Short-term and long-term effects of GDP on traffic deaths in 18 OECD countries, 1960–2011

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ABSTRACT

Background Research suggests that increases in gross domestic product (GDP) lead to increases in traffic deaths plausibly due to the increased road traffic induced by an expanding economy. However, there also seems to exist a long-term effect of economic growth that is manifested in improved traffic safety and reduced rates of traffic deaths. Previous studies focus on either the short-term, procyclical effect, or the long-term, protective effect. The aim of the present study is to estimate the short-term and long-term effects jointly in order to assess the net impact of GDP on traffic mortality.

Methods We extracted traffic death rates for the period 1960–2011 from the WHO Mortality Database for 18 OECD countries. Data on GDP/capita were obtained from the Maddison Project. We performed error correction modelling to estimate the short-term and long-term effects of GDP on the traffic death rates.

Results The estimates from the error correction modelling for the entire study period suggested that a one-unit increase (US$1000) in GDP/capita yields an instantaneous short-term increase in the traffic death rate by 0.58 ($p<0.001$), and a long-term decrease equal to −1.59 ($p<0.001$). However, period-specific analyses revealed a structural break implying that the procyclical effect outweighs the protective effect in the period prior to 1976, whereas the reverse is true for the period 1976–2011.

Conclusions An increase in GDP leads to an immediate increase in traffic deaths. However, after the mid-1970s this short-term effect is more than outweighed by a markedly stronger protective long-term effect, whereas the reverse is true for the period before the mid-1970s.

INTRODUCTION

In 2013, 1.25 million lives worldwide were lost on the roads, which makes traffic crashes the ninth leading cause of death.[1] It is thus of great importance to get a better understanding of the driving forces behind changes in traffic deaths. The present paper will focus on the role of economic development as indicated by per-capita gross domestic product (GDP).

Previous research shows that increases in GDP are associated with increases in traffic deaths; this is a short-term effect mainly due to the increased road traffic induced by an expanding economy. However, at least in high-income countries, there seems to exist a long-term effect of economic growth that is manifested in improved traffic safety and reduced rates of traffic deaths. Extant research in the field tends to focus on either the short-term, procyclical effect, or the long-term, protective effect. However, both of these effects need to be considered jointly in order to assess the net impact of GDP on traffic mortality. In the present paper, we achieve this by analysing cross-sectional time series data for 18 affluent countries spanning the time period 1960–2011.

BACKGROUND

The relation between economic fluctuations and population health is complex and seemingly contradictory. This may explain why the received wisdom concerning this relationship has undergone some quite substantial shifts. It is clear that economic downturns in past historical centuries led to severe malnutrition and starvation and thus worsened population health. Economic growth, on the other hand, was conducive to education, improved sanitation and living conditions and, in the end, lowered mortality.[2,3] However, as demonstrated by Preston,[4] there is a diminishing health return to economic growth, and there are even indications that economic downturns in highly industrialised societies may improve population health. The explanation to this counterintuitive finding is that although a downturn in all probability has a detrimental health effect on those who are severely hit, for example, by losing their jobs, this negative effect may be more or less offset by a beneficial health effect on the remaining, and much larger, part of the population. Several plausible mechanisms underlying the latter effect have been suggested and substantiated. A slowdown in the economy is thus associated with reduced overtime and work-related stress, less driving and car crashes, less air pollutions and reduced intake of unhealthy products such as alcohol and tobacco.[5–7] Already in the early 20th century, there were reports[8] suggesting that economic booms were associated with above average mortality, whereas the opposite was true for economic downturns. However, these results were ignored for a long time, probably because they appeared to run counter to intuition.[9]

The investigation by Ruhm[7] was one of the first well-designed studies in the field; on the basis of fixed-effects modelling of US state data for the period 1972–1991, he found that recessions are associated with lowered all-cause mortality. More detailed, cause-specific, analyses revealed that traffic deaths especially decreased during bad times. The procyclical relation between macroeconomic conditions and traffic deaths is echoed in other single-country studies, including Neumayer,[10] who analysed German state-panel data, Farmer[11] using US monthly time-series data and studies relying on annual US state-panel data,[12,13] as well as in large-scale studies based on cross-sectional time-series data covering a large number of countries[14–17] (see Hakim *et al*[18] for a review of older studies pointing in the same direction).

Various mechanisms underlying the procyclical effect on traffic deaths have been suggested in the literature. The most self-evident is that increased income tends to increase exposure, that is, driving, including commuting and freight transportation.[18] Macroeconomic fluctuations also tend to affect the composition of drivers in a way that impacts on traffic risks. Thus, young people, who have an elevated accident risk, are often more likely to become unemployed and thus drive less compared to others in bad times. Further, the number of inexperienced drivers may decrease in recessions due to a decreased number of new driving license holders.

However, considering the steady growth in GDP and the marked downward trend in traffic death rates in affluent countries during the last half-century,[19] there must reasonably exist some mechanism countervailing the procyclical effect. In fact, although the procyclical short-term effect of GDP on traffic deaths seems plausible and well substantiated empirically, a long-term protective effect seems equally likely. Thus, safer roads, safer vehicles[20 21] and improved medical treatment[22 23] are three factors that have been found important for improving traffic safety and reducing traffic deaths, and these three factors are in all probability correlated with GDP. Additional efficient preventive measures that are likely to be linked to GDP include speed limits,[24 25] seat-belt usage,[26] and legal maximum alcohol limits for driving.[27] In regard to empirical evidence of a protective effect, the studies by Kopits and Cropper[28] and van Beeck *et al*,[19] based on data for a large number of countries, suggest that increasing prosperity is protective against traffic deaths in developed countries.

In conclusion, the hypothesis of a procyclical short-term and the hypothesis of a protective long-term effect of GDP on traffic deaths seem well corroborated and empirically supported. However, extant research has tended to focus on one or the other of these effects, but to get insights about the net effect it is necessary to consider them jointly by applying a more comprehensive approach. Such an approach is indeed a logical sequel of two of the more recent studies in the field.[15 16] Although both of them focus the procyclical short-term effect, Chen[16] hints at possible beneficial effects of economic prosperity on road safety from a long-term perspective, whereas Yannis *et al*[15] emphasise that future research should also consider the long-term relationship between GDP and traffic deaths by applying the type of statistical techniques that we will actually make use of. The main aim of our study is thus to apply a modelling technique that estimates the short-term as well as long-term impact of GDP on traffic deaths.

However, there are two additional topics that we will address; the possibility of a structural shift and the potential impact of seat belt legislation. On the basis of data for 21 OECD countries, van Beeck *et al*[19] report a reversal in the cross-sectional relation between GDP and traffic death rates; the correlation was positive prior to the mid-1970s, thereafter it became negative. A plausible explanation of this shift, offered by the authors, is that in the early, less prosperous period, there was a stronger link between GDP and exposure (driving) than in the later period when mobility had levelled off. In this later period, GDP instead became protective by facilitating, for example, improvements in traffic infrastructure. To investigate whether a corresponding shift is present in the temporal association between GDP and traffic deaths, we analysed two subperiods, 1960–1975 and 1976–2011.

Although it would be of interest to include additional factors potentially impacting traffic death rates, lack of comparable data makes us confine ourselves to one additional factor, namely, the implementation of seat belt legislation. Seat belt use is considered to be the single most effective means of reducing injuries in the event of a motor vehicle crash.[26] Mandatory seat belt laws should thus have a considerable potential in affecting traffic mortality rates. This is also borne out in a review of evaluations of such laws.[26] Such evaluations are typically before- and after-trials without control areas, although there are certainly more sophisticated studies as well, for example[29] relying on US state-panel data.

DATA AND METHOD

The study comprises 18 OECD countries, and the longest observation period is 1960–2011, although it is appreciably shorter for some countries (see table 1). Age-specific road traffic mortality data for women and men were obtained from the WHO Mortality Database (Geneva). (Table 2 shows which ICD codes were included.) Age-standardised mortality rates (number of deaths per 100 000 population) were constructed following WHO World Standard.[30] Different ICD classifications have been used during the study period, from ICD-7 to ICD-10. Possible influences of revisions of ICD classification were captured by dummy variables. Missing mortality data (table 1) were imputed through linear interpolation; dummy variables were created for these years. Data on per-capita GDP, expressed in Purchasing Power Parity (PPP), converted into US dollars of 1990 years value, were obtained from the Maddison Project.[31] We performed age-specific analyses in addition to analyses for the adult population (20+), which we regard as the main outcome. Data on mandatory seat belt legislation were obtained from ref. [32] and various national sources. A dummy variable was created that took the value 1 at the year of legislation and onwards, and 0 otherwise. An alternative coding assumed a

Table 1 Descriptive statistics (period average) for GDP/capita (US$1000) and traffic deaths per 100 000 in the age group 20 years and above

Country	Observation period	GDP	Mortality
Australia	1960–2011	13.05	20.55
Austria	1960–2009	11.26	21.59
Belgium	1960–2010	11.92	21.94
Canada	1960–2009	13.46	18.93
Denmark	1960–2009	13.35	13.94
Finland	1960–2009	10.9	14.63
France	1960–2010	11.79	20.85
Germany	1960–2011	11.27	17.48
Ireland	1960–2009	9.17	14.82
Italy	1960–2010	9.98	18.97
Japan	1960–2011	10.53	13.07
New Zealand	1960–2009	11.49	13.16
Norway	1960–2010	13.07	19.89
Sweden	1960–2009	12.8	8.98
Switzerland	1960–2009	15.71	10.69
The Netherlands	1960–2010	12.54	16.97
UK	1960–2010	12.56	10.24
USA	1960–2011	16.92	21.78
Total		12.32	16.58

GDP, gross domestic product.

Table 2 ICD codes for traffic mortality data

	Cause of death	ICD-10	ICD-9	ICD-8	ICD-7
1	Pedestrian injured in collision with two-wheeled or three-wheeled motor vehicle	V02			
2	Pedestrian injured in collision with car, pick-up truck or van	V03			
3	Pedestrian injured in collision with heavy transport vehicle or bus	V04			
4	Pedal cyclist injured in collision with two-wheeled or three-wheeled motor vehicle	V12			
5	Pedal cyclist injured in collision with car, pick-up truck or van	V13			
6	Pedal cyclist injured in collision with heavy transport vehicle or bus	V14			
7	Motorcycle rider injured in transport accident	V20–V29			
8	Occupant of three-wheeled motor vehicle injured in transport accident	V30–V39			
9	Car occupant injured in transport accident	V40–V49			
10	Occupant of pick-up truck or van injured in transport accident	V50–V59			
11	Occupant of heavy transport vehicle injured in transport accident	V60–V69			
12	Bus occupant injured in transport accident	V70–V79			
13	Person injured in unspecified motor vehicle accident, traffic	V89.2			
	Total of 1–13		B471	A138	A138

gradual impact where the legislation year was coded 0.5, next year 0.75 and then 1.

We included an interaction term to capture the possible excess effect of GDP during the years of the financial crisis. The interaction term was constructed as follows:

$$\mathrm{GDPcrisis}_{it} = \mathrm{GDP}_{it} \times \mathrm{Crisis}_{it} \quad (1)$$

where Crisis is a country-specific variable that takes the value 0 in years with no recession, 0.25 in years with a 1-quarter recession and so forth, and 1 in years with 4 quarters of recession. The common recession definition was used, that is, that a recession occurred when GDP has contracted at least two consecutive quarters. Data were obtained from Eurostat and OECD.

We used two different methodological techniques to investigate the relation between GDP and traffic deaths. The rationale for this is that triangulating findings from different methods should reduce the risk of obtaining method-bound results. Both methods explore within-country variation only (fixed-effects models). The first method relies on the error correction model (ECM), whereas the second method is based on a model including contemporaneous GDP (to gauge the short-term effect), and a weighted sum of past GDP (to assess the long-term effect). A brief description of the two methods is given below.

Although error correction modelling is a standard tool in economics, it is, as pointed out by De Boef and Keele,[33] underused in other branches of social science. Error correction modelling is useful when short-term and long-term dynamics are focused;[34] its feasibility in the present context is highlighted by Yannis *et al*,[15] although they described it as demanding and did not apply it. We chose the single-equation approach for estimating our ECMs. The simulation results presented by Durr[35] suggest that this approach performs at least as well as the more complex two-step procedure developed by Engle and Granger.[36] Following standard specification,[35 37 38] our ECM looks as follows in its most basic form:

$$\Delta\mathrm{Mortality}_{it} = \alpha + \beta_0\Delta\mathrm{GDP}_{it} + \beta_1\mathrm{Mortality}_{it-1} + \beta_2\mathrm{GDP}_{it-1} + \varepsilon_{it} \quad (2)$$

In this equation, β_0 indicates the instantaneous, short-term effect of a change in GDP on mortality, whereas β_1 estimates the speed at which the long-term effect operates. If such an effect does exist, the estimate of β_1 should be negative and statistically significant. The model assumes that the long-term effect decays geometrically; thus $1-(-1\times\beta_1)$ corresponds to the lag parameter in a lag scheme with geometrically declining lag weights (which we will make use of in our second modelling approach). The total long-term effect is calculated as $\beta_2/(-1\times\beta_1)$.

Prior to estimating an ECM, it is necessary to carry out some key tests. These analyses comprised two steps; first, we tested for unit root using the Fisher-type ADF panel unit root test.[39] If the independent and dependent variables prove to be integrated of the order $I(1)$, the next step is to test whether they are cointegrated. We used the panel cointegration tests developed by Westerlund,[40] denoted P_t and P_a. Simulation results[40] indicate that the tests have better small-sample properties and power than other commonly used panel cointegration tests, eg, the Pedroni tests.[41] The simulations further indicate that each of the two tests has its own merits and limitations and should thus be considered jointly. The tests accommodate various forms of heterogeneity and also generate p values that are robust against cross-sectional dependencies via bootstrapping.[40] Provided the tests indicate cointegration, it is appropriate to proceed to error correction modelling.

Our second methodological technique is a modified version of an approach that is commonly applied in alcohol epidemiology to assess a relation that involves a marked lag-structure, for example, the relation between per-capita alcohol consumption and liver cirrhosis mortality.[42] We will refer to the model as weighted lag model (WLM), and it specified as follows:

$$\Delta\mathrm{Mortality}_{it} = \alpha + \beta_0\Delta\mathrm{GDP}_{it} + \beta_1\Delta\mathrm{GDPW}_{it} + \varepsilon_{it} \quad (3)$$

In this model, β_0 indicates the instantaneous, short-term effect of a change in GDP on mortality, whereas the long-term effect is assessed by the estimated effect of a weighted sum of lagged values of GDP, computed as follows:

$$\mathrm{GDPW}_{it} = (\lambda\mathrm{GDP}_{it-1} + \lambda^2\mathrm{GDP}_{it-2} + \lambda^3\mathrm{GDP}_{it-3} + \cdots + \lambda^n\mathrm{GDP}_{it-n}) / \sum_{k=1}^{n}\lambda^k \quad (4)$$

The lag scheme was truncated at lag 15, and the lag parameter (λ) was fixed a priori to the value estimated by the ECM, as described above. In the age-specific estimations of model (4), we used the estimated lag parameter (λ) from the corresponding ECM. As noted above, the observation period for the mortality data starts 1960. However, to not lose observations in the analyses that include the weighted GDP-indicator, the series for GDP begin 1945.

All estimated models included the crises variable (as specified above), dummy variables for the interpolations and various ICD classifications. We also included country-specific dummies to account for the possible heterogeneity due to unobserved characteristics that may remain after differencing.

A complication with time-series cross-sectional data is the likely presence of serial and spatial (cross-country) dependence of the errors, which yields a downward bias of the OLS estimates of the SEs. We thus chose a modelling technique that addresses this complication in two ways. First, it accounts for spatial dependence of the errors by applying the more conservative panel-corrected SEs suggested by Beck and Katz.[43] Simulation results indicated that the panel-corrected SEs performed excellently; the procedure also yields a correction for any panel heteroscedasticity.[43] Secondly, our modelling technique accounts for serial dependence by including panel-specific autoregressive parameters for estimation of residual autocorrelation.

On the basis of the panel-corrected SEs, we used the Bewley transformation regression[44] (also described in De Boef and Keele[33]) to estimate SEs and significance levels of the long-term effect in the ECMs.

As a robustness test, we estimated equation (2) by using a heterogeneous method, that is, Pesaran and Smith's[45] mean group estimator (MG), which accommodates heterogeneous effects (slope coefficients) across panels.

All statistical analyses were performed with Stata V.14 (StataCorp, College Station, Texas, USA).

RESULTS

Descriptive statistics are found in table 1. As can be seen in figure 1, all countries experienced a steady growth in GDP during the study period. Another trait common to most countries is the decreasing trend in the death rate following an initial increase, although the length of the initial increase varies across countries.

Mortality data are missing 1998–2001 for Belgium, 2004–2005 for Italy, 2000 for UK, 2005 for Australia and 2006 for Canada.

The outcome of the panel unit root tests of GDP and various traffic death rates (table 3) suggests that for most of the eight variables the null hypothesis of unit root cannot be rejected by any of the four statistics, and the null cannot be rejected for any of the variables by the Pm-test, which is a recommended test in large panels.[39] We thus regard all our variables as having a unit root and proceed to test whether the relation between GDP and traffic deaths is cointegrated. Table 4 shows that the null hypothesis of no cointegration was rejected by at least one of the two panel tests in all age groups, except for the age group 0–19 years. We thus proceed to the estimation of the ECMs for the age groups above 19 years.

Table 5 displays the estimates of the ECMs. According to the outcome, the short-term effect implies that a one-unit increase (US$1000) in GDP/capita yields an instantaneous increase in the total death rate by 0.58 in the adult population (20+). As expected, the long-term effect has a negative sign and is estimated at −1.59. Both of these estimates were strongly statistically significant. The estimates from the alternative model (WLM), displayed in table 6, were fairly consistent with those from the ECM. All age-specific estimates but one were statistically significant; the variation in effects across age groups does not show any systematic pattern.

The interaction term (GDPcrisis) capturing the possible excess effect of GDP during the years of the financial crisis was clearly insignificant in all model estimations (estimates not shown). The dummy variables for changes in ICD classifications were also statistically insignificant, except for the ICD-10 dummy variable that was significant in some of the age-specific analyses (estimates not shown). The estimated effects of seat belt legislation had the expected negative sign, but did not reach statistical significance in any of the age groups (estimates not shown). The outcome from the robustness test (reported in online supplementary appendix) where we used a method[45] that allows for heterogeneous effects across panels is consistent with the estimates reported above.

The period-specific model estimates (table 5, last rows) suggest a structural shift in the relation between GDP and traffic deaths. The protective long-term effect is about equally strong in both periods, whereas the procyclical short-term effect is markedly stronger in the early period than in the late period (t-value for difference=3.15, $p<0.002$). Further, in the late period the protective effect outweighs the procyclical effect, whereas the reverse is true for the early period.

The diagnostics of the residuals are satisfactory with regard to stationarity, whereas the autocorrelation is significant in the models for the three oldest age groups, but not in the model for our main outcome (20+). The cross-unit correlations are not very strong, but still statistically significant. However, this should not be a concern as the SEs we use are corrected for this kind of spatial correlation as described above. (The uncorrected SEs in the model for our main outcome (20+) are about 35% smaller.)

DISCUSSION

Previous research suggests that an increase in GDP is associated with an increase in traffic deaths; the most important mechanism underlying this relation is likely increased private and commercial road transport spurred by an expanding economy. On the other hand, there is also empirical support for the obvious assumption that economic growth creates resources that can be invested in safer traffic infrastructure leading to a long-term decrease in death rates. In the present study, we have strived to integrate these two strands of the literature and to apply a more comprehensive modelling approach in which the short-term and long-term effects were estimated jointly. Our results are indeed in line with these previously reported findings that road mortality is procyclical in the short run, but protective in the long run. However, the novelty of our findings is that they indicate the net of these opposing effects. In the analysis of the entire period, the long-term effect was markedly stronger than the short-term effect. However, period-specific analyses revealed a structural break implying that the protective effect outweighs the procyclical effect only in the period after 1975, whereas the reverse is true for the period 1960–1975. This outcome accords with the common pattern of a positive trend in GDP accompanied by an initial increase in the death rate, which was followed by a decreasing trend.

Our findings should also be regarded in a wider context. As noted in the introduction, there is a large number of studies suggesting that overall mortality, a common proxy for population health, is procyclical. It is worth pointing out that this is to a substantial extent driven by the procyclical character of traffic deaths and that the long-term protective dynamics are typically not considered in this literature.

Our finding that there is no excess effect of the economic crisis that bursted in the fall of 2007 (the Great Recession) accords with the outcome reported in a study[49] with a similar design as the present study. That investigation found a statistically significant effect of the unemployment rate on suicide, but this effect was thus not reinforced by the Great Recession. One possible reason for the absence of any significant impact of seat belt legislation is that the implementation of this regulation was fairly synchronised across countries, occurring typically in 1975

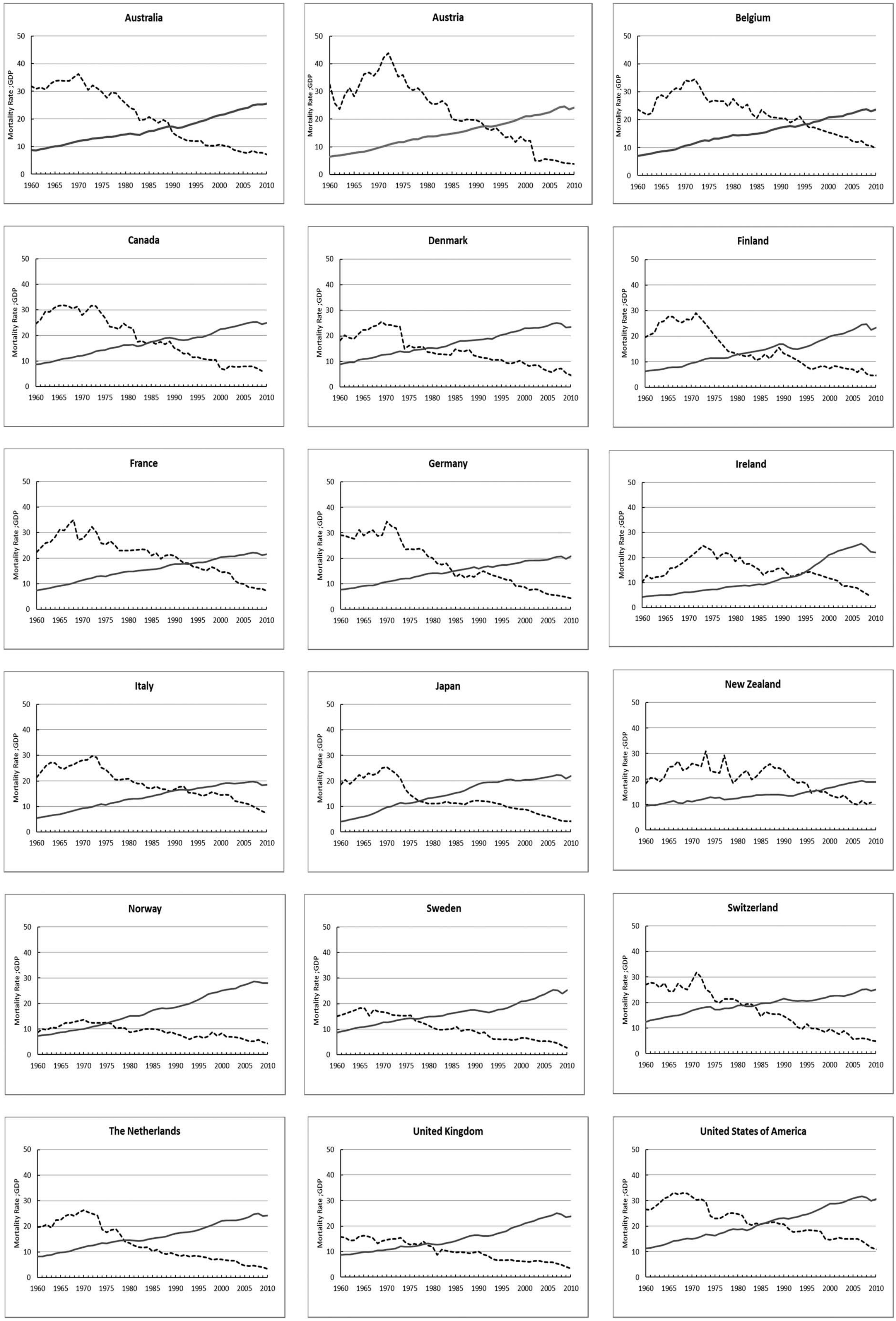

Figure 1 Trends in GDP/capita (US$1000, solid line) and traffic deaths per 100 000 in the age group 20 years and above (dashed line). GDP, gross domestic product.

Table 3 Fisher-type ADF panel unit root tests of H0: all panels contain unit roots against H1: at least one panel is stationary

Test		GDP/capita		0–19		20–34		35–49		50–64		65+		0+		20+	
		Statistic	p Value	Statistic	p Value	Statistic	p Value	Statistic	p Value	Statistic	p Value	Statistic	p Value	Statistic	p Value	Statistic	p Value
Inverse χ^2	P	14.12	0.999	31.42	0.686	30.32	0.735	40.96	0.262	45.08	0.143	42.12	0.223	30.80	0.71	32.10	0.66
Inverse normal	Z	2.84	0.998	−0.71	0.238	−0.43	0.334	−1.78	0.038	−2.25	0.012	−1.86	0.032	−0.55	0.29	−0.74	0.23
Inverse logit	L	2.81	0.997	−0.64	0.262	−0.39	0.348	−1.62	0.054	−2.05	0.022	−1.70	0.046	−0.50	0.31	−0.67	0.25
Modified inv. χ^2	Pm	−2.58	0.995	−0.54	0.706	−0.67	0.748	0.59	0.279	1.07	0.142	0.72	0.235	−0.61	0.73	−0.46	0.68

Table 4 Westerlund panel cointegration tests of H0: no cointegration for panels against H1: cointegration for all panels

Test	0–19			20–34			35–49			50–64			65+			0+			20+		
	Statistic	p Value	Robust P	Statistic	p Value	Robust P	Statistic	p Value	Robust P	Statistic	p Value	Robust P	Statistic	p Value	Robust P	Statistic	p Value	Robust P	Statistic	p Value	Robust P
Pa	−7.27	0.875	0.781	−9.99	0.233	0.255	−12.39	0.008	0.035	−10.71	0.109	0.135	−10.87	0.090	0.131	−9.69	0.300	0.255	−11.48	0.039	0.057
Pt	−9.36	0.326	0.369	−10.53	0.037	0.100	−12.51	<0.001	0.004	−11.46	0.002	0.025	−11.08	0.008	0.049	−11.21	0.005	0.030	−12.08	<0.001	0.016

Robust P are p values which are robust against cross-sectional dependencies obtained via bootstrapping (number of bootstraps was set to 800).

Table 5 Estimates of GDP/capita (US$1000) on traffic death rates (per 100 000) based on ECMs

Age group	N	ΔGDP_t			$Mortality_{t-1}$			GDP_{t-1}			Long-term effect			Residual diagnostics						
														1		2		3		4
		Est	SE	p Value	Est	SE	p Value	Est	SE	p Value	Est	SE	p Value	Statistics	p Value	Statistics	p Value	Statistics	p Value	Correlation
20+	906	0.58	0.18	0.001	−0.10	0.02	<0.001	−0.16	0.02	<0.001	−1.59	0.02	<0.001	−18.89	<0.001	1.40	0.25	12.03	<0.001	0.183
20–34	906	0.90	0.20	<0.001	−0.09	0.02	<0.001	−0.14	0.02	<0.001	−1.50	0.02	<0.001	−19.48	<0.001	0.44	0.51	6.52	<0.001	0.151
35–49	906	0.32	0.17	0.06	−0.12	0.02	<0.001	−0.13	0.02	<0.001	−1.05	0.02	<0.001	−19.64	<0.001	8.62	0.01	9.02	<0.001	0.190
50–64	906	0.48	0.21	0.02	−0.11	0.02	<0.001	−0.17	0.03	<0.001	−1.63	0.02	<0.001	−19.51	<0.001	8.77	0.01	10.53	<0.001	0.195
65+	906	0.78	0.33	0.02	−0.09	0.02	<0.001	−0.25	0.04	<0.001	−2.72	0.03	<0.001	−19.29	<0.001	4.70	0.04	10.14	<0.001	0.167
20+;<=1975	270	2.49	0.66	<0.001	−0.27	0.07	<0.001	−0.26	0.12	0.030	−0.98	0.14	<0.001	−17.25	<0.001	2.65	0.12	7.98	<0.001	0.263
20+; >1975	636	0.43	0.10	<0.001	−0.08	0.02	<0.001	−0.07	0.02	<0.001	−0.87	0.01	<0.001	−19.14	<0.001	1.64	0.22	1.89	0.06	0.168

Residual diagnostics:
1. Pesaran's panel data unit root test for stationarity (CIPS, robust against cross-sectional dependencies).[46] H0: panels contain unit roots; H1: panels are stationary.
2. Wooldridge test for autocorrelation in panel data.[47] H0: no first-order autocorrelation; H1: first-order autocorrelation.
3. Pesaran's test of cross-sectional independence.[48] H0: cross-units are independent; H1: cross-units are dependent.
4. Averaged absolute cross-panel correlation coefficient.
ECMs, error correction models; GDP, gross domestic product.

Table 6 Estimates of GDP/capita (US$1.000) on traffic death rates (per 100 000) based on WLMs

		ΔGDP_t			$\Delta GDPW_t$			Residual diagnostics						
								1		2		3		4
Age group	N	Est	SE	p Value	Est	SE	p Value	Statistics	p Value	Statistics	p Value	Statistics	p Value	Correlation
20+	906	0.67	0.19	<0.001	−1.31	0.47	0.005	−19.17	<0.001	1.22	0.285	14.27	<0.001	0.193
20–34	906	1.02	0.22	<0.001	−1.52	0.56	0.006	−19.61	<0.001	0.44	0.516	8.78	<0.001	0.154
35–49	906	0.39	0.18	0.027	−1.04	0.42	0.013	−19.71	<0.001	8.92	0.008	9.54	<0.001	0.160
50–64	906	0.53	0.22	0.015	−1.31	0.55	0.017	−19.83	<0.001	9.45	0.007	10.83	<0.001	0.195
65+	906	0.93	0.35	0.007	−1.70	0.78	0.029	−19.50	<0.001	4.97	0.040	11.51	<0.001	0.179

Residual diagnostics:
1. Pesaran's panel data unit root test for stationarity (CIPS, robust against cross-sectional dependencies).[46] H0: panels contain unit roots; H1: panels are stationary.
2. Wooldridge test for autocorrelation in panel data.[47] H0: no first-order autocorrelation; H1: first-order autocorrelation.
3. Pesaran's test of cross-sectional independence.[48] H0: cross-units are independent; H1: cross-units are dependent.
4. Averaged absolute cross-panel correlation coefficient.
GDP, gross domestic product; WLMs, weighted lag models.

or 1976. Further, the degree and pace by which legislation affected actual seat belt usage probably varies between countries.

Before concluding, we wish to highlight the major strengths and limitations of our study. Our findings are based on two conservative methods each of which has its own, but not identical weaknesses. Although the consistency of the outcomes thus seems reassuring, the risk of omitted variable bias can never be dismissed in the present kind of research. However, it should be noted that although there are numerous factors that affect the traffic death rate, only omitted factors that also are synchronised with changes in traffic mortality as well as GDP would bias our outcomes. Our data comprise a large number of countries spanning quite a long time period. However, these data represent affluent countries during a fairly prosperous historical epoch, which limits the generalisability of our findings.

In conclusion, an increase in GDP leads to an immediate increase in traffic deaths. However, after the mid-1970s this short-term effect is more than outweighed by a markedly stronger protective long-term effect, whereas the reverse is true for the period before the mid-1970s.

What is already known on this subject

Increases in gross domestic product (GDP) lead to increases in traffic deaths, plausibly due to the increased road traffic induced by an expanding economy. However, there also seems to exist a long-term effect of economic growth that is manifested in improved traffic safety and reduced rates of traffic deaths. It is not known which of these opposing effects that is dominating.

What this study adds

Our study, based on cross-sectional time-series data for 18 OECD countries spanning the period 1960–2011, suggests that an increase in GDP leads to an immediate increase in traffic deaths. However, after the mid-1970s this short-term effect is more than outweighed by a markedly stronger protective long-term effect, whereas the reverse is true for the period before the mid-1970s.

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