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On the relationship between congestion and road safety in cities

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ABSTRACT

We empirically examine the relationship between traffic congestion and deaths in road accidents at the city level. We use panel data from 129 large cities in Europe for the period 2008–2017. We find strong evidence of a quadratic relationship between congestion and deaths in accidents, using both parametric and non-parametric econometric techniques. The threshold point at which the relationship between congestion and deaths in accidents is reversed and becomes positive occurs when congestion results in about a 30 per cent increase in travel time compared to a free flow situation. For most congested cities, any effective measure to contain congestion may also lead to better safety outcomes.

1. Introduction

Economic and social transformation has rapidly increased mobility demand leading to a growth in car use, which has been aggravated by urban sprawl and new commuting needs. City planners are increasingly aware of the need to maintain a balance between facilitating mobility – essential for cities' economic and social vitality – and managing or mitigating its negative effects. Therefore, in urban areas, addressing the negative externalities of transport,[1] including congestion, road accidents and pollution, is considered an essential challenge of modern times. Among these externalities, the European Union considers that congestion needs urgent attention, given the expected growth in transport demand and the associated economic cost: nearly 1% of annual European GDP (EU Commission, 2018; Christidis and Ibáñez, 2012). There is no doubt that congestion is, above all, an urban phenomenon, either in the core of large cities or on the interurban roads accessing and connecting urban hubs. Cities are at the forefront of economic growth, employment, knowledge and innovation – around 85% of the EU's GDP is generated in European cities (European Commission, 2017) – which could be at risk or, at least, dampened by the inefficiencies produced by congestion. Moreover, congestion is set to continue being a huge burden on future society, with congestion costs projected to increase by about 50%, to nearly €200bn annually, by 2050 (European Commission, 2011).

Congestion is not only a negative externality in its own right, but it can also aggravate other negative externalities. Indeed, the interaction of congestion with other externalities like pollution has fueled recent research interests. These studies have shown how congestion correlates with higher emissions of pollutants, producing unfavorable health outcomes and undermining quality of life (see Currie and Walker, 2011; Bigazzi and Figliozzi, 2013; Bel and Rosell, 2013; Beaudoin et al., 2015 and Simeonova et al., 2018, among others). However, the effects of road congestion on road safety outcomes have received less attention, particularly in urban areas, and the empirical literature is characterized by delivering mixed results and conclusions, indicating complexity in the relationship between these two externalities.

The interrelations between congestion and accidents are of great importance for sustainable mobility in urban environments. First, because of the high economic and social cost of accidents when added to the costs of congestion. In the EU, the external economic costs of road accidents were estimated at 1.7% of GDP for 2008 and the annual number of fatalities exceeds 25,000, with a further 135,000 receiving serious injuries. Urban areas, moreover, are shown to account for 67% of these accidents and 37% of fatalities. Second, because any action designed to deal with congestion might have an indirect effect on road safety outcomes, there is a need to develop a good understanding of the relationship between congestion and road safety before producing transport policy.

This paper is the first to draw on an international database of European cities to empirically estimate the impact of congestion on urban road safety outcomes. While most studies in the literature evaluating this relationship have focused on specific roads (highways or road networks) or single cities (case studies), there is a dearth of papers examining the relationship across several cities. Here, we consider a total of

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[1] An externality is the cost or benefit that affects a party who did not choose to incur in that cost of benefit, and it is not reflected in market prices.

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129 European cities – each with more than 300,000 inhabitants – in 18 countries, between 2008 and 2017, giving us a total of 1090 observations. We apply panel data econometric techniques to empirically contribute to shedding light on the complex relationship between congestion and road safety outcomes. Our parametric and non-parametric results indicate that congestion effects on road safety outcomes are non-linear. We find a quadratic relationship that suggests that increases in congestion in less congested cities moderately reduce the number of deaths per capita (safety effect). Yet, an increase in congestion is found to have an adverse, detrimental effect on road safety when congestion levels are high (detrimental effect). Specifically, we find that a rough threshold between both effects is found around 30 per cent increase in travel time compared to a free flow situation.

The remainder of this paper is organized as follows. The next section provides a comprehensive review of the related literature relevant to our study. Section 3 explains the empirical approach by describing our data and the methods employed. Section 4 displays our main results and the article finishes with some discussion and concluding remarks in section 5.

2. Related literature

Existing research has not yet reached an agreement on the impact of traffic congestion on road safety outcomes (Wang et al., 2013a). One strand of the literature uses volume to capacity ratios (V:C ratios) as a proxy of congestion. This literature generally find support to the Shefer's hypothesis (Shefer, 1994), which establishes a negative relationship between congestion and road safety, mainly due to speed decrease (Shefer and Rietveld, 1997; Ivan et al., 2000; Lord et al., 2005 among others). Another strand of empirical papers proxy congestion with average daily traffic (ADT) as a measure of traffic density. Although some of these also find support to the negative relationship hypothesis (Martin, 2002; Wong et al., 2007), most studies taking this approach find the opposite result concluding that road safety deteriorates with traffic density (Voigt and Bared, 1998; Milton and Mannering, 1998 and Lord et al., 2005; among others).

However, these works were not specifically examining congestion, what had typically been overlook in the early literature (Wang et al., 2013). The closest approach was to distinguish the effects by time of the day (Peak vs. valley), what in the case of V:C papers served to consolidate the positive externality of congestion (Shefer and Rietveld, 1997; Baruya, 1998). Indeed, this literature contrasts with another vast group of more recent empirical studies using congestion indexes, which find either that congestion has little or no impact on the frequency and severity of accidents (Noland and Quddus, 2005; Wang et al., 2009; Quddus, 2010), or even more fatal and serious injury accidents, especially during peak times (Wang et al., 2013b; Shi et al., 2016).

An intimately related strand of literature is the one has focused on evaluating the effects produced by congestion charges. This policy, has proved effective in reducing congestion, but it is also expected to produce indirect road safety effects by means of changing traffic flow conditions. Research shows an overall safety improvement due to the congestion charging scheme in London (Transport for London, 2007; Lee et al., 2012; Green et al., 2016), although Noland et al. (2008) find mixed or less positive results.

One of the most important aspects of the literature review is the evidence of the non-linear relationship between traffic density and road safety outcomes. Interestingly, some works find that accident rates increased more steeply once certain high traffic thresholds had been crossed (See Kononov, 2008; Harwood et al., 2013), what suggests exponential or parabolic relationships with the highest crash rates being recorded at low and high traffic densities. This evidence is in line with Dickerson et al. (2000), who had estimated that the marginal accident rate rises substantially above the average rate at higher traffic flows, pointing to the presence of external accident costs (see Maddison et al., 1996; Newbery, 1988). Other papers identifying non-linear relationships – even if some were finding decreasing relationships – are Zhou and Sisiopiku (1997), Ivan et al. (2000) and Lord et al. (2005). This suggests that models assuming linear relationships might neglect possible non-linearities. If the relationship for accidents involving injuries and fatalities become positive at the highest values of the V:C ratio (high congestion) or other traffic density metrics, this could be interpreted as being the consequence of more traffic conflicts attributable to congestion.

Some studies provide different reasons to explain the positive relationship between congestion and safety outcomes at highly congested scenarios. Although fewer (serious) collisions are expected to occur, for example, within a congested queue on a motorway, the review by Marchesini and Weijermars (2010) indicate that at the tail of the queue more severe rear-end crashes are to be expected, especially if congestion surprises drivers arriving at or already in the queue. According to Elvik et al. (2009), this result can also be explained in urban areas – which is our framework-, where the main roads were built for lower than actual volumes of traffic because, in highly congested scenarios, drivers take diversionary routes, choosing alternative roads and streets less suited for high traffic flows. In line with Zhou and Sisiopiku (1997), they believe that the accident rate (per mile driven) may be high for low traffic V:C ratios because of higher speeds and night-time driving. But this decreases with the increase in the V:C ratio, up to 0.5 for property damage-only accidents and 0.7 (approx.) for injury-related accidents. Thus, the change in traffic conditions from free flow to dense traffic will necessarily result in a negative relationship that associates more traffic with fewer accidents, which is what most of the literature examining V:C ratios has found. Above these V:C ratio values, the accident rate increases again, ultimately displaying a U-shaped functional form that illustrates the negative safety externality produced by congestion that increases exponentially with traffic volumes. Sun et al. (2016) also argue that the increase in the number of crashes is probably due to drivers' frequent lane changes and keeping too close to the vehicle in front. They also point to the complexity of interactions among vehicles as an increasing risk factor.

In this research, we test whether the non-linear relationship between accidents and congestion holds at the city level. Our focus on the urban context represents an important contribution to the existing literature. Indeed, traffic congestion is primarily an urban concern (Bull, 2004; OECD, 2007; Parry et al., 2007) and policy debates about the implementation of measures to deal with congestion are usually centered in cities. Furthermore, traffic accidents in urban roads may differ from accidents in inter-urban roads because many accidents involve pedestrians or cyclists (Ewing et al., 2014; Graham et al., 2003). Hence, it is valuable to examine the relationship between accidents and congestion at the city level.

Few previous studies at the city level tend to focus on just one specific city. In contrast, we adopt a more general approach and take advantage of panel data for a large sample of cities in Europe. Finally, another added value of our analysis is the use of a novel dataset provided by TomTom in which drivers' travel time is collected on actual GPS based measurements for each city. Hence, we use a congestion index that measures the amount of extra travel time experienced by drivers compared to what it would be in local free flow conditions.

3. Methods

3.1. Data bases

We used data on congestion for 130 cities in countries of the EU whose urban population exceeds 300,000 inhabitants. These data are available from 2008 to 2017 and have been obtained from TomTom (https://www.tomtom.com/en_gb/trafficindex). We cross this congestion data with information available in Eurostat. However, there are missing values for some cities/years so that our final sample, with information on both congestion and deaths in accidents, contains 130 cities from 18 countries giving a total of 1090 observations.

Our dependent variable is the number of deaths in road accidents at the city level per year. Data have been obtained from Eurostat. The main explanatory variable is the level of congestion at the city level per year. We use the congestion index built by TomTom.

Following Shi et al. (2016), congestion measures can be broken down into three general categories: density-based, travel time-based and travel speed-based. The TomTom Congestion Index belongs to this second category.

Rather than relying on theoretical models or simulations, TomTom obtains real data on drivers' travel time from its anonymous customers in all cities where it is active. TomTom includes in its analysis local roads, arterials and highways, based on actual GPS based measurements for each city.

The congestion index is built by establishing first a baseline of travel times during uncongested, free flow conditions across each road segment in each city. Then, average travel times across the entire year (24/7) per every vehicle in the entire network of the city are calculated. This information is compared against free flow periods to derive extra travel time.

Hence, the congestion index represents the measured amount of extra travel time experienced by drivers across the entire year in the city due to traffic conditions. For example, a congestion level of 36% corresponds to 36% extra travel time for any trip, anywhere in the city, at any time compared to what it would be in local free flow conditions.[2]

Note that our congestion index is measured in the empirical analysis as a proportion over 1. In order to convert the extra travel time measure into a travel time measure we add 1 to all observations. For example, if the mean extra travel time is 0.2 the travel time measure is 1 + 0.2.

As control variables, we consider different characteristics of the cities or the surrounding region that may have an influence on safety outcomes. First, we consider the total number of inhabitants per year in the city. Furthermore, we consider the population density of the surrounding region that is defined as the number of inhabitants per square kilometer per year at the NUTS 3 level. The gross domestic product (GDP) per capita per year, with data at the region level (NUTS 2 level), is also included as explanatory variable. Finally, we consider an old age dependency ratio, with data per year at the city level. This is the ratio between inhabitants aged 65 and over and the population aged between 20 and 64. Data for all these variables been obtained from Eurostat.

We also consider a variable that measures the network length of the rail system measured in line kilometers as a proxy of the quality of public transportation provided in the city. Note that we only account for rail lines within the city, not rail lines that link the city center with surrounding cities. Data have been obtained from Urban rail and World Metro database websites and websites of operators. Finally, as a proxy of the quality of roads we also include a variable for the share of highways over total kilometers of roads in the city according to the information provided by TomTom. A limitation of this variable is that data are only available for 2017 so that we assign the values of 2017 for previous years. While we may expect that variability over time for cities in our sample in terms of highway expansions is low, this limitation in the availability of data must be taken into account in the interpretation of results for this variable.

3.2. Statistical modelling

The use of count models is common in the analysis of the determinants of road traffic accidents. Our preferred regressions, consistent with the literature, use the Negative Binomial Distribution. The empirical equation to estimate for city c in year t is as follows:

$$\text{Deaths}_{ct} = \alpha + \beta_1\text{Traveltime}_{ct} + \beta_2\text{Traveltime\_square}_{ct} + \beta_3\text{Density}_{ct} + \beta_4\text{GDP per capita}_{ct} + \beta_5\text{Old}_{ct} + \beta_6\text{Share\_highways}_{ct} + \beta_7\text{Rail}_{ct} + \lambda'\text{Country} + \gamma'\text{Year} + \varepsilon \quad (1)$$

The dependent variable in equation (1) is the total number of deaths in road accidents on each city per year. As we mention above, we estimate a negative binomial model in the analysis of the determinants of deaths in accidents so that the city population variable is included as an exposure variable to enable us to interpret the results in terms of rates per capita. As the exposure variable, the coefficient of the population variable is restricted to 1. However, as a robustness check, we also estimate the equation of the determinants of accidents using the Ordinary Least Squares (OLS) method. In this latter case, the dependent variable is expressed in terms of deaths per capita.

The main explanatory variable is the mean travel time in the city per year (1 + Congestion index values). To the test the existence of a non-linear relationship between accidents and congestion, we add the square of the travel time variable as the explanatory variable (traveltime_square).[3]

From a theoretical point of view, we should consider the potential endogeneity bias due to the simultaneous determination between accidents and congestion. Indeed, it could be argued that accidents may also have an influence on the congestion records of a city.

In this regard, our data for congestion refer to a mean annual average value for the entire city. Furthermore, our variable for safety refers to deaths in accidents, meaning only the most serious accidents are considered. These represent a very low proportion of total trips made in a city during a year. This point made can be illustrated by means of an example. The number of deaths in road accidents are about 300 per year in London, the city with the maximum values for this variable every year in our sample. According to Transport for London (TfL) annual reports, the number of car trips per day are about 26 million. TomTom does not specify the number of car trips involved in the calculation of the congestion index, but they specify that the kilometers of GPS data from actual driven trips used to calculate the congestion in London was 4,484,839,830 in 2017. Thus, several million of trips per year are used to build the congestion index. The low number of trips with serious accidents in relation to the total number trips suggest that our travel time variable is not affected by trips with serious accidents.

While we do not expect a potential simultaneous bias to be driving our results, we report the results of additional regressions to examine this possibility. Hence, we use a standard approach to deal with the potential endogeneity bias that is using lags of the endogenous explanatory variable as instruments. We can expect that lagged values of travel time variables are correlated with their contemporaneous values. Furthermore, the value of the travel time variable should not be affected by accidents that take place in later years.

As we mention above, we include as control variables population density (Density), Gross Domestic Product per capita (GDP per capita), the old age dependency ratio (Old), the length of rails (Rail) and the share of highways (Share_highways). Furthermore, we add year dummies to control for yearly effects that are common to all cities. Finally, we include country dummies to control for omitted variables that are correlated with the variables of interest and which do not change over time. In this regard, some relevant omitted factors may have a strong influence on safety outcomes. This is the case, for example, with specific road safety policies such as the maximum blood/alcohol concentration allowed, the maximum speed limits on urban roads and

[2] Speed measurements are used to compute travel times on individual road segments and over entire networks within the city. A weighting is then applied, considering the number of measurements. By weighting the number of measurements, busier and more important roads in the network have more influence on the city's congestion level than quieter, less important roads.

[3] Results are essentially identical when considering the congestion index variable measured as extra travel time and its square as main explanatory variables.

whether a penalty point system for driver licensing is in force. These road safety policies are enacted through national legislation but variations in the period considered are very low as legislation across the countries has generally remained consistent since before 2008. Thus, most of the impact of these road safety policies should already be captured by the country dummies.

Note that in all regressions, standard errors are robust to heteroscedasticity and clustered at the city level to account for any autocorrelation problem. Table 1 shows the descriptive statistics of all variables used in the empirical analysis.

4. Results

Table 2 displays the results of the estimates. In columns (I) to (IV), we show the results when the estimation is made using the negative binomial method. As discussed above, we use population as an exposure variable so that we are effectively estimating the ratio of traffic fatalities to population. In column (I), we show the results when considering, as explanatory variables, only the two variables of travel time. In column (II), we show the results when adding the rest of the control variables related to the characteristics of the city or the surrounding region. In column (III), we include the population as an explanatory variable rather than as an exposure variable so that the coefficient of the variable is estimated and not restricted to be 1. Finally, in column (IV) we add the country dummies. An interesting complementary regression would be to include city dummies instead of country dummies but the negative binomial regression with city dummies does not converge to any value.

In all four regressions, we find evidence of a quadratic relationship between number of deaths in accidents and travel time. The variable of travel time is negative and statistically significant at the 1% level, while the square of the travel time variable is positive and statistically significant at 1%. This means that the change from low to moderate levels of congestion leads to a decrease in the number of deaths in accidents. However, the change from moderate to high levels of congestion leads to an increase in the number of deaths in accidents. In cities with low levels of congestion, an increase in traffic may be associated with a reduction in the speed of vehicles, as found in most research using V:C ratios. In cities with high levels of congestion, greater exposure to accidents seems to be more strongly linked than the speed of vehicles to the incidence of road traffic fatalities. Our results are, therefore, in line with those in the empirical literature cited, pointing to a U-shaped relationship.

We also find that the number of deaths in accidents are higher in denser cities. The concentration of traffic at fewer points seems to lead to poorer safety outcomes. Taking into account that we expect a positive relationship between congestion and density, the results for the density variable reinforce our previous finding that high levels of congestion imply more deaths in accidents.

We also find a greater number of deaths in accidents in cities with a higher proportion of over 65s in the population. Old people may be more vulnerable to accidents. An additional result is a lower number of deaths in accidents in cities that have a higher proportion of motorways. Hence, the quality of roads seems to help improving road safety outcomes. However, note that these two latter results do not hold when we add country dummies. Finally, the number of deaths in accidents is higher in bigger cities.

In columns (V) to (VI), we show the results when the estimation is made using the OLS method. Although our preferred method is the negative binomial, we show the results when using the OLS, as a robustness check. Recall that the dependent variable here is the number of deaths in accidents per capita. In column (V), we show the results of a regression that considers all explanatory variables including country dummies. Column (VI) considers city dummies instead of country dummies.

The results of these additional regressions confirm the quadratic non-linear relationship between congestion and deaths in road accidents. Thus, our main result holds, regardless of the econometric technique employed. In terms of controls, only the variable of density is positive and statistically significant when considering country fixed effects.

Results for control variables become distorted when we add city dummies. Note that this last regression relies on the within variation, which is low for all the explanatory variables considered. In this regard, the control variables that are statistically significant is that for density and older inhabitants, but the sign is the opposite of that obtained in previous regressions. More importantly, the travel time variable remains negative while the square of travel time remains positive. Hence, the positive relationship between congestion and deaths in accidents for highly congested cities holds, even after adding hundreds of city dummies in the regression. Thus, we can conclude that there is strong evidence that an increase in congestion in highly congested cities leads to poorer safety outcomes.

Table 1
Descriptive statistics of the variables used in the empirical analysis.

	Type	Description	Source	Mean	Standard deviation
Deaths	Dependent variable (negative binominal regressions)	Total number of deaths in road accidents on each city per year	Eurostat	19.08	27.75
Deaths_capita	Dependent variable (OLS regression)	Total number of deaths per capita in road accidents on each city per year	Eurostat	0.00003	0.00002
Congestion	Main explanatory variable	Mean extra travel time (in percentage) compared to what it would be in local free flow conditions	TomTom	0.25	0.07
Travel time	Main explanatory variable	1 + Congestion	TomTom	1.25	0.07
Density	Control factor	Total number of inhabitants per square kilometer per year at the NUTS 3 level	Eurostat	1695.60	2359.67
GDP per capita	Control factor	Gross domestic product per capita per year at NUTS 2 level.	Eurostat	29626.82	11341.36
Old	Control factor	Ratio between inhabitants aged 65 and over and the population aged between 20 to 64 per city per year	Eurostat	28.82	7.42
Share_highways	Control factor	Share highways over total roads (proportion over total kilometers)	TomTom	0.55	0.16
Rail	Control factor	Length of rail (kilometers)	Urban rail ((http://www.urbanrail.net/), World Metro database ((http://mic-ro.com/metro/table.html) and websites of operators	43.23	59.85
Population	Exposure variable in negative binomial regressions	Total number of inhabitants per year at the city	Eurostat	686,257.1	886,873.7

Table 2
Estimation results.

	Dependent variable: deaths – negative binomial				Dependent variable: deaths per capita - OLS	
Variables	*(I)*	*(II)*	*(III)*	*(IV)*	*(V)*	*(VI)*
Traveltime	−54.51	−48.57	−14.55	−21.31	−0.0009	−0.0004
	(13.41)***	(11.66)***	(5.76)***	(4.32)***	(0.0002)***	(0.0002)**
Traveltime_square	21.59	19.20	6.81	8.24	0.0003	0.0002
	(5.22)***	(4.52)***	(2.25)***	(1.69)***	(0.0001)***	(0.00009)**
Population	1	1	0.0007	1	–	–
			(0.00003)***			
Density	–	0.00004	0.00004	0.00004	1.32e-09	−3.48e-09
		(0.00002)**	(0.00002)**	(5.31e-06)***	(6.57e-10)**	(1.95e-09)*
GDP per capita	–	−4.68e-06	−0.00001	−2.16e-06	−2.21e-11	6.62e10
		(3.09e-06)	(2.27e-06)***	(1.62e-06)	(1.05e10)	(4.73e-10)
Old	–	0.03	0.028	0.007	2.94e-08	−9.11e-07
		(0.004)***	(0.002)***	(0.008)	(2.68e-07)	(4.47e-07)**
Share_highways	–	−0.67	0.19	−0.25	−8.96e-06	–
		(0.23)***	(0.14)	(0.20)	(6.10e-06)	
Rail	–	−0.0006	−0.0006	−0.0001	−4.10e-09	3.86e-08
		(0.0005)	(0.0004	(0.0006)	(1.67e-08)	(1.98e-07)
Intercept	24.09	20.14	9.35	2.68	0.0006	0.0003
	(8.58)***	(7.51)***	(3.69)***	(2.44)	(0.00001)***	(0.0001)**
Year dummies	YES	YES	YES	YES	YES	YES
Country dummies	NO	NO	NO	YES	YES	NO
City dummies	NO	NO	NO	NO	NO	YES
Maximum Likelihood R^2	0.15	0.31	0.64	0.54	–	–
Log *pseudolikelihood*	−3789.35	−3582.81	−4303.16	−3369.45	–	–
Likelihood ratio chi-square (joint sign.)	182.00***	413.09***	1135.76***	839.80***	–	–
Akaike's Information Criterion (AIC)	6.81	6.60	6.89	6.24	–	–
R^2	–	–	–	–	0.52	0.71
F test (joint. Sign.)	–	–	–	–	36.94***	16.57***
N	1090	1090	1090	1090	1090	1090

Note: Standard errors in parenthesis (robust to heterocedasticity and clustered at the city level). Statistical significance at 1% (***), 5% (**) and 10% (*).

Table 3
Estimation results (lags of congestion variables as regressors).

	Technique: Use of lags instead of contemporaneous values of congestion variables								
	Dependent variable: deaths – negative binomial								
Lags	One lag	Two lags	Three lags	Four lags	Five lags	Six lags	Seven lags	Eight lags	Nine lags
Variables									
Traveltime	−49.86	−49.03	−41.96	−43.91	−49.06	−53.02	−52.19	−54.70	−68.83
	(9.85) ***	(10.41) ***	(10.48) ***	(10.44) ***	(10.93) ***	(11.42) ***	(12.47) ***	(12.66) ***	(23.62) ***
Traveltime_ Square	19.70	19.39	16.56	17.25	19.22	20.68	20.41	21.34	26.85
	(3.79) ***	(4.00) ***	(4.02) ***	(4.00) ***	(4.22) ***	(4.42) ***	(4.84) ***	(4.90) ***	(8.99) ***
N	969	850	736	610	496	375	259	153	47
Maximum Likelihood R^2	0.32	0.32	0.33	0.32	0.33	0.35	0.36	0.37	0.51
	Technique: Instrumental variables regression with lags of congestion variable as instruments								
	Dependent variable: deaths per capita								
Lags	One lag	Two lags	Three lags	Four lags	Five lags	Six lags	Seven lags	Eight lags	Nine lags
Variables									
Traveltime	−0.002	−0.002	−0.002	−0.002	−0.002	−0.002	−0.003	−0.003	−0.003
	(0.0004) ***	(0.0006) ***	(0.0006) ***	(0.0007) ***	(0.0008) ***	(0.0007) ***	(0.0008) ***	(0.0008) ***	(0.001) ***
Traveltime_ Square	0.0008	0.001	0.0009	0.001	0.001	0.001	0.001	0.001	0.001
	(0.0001) ***	(0.0002) ***	(0.0002) ***	(0.0003) ***	(0.0003) ***	(0.0003) ***	(0.0003) ***	(0.0003) ***	(0.0005) ***
R^2	0.79	0.78	0.78	0.77	0.76	0.76	0.77	0.78	0.77
N	969	850	736	610	496	375	259	153	47
Under-identification test (instruments)	16.08 ***	13.72 ***	10.90 ***	8.43 ***	10.29 ***	13.78 ***	20.20 ***	20.99 ***	6.21 **

Note: Standard errors in parenthesis (robust to heterocedasticity and clustered at the city level). Statistical significance at 1% (***), 5% (**) and 10% (*). All regressions include the rest of control variables and year dummies.

Table A1 in the appendix shows the results using the negative binomial method but excluding the square of the travel time variable as explanatory variable. We consider the equation with all explanatory variables. In column (I), country dummies are not considered. Column (II) add country dummies. In both regressions, the travel time variable is not statistically significant. Therefore, we do not find a significant relationship between road safety and congestion when the functional form is modelled as linear. The identification of such relationship seems to be more accurate when the functional form is modelled as quadratic.

As we mention above, we do not expect a potential simultaneous bias to be driving our results but Table 3 shows the results of additional regressions that examine this possibility. Table 3 shows the results of additional regressions for congestion variables considering separately all available lags (up to nine) of such congestion variables as instruments. In particular, the negative binomial regression uses directly the lags of congestion variables as regressors because an instrumental variables procedure cannot be implemented (in theory, both procedures are equivalent). In the equation where the dependent variable is deaths per capita, we implement the instrumental variables procedure with the lags of congestion variables as instruments. In these latter regressions, we can also show the results of the underidentification test that confirms that instruments are strong. Results for congestion variables with the lags approach are very similar to previous regressions. Hence, we can confirm that any potential endogeneity bias should not distort our analysis.

We also examine the relationship between deaths in accidents and congestion through a non-parametric analysis. In this regard, Fig. 1 shows the range scatter that illustrate the relationship road safety and congestion for all observations in our sample. While there is a high dispersion in the data, cities with high levels of congestion have usually poor safety outcomes.

Fig. 2 provides additional evidence of the quadratic relationship between deaths in accidents and congestion. This figure shows a median spline graph that estimates the relationship between congestion and deaths in accidents per capita with no assumptions about the functional form. The median spline graph is based on the calculation of cross medians between the two variables and then the cross medians are used as knots to fit a cubic spline that is graphed as a line plot.

The median spline graph confirms the quadratic relationship that we have found in the multivariate econometric analysis. Interestingly, the threshold point at which the relationship between congestion and deaths in accidents is reversed and becomes positive occurs when congestion results in a 30 per cent (approx.) increase in travel time.

Fig. 3 shows the histogram of the congestion variable. A large number of cities in our sample have congestion records that are close to or greater than the threshold of 30%. Specifically, 24% of cities in our sample have congestion records greater than 30% while 43% have congestion records greater than 25%. For all these congested cities, any effective measure to contain congestion may also lead to better safety outcomes.

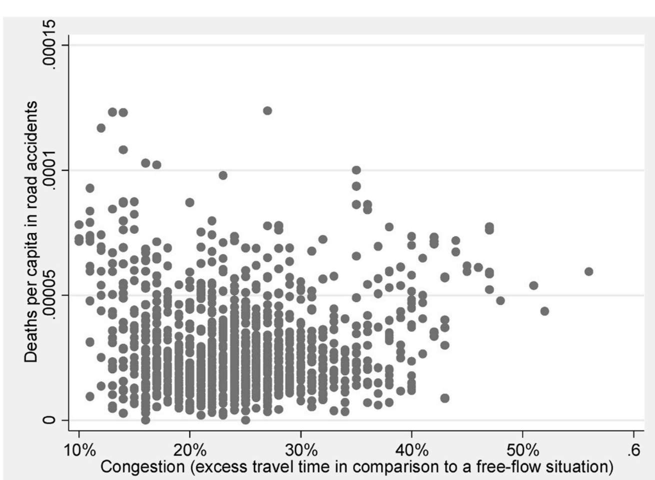

Fig. 1. Scatter plot between deaths per capita in road accidents and congestion.

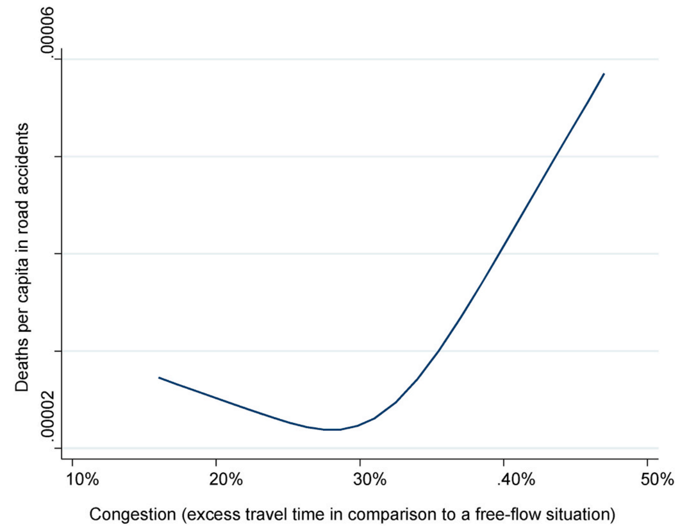

Fig. 2. Median spline between deaths per capita in road accidents and congestion.

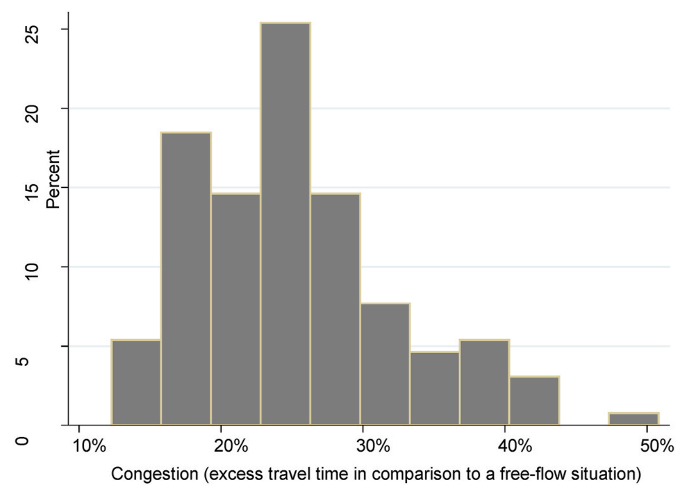

Fig. 3. Histogram of the congestion variable.

5. Discussion and conclusions

The mitigation of transport-related negative externalities is a major challenge faced by large cities and urgently needs transport policies that can provide a more sustainable and efficient mobility model. However, policy action to tackle these negative externalities must be based on a sound understanding of their causes and effects, as well as of their impacts on other linked externalities. The limited availability of empirical evidence on the interrelation between congestion and road accidents, and the mixed results obtained, hamper this task, allowing only inconclusive predictions of the impact of lowering congestion levels on road safety. The literature presents this relationship as complex and published results are ambiguous and highly dependent on the methods and data used and the context considered. Some papers indicate a positive safety effect produced by congestion; others report a contrary detrimental impact. In order to add to our knowledge and shed more light on this complex relationship, this paper has empirically explored both externalities with a sample of 130 European cities monitored between 2008 and 2017.

Our parametric and non-parametric results suggest a non-linear quadratic relationship that confirms a beneficial safety effect for low-congested cities, and a detrimental effect for highly congested cities. On this regard, our results align with the recent literature showing a non-linear relationship that suggests that the most damaging impacts of congestion on road safety is found for the most highly congested states of traffic (Harwood et al., 2013; Shi et al., 2016, among others). Therefore, we call for the importance of considering this non-linearity to avoid misleading conclusions regarding the study on the relationship of congestion and road safety in line with Zhou and Sisipiku (1997).

This result may seem counter-intuitive if the reader thinks of a single motorway, because increasing V:C ratios should necessarily reduce average speeds, contributing to fewer injury-related crashes. Even in this framework, there is evidence supporting that congestion may also be associated with severe accidents. Wang, Ison and Quddus (2013b) found that traffic congestion was associated with more fatal and serious injury accidents due to the higher speed variance among vehicles within and between lanes and erratic driving behavior in the presence of congestion. Similarly, Shi et al. (2016) found that since congestion causes stop-and-go traffic conditions, rear-end crashes at all severity levels are more likely to occur, what was consistent with Marchesini and Weijermars (2010), who found that at the tail of the queue more severe rear-end crashes are to be expected, especially if congestion surprises drivers.

Furthermore, note our units are whole metropolitan areas with large networks of roads and streets, and not just a single road. Thus, our results might be interpreted as evidence supporting the thesis of Elvik et al. (2009), which stated that in urban areas the main roads were built for lower than actual volumes of traffic and in highly congested scenarios, drivers take diversionary routes, choosing alternative roads and streets less suited for high traffic flows. This network-based explanation points out to the role of spatial spillovers and negative externalities of congestion being produced in a large network of roads, particularly damaging the road safety of less central – and therefore relatively less congested - parts of the network. These roads and streets may receive traffic with high speed variance and might be technically less prepared – in terms of infrastructure and circulation systems-for throughput flows. If erratic driving and high-speed variance is found in congested motorways, it seems also reasonable to expect high speed variance, re-routing, and erratic driving also along the wider set of alternative routes of a network.

Moreover, because our dependent variable accounts for all road fatalities, whatever the vehicle involved, another connected potential and complementary explanation is the effect of congestion on the safety of other types of vehicles and pedestrians. The literature has showed how congestion imposes costs to travelers – mainly via in-vehicle travel time- and influence their modal choice (See for example the recent contribution by Ha et al., 2020). Avoiding congestion might be easier using alternative vehicles such as powered two-wheelers and bicycles, whose drivers are more vulnerable than car drivers (Blaizot et al., 2013). Modal shift produced by congestion to these modes might also imply an increase of interactions with vulnerable drivers and vulnerable pedestrians. Modal shifts produced by congestion and congestion-relief measures (i.e. congestion charging) on road safety is an important future research area.

In all, our results also have policy implications. Urban planners and policy makers should take into account the degree of congestion in their cities before designing transport policies to tackle congestion. According to our results, active policies to tackle congestion are urgently needed and might be further justified by the congestion-related additional cost regarding road safety outcomes in highly congested cities. Cities in which the average extra travel time compared to free flow situations rises above 30% show great potential for reducing both externalities via the taking of policy action. However, note that this percentage is just the result of a bivariate regression not considering other predictors. In any case, our multivariate analysis results suggest a virtuous circle of reinforcement between both externalities. Yet, in low-congested cities, the impact of these policies might be just the opposite, given that easing traffic flows may result in worse road safety outcomes. In this regard our findings are in line with papers that identify a positive externality of congestion, but only in cases of moderate levels of congestion. More attention, therefore, should be paid to the worst case scenarios, that is, those cities with the highest levels of congestion. Here, our results identify a number of cities – 24% of our sample – with congestion levels that exceed this 30% threshold.

This empirical analysis is not free of limitations, which should be underlined calling for caution in the interpretation of our results. First, data used are aggregated at the annual and city level. The results of our study could be complemented with further research that uses a more disaggregated level of information both geographically, distinguishing between different types of roads within the city, and temporally, distinguishing between peak and off-peak periods. In addition, it is necessary to analyze in greater detail the possible simultaneous determination between accidents and congestion. Finally, this analysis is centered in large European cities. Further studies could examine whether the non-linear relationship between road accidents and congestion is confirmed for smaller cities and cities from other geographical areas.

Author statement

Daniel Albalate: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Xavier Fageda: Conceptualization, Methodology, Formal analysis, Data curation, Investigation, Writing – original draft, Writing – review & editing.

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APPENDIX

Table A1
Estimation results (negative binomial excluding traveltime_square as covariate)

Variables	*(I)*	*(II)*
Traveltime	0.55	−0.29
	(0.57)	(0.42)
Population	1	1
Density	0.00003	0.00004
	(0.00002)*	(0.00001)***

(*continued on next page*)

Table A1 (*continued*)

Variables	*(I)*	*(II)*
GDP per capita	−4.70e-06	−1.49e-06
	(3.47e-06)	(3.39e-06)
Old	0.03	0.007
	(0.004)***	(0.008)
Share_highways	−0.62	−0.18
	(0.26)***	(0.20)
Rail	−0.0007	−0.0001
	(0.0006)	(0.00007)
Intercept	−11.22	−10.78
	(0.82)***	(0.66)***
Year dummies	YES	YES
Country dummies	NO	YES
City dummies	NO	NO
Maximum Likelihood R^2	0.25	0.52
Log *pseudolikelihood*	−3631.39	−3381.31
Likelihood ratio chi-square (joint sign.)	315.93***	816.08***
Akaike's Information Criterion (AIC)	6.69	6.26
N	1090	1090

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