Improving fatalities forecasting in times of recession in Europe

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Abstract

Modeling road safety is a complex task, which needs to consider both the quantifiable impact of specific parameters, as well as the underlying trends that cannot always be measured or observed. One of the key relationships in road safety links fatalities with risk and exposure, where exposure reflects the amount of travel, which in turn translates to how much travelers are exposed to risk. It is reasonable to expect that –for the same level of risk– when there is a higher amount of travel, fatalities may increase, solely due to the increased exposure. Similarly, of course, when exposure is reduced (e.g. due to a slow-down of the economy), fatalities may decrease, solely on account of this phenomenon, and not due to some underlying road safety improvement. In general the two economic variables: GDP and unemployment rate are selected to analyse the statistical relationships with some indicators of road accident fatality risk.

The objective of this research is to provide an overview of relevant literature on the topic and outline some recent developments in macro-panel analysis that have resulted in ongoing research that has the potential to improve our ability to forecast traffic fatality trends, especially under turbulent financial situations. For this analysis, time series of the number of fatalities and GDP in 30 countries for a period of 38 years are used. This process starts by estimating short-term models (as captured by analysis of panel data) and long-term models (as captured by long term time-series models, which model each country separately). Based on these developments, directions for the combination of short term and long term models, utilizing state-of-the-art modelling and analysis techniques such as the error-correction representation, are outlined.

Introduction

Modeling road safety is a complex task, which needs to consider both the quantifiable impact of specific parameters, as well as the underlying trends that cannot always be measured or observed. One of the key relationships in road safety links fatalities with risk and exposure, where exposure reflects the amount of travel, which in turn translates to how much travelers are exposed to risk. It is reasonable to expect that –for the same level of risk– when there is a higher amount of travel, fatalities may increase, solely due to the increased exposure. Similarly, of course, when exposure is reduced, fatalities may decrease, solely on account of this phenomenon, and not due to some underlying road safety improvement. Examples of such analyses exist in the literature. One of the oldest studies relates to the impact of the petrol crisis and the reduction of the speed limit in the US in the early 70s, which led to a reduction to the number of crashes and traffic fatalities in the US (Tihansky, 1974). Several studies attempted to model the impact of the economic recession that was experienced in the early 80s (Wagenaar, 1984; Hedlund et al., 1984; Reinfurt et al., 1991). Kweon (2011) found that annual changes in unemployment rate and consumer price index (CPI) correlated strongly with the annual trends of the number of crashes and traffic fatalities in the US.

Exposure can vary due to a large number of underlying factors; in the current economic situation, lower Gross Domestic Product (GDP) and rising unemployment are such contributing factors. Antoniou and Yannis (2013) provide a discussion of using different proxy measures to the economic situation (such as the number of vehicles in circulation or the fuel consumption), when actual exposure measurements are not available. Kopits and Cropper (2005) develop models to examine the relationship between traffic fatality risk and per capita income and use it to forecast traffic fatalities for multiple regions. Söderlund and Zwi (1995), after adjusting for motor vehicle numbers, find that the poorest countries show the highest road traffic-related mortality rates. Bishai et al. (2006) observe that traffic fatalities increase with GDP per capita in lower income countries and decrease with GDP per capita in wealthy countries and explore this finding using fixed effects regression. This is an alarming finding, as it implies that as lower income countries become richer, traffic fatalities are expected to increase (and indeed the WHO predicts that the current number of 1.3 million global road fatalities per year, may rise to 1.9 million by 2020 (WHO, 2011)).

The objective of this research is to provide an overview of relevant literature on the topic and outline some recent developments in macro-panel analysis that have resulted in ongoing research that has the potential to improve our ability to forecast traffic fatality trends, especially under turbulent financial situations. This process starts by estimating short-term models (as captured by analysis of panel data; see e.g. Yannis et al., 2014) and long-term models (as captured by long term time-series models, which model each country separately; see e.g. Antoniou et al., in press). Based on these developments, directions for the combination of short term and long term models, utilizing state-of-the-art modelling and analysis techniques such as the error-correction representation, are outlined.

Background

In general the two economic variables: GDP and unemployment rate are selected to analyse the statistical relationships with some indicators of road accident fatality risk. The nature of these time series are different: GDP follows a random walk with drift with two components which are a deterministic trend usually increasing linearly and a sum of stochastic shocks coming from a random walk, unemployment rate follows just a random walk. The dependency of these two economic variables is not straightforward. GDP is privileged in the analysis because of its direct influence on the number of kilometre driven which is a measure of the exposure to the risk of accident directly proportional to the number of fatalities. Figure 1 outlines some of the general mechanisms through which economic conditions may be linked to road safety. In particular, changes in the available resources can result in changes in the levels of road safety investment, but also at the behaviour of the users, leading them to reduce their speed or change their drinking habits. Both of these changes affect the traffic risk. Furthermore, economic changes have direct effects on the amount of traffic (exposure) and both terms (risk and exposure) result in changes in the total number of road crashes and associated fatalities.

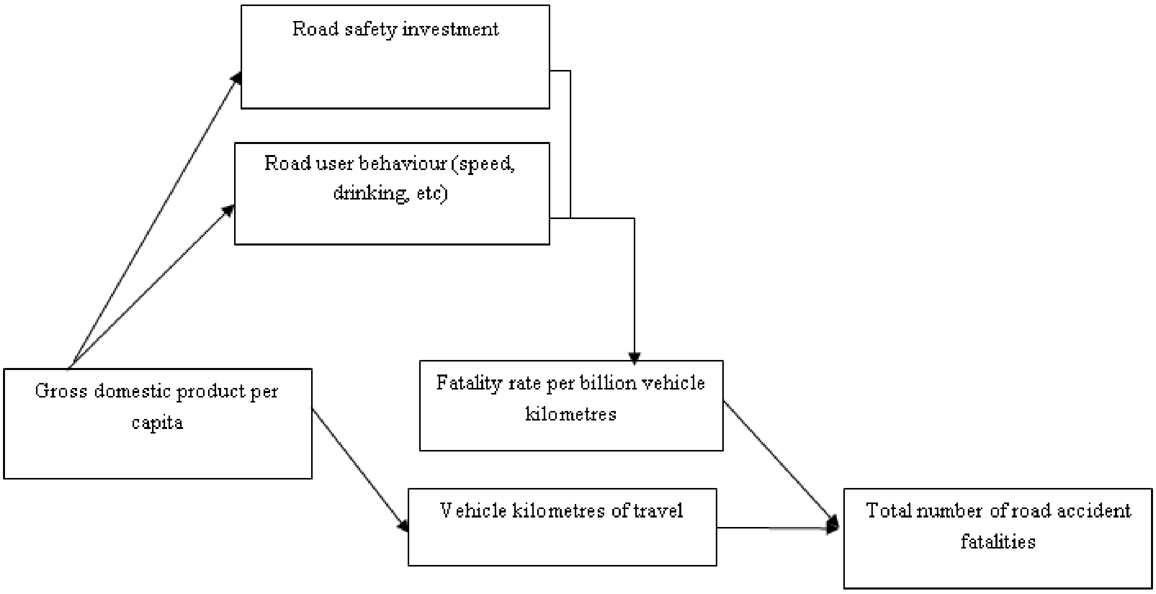

Figure 1. Schematic of the connection between economy and road safety

Such influences are rather immediate as seen in Table 1, which provides an overview of the number of fatalities and GDP per capita during the crisis for selected European countries. Several interesting observations can be made from these data, even before developing models. For several countries, for which the economy recovers after 2009, an increase in fatalities can be observed (either the same year or one year later); these countries include Belgium, Germany, Italy, Finland, Sweden and the UK. On the other hand, in some countries (such as Greece, Ireland, Spain and Portugal), both GDP and fatalities are still dropping in 2011. It is noted that there are a few exceptions (such as Austria, the Netherlands, Hungary and the Czech Republic), where GDP recovers, but fatalities continue decreasing. Monitoring of future developments in these countries (growth and safety measures) will provide further insight into the exact processes underway.

	Fatalities					GDP per capita				
	2007	2008	2009	2010	2011	2007	2008	2009	2010	2011
Belgium	1071	944	942	840	843	38.27	38.61	37.51	38.29	39.14
Czech Republic	1221	1076	901	802	769	13.80	14.15	13.58	13.91	14.29
Germany	4949	4477	4152	3648	4006	35.83	36.30	34.53	35.89	37.01
Estonia	196	132	100	79	101	12.48	11.92	10.33	10.58	11.31
Ireland	338	280	238	212	188	50.80	47.94	43.70	42.84	41.98
Greece	1612	1553	1456	1281	1100	24.79	25.01	24.46	23.34	22.16
Spain	3823	3100	2714	2478	2298	26.92	26.74	25.53	25.38	25.41
France	4620	4275	4273	3992	3969	35.11	34.88	33.73	34.05	34.42
Italy	5131	4725	4237	3934	3941	30.95	30.31	28.55	28.78	28.86
Lithuania	740	499	370	300	299	8.61	8.88	7.60	7.72	8.15
Hungary	1232	996	822	739	639	11.15	11.26	10.52	10.66	10.97
Netherlands	709	677	644	640	550	41.92	42.55	40.69	41.20	41.71
Austria	691	679	633	552	521	39.70	40.54	38.94	39.69	40.62
Poland	5583	5437	4572	3907	4164	8.95	9.41	9.57	9.94	10.36
Portugal	974	885	840	845	782	18.72	18.66	18.14	18.34	17.97
Finland	380	344	279	272	290	41.69	42.05	38.55	39.92	41.44
Sweden	471	397	358	266	311	44.22	43.87	41.47	43.70	45.55
United Kingdom	3059	2645	2222	1905	1998	39.29	39.02	36.90	37.15	37.32

Table 1. Overview of number of fatalities and GDP per capita during the crisis for selected European countries (Source: Yannis et al., 2014).

Methodological approaches

Table 2 provides a systematic classification of analysis approaches for different types of data. When a single country is considered and a sufficiently long time-series is available, then univariate time series models can be used (Commandeur et al., 2013). Different types of functional forms can be specified, e.g. autoregressive regression with linear trend, ARIMAX, structural model (bivariate). When a large number of countries is available (e.g. 30), but only a small number of time observations are available, then cross-sectional and micro-panel analysis can be performed using (Poisson or negative binomial) regression, possibly with autoregressive terms. Finally, when there are data that span multiple countries and offer a sufficient number of time observations, then macro-panel analysis with regression considering co-integration of the time-series can be performed.

	Time T	
Country N	**Small (1 to 5)**	**Large (30)**
Small (1)		Univariate time series model: autoregressive regression with linear trend, ARIMAX, structural model (bivariate)
Large (30)	Cross-sectional and micro panel analysis with (Poisson or NB) regression (+autoregression)	Macro-panel analysis with regression (cointegration)

Table 2. Analysis methods

In the presented methodological framework, two statistical techniques are going to be used to analyse the panel data of European countries:

- A macro-panel regression of the first difference of the logarithm of the number of fatalities by the first difference of the logarithm of GDP. This corresponds to a short-term analysis of the relationship between the annual changes in safety and economy or to a growth rate model.

$$\log FAT_{it} - \log FAT_{it-1} = \alpha_i + \beta_{0i}(\log GDP_{it} - \log GDP_{it-1}) + \nu_{it}$$

- A macro-panel regression of the logarithm of the number of fatalities by the logarithm of GDP. This corresponds to a long-term analysis of the relationship between safety and economy or to a static model.

$$\log FAT_{it} = \alpha_i + \beta_{0i} \log GDP_{it} + \nu_{it}$$

These two models are special cases of a general dynamic model called the autoregressive distributed lag model with restrictions on the model parameters ($\beta_{i1}= \beta_{i2}=0$ for static, $\beta_{i1}=-\beta_{i0}$, $\beta_{i2}=1$ for differenced model)

$$\log FAT_{it} = \alpha_i + \beta_{i0} \log GDP_{it} + \beta_{i1} \log GDP_{it-1} + \beta_{i2} \log FAT_{it-1} + \nu_{it}$$

The main interest in macro-panel analysis is to get more robust estimates of the effects of economic variables on the number of fatalities by aggregating or grouping the regressions undertaken, which can give more reliable predictions than from one country alone. Furthermore, there is also a gain in parsimony and precision of the grouping models for a set of countries used to predict the number of fatalities compared to the compilation of individual and independent model country per country.

Macro-panel analysis allows two kinds of estimates of the short and long term elasticities. Either we suppose that they are homogeneous among the countries, and the pooled estimate is recommended, or they are heterogeneous and the mean-group estimate based on individual country regressions is recommended. Most of the models are fixed effect models on the intercepts rather than random effect models, because there are large differences in terms of risk level between the European countries.

Exploratory analysis

Nature of the time series

We have at our disposal for this analysis 30 time series of the number of fatalities and GDP for a period of 38 years. From previous econometric models on economic growth in the EU, it is known that the Gross National Production deflated by the price index is non stationary and integrated of order 1 I(1) (Arpaia and Turrini, 2008). The structural models of the number of fatalities developed in the European DaCoTA project include either a random level component or a random slope component, meaning that the time-series on fatalities are non stationary integrated of order 1 or 2 (Dupont et al., 2012).

Table 3 presents the significance of the level and slope variances in structural models of the number of fatalities and induced order of integration from models estimated within the DaCoTA project. There are 13 countries integrated of order 0: AT, BG, CH, CY, DE, FI, HU, IE, IS, IT, LT, LU, MT; 7 of order 1: BE, NO, PL, PT, SE, SI, SF; and 10 of order 2: CZ, DK, EE, EL, ES, FR, LV, NL, RO, UK. As we suspect some time-series to be I(2), we carried out a set of Augmented Dickey-Fuller (ADF) test with and without trend on first differenced time series of the number of accidents; the hypothesis of unit root, which in that case means that the time-series is I(2), is not rejected for three countries: CZ, ES, and UK. Then from another set of Augmented Dickey-Fuller test with and without trend on all time series, the hypothesis of unit root is not rejected in all the countries but MT, which is supposed to be stationary.

	level	slope	integration
AT	NS	NS	0
BE	S	NS	1
BG	NS	NS	0
CH	NS	NS	0
CY	NS	NS	0
CZ	NS	S	2
DE	NS	NS	0
DK	NE	S	2
EE	NS	S	2
EL	S	S	2
ES	NS	S	2
FI	NS	NS	0
FR	NS	S	2
HU	NS	NS	0
IE	NS	NS	0
IS	NS	NS	0
IT	NS	NS	0
LT	NS	NS	0
LU	NS	NS	0
LV	S	S	2
MT	NS	NS	0
NL	S	S	2
NO	S	NS	1
PL	S	NS	1
PT	S	NS	1
RO	NS	S	2
SE	S	NS	1
SI	S	NS	1
SK	S	NS	1
UK	NS	S	2

Table 3. Significance of the level and slope variances in structural models of the number of fatalities and induced order of integration (Source: DaCoTA project, Deliverable 4.4)

Panel unit root tests have been ran on both sets of time series transformed with logarithm (Table 4). The Im, Pesaran, and Shin (IPS) test allows for some of the series to have a unit root under the alternative because the short-term dynamics is heterogeneous. Some lags can be added. The time-series are demeaned by the cross-sectional averages and a linear trend is introduced. This test assumes the independence of the countries.

		lags	statistic	p-value
GDP	IPS (trend)	0	1.60	0.945
	CADF(trend)	0	5.65	1.00
Fatalities	IPS (trend)	1	-1.32	0.093
	CADF	1	-0.419	0.338
	CADF (trend)	1	-2.089	0.018

Table 4. Statistics and p-value for the Im, Pesaran, and Shin (IPS) test (Stata procedure xtunitroot) and Pesaran's CADF test (Stata procedure pescadf).

We accept the null hypothesis that both series contain a unit root, with a greater certainty for GDP. There is a greater variety of time-series models for the number of fatalities: deterministic linear trend, random walk plus drift (integrated of order 1), or random slope plus drift (integrated of order 2). Furthermore these time-series are subject to breaks in the level due to national safety measure implementations. When the thirty countries are divided in three groups, the IPS tests confirm that in the first group we reject the hypothesis of unit root and we accept the hypothesis in the second and third group.

group	statistic	p-value
I(0)	-3.36	0.0004
I(1)	-1.43	0.076
I(2)	0.17	0.57

Table 5. Statistics and p-value for the Im, Pesaran, and Shin (IPS) test (Stata procedure xtunitroot) for the number of fatalities without trend and lags.

Analysis of individual countries

An example of analysis of the impact of GDP on the traffic fatalities in a single country can be found in Antoniou and Yannis (2013). In this analysis, latent-risk models are used to model the interaction between exposure and risk using GDP and fatalities data from Greece between 1995 and 2010.

Figure 2 presents the forecast plots for a model without explicit modelling of recession (top) and a modified model that explicitly accounts for a recession, which at the time was projected to be over after 2013. There are several observations that can be made about this figure. Starting from the top left subfigure, the projection of the GDP for Greece appears to follow a downward trend all the way to 2020. While this is not impossible, it is highly unlikely. The reason for this trend is that the model detects the drop in the GDP in the last couple of years (due to the recession), but has no way to tell whether this trend will be reversed at some point. One way to overcome this would be to add an additional intervention variable to the model, which would indicate that the last few observations are part of a temporary recession phenomenon. This variable could then be used to indicate when the recession is expected to be over. Another way to indicate the same point (i.e. that these points are an intermediate disruption of an otherwise constant trend) would be to fix the slope of the exposure. However, the latter option would imply that the recovery would start from the first predicted point (i.e. 2011), which is clearly not the case. Therefore, the approach of an intervention recession variable has been selected, using 2013 as the last recession year. The bottom subfigures of Figure 2 show the results of this model, i.e. assuming that the recession is expected to last until 2013.

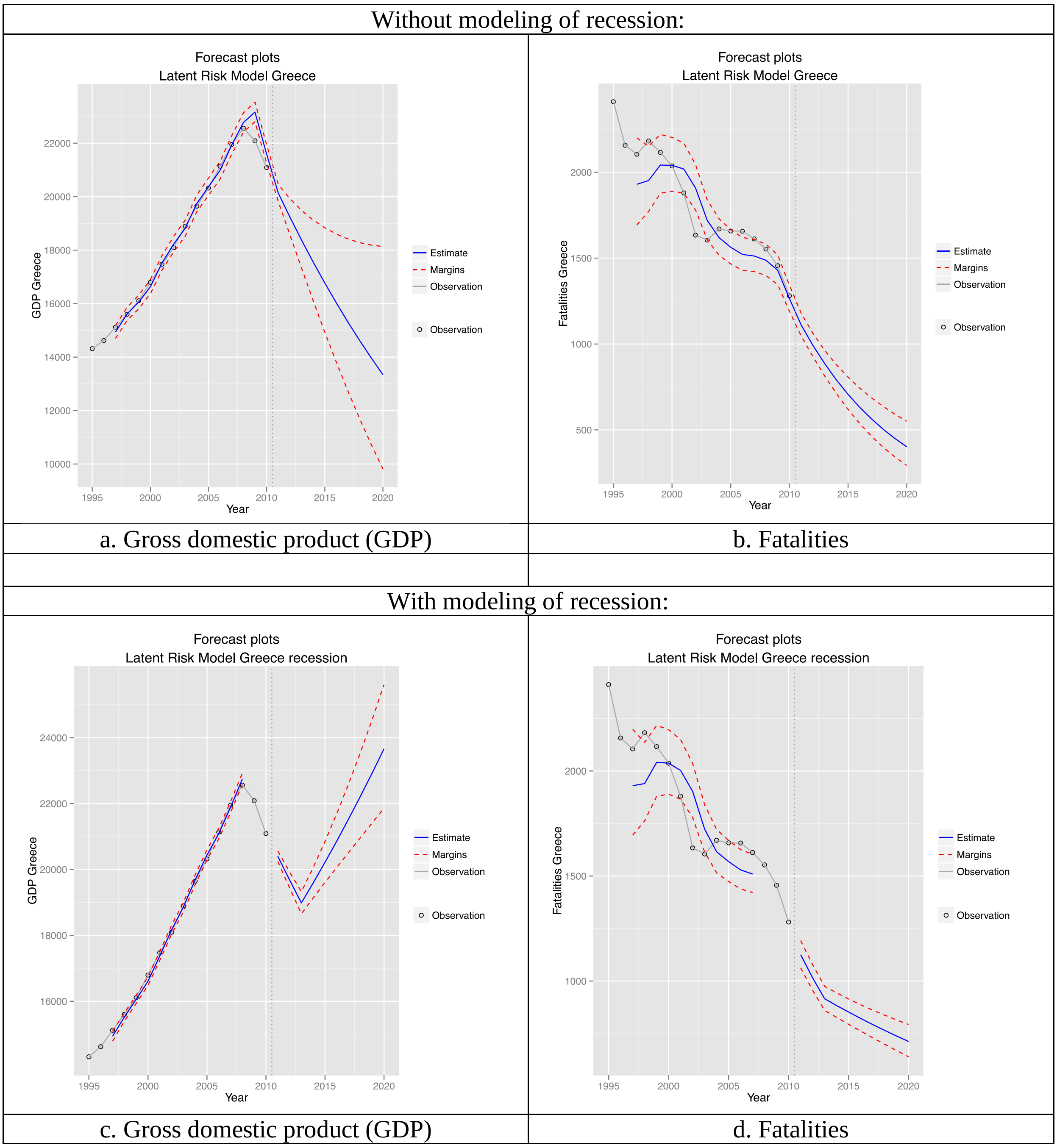

Figure 2. The impact of the explicit modelling of recession for Greece (Source: Antoniou and Yannis, 2013)

Analysis of a panel of countries

In this section we look at the analysis of several countries, without explicitly developing a model that combines the data. However, such analyses are useful in understanding the underlying similarities of the various countries, which can in turn be useful in developing richer models.

Figure 3 shows the evolution of the per capita GDP and the number of fatalities per million population in selected European countries. The nature of the time-series (most of which are integrated of order 1, that is to say following a random walk with or without drift) adds some difficulties to the exploratory analysis.

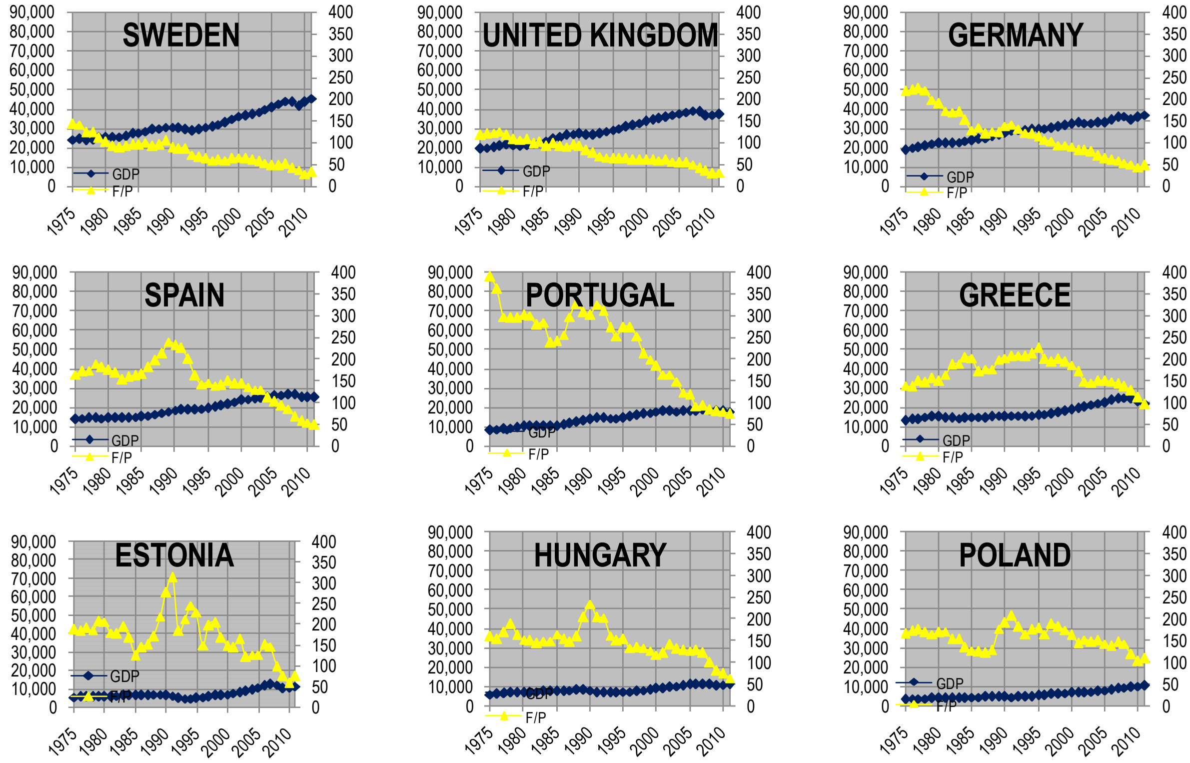

Figure 3. Evolution of per capita GDP and number of fatalities in road crashes per million population in selected European countries (Source: Yannis et al., 2014)

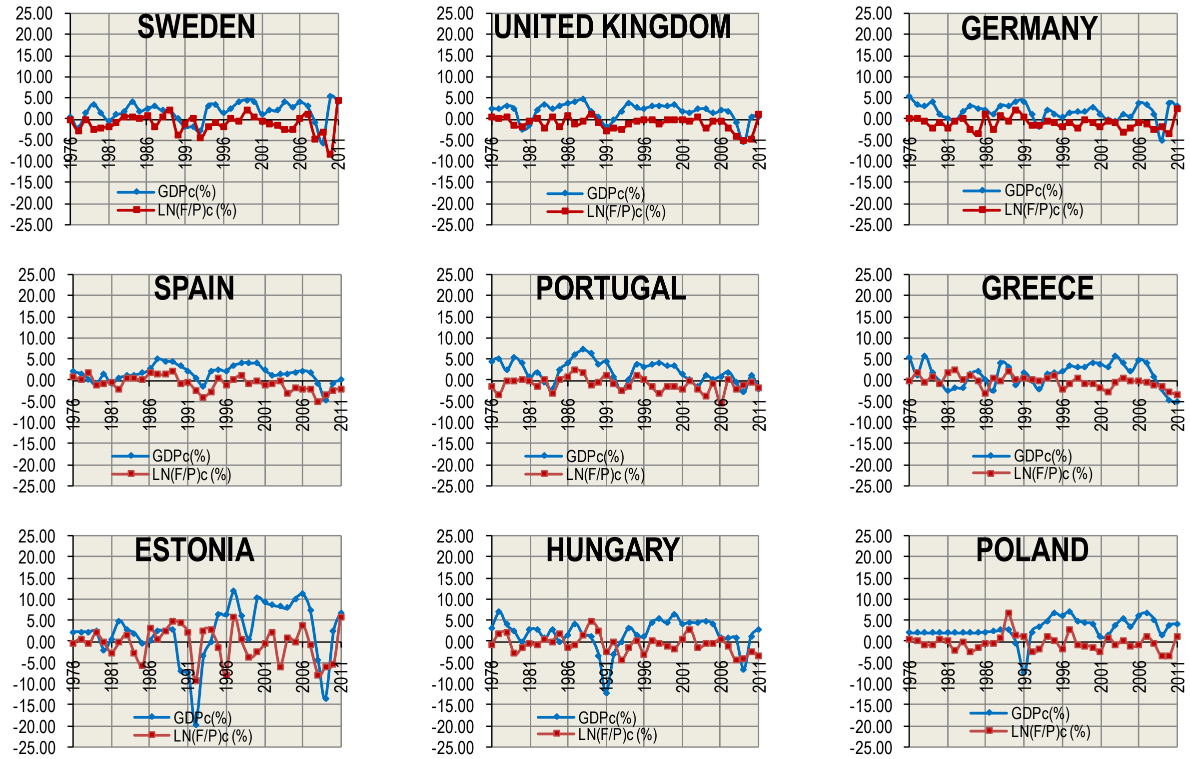

Figure 4. Evolution of annual change in per capita GDP and annual change in the number of traffic fatalities per million population in selected European countries (Source: Yannis et al., 2014)

While some general trends can be visually inferred from this figure, transformations of the data are necessary to provide further insight to visualize the interactions. Such a transformation is to take the first difference in the logarithm of GDP and the number of fatalities, in order to get the relative change from one year to another. For example, Figure 4 shows the evolution of the annual change in per capita GDP and annual change in the number of traffic fatalities per million population in selected European countries, which provides a visual cue of the possible correlation of the two indicators.

Figure 5 provides a clustering of European countries in three somewhat homogeneous groups, in terms of the long-term trends of the number of fatalities, in a way that allows the extraction of some macroscopic patterns or stylized facts for a period of more than 35 years. The top subfigure includes northern and western countries, in which a decreasing trend in the fatality rate across the entire study period can be observed. The middle subfigure includes central and eastern countries, for which the fatality rate shows larger volatility. Furthermore, the effect of the changes in the political regimes in the early nineties is evident in this subfigure. The bottom subfigure includes southern countries, for which the decrease in the number of fatalities per population started later than the northern and western countries, following an initial increasing trend. (A discussion on this breakpoint can be found in Yannis et al., 2011).

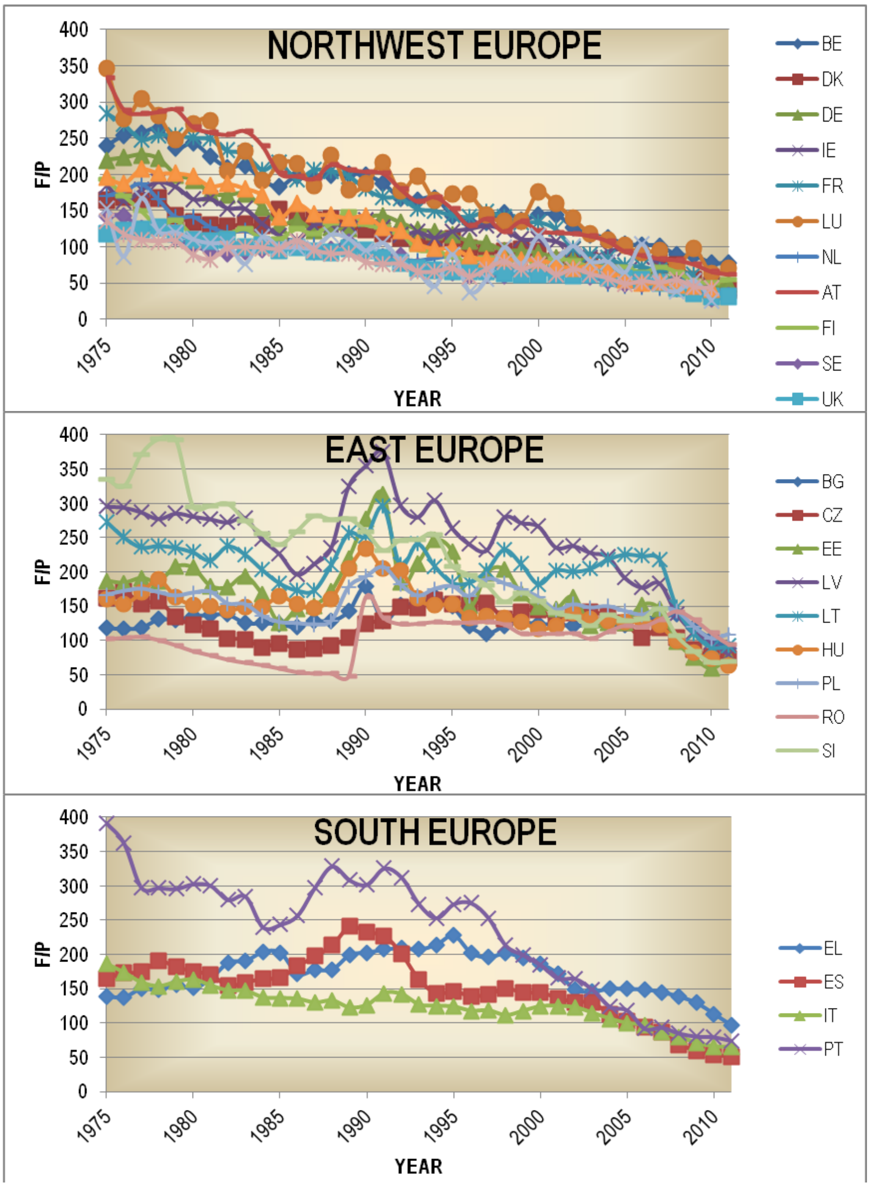

Figure 5. Data exploration through grouping of countries (Source: Yannis et al., 2014)

Short-term macro-panel regression

Most of the short-term models are estimated on one country data with some ARIMAX models. Short-term macro-panel models are relatively rare in the literature about aggregated accident risk model. Yannis et al. (2014) provide such an example on a panel of European countries. The regressors of the first difference in the logarithm of the number of fatalities are the first difference in the logarithm of GDP and an indicator of the group of countries according to the pattern of the long-term trend of the mortality rate:

$$\log \mathrm{FAT}_{it} - \log \mathrm{FAT}_{i(t-1)} = \alpha + \beta_1[\log \mathrm{GDP}_{it} - \log \mathrm{GDP}_{i(t-1)}] + \beta_2 \mathrm{CountryGroup}_{it} + \varepsilon_{it}$$

In fact the effect of the change depends on its sign: increase or decrease, and is estimated by country groups. It is a linear model: two fixed coefficients are estimated relative to an increase and a decrease in GDP for each group of countries, and the coefficients of the country group effect. The error-term follows an autoregressive structure of order 1. This model has also been fitted separately for each group of countries under the hypothesis of an homogeneous slope coefficient (or elasticity) among countries of each group and the results are summarized in Table 6.

There is a long-term linear decreasing trend from 1.75% to about 0.95% per year according to group of countries. The effects relative to an increase of GDP have similar amplitude according to the group of countries from 0.42 to 0.66. In case of recession, the effect is similar in northern countries, not significantly different from 0 in eastern countries and weaker in southern countries. The effect value for a 1% change can be assimilated to the elasticity of the number of fatalities to GDP. There are some autocorrelations, positive for northern and negative for southern countries. It means that the predictions one step ahead depends on the previous residual between the observed and predicted annual change in the number of fatalities.

	Northern	Eastern	Southern
Mean change (0%)	-1.25	-0.96	-1.75
Effect of 1% increase	0.66 (**)	0.42(*)	0.45(**)
Effect of 1% decrease	-0.75(**)	-0.60(NS)	-0.15(**)
rho	-0.29(**)	0.34(**)	-0.04(NS)

Table 6. Effects in % of changes for separate country regressions (** significant at 5%; * significant at 10%, NS non significant).

When we estimate a first differenced model on the European panel data with a pooled model (homogenous short term elasticity) and a group-mean model (heterogeneous short-term elasticity) with fixed effect, we get estimates which are higher for the elasticity compared to the previous model, but comparable between the two kinds of models and greater for the mean-group estimation (Table 7).

	Pooled	Mean-Group
Mean change (0 %)	-0.046 (0.005)**	-0.048 (0.044)**
Effect of 1% change	0.64 (0.11) **	0.79 (0.18)**
sigma	0.137	0.134

Table 7. Effects in % of change with their standard errors for pooled and mean-group models. (** significant at 5%).

The intercepts (Table 8) are mostly significantly negative, meaning that there is a decreasing deterministic linear trend with an average slope of 4.8% per year. 13 countries have a significant positive short-term elasticities: DK, DE, EE, IE, ES, IT, CY, LV, LT, PT, SK, FI, UK. For the remaining 17 countries the elasticity is not significantly different from zero. Elvik (2014) with a regression model on first differences of GDP and unemployment plus a linear trend found among 12 European countries 3 countries with a positive significant elasticity: FI, IE and UK (DK and DE have a non significant elasticity).

	intercept	tvalue	elasticity	tvalue	elasticity Elvik	tvalue
AT	-0.047	2.61	0.11	0.16	-0.051	0.61
BE	-0.055	3.52	1.18	1.80	0.34	0.53
BG	-0.020	1.06	0.45	1.21		
CH	-0.046	3.24	0.26	0.37	0.28	0.33
CY	-0.094	2.68	3.80	2.84		
CZ	-0.016	0.86	-0.31	-0.63		
DE	-0.062	4.45	1.01	1.91	0.54	0.71
DK	-0.070	3.52	1.67	2.19	0.36	0.3
EE	-0.052	1.59	1.08	2.33		
EL	-0.016	1.30	0.40	1.11		
ES	-0.078	5.33	2.56	4.45		
FI	-0.065	3.77	1.34	2.90	1.57	2.13
FR	-0.057	4.30	1.01	1.56	0.33	0.36
HU	-0.038	2.11	0.74	1.62		
IE	-0.083	5.51	1.26	4.19	1.21	2.33
IS	-0.050	0.66	0.56	0.30		
IT	-0.043	4.42	0.94	2.53		
LT	-0.038	1.78	0.70	2.44		
LU	-0.045	1.19	-0.02	-0.02		
LV	-0.041	2.23	0.40	1.97		
MT	0.014	0.10	-1.91	-0.44		
NL	-0.053	3.41	0.52	0.80	0.26	0.25
NO	-0.053	1.65	0.64	0.58	0.38	0.28
PL	-0.013	0.54	-0.06	-0.10		
PT	-0.071	4.07	1.25	2.38		
RO	0.000	0.00	-0.11	-0.17		
SE	-0.060	3.36	1.10	1.77	1.18	0.24
SI	-0.060	2.85	0.54	1.24		
SK	-0.058	2.02	0.95	2.06		
UK	-0.067	6.30	1.61	4.03	1.46	2.85

Table 8. Estimates of intercept and elasticity with t value for mean group regressions without and with unemployment rate (Elvik, 2014).

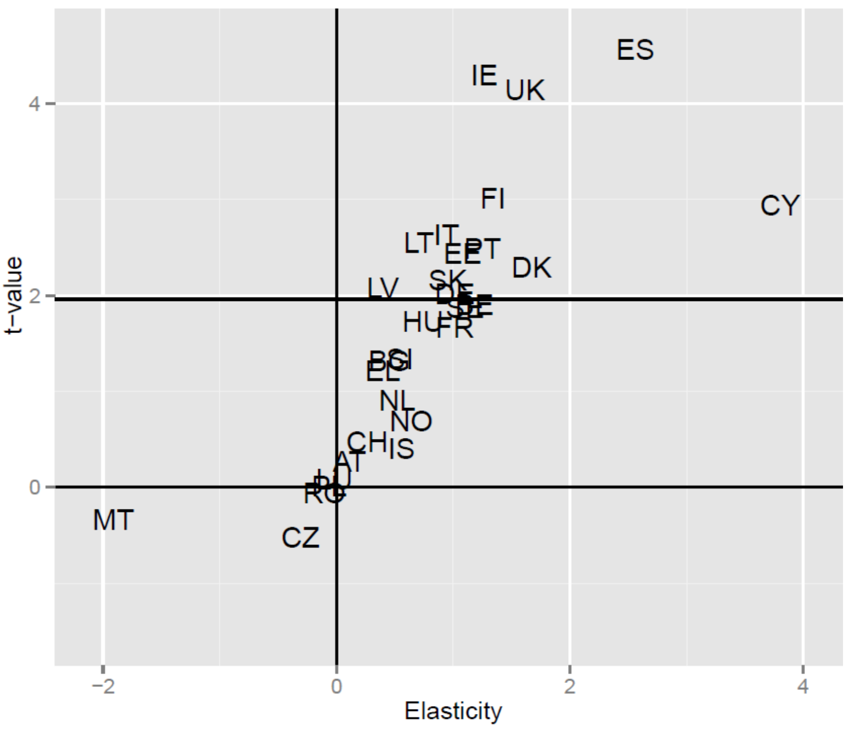

Figure 6. Short term elasticities estimates versus t values.

Long-term macro-panel regression

Various researchers have developed long-term static models of the number of fatalities related to GDP starting in 1996. A number of such studies have been summarized in Table 9. The main characteristic of these models is that the elasticity of the GDP related to the number of fatalities is homogeneous over the countries as a linear trend (when introduced). They differ on the form of the elasticity: either the elasticity is constant (linear) or depending monotonically on the GDP (decreasing or increasing). In this case, the function is either a spline function, or a linear function by pieces, or a quadratic and sometimes a cubic function of GDP.

	Countries	Data	Time	GDP	Motorisation	Other variables
Ruhm, 1996	50 American states + District of Columbia	1972-1991	No	Homogeneous linear	No	Unemployment Socio-demographic
Van Beeck et al., 2000	21 OECD	1962-1990	No	Homogeneous cubic in log	No (subject to same model form)	
Noland, 2003	50 US states	1984-1997	Homogenous linear trend	Homogeneous linear in log	No	Socio-demographic Infrastructure Health
Kopits, Cropper, 2005	88 worldwide	1963-1999	Regional linear trend	Homogeneous spline on log	No (subject to same model form)	
Kopits, Cropper, 2008	32 IRTAD OECD	1970-1999	Homogeneous linear trend	Homogeneous linear, quadratic, spline on log	Yes (fatalities per million miles travelled)	Socio-demographic Interactions with GDP
Anbarci et al., 2006, 2009	79 (23 Africa, 12 America, 26 Europe, 18 Asia)	1970-2000	Homogeneous linear trend	Homogeneous quadratic on log	Yes	Inequality Corruption Health
Bishai et al., 2006	41	1992-1996	No	Homogeneous linear on log (High/low income)	Yes	Population (Smeed)
Traynor, 2009	48 American states	1999-2003	No	Homogeneous linear on log	Yes (fatalities per million miles travelled)	Law Unemployment
Law et al., 2010, 2011	60	1972-2004	Homogeneous linear trend	Quadratic on log for less/highly developed countries	Yes	Corruption Health
Castillo-Manzano et al.,	EU-27	1999-2009	Homogeneous linear trend	Quadratic	Yes	Health Passenger*kilometre
Grimm et al., 2012	21 Indian states	1994-2006	Year effects	Quadratic in log	Yes	Socio-demographic

Table 9. Characteristics of the data and the model used in macro-panel analysis of the annual number of fatalities.

As both time-series are I(1) integrated of order 1 over a macro-panel of 30 european countries, the estimation of the elasticity of the number of fatalities to the GDP requires to take into account various problems, such as error cross-section dependence and persistent autocorrelation. We suppose that the coefficients of the slope or the elasticities are heterogeneous among the countries. The cross section dependence is introduced via some common factors, either related to the number of fatalities or to the GDP.

One of the most robust mean group type estimator is the Common Correlated Effects Mean Group estimator which is based on individual regression augmented by the mean value of both dependent and independent variables (Pesaran, 2006; Coakley and al., 2006). The mean values are instrumental and supposed to give information on the common factors if present. Some interventions are introduced to take into account mostly breaks in the level of the number of fatalities due to important national safety measures taken such as speed limits for exemple.

As a group mean estimate, the long-run elasticity of the number of fatalities to GDP is taken as the unweighted average of the respective coefficients. Similarly we get the long-term linear trend (interpreted as an annual change) as the average of the respective coefficients. In that case the elasticity is supposed to be constant over the period and not depending on GDP. A non-linear dependence of the number of fatalities to GDP can be approximated by a polynomial of the second order. We get the Kuznets curve (an U inverted curve) with a concave parabola.

		Pooled +interventions	GM linear	GM linear +interventions	GM linear	GM Non linear
LGDP	coef	-0.28	0.45	0.63	0.61	14.2
	std. err.	0.062	0.25	0.23	0.16	8.8
	z	-4.53	1.81	2.72	3.82	1.62
t	coef	-0.024	-0.008	-0 .023	0.11	-0.002
	std. err.	0.0014	0 .008	0.008	0.14	0.014
	z	-16.2	-1	-2.75	0.74	-0.16
t^2	coef				-0 .0005	
	std. err.				0.00028	
	z				-1.64	
$LGDP^2$	coef					-0.68
	std. err.					0.46
	z					-1.48
RMSE(sigma)		0.239	0.107	0.080	0.097	0.120

Table 10. Pooled and Group mean estimates of the coefficients of the regressions according to trends' forms and linear and non linear relationships.

The pooled estimate with fixed effects provides a negative value of -0.28 in total disagreement with the positive estimates of mean-group models which are much better fitted according to the RMSE. In case of an heterogeneous elasticity (linear effect), the basic model with a linear trend and no interventions leads to a lower estimate of the average elasticity 0.45 with a higher standard deviation. The model with a linear trend plus intervention and the model with a parabolic trend give an identical estimate of elasticity equal to 0.6. Both models help to capture the different patterns of evolution of the number of fatalities over time as seen on Figure 5. The main incidence of interventions is to correct the estimation of negative elasticities for some countries into positive ones that take into account the special structure of the evolution of risk in those countries. The model with a non linear effect in the form of a Kuznets curve has to be rejected as the mean group coefficient of the square term is not significant.

The heterogeneity of the elasticity between countries from the best model fit (linear + interventions) can be explored in Figure 7. A great majority of the elasticities are positive. The elasticity is significant for 12 countries with positive values: BE, DK, FR, IE, IT, LT, NL, NO, PT, RO, SE, UK. For the 18 remaining countries, the elasticity is not significant from zero. The sensibility of the number of fatalities to the variations of GDP is rather different according to countries. It means that the predictions have to be based on individual regressions rather than using the mean group estimate of the elasticity.

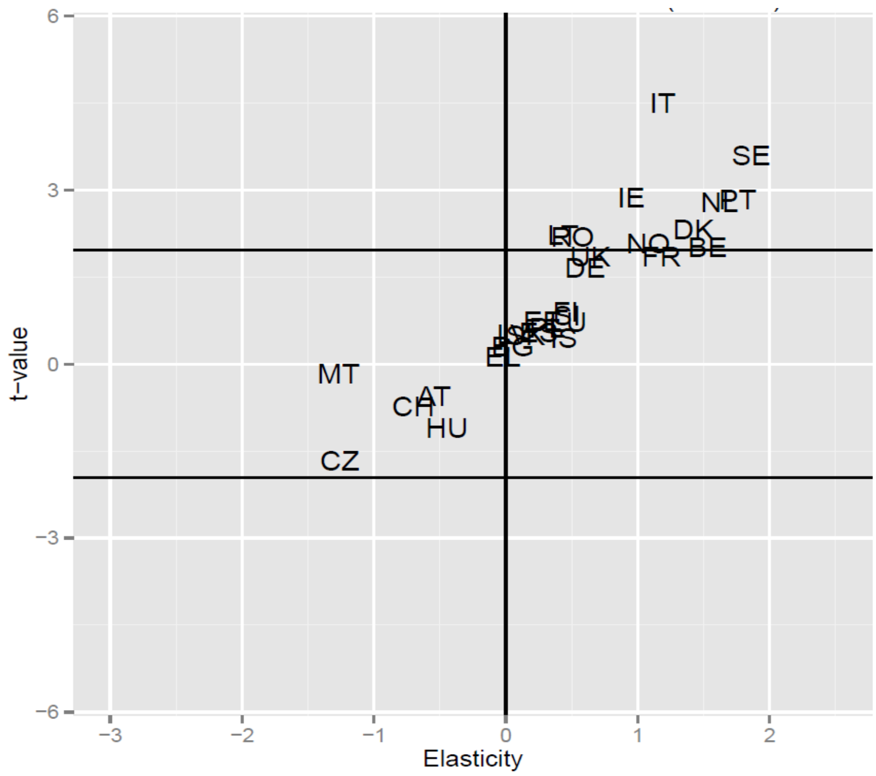

Figure 7. Individual elasticities' estimates versus the t statistics of the estimates for the model with a linear trend and interventions.

Elvik (2014) gave the estimates of a Negative binomial individual regression model of the number of fatalities on the logarithm of GDP and of the unemployment rates for 12 European countries with some interventions. Four countries have a positive significant elasticity to GDP: BE, NL, SE, UK, while three have a nearly significant elasticity: AT, DE, NO. Two countries have a negative significant elasticity: CH, DK. For the remaining countries (FI, FR, IE), the elasticity is not significantly different from zero.

The results of both models are converging for six countries BE, DE, NL, NO, SE and UK and diverging for two countries: AT and DK.

	Elasticity	t-value	Elasticity Elvik	p-value
AT	-0.55	-0.72	1.27	0.01
BE	1.53	1.84	1.35	0.008
BG	0.05	0.14		
CH	-0.70	-0.91	-4.09	0.001
CY	4.41	2.78		
CZ	-1.26	-1.83		
DE	0.60	1.48	1.1	0.07
DK	1.42	2.15	-1.75	0.06
EE	0.28	0.57		
EL	-0.02	-0.05		
ES	0.25	0.38		
FI	0.45	0.73	0.7	0.52
FR	1.18	1.68	0.7	0.54
HU	-0.45	-1.27		
IE	0.95	2.70	0.69	0.43
IS	0.44	0.27		
IT	1.19	4.33		
LT	0.43	2.04		
LU	0.47	0.54		
LV	0.06	0.35		
MT	-1.27	-0.34		
NL	1.62	2.62	1.27	0.05
NO	1.08	1.91	0.92	0.13
PL	0.31	0.45		
PT	1.76	2.66		
RO	0.50	2.02		
SE	1.86	3.43	1.43	0.02
SI	0.46	0.67		
SK	0.15	0.32		
UK	0.64	1.68	3.61	0.001

Table 11. Long-term elasticity's estimates with t-value and p-value for group-mean regressions without and with unemployment rate (Elvik, 2014).

Conclusion

The relationship between road safety measured by the number of fatalities and the economic development measured by the GDP is not straightforward. If the GDP time-series is integrated of order 1 I(1) for all the thirty European countries, there is a mixture of stationary I(0) and non stationary I(1) and I(2) among the time series of the number of fatalities of the European countries. The different nature of the time-series makes complicated the regressions between the time-series transformed by logarithm and leads to use special technics of estimation on macro-panel data.

Concerning the short term regression between the first differences, there is a strong heterogeneity of the short term elasticity with a mean value of 0.79 which is significantly different from 0. Thirteen countries (out of 30) have significant positive short-term elasticities: DK, DE, EE, IE, ES, IT, CY, LV, LT, PT, SK, FI, UK. The short-term relationship is found on only half of the European countries, but when it exists, the relationship is rather elastic with an average of 0.79.

Concerning the long-term relationship, there is a strong heterogeneity of the long-term elasticity with a mean value of 0.63, which is significantly different from zero. The long-term elasticity is significant and positive for 12 countries: BE, DK, FR, IE, IT, LT, NL, NO, PT, RO, SE, UK.

On both regression models, there is a constant decreasing linear trend of the number of fatalities for almost all countries with some exceptions. It is equal to 2.3% per year in the long-term model and 4.8% per year for the short-term model.

Towards a joint short-term and long-term model

Modeling advances and the availability of software that allows the modeling of co-integration between macroscopic time-series panel data and error correction model formulations are valuable tools that open the road for more advanced models. They have the potential to provide better understanding of the short-term and long-term dynamics of the problem.

If the number of fatalities and GDP (logarithmical transformed) are cointegrated, the error term is stationary I(0). In the error-correction model the short-term dynamics depends on the deviation from the equilibrium given by the linear long-term relationships. We expect that the coefficient is negative and if it is significant we can infer about the cointegration of the number of fatalities and GDP.

With a Pooled Mean-Group PMG estimation, there is a common long-run GDP elasticity and heterogeneous short-term dynamics.

When the hypothesis of elasticity and linear time trend homogeneity among countries is unacceptable, the Mean-Group estimation MG is preferred and the estimates are the unweighted means of the individual regression coefficients. Finally we can pool all the estimates by imposing the homogeneity of the long-term elasticities, the linear trends, the speeds of adjustment and the short-term effects.

		PMG	MG	P
LGDP	coef	0.59	0.67	-0.35
	std. err.	0.11	0.49	0.29
	z	5.5	1.4	-1.22
t	coef	-0.057	-0 .026	-0.030
	std. err.	0.003	0.035	0.008
	z	-21.7	-0.75	-3.8
DLGDP	coef	0.49	0.34	0.68
	std. err.	0.29	0 .20	0.11
	z	1.66	1.69	6.15
EC	coef	-0.23	-0.38	-0.15
	std. err.	0.043	0.056	0.05
	z	-5.43	-6.65	-3.03
Log Likelihood		1078.4		

Table 12. Estimates of the error-correction models with PMG, MG and P estimation (Stata procedure xtmpg)

The elasticities are positive and similar to the estimates of the previous long-term models, slighty higher for the MG estimate. The hypothesis of homogenous elasticity and linear time trend can be tested with an Hausmann test which gives the value 0.70 leading to an acceptance of this hypothesis.

The speed of adjustment estimate given by the coefficient of the error-correction term is equal to 0.23, implying a return duration time of 4.3 years in average. The introduction of interventions (differenced) does not change the results. The pooled estimates give a negative non significant long-term elasticity.

Half of the countries have a significant negative speed of adjustment: MT, IS, CY, LU, ES, IS, CH, EL, SK, NL, AT, IE, BE, NO, FR, DE, UK. The first countries in this list have a very high speed of adjustment with a return duration time round 2 years.

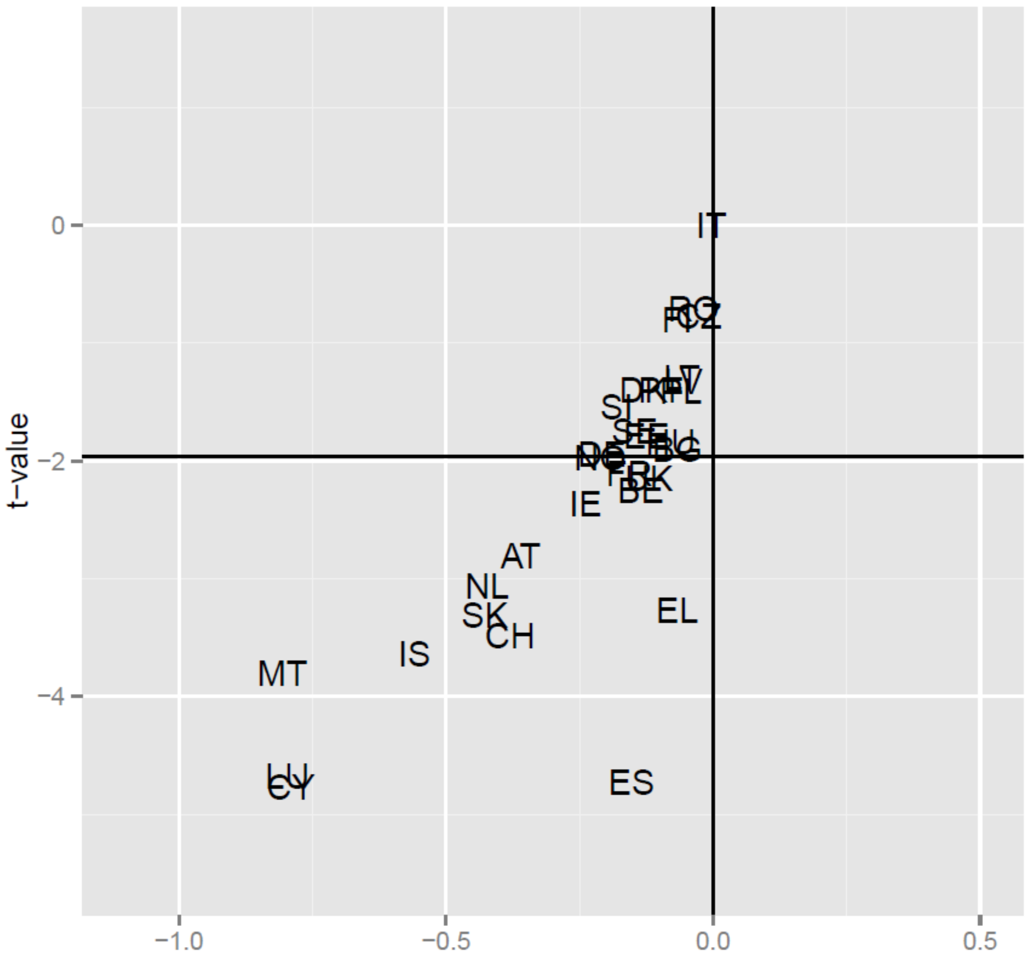

Figure 8. Speeds of adjustment versus t-value from the PMG model by country.

The tests of the hypothesis of no cointegration can be performed using the Stata procedure xtwest, which implements the four statistics and tests designed by Westerlund (2007). The first two are based on group-mean estimates and the last two on panel estimates without and with a correction on the standard deviations. The tests are not significant, when we introduce a constant and a linear trend. We accept the hypothesis of no cointegration between the number of fatalities and GDP, which implies that the model on differences is the most appropriate for predictions.

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