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ROAD ACCIDENTS IN SPAIN: ARE THEY PERSISTENT?

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ABSTRACT

Traffic accidents involve great costs both at an economic and a human level. This demands that governments implement strategies to reduce their number and impact. The knowledge of the nature of the phenomenon through the study of time series of accidents enables the design of suitable policies for the desired objectives to be achieved. Thus, this paper deals with the analysis of the statistical properties of the number of road accidents on Spanish roads by using time series techniques based on the concept of fractional integration. The results indicate that the series examined display very low degrees of persistence, with the orders of integration being around 0 and thus showing a short memory pattern. This implies that shocks will be transitory, disappearing fast, and requiring strong policy measures in the case of positive shocks that reduce the number of deaths if we want to maintain that effect in the long run.

Keywords: Road accidents; Spain: persistence; fractional integration

JEL Classification: C22; I18**;** R41

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Comments from the Editor and two anonymous reviewers are gratefully acknowledged.

1. INTRODUCTION

Traffic accidents are currently one of the most important public health problems faced by modern societies and their importance in the future will increase according to the World Health Organization (WHO) [1]. This organization has published several reports that warn that many more people die as a result of road traffic injuries than from suicides or homicides. In addition to the moral cost to society of loss of life or loss of health, road traffic accidents are associated with further costs, also of great importance, such as the economic cost. Road accidents represent a huge social problem. Many of these accidents are preventable and by preventing them, society increases the supply of scarce resources that can be used to increase income and improve welfare.

Road transport enables greater economic efficiency, reducing travel time while simultaneously having a negative impact on the environment and on safety, resulting therefore, in conflicting objectives. The reduction of these costs (environment and health) makes the analysis of traffic accidents vital for safer and more sustainable societies.

In this paper we focus on road accidents in Spain, looking at daily (and monthly) time series data and focussing on issues such as persistence, seasonality and time trends, which are features commonly observed in this type of dataset. This information is useful not only to predict the future path of the series but also to determine if shocks in the series will have transitory or permanent effects, with the implications that this has in terms of policy actions. Thus, for example, if a series is very persistent and there is a shock that increases the number of accidents, if no action is implemented, the shock will persist forever. On the other hand, low levels of persistence will be associated with transitory shocks.

2. CONTEXT

In Spain, the evolution of road accidents has followed a trend that has been affected by different policies, advertising campaigns, the extension of the vehicle fleet, as well as the renewal of this with safer and faster cars. The total number of people involved in accidents followed an upward trend from 1993 to 2003, from 2004 it followed a downward trend until 2011 and from 2012 until 2016 it again followed an upward trend (Fig.1).

The number of deaths and injuries in hospitals followed a downward trend, but has stabilized and even increased slightly over the past three years. The number of non-hospitalized injured in the period considered shows an increasing trend, in general, with some years of decrease from 2008-2011. In 2017 there seems to be a fall in the number of deaths and injuries in hospitals and an increase in the number of non-hospitalised injured (Fig.2-4).

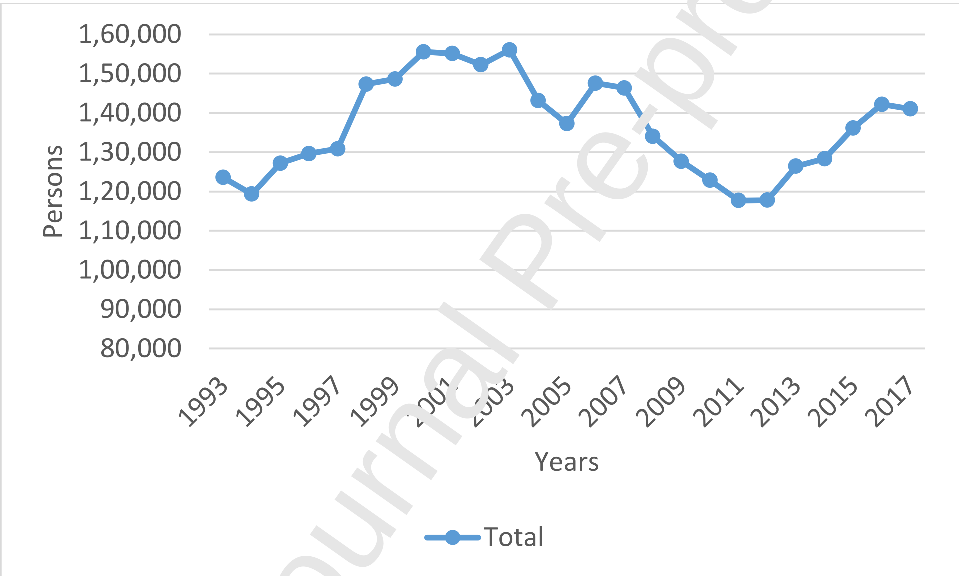

Fig. 1: **Total persons involved in road accidents 1993-2017 in Spain (Spanish Directorate General of Traffic [1])**

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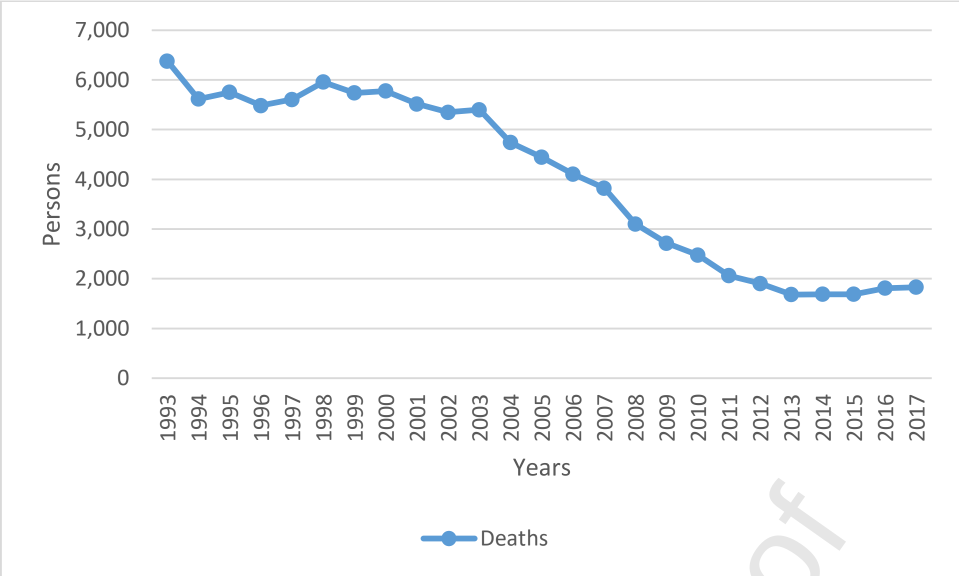

***Fig. 2:* Deaths[1] in road accidents**

Source: Spanish Directorate General of Traffic

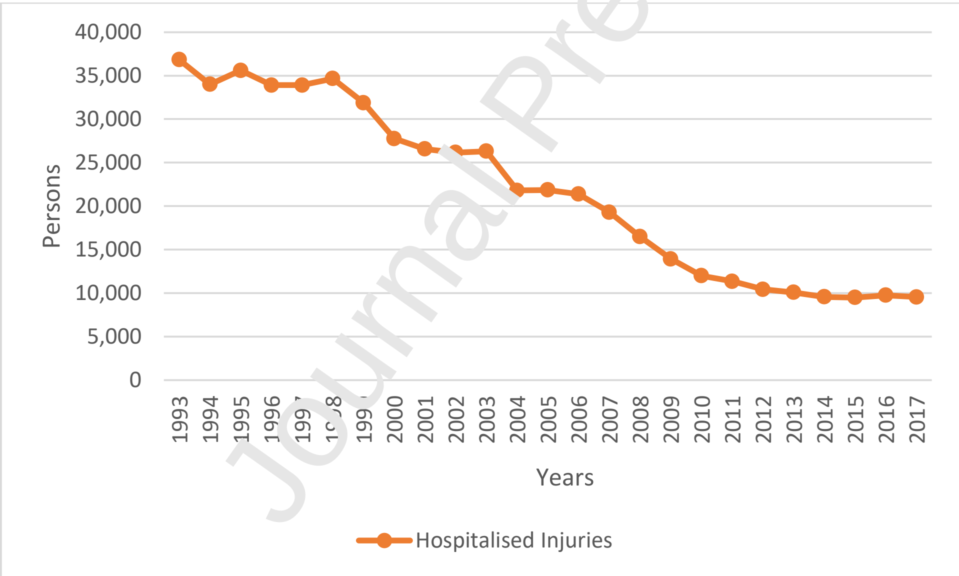

***Fig. 3:* Hospitalised injuries[2] caused by road accidents**

Source: Spanish Directorate General of Traffic

[1] Any person who, as a result of a traffic accident, dies immediately or within thirty days, excluding confirmed cases of natural death or suicides cases.
[2] Any person who, as a result of a traffic accident, for whom the established definition of death does not apply and he/she requires hospitalization of more than twenty-four hours.

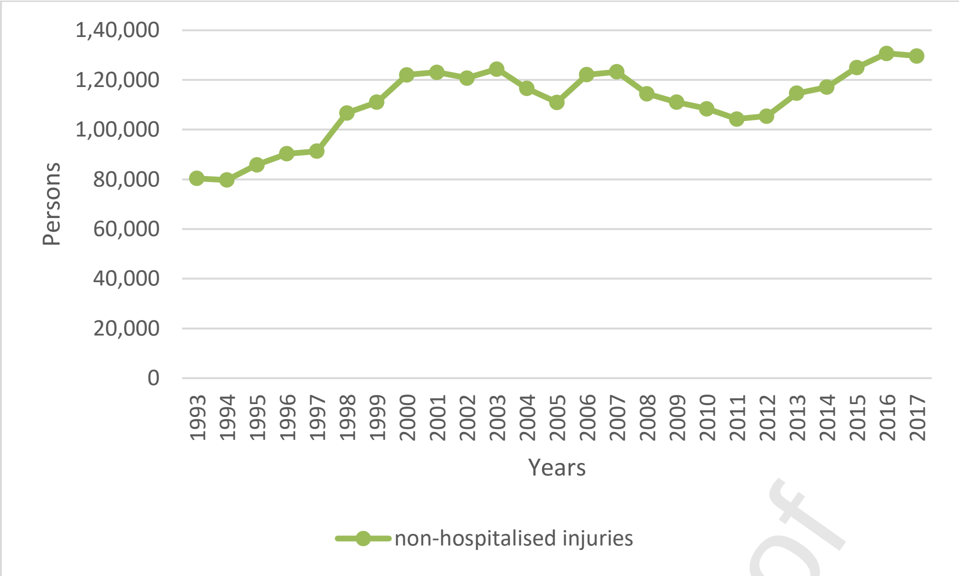

Fig. 4: **Non-hospitalised injuries[3] caused by road accidents**

Source: Spanish Directorate General of Traffic

In the surrounding European countries, the trend in the number of deaths in road accidents is downward. Greece and Poland stand out in the number of deaths with respect to the rest. Until 2003 Spain had quite high figures, above the rest of the European countries although not reaching the figures of Poland and Greece, but from 2004 onwards the numbers fell considerably to the same level as the countries with lower figures such as the Netherlands, Germany, the United Kingdom, Finland and Sweden (Fig.5).

In terms of the number of injured per million inhabitants, Belgium, Austria, Germany and the United Kingdom have the highest figures, with a decreasing trend in recent years, more markedly in the United Kingdom. Spain has shown a downward trend since 2002, and the number of injured has increased, exceeding the number of injured in the United Kingdom in 2017 (Fig.6).

[3] Any person who, as a result of a traffic accident, for whom the established definition of death does not apply and he/she does not require medical assistance of more than twenty-four hours.

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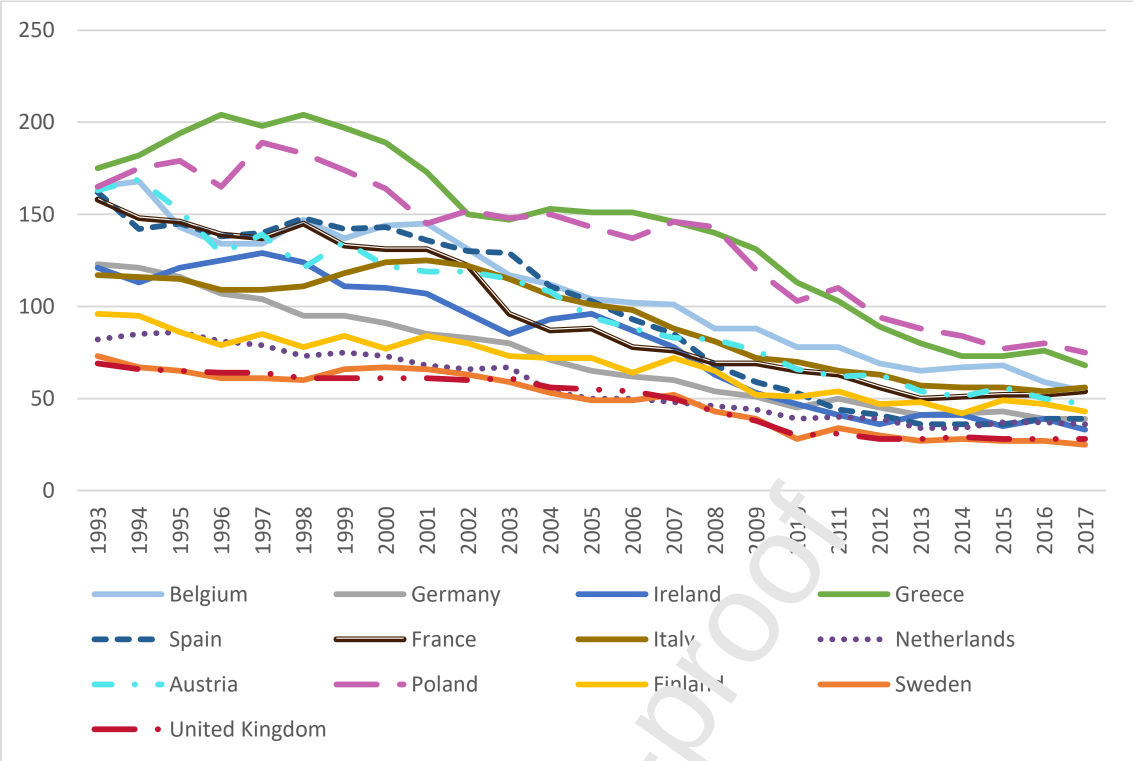

Fig. 5: **Killed per million inhabitants 1993-2017 (Eurostat [2])**

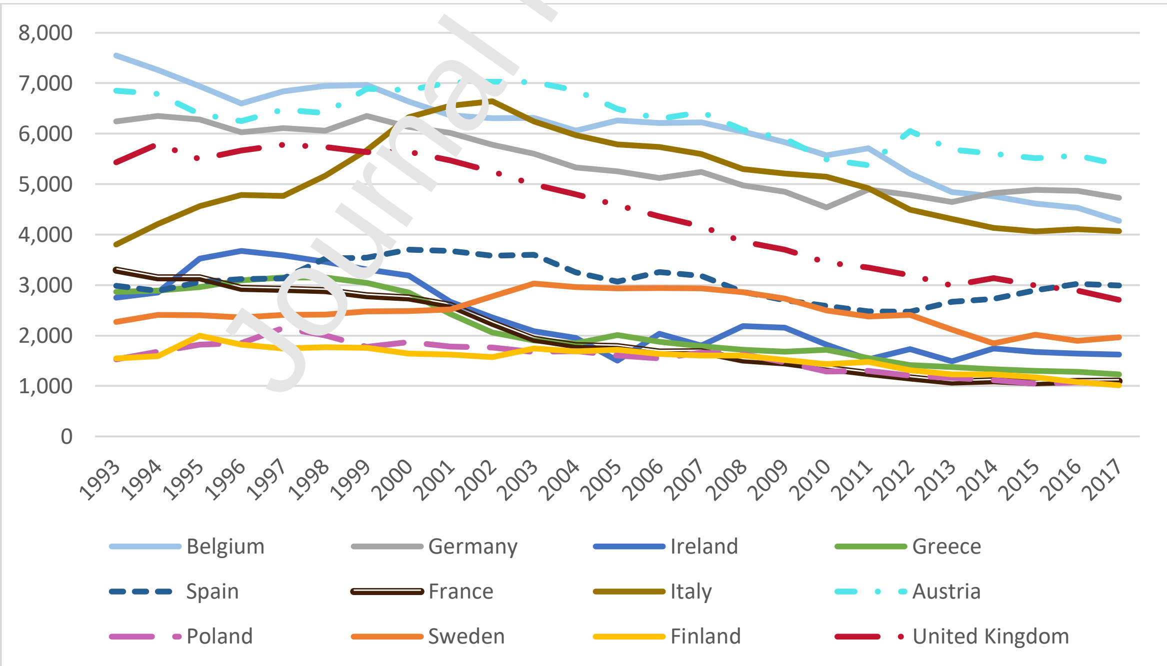

Fig. 6: **Injured per million inhabitants 1993-2017 (Eurostat)**

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In this paper we focus on the analysis of road accidents in Spain by using updated time series techniques based on the concept of fractional integration, which have not been used so far in the analysis of this type of data. This methodology is very convenient to investigate issues such as persistence, seasonality, time trends and the nature of shocks, which are all very relevant in the analysis of road accidents series.

The rest of the paper is organized as follows. Section 3 presents a brief review of the literature. The data and the methodology used in the paper are described in Section 4, while Section 5 focuses on the results. Section 6 contains a discussion and some concluding comments.

3. REVIEW

Traffic road accidents are a major problem and concern in all countries in terms of lives and costs or losses; the World Health Organization (WHO, [1] estimates that road traffic accidents cost most countries about 3% of their Gross Domestic Product (GDP), and nowadays it is the main cause of death of young people aged 5-29 years old.

Although mortality rates in relation to global population have stabilized in recent years, even with a tendency to decrease ([1]), the evolution is unequal according to several factors such as economic development and infrastructure and road safety policies. Al-Madani [2] employed curve fitting regression models to analyse accident deaths in the period from 1980 to 2014. This analysis serves as a basis to forecast future global and continental road injury mortalities up to 2030 for each continent. The results show that an 18% decrease is expected by 2025 in all continents (except Africa and South America), compared to 2014 in the number of deaths from accidents. On the other hand, road deaths are expected to increase by at least 34% in Africa and South America until 2025. At a global level, the drop is expected to be around 12%.

All countries invest a great effort and substantial funding to reduce accidents on their roads and many studies have been carried out over recent years to analyse the evolution in the causes, the impact and number accidents. Progress in road safety is also included in the commitments assumed in the Sustainable Development Agenda 2030 [3].

Many studies apply time series methods to analyse transport and road safety of ease application and consolidate theoretical foundation, Helgason [4], Lavrenz et al. [5]. A drawback here is the difficulty of data collection and a limited knowledge about the proper methodology. In recent years, new types of high-resolution traffic safety data have made time series modelling techniques an increasingly important subject of study [5].

In this line, Karlaftis and Vlahogianni [6] employ fractionally integrated dual memory models and compare their results with those based on classical time-series models in a traffic engineering context. They conclude that dual memory models offer a better representation of the original time-series than the classical models. Huitema et al. [7] develop time-series analysis to study the impact of pedestrian countdown timers, to reduce traffic fatalities in large cities. Gil-Alana et al. [8] use fractional integration to analyse Brazilian monthly aircraft accidents with the aim of analysing their degree of persistence. Meiβner et al. [9] apply a determined geographical and temporal analysis to predict and interpret future accident numbers. In the same line, Kumar and Toshniwal [10] present a framework to analyze road accident time series data using 39 series from the Indian states of Gujarat and Uttarakhand .

Some studies have used a combination of models to more accurately represent the data. Sebego et al. [11] examine the effect of several safety-related policies on crash rates and single-vehicle fatalities in Botswana.

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McIlroy et al. [12] based their research on the adaptation of the Rasmussen Risk Management Framework to the road safety systems of five countries: Bangladesh, China, Kenya, the United Kingdom and Vietnam. They compare the road safety systems of these countries, related agencies, and the road security performance in these nations. In addition to the three traditional approaches engineering, enforcement, and education to study road safety (e.g. [12]), the authors propose economics as an additional factor since, as noted above, road traffic accidents have a major impact on the economy of all countries. Although the cost-benefit analysis of a proper road safety policy is clearly positive for society not only in economic terms, economic considerations rarely figure in road safety discussions [12]. Traynor [13] concludes that there exists a significant interaction between per capita income and the percentage of highway vehicle miles travelled, indicating a non-linear correlation between per capita income and fatality rates. In this respect, Gaygisiz [14] obtains positive associations between favourable economic conditions (high income per capita, high employment rate, and low income inequality) and high traffic safety in more than 30 member countries of the Organisation for Economic Co-operation and Development (OECD).

In another line of research, several studies have investigated the impact that certain policy actions for the improvement of road safety have on road accident rates. Abbondati et al. [15] analyse the effectiveness of the installation of speed cameras on accidents on rural roads in Lithuania and Italy. Mawson and Kenneth [16] propose that an effective long-term strategy for reducing motor vehicle accident-related injuries would be continued technological innovation in vehicle design, aimed at progressively removing the driver from routine operational decision-making.

To identify road blackspots (road sections where the number of accidents is significantly higher than in other sections) as an important factor in improving road safety management is the main aim of some studies carried out using Monte Carlo simulation (Cafiso and Di Silvestro [17], databases from a series of speed measurements and vehicle ranges (De Luca and Del Acqua [18]), Pareto and Lomax distributions (Prieto et al [19]).

Gómez Barroso et al. [20] estimate the areas of greatest density of road traffic accidents with deaths at 24 hours per km^2/year in Spain from 2008 to 2011, using a geographical information system, showing areas where there was a greater density of accidents.

In relation to the economic and social consequences of road accidents, Alemany et al. [21] examined the needs for care and the economic and social impact of road accidents in Spain in the long term. They conclude that, demographically, accidents mainly affect people in the middle age group. From an economic point of view, road accidents generate a high cost both for the family and for the political authorities, amply justifying the strengthening of policies for the prevention of traffic accidents.

4. DATA AND METHODOLOGY

4.1 Data

We use daily data from January 1, 2014 until December 31, 2017 referring to variables dealing with accidents with victims.[4] (Traffic accidents with casualties are those which occur, or originate in one of the roads or areas subject to traffic, motor vehicle and road safety legislation, involve at least one vehicle in motion and result in the death and/or injury of one or more persons), according to the following definitions: persons killed or

[4] We use daily data given that permits us to consider a greater number of observations, which is useful in the context of fractional integration. This is despite the fact that daily data are subject to greater fluctuations, especially with regard to the day of the week, which has been considered throughout the nonparametric autocorrelation case for the disturbance term. Monthly data are also considered in the second part of the empirical application.

deaths (persons killed immediately or dying within 30 days as a result of an accident, excluding suicides), injured persons (persons who as result of an injury accident were not killed immediately or did not die within 30 days, but sustained an injury, normally needing medical treatment, excluding attempted suicides), persons seriously injured (persons injured who were hospitalized for a period of more than 24 hours) and persons slightly injured (persons injured excluding persons killed or seriously injured). The number of deaths during the first twenty-four hours will be determined by monitoring all the cases; the number of deaths within thirty days will be determined, until such time as the actual monitoring of all the injured during that period is fully guaranteed, by applying to the number of deaths at twenty-four hours the correction factor that is deduced from the actual monitoring of a representative sample of seriously injured persons, which, at least every four years, will be carried out by the Directorate General of Traffic, under the supervision of the Higher Council for Traffic and Road Safety. The analysis is also conducted on a monthly basis, using both flows and stock data. The data source is the Ministry of the Interior's General Directorate of Traffic [3]. Stock and flow data are calculated as the sum and arithmetic average of monthly data for each year, respectively. The time series plots are displayed across Figures 7 - 12.

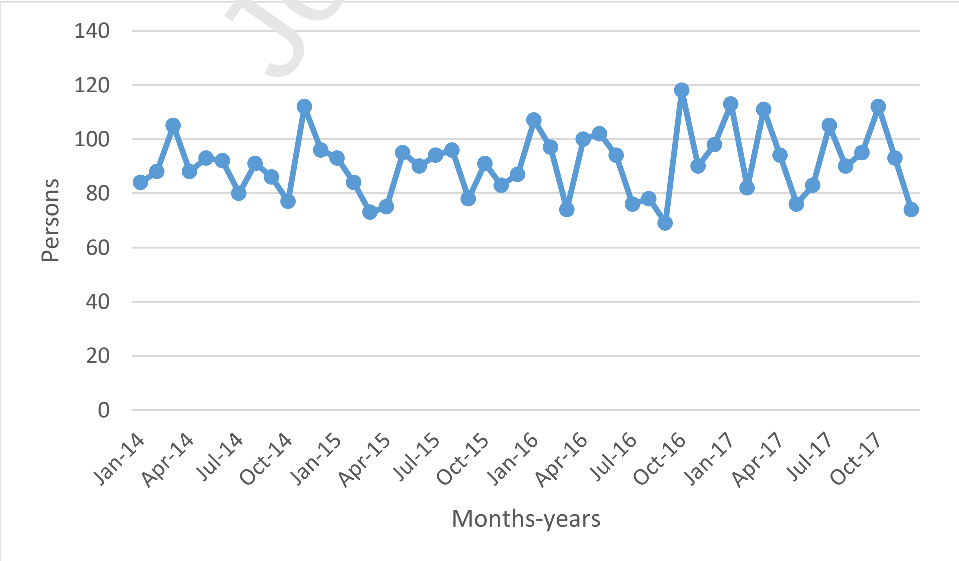

Fig. 7: **Deaths in road accidents (Monthly Time Series-Stock Data, Jan-2014-Nov-2017)**

Source: Spanish Directorate General of Traffic

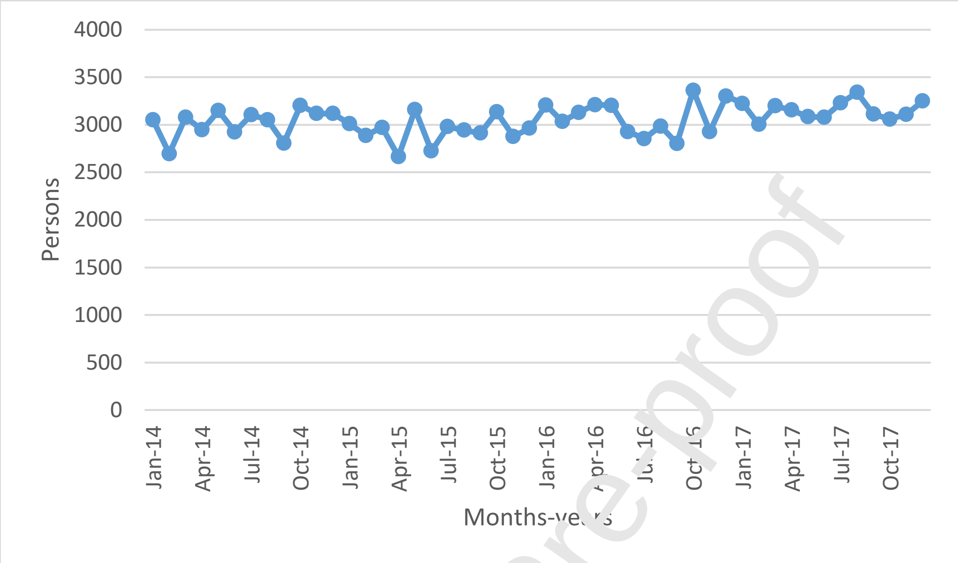

Fig. 8: **Hospitalised injuries caused by road accidents (Monthly Time Series-Stock, Data Jan-2014-Nov-2017)**

Source: Spanish Directorate General of Traffic

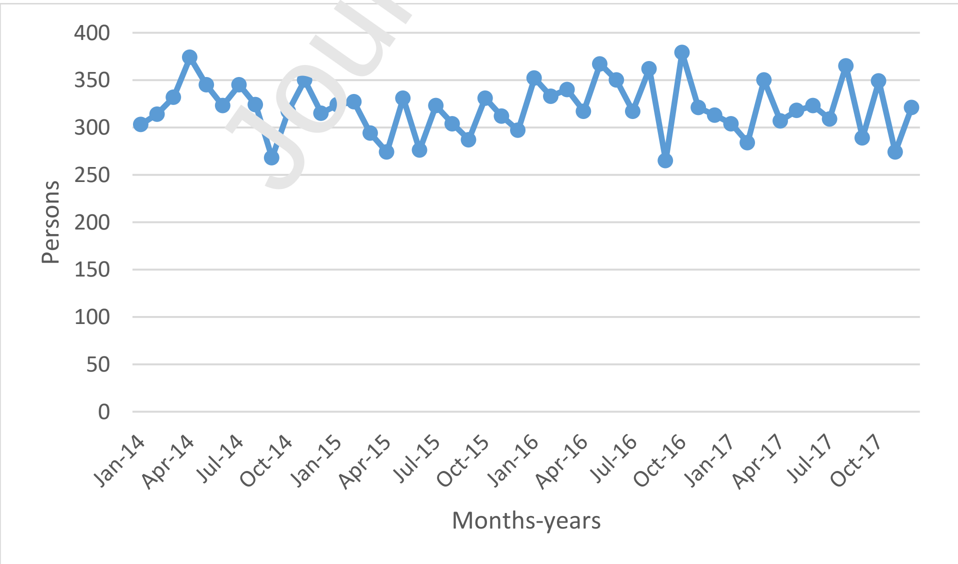

Fig. 9: **Non-hospitalised injuries caused by road accidents (Monthly Time Series-Stock Data, Jan-2014-Nov-2017)**

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Source: Spanish Directorate General of Traffic

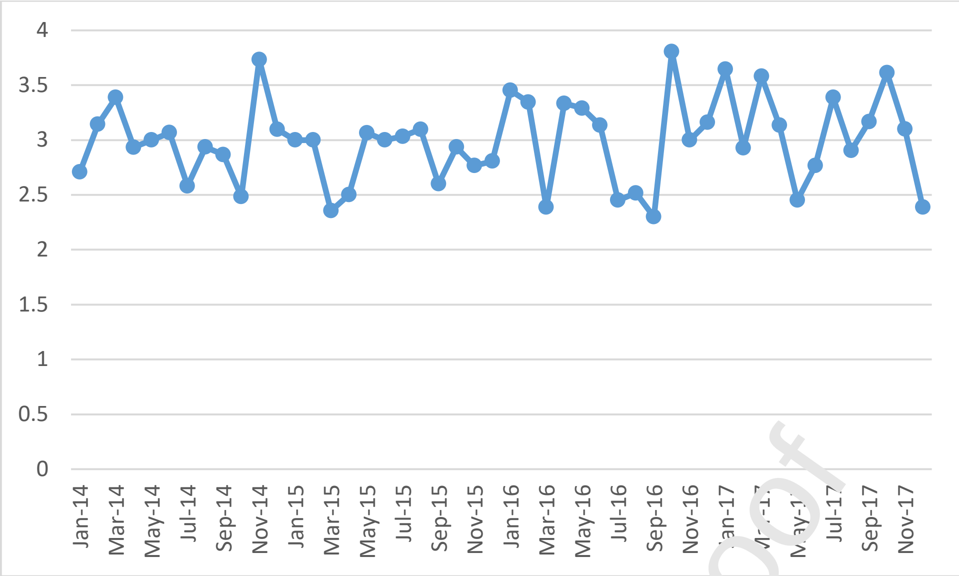

Fig. 10: **Deaths in road accidents (Monthly Time Series-Flow Data, Jan-2014-Nov-2017)**

Source: Spanish Directorate General of Traffic

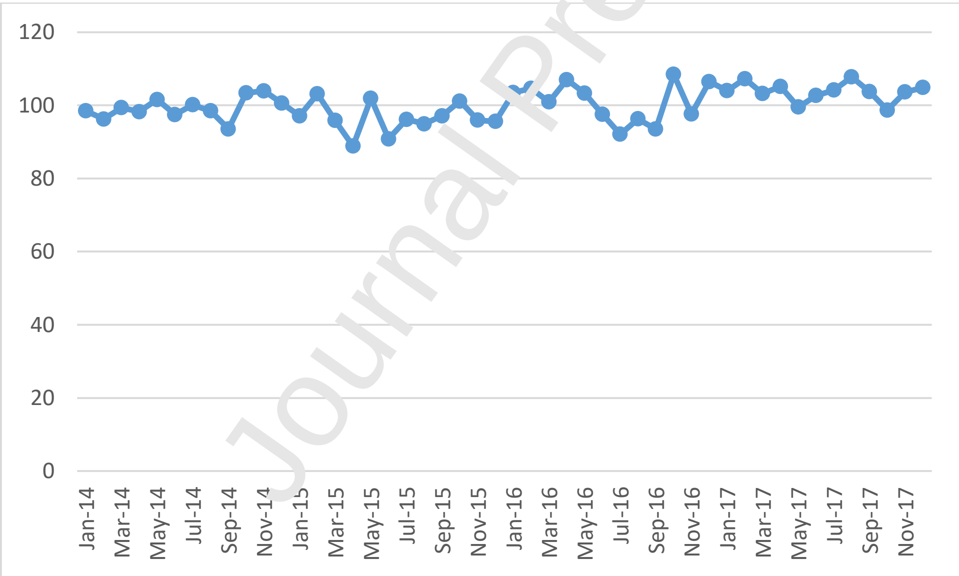

Fig. 11: **Hospitalised injuries caused by road accidents (Monthly Time Series-Flow, Data Jan-2014-Nov-2017)**

Source: Spanish Directorate General of Traffic

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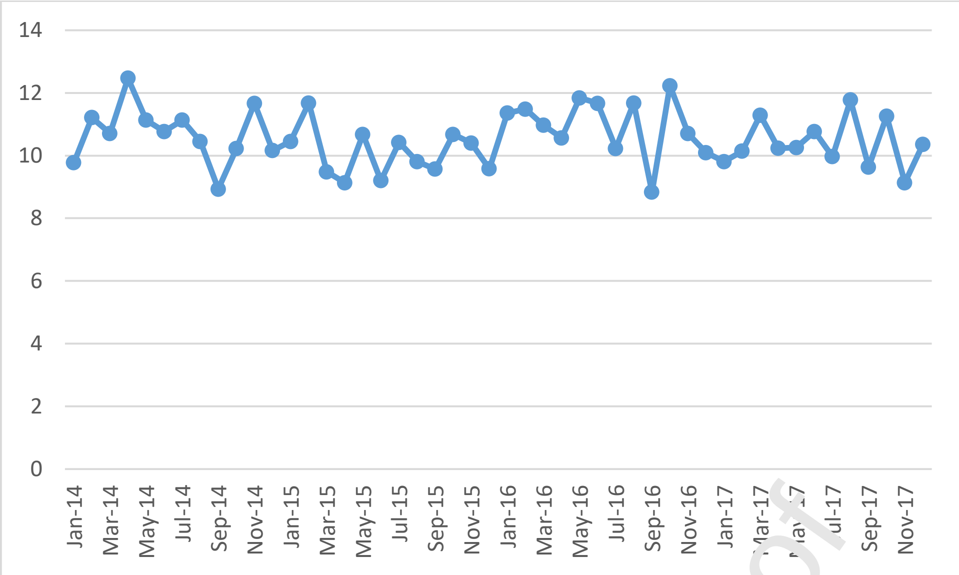

Fig. 12: **Non-hospitalised injuries caused by road accidents (Monthly Time Series-Flow Data, Jan-2014-Nov-2017)**

Source: Spanish Directorate General of Traffic

The definitions of the variables are found in Order INT/2223/2014 of October 27 [22]. The traffic accident statistics compiled by the Directorate General of Traffic for research purposes have been compiled from the data contained in the accident statistics questionnaires, which must be completed by the competent agents of authority involved in the accidents.

The National Registry of Traffic Accident Victims is an instrument to provide the necessary information to determine the causes and circumstances in which traffic accidents have occurred, as well as their consequences, in accordance with the latest modification of the aforementioned text articulated by Law 6/2014, of 7 April [23]. The information received in the National Registry of Traffic Accident Victims will be used to draw up the national statistics on traffic accidents with victims.

The legal obligation to provide data affects all those involved in a traffic accident (agents, health centres, as well as other autonomous or local public administrations), in

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accordance with the provisions of articles 10 and 40 of the aforementioned Law 12/1989, of 9 May [24].

The information collected in these forms will enable the Directorate General for Traffic to calculate the average social cost of fatal accidents and serious accidents occurring in Spain, in accordance with the provisions of Royal Decree 345/2011 of 11 March [25] on the management of road infrastructure safety on the State Road Network. The result of these statistics will make it possible to evaluate the measures taken and to draw up action programmes.

4.2 Methodology

A standard classification in time series is the one that separates stationary I(0) series from the nonstationary I(1) ones, and the literature is full of articles proposing statistical methods to distinguish between the two. Starting with the classical ADF-test [26], other more elaborated approaches were proposed in the following years ([27] – [30]). All these testing procedures distinguish between the I(0) and the I(1) specifications, and in their simplest form, they nest the latter model in an autoregressive (AR) alternative of the form:

$$(1 - \alpha L)\, x_t \;=\; u_t, \qquad t \;=\; 1, 2, ..., \tag{1}$$

where L is the lag-operator ($L^k = x_{t-k}$) and u_t is supposed to be I(0).[5] Thus, the unit root or I(1) case is obtained throughout the null hypothesis:

$$H_o\!: \alpha \;=\; 1, \tag{2}$$

[5] An I(0) process is defined as a covariance stationary process with the infinite sum of the autocovariances being finite. It is also termed short memory because the low degree of dependence between the observations.

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in (1), while the stationary I(0) case holds if H_o (2) is rejected in favour of H_a: $|\alpha| < 1$. These two approaches (the I(0) and I(1) cases), however, can be considered in a more general framework, by using a fractional set-up of the form:

$$(1 - L)^d x_t = u_t, \qquad t = 1, 2, ..., \tag{3}$$

where the unit root case is now obtained with the null hypothesis:

$$H_o: d = 1, \tag{4}$$

in (3). In fact, this is the approach used in this paper, which is more general than the unit root methods mentioned above in the sense that the null hypothesis can be specified as:

$$H_o: d = d_o, \tag{5}$$

where d_o can be any real value, including thus 0 and 1 as particular cases, but also fractional values below 0, between 0 and 1, or even above 1.

In the empirical application carried out in the following section we use a simple version of a testing procedure due to Robinson [31] that allows us to consider unit and fractional orders of integration. This flexibility is important because it allows us to consider many cases of interest such as:

a) Stationarity I(0) or short memory, when d = 0,

b) Stationary long memory processes, if 0 < d < 0.5,

c) Nonstationary but mean reverting processes, when 0.5 ≤ d < 1,

d) Nonstationarity I(1), when d = 1, and

e) Explosive patterns, when d > 1.

Note that in the context of road accidents, it is important to determine if changes produced by exogenous shocks are going to have a transitory (d < 1) or a permanent (d ≥ 1) nature, and using fractional integration, we allow for a much higher degree of flexibility in the dynamic specifications of the series, with shocks being transitory as long as d is strictly smaller than 1.

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The research question in this work is first to determine the degree of persistence in the number of road accidents in Spain; then, based on this feature, we will be able to determine if shocks in the series have permanent or transitory effects with the implications that this has in terms of policy actions.

The estimation of d is conducted on three series classified according to the severity (deaths, seriously injured and slightly injured), using the specification given below in equation (7) and using three potential cases as specified below (with no deterministic terms, with an intercept, and with an intercept and a linear time trend), and using for the estimation of d the Whittle function expressed in the frequency domain (Robinson, [31]).

Figure 13 summarizes the dataset used and the results obtained in the following section, showing evidence of short memory patterns, with transitory shocks and thus requiring strong policy actions in case of positive shocks to maintain the series in the new levels.

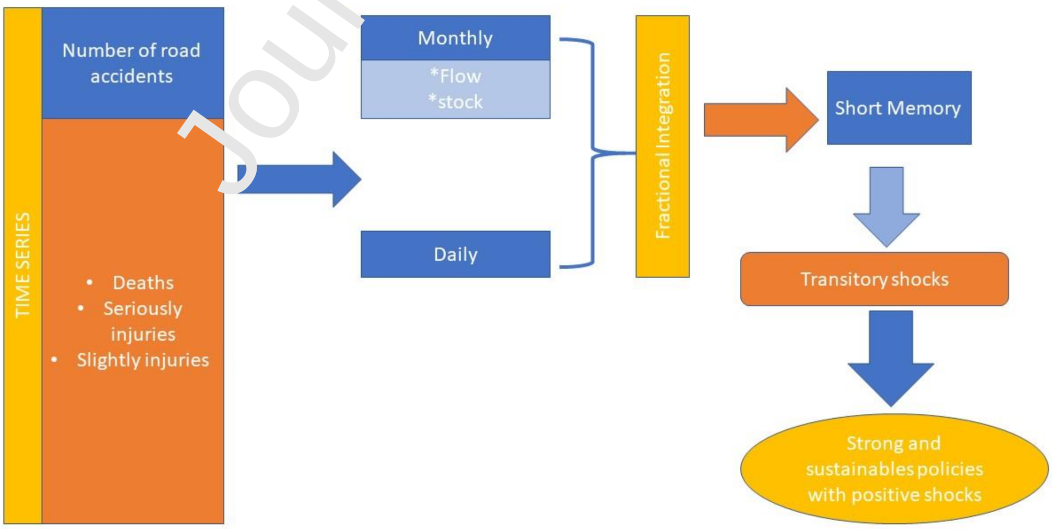

Figure 13: Data and results: graphical resume

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5. EMPIRICAL RESULTS

Following standard parameterizations in time series ([32], [33]), we consider the following regression model,

$$y_t = \alpha + \beta t + x_t, \qquad t = 1, 2, ..., \tag{6}$$

where y_t is the time series we observe, α and β are unknown coefficients referring to an intercept and a linear time trend respectively, and the regression errors x_t are supposed to be given by (3), i.e., following an I(d) process. Thus, under the null hypothesis (5), the examined model is given by:

$$y_t = \alpha + \beta t + x_t, \qquad (1 - L)^{d_o} x_t = u_t, \qquad t = 1, 2, ..., \tag{7}$$

where, to allow some degree of generality, d_o will adopt values from -1 to 2 with 0.01 increments. Across the tables presented below, we display the estimated values of d along with the 95% confidence intervals of the non-rejection values of d_o using the tests of Robinson [31]. We present these values for the three standard cases examined in the literature, and corresponding to i) no deterministic terms (i.e., imposing α = β = 0 in (7)); ii) including an intercept (i.e., estimating α but imposing β = 0 a priori), and iii) with a linear time trend (i.e., estimating α and β from the data along with d).

We start with the daily observations. In Tables 1 and 2 we assume that u_t in (7) is a white noise process, so no autocorrelation is permitted; however, in Tables 3 and 4, autocorrelation is permitted. However, instead of imposing any specific ARMA-type of model, we use a non-parametric approach due to Bloomfield [34] that approximates this behaviour. An advantage of this method is that its autocorrelations decay exponentially fast as in the AR case; however, unlike the AR model, it is stationary independent of the magnitude of its coefficients. Across the tables, we have also marked in bold the selected cases in relation with the deterministic terms ((ii) and (iiii)), choosing the most appropriate specification based on the t-values of the estimated coefficients in the d_o-differenced processes.

Starting with the results based on white noise errors, we observe that the time trend coefficient is only required for the minor injuries series, an intercept being sufficient to describe the deterministic part in the remaining two series. Focussing on the estimated coefficients, in Table 2, we see that the estimated values of d are very close to 0 in the three series, (-0.02 with the number of deaths, and 0 and 0.04 with seriously and slightly injured) and the I(0) hypothesis cannot be rejected in any single case. Thus, the results support the short memory hypothesis in the three series examined. Finally, we also observe a positive time trend in the minor injuries series.

[Insert Tables 1 – 4 about here]

In Tables 3 and 4 we allow for autocorrelation by using the non-parametric approach of [34]. Here the same structure with respect to the deterministic terms holds, and a positive time trend is found to be statistically significant only in the case of slightly injured. The I(0) hypothesis cannot be rejected for the number of deaths and seriously injured (with estimates of d of -0.02 and 0.08 respectively), but it is now rejected in favour of long memory (d > 0) for the minor injuries series (with an estimated value of d of 0.43).

The above results indicate that there is very little persistence in the series, implying that exogenous shocks disappear very fast. This is good in the case of negative shocks; however, with positive shocks reducing the number of road accidents, strong actions must be conducted if we want to remain at these lower levels.

In the second part of this empirical work, we focus on monthly data by looking at the flows (in Tables 5 and 6) and the stocks (in Tables 7 and 8) in road accidents.

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Here, and based on the monthly nature of the data, we also consider a third specification for the error term, by using a seasonal AR(1) model of form:

$$u_t = \rho u_{t-12} + \varepsilon_t, \qquad t = 1, 2, ..., \tag{8}$$

where ε_t is a white noise process.

We start with the flows series. The first thing that we notice here is that for the three specifications of the error term, the linear trend is now required for the number of deaths and the seriously injured (Table 5), obtaining significant positive trends in the two cases (Table 6). Looking at the estimated values of d, the confidence intervals are now much wider, clearly due to the smaller sample sizes, and the I(0) hypothesis cannot be rejected now in any single case. The estimates of d range now between -0.84 (deaths with autocorrelation) and 0.08 (seriously injured with white noise and monthly AR errors) but the value of 0 is included in all confidence bands across all the examined cases.

[Insert Tables 5 – 8 about here]

Focussing on the stocks, in Tables 7 and 8, the same conclusion holds with respect to the degree of persistence, since the I(0) hypothesis cannot be rejected in any single case, (the values of d ranging now from -0.88 to 0.15), and the only difference with respect to the deterministic terms is that the time trend is unrequired now in the case of the deaths under the white noise specification.

We can conclude by saying that there is very little evidence of persistence in the series examined. This lack of persistence is obtained independently of the series examined and the specification of the error term. This has both positive and negative effects depending on the nature of the shock. In the present context, with the sanitary crisis caused by the COVID-19 affecting transportation all over the world, we should expect a reduction in the number of road accidents; however, based on the short memory nature of the series, this effect should be transitory, disappearing relatively fast once the crisis is surpassed. In the same way, a negative shock, increasing the number of accidents should also have a transitory effect, disappearing relatively fast and not requiring strong measures to recover the original trends.

6. DISCUSSION AND CONCLUDING COMMENTS

The time series analysis conducted on this work and based on the number of road accidents in Spain indicate that the series (daily and monthly) display very little persistence, which is a good thing in the case of negative shocks which abruptly increase the number of accidents; however, it is bad news with respect to positive shocks that reduce the number of accidents since the series will return by itself to its original long term projection. In this respect, once a specific measure is adopted, and once verified it is positive, policy actions still should continue to remain active and positive during some period of time.

Results based on disaggregated data by Autonomous Communities can also be documented and some preliminary results confirmed those obtained in this work based on very low degrees of persistence. The same type of analysis can also be conducted with series from other countries to verify if this low degree of persistence holds all over the world. The comparison of results with other countries will make it possible to analyze whether or not patterns of behaviour are repeated, helping to expand knowledge of accidents and contributing to improvements in the design of road safety policies. From a methodological viewpoint, the I(d) framework employed in this work can be extended in several directions, including non-linearities in the deterministic components (such as the model proposed in Cuestas and Gil-Alana, [35]), the study of potential breaks in the data ([36], [37]) or the presence of asymmetric shocks, which makes sense in the context of road accidents data.

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Table 1: Estimates of d based on white noise errors and daily data

Series (daily)	i) No terms	ii) An intercept	iii) A linear trend
Deaths	-0.01 (-0.04, 0.02)	**-0.02 (-0.05, 0.02)**	-0.02 (-0.06, 0.02)
Seriously injured	0.00 (-0.03, 0.08)	**0.00 (-0.04, 0.04)**	0.00 (-0.04, 0.04)
Slightly injured	0.24 (0.20, 0.28)	0.04 (0.01, 0.08)	**0.03 (-0.01, 0.06)**

The values in parenthesis refer to the 95% band of the non-rejection values of d; In bold, the selected specification in relation with the deterministic terms.

Table 2: Estimated coefficients of the selected models in Table 1

Series (daily)	d	Intercept (t-value)	Time trend (t-value)
Deaths	-0.02 (-0.05, 0.02)	2.9858 (61.99)	---
Seriously injured	0.00 (-0.04, 0.04)	10.5400 (79.37)	---
Slightly injured	0.03 (-0.01, 0.06)	96.9032 (7.57)	0.0044 (2.92)

The values in parenthesis in the last two columns refer to their corresponding t-values.

Table 3: Estimates of d based on autocorrelated errors and daily data

Series (daily)	i) No terms	ii) An intercept	iii) A linear trend
Deaths	-0.02 (-0.05, 0.03)	**-0.03 (-0.08, 0.04)**	-0.03 (-0.09, 0.03)
Seriously injured	0.08 (-0.04, 0.20)	**-0.02 (-0.07, 0.05)**	-0.02 (-0.07, 0.05)
Slightly injured	0.43 (0.38, 0.47)	0.09 (0.02, 0.13)	**0.05 (0.00, 0.13)**

The values in parenthesis refer to the 95% band of the non-rejection values of d; In bold, the selected specification in relation with the deterministic terms.

Table 4: Estimated coefficients of the selected models in Table 3

Series (daily)	d	Intercept (t-value)	Time trend (t-value)
Deaths	-0.03 (-0.08, 0.04)	2.9858 (66.39)	---
Seriously injured	-0.02 (-0.07, 0.05)	10.5405 (91.07)	---
Slightly injured	0.05 (0.00, 0.13)	96.9340 (100.12)	0.0044 (2.46)

The values in parenthesis in the last two columns refer to their corresponding t-values.

Table 5: Estimates of d based on the monthly flows series

1) White noise errors		
Series (flows)	ii) With an intercept	iii) With a linear trend
Deaths	-0.18 (-0.36, 0.17)	**-0.32 (-0.56, 0.13)**
Seriously injured	0.20 (0.07, 0.40)	**0.08 (-0.11, 0.34)**
Slightly injured	**-0.09 (-0.25, 0.13)**	-0.09 (-0.24, 0.13)
2) With autocorrelation (Bloomfield)		
Deaths	-0.53 (-0.90, 0.16)	**-0.84 (-1.18, 0.43)**
Seriously injured	0.26 (-0.03, 0.74)	**-0.02 (-0.43, 0.63)**
Slightly injured	**0.05 (-0.48, 0.71)**	0.10 (-0.42, 0.72)
3) With monthly AR (1) autocorrelation		
Deaths	-0.18 (-0.36, 0.17)	**-0.32 (-0.55, 0.13)**
Seriously injured	0.20 (0.07, 0.40)	**0.08 (-0.11, 0.34)**
Slightly injured	**-0.04 (-0.33, 0.26)**	-0.04 (-0.30, 0.25)

The values in parenthesis refer to the 95% band of the non-rejection values of d; In bold, the selected specification in relation with the deterministic terms.

Table 6: Estimated coefficients of the selected models in Table 5

1) White noise errors			
Series (flows)	d	Intercept (t-value)	Time trend (t-value)
Deaths	-0.32 (-0.56, 0.13)	2.8982 (61.87)	0.0036 (1.93)
Seriously injured	0.08 (0.11, 0.34)	96.8587 (65.16)	0.1348 (2.61)
Slightly injured	-0.09 (-0.25, 0.13)	10.5423 (114.25)	---
2) With autocorrelation (Bloomfield)			
Series (flows)	d	Intercept (t-value)	Time trend (t-value)
Deaths	-0.84 (-1.18, 0.43)	2.9013 (240.13)	0.0036 (1.93)
Seriously injured	-0.02 (-0.43, 0.63)	96.7583 (76.92)	0.1366 (3.03)
Slightly injured	0.05 (-0.48, 0.71)	10.5395 (59.3[illegible])	---
3) With monthly AR (1) autocorrelation			
Series (flows)	d	Intercept (t-value)	Time trend (t-value)
Deaths	-0.32 (-0.55, 0.13)	2.8982 (61.87)	0.0036 (1.93)
Seriously injured	0.08 (-0.11, 0.34)	96.8587 (65.16)	0.1348 (2.61)
Slightly injured	-0.04 (-0.33, 0.26)	10.5414 (95.94)	---

The values in parenthesis in the last two columns refer to their corresponding t-values.

Table 7: Estimates of d based on the monthly stocks series

1) White noise errors		
Series (stocks)	ii) With an intercept	iii) With a linear trend
Deaths	**-0.20 (-0.35, 0.12)**	-0.38 (-0.62, 0.04)
Seriously injured	0.06 (0.06, 0.22)	**-0.13 (-0.29, 0.09)**
Slightly injured	**-0.12 (-0.27, 0.09)**	-0.12 (-0.28, 0.09)
2) With autocorrelation (Bloomfield)		
Deaths	-0.48 (-0.83, 0.12)	**-0.88 (-1.22, 0.45)**
Seriously injured	0.29 (-0.01, 0.70)	**0.03 (-0.43, 0.66)**
Slightly injured	**0.15 (-0.33, 0.92)**	0.16 (-0.39, 0.92)
3) With monthly AR (1) autocorrelation		
Deaths	-0.21 (-0.38, 0.12)	**-0.40 (-0.62, 0.04)**
Seriously injured	0.13 (-0.01, 0.32)	**-0.08 (-0.28, 0.22)**
Slightly injured	**-0.06 (-0.40, 0.26)**	-0.06 (-0.42, 0.26)

The values in parenthesis refer to the 95% band of the non-rejection values of d; In bold, the selected specification in relation with the deterministic terms.

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Table 8: Estimated coefficients of the selected models in Table 7

1) White noise errors			
Series (stocks)	d	Intercept (t-value)	Time trend (t-value)
Deaths	**-0.20 (-0.35, 0.12)**	90.8333 (111.40)	---
Seriously injured	**-0.13 (-0.29 0.09)**	2934.501 (94.92)	4.5399 (3.94)
Slightly injured	**-0.12 (-0.27, 0.09)**	320.8756 (122.60)	---
2) With autocorrelation (Bloomfield)			
Series (stocks)	d	Intercept (t-value)	Time trend (t-value)
Deaths	**-0.88 (-1.22, -0.45)**	87.9821 (254.93)	0.1193 (6.95)
Seriously injured	**0.03 (-0.43, 0.66)**	2963.257 ([illegible].18)	4.5493 (2.56)
Slightly injured	**0.15 (-0.33, 0.92)**	320.6611 (47.31)	---
3) With monthly AR (1) autocorrelation			
Series (stocks)	d	Intercept (t-value)	Time trend (t-value)
Deaths	**-0.40 (-0.62, 0.04)**	87.8348 (75.87)	0.1261 (2.63)
Seriously injured	**-0.08 (-0.28, 0.22)**	2934.847 (83.36)	4.5469 (3.54)
Slightly injured	**-0.06 (-0.40, 0.26)**	320.8414 (95.94)	---

The values in parenthesis in the last two columns refer to their corresponding t-values.

HIGHLIGHTS

- The number of road accidents in the Spanish roads is examined
- The methodology is based on fractional integration
- The orders of integration are around 0 and thus showing a short memory pattern
- This implies that shocks will be transitory, disappearing fast
- This requires strong policy measures in case of positive shocks if we want to maintain that effect in the long run