



Universidad Autónoma
de Madrid

Biblos-e Archivo
Repositorio Institucional UAM

Repositorio Institucional de la Universidad Autónoma de Madrid
<https://repositorio.uam.es>

Esta es la **versión de autor** del artículo publicado en:
This is an **author produced version** of a paper published in:

Accident Analysis & Prevention 144 (2020): 105549

DOI: <https://doi.org/10.1016/j.aap.2020.105549>

Copyright: © 2020 Elsevier. This manuscript version is made available under the
CC-BY-NC-ND 4.0 licence <http://creativecommons.org/licenses/by-nc-nd/4.0/>

El acceso a la versión del editor puede requerir la suscripción del recurso
Access to the published version may require subscription

Revisiting the relationship between traffic accidents, real economic activity and other factors in Spain*

Antonio García-Ferrer^{†1}, Marcos Bujosa², Aránzazu de Juan¹ and
Rocío Sánchez-Mangas¹

¹Universidad Autónoma de Madrid, Madrid, Spain

²Universidad Complutense de Madrid, Madrid, Spain. Instituto Complutense del Análisis Económico *ICAE*, Madrid, Spain

October 18, 2019

Abstract

This paper analyzes the relationship between road traffic accidents and real economic activity in Spain, using data on accidents, fatalities and injuries from January 1975 to December 2016. Our results show the historical asymmetric cyclical behaviour of traffic accidents variables. This relationship is more evident for accidents and injuries, while fatalities have shown a different pattern since 2002. Besides using aggregate data, we have analyzed urban and nonurban accidents separately. We analyze the effect of economic variables, public policy interventions and other potential factors affecting traffic series. Regarding policy interventions, we confirm a permanent reduction in all accident rates associated with the mandatory use of seatbelts on car passengers since 1992, as well as with methodological changes in the data collection from January 2006. However, the penalty points system introduced in July 2006 has only had temporary effects. We have also shown the effect of economic variables such as Industrial Production Index, gasoline and diesel consumption and registration of new vehicles and, as a novelty, the benefits of using the composite coincident and leading indicators of the Spanish economy.

Keywords: traffic accidents, time series analysis, unobserved component models, composite coincident and leading indicators.

JEL codes: R41, I18, C22, C51

*Projects (financial support): Spanish Ministry of Science and Technology (Grant ECO2015-641467-R, MINECO/FEDER, ECO2015-70331-C2-1-R), Comunidad de Madrid (Grant MADECO S2015/HUM-3444) and Cooperación interuniversitaria UAM-Banco Santander con América Latina (Grant CEAL-AL/2017-23).

[†]Corresponding author

1 Introduction

Road safety is one of the main public health issues in developed countries. According to the [European Commission \(2018\)](#), every year more than 25,000 people lose their lives on EU roads and another 135,000 are seriously injured. This has enormous socio-economic consequences, with an estimated cost to society of around EUR 120 billion. The Road Safety Programme adopted by the European Commission for 2011-2020 had the objective to cut road deaths in Europe in half by 2020 ([European Commission, 2010](#)). To achieve this goal, the programme focused on improving vehicle safety, the safety of infrastructure and road users' behavior. What is the degree of fulfillment of these objectives? From 2010 to 2013, the number of road fatalities in Europe decreased considerably, resulting real figures not far from the targeted ones. However, from 2013 to 2016, fatality reduction rates have plateaued and we can even observe a slight increase in some countries. Is the economic recession started in 2007 behind the decline in the number of fatalities? Can the end of the recession explain its posterior flat or even increasing pattern?

The relationship between road traffic accidents and fatalities and economic activity has been largely analyzed in the literature. Most of the recent papers find that accidents and fatalities exhibit a cyclical behavior. Evidence of this finding in the US is reported in [Lam and Piérard \(2017\)](#), [Noland and Zhou \(2017\)](#), [Ruhm \(2000, 2015\)](#), [Cotti and Tefft \(2011\)](#) and [French and Gumus \(2014\)](#), among others. Similar evidence is found in several studies for other countries. See, for example, [García-Ferrer et al. \(2007\)](#), [Rodríguez-López et al. \(2016\)](#) for the case of Spain, [Antoniou et al. \(2015\)](#) for 30 European countries, [Elvik \(2015\)](#) for 14 OECD countries and [Bergel-Hayat et al. \(2015\)](#) for a small group of countries in Europe. Most of these papers measure changes in economic activity through changes in unemployment and/or GDP.

What are the mechanisms that explain the relationship between economic activity and traffic fatalities? Several explanations have been proposed (see [Wegman et al. \(2017\)](#) for an excellent review of studies on this relationship). On the one hand, regarding economic recessions, a reduction in the number of kilometers traveled implies less exposure (see, for example, [Noland and Zhou \(2017\)](#) for US). On the other hand, economic recessions might have an effect on road users behavior. [He \(2016\)](#), using US data in the period 2003-2013, finds that risk factors related to drivers behavior are much more important than less exposure to explain the reduction in fatalities. In this sense, the economic recession has implied a reduction of driving that is more pronounced among high-risk drivers. Similar findings are found in [Yannis et al. \(2014\)](#) using data from 27 European countries in the period 1975-2011, or [Maheshri and Winston \(2016\)](#) for the state of Ohio using data from 2009 to 2013. Other studies that focus on drivers behavior as a channel through which traffic fatalities and economic recession are connected are, among others, [Lloyd et al. \(2015\)](#) for Great Britain or [Bertoli et al. \(2018\)](#) for Spain, with mixed results.

In this paper we analyze the relationship between road traffic accidents, including fa-

talities and injuries, and real economic activity in Spain using monthly data for the period 1975-2016. We update the previous work by [García-Ferrer et al. \(2007\)](#), that covered the years 1975-2004, by providing new evidence in a period that includes the last economic recession. The case of Spain is particularly interesting since it is one of the countries hardest hit by that recession. Two facts are worth mentioning. First, the series of accidents and injured victims follow a common cyclical behavior during the main recession and expansion periods in the time span considered. Thus, the deep recession period started in 2007 and the subsequent recovery of the economic activity from around 2012 has not changed this relationship. In fact, the series of accidents and injuries exhibit a very clear increase from 2012. Second, the series of fatalities has shown a different pattern. The behavior that mimics the evolution of the economic activity is only observed until 2002 (see [García-Ferrer et al. \(2007\)](#)). In fact, the number of fatalities has experienced a permanent reduction from the early nineties almost every year, with the exception of 1995, 1997, 1998 and 2000. There are some potential factors behind this pattern. Regarding policy interventions, whose importance has been highlighted in several studies (see [Brüde and Elvik, 2015](#)), the mandatory use of seat-belts from June 1992 in Spain and the implementation of the penalty points system from July 2006 can explain part of this behavior. However, the adoption of this latter policy measure has coincided in time, from one year after its entry into force, with the deep recession period started in 2007. Then, it is difficult to distinguish to which extent the reduction in the number of fatalities in the subsequent years is due to the effect of the new driver license scoring legislation or to the evolution of the economic activity and/or the rise of fuel prices during the Spring of 2008. Contrary to what happened with the series of accident and injuries, the number of fatalities has continued to decrease even after 2012, when the economic performance pointed to a recovery period. It is only from 2014 on when the series of fatalities has moderated its decline or even has shown a slight increase in 2016, and the preliminary data of 2017.

Our objective in this paper is to disentangle the contribution of the different potential factors to explain the observed patterns in the road traffic indicators. To do so, we analyze the relationship of accidents, fatalities and injuries with policy interventions and economic variables. As we mentioned above, most of the papers that have analyzed this relationship have used the GDP and the unemployment rate to measure the economic performance. As in [García-Ferrer et al. \(2007\)](#), we use Industrial Production Index, gasoline and diesel consumption and registration of new vehicles, since these variables are less subject to measurement errors. As a novelty in this literature, we will use the Composite Coincident Indicator (CCI) and the Composite Leading Indicator (CLI) of the economic activity developed in [Bujosa et al. \(2013, 2019\)](#). The importance of these indicators is twofold. First, they can outperform the forecast accuracy of previous existing models. Second, since the CLI anticipates the economic expansion and recession periods, it can be used as a policy instrument of crucial importance for road safety issues. The importance of anticipating the evolution of the economy in this context has also been highlighted in [Yannis et al. \(2014\)](#).

Our contribution to the literature on road safety is twofold: on one side, we focus on traffic accident variables in a country severely hit by the economic crisis. On the other side, we use coincident and leading indicators of the economic activity to explain and anticipate road traffic indicators, with clear policy implications.

The rest of the paper is organized as follows. In Section 2 we offer a descriptive analysis of both our monthly and annual data. In Section 3 we present a cycle characterization of monthly data based on [García-Ferrer and Bujosa-Brun \(2000\)](#). Section 4 offers the econometric models for both monthly and annual data. The results have important policy implications, that are reported in Section 5. Finally, Section 6 offers the main conclusions.

2 Descriptive analysis of the data

Giving the absence of data on a weekly or daily basis, our analysis is concentrated in a collection of monthly and annual data at an aggregate level. Also, some important variables such as road conditions and traffic flows as well as the number of vehicle-miles traveled or the effects of prompt medical assistance are only available for a few and sparse episodes that are not appropriate for time series analysis.

2.1 Monthly data

The choice of monthly data was established in [García-Ferrer et al. \(2007\)](#) on the basis of three concerns: non-stationary seasonal behavior, the influence of some exogenous variables that take place during the year and tend to disappear when using annual data and a methodological requirement to further obtain cycle datings. Definitions of the main variables appear in Table 1 and their plots are shown in Figure 1 (accident variables) and Figure 2 (economic variables). All accident variables show a changing trend characteristic of a non-stationary behavior as well as strong and varying seasonality. Furthermore, Spanish accident data show some peculiarities worth mentioning. First, crash-related fatalities are associated with individuals dying during the first 24 hours after the accident.¹ Second, for each accident related variable we have disaggregated data in urban and road series that will be denoted adding an U or R to the acronyms used for the aggregated series. Sometimes, public attention in most countries is only paid to road accidents as if its urban counterparts were less important. This view is misleading in the Spanish case, since ACCU and INJU represented 64% and 60% of ACC and INJ in 2016, and FATR includes a 75% of total fatalities. The growing

¹Although after 1993 Spain has adopted the definition of the Vienna Convention and considered deaths at the scene or the crash or within 30 days following the crash, the series using the 30-day time frame are too short and present some inconsistencies due to the way the data is collected. Thus, we use 24 hours data in the case of fatalities, since the series are longer and compatible with the data base used in [García-Ferrer et al. \(2007\)](#). Only when making international comparisons the 30-day time frame shall be used.

share of urban accidents is remarkable after 2006 and, as we will see later, it may have consequences both in estimated models and tentative policy implications. Third, seasonality is further complicated by the presence of “moving” holidays and the intervention variables that change from year to year. As shown in [García-Ferrer et al. \(2007\)](#), Easter holidays (EAST) and the number of working days (NWD) showed magnitudes of different sign depending on the series and their level of aggregation. These effects remain when enlarging the data set in recent times.

Regarding economic variables in Figure 2, IPI, new registration of vehicles and gasoline and diesel consumption show non-stationary behaviour and marked seasonality. Two facts are worth mentioning. First, the clear decreasing pattern in IPI and new registration of vehicles that coincides with the last economic recession. Second, the different evolution of gasoline and diesel consumption, especially in the last part of the sample, when the share of diesel has grown considerably.

2.2 Annual data

Previous monthly data can be easily converted into annual data by simple manipulation, either by adding monthly observations or by using the geometric mean in the case of Industrial Production Index (IPI). Our annual data runs from 1975 to 2016. Additionally, we have included annual data for two variables that critically affect traffic flows and accidents: (1) Total number of available road kilometers of free motorways (FM), and (2) Total number of available road kilometers of toll motorways (TM).

Plots of the annual accident data are shown in Figure 3. Accident variables show different cyclical behavior around the trend with remarkable differences in the road and urban components, particularly after 2005. On the other hand, FM and TM have a growing trend characteristic of a non-stationary behavior. Given these attributes, these variables will be transformed into annual growth rates in the empirical implementation of annual models.

Accident variables	Definitions	Period	Obs.	Source
ACC	Number of accidents with injured passengers	1975M01 – 2016M12	504	DGT ¹
ACCR	As ACC in roads	1975M01 – 2016M12	504	DGT ¹
ACCU	As ACC in urban areas	1975M01 – 2016M12	504	DGT ¹
INJ	Number of injured passengers	1975M01 – 2016M12	504	DGT ¹
INJR	As INJ in roads	1975M01 – 2016M12	504	DGT ¹
INJU	As INJ in urban areas	1975M01 – 2016M12	504	DGT ¹
FAT	Number of killed passengers	1975M01 – 2016M12	504	DGT ¹
FATR	As FAT in roads	1975M01 – 2016M12	504	DGT ¹
FATU	As FAT in urban areas	1975M01 – 2016M12	504	DGT ¹
Economic Variables				
IPI	Industrial Production Index	1975M01 – 2016M12	504	INE ²
NUVE	New Registration of vehicles	1975M01 – 2016M12	504	INE ²
CGAS	Gasoline consumption in million of liters	1975M01 – 2016M12	504	INE ²
CDIESEL	Diesel consumption in million of liters	1982M01 – 2016M12	420	INE ²
CCI	Spanish Composite coincident economic indicator	1982M01 – 2016M12	420	³
CLI	Spanish Composite leading economic indicator	1978M01 – 2016M12	468	³

Table 1: Definitions of the main variables of monthly data. Sources: (1) Dirección General de Tráfico; (2) Instituto Nacional de Estadística; and (3) see [Bujosa et al. \(2019\)](#).

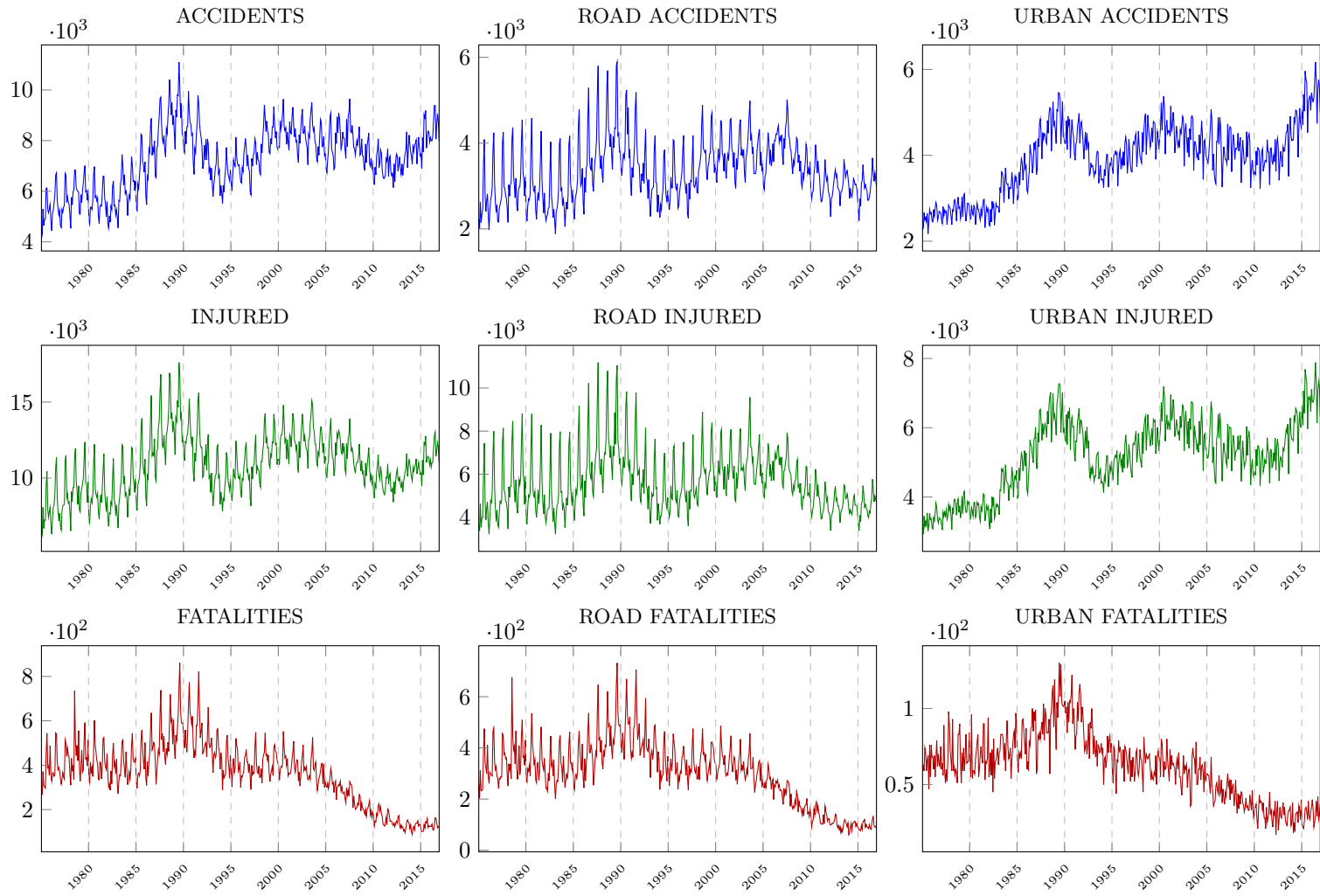


Figure 1: Accident related monthly data: January 1975 - December 2016.

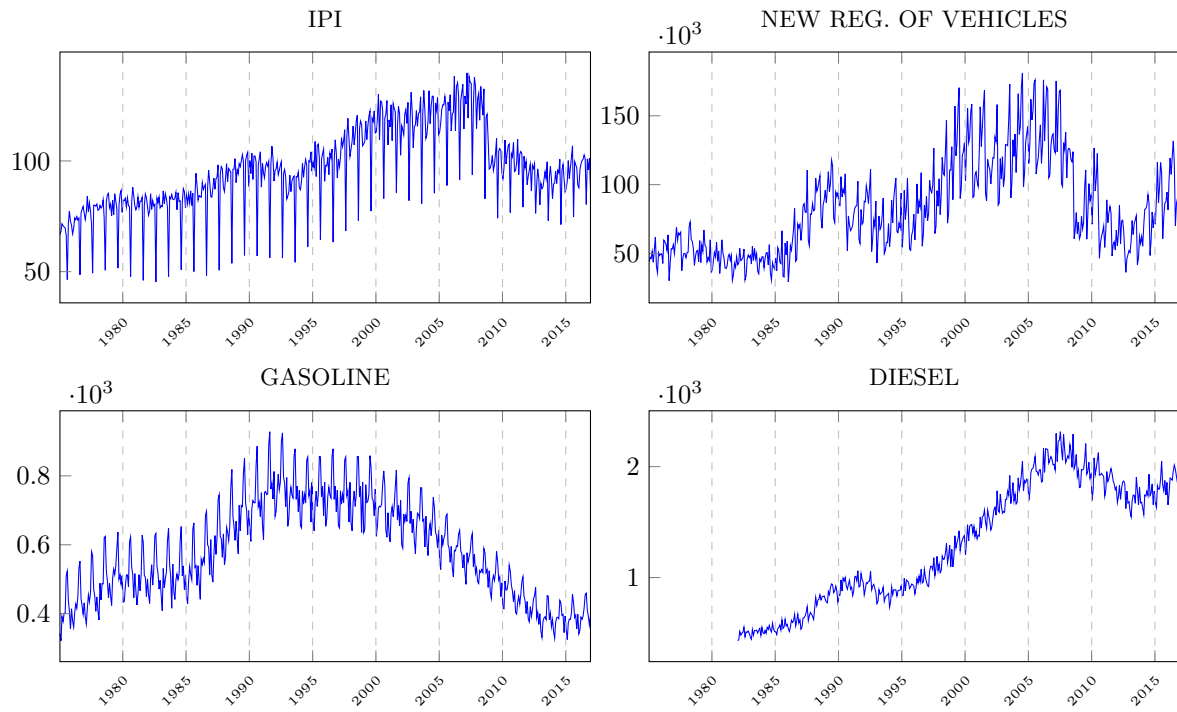


Figure 2: Economy related monthly data: January 1975 - December 2016.

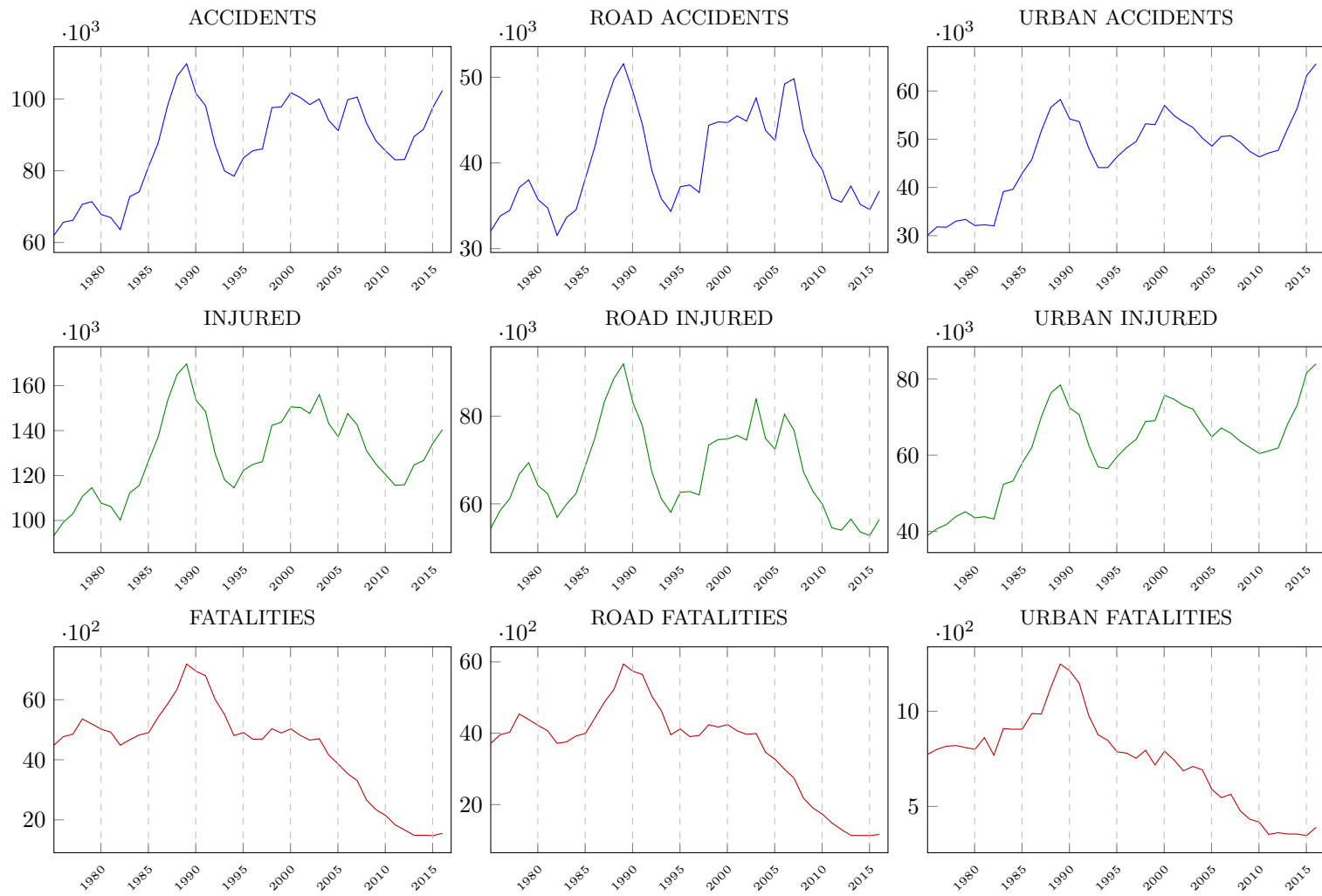


Figure 3: Main variables in annual models: 1975 - 2016.

3 A cyclical characterization of monthly data

In our case of seasonally unadjusted data, we will use the state-space proposal of [García-Ferrer and Bujosa-Brun \(2000\)](#) and later applied in [García-Ferrer et al. \(2007\)](#). The theoretical framework is briefly sketched in the next subsection and the turning point characterization is presented later.

3.1 Dynamic Harmonic Regression (DHR) model

Consider the hypothesis that an observed time series $\mathbf{y} \equiv \{y_t\}_{t \in \mathbb{Z}}$ is periodic or quasi-periodic and can be decomposed into several unobserved components whose variances are concentrated around certain fundamental frequencies plus an *irregular* component:

$$\mathbf{y} = \mathbf{T} + \mathbf{S} + \mathbf{e};$$

where the variance of the *trend* component, \mathbf{T} , is concentrated around the zero frequency, the variance of the *seasonal* component, \mathbf{S} , is concentrated around the seasonal frequency and its sub-harmonics, and the *irregular* component, \mathbf{e} , is i.i.d with zero mean and variance σ_e^2 . This hypothesis is often appropriate for observed non-stationary and seasonal time series with well defined spectral peaks, as it is the case with the monthly variables used in this paper.

The Dynamic Harmonic Regression (DHR) model, developed by [Young et al. \(1999\)](#), consist of several unobserved components:

$$\mathbf{y} = \sum_{j=0}^R \mathbf{s}^j + \mathbf{e} \quad (1)$$

where each DHR component \mathbf{s}^j is an oscillatory process with frequency ω_j :

$$s_t^j = a_t^j \cos(\omega_j t) + b_t^j \sin(\omega_j t), \quad t \in \mathbb{Z}. \quad (2)$$

Oscillations of each DHR component, \mathbf{s}^j , are modulated by two stochastic processes $\{a_t^j\}_{t \in \mathbb{Z}}$ and $\{b_t^j\}_{t \in \mathbb{Z}}$. Within the framework of the Generalized Random Walk (GRW) models, both stochastic processes are either Random Walk (RW) processes (and we say that the corresponding DHR component, \mathbf{s}^j , follows a RW model) or both are AR(2) processes *with at least one unit root* (when both roots are 1 we say that \mathbf{s}^j follows an Integrated Random Walk (IRW); and when one of the roots is less than 1 in absolute value we say \mathbf{s}^j follows a Smooth Random Walk (SRW)). The first index, $j = 0$, corresponds to the trend (or zero frequency term) and the other components ($j = 1, \dots, R$) correspond to the seasonal frequency and its harmonics; hence, $\mathbf{T} = \mathbf{s}^0$ and $\mathbf{S} = \sum_{j=1}^R \mathbf{s}^j$.

	ACC	ACCR	ACCU	FAT	FATR	FATU	INJ	INJR	INJU
1976	5.9	5.5	5.8	6.3	6.6	3.5	6.3	7.6	4.5
1977	0.9	1.9	-0.2	1.8	1.7	2.0	3.8	4.6	2.8
1978	6.7	7.8	4.0	10.4	12.7	0.5	7.5	9.1	5.0
1979	1.1	2.4	1.1	-3.1	-3.4	-1.3	3.5	4.0	2.8
1980	-5.0	-6.1	-3.8	-3.4	-3.8	-1.1	-6.0	-7.6	-3.5
1981	-1.3	-2.6	0.5	-1.9	-3.5	7.6	-1.4	-2.8	0.7
1982	-5.0	-9.2	-0.7	-8.8	-8.7	-10.7	-5.7	-8.7	-1.4
1983	14.5	6.6	22.2	4.0	1.1	18.2	12.1	5.3	21.1
1984	1.8	2.6	1.2	3.5	4.4	-0.4	2.9	4.1	1.6
1985	9.6	10.8	8.6	1.6	1.9	0.1	9.8	10.3	9.1
1986	8.0	9.7	6.5	10.5	10.9	9.1	8.2	9.2	6.9
1987	11.9	10.9	13.0	8.1	10.0	-0.3	11.8	11.0	12.9
1988	8.3	7.0	9.5	8.4	7.2	14.1	7.5	6.3	9.0
1989	3.2	3.6	2.9	13.2	13.7	11.0	2.9	3.8	2.8
1990	-7.6	-6.3	-6.9	-3.3	-3.4	-2.9	-9.5	-9.6	-7.7
1991	-3.3	-7.9	-1.0	-2.2	-1.5	-5.4	-3.3	-6.4	-2.4
1992	-11.0	-12.1	-10.2	-11.5	-10.9	-14.7	-12.5	-13.6	-11.3
1993	-8.4	-8.5	-8.4	-8.4	-8.1	-10.4	-9.1	-9.1	-9.1
1994	-1.8	-4.1	0.0	-12.7	-14.5	-3.3	-3.0	-5.0	-0.9
1995	6.5	8.3	5.1	2.1	4.0	-7.1	6.8	7.8	5.7
1996	2.4	0.6	3.8	-4.5	-5.2	-0.9	2.2	0.3	4.2
1997	0.6	-2.4	2.8	0.1	0.8	-3.5	1.0	-1.2	3.2
1998	13.4	21.4	7.4	7.3	7.6	5.6	12.8	18.4	7.4
1999	0.2	0.9	-0.3	-2.8	-1.5	-9.7	1.0	1.7	0.3
2000	4.0	-0.1	7.5	2.9	1.6	10.0	4.7	0.2	9.6
2001	-1.3	1.7	-3.7	-4.4	-4.1	-5.8	-0.1	1.1	-1.4
2002	-2.0	-1.3	-2.5	-3.3	-2.5	-7.7	-1.8	-1.4	-2.2
2003	1.6	6.0	-2.1	1.1	0.7	3.3	5.7	12.6	-1.3
2004	-6.0	-7.9	-4.2	-11.6	-13.2	-2.5	-8.3	-10.7	-5.4
2005	-3.0	-2.7	-3.3	-7.2	-5.7	-14.9	-4.1	-3.3	-5.0
2006	9.4	15.5	4.1	-8.3	-8.5	-7.3	7.5	11.0	3.6
2007	0.7	1.2	0.2	-6.5	-8.3	3.3	-3.4	-4.5	-2.1
2008	-7.3	-12.0	-2.7	-19.6	-20.5	-15.6	-8.1	-12.4	-3.2
2009	-5.3	-6.9	-3.8	-12.0	-12.7	-9.0	-4.6	-6.6	-2.5
2010	-3.1	-4.0	-2.4	-8.1	-9.1	-3.7	-3.7	-4.7	-2.6
2011	-2.9	-8.4	1.8	-14.4	-14.2	-15.3	-3.9	-9.0	1.1
2012	0.1	-1.3	1.1	-9.5	-12.3	2.5	0.2	-1.0	1.3
2013	7.7	5.3	9.5	-10.5	-12.8	-1.9	7.6	4.7	10.2
2014	2.3	-5.8	8.0	-0.1	-0.2	0.0	1.5	-5.3	7.2
2015	6.8	-1.7	12.0	-0.6	-0.1	-2.3	6.2	-1.4	11.7
2016	4.7	6.3	3.9	4.9	2.7	12.4	4.4	6.9	2.8

Table 2: Annual growth rates (%) of the variables — Full sample

	ACC	ACCR	ACCU	FAT	FATR	FATU	INJ	INJR	INJU
Main descriptive statistics — full sample									
Mean	1.41%	0.60%	2.10%	-2.27%	-2.47%	-1.33%	1.20%	0.38%	2.08%
Median	0.86%	0.58%	1.15%	-2.80%	-2.46%	-1.34%	1.53%	0.18%	1.58%
Maximum	14.48%	21.44%	22.19%	13.23%	13.71%	18.21%	12.79%	18.39%	21.13%
Minimum	-11.04%	-12.08%	-10.18%	-19.64%	-20.47%	-15.60%	-12.46%	-13.55%	-11.26%
Std.D.	6.17	7.52	6.24	7.63	8.11	8.15	6.46	7.72	6.37
Main descriptive statistics — sample 1976–2004									
Mean	1.6%	1.3%	2.0%	0.0%	0.0%	-0.1%	1.7%	1.4%	2.2%
Median	1.1%	1.7%	1.1%	0.1%	0.7%	-0.9%	2.9%	1.7%	2.8%
Max.	14.5%	21.4%	22.2%	13.2%	13.7%	18.2%	12.8%	18.4%	21.1%
Min.	-11.0%	-12.1%	-10.2%	-12.7%	-14.5%	-14.7%	-12.5%	-13.6%	-11.3%
Std.D.	6.54	7.54	6.69	6.94	7.36	7.79	6.87	7.97	6.80
Main descriptive statistics — sample 2005–2016									
Mean	0.8%	-1.2%	2.4%	-7.7%	-8.5%	-4.3%	0.0%	-2.1%	1.9%
Median	0.4%	-2.2%	1.5%	-8.2%	-8.8%	-3.0%	-1.6%	-3.9%	1.2%
Max.	9.4%	15.5%	12.0%	4.9%	2.7%	12.4%	7.6%	11.0%	11.7%
Min.	-7.3%	-12.0%	-3.8%	-19.6%	-20.5%	-15.6%	-8.1%	-12.4%	-5.0%
Std.D.	5.41	7.47	5.27	6.65	6.74	8.56	5.39	6.73	5.44

Table 3: Main descriptive statistics of annual growth rates shown in Table 2

Bujosa et al. (2007) showed that DHR components \mathbf{s}^j have an equivalent representation as ARIMA processes with some AR roots on the unit circle.

$$\phi^j(B)s_t^j = \theta^j(B)w_t^j, \quad j = 0, \dots, R; \quad (3)$$

where $\{w_t^j\}_{t \in \mathbb{Z}}$ is a zero mean white noise process with variance σ_j^2 , and $\phi^j(B)$ and $\theta^j(B)$ are, respectively, the AR and MA polynomials. The noise variance ratios ($NVR_j = \sigma_j^2/\sigma_e^2$) work as smoothing parameters; the smaller the NVR_0 , the closer to a linear deterministic trend the estimated trend is. In the limit, when the $NVR_0 = 0$ the estimated trend is linear. In the case of seasonal components, the smaller the NVR_j , the smoother the changes in the amplitude of the oscillations of \mathbf{s}^j (see Young et al., 1999). Here we use the method described in Bujosa et al. (2007), hence, the hyper-parameters NVR_j are estimated by linear fitting of the *pseudo-spectrum* of the DHR model to the periodogram of the observed series. Then, the unobserved components are estimated using the Kalman filter and the fixed interval smoothing.

3.2 Cycle characterization

We use the characterization proposed in García-Ferrer and Bujosa-Brun (2000), which is directly linked to the first difference of the Integrated Random Walk (IRW) trend estimates outlined in Section 3.1. The *anticipation of a recession* at time t is the point where the first difference of trend reaches its local maximum numerical value, and the *confirmation of a recession* is the point where the first difference becomes negative if it remains so for at least six months. Analogously, we define the *anticipation of an expansion* at the local first difference's minimum; and the *confirmation of an expansion* when the first difference becomes positive if it remains so for at least nine months. The empirical time differences for an expansion and a recession are somehow heuristic and based on empirical observations over a large set of IRW trends of monthly economic series. Additionally, the turning point characterization following these rules must always agree with the information provided by annual growth rates of the reference variable. We will follow the same characterization for the cycle when dealing with our composite indicators.

In Table 2, annual growth rates of accident variables are presented. In Table 3 we report a summary of the main descriptive statistics for the full sample and for different sub-samples. For the aggregate variables ACC and INJ, and with minor exceptions, four common recession periods can be identified: 1980–1982, 1990–1994, 2001–2005 (excepting 2003) and 2008–2012. However, around 2004 both aggregate FAT (as well as its components FATR and FATU) show a continuously decreasing growth, independently of the stage of the business cycle until its recent turning point in 2016. Certainly, this is a new finding that shall be discussed in detail in Section 5.

Estimated IRW cycles heavily depend on the Noise Variance Ratio (NVR) recursive estimates of the DHR models, which implies the trend's NVR as well as the NVR estimates of

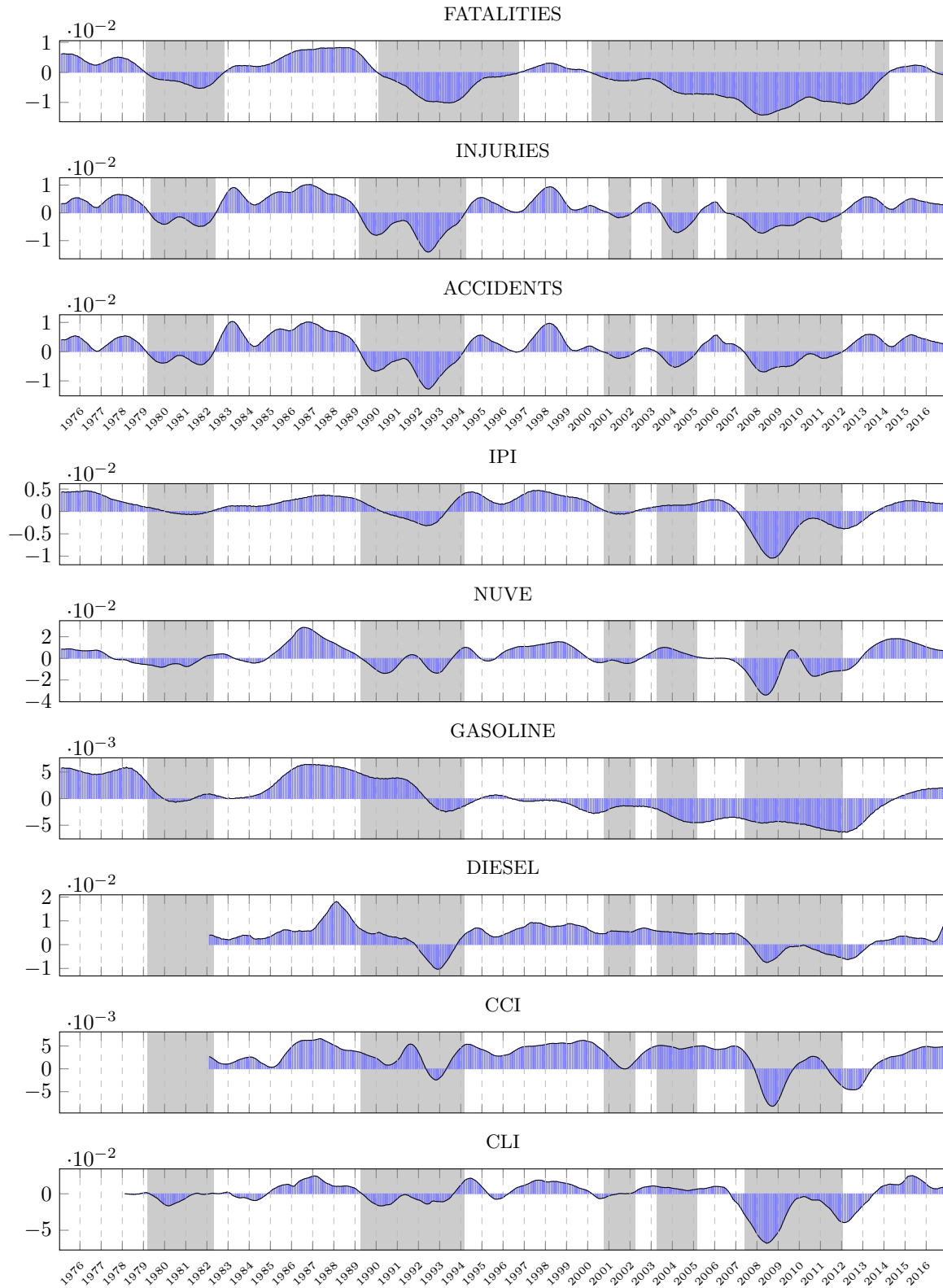


Figure 4: Estimated cycles for the main monthly variables. Shaded areas are recessions periods of ACC except for INJ and FAT that show their own cycles.

the main seasonal frequency and its harmonics. Although there are some minor differences in the trend NVR estimates, all series exhibit smooth trends and similar seasonal frequencies². IRW cycles are plotted in Figure 4, where shaded areas are recession periods according to the definitions stated earlier. The complete turning point characterization for accident variables is summarized in Table 4. Results from this table are very important in checking whether the length and timing of the recessions are in agreement with results shown by the annual growth rates in Table 2. If this is the case, we can be reasonably sure about the good properties of our dating procedure. The fourth column in Table 4 indicates the duration of the contractions (in months). As we can see, those periods identified as recessions in Table 4 are in agreement with negative annual growth rates in Table 2.

	Recessions			Expansions			ratio
	Begins	Ends	months	Begins	Ends	months	
ACC	1978M03	1982M05	50	1982M06	1989M03	69	1.38
	1989M04	1994M03	59	1994M04	2000M09	74	1.25
	2000M10	2002M03	17	2002M04	2003M03	12	0.71
	2003M04	2005M02	22	2005M03	2007M05	26	1.18
	2007M06	2012M01	55	2012M02			
FAT	1979M03	1982M12	45	1983M01	1990M02	86	1.91
	1990M03	1996M06	75	1996M07	1999M12	41	0.55
	2000M01	2014M02	170	2014M03	2016M02	23	0.14
	2016M03						
INJ	1979M05	1982M05	36	1982M06	1989M02	80	2.2
	1989M03	1994M03	60	1994M04	2001M02	82	1.4
	2001M03	2002M01	10	2002M03	2003M06	15	1.5
	2003M07	2005M03	20	2005M04	2006M07	15	0.75
	2006M08	2011M12	64	2012M01			

Table 4: Complete turning point characterization for the main monthly accident variables. The last column shows the expansion/recession length ratios.

Although the estimated cycles now use the full information provided by the larger data set (1975–2016), the new results are very much in agreement with those found by [García-Ferrer et al. \(2007\)](#) where the sample ended in 2004. The turning point characterization for economic variables is shown in Table 5. Recession periods are also in agreement with negative annual growth rates for these variables.³ Therefore, the definitions proposed earlier

²NVR estimates for all monthly variables are available from the authors upon request.

³The annual growth rates for all the economic variables are available from the authors upon request.

	Recessions			Expansions			ratio
	Begins	Ends	months	Begins	Ends	months	
IPI	1980M02	1982M01	24	1982M02	1990M04	98	4.1
	1990M05	1993M04	35	1993M05	2000M11	90	2.6
	2000M12	2002M02	15	2002M03	2007M01	58	3.9
	2007M02	2013M07	77	2013M08			
NUVE	1977M08	1981M09	49	1981M10	1983M04	18	0.37
	1983M05	1984M10	17	1984M11	1989M04	54	3.2
	1989M05	1991M04	23	1991M05	1992M01	8	0.35
	1992M02	1993M07	17	1993M08	1994M11	15	0.88
	1994M12	1995M08	8	1995M09	1999M12	51	6.4
	2000M01	2002M06	30	2002M07	2006M06	47	1.57
	2006M07	2009M04	33	2009M05	2009M12	7	0.21
	2010M01	2012M11	35	2013M01			
CGAS	1980M01	1981M04	16	1981M05	1992M05	133	8.31
	1992M06	1994M11	30	1994M12	1996M05	18	0.6
	1996M06	2014M06	217	2014M07			
CDIESEL	1991M11	1993M10	24	1993M11	2007M09	166	6.92
	2007M10	2013M04	68	2013M05			
CCI	1992M05	1993M04	12	1993M05	2007M11	174	14.4
	2007M12	2009M09	22	2009M10	2011M04	19	0.86
	2011M04	2013M05	26	2013M06			
CLI	1979M05	1982M02	34	1982M03	1983M02	12	0.35
	1983M03	1984M10	19	1984M11	1989M04	54	2.84
	1989M05	1993M08	60	1993M09	1995M04	20	0.33
	1995M05	1996M03	11	1996M04	2000M03	48	4.36
	2000M04	2001M05	14	2001M06	2006M09	64	4.57
	2006M10	2013M06	82				

Table 5: Complete turning point characterization for the main monthly economic variables. The last column shows the expansion/recession length ratios.

properly characterize most of the turning points in the data.⁴ Results from Table 4, Table 5 and Figure 4 can be summarized as follows:

1. There is a common cyclical behavior between traffic accidents and real economic activity during the main recession and expansion periods.
2. We also observe idiosyncratic short and long cycles in some accidents that do not coincide with those of economic variables and viceversa. As in [García-Ferrer et al. \(2007\)](#), these results indicate the presence of a common component in the long run but a varying lead lag relationship depending on the cycle.⁵
3. Aggregate ACC and INJ cycles are very similar [$corr(ACC, INJ) = 0.979$] but the number of FAT cycles is smaller [$corr(ACC, FAT) = 0.664$] and they show longer duration than the other two accident variables, particularly during its long recession from 2000 to 2014.
4. There is also a huge variability on the expansion/recession ratios ranging from 0.14 to 14.4 months confirming a considerable asymmetric cyclical behavior during the whole period.

4 Empirical results

In this section we present estimates of alternative econometric models based on both monthly and annual periodicities. As usual, monthly models will be estimated following the logical sequence used in building time series models: univariate and intervention models first, and dynamic econometric models later. Presenting results in this way, will also facilitate comparisons with those obtained by [García-Ferrer et al. \(2007\)](#) when using more recent data.

4.1 Monthly models

A general dynamic econometric model can be written as:

$$\nabla^d \nabla^D y_t = \sum_{i=1}^k v_i(B) \nabla^d \nabla^D x_{it} + \sum_{j=1}^m \delta_j(B) \nabla^d \nabla^D z_{jt} + \frac{\theta(B)\Theta(B^s)}{\phi(B)\Phi(B^s)} a_t \quad (4)$$

where x_{it} are intervention variables, $v_i(B)$ includes the dynamic model for the i^{th} intervention variable, z_{jt} are the exogenous economic variables, $\delta_j(B)$ includes the dynamic model for the

⁴Restricting to the common period and common variables in this paper and [García-Ferrer et al. \(2007\)](#), the average percentage of coincidence when dating recession and expansion is larger than 93%, which confirms the robustness of the previous results in terms of cycle characterization.

⁵This finding is crucial in understanding the difficulties associated to the specification and estimation of the econometric models in Section 4.

j^{th} economic variable, $\theta(B)$ and $\Theta(B^s)$ are the regular and the seasonal moving average operators, and $\phi(B)$ and $\Phi(B^s)$ are the regular and seasonal autoregressive operators. The process a_t is assumed to be white noise, and ∇^d and ∇^D allow for regular and seasonal differencing. If the usual stationarity and invertibility conditions hold, Peña (2011) showed that most outlier specifications in the literature are embedded in Equation 4 under proper parametrization of the polynomial operator $v_i(B)$. Outliers are identified and estimated using the SEATS/TRAMO software and all economic and accident related variables are in logs.

4.1.1 Assessing the effects of the intervention variables

Estimation results of the ARIMA models together with detailed definitions of the main intervention variables are included in Table 6. To make results comparable with those from alternative econometric models described later, the common sample period runs from 1982M01 to 2016M12. The following comments are worth mentioning:

1. As in García-Ferrer et al. (2007), the Easter effects show opposite signs on road (positive) and urban (negative) accident rates. This opposite behavior may render non-significant coefficients in the aggregate estimates (ACC, FAT and INJ). In spite of a much larger data set, our results confirm their previous findings.

Similar results are found in the NWD case. The effect of the number of working days (NWD) is negative and significant for road variables and aggregated INJ and FAT variables, and usually positive but not always significant for urban variables. Although signs agree with the previous results, the magnitude of the estimated effects is marginally lower with the new augmented sample. Now the largest magnitude corresponds to INJR (-1.12%) and the lowest one to ACCR (-0.56%).⁶

2. The effect of JUN92 is identified as a level shift (LS) in all traffic variables as a consequence of the June 1992 Traffic Security Plan.⁷ Its permanent effect implies a considerable reduction in all accident rates, especially in FATR (-18.0%). Interestingly, empirical results with the larger data set also mimic the results found in García-Ferrer et al. (2007); namely, the resulting estimates are extremely closed to those found here and these results are rather robust to alternative dynamic model specifications in the forthcoming section.⁸
3. The SEATS/TRAMO software identifies the effect of JAN06 as a level shift (LS) outlier. According to the DGT, the new ARENA program (started on January 2006)

⁶A non significant coefficient only means that, with our data, we have not found evidence against the hypothesis of no effect. This comment applies to all the estimation results in this paper.

⁷Among other legal norms, JUN92 established the mandatory use of seat belts on car passengers.

⁸A detailed comparison of estimation results (coefficients and confidence intervals) concerning the intervention variables EAST, NWD and JUN92 with the results in García-Ferrer et al. (2007) are available from the authors upon request.

changed the methodology of data collection that affected basically ACC and INJ but not FAT. This seems to be a sensible explanation to understand our estimates in Table 6 (Dirección General de Tráfico, 2007).⁹ While the three fatalities series have statistically nonsignificant coefficients, all remaining ACC and INJ variables show positive and highly significant coefficients with effects ranging to 21% to 23%.

4. The penalty points system (PPS) was introduced in Spain in July 2006 and its effects have been analyzed, among others, by Rodríguez-López et al. (2016), Aparicio-Izquierdo et al. (2011) and Castillo-Manzano et al. (2010). Their results, however, differ substantially. Rodríguez-López et al. (2016) found that the introduction of the PPS in Spain was significant in reducing fatal accidents, but not non-fatal or total accidents. Regarding the lasting effects of the PPS, while Aparicio-Izquierdo et al. (2011) found that the introduction of the PPS in Spain had a very positive and permanent effect in reducing the number of fatalities on the road and “this effect has endured to the present time”, Castillo-Manzano et al. (2010) found only evidence of a temporary effect lasting from 12 to 18 months depending on the series. Our results in Table 6 also indicate the presence of even shorter temporary effects lasting from 1 to 3 months. Given these differences, it seems interesting at this stage to understand the discrepancies. First, the estimation periods are very different. In Aparicio-Izquierdo et al. (2011) their sample ends in 2009 while in the case of Castillo-Manzano et al. (2010), the sample ends in 2007. Ours has 7 and 9 years more, respectively. When an important outlier appears at the end of the estimation period, a considerable amount of additional data is needed, particularly if we want to check for permanent effects. Second, empirical results may also differ as a consequence of a different methodology and software used.¹⁰ In order to clarify this issue, in Table 7 we have shown the results of an alternative specification of our Temporary Change (TC) restricted polynomial approach for JUL06 when using the classical one $\frac{\omega_i}{(1+\alpha_i B)} I_{it}$ proposed by Box and Tiao (1975) and used in Castillo-Manzano et al. (2010). Interestingly, the largest total effect happens in ACCU and the lowest in FAT and similarly so when looking at their respective mean lags. In the absence of other policy measures that might affect differently individual accident variables, the effect of PPS must be similar in all accident rates. PPS aims at increasing drivers attention under the threat of serious fines and/or potential loss of their driving licenses. *Ceteris paribus*, as far as this policy is successful in reducing accident rates, a proportional decrease in INJ and FAT will follow. With the exception of ACCU, this is what results in Table 7 confirm.¹¹

⁹The ARENA software, that automatically records the accident at the time it occurs, has increased the reporting of less severe accidents, thus increasing the number of ACC and INJ. The reporting of FAT is not affected, since it always implies the presence of a judge to certify the demise.

¹⁰Alternative estimation results using SCA, GRETl and SEATS/TRAMO are available from the authors upon request.

¹¹The case of ACCU will be discussed in more detail later.

4.1.2 Econometric Models

In theory, the explanatory power of the univariate/intervention models may be improved if additional economic information is added in the form of a dynamic relationship between our output variables and the corresponding economic inputs that measure general economic activity and the degree of car utilization by specifying the \mathbf{z}_j vector and $\delta(B)$ in Equation 4. Both variants of a *single input / single output* and *single output / multiple output* models are estimated where the characteristics of the input variables are taken into account to avoid the usual problems of orthogonality among inputs (e.g. [Liu and Hanssens, 1982](#)).

Empirical results of the alternative specifications are included in Table 8. Please, note that we only include CDIESEL and CGAS as explanatory variables to avoid severe multicollinearity effects given the high correlation of economic variables along the business cycle¹². All causal models also include the corresponding intervention variables used in Table 6. Their corresponding estimates change very little with those shown in Table 6, indicative of considerable robustness of the results.

¹²The remaining causal models with different combinations of all inputs are available from the authors upon request.

	Intervention variables (*)							σ	AIC
	EAST	NWD	JUN92	JAN06	JUL06	MA(1)	MA(1) _{s=12}		
ACC	-0.004 (0.596)	$6.45 \cdot 10^{-7}$ (0.999)	-0.136 (0.000)	0.218 (0.000)	$\begin{pmatrix} -0.117 & -0.063B \\ (0.000) & (0.052) \end{pmatrix}$	0.479 (0.000)	0.733 (0.000)	0.039	-1462
ACCR	0.031 (0.003)	-0.006 (0.000)	-0.159 (0.000)	0.217 (0.000)	$\begin{pmatrix} -0.116 & -0.078B \\ (0.006) & (0.067) \end{pmatrix}$	0.515 (0.000)	0.689 (0.000)	0.051	-1240
ACCU	-0.031 (0.000)	0.005 (0.000)	-0.113 (0.002)	0.230 (0.000)	$\begin{pmatrix} -0.139 & -0.099B & -0.076B^2 \\ (0.000) & (0.012) & (0.047) \end{pmatrix}$	0.471 (0.000)	0.828 (0.000)	0.044	-1354
FAT	-0.001 (0.949)	-0.008 (0.008)	-0.153 (0.005)	0.088 (0.115)	$\begin{pmatrix} -0.248B \\ (0.002) \end{pmatrix}$	0.751 (0.000)	0.842 (0.000)	0.086	-808
FATR	0.006 (0.810)	-0.010 (0.002)	-0.180 (0.003)	0.084 (0.167)	$\begin{pmatrix} -0.254B \\ (0.004) \end{pmatrix}$	0.769 (0.000)	0.837 (0.000)	0.097	-715
FATU	-0.053 (0.226)	0.002 (0.690)	-0.214 (0.005)	0.047 (0.584)	$\begin{pmatrix} 0.054 & -0.255B \\ (0.734) & (0.106) \end{pmatrix}$	0.972 (0.000)	0.879 (0.000)	0.166	-268
INJ	0.005 (0.599)	-0.004 (0.001)	-0.159 (0.000)	0.216 (0.000)	$\begin{pmatrix} -0.126 & -0.088B \\ (0.001) & (0.002) \end{pmatrix}$	0.537 (0.000)	0.705 (0.000)	0.044	-1368
INJR	0.041 (0.001)	-0.011 (0.000)	-0.173 (0.000)	0.215 (0.000)	$\begin{pmatrix} -0.123 & -0.120B \\ (0.009) & (0.011) \end{pmatrix}$	0.592 (0.000)	0.686 (0.000)	0.056	-1161
INJU	-0.033 (0.001)	0.002 (0.212)	-0.138 (0.000)	0.232 (0.000)	$\begin{pmatrix} -0.145 & -0.077B \\ (0.000) & (0.057) \end{pmatrix}$	0.505 (0.000)	0.819 (0.000)	0.047	-1299

Table 6: IARIMA Estimation Results - Sample 1982M01–2016M12. All accident related variables are in logs with both first and seasonal differences. EAST: 1 in easter month; 0 otherwise (EASTER effect). NWD: Number of working days per month (Trading day effect). JUN92: 0 before 1992.06, 1 after 1992.06 (Traffic law effect–mandatory seatbelt). JAN06: 0 before 2006.01, 1 after 2006.01 (ARENA project takes effect). JUL06: 1 in 2006.07; 0 otherwise (Penalty Point System takes effect). σ : Residual standard error. B : Backshift operator. p-values in parenthesis.

	JUL06	Total Effect	Mean Lag
ACC	$\frac{-0.142}{1-0.682B}$	-0.446	2.14 months
ACCR	$\frac{-0.140}{1-0.659B}$	-0.410	1.93 months
ACCU	$\frac{-0.158}{1-0.785B}$	-0.738	3.65 months
FAT	-0.249	-0.249	1 month
FATR	-0.258	-0.258	1 month
FATU	—	—	—
INJ	$\frac{-0.150}{1-0.650B}$	-0.423	1.85 months
INJR	$\frac{-0.160}{1-0.651B}$	-0.451	1.86 months
INJU	$\frac{-0.165}{1-0.665B}$	-0.495	1.99 months

Table 7: Total effect and mean lag of JUL06. Estimation results using SCA for the 1982M01–2016M12 period.

Regarding the effects of the exogenous variables, the following comments are worth mentioning.

1. As in [García-Ferrer et al. \(2007\)](#) all estimated coefficients show the expected signs and the dynamic responses, in most cases, are either contemporaneous (lag 0) or short leading (1 and 2 lags). Also, the total effects (dynamic gain) of some inputs change very little among alternative specifications.
2. The gain in terms of statistical fitting (with respect to the intervention models of Table 6 measured by residual variance reduction) is marginal, indicating only a modest improvement in the explanatory power of the dynamic econometric models. When comparing estimated σ of the ARIMA models with the ones corresponding to the “best” causal models (using all combinations of inputs), the largest improvement is -6.8% (for ACCR, using CGAS and CDIESEL as inputs) and the lowest -1.02% corresponds to FATU with the same inputs (Table 8). Again, these results are similar to the ones shown in [García-Ferrer et al. \(2007\)](#)¹³. Based in the frequency context of the dynamic response of these results, [García-Ferrer et al. \(2006\)](#) showed how they are not all surprising.

¹³In [García-Ferrer et al. \(2007\)](#) the improvement in terms of residual standard error varies between -5.1% and -2.1%.

	Intervention variables (*)					CDIESEL	CGAS	MA(1)	MA(1) _{s=12}	σ	AIC
	EAST	NWD	JUN92	JAN06	JUL06						
ACC			-0.1364 (0.000)	0.2136 (0.000)	$\begin{pmatrix} -0.1226 & -0.0601B \\ (0.000) & (0.063) \end{pmatrix}$	$\begin{pmatrix} 0.151B + 0.0799B^2 \\ (0.009) & (0.096) \end{pmatrix}$	-0.0918B (0.182)	0.5055 (0.000)	0.7262 (0.000)	0.03829	-1417
ACCR		-0.0058 (0.000)	-0.1567 (0.000)	0.2046 (0.000)	$\begin{pmatrix} -0.131 & -0.0804B \\ (0.001) & (0.042) \end{pmatrix}$	$\begin{pmatrix} 0.3076B + 0.1642B^2 \\ (0.000) & (0.005) \end{pmatrix}$	-0.2642B (0.002)	0.5184 (0.000)	0.6670 (0.000)	0.04774	-1244
ACCU	-0.0433 (0.000)		-0.1126 (0.002)		$\begin{pmatrix} -0.1256 & -0.0774B \\ (0.001) & (0.050) \end{pmatrix}$	$\begin{pmatrix} 0.0035B \\ (0.958) \end{pmatrix}$	-0.0418B (0.603)	-0.5101 (0.000)	0.8263 (0.000)	0.04356	-1313
FAT			-0.1194 (0.015)		$\begin{pmatrix} -0.2186B \\ (0.005) \end{pmatrix}$	$\begin{pmatrix} 0.4751B \\ (0.000) \end{pmatrix}$	0.0926B (0.574)	0.8135 (0.000)	0.8415 (0.000)	0.08461	-798
FATR		-0.0074 (0.027)	-0.1175 (0.025)		$\begin{pmatrix} -0.2259B \\ (0.009) \end{pmatrix}$	$\begin{pmatrix} 0.4404B + 0.2192B^2 \\ (0.001) & (0.043) \end{pmatrix}$	0.1752B (0.347)	0.8398 (0.000)	0.8335 (0.000)	0.09386	-710
FATU						$\begin{pmatrix} 0.3105B \\ (0.109) \end{pmatrix}$	0.3340B (0.192)	0.8942 (0.000)	0.8867 (0.000)	0.16457	-273
INJ			-0.1615 (0.000)	0.1976 (0.000)	$\begin{pmatrix} -0.1353 & -0.085B \\ (0.000) & (0.017) \end{pmatrix}$	$\begin{pmatrix} 0.2955B + 0.1135B^2 \\ (0.000) & (0.033) \end{pmatrix}$	-0.1381B (0.075)	0.5587 (0.000)	0.6908 (0.000)	0.04252	-1336
INJR		-0.0101 (0.000)	-0.1708 (0.000)	0.1986 (0.000)	$\begin{pmatrix} -0.139 & -0.119B \\ (0.002) & (0.008) \end{pmatrix}$	$\begin{pmatrix} 0.3955B + 0.1955B^2 \\ (0.000) & (0.003) \end{pmatrix}$	-0.2626B (0.011)	0.5963 (0.000)	0.6721 (0.000)	0.05389	-1148
INJU	-0.0381 (0.000)		-0.1358 (0.001)	0.2324 (0.000)	$\begin{pmatrix} -0.1470 & -0.076B \\ (0.000) & (0.063) \end{pmatrix}$	$\begin{pmatrix} 0.0275B \\ (0.707) \end{pmatrix}$	0.0069B (0.937)	0.5102 (0.000)	0.8159 (0.000)	0.04781	-1244

Table 8: Estimated monthly models using CDIESEL and CGAS as inputs - Sample 1982M01–2016M12. All economic and accident related variables are in logs with both first and seasonal differences. B : Backshift operator. p-values in parenthesis. (*)Intervention variables are defined in Table 6.

	JUN92	JAN06	JUL06	MA(1)	MA(1) _{s=12}	CCI	σ	AIC
ACC	-0.128 (0.000)	0.125 (0.000)	(-0.115 - 0.063B) (0.007) (0.045)	0.490 (0.000)	0.730 (0.000)	(57.76 - 110.28B + 53.88B ²) (0.001) (0.001) (0.002)	0.040	-1448
ACCR	-0.159 (0.000)	0.147 (0.001)	(-0.109 - 0.078B) (0.011) (0.050)	0.555 (0.000)	0.701 (0.000)	(-63.27 - 121.61B + 59.83B ²) (0.000) (0.001) (0.004)	0.053	-1348
ACCU	-0.105 (0.004)	--	(-0.126 - 0.077B) (0.001) (0.045)	0.565 (0.000)	0.826 (0.000)	(39.57 - 74.95B + 36.35B ²) (0.035) (0.044) (0.043)	0.044	-1331
FAT	-0.132 (0.010)	0.165 (0.034)	-0.251B (0.001)	0.807 (0.000)	0.835 (0.000)	(60.95 - 117.41B + 58.16B ²) (0.005) (0.007) (0.008)	0.086	-806
FATR	-0.151 (0.001)	0.190 (0.030)	-0.260B (0.003)	0.823 (0.000)	0.843 (0.000)	(59.04 - 113.32B + 56.06B ²) (0.012) (0.015) (0.017)	0.096	-715
FATU	--	--	--	0.873 (0.000)	0.870 (0.000)	0.856 (0.039)	0.167	-276
INJ	-0.154 (0.000)	0.138 (0.000)	(-0.118 - 0.087B) (0.002) (0.021)	0.579 (0.000)	0.706 (0.000)	(51.49 - 97.77B + 47.49B ²) (0.004) (0.006) (0.008)	0.045	-1336
INJR	-0.168 (0.000)	0.174 (0.001)	(-0.106 - 0.116B) (0.040) (0.025)	0.659 (0.000)	0.711 (0.000)	(50.60 - 95.52B + 46.17B ²) (0.016) (0.021) (0.028)	0.060	-1093
INJU	-0.131 (0.002)	0.105 (0.011)	(-0.142 - 0.078B) (0.001) (0.069)	0.545 (0.000)	0.817 (0.000)	(47.93 - 91.33B + 44.41B ²) (0.028) (0.034) (0.042)	0.050	-1242
	JUN92	JAN06	JUL06	MA(1)	MA(1) _{s=12}	CLI	σ	AIC
ACC	-0.127 (0.000)	0.128 (0.000)	(-0.117 - 0.061B) (0.000) (0.068)	0.471 (0.000)	0.739 (0.000)	(8.30B ⁷ - 16.02B ⁸ + 7.93 ⁹) (0.013) (0.016) (0.019)	0.040	-1441
ACCR	-0.152 (0.000)	0.152 (0.000)	(-0.114 - 0.076B) (0.010) (0.047)	0.548 (0.000)	0.701 (0.000)	(13.07B ⁷ - 25.32B ⁸ + 12.52 ⁹) (0.001) (0.002) (0.002)	0.053	-1207
ACCU	-0.106 (0.008)	--	(-0.126 - 0.078B) (0.002) (0.065)	0.516 (0.000)	0.840 (0.000)	0.12B ⁶ (0.061)	0.048	-1291
FAT	-0.128 (0.009)	0.180 (0.021)	-0.249B (0.001)	0.810 (0.000)	0.856 (0.000)	(-22.86B ⁶ + 72.22B ⁷ - 75.28 ⁸ + 26.16B ⁹) (0.019) (0.011) (0.008) (0.008)	0.084	-823
FATR	-0.149 (0.005)	0.207 (0.018)	-0.255B (0.004)	0.826 (0.000)	0.856 (0.000)	(-26.48B ⁶ + 81.97B ⁷ - 83.75 ⁸ + 28.53B ⁹) (0.016) (0.010) (0.088) (0.010)	0.09	-729
FATU	--	--	--	0.887 (0.000)	0.882 (0.000)	0.17B ⁶ (0.006)	0.166	-278
INJ	-0.153 (0.000)	0.142 (0.000)	(-0.121 - 0.085B) (0.014) (0.025)	0.565 (0.000)	0.715 (0.000)	(9.54B ⁷ - 18.34B ⁸ + 9.01 ⁹) (0.005) (0.007) (0.009)	0.045	-1343
INJR	-0.164 (0.000)	0.179 (0.001)	(-0.112 - 0.116B) (0.031) (0.026)	0.656 (0.000)	0.712 (0.000)	(12.48B ⁷ - 23.91B ⁸ + 11.65 ⁹) (0.002) (0.003) (0.005)	0.061	-1096
INJU	-0.135 (0.001)	0.106 (0.011)	(-0.142 - 0.076B) (0.001) (0.075)	0.536 (0.000)	0.826 (0.000)	0.11B ⁶ (0.081)	0.050	-1261

Table 9: Estimated models for monthly data with composite indicators - Sample 1982M01–2016M12. All accident related variables are in logs with both first and seasonal differences. CCI and CLI with regular difference. Intervention variables JUN92, JAN06 and JUL06 are defined in Table 6. p-values in parenthesis.

4.1.3 Econometric models with Composite Indicators

A feasible way to avoid serious multicollinearity problems when using several economic inputs is to use single composite indicators representing the present and future state of the economy. In this regard, [Bujosa et al. \(2013\)](#) and [Bujosa et al. \(2019\)](#) have developed a Composite Leading Indicator (CLI) and a Composite Coincident Indicator (CCI) for the Spanish economy. The CCI shows a remarkable similar behavior with the index proposed by the Spanish Economic Association (AEE) and captures very well the beginning and end of the official recession and expansion periods. On the other hand, the CLI systematically predicts the peaks and troughs of the official index and provides significant aid in forecasting annual GDP growth rates (see [Bujosa et al., 2019](#)).

In Table 9 empirical results with both CCI and CLI are shown. Estimation period goes from 1982M01 to 2016M12. Some results from Table 9 are worth mentioning:

1. Estimates of the intervention variables are very much in line with those appearing in tables 6 and 9.
2. The statistical fitting measured by the residual variances is also very similar to the ones found in those tables. Again, the use of CCI does not improve the explanatory power of the previous dynamic econometric and intervention models.
3. However, the dynamic structure of the input variables are now much longer and the dynamic responses in most cases are either short leading (1 and 2 lags) in the case of CCI or long leading (up to nine months) in the case of CLI. This finding is very important if we are interested in doing real time forecasting of accident rates using the CLI as a leading indicator.¹⁴

¹⁴Interestingly, the length of the lead is similar to the one found by [Bujosa et al. \(2019\)](#) when the CLI is used to predict the index of Spanish Economic Association (AEE).

Variables	Model	c	FM	TM	DIESEL	GAS	JUN92	JAN06	JUL06	CCI	AIC	\bar{R}^2	σ_a^2
ACC	I	0.010 (0,330)	-0.165 (0,004)	-0.614 (0,165)	0.728 (0,001)	0.111 (0,637)	---	---	---	---	-2.935	0.331	0.052
	II	---	---	---	---	---	-0.053 (0,006)	0.052 (0,039)	0.033 (0,569)	1.069 (0,000)	-2.941	0.319	0.052
ACCR	I	-0.012 (0,377)	-0.175 (0,001)	-0.249 (0,689)	0.886 (0,002)	0.108 (0,724)	---	---	---	---	-2.554	0.327	0.063
	II	---	---	---	---	---	-0.048 (0,036)	0.016 (0,599)	0.121 (0,089)	1.006 (0,003)	-2.550	0.307	0.064
ACCU	I	0.026 (0,038)	-0.160 (0,021)	-0.922 (0,021)	0.604 (0,005)	0.096 (0,672)	---	---	---	---	-2.751	0.220	0.057
	II	---	---	---	---	---	-0.055 (0,008)	0.078 (0,005)	-0.041 (0,505)	1.074 (0,000)	-2.811	0.247	0.056
INJ	I	0.007 (0,503)	-0.186 (0,003)	-0.680 (0,126)	0.777 (0,000)	0.133 (0,597)	---	---	---	---	-2.895	0.365	0.053
	II	---	---	---	---	---	-0.052 (0,014)	0.044 (0,110)	0.024 (0,696)	1.030 (0,001)	-2.767	0.260	0.057
INJR	I	-0.012 (0,348)	-0.200 (0,001)	-0.355 (0,540)	0.896 (0,001)	0.190 (0,517)	---	---	---	---	-2.549	0.355	0.063
	II	---	---	---	---	---	-0.050 (0,004)	0.012 (0,714)	0.088 (0,235)	1.005 (0,004)	-2.440	0.262	0.067
INJU	I	0.024 (0,052)	-0.165 (0,012)	-1.010 (0,017)	0.669 (0,003)	0.061 (0,813)	---	---	---	---	-2.736	0.255	0.058
	II	---	---	---	---	---	-0.052 (0,018)	0.071 (0,016)	-0.039 (0,548)	1.016 (0,002)	-2.671	0.186	0.060
FAT	I	-0.029 (0,023)	-0.127 (0,006)	-0.821 (0,005)	0.767 (0,000)	0.948 (0,000)	---	---	---	---	-3.221	0.688	0.045
	II	---	---	---	---	---	-0.099 (0,000)	0.013 (0,589)	-0.072 (0,194)	1.313 (0,000)	-3.020	0.609	0.050
FATR	I	-0.032 (0,017)	-0.146 (0,001)	-0.764 (0,010)	0.793 (0,001)	1.061 (0,000)	---	---	---	---	-3.176	0.709	0.046
	II	---	---	---	---	---	-0.099 (0,000)	0.001 (0,981)	-0.064 (0,273)	1.347 (0,000)	-2.918	0.614	0.053
FATU	I	-0.219 (0,230)	-0.039 (0,557)	-1.046 (0,086)	0.688 (0,033)	0.422 (0,314)	---	---	---	---	-2.193	0.243	0.076
	II	---	---	---	---	---	-0.100 (0,000)	0.062 (0,068)	-0.102 (0,197)	1.166 (0,002)	-2.318	0.315	0.072

Table 10: Estimated models for annual growth rates of accident variables. Estimation period: 1983–2016. p-values in parenthesis.

4.2 Annual data models

Previous monthly models are very useful devices for short-term analysis and short-term forecasting, but of limited usefulness for policy analysis. Therefore, we have estimated a restricted equation of the monthly models shown in tables 8 and 9 using annual data (obtained by aggregating monthly figures) from 1983 to 2016.¹⁵ All accident and economic variables are $\nabla \log$ transformed, while the composite indicator CCI is transformed using first differences. We have estimated a pair of models for each accident variable. *Model I* includes variables representing the degree of car utilization (GAS and DIESEL) plus two new variables representing the level of road infrastructure: the number of available kilometers of free and toll motorways (FM and TM, respectively). *Model II* only includes a measure of aggregate economic activity like the CCI plus a set of intervention variables to assess its long-run effects. Empirical results are shown in Table 10, where some differences with their monthly counterparts are worth mentioning:

1. For most accident variables, but particularly for the three FAT variables, the effect of the two motorway variables show the expected signs but their coefficients size effects are remarkably different. While a 1% increase in FM roughly produces a -0.13% in FAT and -0.15% decreases in FATR, the effect of a similar increase in TM shows much larger size effects (-0.82% and -0.76%, respectively). These effects are repeated in the cases of ACCU and INJU, but not so for ACC, ACCR and INJ, indicating that TM has been very effective in reducing fatalities and of lesser importance for aggregate ACC and INJ.¹⁶
2. As regards car utilization proxies, both DIESEL and GAS show the expected signs, but their size effects are remarkably different as a consequence of the increasing share of diesel cars and trucks vehicles.¹⁷ All DIESEL coefficients are statistically significant with high size effects, ranging from 0.89 to 0.60 for all variables. As found in other studies (e.g. Bishai et al. (2006) and García-Ferrer et al. (2007)), greater gas use is related to more traffic accidents, all else equal. Also, and contrary to some results in the literature (Bishai et al. (2006) and van Beeck et al. (2000)), our results do indicate that economic growth has had a similar effect in all traffic accident related variables. In this regard, our results with annual data confirm our previous findings when monthly data were used to date economic and traffic accident cycles.
3. Results from *Model II* also confirm similar findings when an aggregate economic indicator like CCI is used. Here, all CCI coefficients show the expected signs and are

¹⁵Data from DIESEL is not available before 1982.

¹⁶Although not strictly comparable due to different sampling periods, our recent results are very much in line with those obtained by García-Ferrer et al. (2007) using a shorter sample.

¹⁷In García-Ferrer et al. (2007), the magnitude of the coefficients of gasoline and diesel consumption was quite similar, only slightly higher for gasoline.

statistically significant for all variables. Moreover, their size effects, ranging from 1.00 to 1.347, are similar among fatalities, traffic injuries and crashes. The introduction of the main three interventions (JUN92, JAN06 and JUL06) in the equations of *Model II* also show interesting confirmatory results. The mandatory seat belt legislation (JUN92) continues to be statistically significant 25 years after its implementation. Its permanent effect is still important for all variables, but particularly so in the case of all fatality variables. This is not so for the other interventions, particularly in the case of JUL06 representing the introduction of the penalty point system (PPS) in July 2006. In Section 4.1.1. using monthly models, we found that its effect on traffic accident related variables was temporary, lasting between one to three months. When using annual data this temporary effect vanished and its permanent effect is nil.¹⁸

From the empirical results shown in this section, we summarize the main findings in relation to those that were also analyzed in [García-Ferrer et al. \(2007\)](#).¹⁹ Regarding monthly models: (i) the introduction of mandatory seatbelts in June 1992 has had a permanent reduction effect in the accident variables, especially in fatalities, and this empirical effect remains when using the extended sample; (ii) the effect of Easter as well as the number of working days have opposite sign in road and urban accident variables, and these results also remain with the extended sample, although the magnitude is slightly lower in the latter case; (iii) in terms of statistical fitting, the gain when economic variables (besides the intervention variables) are included in the model is quite modest, with both the short and the extended sample. Regarding annual models: (i) in terms of road infrastructure, toll motorways are much more effective in reducing accident rates than free motorways. This is a pattern observed with both the short and the extended sample. However, the significance is higher for accident and injuries in the short sample and for fatalities in the extended sample; (ii) in terms of car utilization, measured by diesel and gasoline consumption, both variables are associated with an increase in the accident rates in both samples. However, in the short sample the magnitude is slightly higher for gasoline, while in the extended sample the effect of car use is mainly captured by the diesel consumption, given the increasing share of diesel vehicles. Overall, most of the findings found in [García-Ferrer et al. \(2007\)](#), when they can be compared, still remain with the extended sample, although the new situation brings also new findings, as we have explained along this Section.

¹⁸This result is not surprising given our definition of JUL06 as a temporary change dummy variable. Had we considered it a level shift variable its effect would have been indistinguishable from those of JAN06 due to the perfect collinearity between both variables on annual basis. Although this is a debatable question, we are more in favour of considering the new data collection methodology introduced in the ARENA programme as the main cause of level shift changes in both ACC and INJ variables. As we can see in Table 6, its effects on all FAT series is never statistically significant.

¹⁹There are new findings from our analysis that cannot be compared with the results in [García-Ferrer et al. \(2007\)](#) since the econometric specification changes. This has to do with the new intervention variables that were not present in the short sample and the use of the composite indicators.

5 Policy issues

In 2004, Spain had a similar number of fatalities that it had 30 years earlier. Over the period 1975-2004 the mean annual growth rate of traffic accidents was 1.6% and a similar figure (1.7%) was observed in the case of injured passengers. That growing process of traffic accidents took place in spite of considerable technological improvements in automobile safety, generous spending in numerous traffic security campaigns and huge infrastructure investments.²⁰ When compared to the official statistics of other European countries with good road safety records like Germany or United Kingdom, we observed that for many traffic safety indicators (vehicles/population, deaths per 100,000 vehicles, crashes or injuries per 100,000 vehicles, etc.), Spain had already converged to the average European figures before 2004. Even its accident rate level (per 100,000 inhabitants) in 2004 was 250, considerably lower than the 456 and 402 figures for Germany and United Kingdom, respectively. While by 2004 Spain had already converged to the average European figures in most of traffic accidents safety measures, its fatalities/accidents (F/A hereafter) ratio was considerably larger than the ones observed in many European countries. As Table 11 shows, its F/A ratio in 2004 was 5.1%, much larger than the European Union mean (3.5%) and three times the ones observed in Germany (1.7%) and United Kingdom (1.6%), which had set ambitious targets to reduce fatalities and serious injuries by one third as early as 1987 (see Raeside (2004)).²¹

	Countries or regions					
Years	Austria	Belgium	Germany	U.K.	EU (mean)	Spain
1992	3.1	3.0	2.7	1.8	5.0	9.0
1996	2.7	2.8	2.3	1.5	4.2	6.4
2000	2.3	3.0	2.0	1.5	3.8	5.7
2004	2.1	2.4	1.7	1.6	3.5	5.1
2008	1.7	2.2	1.4	1.5	3.1	3.3
2012	1.3	2.0	1.2	1.2	2.6	2.3
2015	1.3	1.8	1.1	1.2	2.4	1.7

Table 11: F/A ratio (%) in some EU countries.

Based on a relatively constant fatality elasticities (with respect to traffic accidents) find-

²⁰In particular, regarding the number of available kilometers of free and toll motorways in the road network, while in 1975 the sum of FM and TM was 1,136 kms. (0.8% of the road network), this number increased to 12,444 kms. (7.6%) in 2004 and to 17,109 kms. (11.5%) in 2016.

²¹The observed decrease in 2008 with respect to 2004 can be partly explained by the change in the data collection methodology that took place in 2006, the ARENA programme. However, the observed decrease in the subsequent years is not affected by this fact, since the data collection methodology did not change after 2006.

ing, [García-Ferrer et al. \(2007\)](#) used a simple model to simulate when the F/A Spanish ratio would reach similar levels as the ones shown by the European mean and Germany or United Kingdom in 2004. The simulation exercise was performed under four alternative scenarios for the F/A growth: (*S1*) assumed the same annual growth rate during the whole sample period 1975-2004, that is -1.3%, (*S2*) assumed a -2.8%, identical to the one observed since 1992, (*S3*) assumed a -5% growth and (*S4*) assumed a -10% growth rate per year. Results from that simulation exercise together with the true convergence dates are shown in Table 12. As can be seen, the observed convergence has already been reached, which indicate a very successful policy for Spanish traffic authorities. However, as results from Table 11 indicate for countries like Austria, Germany or the United Kingdom, the present F/A values represent the lowest bounds of this F/A ratio. Further lowering of these ratios between 1.5 and 1.0 may not been feasible for most European countries and Spain is already very close to it.²²

Rate of F/A in 2004	<i>S1</i>	<i>S2</i>	<i>S3</i>	<i>S4</i>	Observed convergence
EU-15 mean (2.8)	2037	2020	2013	2009	2010
Germany (1.7)	2078	2039	2023	2014	2015
England (1.6)	2082	2041	2024	2014	2016

Table 12: Simulated and observed convergence between Spanish F/A ratios and similar values of other European countries

However, there are still many areas of traffic accidents that deserve serious attention from public authorities. One of them is related to the positive effects of new quick emergency medical care services and another one is related to the continuous observed shift between road and urban accidents since 2006. Regarding the first issue, [Sánchez-Mangas et al. \(2010\)](#) found, using microdata on Spanish road accidents in May 2004 and in line with previous studies for other countries, that a reduction in the medical response time (defined as the time interval between the crash and the arrival of the emergency medical services to the crash scene) was associated to an important decrease in the probability of death on both motorways and conventional roads. In this sense, it is worth mentioning the new European policy that got into force on April 1st, 2018. According to this policy, all new cars sold within the European Union from that date must be equipped with the eCall device, an in-vehicle emergency call service that automatically dials the European emergency number 112

²²For instance, it took 25 years to Germany and United Kingdom to reduce their F/A ratios from 2.7% to 1.1% (Germany) and from 1.8% to 1.2% (United Kingdom). In Spain, the effect of free and toll motorways infrastructure has had a big impact in reducing road fatalities but there are no plans to increase their numbers in a foreseeable future. According to the DGT (2017) the F/A ratio decrease since 1993 is not only due to the fall in the number of deaths, but also in the increase in the number of casualties who were admitted to hospital service. That number accounted for 92% of recorded casualties while in 1993 it represented a 65%.

in the event of a serious accident, pinpointing the exact location of the crash. The European Commission estimates that the eCall can reduce medical response time by 50% in rural areas and 40% in urban areas, leading to a reduction of fatalities estimated to be between 2% and 10%, and reduction of severity of injuries between 2% and 15%, depending on the country considered ([European Commission, 2011](#)).

Regarding the second issue, the changing weights of the road/urban accidents decomposition require further analysis and potential new legal and administrative policies. While in 2004 ACCU and INJU represented 53% and 48% of ACC and INJ, and FATR included 83% of total fatalities, in 2016 these percentages are 64%, 61% and 71%, respectively. As [Table 13](#) shows, this is the result of remarkable differences on the growth rates of the aggregates and its urban/road components. For the 2005-2016 period, for instance, ACCU and INJU show positive growth rates (2.4% and 1.9%, respectively) and FATU (-4.3%) was only about half of the FAT decrease (-7.7%). This is a clear indication that public attention should focus on the urban component as equally important as its road counterpart.

ACC	ACCR	ACCU	FAT	FATR	FATU	INJ	INJR	INJRU
0.8	-1.2	2.4	-7.7	-8.5	-4.3	-0.1	-2.1	1.9

Table 13: Percentage mean growth rates of traffic accident variables. Sample 2005–2016

In 2016, 389 pedestrians were killed in traffic accidents, representing 21% of total fatalities. Out of it, 252 pedestrians were killed on urban roads, accounting for 65% of pedestrian fatalities, mostly as a result of pedestrians being struck by a vehicle. Also, pedal cyclist were involved in 7673 accidents in which 67 cyclists were killed, mostly on interurban roads (60%), and motorcycle users represented 24% of the total casualty accidents. For this type of vehicle, again 76% of motocycling fatalities took place on interurban roads. Also the number of traffic fatalities has evolved differently by mode of travel with important increases in pedestrians, cyclists and motorcycles. Any new public road safety programme must take into account these changes when setting future credible targets.

In this sense, it is worth mentioning the Valletta Declaration on Road Safety, in which transport ministers of the European Union highlighted the number of fatalities among pedestrians and cyclists as an issue of particular concern and agreed on the necessity to “take cycling and walking into account in mobility plans, safety policies and measures and, where feasible, consider the inclusion of dedicated infrastructure” ([European Union, 2017](#)).

6 Conclusions

This paper analyzes the aggregate relationship between traffic accidents and real economic activity in Spain when new data base is added to the previous data ending in 2004. Using

seasonal monthly data, the new evidence shows a pattern of accident rates reduction together with a visible cyclical behavior compatible with the general economic cycle. As shown earlier, our new empirical results confirm that economic activity and traffic accidents have a common cyclical behavior during the main recession and expansion periods, but also idiosyncratic short cycles in some accident variables that do not coincide with those of economic variables and viceversa. In any case, the historical asymmetrical cyclical behavior of these series when the sample is expanded, still remains. This relationship is particularly true for the accidents and injuries while the series of fatalities has shown a different pattern since 2002.

One of the main objectives of this paper has been to disentangle the effects of economic variables from those coming from exogenous events as well as public policy interventions. To do so, disaggregating urban and non-urban accidents becomes mandatory. As a matter of fact, the effects of two important variables like moving Easter holidays and the number of working days (NWD) show opposite signs on road and urban accidents rates. In the case of EASTER, this opposite behavior may render non-significant coefficients in the aggregate estimates (ACC, FAT, and INJ).

Among the remaining policy intervention variables, the JUN92 Traffic Security Plan that established the mandatory seat-belts on car passengers induced a permanent reduction in all accident rates, especially on FATR (-18%). As regards as JAN06, identified as a level shift (LS) outlier, our explanation differs from previous ones in the literature based on bad weather conditions. We present evidence that this intervention is the result of a methodological change of the new ARENA data collection software launched in January 2006, that affected ACC and INJ but not FAT. Similar comments apply to the penalty points system (PPS) introduced in July 2006. Previous literature found substantial different results ranging from 12 to 18 months. Our results, however, indicate the presence of even shorter temporary effects lasting from 1 to 3 months.

Estimated econometric models confirm the expected signs of all estimated coefficients. The dynamic responses, in most cases, are either contemporaneous (lag 0) or short leading and the dynamic gain of most inputs changes very little among alternative specifications. However, the gain in terms of statistical fitting (with respect to the intervention models) measured by residual variance reduction is marginal, indicating only a modest improvement in the explanatory power of the dynamic econometric models. Empirical results with annual data also confirms our previous findings with monthly data although the temporary effect of some intervention variables vanishes within the year. An interesting novelty in this paper, however, is the development of econometric models with the recently published composite coincident and leading indicators of the Spanish economy. The dynamic structure of the two input variables is much longer and the dynamic responses in most cases are either short leading (1 and 2 lags) in the case of CCI, or long leading (up to nine months) in the case of CLI. This finding is very promising if we are interested in doing real time forecasting of accident rates using CLI as a leading indicator.

Any research based on aggregated data sets has severe limitations for policy actions. Ours

is not an exception. The lack of relevant data related to advances in information technology, legislation, psychological factors affecting law-breaking drivers and the lack of regular epidemiological studies that investigate causation, bias our estimation results. Also a wider disaggregation by geographical areas, demographic structure, road conditions, accident timing, and medical response ([Sánchez-Mangas et al., 2010](#)) will improve information regarding policy targets. At present, however, the disaggregation between urban and road accidents has already shed some light about the direction of future policies. The growing share of urban accidents should attract the interest of all national and local agencies in establishing common policies guided to further reductions in car accidents. In 2000, the probability of death (in a car accident) in Spain was 2.8 times the one in Germany and 3.8 times greater than England. Fifteen years later, this gap has been reduced to about 1.4 times and is already much lower than the EU mean. Further reductions, independent of economic cycle, will necessarily imply additional focus on urban accidents, particularly, in pedestrians, cyclists and new fashionable models of unregulated transportation (scooters).

In this sense, the transport ministers of the European Union have highlighted the importance of promoting a Europe-wide road safety culture that takes into account the specific needs of vulnerable road users (European Union, 2017).

References

- Antoniou, C., G. Yannis, E. Papadimitriou, and S. Lassarre (2015, October). Improving fatalities forecasting in times of recession in Europe. See [OCDE/International Transport Forum \(2015\)](#), Chapter 4, pp. 143–168.
- Aparicio-Izquierdo, F., B. A. Ramírez, J. M. McWilliams, and J. P. Ayuso (2011). The endurance of the effects of the penalty point system in Spain three years after. Main influencing factors. *Accident Analysis & Prevention* 43(3), 911–922.
- Bergel-Hayat, R., Z. Christoforou, and S. Ferrière (2015, October). The impact of the economic crisis on road mortality: an exploratory approach for some countries in Europe. See [OCDE/International Transport Forum \(2015\)](#), Chapter 5, pp. 169–182.
- Bertoli, P., V. Grembi, and J. V. Castello (2018). Not all silver lining? The Great Recession and road traffic accidents. *Regional Science and Urban Economics* 70, 274–288.
- Bishai, D., A. Quresh, P. James, and A. Ghaffar (2006). National road casualties and economic development. *Health Economics* 15(1), 65–81.
- Box, G. E. and G. C. Tiao (1975). Intervention analysis with applications to economic and environmental problems. *Journal of the American Statistical Association* 70(349), 70–79.

- Brüde, U. and R. Elvik (2015). The turning point in the number of traffic fatalities: two hypotheses about changes in underlying trends. *Accident Analysis & Prevention* 74, 60–68.
- Bujosa, M., A. García-Ferrer, and A. de Juan (2013). Predicting recessions with factor linear dynamic harmonic regressions. *Journal of Forecasting* 32(6), 481–499.
- Bujosa, M., A. García-Ferrer, A. de Juan, and A. Martín-Arroyo (2019, May). Evaluating early warning and coincident indicators of business cycles using smooth trends. *Journal of Forecasting*. <https://doi.org/10.1002/for.2601>.
- Bujosa, M., A. García-Ferrer, and P. C. Young (2007, October). Linear dynamic harmonic regression. *Comput. Stat. Data Anal.* 52(2), 999–1024.
- Castillo-Manzano, J. I., M. Castro-Nuno, and D. J. Pedregal (2010). An econometric analysis of the effects of the penalty points system driver’s license in Spain. *Accident Analysis & Prevention* 42(4), 1310–1319.
- Cotti, C. and N. Tefft (2011). Decomposing the relationship between macroeconomic conditions and fatal car crashes during the Great Recession: alcohol-and non-alcohol-related accidents. *The BE Journal of Economic Analysis & Policy* 11(1), 1–22.
- Dirección General de Tráfico (2007). Las principales cifras de siniestralidad vial. España 2006. Technical report, Observatorio Nacional de Seguridad Vial, Ministerio del Interior, Gobierno de España.
- Elvik, R. (2015, October). An analysis of the relationship between economic performance and the development of road safety. See [OCDE/International Transport Forum \(2015\)](#), Chapter 3, pp. 43–142.
- European Commision (2010). *Road Safety Programme 2011-2020*. European Commision.
- European Commision (2018, April). *Road safety in the European Union: Trends, statistics and main challenges*. European Commision. Mobility and Transport.
- European Commission (2011). On support for an EU-wide eCall service in electronic communication networks for the transmission of in-vehicle emergency calls based on 112 (eCalls). Technical report, Accompanying document to Commission Recommendation 2011/750/EU.
- European Union (2017, March). Valletta declaration on road safety. Council of the European Union.
- French, M. T. and G. Gumus (2014). Macroeconomic fluctuations and motorcycle fatalities in the US. *Social Science & Medicine* 104, 187–193.

- García-Ferrer, A. and M. Bujosa-Brun (2000, Jun). Forecasting OECD industrial turning points using unobserved components models with business survey data. *International Journal of Forecasting* 16(2), 207–227.
- García-Ferrer, A., A. De Juan, and P. Poncela (2006). Forecasting traffic accidents using disaggregated data. *International Journal of Forecasting* 22(2), 203–222.
- García-Ferrer, A., A. De Juan, and P. Poncela (2007). The relationship between road traffic accidents and real economic activity in Spain: common cycles and health issues. *Health Economics* 16(6), 603–626.
- 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.
- Lam, J.-P. and E. Piérard (2017). The time-varying relationship between mortality and business cycles in the USA. *Health Economics* 26(2), 164–183.
- Liu, L.-M. and D. M. Hanssens (1982). Identification of multiple-input transfer function models. *Communications in statistics-theory and methods* 11(3), 297–314.
- Lloyd, L., C. Wallbank, and J. Broughton (2015). A collection of evidence for the impact of the economic recession on road fatalities in Great Britain. *Accident Analysis & Prevention* 80, 274–285.
- Maheshri, V. and C. Winston (2016). Did the great recession keep bad drivers off the road? *Journal of Risk and Uncertainty* 52(3), 255–280.
- Noland, R. B. and Y. Zhou (2017). Has the great recession and its aftermath reduced traffic fatalities? *Accident Analysis & Prevention* 98, 130–138.
- OCDE/International Transport Forum (2015). *Why Does Road Safety Improve When Economic Times Are Hard?* International Traffic Safety Data and Analysis Group.
- Peña, D. (2011). Outliers, influential observations, and missing data. See [Peña et al. \(2011\)](#), Chapter 6, pp. 136–170.
- Peña, D., G. C. Tiao, and R. S. Tsay (2011). *A course in time series analysis*, Volume 322. John Wiley & Sons.
- Raeside, R. (2004). Predicting and monitoring casualty numbers in Great Britain. *Journal of Transportation and Statistics* 7(1), 61–68.
- Rodríguez-López, J., G. A. Marrero, R. M. González, and T. Leal-Linares (2016). Road accidents and business cycles in Spain. *Accident Analysis & Prevention* 96, 46–55.

- Ruhm, C. J. (2000). Are recessions good for your health? *The Quarterly Journal of Economics* 115(2), 617–650.
- Ruhm, C. J. (2015). Recessions, healthy no more? *Journal of Health Economics* 42, 17–28.
- Sánchez-Mangas, R., A. García-Ferrer, A. De Juan, and A. M. Arroyo (2010). The probability of death in road traffic accidents. How important is a quick medical response? *Accident Analysis & Prevention* 42(4), 1048–1056.
- van Beeck, E. F., G. J. Borsboom, and J. P. Mackenbach (2000). Economic development and traffic accident mortality in the industrialized world, 1962–1990. *International Journal of Epidemiology* 29(3), 503–509.
- Wegman, F., R. Allsop, C. Antoniou, R. Bergel-Hayat, R. Elvik, S. Lassarre, D. Lloyd, and W. Wijnen (2017). How did the economic recession (2008–2010) influence traffic fatalities in OECD countries? *Accident Analysis & Prevention* 102, 51–59.
- Yannis, G., E. Papadimitriou, and K. Folla (2014). Effect of GDP changes on road traffic fatalities. *Safety Science* 63, 42–49.
- Young, P. C., D. Pedregal, and W. Tych (1999, November). Dynamic Harmonic Regression. *Journal of Forecasting* 18, 369–394.