discontinuity in the series of interest (Hausman & Rapson, 2018).[18] When examining the effects of the mobile phone intervention, we assume drivers involved in serious or fatal accidents are treated (subject to the higher penalty regime) if the accident occurs on or after 1 March 2017 and untreated if the accident occurs earlier. In the case of the speeding fine increase, we assume our drivers are treated if the accident occurs on or after 24 April 2017 and untreated if the accident occurs prior to this.

According to Athey and Imbens (2017), 'a regression discontinuity design enables the estimation of causal effects by exploiting discontinuities in incentives or ability to receive a discrete treatment' (p. 5). The discontinuity is introduced by an exogenous change in a running variable that changes the probability of an outcome.

We can estimate causal effects of the treatment on the outcome by assuming observations close to each other but either side of the treatment 'threshold' are otherwise the same. By taking a relatively short window either side of the threshold and controlling for other factors in the first step of our procedure, there is very little scope for other factors to have changed, so our estimate identifies the causal effect. The result is interpreted as the average treatment effect.

Porter (2003) suggests using a non-parametric local linear regression to estimate the treatment effects. Using a rectangular kernel, this involves estimating a linear regression of the outcomes on the running variable either side of the discontinuity and testing for a significant difference at the point of the discontinuity.

In order to identify the effect of the first intervention (mobile phone penalties), we model serious or fatal accidents at the daily level for approximately 8 weeks (54 days) either side of the intervention. This time period occurs before the speeding fine intervention and thus shows an unconfounded effect. To make results comparable between the two interventions, we restrict attention to LAs in England and Wales (which were subject to both interventions).

[18] The two step RDiT procedure is similar to the Interrupted Time Series (ITS) approach, although ITS uses one step. Both procedures rely on the assumption of smoothness of all confounders across the threshold.

The effect of the mobile phone intervention on accidents is identified using a single intercept shift that represents the average effect over the sample period after the date of introduction (1 March 2017). We use a pooled regression model specified at LA level.

Our RDiT model is specified as:

$$\widetilde{ksi_{it}} = \gamma_0 + \gamma_1 Post\_mob_t + u_{it}$$

(i=1, …, 348; t=6/1/2017, …, 23/4/2017) (2)

where $\widetilde{ksi_{it}}$ is the adjusted number of serious or fatal accidents in LA i (within England and Wales) on day t (in effect, the residuals from step one), Post_mob is a dummy variable indicating whether the day is before or after the mobile penalty increase. In this equation, γ_1 is the parameter of interest and shows the average effect of the penalty increase on numbers of serious or fatal accidents for England and Wales over 54 days.

To identify the effect of the second (speeding) intervention, we again model daily serious or fatal accidents for each LA over 365 days pre and post intervention (i.e. centred around 24 April 2017).

In this case, our effect may be confounded by the overlapping effect of the mobile intervention, so we adapt our previous RDiT specification to incorporate the effects of both interventions. Thus our pooled RDiT model is:

$$\widetilde{ksi_{it}} = \delta_0 + \delta_1 Post\_mob_t + \delta_2 Post\_speed_t + v_{it}$$

(i=1, …, 348; t=24/4/2016, …, 24/4/2018) (3)

where Post_speed is a dummy variable identifying days before and after the intervention and all other variables are defined as before. δ_2 is the parameter of interest, showing the average effect over one year.

Ordinarily, an RDD (or RDiT) identifies the causal effect of an intervention using a small window before and after the change so as to effectively hold other factors constant across the two parts of the sample. In this case, we adopt a wider window to allow for an adjustment process in which individuals take time to recognise the regime change and adapt their driving in response.[19] This means we estimate a longer-term effect of the intervention. Robust standard errors are estimated as there is only one level in the treatment (all LAs under consideration are subject to the treatment) and this precludes clustering the standard errors.

The two interventions may have different effects on drivers from different income groups, so we proxy income by the Index of Multiple Deprivation (IMD) decile of the driver and explore heterogeneity in our main results. To do this, we identify accidents involving one or more drivers from a particular IMD decile and estimate an RDiT model on this subsample of accidents. We can then compare treatment effects across different types of drivers/accidents.

Our main set of results estimates a single treatment effect. Since effects could change with time since the intervention, in the appendix we explore the robustness of our main results by changing the sample period included (usually termed the 'bandwidth') and by allowing for non-linear treatment effects (by month and by quarter).[20]

5.5.3 Difference-in-Difference (DiD)

An alternative way to identify the causal effect of an intervention is to compare outcomes for a 'treatment' and 'control' group over time using a DiD approach in step two of our analysis. DiD has been a fairly standard tool for causal analysis since the 1990s (Athey & Imbens, 2017), though the basic idea was introduced in economics in Obenauer and von der Nienburg (1915) and has been used in seminal papers such as Ashenfelter (1978) and Ashenfelter and Card (1985). In the road accident literature the technique has also been used to study the effects of congestion charging (see, for example, Green, Heywood, & Navarro, 2016; Li, Graham, & Majumdar, 2012), alcohol-specific interventions (see, for example, Green, Heywood, & Navarro, 2014; Lovenheim & Slemrod, 2010), and behavioural road safety interventions (see, for example, Corsaro, Gerard, Engel, & Eck, 2012).

This methodology takes the average change over time in a control group and subtracts it from the average change in the treatment group to identify the treatment effect.[21] That is, we estimate

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[19] This has the added benefit of improving the power of our estimates.

[20] Such non-linear treatment effects estimated in this way make the RDiT similar to an event study, in which the effect of the event or treatment evolves over time.

[21] Thus we estimate an average treatment effect rather than multiple effects over time as we would in an event study.

a counterfactual change for the treatment group assuming it was untreated (Athey & Imbens, 2017). Such double differencing removes biases that could be due to inherent differences between the two groups or due to confounding effects over time that are not related to the treatment (Imbens & Wooldridge, 2009), although with multiple time periods it is critical that the two groups are assumed to have parallel trends leading up to the intervention. Our use of the two-step approach, in which we adjust the data for trends and seasonality in step one is important for the DiD in step two, as without this correction a difference in trends or seasonality at the LA level between the treatment and control groups could violate the parallel trends assumption.

In our case we have two treatments we examine: the mobile phone intervention and the speeding fine intervention.

We use DiD to explore heterogeneity by road type as there may be different effects on motorways relative to B and C roads (different speeding fine caps, different probability of detection of mobile use). In these analyses, we use serious or fatal accidents on B and C roads as a control group relative to those on motorways as the treatment group.

Using DiD, we also explore the robustness of our findings from the RDiT analysis of the speed intervention by comparing serious or fatal accidents in LAs in England and Wales (treatment) with those in Scotland (control). For a more targeted analysis we also compare LAs on either side of the Scotland/England border.

Thus our definitions of treatment and control groups (and our sample) differ according to the research question. The most general specification for our DiD model is as follows.

$$\widetilde{ksi_{it}} = \xi_0 + \xi_1 T_t + \xi_2 G_i + \xi_3 T_t \cdot G_i + \xi_4 Post\_mob_t + \epsilon_{it}$$

(i=1, …, 380; t=24/4/2016, …, 24/4/2018) (4)

where $\widetilde{ksi_{it}}$ is the adjusted number of serious or fatal accidents in LA *i* on day *t* (in effect, the residuals from step one), T_t is an indicator for before/after the intervention, G_i indicates treatment or control group and ξ_3 is the DiD (average) treatment effect. When analysing the mobile reform, we opt for a 54 day window either side of the intervention so as not to confound the treatment effects with those for the speeding reform. For the speeding reform we use a +/–365 day window and include an intercept shift for the mobile intervention (Post_mob).

Robust standard errors are estimated because there the treatment only varies by country and road type (i.e. there are two groups) and this precludes clustering the standard errors.

All analysis was carried out using Stata15.

5.6 Results

Results for the main RDiT models for the two interventions are shown in tables 5.6 and 5.7. Table 5.6 shows the effects of the mobile phone reform on serious or fatal accidents in England and Wales to be statistically and economically insignificant. That is, over 54 days post intervention there is no appreciable effect, likely due to no change in driver behaviour with respect to the use of mobile phones. A lack of effect on behaviour could result if individuals do not consider the £100 increase in fine to be significant (low income elasticity), if they deem the probability of conviction to be low, or if they are largely unaware of the change.

Table 5.6: Step 2 RDiT (pooled) modelling results, mobile intervention, England and Wales[a]

Variables	Coefficient (SE)
Post_mob	-0.003
	(0.004)
Constant	0.010***
	(0.003)
Adjusted R-squared	0.000

[a]The RDiT sample covers 54 days either side of the mobile phone intervention (March 1, 2017). Mean number of serious or fatal accidents over this sample is 0.166 (SD 0.429). Dependent variable is the residuals from the first step model. Robust standard errors are shown in parentheses. n=37,932. Step one modelling results are given in Table A.5.3 in the appendix. *** p < 0.01, ** p < 0.05, * p < 0.1.

In terms of the speeding fine intervention, table 5.7 shows there is also no significant effect on serious or fatal accidents in England and Wales. Again, this could be due to a low income elasticity, a perceived low probability of detection/conviction and/or being unaware of the change.

Table 5.7: Step 2 RDiT (pooled) modelling results, speed intervention, England and Wales[a]

Variables	Coefficient (SE)
Post_mob	0.003
	(0.003)
Post_speed	-0.000
	(0.003)
Constant	0.003**
	(0.001)
Adjusted R-squared	0.000

[a]The RDiT sample covers 365 days either side of the speeding intervention (April 24, 2017) and includes an intercept shift from the date of the mobile intervention (Post_mob=1 from March 1, 2017). Post_speed is the variable of interest. Mean number of serious or fatal accidents over this sample period is 0.176 (SD 0.441). Dependent variable is the residuals from the first step model. Robust standard errors are shown in parentheses. n=254,388. Step one modelling results are given in Table A.5.3 in the appendix. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.6.1 Heterogeneity analysis

Individuals might react to these penalties differently according to their income levels or the type of roads they drive on. Therefore the lack of an overall effect could disguise heterogeneity in the responses of some groups of individuals. In this section we explore these effects.

For the mobile phone intervention, the level of fines doubled, as did the number of penalty points. Fines have a direct link with foregone income, whereas penalty points have an indirect link via licence suspension if enough points are accrued. Licence suspension may increase the cost of transport and in some cases lead to job loss. In the case of the speeding fine intervention, levels of fines are proportional to income, and the intervention raised the fine to 150% of relevant weekly income.

A downward sloping demand curve (consistent with the income effect) would imply an increase in the ‘price’ of offending reduces demand for offending and that this reduces numbers of consequent serious or fatal accidents. The magnitude of this effect may differ by income for two reasons.

First, a doubling in the level of a mobile phone fine may have a larger effect on low income individuals. However, in the case of speeding fines, if individuals respond to the level of the fine rather than the proportion of income, the same change in the proportion of income is a higher amount for high income individuals and might provide stronger incentive for them to reduce speed.

Second, in the case of speeding fines, which are linked by and large to wage income, individuals at different ends of the wealth distribution may have different financial resources available to 'cushion' the effect of the fine increase. For example, wealthier individuals might have savings to draw upon and poorer individuals might have benefits that are excluded from the income assessment.

To distinguish effects across the income distribution would require data on driver income (or at least a measure of socioeconomic status (SES)), which is not available in the data. We do have an Index of Multiple Deprivation (IMD) that is recorded for each driver's area of residence. Whilst this does not directly measure a driver's SES, it does give some idea about relative disadvantage the area in which he or she lives and can be used to proxy SES. An outline of the IMD measures for England, Wales and Scotland is given in the appendix.

For this analysis, we identify serious or fatal accidents involving *at least one* driver from the relevant IMD decile and use our main model to identify the effects of each intervention. Although not perfect, this should go some way to identifying different income effects.

For the mobile intervention, we might expect to see drivers from more disadvantaged areas having lower incomes and therefore a larger response to the fine increases and additional penalty points associated with being caught using a mobile phone while driving. We would therefore expect to see fewer numbers of serious or fatal accidents involving a driver from an IMD1 area (the most deprived). However, there is no significant response to the mobile phone intervention for any of the IMD groups over the 54 days post-intervention (table 5.8).

Table 5.8: Step 2 RDiT (pooled) modelling results, mobile intervention by IMD, England, Wales and Scotland[a]

	Post_mob		Constant			
IMD decile	Coefficient	SE	Coefficient	SE	Adjusted R-squared	Mean no. serious or fatal accidents[b]
1	0.001	(0.002)	-0.001	(0.001)	-0.000	0.020
2	-0.001	(0.002)	0.001	(0.001)	-0.000	0.021
3	-0.000	(0.002)	0.000	(0.001)	-0.000	0.021
4	0.001	(0.002)	-0.000	(0.001)	-0.000	0.021
5	-0.001	(0.001)	0.000	(0.001)	-0.000	0.019
6	0.001	(0.001)	-0.001	(0.001)	-0.000	0.020
7	0.002	(0.001)	-0.000	(0.001)	-0.000	0.020
8	0.001	(0.001)	-0.000	(0.001)	-0.000	0.018
9	0.001	(0.001)	-0.001	(0.001)	-0.000	0.017
10	-0.001	(0.001)	-0.000	(0.001)	-0.000	0.015

[a]The RDiT sample covers 54 days either side of the mobile phone intervention (March 1, 2017). [b]Accidents per region per day. Dependent variables are the residuals from the first step models. Robust standard errors are shown in parentheses. n=41,420. Step 1 modelling results are given in Table A.5.6 in the appendix. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Relative to the mobile phone intervention, the speeding intervention typically involves a much larger increase in the fine (which is income-based). If individuals react to the level of the fine rather than the proportion of income (a cognitively simpler task, consistent with bounded rationality), we might expect individuals at the higher end of the income distribution to respond more strongly to the change. There is indeed some evidence of this as there are fewer serious or fatal accidents involving drivers from the sixth, seventh and eighth IMD deciles (and, to a lesser extent the ninth IMD decile) after the fine increase (table 5.9). Interestingly, there is also a significant reduction in serious or fatal accidents involving a driver from the lowest IMD decile. This would be consistent with these individuals having no access to other forms of income to 'cushion' the impact of the increased fine. There is also a small and marginally significant reduction in serious or fatal accidents involving a driver from IMD decile 4.[22]

[22] Although adjustment for multiple hypothesis tests (not shown) using Stata's wyoung command with 5000 bootstraps showed many of the speed intervention coefficients became insignificant.

Table 5.9: Step 2 RDiT (pooled) modelling results, speed intervention by IMD, England and Wales[a]

IMD decile	Post_mob Coefficient	Post_mob SE	Post_speed Coefficient	Post_speed SE	Constant Coefficient	Constant SE	Adjusted R-squared	Mean no. KSI accidents
1	-0.000	(0.001)	-0.003**	(0.001)	0.001**	(0.001)	0.000	0.022
2	-0.001	(0.001)	-0.002	(0.001)	0.001***	(0.001)	0.000	0.023
3	-0.001	(0.001)	-0.002	(0.001)	0.001*	(0.000)	0.000	0.022
4	-0.001	(0.001)	-0.002*	(0.001)	0.001*	(0.001)	0.000	0.023
5	-0.003**	(0.001)	-0.001	(0.001)	0.001**	(0.001)	0.000	0.022
6	-0.001	(0.001)	-0.003**	(0.001)	0.001**	(0.000)	0.000	0.022
7	0.001	(0.001)	-0.004***	(0.001)	0.001**	(0.000)	0.000	0.021
8	-0.000	(0.001)	-0.003***	(0.001)	0.001***	(0.000)	0.000	0.020
9	-0.001	(0.001)	-0.002*	(0.001)	0.001**	(0.000)	0.000	0.020
10	-0.002	(0.001)	-0.001	(0.001)	0.001***	(0.000)	0.000	0.017

[a]The RDiT sample covers 365 days either side of the speed intervention (April 24, 2017). Post_speed is the variable of interest. Dependent variables are the residuals from the first step models. Robust standard errors are shown in parentheses. n= 254,388. Step 1 modelling results are given in Table A.5.6 in the appendix. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The mobile intervention may have different effects on motorways versus more minor roads if individuals have different expectations about the probability of detection and therefore conviction on such roads. If individuals perceive there is less chance of being caught on minor roads (as there may be less police activity and poorer lighting conditions), there may be a smaller effect on serious or fatal accidents on B and C roads relative to motorways.

Although the speed intervention increases fines as a proportion of income, there are caps on the amount that can be imposed. The maximum fine remains unchanged at £2500 for offences occurring on motorways and at £1000 for those on non-motorways. This implies that wealthy individuals may pay less than 150% of their income under the new regime and that the actual percentage will vary by road type.

To gauge these effects, we consider accidents by road type. While non-motorways are spread across Britain, motorways are few and (often) far between. A map of motorways is shown in the appendix (Figure A.5.5). Tables 5.10 and 5.11 report results of a DiD analysis comparing road types in England and Wales (motorways and B/C roads) before and after the interventions. We consider only England and Wales to keep the analyses comparable geographically. Results for the mobile intervention show serious or fatal accidents are significantly fewer on motorways than on B/C roads but that the trends remain parallel after the intervention (no significant difference in the DiD interaction term). Thus we cannot say there is a significant effect of the intervention on one road type relative to the other.

Table 5.10: Step 2 DiD (pooled) modelling results, mobile intervention by road type, England and Wales[a]

Variables	Coefficient (SE)
T (1=post)	-0.001
	(0.002)
G (1=motorway)	-0.003*
	(0.002)
DiD	0.002
	(0.002)
Constant	0.002
	(0.001)

[a]The DiD sample covers 54 days either side of the mobile intervention (March 1, 2017). Dependent variable is the residuals from the first step models. Robust standard errors are shown in parentheses. Adjusted R-squared=0.000. n=58,206. Step 1 modelling results are given in Table A.5.5 in the appendix. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Results for the speed intervention indicate the small gap in numbers of serious or fatal accidents between motorways and B/C roads is narrowing significantly post-intervention. This would indicate a smaller decrease in such accidents on motorways (or a larger decrease on B/C roads). Perhaps this is linked to average speeds travelled on these different roads and the 'power curve' linking speed to accident severity: for the same effect on speeding behaviour, the accident outcome (and therefore number of serious or fatal accidents) is likely to be worse on a motorway than a B or C road, closing the gap in numbers of such accidents. Individuals may also consider there is a relatively larger risk of detection on B/C roads and reduce speed accordingly.

Table 5.11: Step 2 DiD (pooled) modelling results, speed intervention by road type, England and Wales[a]

Variables	Coefficient (SE)
Post_mob	-0.000
	(0.001)
T (1=post)	-0.002
	(0.001)
G (1=motorway)	-0.001
	(0.001)
DiD	0.002**
	(0.001)
Constant	0.001**
	(0.001)

[a]The DiD sample covers 365 days either side of the speed intervention (April 24, 2017). Dependent variable is the residuals from the first step models. Robust standard errors are shown in parentheses. Adjusted R-squared=0.000. n=390,354. Step 1 modelling results are given in Table A.5.5 in the appendix. *** p < 0.01, ** p < 0.05, * p < 0.1.

5.7 Robustness checks

Effects of the interventions may change over time as individuals adapt their driving behaviour and accidents respond. Thus far we have investigated a single average treatment effect for the speed intervention over one year.[23] In this section we explore the robustness of these results in two ways. Firstly, we allow for behavioural adaptation by allowing intervention effects to vary over time using an RDiT framework. Secondly, we use a DiD analysis to compare the effects of the speed intervention in England and Wales relative to outcomes in (untreated) Scotland.

5.7.1 RDiT speed intervention effects over time

The effects of the intervention on numbers of serious or fatal accidents may change over time. There are two ways we may observe these changes: by varying the estimation sample around the intervention date (referred to in the regression discontinuity literature as changing the bandwidth) and by explicitly allowing the effects to vary over time using the full sample and estimating different coefficients for different points in time (allowing for non-linear effects).

By changing the bandwidth over which we estimate the RDiT, we can observe how the effect changes. Changes typically represent a tradeoff between bias and precision in the estimates,

[23] The mobile phone intervention is examined over a much shorter window (54 days) and there is therefore less scope for behaviour to vary within that timeframe.

such that we get more precision with a larger bandwidth but allow for more bias in the estimate (for example if the relationship is non-linear). If this is the only consideration, ideally in a well-specified model we would like to see stability in the coefficients. If the effect of the speed intervention is changing over time we will also see changes in the coefficients as they represent an average effect over different time windows.

Table 5.12 reports RDiT modelling results for different bandwidths. For each bandwidth the effect is not significantly different from zero and is small. This suggests there is little change in the effect throughout the year.

Table 5.12: Step 2 RDiT (pooled) modelling results, speed intervention by bandwidth, England and Wales[a]

Bandwidth Variable	30 days Coefficient (SE)	60 days Coefficient (SE)	90 days Coefficient (SE)	180 days Coefficient (SE)	365 days Coefficient (SE)
Post_mob	n/a	-0.000	-0.004	-0.002	0.003
	n/a	(0.010)	(0.005)	(0.004)	(0.003)
Post_speed	-0.002	-0.001	0.004	-0.001	-0.000
	(0.010)	(0.004)	(0.004)	(0.004)	(0.003)
Constant	0.007	0.007	0.011***	0.009***	0.003**
	(0.004)	(0.009)	(0.004)	(0.002)	(0.001)
n	21,228	42,108	62,988	125,628	254,388
Adjusted R-squared	0.000	0.000	0.000	0.000	0.000

[a]The RDiT sample covers up to 365 days either side of the speed intervention (April 24, 2017), as shown by the relevant bandwidth. Post_speed is the variable of interest. Dependent variables are the residuals from the first step model. Robust standard errors are shown in parentheses. Step 1 modelling results are given in Table A.5.3 in the appendix. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Another way to observe whether the effect of the speeding intervention changes over time is to explicitly allow for such changes in the model. The intervention may have several effects on driver behaviour and therefore accidents, as illustrated in figure 5.6. On the left hand side we show a regression line for daily numbers of accidents adjusted for mean levels, and long-term trend and seasonal effects. After the intervention, when penalties increase, there might be a one-off change in behaviour for everyone that permanently lowers accidents but leaves them on the same trend (the dotted blue line). Alternatively, there might be an increasing adjustment to the new levels of fines as information about the policy change spreads throughout the population and behaviour adjusts permanently (the grey line). Yet again, there might only be a temporary change in behaviour, whereby accidents decline immediately following the policy change but then revert to pre-intervention levels (the dashed yellow line), or there may be no change in behaviour (the green line).

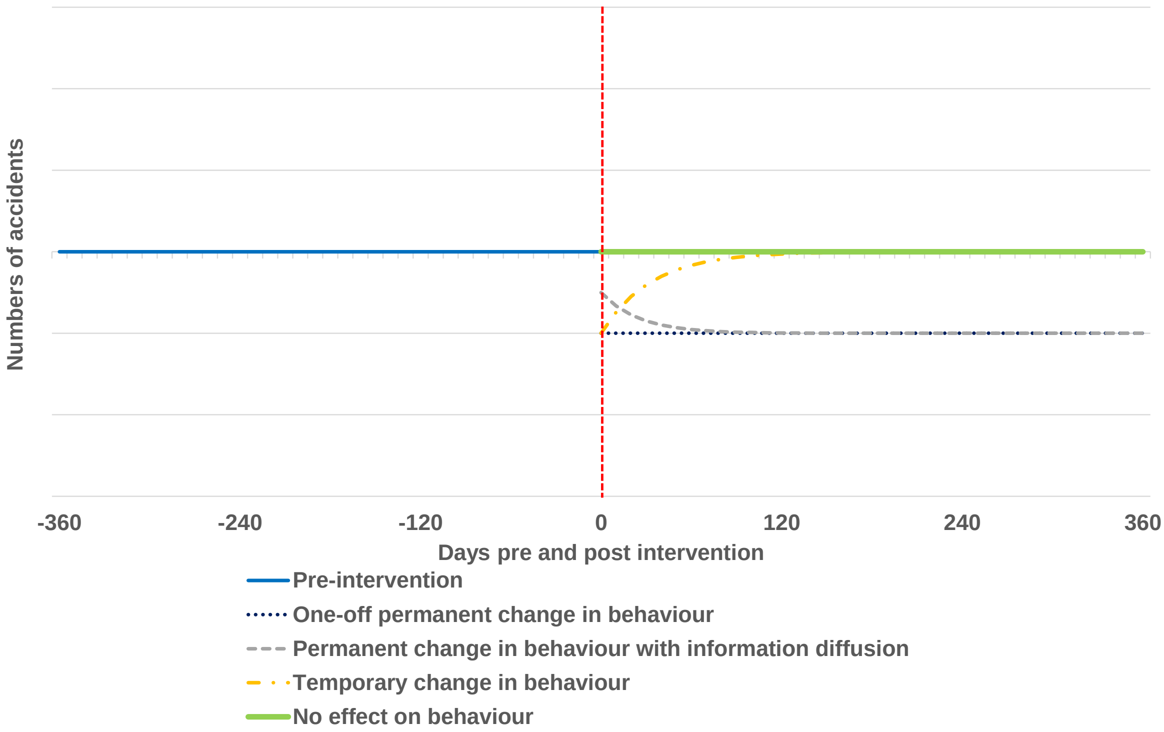


Figure 5.6: Potential effects on accidents of increased penalties

To allow for such changes in behaviour we include a separate step function for each time period of interest after the intervention. By comparing the effects over time, we can gauge what type of behavioural change, if any, has occurred.

In table 5.13 we report results for monthly and quarterly effects over the 365-day bandwidth. Each month represents 30 days and each quarter 90 days (except the final month and quarter, which only cover 5 days). For the quarterly results we see no significant effects in the main (although there is a significant positive effect for the final 5 days of the year, which given the time since the intervention is likely due to other factors). There remains scope for different effects within a quarter and this is what we see in the monthly results. Despite significant increases in serious or fatal accidents at 3 months, 8 months and 13 months relative to the intercept, figure 5.7 shows the confidence intervals for the monthly coefficients and only the 'spike' at month 8 is significantly different from the surrounding month effects (but then, at a delay of 8 months, this (counterintuitive) positive effect is likely due to other factors).

Table 5.13: Step 2 RDiT (pooled) modelling results, speed intervention by month/quarter, England and Wales[a]

Variable	Month Coefficient (SE)	Quarter Coefficient (SE)
Post_mob	0.003	0.003
	(0.003)	(0.003)
Post_speed effects		
Post_mth1	-0.002	
	(0.005)	
Post_mth2	-0.001	
	(0.005)	
Post_mth3/Post_qtr1	0.015***	0.004
	(0.006)	(0.004)
Post_mth4	-0.008	
	(0.005)	
Post_mth5	-0.004	
	(0.005)	
Post_mth6/Post_qtr2	-0.006	-0.006
	(0.005)	(0.004)
Post_mth7	-0.007	
	(0.005)	
Post_mth8	0.020***	
	(0.005)	
Post_mth9/Post_qtr3	-0.005	0.003
	(0.005)	(0.004)
Post_mth10	0.005	
	(0.005)	
Post_mth11	-0.007	
	(0.005)	
Post_mth12/Post_qtr4	-0.004	-0.002
	(0.005)	(0.004)
Post_mth13/Post_qtr5	0.025**	0.025**
	(0.012)	(0.012)
Constant	0.003**	0.003**
	(0.001)	(0.001)
Adjusted R-squared	0.000	0.000

[a]The RDiT sample covers 365 days either side of the speed intervention (April 24, 2017). Dependent variables are the residuals from the first step model. Each month represents 30 days and each quarter 90 days, with the final month and quarter covering 5 days. Robust standard errors are shown in parentheses. n=254,388. Step 1 modelling results are given in Table A.5.3 in the appendix. *** p < 0.01, ** p < 0.05, * p < 0.1.

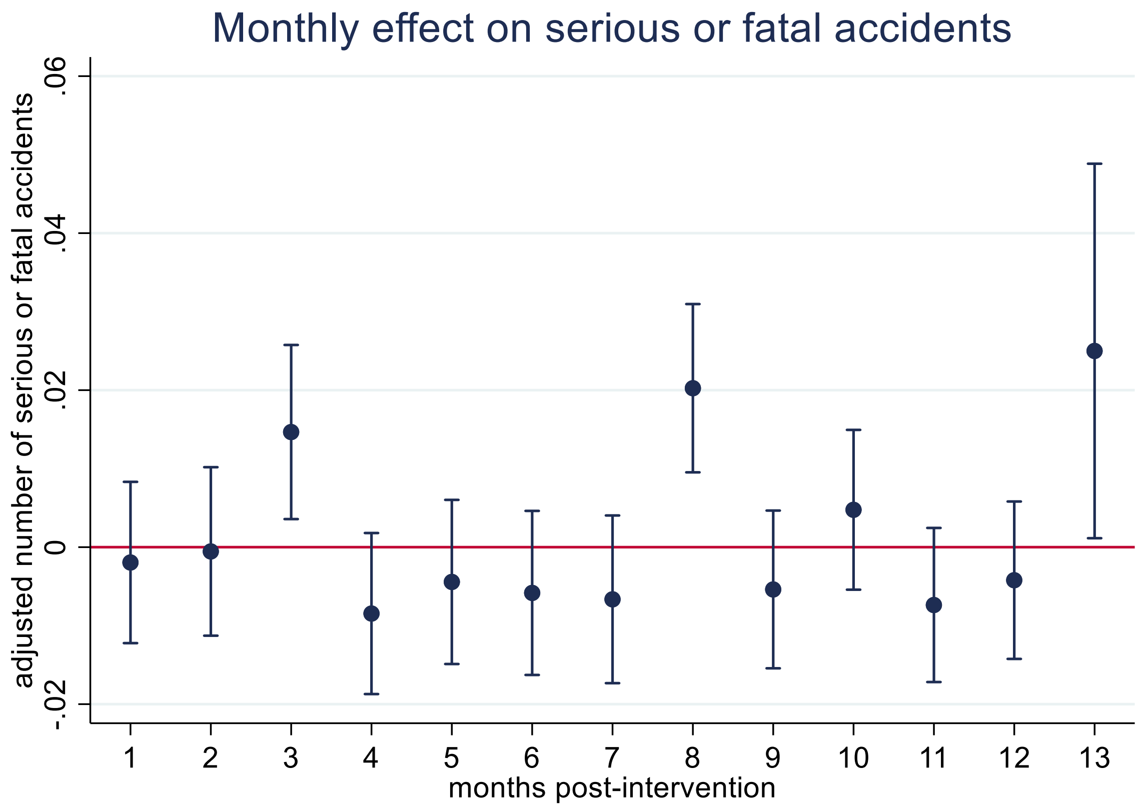


Figure 5.7: Coefficients and 95% confidence intervals for monthly effects of the speeding intervention

5.7.2 DiD speed intervention effects by country

So far we have seen a distinct lack of effect of the speeding intervention on numbers of serious or fatal accidents in England and Wales. In spite of this, it would be useful to compare this result to a control area that did not have the intervention. As the intervention was not implemented in Scotland, we can use that country as a control and use DiD analysis to compare the effects of the speed intervention in England and Wales relative to outcomes in (untreated) Scotland. The idea is to use outcomes in Scotland and assume parallel trends in serious or fatal accidents over the year prior to the intervention to construct a counterfactual estimate of numbers of accidents in England and Wales in the post-treatment period as if the treatment had not occurred. Comparing this counterfactual estimate with the observed outcome allows us to see the treatment effect.

With the lack of a treatment effect when studying England and Wales in the RDiT analysis, it might be that accidents should have risen in the absence of the treatment due to other factors.

If we observe such an increase in Scotland, then this type of analysis would indicate a treatment effect that reduced accidents below what they otherwise might have been.

Table 5.14 reports the DiD estimates of the treatment effect of the speeding intervention and shows no significant treatment effect. That is, there would appear to be parallel trends between England/Wales and Scotland after the intervention.

Table 5.14: Step 2 DiD (pooled) modelling results, speed intervention, England/Wales and Scotland[a]

Variables	Coefficient (SE)
Post_mob	0.004
	(0.003)
T (1=post)	-0.008
	(0.006)
G (1=England/Wales)	0.001
	(0.004)
DiD	0.007
	(0.005)
Constant	0.002
	(0.004)

[a]The DiD sample covers 365 days either side of the speed intervention (April 24, 2017). Dependent variable is the residuals from the first step models. Robust standard errors are shown in parentheses. Adjusted R-squared=0.000. n=277,780. Step 1 modelling results are given in Table A.5.5 in the appendix. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

There is considerable scope for heterogeneity in driver behaviour and accidents across all of England, Wales and Scotland. To remove some of that heterogeneity, a better comparison might be between areas close to the England/Scotland border. Thus we repeat the DiD analysis including only LAs close to the border. The border LAs are: Allerdale, Barrow-in-Furness, Carlisle, Copeland, Eden, Northumberland, South Lakeland in England and City of Edinburgh, Dumfries and Galloway, East Lothian, Midlothian, Scottish Borders and West Lothian in Scotland.

When we repeat the DiD analysis (table 5.15), we still see no significant effect of the intervention, suggesting driver behaviour has not changed appreciably in response to the speeding intervention.

Table 5.15: Step 2 DiD (pooled) modelling results, speed intervention, England and Scotland border[a]

Variables	Coefficient (SE)
Post_mob	0.011
	(0.034)
T (1=post)	-0.044
	(0.038)
G (1=England/Wales)	0.002
	(0.024)
DiD	0.025
	(0.033)
Constant	0.022
	(0.018)

[a]The DiD sample covers 365 days either side of the speed intervention (April 24, 2017). Dependent variable is the residuals from the first step models. Only LAs near the Scottish border are included. Robust standard errors are shown in parentheses. Adjusted R-squared=-0.000. n=4,630. Step 1 modelling results are given in Table A.5.5 in the appendix. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.8 Reasons for lack of effect

At the time of the increase in mobile phone penalties, ratings information suggests 29 million people saw the promotional advertisements and 12 million people saw related content on social media. As a result, 90% of people were likely aware of the increase in penalties.[24] Royal Automobile Club survey data indicate there had been a significant decline in stated mobile use from 2016 to 2017, with making or receiving calls down from 31% to 23% of drivers, checking texts, emails or social media down from 27% to 18%, and taking photos or video down from 15% to 11% (UK Royal Automobile Club, 2017).

Some 15 months on, a survey of 1808 drivers by the Royal Automobile Club found 25% admitted to making or receiving calls while driving, 19% checked texts, email or social media, 16% texted, emailed or posted on social media and 14% took photos or video with their phone and these figures had remained stable from the previous year when the penalties were increased (UK Royal Automobile Club, 2018). These were not significant differences from 2017, so it appears that the improvement in behaviour observed in 2017 was maintained in 2018.

[24] See: https://www.gov.uk/government/news/tens-of-thousands-of-drivers-get-increased-fines-for-using-mobiles-at-wheel.

However, only 36% of those surveyed were aware of the new penalties and only 26% were aware of the change.[25] To the extent that a large proportion of drivers remain unaware/unaffected by the penalty change, we would not expect to see a large decrease in serious or fatal accidents after the change.

Annual data on accidents where use of a mobile phone was identified as a contributory factor show a small reduction in overall accidents although the share of accidents involving a mobile phone has remained stable over the 2016/2017 period (table 5.16). Despite this stability, there seems to be a small reduction in the share of fatal or serious accidents involving a mobile phone.

Table 5.16: Selected statistics on mobile use as an accident contributory factor in Britain, 2012–2017[a]

	2012	2013	2014	2015	2016	2017
All accidents						
Using a mobile phone was a contributory factor	378	422	492	440	478	431
Total number of reported accidents with a contributory factor	114,696	108,934	115,673	108,211	100,296	93,125
Percentage of reported accidents where using a mobile phone was a contributory factor	0.33	0.39	0.43	0.41	0.48	0.46
Fatal or serious accidents						
Using a mobile phone was a contributory factor	84	95	105	97	137	123
Total number of reported accidents with a contributory factor	19,693	18,460	19,640	18,645	18,936	19,705
Percentage of reported accidents where using a mobile phone was a contributory factor	0.43	0.51	0.53	0.52	0.72	0.62

[a]Only includes accidents where a police officer attended and at least one contributory factor was recorded.
Source: Based on UK Department for Transport (2017).

There may be limited scope for the increase in fines to greatly affect numbers of serious or fatal accidents, as the target population of serious speeders might be relatively small and/or there might be limited enforcement activity.

[25] See: https://www.bbc.com/news/uk-44584261, https://www.rac.co.uk/drive/news/motoring-news/six-in-10-drivers-dont-know-penalties-for-mobile-phone-use/.

In Britain, the bulk of traffic consists of cars and light commercial vehicles (LCVs). In 2017, these two forms of transport represented some 87% of free-flow motorway traffic and 92–95% of free-flow traffic on single carriageway, 30 and 20 mph roads (UK Department for Transport, 2018c). Data are not available for drivers targeted by the policy intervention, but we can get some idea about overall speeding behaviour from published information (table 5.17). For example, the percentage of vehicles exceeding the speed limit by 10mph or more is largest for motorways and 20mph roads, though such speeding behaviour is more likely to occur on motorways due to higher traffic volumes (partly associated with more counters). Additional data from the same source indicates travelling 20mph or more over the speed limit is limited to under 2% of cars and LCVs. For some road types, such as national speed limit single carriageways and motorways, numbers of drivers affected by the policy intervention will be smaller again.

Table 5.17: Selected statistics on speeding in Britain, 2017[a]

	Motorways		National speed limit single carriageways		30 mph roads		20 mph roads	
	Cars	LCV	Cars	LCV	Cars	LCV	Cars	LCV
Number of counters	20	20	23	23	23	23	8	8
Applicable Speed limit (mph)	70	70	60	np	30	30	20	20
Exceeding speed limit (%)	47.6	48.6	9.4	np	51.8	55.0	86.1	84.0
Exceeding speed limit by 5 mph or more (%)	25.7	28.1	3.1	np	19.7	22.3	49.8	48.9
Exceeding speed limit by 10 mph or more (%)	11.6	13.6	1.1	np	6.0	7.0	17.7	18.3
Average free flow speed (mph)	68.9	69.1	50.1	50.3	30.9	31.1	25.6	25.4
Number observed (traffic count, thousands)	343,536	90,448	36,481	7,636	51,310	8,383	15,295	2,532

[a]Measurements are from approximately 100 automatic traffic counters, based on 'free-flow' speeds — the speed at which drivers choose to travel when unrestricted by congestion, external factors (such as road topography, roadworks or local events) or traffic calming measures. LCV light commercial vehicles. np not published, as different speed limits apply according to the maximum weight of the vehicle and this cannot be determined by the counters.
Source: UK Department for Transport (2018c, 2019c).

One measure of driver behavioural change is the number of offenders found guilty of speeding. There is some evidence that numbers of offenders declined in 2017, although the number has increased back in line with the trend in 2018 (table 5.18). This suggests any short term reduction in speeding offences after the intervention has been subsequently offset through a reversion to prior behaviour some time after the intervention.

Table 5.18: Offenders and speed limit offences in England and Wales, 2011–2018[a]

Year	Proceeded against for speed limit offences at the magistrates' courts	Offenders found guilty of speed limit offences in any court
2011	122,566	112,032
2012	123,394	113,414
2013	126,695	115,936
2014	159,288	148,429
2015	179,886	166,699
2016	183,219	167,982
2017	176,442	159,869
2018	189,111	168,967

[a]These figures relate to defendants for whom speeding offences were the principal offences with which they were charged.
Source: UK Department for Transport (2019b).

In terms of the subset of accidents involving speed, while aggregate statistics indicate there was some reduction in the more severe accidents in 2017 compared to earlier years, the data for 2017 cannot distinguish changes before and after the intervention (table 5.19).

Table 5.19: Selected statistics on speed as an accident contributory factor in Britain, 2012–2017[a]

	2012	2013	2014	2015	2016	2017
All accidents						
Exceeding speed limit was a contributory factor in reported accident	4,745	4,753	5,309	5,272	5,102	4,805
Total number of reported accidents	114,696	108,934	115,673	108,211	100,296	93,125
Percentage of reported accidents where exceeding the speed limit was reported	4.1	4.4	4.6	4.9	5.1	5.2
Fatal or serious accidents						
Exceeding speed limit was a contributory factor in reported accident	1,214	1,309	1,453	1,374	1,455	1,415
Total number of reported accidents	19,693	18,460	19,640	18,645	18,936	19,705
Percentage of reported accidents where exceeding the speed limit was reported	6.2	7.1	7.4	7.4	7.7	7.2
Fatal accidents						
Exceeding speed limit was a contributory factor in reported accident	173	216	254	222	217	203
Total number of reported accidents	1,497	1,486	1,543	1,469	1,445	1,466
Percentage of reported accidents where exceeding the speed limit was reported	11.6	14.5	16.5	15.1	15.0	13.8

[a] Only includes accidents where a police officer attended and at least one contributory factor was recorded.
Source: Based on UK Department for Transport (2018d).

Enforcement activity can also affect the expected penalty that individuals respond to. One measure of enforcement activity is the number of officers likely to be enforcing mobile phone bans and speed limits. We are not able to separately identify numbers of such officers, but we may get a general idea of trends by looking at the number of police constables (from which a subgroup will be involved in mobile detection/speed enforcement). Table 5.20 shows the number of full-time equivalent constables across England and Wales. Since 2010, there has been a steady decline in numbers although this trend has levelled off since 2016. With overall numbers of constables remaining steady about the time of the interventions, we might expect drivers to also consider enforcement activity to have remained fairly constant and this would lower the expected penalty compared to a situation in which policing activity increased, thus increasing incentives to offend.[26]

Table 5.20: Full-time equivalent police constables in England and Wales, 2010–2019[a]

Year/.	Number of full-time equivalent constables
2010	107,922
2011	104,803
2012	100,827
2013	97,397
2014	96,916
2015	97,031
2016	94,310
2017	93,579
2018	93,213
2019	94,131

[a]As at 31 March. Excluding those on career breaks or maternity/paternity leave.
Source: UK Home Office (2019).

Of course, drivers will only respond to incentives if they are aware of those incentives. A small scale survey of drivers in the UK at the time of the change in speeding fines revealed that 58% of respondents were not aware of the change (Hudson, 2017). Rather than using survey data, we can also get some idea about information penetration by analysing numbers of media articles and internet searches. Figure 5.8 shows numbers of media articles by day from 1 Jan 2017 to 30 April 2017. Details of the search strategy and results are given in the appendix. The chart shows there were some articles about the mobile phone penalty increase published prior to the intervention, but that peak interest occurred on the day. There was also a spike in articles on 10 April, some 5–6 weeks after the intervention. There was a relatively small number of articles published on the speed intervention throughout this sample period (partly as a result of the announcement of the speed intervention on 24 Jan 2017). Articles mentioning both interventions only began to appear from 1 March and were few in number.

[26] Policing activity can be endogenous and may have increased at the time the increase in penalties was announced earlier in 2017. Unfortunately, available data on policing is only annual, so we are unable to identify any change in policing activity at the time the penalties were announced.

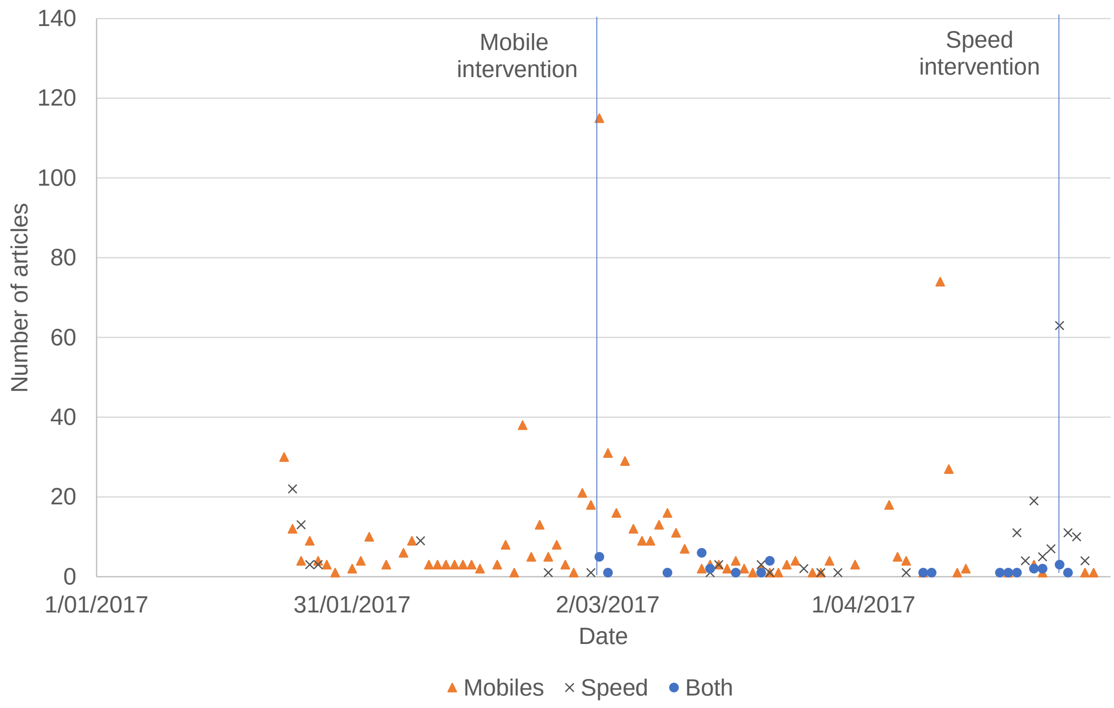


Figure 5.8: Numbers of media articles relating to the two interventions

Source: Newsbank newspapers search.

Figure 5.9 shows Google trends data for various internet searches relating to the mobile and speed interventions. Numbers represent relative interest as measured by numbers of searches relative to the peak over the time period shown. Interest in the mobile intervention peaked on or about the date of the intervention, although there was also substantial interest either side of this date (but we cannot say what proportion of the population might have been responsible for these searches and the numbers may have been small). Searches relating to the speed intervention peaked at the time of implementation and about one month later. Apart from the general search of the term 'fine', there were relatively few searches relating to the speed intervention. This suggests individuals might have been aware of the immediate changes associated with the interventions but that recall might have been adversely affected. Based on this analysis, we would not expect significant changes in behaviour and therefore accidents.

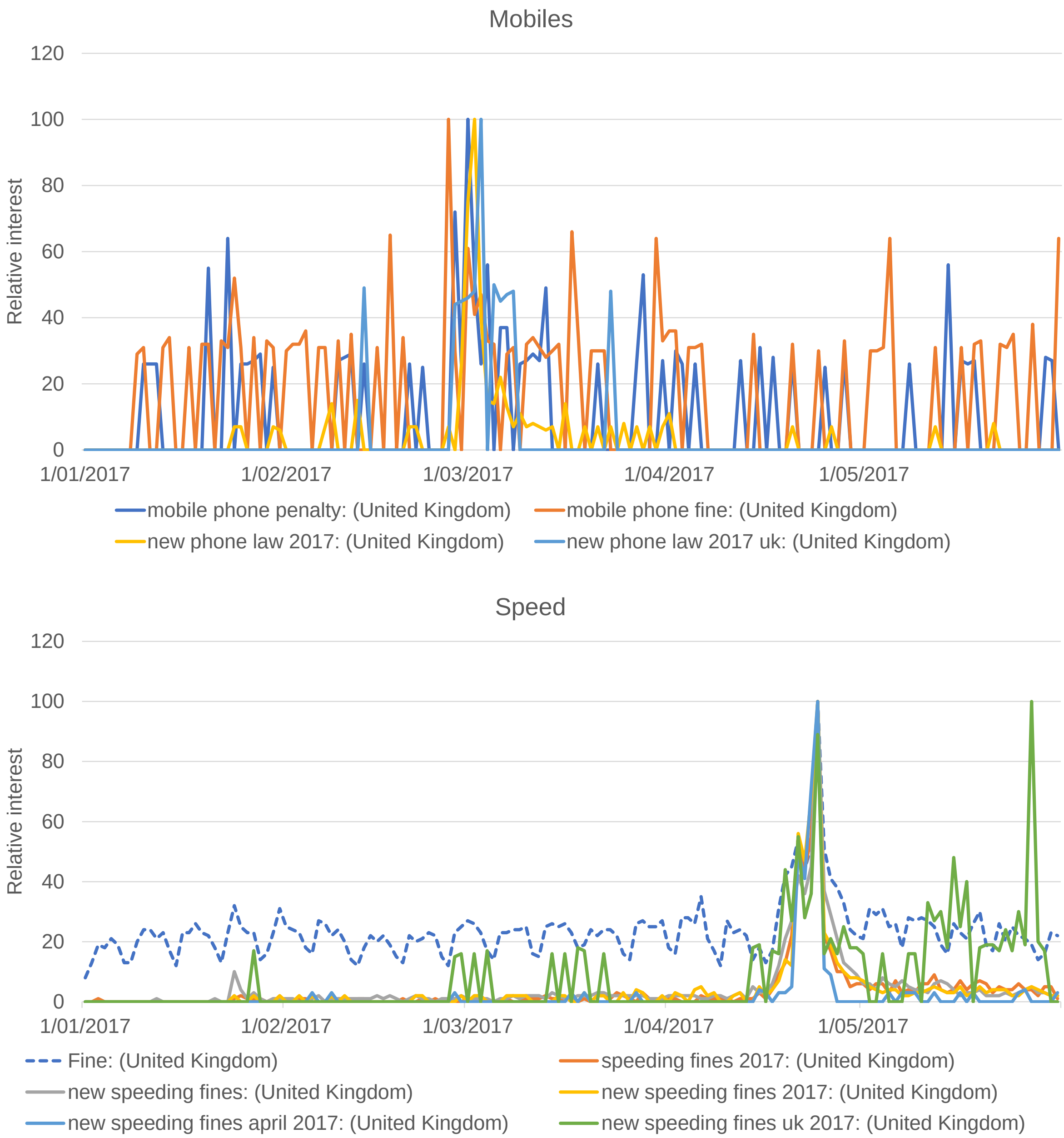


Figure 5.9: Google searches relating to each intervention

Source: Google trends search.

Finally, on 22 April 2016, new rules came into effect for local authorities to remove unnecessary road signs and this included repeat speed limit signs.[27] Removing signs indicating a reduction in speed limit might increase numbers of drivers exceeding the speed limit

[27] See: https://www.gov.uk/government/news/councils-get-new-powers-to-tear-down-pointless-road-signs.

(increasing fines) but is unlikely to affect accident numbers relative to previous, as drivers would not be increasing their actual speed.

5.9 Conclusions

In analysing the economics of crime, penalties are designed to modify behaviour according to the socially optimum outcome. One type of crime that can have significant health impacts via road accidents is behavioural driving offences, such as using a mobile phone while driving, and speeding. Using data on all injury accidents reported to police in Britain, we have examined the effects of two penalty interventions on numbers of serious or fatal accidents. By analysing the link between penalties and accidents, our contribution is unique. As the literature considers the effects of penalties on infringement notices rather than accidents, we have no point of comparison for our results.

Overall, we find no effect of either intervention and this result is robust to variations in the sample and allowing for non-linearities in effects, although the speed intervention has a small effect on accidents on motorways relative to those on B and C roads. Thus, in the main, our hypotheses are not supported and our results are robust to specifications in which we allow effects to vary over time and in which we compare speed intervention effects in England and Wales relative to untreated Scotland.

The lack of a large effect could be due to inadequate publicity about the change and/or insufficient enforcement activity. To be effective in reducing accidents and their severity, penalties need to be appropriate to the severity of the offence and the resources of the offender and to be well publicised and enforced in order to deter errant behaviour. In the case of speeding fines, it could also be that fines reduced speed but not sufficiently to significantly lower the probability of a fatality or serious injury occurring in an accident. Perhaps fines reduce speeding on low speed roads where fatality risk is lower and does not change much with large variations in speed.

Adapting the argument from Bar-Ilan and Sacerdote (2004), we may find no effect on fatal or serious accidents despite a reduction in overall speeding behaviour and in fines issued. This would occur if there were two types of drivers: one that rarely speeds and is quite careful about the circumstances when they speed (little other traffic is about) and one that speeds routinely with no care for the safety of other road users. If the former type shows improved behaviour and reduced speeding infringements and the latter have no care for fines and cause all of the fatal accidents, we could then see no effect of increased fines on fatal accidents. Similarly, the former type may choose to reduce their activity level (driving) rather than just the behaviour (speeding) and this would also reduce speeding infringements (Polinsky & Shavell, 2000).

Another potential explanation proposed by Bar-Ilan and Sacerdote (2004) is that an individual's response to a financial penalty might depend on how likely he or she is to comply with the penalty imposed. For some individuals, the expected penalty may be insufficient to deter offending behaviour. For example, these individuals may have a very high value of time and therefore be prepared to pay large fines for, say, the 'privilege' of speeding or the convenience of using a mobile phone while driving. A novel intervention on trial in Estonia is to have speeding drivers take a 'time out' before resuming their trip, waiting 45 or 60 minutes depending on their speed (ERR News, 2019; "The nick of time; Estonia," 2019). The trial is designed to see whether lost time is a stronger deterrent than lost money. However, without advances in technology, enforcement requires labour and this would limit the usefulness of this sanction in combatting speeding. Perhaps individuals who offend the most are also those who disregard penalties.

Bourgeon and Picard (2007) develop a theoretical model that shows fines are less effective in deterring most drivers from committing driving offences than are penalty points (leading to licence suspension/withdrawal). In particular, some drivers are 'chronically reckless' and do not respond to fines so incapacitation strategies such as revoking their licence (or imprisonment) is the only way to stop such behaviour — by keeping them off the roads (Bourgeon & Picard, 2007). This is partly the idea behind increasing penalty points for mobile phone use.

In terms of the policy implications, individuals respond to the expected penalty, which comprises the actual penalty and the probability of conviction (driven by enforcement activity). Therefore, road safety may be improved by modifying penalties (further increasing fines and/or penalty points or by changing licence suspension periods) and/or increasing enforcement activity.

Appendix

Table A.5.1: Data processing steps

Stats19 data
Accident data (2009-2018)
Extract accident data and rename variables for consistency.
Append data for each year.
Generate variables indicating county, GOR, country.
Generate date and weekday variables.
Driver IMD data (2016-2018)
Rename variables for consistency.
Generate indicator variables for driver Index of Multiple Deprivation (IMD) decile.
Aggregate to accident level.
Append data for each year.
Combined accident data
Merge accident and driver data.
Create consistent Local Authority (LA) classification for use with weather data.
Process accidents data to fill missing dates/areas with zero accidents
Create dataset of date by LA (no gaps).
Weather data (2009-2018) (separate processing for temperature and rainfall)
Extract data from the UK Centre for Environmental Data Analysis (CEDA).
Using a shapefile, calculate geographic centroid for each LA.
Separately process temperature and rainfall datasets
Consolidate annual datasets.
Drop station/date observations with no weather recording.
Create consistent date variable for eventual match merging with accidents data.
Merge station latitude and longitude data.
For each date, assign LA centroid to closest weather station with recordings using Stata's geonear procedure.
Consolidate weather datasets
Append daily weather by LA files.
Merge temperature and rainfall datasets.
Create consistent LA classification and date variables for matching with accidents data.
Merge date by LA dataset so we have variables on which to match merge accidents data.
Merged accident and weather data (processed separately for all KSI accidents and by road type)
Aggregate accident data to LA by date.
Merge weather data.
Fill dates/LAs with no accidents (missing values) with zeros.
Calculate numbers of KSI accidents.
Generate additional variables for modelling
Generate pre-post variables for each intervention.
For road type dataset, identify subset of LAs that contain motorways.
Create dummy variables for each public holiday.
Generate LA-specific trends.

Speed and the probability of a fatality

As the power curve implies increases in speed will increase the probability of death without limit, Elvik (2012), Rosén and Sander (2009) and US Department of Transport National Highway Traffic Safety Administration (2005) use a logistic curve to demonstrate the relationship between impact speed and the probability of death for car occupants and pedestrians (Figure A.5.1). At low impact speeds (consistent with slow travelling speed or a long braking distance), there is a low risk of a fatality and the risk changes little with moderate variations in speed. At very high impact speeds, death is almost a certainty and the risk of a fatality also changes little with moderate variations in speed. However, at moderately fast speeds of about 50 mph, small variations in vehicle speed can have large effects on the risk of a fatality occurring.

Figure A.5.1: Impact speed and the probability of death

Source: Based on Elvik (2012), Rosén and Sander (2009) and US Department of Transport National Highway Traffic Safety Administration (2005).

Media search strategy

A search of the Newsbank Newspapers database was conducted to find articles related to the two penalties. Newspapers were included from England, Scotland, Wales and the UK. Using the search terms ‘mobile phone fine penalty’ over the period 1 Jan 2017 to 30 Apr 2017 yielded 1119 articles of which 685 were deemed relevant. Using the terms ‘speed fine’ returned 3964 articles over the same period, of which 199 were relevant to our purpose. A search on ‘mobile phone speed penalty’ led to 128 articles (34 relevant).

Table A.5.2: Dates of public holidays

Date	Holiday
January 1st, 2009	New Year's Day
April 10th, 2009	Good Friday
April 13th, 2009	Easter Monday
May 4th, 2009	Early May Bank Holiday
May 25th, 2009	Spring Bank Holiday
August 31st, 2009	August Bank Holiday
December 25th, 2009	Christmas Day
December 28th, 2009	Substitute day (for Boxing Day)
January 1st, 2010	New Year's Day
April 2nd, 2010	Good Friday
April 5th, 2010	Easter Monday
May 3rd, 2010	Early May Bank Holiday
May 31st, 2010	Spring Bank Holiday
August 30th, 2010	August Bank Holiday
December 27th, 2010	Substitute day (for Christmas Day)
December 28th, 2010	Substitute day (for Boxing Day)
January 3rd, 2011	Substitute day (for New Year's Day)
April 22nd, 2011	Good Friday
April 25th, 2011	Easter Monday
April 29th, 2011	Royal Wedding Bank Holiday
May 2nd, 2011	Early May Bank Holiday
May 30th, 2011	Spring Bank Holiday
August 29th, 2011	August Bank Holiday
December 26th, 2011	Boxing Day
December 27th, 2011	Substitute day (for Christmas Day)
January 2nd, 2012	Substitute day (for New Year's Day)
April 6th, 2012	Good Friday
April 9th, 2012	Easter Monday
May 7th, 2012	Early May Bank Holiday
June 4th, 2012	Spring Bank Holiday
June 5th, 2012	The Queen's Diamond Jubilee Holiday
August 27th, 2012	August Bank Holiday
December 25th, 2012	Christmas Day
December 26th, 2012	Boxing Day
January 1st, 2013	New Year's Day
March 29th, 2013	Good Friday
April 1st, 2013	Easter Monday
May 6th, 2013	Early May Bank Holiday
May 27th, 2013	Spring Bank Holiday
August 26th, 2013	August Bank Holiday
December 25th, 2013	Christmas Day
December 26th, 2013	Boxing Day

Table A.5.2 *(Continued)*

Date	Holiday
January 1st, 2014	New Year's Day
April 18th, 2014	Good Friday
April 21st, 2014	Easter Monday
May 5th, 2014	Early May Bank Holiday
May 26th, 2014	Spring Bank Holiday
August 25th, 2014	August Bank Holiday
December 25th, 2014	Christmas Day
December 26th, 2014	Boxing Day
January 1st, 2015	New Year's Day
April 3rd, 2015	Good Friday
April 6th, 2015	Easter Monday
May 4th, 2015	Early May Bank Holiday
May 25th, 2015	Spring Bank Holiday
August 31st, 2015	August Bank Holiday
December 25th, 2015	Christmas Day
December 28th, 2015	Substitute day (for Boxing Day)
January 1st, 2016	New Year's Day
March 25th, 2016	Good Friday
March 28th, 2016	Easter Monday
May 2nd, 2016	Early May Bank Holiday
May 30th, 2016	Spring Bank Holiday
August 29th, 2016	August Bank Holiday
December 26th, 2016	Boxing Day
December 27th, 2016	Substitute day (for Christmas Day)
January 2nd, 2017	Substitute day (for New Year's Day)
April 14th, 2017	Good Friday
April 17th, 2017	Easter Monday
May 1st, 2017	Early May Bank Holiday
May 29th, 2017	Spring Bank Holiday
August 28th, 2017	August Bank Holiday
December 25th, 2017	Christmas Day
December 26th, 2017	Boxing Day
January 1st, 2018	New Year's Day
March 30th, 2018	Good Friday
April 2nd, 2018	Easter Monday
May 7th, 2018	Early May Bank Holiday
May 28th, 2018	Spring Bank Holiday
August 27th, 2018	August Bank Holiday
December 25th, 2018	Christmas Day
December 26th, 2018	Boxing Day

Table A.5.3: Step 1 modelling results, main model[a]

Variable	No. serious or fatal accidents	Total number of accidents
LA-specific time trends	✓	✓
LA fixed effects	✓	✓
February	0.000	-0.006
	(0.002)	(0.005)
March	-0.007***	-0.040***
	(0.002)	(0.005)
April	-0.012***	-0.066***
	(0.002)	(0.005)
May	-0.004**	-0.014**
	(0.002)	(0.005)
June	-0.007***	0.002
	(0.002)	(0.006)
July	-0.009***	0.001
	(0.002)	(0.006)
August	-0.017***	-0.074***
	(0.002)	(0.006)
September	0.000	0.032***
	(0.002)	(0.006)
October	0.008***	0.086***
	(0.002)	(0.005)
November	0.023***	0.174***
	(0.002)	(0.005)
December	0.008***	0.054***
	(0.002)	(0.005)
Monday	0.007***	0.274***
	(0.001)	(0.003)
Tuesday	0.015***	0.313***
	(0.001)	(0.003)
Wednesday	0.014***	0.314***
	(0.001)	(0.003)
Thursday	0.017***	0.317***
	(0.001)	(0.003)
Friday	0.035***	0.413***
	(0.001)	(0.004)
Saturday	0.017***	0.164***
	(0.001)	(0.003)

Table A.5.3 *(Continued)*

Variable	No. serious or fatal accidents	Total number of accidents
New Year's Day	-0.008	-0.383***
	(0.007)	(0.019)
Good Friday	-0.033***	-0.287***
	(0.007)	(0.016)
Easter Monday	-0.010	-0.285***
	(0.007)	(0.016)
May Bank Holiday	-0.004	-0.276***
	(0.007)	(0.016)
Spring Bank Holiday	-0.028***	-0.318***
	(0.007)	(0.016)
August Bank Holiday	-0.006	-0.202***
	(0.007)	(0.017)
Christmas Day	-0.069***	-0.629***
	(0.005)	(0.015)
Boxing Day	-0.057***	-0.503***
	(0.006)	(0.015)
Royal Wedding Day	-0.007	-0.475***
	(0.022)	(0.050)
Diamond Jubilee Day	-0.003	-0.375***
	(0.024)	(0.050)
Maximum temperature	0.005***	0.016***
	(0.000)	(0.000)
Minimum temperature	-0.002***	-0.012***
	(0.000)	(0.000)
Precipitation amount	-0.000	0.002***
	(0.000)	(0.000)
Constant	0.097***	0.769***
	(0.002)	(0.005)
Adjusted R-squared	0.073	0.363

[a]n=1,270,896. Robust standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.5.4: Step 2 RDiT (pooled) modelling results, main model, number of accidents overall[a]

Variables	Adjusted numbers of overall accidents[b]
Post_mob	-0.003
	(0.010)
Post_speed	-0.025**
	(0.010)
Constant	0.018***
	(0.004)
Adjusted R-squared	0.000

[a]The RDiT sample covers 365 days either side of the speeding intervention (April 24, 2017) and includes an intercept shift from the date of the mobiles intervention (Post_mob=1 from March 1, 2017). Post_speed is the variable of interest. [b]These are residuals from the first step model. Robust standard errors are shown in parentheses. n=254,388. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

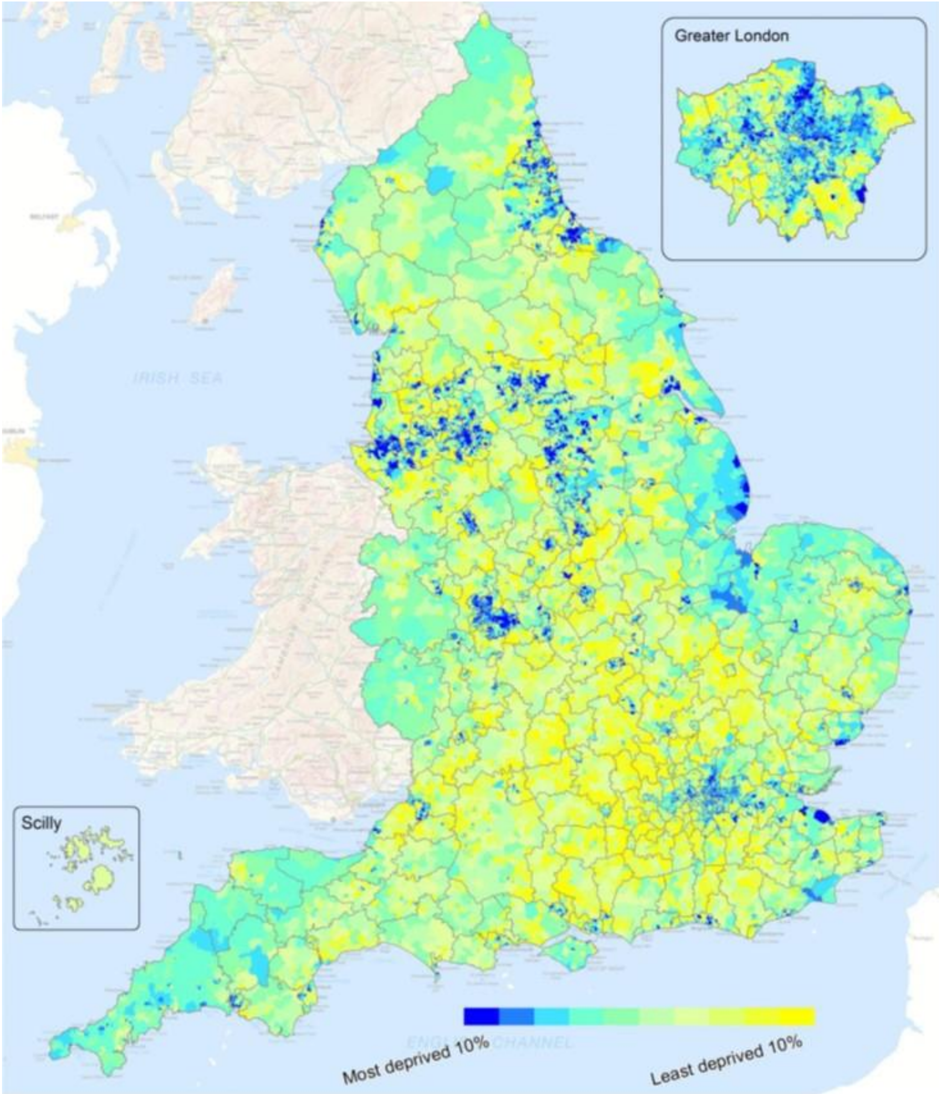
Indices of Multiple Deprivation (IMD)

A separate IMD measure is calculated for England (IMD), Wales (WIMD) and Scotland (SIMD). For England, the Index is calculated from a set of 37 indices which measure relative levels of deprivation across 7 domains in neighbourhoods, called Lower-layer Super Output Areas (LSOA) (UK Department for Communities and Local Government, 2015). Data for the indices come from administrative data and the Census. The Income Deprivation Domain and the Employment Deprivation Domain have the highest weight in the Index (some 45%), with Education, Skills and Training, Health/Disability, Crime, Barriers to Housing and Services and Living Environment also contributing. The 2015 Index is based on indicator data mostly from 2012/13 and is calculated at LSOA level.

In using the Index, it should be borne in mind that the index is an average across individuals and some individuals in the most deprived areas may not be highly deprived (and there might be some highly deprived individuals in the least deprived areas).

LSOAs are ranked by their IMD and ranks are split into deciles, to indicate cutpoints on a spectrum of disadvantage. Although the deciles split the areas evenly, their *levels* of disadvantage are not split evenly.

Figure A.5.2 shows the distribution of the IMD for England. Areas of greatest disadvantage are mostly concentrated in the North West, North East and London. Areas of least disadvantage are mostly in the lower Midlands, East, South East, South West and the outskirts of London.



Contains OS data © Crown copyright (2015)

Figure A.5.2: Distribution of the Index of Multiple Deprivation, 2015

Source: UK Department for Communities and Local Government (2015).

The 2014 Welsh Index of Multiple Deprivation (WIMD) is calculated at LSOA level and comprises 8 domains similar to those of the English IMD, based on 33 indicators that use administrative and census data mostly over the period 2010–2014. Income and employment domains contribute 47% to the Index. As with the English IMD, the WIMD provides the level of disadvantage rank for an area, rather than levels for individuals.

Figure A.5.3 shows how the WIMD varies across Wales. The most disadvantaged areas are in Neath Port Talbot, Central Valleys, Gwent Valleys, Cardiff and Newport. Although only identified as in the top 50% of IMD ranks, this map indicates the least disadvantaged areas are likely to be in East Wales, South West Wales and along the coastline.

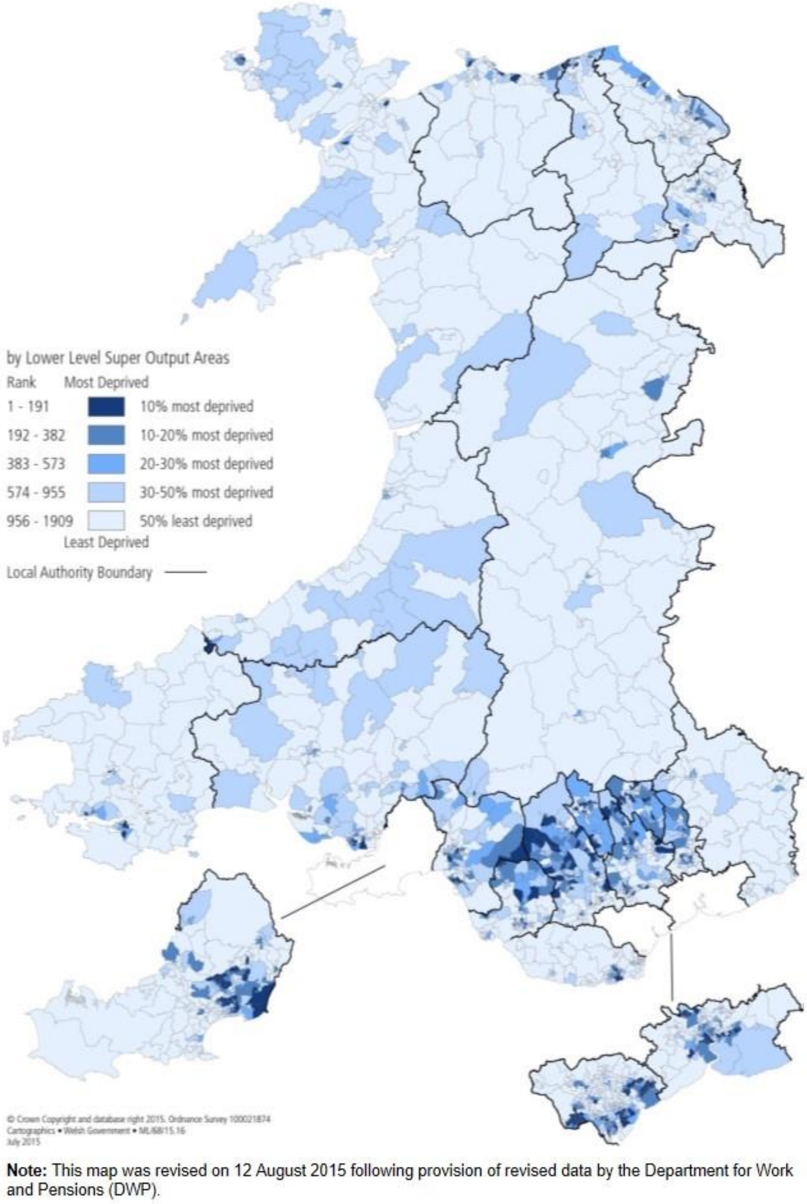


Figure A.5.3: Distribution of the Welsh Index of Multiple Deprivation, 2014

Source: Statistics for Wales (2014).

The Scottish Index of Multiple Deprivation (SIMD) is calculated for some 6976 data zones in Scotland and combines data on 38 indicators into 7 domains, which are then combined into the SIMD (UK Office of National Statistics, 2016). The methodology is similar to that of the English and Welsh IMDs and uses administrative data provided by a selection of organisations and 2011 Census information. The income and employment domains contribute about 56% to the overall SIMD.

Figure A.5.4 shows the distribution of the SIMD. The most disadvantaged areas are in South Ayrshire, Orkney, the north eastern Highlands and some areas of North Lanarkshire and Falkirk. The least disadvantaged areas are in Aberdeenshire and Edinburgh. As with the English and Welsh IMDs, the Scottish IMD measures disadvantage of an area rather than of individuals.

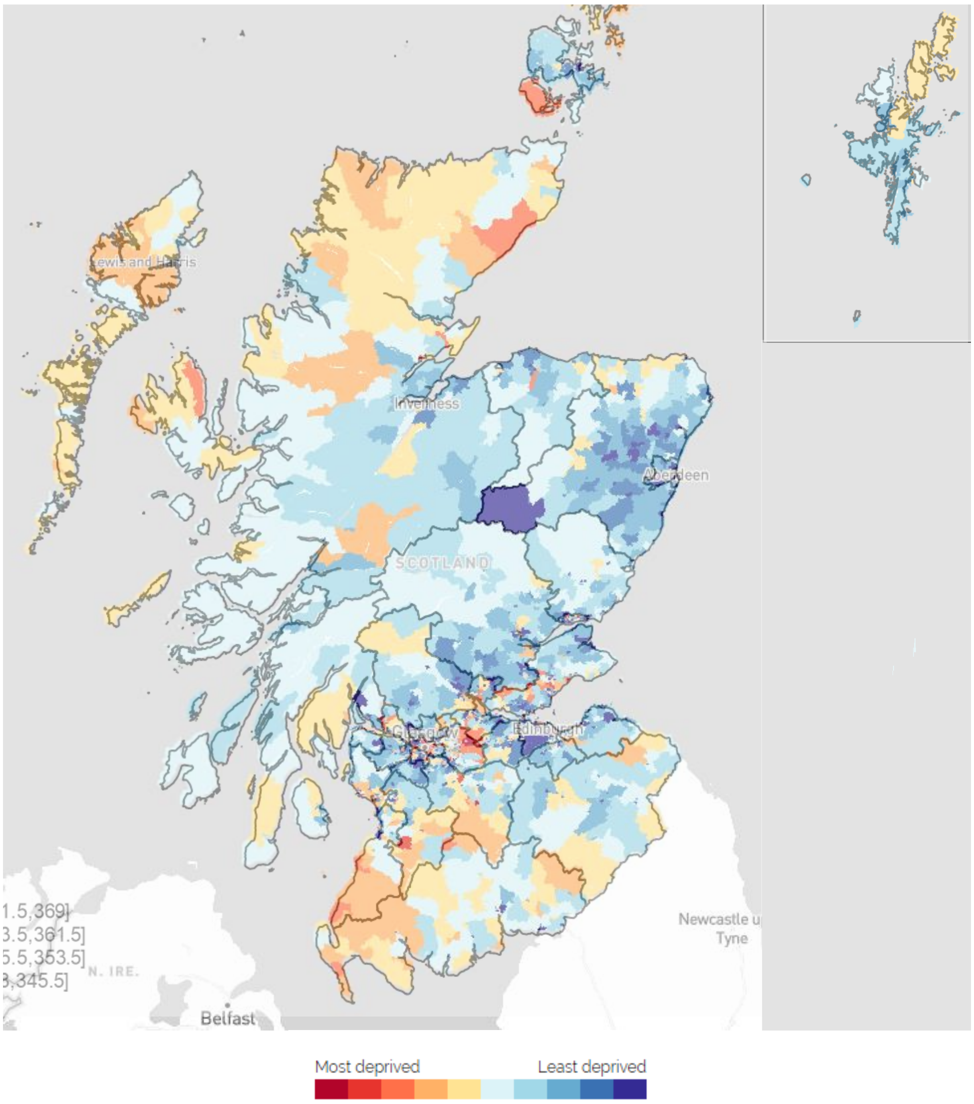


Figure A.5.4: Distribution of the Scottish Index of Multiple Deprivation, 2016

Source: Based on https://jamestrimble.github.io/imdmaps/simd2016/.

Table A.5.5: Step 1 modelling results, Difference-in-Difference models, number of serious or fatal accidents[a]

Variables	Motorways	B and C roads	All LAs England and Wales	Scotland	Border LAs England and Wales	Scotland
LA-specific time trends	✓	✓	✓	✓	✓	✓
LA fixed effects	✓	✓	✓	✓	✓	✓
February	0.000	-0.000	0.000	-0.003	-0.004	-0.046*
	(0.001)	(0.001)	(0.002)	(0.006)	(0.021)	(0.024)
March	-0.001**	-0.003***	-0.007***	-0.018***	0.025	-0.020
	(0.001)	(0.001)	(0.002)	(0.005)	(0.023)	(0.025)
April	-0.001*	-0.004***	-0.012***	-0.014**	0.046*	-0.036
	(0.001)	(0.001)	(0.002)	(0.006)	(0.025)	(0.026)
May	-0.001	-0.003***	-0.004**	0.000	0.046*	-0.002
	(0.001)	(0.001)	(0.002)	(0.006)	(0.026)	(0.028)
June	-0.000	-0.003***	-0.007***	0.010	0.025	0.078**
	(0.001)	(0.001)	(0.002)	(0.007)	(0.029)	(0.031)
July	0.001	-0.004***	-0.009***	-0.010	0.027	0.034
	(0.001)	(0.001)	(0.002)	(0.007)	(0.030)	(0.034)
August	0.001	-0.006***	-0.017***	0.003	0.050*	0.077**
	(0.001)	(0.001)	(0.002)	(0.007)	(0.029)	(0.032)
September	-0.000	-0.001	0.000	0.009	0.024	0.066**
	(0.001)	(0.001)	(0.002)	(0.007)	(0.028)	(0.031)
October	0.000	0.001	0.008***	-0.002	0.008	0.005
	(0.001)	(0.001)	(0.002)	(0.006)	(0.025)	(0.027)
November	0.000	0.005***	0.023***	0.009	0.000	-0.002
	(0.001)	(0.001)	(0.002)	(0.006)	(0.022)	(0.025)
December	0.001	0.001*	0.008***	-0.003	-0.006	0.001
	(0.001)	(0.001)	(0.002)	(0.005)	(0.021)	(0.025)
Monday	-0.000	0.001**	0.007***	0.002	-0.094***	-0.030
	(0.000)	(0.001)	(0.001)	(0.004)	(0.018)	(0.019)
Tuesday	-0.001***	0.003***	0.015***	0.004	-0.072***	-0.022
	(0.000)	(0.001)	(0.001)	(0.004)	(0.018)	(0.019)
Wednesday	-0.001***	0.003***	0.014***	0.007*	-0.079***	-0.008
	(0.000)	(0.001)	(0.001)	(0.004)	(0.018)	(0.019)
Thursday	-0.001**	0.003***	0.017***	0.011***	-0.068***	-0.010
	(0.000)	(0.001)	(0.001)	(0.004)	(0.018)	(0.019)
Friday	0.001***	0.007***	0.035***	0.027***	-0.046**	0.005
	(0.000)	(0.001)	(0.001)	(0.004)	(0.018)	(0.019)
Saturday	-0.001	0.004***	0.017***	0.027***	-0.018	0.033*
	(0.000)	(0.001)	(0.001)	(0.004)	(0.019)	(0.019)

Table A.5.5 *(Continued)*

Variables	Motorways	B and C roads	All LAs England and Wales	Scotland	Border LAs England and Wales	Scotland
New Year's Day	0.000	-0.005	-0.008	-0.048***	0.012	-0.043
	(0.002)	(0.003)	(0.007)	(0.017)	(0.107)	(0.102)
Good Friday	-0.002	-0.006*	-0.033***	-0.039**	-0.093	0.074
	(0.002)	(0.003)	(0.007)	(0.019)	(0.087)	(0.087)
Easter Monday	0.003	0.002	-0.010	-0.004	0.110	-0.009
	(0.002)	(0.003)	(0.007)	(0.020)	(0.129)	(0.080)
May Bank Holiday	0.005*	-0.000	-0.004	0.022	0.047	0.219
	(0.003)	(0.003)	(0.007)	(0.026)	(0.102)	(0.141)
Spring Bank Holiday	-0.002	-0.005	-0.028***	0.008	0.079	0.125
	(0.002)	(0.003)	(0.007)	(0.023)	(0.113)	(0.100)
August Bank Holiday	0.003	-0.002	-0.006	-0.016	0.039	-0.124
	(0.003)	(0.003)	(0.007)	(0.021)	(0.101)	(0.083)
Christmas Day	-0.001	-0.014***	-0.069***	-0.033*	0.095	-0.110
	(0.002)	(0.003)	(0.005)	(0.019)	(0.177)	(0.083)
Boxing Day	0.001	-0.011***	-0.057***	-0.058***	0.047	-0.147**
	(0.002)	(0.003)	(0.006)	(0.015)	(0.118)	(0.067)
Royal Wedding Day	-0.005	-0.003	-0.007	0.131	0.684**	1.371**
	(0.005)	(0.011)	(0.022)	(0.113)	(0.310)	(0.663)
Diamond Jubilee Day	-0.003	0.004	-0.003	-0.013	-0.432***	-0.397***
	(0.005)	(0.011)	(0.024)	(0.065)	(0.026)	(0.055)
Maximum temperature	0.000***	0.001***	0.005***	0.004***	0.007***	0.000
	0.000	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)
Minimum temperature	-0.000***	-0.001***	-0.003***	-0.002***	-0.006***	-0.001
	0.000	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)
Precipitation amount	0.000***	-0.000	-0.000	0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.007***	0.028***	0.097***	0.130***	0.203***	0.318***
	(0.001)	(0.001)	(0.002)	(0.006)	(0.027)	(0.026)
n	679,272	1,270,896	1,270,896	116,864	12,613	12,012
Adjusted R-squared	0.007	0.021	0.073	0.084	0.052	0.032

[a]Border LAs are: Allerdale, Barrow-in-Furness, Carlisle, Copeland, Eden, Northumberland, South Lakeland in England and City of Edinburgh, Dumfries and Galloway, East Lothian, Midlothian, Scottish Borders and West Lothian in Scotland. Robust standard errors are shown in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

British Motorways

Motorways are concentrated around Greater London, Birmingham in the West Midlands, Liverpool/Manchester in the North West, Leeds in Yorkshire and the Humber, and around Glasgow in Scotland. Wales has only one motorway — the M4 in the south (Figure A.5.5).

Figure A.5.5: Motorways of Britain

Source: https://commons.wikimedia.org/wiki/File:UK_motorways_map_2016.svg.

Table A.5.6: Step 1 modelling results, Difference-in-Difference models by IMD decile, England and Wales serious or fatal accidents[a]

VARIABLES	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
LA-specific time trends	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LA fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
February	0.001	-0.001	-0.001	-0.001	-0.000	0.001	0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
March	-0.002	-0.001	-0.003***	-0.001	-0.002*	-0.002*	-0.004***	-0.003**	-0.001	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
April	-0.002	-0.0010	-0.002*	-0.003**	-0.001	-0.003**	-0.002	-0.003**	-0.001	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
May	-0.001	-0.002	-0.002	-0.003	0.000	-0.002	-0.001	-0.000	-0.000	-0.001
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
June	-0.002	-0.004**	-0.005***	-0.004***	-0.002	-0.003	-0.002	0.001	-0.000	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
July	-0.003	-0.004**	-0.005***	-0.005**	-0.003	-0.004**	-0.002	-0.002	-0.002	-0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
August	-0.004	-0.005***	-0.007***	-0.008***	-0.004**	-0.006***	-0.004**	-0.004**	-0.003*	-0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
September	-0.004*	-0.003*	-0.004***	-0.003*	-0.002	-0.004**	-0.003	-0.001	-0.001	-0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
October	-0.002	-0.001	-0.002	-0.003*	-0.001	-0.003**	-0.002	-0.001	0.000	-0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
November	0.002	0.001	-0.001	-0.000	0.002	0.001	-0.000	0.002	0.003**	-0.002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
December	-0.003*	-0.001	-0.003	-0.001	-0.002	-0.001	-0.002	-0.001	-0.001	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Table A.5.6 *(Continued)*

VARIABLES	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Monday	0.000	0.001	0.003***	0.001	0.003***	0.002***	0.003***	0.003***	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tuesday	0.002**	0.002**	0.005***	0.005***	0.002*	0.004***	0.004***	0.004***	0.002*	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Wednesday	0.002**	0.003***	0.005***	0.004***	0.003***	0.003***	0.004***	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Thursday	0.002**	0.002***	0.003***	0.004***	0.002**	0.004***	0.005***	0.004***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Friday	0.005***	0.005***	0.007***	0.005***	0.005***	0.005***	0.007***	0.007***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Saturday	0.002*	0.001	0.002**	0.001	0.001	0.001	0.003***	0.001*	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
New Year’s Day	-0.003	0.010*	0.003	0.000	-0.006	-0.003	-0.006	-0.006	-0.002	0.004
	(0.004)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Good Friday	-0.001	-0.005	-0.007*	0.005	-0.009**	-0.001	-0.007*	-0.004	-0.009***	-0.008**
	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)
Easter Monday	-0.003	-0.009**	-0.006	-0.005	-0.006	-0.004	-0.007**	-0.006*	-0.003	-0.006*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
May Bank Holiday	0.004	0.003	0.003	-0.001	-0.005	0.003	-0.001	-0.001	0.001	-0.001
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Spring Bank Holiday	-0.001	0.002	-0.008*	-0.007*	-0.000	-0.008*	-0.007*	-0.008**	-0.003	-0.007
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
August Bank Holiday	-0.001	0.007	0.003	0.010*	0.010*	-0.001	-0.004	0.001	-0.003	-0.003
	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)

Table A.5.6 *(Continued)*

VARIABLES	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Christmas Day	-0.003	-0.004	-0.010***	-0.014***	-0.011***	-0.003	-0.008**	-0.012***	-0.009***	-0.011***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)
Boxing Day	-0.006	-0.009**	-0.006	-0.010***	-0.004	-0.009**	-0.002	-0.009***	-0.008**	-0.006*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Maximum temperature	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Minimum temperature	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***	-0.001***	-0.001***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation amount	-0.000	0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.006	0.001	0.001	0.004	0.005	0.011**	0.006	0.004	0.009**	0.010
	(0.012)	(0.012)	(0.011)	(0.008)	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)	(b)
Observations	381,408	381,408	381,408	381,408	381,408	381,408	381,408	381,408	381,408	381,408
Adjusted R-squared	0.065	0.031	0.022	0.018	0.016	0.012	0.011	0.011	0.012	0.019

[a]Each dependent variable represents the number of serious or fatal accidents involving at least one driver from the relevant IMD. IMD1 is the lowest decile and represents drivers from addresses in areas with the highest level of deprivation. Robust standard errors are shown in parentheses. [b]The model is unable to estimate a standard error for the constant as there is one region with a collinear (i.e. constant) time trend (zero accidents involving an IMD10 driver throughout the sample). IMD data only available from 1 Jan 2016 to 31 Dec 2018. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.5.7: Step 1 modelling results, Difference-in-Difference models by IMD decile, England, Wales and Scotland, serious or fatal accidents[a]

VARIABLES	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
LA-specific time trends	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LA fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
February	0.001	-0.001	-0.001	-0.001	-0.000	0.001	0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
March	-0.002	-0.001	-0.003***	-0.001	-0.002*	-0.002*	-0.004***	-0.002**	-0.001	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
April	-0.002	-0.001	-0.002*	-0.003**	-0.002	-0.003**	-0.001	-0.002**	-0.000	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
May	-0.001	-0.002	-0.002	-0.002	0.000	-0.002	-0.001	-0.000	-0.000	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
June	-0.002	-0.004**	-0.004***	-0.004**	-0.002	-0.002	-0.002	0.001	-0.000	-0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
July	-0.003	-0.003**	-0.005***	-0.004**	-0.003	-0.003*	-0.002	-0.002	-0.001	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
August	-0.003*	-0.005***	-0.006***	-0.007***	-0.004**	-0.005***	-0.003*	-0.004**	-0.003*	-0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
September	-0.004*	-0.003*	-0.004***	-0.003	-0.001	-0.003*	-0.002	-0.001	-0.001	-0.002
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
October	-0.002	-0.001	-0.002	-0.003*	-0.001	-0.003*	-0.002	-0.001	0.000	-0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
November	0.001	0.001	-0.001	-0.000	0.002	0.001	-0.000	0.001	0.003**	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
December	-0.003*	-0.001	-0.002	-0.001	-0.002	-0.001	-0.002	-0.001	-0.001	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Table A.5.7 *(Continued)*

VARIABLES	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Monday	0.000	0.001	0.002***	0.001	0.002***	0.002***	0.002***	0.003***	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tuesday	0.002**	0.002**	0.004***	0.004***	0.002*	0.004***	0.003***	0.003***	0.001*	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Wednesday	0.002**	0.003***	0.004***	0.004***	0.002***	0.003***	0.003***	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Thursday	0.002**	0.002***	0.003***	0.003***	0.002**	0.004***	0.005***	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Friday	0.005***	0.004***	0.006***	0.005***	0.004***	0.005***	0.006***	0.006***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Saturday	0.002*	0.001	0.002**	0.001	0.001	0.001	0.003***	0.001*	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
New Year’s Day	-0.003	0.009*	0.003	0.000	-0.006	-0.003	-0.006	-0.005	-0.001	0.004
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
Good Friday	-0.001	-0.005	-0.005	0.005	-0.008**	-0.001	-0.006*	-0.004	-0.008***	-0.007**
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Easter Monday	-0.002	-0.008**	-0.006*	-0.005	-0.006	-0.003	-0.007**	-0.006*	-0.003	-0.005*
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
May Bank Holiday	0.004	0.004	0.002	-0.001	-0.005	0.002	0.000	-0.001	0.002	-0.001
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Spring Bank Holiday	-0.001	0.001	-0.008*	-0.007*	-0.000	-0.007*	-0.007*	-0.007**	-0.003	-0.006
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
August Bank Holiday	-0.001	0.006	0.003	0.009*	0.009*	-0.001	-0.004	0.001	-0.003	-0.003
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)

Table A.5.7 *(Continued)*

VARIABLES	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Christmas Day	-0.003	-0.004	-0.009***	-0.012***	-0.010***	-0.003	-0.008**	-0.011***	-0.008***	-0.010***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)
Boxing Day	-0.005	-0.009**	-0.006	-0.009***	-0.003	-0.008**	-0.002	-0.008**	-0.007**	-0.005*
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Maximum temperature	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Minimum temperature	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***	-0.000***	-0.001***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation amount	-0.000	0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.006	0.001	0.001	0.003	0.005	0.010	0.006	0.004	0.008	0.009*
	(0.013)	(0.012)	(0.011)	(0.010)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)	(0.006)
Observations	416,480	416,480	416,480	416,480	416,480	416,480	416,480	416,480	416,480	416,480
Adjusted R-squared	0.066	0.032	0.023	0.020	0.017	0.014	0.013	0.012	0.014	0.020

[a]Each dependent variable represents the number of serious or fatal accidents involving at least one driver from the relevant IMD. IMD1 is the lowest decile and represents drivers from addresses in areas with the highest level of deprivation. Robust standard errors are shown in parentheses. IMD data only available from 1 Jan 2016 to 31 Dec 2018. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

References

Aarts, L., & van Schagen, I. (2006). Driving speed and the risk of road crashes: a review. *Accident Analysis & Prevention, 38*(2), 215-224. doi:https://doi.org/10.1016/j.aap.2005.07.004

Abouk, R., & Adams, S. (2013). Texting Bans and Fatal Accidents on Roadways: Do They Work? Or Do Drivers Just React to Announcements of Bans? *American Economic Journal: Applied Economics, 5*(2), 179-199. doi:10.1257/app.5.2.179

Anderson, D. M., & Rees, D. I. (2015). Per se drugged driving laws and traffic fatalities. *International Review of Law and Economics, 42*, 122-134. doi:https://doi.org/10.1016/j.irle.2015.02.004

Ashenfelter, O. (1978). Estimating the effect of training programs on earnings. *The Review of Economics and Statistics, 60*(1), 47-57. doi:10.2307/1924332

Ashenfelter, O., & Card, D. (1985). Using the longitudinal structure of earnings to estimate the effect of training programs. *The Review of Economics and Statistics, 67*(4), 648-660. doi:10.2307/1924810

Association of Chief Police Officers. (2013). *ACPO speed enforcement policy guidelines 2011-2015: joining forces for safer roads*. Association of Chief Police Officers of England, Wales and Northern Ireland. London.

Athey, S., & Imbens, G. W. (2017). The state of applied econometrics: causality and policy evaluation. *The Journal of Economic Perspectives, 31*(2), 3-32.

Bar-Ilan, A., & Sacerdote, B. (2004). The response of criminals and noncriminals to fines. *The Journal of Law and Economics, 47*(1), 1-17. doi:10.1086/380471

Becker, G. S. (1968). Crime and punishment: an economic approach. *Journal of Political Economy, 76*(2), 169-217.

Bourgeon, J.-M., & Picard, P. (2007). Point-record driving licence and road safety: an economic approach. *Journal of Public Economics, 91*(1), 235-258. doi:https://doi.org/10.1016/j.jpubeco.2006.05.007

Brubacher, R. J., Chan, H., Erdelyi, S., Lovegrove, G., & Faghihi, F. (2018). Road safety impact of increased rural highway speed limits in British Columbia, Canada. *Sustainability, 10*(10). doi:10.3390/su10103555

Burger, N. E., Kaffine, D. T., & Yu, B. (2014). Did California's hand-held cell phone ban reduce accidents? *Transportation Research Part A: Policy and Practice, 66*, 162-172. doi:https://doi.org/10.1016/j.tra.2014.05.008

Butler, H. N., Drahozal, C. R., & Shepherd, J. (2014). *Economic analysis for lawyers* (3rd ed.). North Carolina: Carolina Academic Press.

Cardamone, A. S., Eboli, L., Forciniti, C., & Mazzulla, G. (2017). How usual behaviour can affect perceived drivers' psychological state while driving. *Transport, 32*(1), 13-22. doi:10.3846/16484142.2015.1059885

Castillo-Manzano, J. I., Castro-Nuño, M., López-Valpuesta, L., & Vassallo, F. V. (2019). The complex relationship between increases to speed limits and traffic fatalities: evidence from a meta-analysis. *Safety Science, 111*, 287-297. doi:https://doi.org/10.1016/j.ssci.2018.08.030

Castriota, S., & Tonin, M. (2019). *Stay or flee? Probability versus severity of punishment in hit-and-run accidents*. IZA Discussion Paper No. 12693. IZA. Bonn.

Corbett, C. (2010). Driving offences. In F. Brookman, M. Maguire, H. Pierpoint, & T. Bennett (Eds.), *Handbook on Crime* (pp. 904-929). Cullompton: Willan Publishing.

Corsaro, N., Gerard, D. W., Engel, R. S., & Eck, J. E. (2012). Not by accident: an analytical approach to traffic crash harm reduction. *Journal of Criminal Justice, 40*(6), 502-514. doi:https://doi.org/10.1016/j.jcrimjus.2012.08.003

De Paola, M., Scoppa, V., & Falcone, M. (2013). The deterrent effects of the penalty points system for driving offences: a regression discontinuity approach. *Empirical Economics, 45*(2), 965-985. doi:10.1007/s00181-012-0642-9

DeAngelo, G., & Charness, G. (2012). Deterrence, expected cost, uncertainty and voting: experimental evidence. *Journal of Risk & Uncertainty, 44*(1), 73-100. doi:10.1007/s11166-011-9131-3

DeAngelo, G., & Hansen, B. (2014). Life and death in the fast lane: police enforcement and traffic fatalities. *American Economic Journal: Economic Policy, 6*(2), 231-257.

Dissanayake, S. (2004). Comparison of severity affecting factors between young and older drivers involved in single vehicle crashes. *IATSS Research, 28*(2), 48-54. doi:https://doi.org/10.1016/S0386-1112(14)60108-4

Donmez, B., & Liu, Z. (2015). Associations of distraction involvement and age with driver injury severities. *Journal of Safety Research, 52*, 23-28. doi:https://doi.org/10.1016/j.jsr.2014.12.001

Elvik, R. (2005). Speed and road safety: synthesis of evidence from evaluation studies. *Transportation Research Record, 1908*(1), 59-69. doi:10.1177/0361198105190800108

Elvik, R. (2011). Effects of mobile phone use on accident risk: problems of meta-analysis when studies are few and bad. *Transportation Research Record, 2236*(1), 20-26. doi:10.3141/2236-03

Elvik, R. (2012). Speed limits, enforcement, and health consequences. *Annual Review of Public Health, 33*(1), 225-238. doi:10.1146/annurev-publhealth-031811-124634

Elvik, R., Vadeby, A., Hels, T., & van Schagen, I. (2019). Updated estimates of the relationship between speed and road safety at the aggregate and individual levels. *Accident Analysis & Prevention, 123*, 114-122. doi:https://doi.org/10.1016/j.aap.2018.11.014

ERR News. (2019). Police to offer first-time speeders timeout instead of fines. *ERR News*. Retrieved from https://news.err.ee/984449/police-to-offer-first-time-speeders-timeout-instead-of-fines. Accessed 13/11/2019.

Farmer, C. M., Braitman, K. A., & Lund, A. K. (2010). Cell phone use while driving and attributable crash risk. *Traffic Injury Prevention, 11*(5), 466-470. doi:10.1080/15389588.2010.494191

Ferdinand, A. O., Menachemi, N., Sen, B., Blackburn, J. L., Morrisey, M., & Nelson, L. (2014). Impact of texting laws on motor vehicular fatalities in the United States. *American Journal of Public Health, 104*(8), 1370-1377. doi:10.2105/AJPH.2014.301894

Gallagher, J., & Fisher, P. J. (2020). Criminal Deterrence When There Are Offsetting Risks: Traffic Cameras, Vehicular Accidents, and Public Safety. *American Economic Journal: Economic Policy, 12*(3), 202-237. doi:10.1257/pol.20170674

Garoupa, N. (1998). Optimal law enforcement and imperfect information when wealth varies among individuals. *Economica, 65*(260), 479-490.

Gehrsitz, M. (2017). Speeding, punishment, and recidivism: evidence from a Regression Discontinuity Design. *The Journal of Law and Economics, 60*(3), 497-528. doi:10.1086/694844

Ginter, J. (1999). Principle of proportionality in sentencing and economic approach in criminology *Juridica International, 4*, 142-146.

Gras, M.-E., Font-Mayolas, S., Planes, M., & Sullman, M. J. M. (2014). The impact of the penalty point system on the behaviour of young drivers and passengers in Spain. *Safety Science, 70*, 270-275. doi:https://doi.org/10.1016/j.ssci.2014.06.014

Green, C. P., Heywood, J. S., & Navarro, M. (2014). Did liberalising bar hours decrease traffic accidents? *Journal of Health Economics, 35*, 189-198. doi:http://dx.doi.org/10.1016/j.jhealeco.2014.03.007

Green, C. P., Heywood, J. S., & Navarro, M. (2016). Traffic accidents and the London congestion charge. *Journal of Public Economics, 133*, 11-22. doi:http://dx.doi.org/10.1016/j.jpubeco.2015.10.005

Hansen, B. (2015). Punishment and deterrence: evidence from drunk driving. *The American Economic Review*, *105*(4), 1581-1617.

Hausman, C., & Rapson, D. S. (2018). Regression discontinuity in time: considerations for empirical applications. *Annual Review of Resource Economics, 10*(1), 533-552. doi:10.1146/annurev-resource-121517-033306

Hillsman, S. T. (1990). Fines and day fines. *Crime and Justice, 12*, 49-98.

Hudson, P. (2017). Speeding fines increase: majority of drivers unaware of changes. *Daily Telegraph, The/The Sunday Telegraph: Web Edition Articles* 2017/04/25. Retrieved from https://www.telegraph.co.uk/cars/news/speeding-fines-increase-majority-drivers-unaware-changes/. Accessed 2/8/19.

Hussain, Q., Feng, H., Grzebieta, R., Brijs, T., & Olivier, J. (2019). The relationship between impact speed and the probability of pedestrian fatality during a vehicle-pedestrian crash: a systematic review and meta-analysis. *Accident Analysis & Prevention, 129,* 241-249. doi:https://doi.org/10.1016/j.aap.2019.05.033

Imbens, G. W., & Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, *47*(1), 5-86.

Kantorowicz-Reznichenko, E. (2015). Day-fines: should the rich pay more? *Review of Law & Economics, 11*(3), 481-501. doi:10.1515/rle-2014-0045

Kaplan, S., & Prato, C. G. (2012). Risk factors associated with bus accident severity in the United States: a generalized ordered logit model. *Journal of Safety Research, 43*(3), 171-180. doi:https://doi.org/10.1016/j.jsr.2012.05.003

Klauer, S. G., Guo, F., Simons-Morton, B. G., Ouimet, M. C., Lee, S. E., & Dingus, T. A. (2014). Distracted driving and risk of road crashes among novice and experienced drivers. *New England Journal of Medicine, 370*(1), 54-59. doi:10.1056/NEJMsa1204142

Li, H., Graham, D. J., & Majumdar, A. (2012). The effects of congestion charging on road traffic casualties: a causal analysis using difference-in-difference estimation. *Accident Analysis & Prevention, 49*, 366-377. doi:https://doi.org/10.1016/j.aap.2012.02.013

Lovenheim, M. F., & Slemrod, J. (2010). The fatal toll of driving to drink: the effect of minimum legal drinking age evasion on traffic fatalities. *Journal of Health Economics, 29*(1), 62-77. doi:https://doi.org/10.1016/j.jhealeco.2009.10.001

McEvoy, S. P., Stevenson, M. R., & Woodward, M. (2007). The contribution of passengers versus mobile phone use to motor vehicle crashes resulting in hospital attendance by the driver. *Accident Analysis & Prevention, 39*(6), 1170-1176. doi:https://doi.org/10.1016/j.aap.2007.03.004

Montag, J. (2014). A radical change in traffic law: effects on fatalities in the Czech Republic. *Journal of Public Health, 36*(4), 539-545. doi:10.1093/pubmed/fdu005

. The nick of time; Estonia. (2019, 2019/11/09/). *The Economist*, *433*, 47(US). Retrieved from https://link.gale.com/apps/doc/A605045591/AONE?u=monash&sid=AONE&xid=6e1c702e. Accessed 12/11/2019.

Nilsson, G. (1982). *The effects of speed limits on traffic crashes in Sweden*. Proceedings of the International Symposium on the Effects of Speed Limits on Traffic Crashes and Fuel Consumption. Organization for Economic Co-Operation and Development (OECD). Dublin.

Nilsson, G. (2004). *Traffic safety dimensions and the power model to describe the effect of speed on safety*. Bulletin 221. Lund Institute of Technology. Lund, Sweden.

O'Donnell, C. J., & Connor, D. H. (1996). Predicting the severity of motor vehicle accident injuries using models of ordered multiple choice. *Accident Analysis & Prevention, 28*(6), 739-753. doi:http://dx.doi.org/10.1016/S0001-4575(96)00050-4

Obenauer, M. L., & von der Nienburg, B. M. (1915). Effect of minimum-wage determinations in Oregon. *Bulletin of the United States Bureau of Labor Statistics, 176*, 5-108.

Papadimitriou, E., Argyropoulou, A., Tselentis, D. I., & Yannis, G. (2019). Analysis of driver behaviour through smartphone data: the case of mobile phone use while driving. *Safety Science, 119*, 91-97. doi:https://doi.org/10.1016/j.ssci.2019.05.059

Peng, Y., & Boyle, L. (2012). Commercial driver factors in run-off-road crashes. *Transportation Research Record: Journal of the Transportation Research Board, 2281*, 128-132. doi:10.3141/2281-16

Pigou, A. C. (1932). *The Economics of Welfare*. London: Macmillan.

Pina-Sánchez, J., Gosling, J. P., Chung, H.-I., Bourgeois, E., Geneletti, S., & Marder, I. D. (2019). Have the England and Wales guidelines affected sentencing severity? An empirical analysis using a scale of severity and time-series analyses. *The British Journal of Criminology, 59*(4), 979-1001. doi:10.1093/bjc/azz005

Polinsky, A. M., & Shavell, S. (1984). The optimal use of fines and imprisonment. *Journal of Public Economics, 24*(1), 89-99. doi:https://doi.org/10.1016/0047-2727(84)90006-9

Polinsky, A. M., & Shavell, S. (1991). A note on optimal fines when wealth varies among individuals. *The American Economic Review, 81*(3), 618-621.

Polinsky, A. M., & Shavell, S. (2000). The economic theory of public enforcement of law. *Journal of Economic Literature, 38*(1), 45-76.

Porter, J. (2003). *Estimation in the Regression Discontinuity model*. Unpublished manuscript.

Pyle, D. J. (1995). The economic approach to crime and punishment. *Journal of Interdisciplinary Economics, 6*(1), 1-22. doi:https://doi.org/10.1177/02601079X9500600101

Raine, J. W., & Dunstan, E. (2009). How well do sentencing guidelines work? Equity, proportionality and consistency in the determination of fine levels in the Magistrates' Courts of England and Wales. *Howard Journal of Criminal Justice, 48*(1), 13-36. doi:10.1111/j.1468-2311.2008.00546.x

Redelmeier, D. A., & Tibshirani, R. J. (1997). Association between cellular-telephone calls and motor vehicle collisions. *New England Journal of Medicine, 336*(7), 453-458. doi:10.1056/NEJM199702133360701

Robbins, A. (2018). Speeding fines increase: here's what you need to know. *Daily Telegraph, The Sunday Telegraph: Web Edition Articles* 2018/11/02. Retrieved from https://www.telegraph.co.uk/cars/advice/the-truth-about-speeding-fines/. Accessed 1/8/2019.

Rocco, L., & Sampaio, B. (2016). Are handheld cell phone and texting bans really effective in reducing fatalities? *Empirical Economics, 51*(2), 853-876. doi:10.1007/s00181-015-1018-8

Rodriguez, R. J. (1990). Penalty schedules and the optimal speed limit. *Eastern Economic Journal, 16*(1), 59-64.

Rosén, E., & Sander, U. (2009). Pedestrian fatality risk as a function of car impact speed. *Accident Analysis & Prevention, 41*(3), 536-542. doi:https://doi.org/10.1016/j.aap.2009.02.002

Sentencing Guidelines Council. (2008). *Magistrates' Court sentencing guidelines*. Sentencing Guidelines Council. London.

Sentencing Guidelines Council. (2017a). *Magistrates' Court sentencing guidelines*. Sentencing Guidelines Council. London.

Sentencing Guidelines Council. (2017b). New sentencing guidelines for Magistrates' Courts [Press release]. Retrieved from https://www.sentencingcouncil.org.uk/news/item/new-sentencing-guidelines-for-magistrates-courts/. Accessed 2/8/19.

Statistics for Wales. (2014). *Welsh Index of Multiple Deprivation (WIMD) 2014 revised*. Welsh Government. Cardiff.

Stevens, A., & Minton, R. (2001). In-vehicle distraction and fatal accidents in England and Wales. *Accident Analysis & Prevention, 33*(4), 539-545. doi:https://doi.org/10.1016/S0001-4575(00)00068-3

Stigler, G. J. (1970). The optimum enforcement of laws. *Journal of Political Economy, 78*(3), 526-536.

Traxler, C., Westermaier, F. G., & Wohlschlegel, A. (2018). Bunching on the Autobahn? Speeding responses to a 'notched' penalty scheme. *Journal of Public Economics, 157*, 78-94. doi:https://doi.org/10.1016/j.jpubeco.2017.11.006

UK Department for Communities and Local Government. (2015). *The English Indices of Deprivation 2015*. Department for Communities and Local Government. London.

UK Department for Transport. (2009). *Behavioural research in road safety 2007: seventeenth seminar*. Department for Transport. London.

UK Department for Transport. (2013). *Reported road casualties in Great Britain: guide to the statistics and data sources*. Department for Transport. London.

UK Department for Transport. (2016a). *A consultation on changes to the Fixed Penalty Notice and penalty points for the use of a hand-held mobile phone whilst driving*. Department for Transport. London.

UK Department for Transport. (2016b). *Reported road casualties Great Britain 2015: annual report*. Department for Transport. London.

UK Department for Transport. (2017). *Table RAS50001 Contributory factors in reported accidents by severity, Great Britain, 2016*. Retrieved from: https://www.gov.uk/government/statistical-data-sets/ras50-contributory-factors

UK Department for Transport. (2018a). *Reported road casualties Great Britain: 2017 annual report*. Department for Transport. London.

UK Department for Transport. (2018b). *Table RAS61001 Motor vehicle offences: findings of guilt at all courts, fixed penalty notices and written warnings by type of offence, England and Wales: 2004 to 2018*. Retrieved from: https://www.gov.uk/government/statistical-data-sets/ras61-motor-vehicle-offences-and-findings-of-guilt

UK Department for Transport. (2018c). *Table SPE0111 Free flow vehicle speeds by road type and vehicle type in Great Britain*. Retrieved from: https://www.gov.uk/government/organisations/department-for-transport/series/speeds-statistics

UK Department for Transport. (2018d). *Table SPE0202 Reported accidents where exceeding the speed limit was reported as a contributory factor, by severity in Great Britain, annual from 2012 to 2017*. Retrieved from: https://www.gov.uk/government/organisations/department-for-transport/series/speeds-statistics

UK Department for Transport. (2019a). *Table MP2 Mobile phone use survey - 2017 tables*. Retrieved from: https://www.gov.uk/government/statistics/seatbelt-and-mobile-phone-use-surveys-2017

UK Department for Transport. (2019b). *Table SPE0201 Motor vehicle offences relating to exceeding the speed limit, annual from 2011 to 2018*. Retrieved from: https://www.gov.uk/government/organisations/department-for-transport/series/speeds-statistics

UK Department for Transport. (2019c). *Vehicle speed compliance statistics: methodology, notes and definitions*. Department for Transport. London.

UK Home Office. (2019). *Table S1 Police workforce, excluding those on career breaks or maternity/paternity leave (comparable with previously published figures), 31 March 1996 to 31 March 2019*. Retrieved from: https://www.gov.uk/government/statistics/police-workforce-england-and-wales-31-march-2019

UK Met Office. (2018). *Met Office Integrated Data Archive System (MIDAS) Land and Marine Surface Stations Data (1853-current).* . NCAS British Atmospheric Data Centre. Retrieved from: http://catalogue.ceda.ac.uk/uuid/220a65615218d5c9cc9e4785a3234bd0

UK Ministry of Justice. (2011). *A guide to criminal justice statistics*. Ministry of Justice. London.

UK Ministry of Justice. (2018). *Table A6.2 - Offenders found guilty at all courts, by motoring offence, 2008 to 2018*. Ministry of Justice. Retrieved from: https://www.gov.uk/government/statistics/criminal-justice-system-statistics-quarterly-december-2018

UK Office of National Statistics. (2016). *Scottish index of multilple deprivation - SIMD16 technical notes*. ONS. London.

UK Royal Automobile Club. (2017). *RAC Report on Motoring 2017*. RAC. Walsall.

UK Royal Automobile Club. (2018). *RAC Report on Motoring 2018*. RAC. Walsall.

United Nations Road Safety Collaboration. (2008). *Speed management: a road safety manual for decision-makers and practitioners*. Global Road Safety Partnership, United Nations Road Safety Collaboration. Geneva.

US Department of Transport National Highway Traffic Safety Administration. (2005). *Tire pressure monitoring system FMVSS No. 138 final regulatory impact analysis*. US Deaprtment of Transport. Washington. Retrieved from http://www.tpmsmaderight.com/pdf/TPMS-2005-FMVSS-No138.pdf

Violanti, J. M., & Marshall, J. R. (1996). Cellular phones and traffic accidents: an epidemiological approach. *Accident Analysis & Prevention, 28*(2), 265-270. doi:https://doi.org/10.1016/0001-4575(95)00070-4

Wang, C., Quddus, M. A., & Ison, S. G. (2013). The effect of traffic and road characteristics on road safety: a review and future research direction. *Safety Science, 57*(Supplement C), 264-275. doi:https://doi.org/10.1016/j.ssci.2013.02.012

World Health Organization. (2018). *Global status report on road safety 2018*. WHO. Geneva.

Yannis, G., Theofilatos, A., Ziakopoulos, A., & Chaziris, A. (2014). Investigation of road accident severity. *Traffic Engineering & Control, 55*, 31-35. Retrieved from http://link.galegroup.com/apps/doc/A377576494/AONE?u=monash&sid=AONE&xid=d8d188e2. Accessed 2019/2/25/.

Chapter 6: Conclusion

This thesis investigates the economics of road accidents and fatalities as consequences of other factors such as changes in economic activity, stock market returns and road safety interventions in Britain. Some consequences may be improvements in road safety, reducing accidents and their severity. However, others may either improve or worsen the situation. These consequences arise from changes in individual behaviour in response to these factors. Knowledge of these effects helps policy makers and road safety stakeholders anticipate these impacts and respond appropriately, improving the health of the nation.

6.1 Summary of findings

Four self-contained empirical chapters investigate how accidents and their severity respond to a variety of economic factors. Each chapter contributes to the relevant (but often limited) literature and broadly show accidents increase in good economic times, but that the relationship with severity has changed over time, having been procyclical pre-GFC but not thereafter. Accidents also increase in response to both improvements and deteriorations in the stock market, but there is no effect on the more severe accidents of large increases in penalties for mobile phone use or speeding.

6.1.1 Economic activity and numbers of accidents

Overall, we find evidence of a procyclical pattern in accidents and fatalities that remains when we disaggregate by characteristics of accidents and drivers. At the aggregate level we find an effect size of about 2% for both accidents and fatalities, which is consistent with the literature. This means that a one percentage point increase in the employment rate is associated with a 2% increase in accidents and fatalities. When disaggregating the totals we find effects vary mostly between 1 and 3%, with the strongest results involving motorcycles or heavy goods vehicles and for accidents occurring at night. Fatalities involving motorcycles, on motorways and A(M) roads and those occurring at night also show strong relationships with economic activity. These findings are relatively stable across different model specifications. There may also be some period of adjustment in behaviours.

6.1.2 *Economic activity and accident severity*

Measuring severity as the probability of an accident resulting in a serious injury or fatality (termed KSI), our findings indicate a relationship between economic activity and accident severity that has been changing over time. Allowing for variations across time and regions (and in some cases vehicle-type fixed effects), overall we find pre-GFC there was a significant procyclical relationship. Post-GFC the relationship is no longer procyclical. Over the period 1992–2001, we estimate there were 422 additional vehicles in KSI accidents in a quarter for each 1 percentage point increase in the employment rate (an increase in the KSI rate of 0.004). Between 2002 and 2008, we estimate the same change in employment over a quarter led to 191 additional vehicles in KSI accidents (0.002 increase in KSI rate). From 2009 to 2015, we estimate 426 *fewer* vehicles in KSI accidents (a reduction in the KSI rate of 0.006). We attribute this link to risky driving in the early period but traffic volumes and congestion in the later period. Adding vehicle fixed effects to more tightly control for variation (comparing accident outcomes for the same make, model and registration year of vehicle in the same region when employment is high versus when it is low) makes little difference to the results.

Disaggregating by accident characteristic we find a similar story: pre-GFC, there is a larger increase in severity at night, consistent with a congestion story dominating during the day, but more risky behaviour at night. However, post-GFC (when there was considerably more variation in economic conditions and increases in penalties for some errant driving behaviours, such as careless driving and mobile phone use while driving) severity declines by more at night, indicating as employment rises, severity falls consistent with more traffic on the roads reducing speeds at these times. By road type, we see that the countercyclical relationship post-GFC does not appear for accidents on B roads, indicating reduced severity consistent with congestion. Considering driver age and sex, strongest positive effects are found for drivers aged 18–24, consistent with their risky driving behaviour. There is a procyclical effect on accident severity pre-GFC for ‘standard’ cars but not for premium or luxury cars, suggesting more conservative behaviour by drivers of higher SES. Post-GFC, there is a significant reduction in severity for drivers of standard and premium cars (although the results suggest more risky driving by drivers of standard cars is occurring.) When we include region-specific time trends, we see little difference in the results.

6.1.3 Stock market returns and accidents

Using our preferred model specification, accidents respond to the absolute value of the change in returns and the function follows a V-shape. For the full sample we see a 1% increase in positive returns leads to a 0.5% increase in accidents and a 1% decrease in negative returns leads to a 0.7% increase in accidents. A similar pattern emerges for the weekday model, as a 1% increase in positive returns leads to a 0.2% increase in accidents (although this is not statistically significant) and a 1% decrease in negative returns leads to a 0.6% increase in accidents. The same pattern is found for weekends (which begin at 5pm on Friday) but the effects are stronger. These results are consistent with the hypothesis that changes in returns (positive or negative) lead to distraction and accidents, and the small effect might reflect low involvement in the stock market or small changes in returns that go unnoticed (Frijters, Johnston, Shields, & Sinha, 2015). There is also a potentially weak effect in anticipating economic change in terms of, for example, job prospects. For fatal accidents, larger negative returns are associated with fewer fatal accidents overall and on weekdays. For the weekend sample there are no statistically significant effects. These results might suggest a substitution effect in accidents — as returns go down people become distracted and potentially drive more conservatively, so overall accident severity declines. The results also indicate that increases in returns leave fatal accident numbers unaffected.

Having outlined our main set of results, we then turn to exploring them in more detail. Disaggregating overall and fatal accidents by accident and driver characteristics, we find most of the results look similar to the full sample (all days) results. Therefore, the overall result is robust to variations in the sample definition. Investigating wealth effects, we find the stock market has the largest effect on the poorer counties and that accidents increase with both positive and negative returns. Accidents in richer counties increase in response to ‘good news’ from the stock market, although the effect is small. Although individuals in the bottom income decile are less likely to own shares, a given return should have a larger relative income/wealth effect for the poor than the rich, leading to a larger effect on accidents. There is no statistically significant relationship between fatal accidents and returns for either the top or the bottom decile counties. For robustness, we investigate the effects of respecifying returns as categorical variables and in continuous form and find similar results to our preferred specification. We also find weaker relationships when measuring returns over 7 days. We find qualitatively similar results when we specify the dependent variables in levels.

6.1.4 Driving penalties and accidents

We find no effect of either the mobile phone or the speed intervention on numbers of serious or fatal accidents at the aggregate level and this result is robust to variations in the sample and allowing for non-linearities in effects. In response to the speed intervention there are some reductions in accidents among income groups and there is a small effect on accidents on motorways relative to those on B and C roads. To be effective in reducing accidents and their severity, penalties need to be appropriate to the gravity of the offence and resources of the offender and to be well publicised and enforced in order to deter errant behaviour. Therefore, the lack of a large effect in our results could be due to inadequate publicity about the change (based on Google Trends search activity and newspaper reports) and/or insufficient enforcement activity. While increased speeding fines may have reduced travelling speeds, the response may not have been large enough to significantly lower the probability of a fatality or serious injury occurring. In addition, the response may have been concentrated on low speed roads, where fatality risk is lower.

6.2 Policy implications

The findings from our analyses are of interest to health economists, road safety organisations, government, consumers and other road safety stakeholders seeking to improve health by reducing accidents and their severity. In addition to better understanding the economics of road accidents, there are a number of potential policy responses to the 'events' studied in this thesis that could reduce accidents and their severity.

First, additional information may be required to bring subjective and objective risks of driving into line (Cawley & Ruhm, 2011). Educating the public, particularly during economic expansions, may reduce accidents by breeding a climate of concern and helping attitudes to shift towards interventions (Peden et al., 2004). More specifically, education campaigns on the dangers of drink and drug driving, fatigue or distraction could be targeted to particular demographic groups periodically as the economy improves or on an ongoing basis as the stock market adjusts. The UK road safety charity Brake (https://www.brake.org.uk/), for example, operates various road safety campaigns that could be better aligned with economic circumstances.

Second, additional financial incentives may be required to bring individual valuations of the costs of risky driving better into line with the social costs. In this way, larger financial incentives targeted at better driving behaviours could reduce accidents. Such incentives could take the form of higher vehicle insurance premiums for individuals caught breaking driving laws or having had accidents that may be associated with fatigue or distraction or harsher fines for hazardous driving behaviours (speeding, mobile use, drink or drug driving).

Third, non-financial incentives may need to be increased. Licence suspension could be more severe in terms of applicable driving behaviours and penalty terms. This would serve to take the more risky drivers off the roads. Raising the minimum legal drinking age and introducing a graduated licensing system for new drivers (which is currently being considered for England by the UK Department for Transport https://www.gov.uk/government/news/government-looks-at-steps-to-make-new-drivers-safer) would target young and/or inexperienced drivers, curbing risky behaviours.

Fourth, the effectiveness of financial and non-financial penalties partly depends on enforcement activity. In the economics of crime, individuals are assumed to respond to the expected penalty, which comprises the actual penalty and the probability of conviction (which is partly driven by enforcement activity). If enforcement activity is too low, individuals will not respond and accident numbers will be unchanged. One solution (although costly) is to increase enforcement activity with greater patrols and more road safety cameras. 'Police enforcement initiatives need to be swift, frequent and sustained over a long period of time to increase the perceived risk of being caught and punished but also random and widespread to increase the chance of detection' (World Health Organization, 2018, p. 24). During good economic times — when accidents are more likely — there is more scope for funding such activities, which could lessen the desire for both legal (but nonetheless risky) and illegal behaviours and therefore reduce accident numbers and their severity.

Fifth, rather than acting on individual driving behaviour, government could focus on accident response efforts. This would involve prioritising emergency service/hospital expenditure when employment is low in anticipation of better economic times when accidents increase.

6.3 Limitations

In addition to several other datasets, the analyses in this thesis rely primarily on British Stats19 data on accidents and their characteristics and circumstances. These data are very rich and available over a long period that complements other available data. This allows us to use detailed econometric techniques to shed light on behavioural aspects of road safety. However, there are limits to what we can learn as some information is not consistently collected at the level required by our analysis, some is collected but has not been made available and some inherently relies on judgement.

Our analyses required variables based on consistent data at a disaggregated geographic level over long periods. There are numerous variables in the Stats19 dataset, of which we only use a few. In our analyses, we were constrained as many variables were collected for shorter windows of time and/or there were changes in coding frames. Uncollected data can also be difficult to work around. One factor affecting road accidents is traffic volume — all else equal, more traffic means more accidents. We were unable to directly control for traffic volumes that vary over time as available data are not collected at an appropriately detailed level of geography and time for our analyses and we had to proxy these effects. In each analysis, our main variables relate to numbers of accidents. However, there is known underreporting of less serious accidents: for example 36% of injuries are not reported to police and 20% of reported accidents are not recorded (Peden et al., 2004). This may or may not have implications for results relating to overall accident numbers, although effects for more serious accidents remain.

Lack of access to data can limit the opportunities to answer interesting research questions. Stats19 data are made available by the UK Department for Transport. Much of the data is publicly available, although vehicle details and contributory factors are considered sensitive and access is restricted. For each analysis, relevant data was requested at the time. The introduction of the Data Protection Act 2018 (the UK's implementation of the EU General Data Protection Regulation — GDPR) has meant data on many contributory factors has been unavailable. This has limited our ability to directly identify some behavioural mechanisms.

Data that are subject to judgement may be less reliable than data based on objective measures. The contributory factors data rely on police judgement of circumstances at the time the accident is reported. Some factors can be difficult to identify if individuals are not forthcoming in admitting to certain behavioural circumstances such as distraction or fatigue and behaviours are not immediately apparent to police. However, our use of data on alcohol and drugs is likely to be more reliable.

6.4 Future research

Road safety is an important topic and there remains scope to better understand triggers of relevant behavioural responses from an economic perspective. Should the data become available, a more thorough examination of contributory factors would provide enlightenment about behavioural mechanisms. Another area of exploration is in terms of road safety interventions. One such intervention is the proposed graduated licensing system in England.

Just as local area crime may affect individuals' mental health and wellbeing, there might well be indirect costs of road traffic accidents through fear and anxiety among individuals in the area. This could also lead to changes in travel behaviour. Local area accidents are important because national government policy may not be effective if there are local factors that drive behaviour. Stats19 data could be used in conjunction with individual-level survey data to investigate such links.

Although there has been some research analysing the effects of the London congestion charge on accidents and fatalities (see, for example, Green, Heywood, & Navarro, 2016; Li, Graham, & Majumdar, 2012), there might be scope to analyse the effects of the congestion charge on fatality rates (per accident) by vehicle type to see whether casualty severity was affected in different ways according to the vulnerability of the transport mode (including the effects for pedestrians). The hypothesis would be that increased rates of fatalities or serious injuries per accident were related to increased vehicle speeds due to lower congestion.

There have been changes in liquor licensing laws in England. Laws changed in England and Wales on 24 November 2005, when the concept of 'permitted hours' for selling/serving alcohol was abolished meaning alcohol could theoretically be sold and served 24/7. Similar changes came into force in Scotland in September 2009, following a transition period starting in February 2008. Earlier, in August 1988, permitted hours for the sale of alcohol in England and Wales were extended by law and the effects of this change on road traffic accidents have been studied (Duffy & Pinot De Moira, 1996), although the data were analysed on an annual basis and this might be the reason for a lack of effect. An analysis of the effects of these law changes on road accidents and their severity would represent a new contribution to the literature as opposed to existing studies of hospital admissions.

Liquor licensing laws affect alcohol sales and may affect numbers of public houses (pubs) in an area. There could be a link between numbers of pubs in an area and numbers of alcohol-related accidents. With exact geographic coordinates in Stats19 data and locations of pubs in Britain available from other sources, there is scope to investigate this link to see whether there are indeed ‘blackspots’ near heavy concentrations of pubs.

This thesis has provided a number of innovations and original contributions in terms of applying a health economics lens to road accidents and in considering the impact of factors beyond road traffic legislation on driver behaviour. In particular, we focus on broad economic factors (economic activity and stock markets). Driving is an everyday activity for most people and driver distraction and excessive speed are known causes of accidents. The pathways to driver distraction and speeding behaviour through our economic lives has been relatively unexplored and this thesis adds significantly to our knowledge. Further we consider the instruments used (penalties) to deter risky driving in terms of their incentive structures regarding behaviours resulting from income lost. Fines and other penalties affecting licence holding impact behaviour through the threat of lost income (and potentially social stigma) but to really understand the impact of any penalty structure requires an understanding of how economic incentives translate into behaviour change. We also contribute to this literature. In essence we provide a substantial body of evidence showing how economic factors translate into driver behaviours and therefore affect health outcomes.

References

Cawley, J., & Ruhm, C. J. (2011). Chapter three - the economics of risky health behaviors. In M. V. Pauly, T. G. McGuire, & P. P. Barros (Eds.), *Handbook of Health Economics* (Vol. 2, pp. 95-199): Elsevier.

Duffy, J. C., & Pinot De Moira, A. C. (1996). Changes in licensing law in England and Wales and indicators of alcohol-related problems. *Addiction Research, 4*(3), 245-271. doi:10.3109/16066359609005571

Frijters, P., Johnston, D. W., Shields, M. A., & Sinha, K. (2015). A lifecycle perspective of stock market performance and wellbeing. *Journal of Economic Behavior & Organization, 112*, 237-250. doi:https://doi.org/10.1016/j.jebo.2015.02.004

Green, C. P., Heywood, J. S., & Navarro, M. (2016). Traffic accidents and the London congestion charge. *Journal of Public Economics, 133*, 11-22. doi:http://dx.doi.org/10.1016/j.jpubeco.2015.10.005

Li, H., Graham, D. J., & Majumdar, A. (2012). The effects of congestion charging on road traffic casualties: a causal analysis using difference-in-difference estimation. *Accident Analysis & Prevention, 49*, 366-377. doi:https://doi.org/10.1016/j.aap.2012.02.013

Peden, M., Scurfield, R., Sleet, D., Mohan, D., Hyder, A. A., Jarawan, E., & Mathers, C. (2004). *World report on road traffic injury prevention*. World Health Organization. Geneva.

World Health Organization. (2018). *Global status report on road safety 2018*. WHO. Geneva.