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Congestion, Road Safety, and the Effectiveness of Public Policies in Urban Areas

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Abstract: Congestion and road accidents are both considered essential challenges for sustainable mobility in large cities, but their relationship is only partially explored by the literature. In this paper, we empirically examine different public policies aimed at reducing urban traffic congestion but which may also have indirect effects on road accidents and casualties. We use data from 25 large urban areas in Spain for the period 2008–2017 and apply econometric methods to investigate how a variety of public policies do affect both negative externalities. Although the relationship between congestion and road safety is complex, we find that the promotion of certain modes of public transportation and the regulation of parking spaces may contribute to making cities more sustainable, both in terms of the time spent traveling and the probability of being affected by an accident. Considering whether policies addressing congestion improve or damage road safety as an indirect result is a useful approach for local policy-makers and planners in their attempt to get sustainable transportation outcomes.

Keywords: congestion; traffic; road safety; accidents; mobility; cities

1. Introduction

Cities are increasingly concerned about urban traffic congestion and its associated negative externalities. Indeed, road congestion is considered an urgent and growing challenge for sustainable mobility, transport policy, and urban governance. In Europe, the costs attributable to congestion are estimated to be around 1% of annual gross domestic product (GDP) [1], and the problem tops the list of urban citizens' concerns about transport quality [2]. The welfare impact of congestion was reported to be as high as 2% of national GDP in some countries [3], while the health costs of air pollution attributable to road transport were estimated at about $0.85 trillion per year [4]. Furthermore, congestion is expected to worsen over time, with the growth in its associated costs becoming one of the main challenges urban planners and policy-makers will have to face in the near future. The 2011 European Commission White Paper indicates that congestion will continue to represent a huge burden on society with congestion costs projected to increase by about 50% annually, to nearly $220 billion by 2050 [5]. The introduction of connected and autonomous cars may make congestion more predictable, but the problem will persist and increase if technological advances, focused on car-centric innovations, increase the attractiveness of private mobility [6].

Above and beyond the direct social cost of the time drivers are made to waste, congestion also produces and aggravates other negative externalities, including pollution, noise, accidents, etc. Indeed, the recent literature on urban economics and transportation, as well as that on environmental policies, paid special attention to the contribution of congestion to pollution and the latter's effects on health outcomes and living conditions [7–10]. However, fewer studies examined the effects of road congestion on road safety outcomes, particularly in metropolitan areas; moreover, this empirical literature is characterized by its mixed results and conclusions, which points to complexity in the relationship between these two variables.

The interrelations between congestion and accidents are of great importance for sustainable mobility in urban environments if we consider (1) the additional high social costs of road accidents, and (2) that public policies designed to mitigate congestion, which are at the core of current urban transport policy strategies, may also have an effect on road safety. Indeed, these policies might have indirect effects—often unexpected or undesired—on road safety outcomes by changing traffic conditions. In relation to the first consideration, according to [11], the societal cost of road accidents remains very high. Apart from road deaths (more than 25,000 per year in Europe), accidents also cause thousands of slight and serious injuries every year. It is estimated that, for every death on Europe's roads, there are an estimated four permanently disabling injuries, such as damage to the brain or spinal cord, eight serious injuries, and fifty minor injuries. In 2016, last available for all EU countries, there were more than one million accidents, with 1.4 million injured and 25,651 fatalities [12]. The external costs of road accidents were estimated at 1.7% of GDP for 2008.

In relation to the second consideration, the mitigation of congestion through public measures produces effects on traffic conditions that may increase or decrease the number of accidents with victims and the severity of injuries received. Thus, it is reasonable to expect that the use of distinct instruments to tackle congestion will have some effect on road safety outcomes. A positive relationship between the two variables would yield, it was claimed, "multiplicative benefits for policies that aim at reducing either of these issues" [13]. Moreover, it would appear that different measures have different indirect effects. Some may offset or add to the social welfare gains of congestion mitigation with changes in road safety outcomes; others effectively tackle congestion without producing any significant road safety effects. Unfortunately, this remains an unexplored area of study, a gap this study seeks to bridge in an effort to improve our understanding of how congestion policies relate to road safety.

The contribution of this paper is twofold. Firstly, it is the first paper to examine empirically the different public policies on congestion and road safety for a wide sample of metropolitan areas, employing a multivariate econometrics method. This paper draws on our own original database of Spanish metropolitan areas, while most studies in the literature focused their analyses on specific roads (highways or road networks) or single cities (case studies), with very few papers considering several cities, and none considering all of Spain's metropolitan areas. The literature on road safety in Spain usually estimates the occurrence of accidents at a national or provincial level rather than at the local scale [14–17].

Secondly, this paper also contributes to the literature by evaluating different transport policies that tackle traffic congestion and explores how they affect road safety outcomes, taking into consideration the complexity of this relationship. This should allow for a better understanding of how transport policy tools, designed for a specific negative externality (congestion), affect another externality derived from private transportation. Thus, we are able to identify the multiplicative or offsetting effects of these measures.

The remainder of this paper is organized as follows: the next section briefly reviews the related literature relevant to our study. The first part reviews the literature on the link between congestion and road safety, and the second part reviews the literature on public interventions introduced to mitigate congestion. 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 concluding remarks in Section 5.

2. Related Literature

2.1. Literature on the Relationship between Congestion and Road Safety

A broad body of literature discussed and examined the externalities of private transportation [18]. Air pollution (and its effects on health outcomes and the degradation of materials), congestion, and traffic accidents were the main negative externalities identified and addressed by researchers, although other externalities or indirect effects were also considered, such as noise, oil dependence, road maintenance costs, and urban sprawl. Despite the extensive literature on these externalities and their solutions, few papers examined the interrelations between the main negative externalities. In the extant literature, most studies focused on the relationship between congestion and pollution, but the relationship between congestion and road safety remains significantly unexplored. Moreover, these studies were mixed and offered unclear results as to how congestion affects road safety outcomes. Existing research is yet to reach an agreement on the impact of traffic congestion on road safety outcomes [19], which signals the complexity of this relationship, as well as the technical limitations and heterogeneities that make the studies difficult to compare. Indeed, an inspection of the literature reveals a variety of contradictory conclusions, with some influential works claiming a negative correlation (improvement of road safety outcomes) [13,20–23] and others concluding just the opposite [24–27]. There are even papers that found no significant relationship between congestion and the road safety externality [28–30].

Apart from the differences in the way congestion was measured in these studies, and the differences in the methodologies they employed and their objects of study (highways, cities, etc.), some identified a possible non-linear relationship between congestion and road safety outcomes. For instance, some papers found a U-shaped relationship [31], with the highest accident rates occurring both at the lowest and highest extremes of the volume-to-capacity ratio. This suggests that models assuming linear relationships (the majority) might neglect possible non-linearities, resulting in misleading conclusions regarding the role of congestion in road safety outcomes. This result was later confirmed by other researchers who focused on the highest levels of congestion [32,33]. In urban areas, this result can be attributed to the limited capacity of both urban and access roads, built for lower volumes of traffic than they actually have to accommodate [34]. In highly congested scenarios, traffic is diverted with drivers choosing alternative roads and streets not intended for high traffic flows. In line with this, the accident rate (per miles driven) may be high for low traffic-volume-to-capacity ratios because of higher speeds and night-time driving. However, this rate decreases with the increase in the volume-to-capacity ratio [31], up to 0.5 for "property damage only accidents", and up to circa 0.7 for "injury accidents". Thus, the change in traffic conditions from free flow to dense traffic will necessarily present a negative relationship, with more traffic being associated with fewer accidents. Beyond these values in the volume-to-capacity ratio, the accident rate increases again, finally displaying a U-shaped functional form that illustrates the negative safety externality produced by congestion that increases exponentially with traffic volumes. Some other authors also argued that, on interurban roads, the increased number of crashes is probably due to driver behavior [35], for example, frequent lane changing and keeping too close to the vehicle in front. They also pointed to the complexity of interactions among vehicles as an increasing risk factor. Although fewer (serious) collisions are expected to occur among cars in congested motorway traffic, a literature review [36] indicated—although they claimed that not enough evidence is yet available to prove it—that more severe rear-end crashes are to be expected at the tail of the queue, especially if congestion surprises drivers arriving at the queue or having just joined the queue.

2.2. Literature on Public Measures to Mitigate Congestion

Congestion is, beyond any doubt, determined by high traffic-volume-to-capacity ratios and is characterized by low average speeds, as well as by increased variations in speed, an increase in potential conflicts, and by incentives to seek alternative routes. Thus, congestion changes the traffic conditions and this, in turn, may have a direct effect on the likelihood of suffering an accident and on its severity. Urban transportation strategies are increasingly concerned about congestion and its direct and indirect costs. Therefore, it is common to find public interventions aimed at tackling congestion, which are easily justified in terms of addressing the existence of several market losses.

Yet, by affecting congestion, these measures may also indirectly impact road safety outcomes, which remains a significantly unexplored area of study.

Transport policies to mitigate congestion might take three different approaches. The first two are supply-oriented. One approach is the classical road capacity enlargement, aimed at expanding road infrastructure to accommodate demand by increasing physical capacity. This is possible by investing in the building of new lanes, new accesses, and/or roads. However, this solution was found to be largely transitory and, ultimately, fruitless [37,38] given that the evidence shows that, in the long run, traffic increases again, exceeding supply, which casts doubt on the cost-effectiveness of this approach [39]. As a matter of fact, capacity enlargement simply reduces the generalized cost of transportation for private mobility, inducing new demand, so that travel speeds on an expanded highway revert to their previous levels, i.e., prior to expansion. This was termed the *Fundamental Law of Congestion* and empirically confirmed in the United States (US) [40] and in Japan [41], the latter even finding lower speeds than before capacity enlargements.

The second approach is to improve the main alternative mode of transportation; thus, a government might opt to invest in the supply of public transportation. This means changing the relative difference between the generalized cost of travel by public transportation and private mobility by improving the attractiveness (new lines, new stations, frequencies, price, time, comfort, accessibility, etc.) of the public alternative. This supply-oriented approach affects modal choice [42], given that public transit is able to attract a share of potential drivers, producing large net benefits.

Consistent with the Wardrop Equilibrium [43], most research cast doubt on a significant reduction in aggregate traffic attributable to improved public transit systems [40,44–47], although there was evidence of marked changes in traffic delays due to public sector strikes and cessations of operations [48–51]. However, the presence of public transit systems and their financing through subsidies are desirable for other reasons, such as returns to scale [49] or the welfare gains for public transportation users [52]. Even if such systems have a minimal impact on total vehicle miles traveled, it seems they may have a large impact on congestion levels, once heterogeneity in driving delays is considered [53]. Moreover, some authors found that public transport supply leads to a small overall reduction in traffic congestion [54], but they identified considerable heterogeneities across urban areas, with an increase in its effect in the most densely populated areas with extensive public transit networks. Furthermore, public transportation consists of different modes and systems that may make different contributions to congestion mitigation and, therefore, to road safety. Reference [39], for instance, estimated that rail lines reduce congestion but that bus lines increase it. Reference [52] also found that the congestion reduction effect of rail is roughly seven times that of bus services. Reference [55] also found that abundant access to railway stations does decrease congestion, but this relationship is mitigated if the substitutability between car and train is higher. Contrary to Reference [39], Reference [56] found that bus networks also contributed to congestion decreases in Melbourne.

Finally, there is a third approach that is based on the use of travel demand management tools. This group of measures aims to affect drivers' behavior by increasing the generalized cost of private transportation in such a way that it approaches optimal traffic management. Among the measures most widely studied and proposed by transport economists is that of road pricing (congestion charges in urban areas and cities). By setting optimal charges for road users, this measure seeks to maximize welfare while eliminating congestion. Some influential studies that examined the effects of congestion charges are References [57–59], among many others. The literature on congestion charging supports the efficiency and effectiveness of this solution in cities where it was implemented, and some studies even credited it with progressive distributive effects as well [60]. Empirical evidence on the impact of congestion charges on traffic congestion is available for Singapore [61,62], London [63–65], Stockholm [66–68], Milan [69,70], and Gothenburg [71], among other cities. As for accident externalities, Reference [61] indicated that congestion charges may produce significant welfare gains by offsetting accident externalities, though these gains are partially offset by increased accidents on competing roadways due to diverted traffic. This negative safety impact due to rerouting was also highlighted in Reference [72] in a study of interurban highways.

However, the unpopularity of such measures led cities to adopt other second-best strategies, such as parking regulations or quantitative restrictions. Parking regulations have relatively low implementation costs, better public acceptance than road pricing, and can be controlled directly by local governments [73–76]. Among the quantity restriction measures, we can identify two types: policies that prohibit circulation on specific days in the city based on some form of identifier and policies that identify low-emission areas and prohibit the transit of high-emission vehicles in those metropolitan areas. These measures, however, are more usually associated with fighting pollution than congestion [77–80], but some studies also analyzed their effectiveness in reducing the flow of private transportation [81,82]. Other transportation demand management measures were less examined but are increasingly being considered by policy-makers and planners to promote sustainable transportation. Among them, we highlight the role of low-emission zones, variable speed regulations, intelligent transportation systems, pedestrian- and bicycle-friendly streets, etc.

The purpose of this paper is to evaluate how metropolitan congestion relates to road safety outcomes, analyzing the interrelation between the effect of these congestion mitigation policies on congestion and their relationship with road safety outcomes. The next section describes our empirical approach.

3. Empirical Strategy

We constructed a new database with data being drawn from 25 large urban areas in Spain between 2008 and 2017. According to the information provided by the Spanish Statistics Institute (INE), our sample population summed 25,272,829 inhabitants in 2017. The urban areas considered constitute 54% of Spain's total population and 79% of its total urban population. All urban areas with more than 300,000 inhabitants were included in our sample with the sole exception of Marbella. With these data, we estimated the following equations for urban area *u* in year *t*:

$$\begin{gathered}\text{Log (Congestion)}_{ut} = \alpha + \beta_1\text{Log (Population)}_{ut} + \beta_2\text{Log (Density)}_{ut}\\ + \beta_3\text{Log (Unemployment)}_{ut} + \beta_4\text{Log (GDP per capita)}_{ut} + \beta_5\text{Log (City/Metropolitan)}_{ut}\\ + \beta_6\text{Log (Rain)}_{\mathbf{ut}} + \beta_7\text{Metro}_{ut} + \beta_8\text{Tram}_{ut} + \beta_9\text{Local\_train}_{ut} + \beta_{10}\text{Log (Bus)}_{ut}\\ + \beta_{11}\text{Log (percentage highways over total network)}_{u} + \beta_{12}\text{Parking\_commercial}_{ut}\\ + \beta_{13}\text{Parking\_residential}_{ut} + \beta_{14}\text{Time\_trend}_{t} + \varepsilon,\end{gathered} \tag{1}$$

$$\begin{gathered}\text{Log (Accidents)}_{ut} = \alpha + \beta_1\text{Log (Population)}_{ut} + \beta_2\text{Log (Density)}_{ut}\\ + \beta_3\text{Log (Unemployment)}_{ut} + \beta_4\text{Log (GDP per capita)}_{ut} + \beta_5\text{Log (City/Metropolitan)}_{ut}\\ + \beta_6\text{Log (Rain)}_{\mathbf{ut}} + \beta_7\text{Metro}_{ut} + \beta_8\text{Tram}_{ut} + \beta_9\text{Local\_train}_{ut} + \beta_{10}\text{Log (Bus)}_{ut}\\ + \beta_{11}\text{Log (percentage highways over total network)}_{u} + \beta_{12}\text{Parking\_commercial}_{ut}\\ + \beta_{13}\text{Parking\_residential}_{ut} + \beta_{14}\text{Time\_trend}_{t} + \beta_{15}\text{Log (Median\_age)} + \varepsilon,\end{gathered} \tag{2}$$

$$\begin{gathered}\text{Log (Accidents)}_{ut} = \alpha + \beta_1\text{Log(Population)}_{ut} + \beta_2\text{Log(Density)}_{ut}\\ + \beta_3\text{Log(Unemployment)}_{ut} + \beta_4\text{Log(GDP per capita)}_{ut} + \beta_5\text{Log(City/Metropolitan)}_{ut}\\ + \beta_6\text{Log(Rain)}_{\mathbf{ut}} + \beta_7\text{Metro}_{ut} + \beta_8\text{Tram}_{ut} + \beta_9\text{Local\_train}_{ut} + \beta_{10}\text{Log(Bus)}_{ut}\\ + \beta_{11}\text{Log(percentage highways over total network)}_{u} + \beta_{12}\text{Parking\_commercial}_{ut}\\ + \beta_{13}\text{Parking\_residential}_{ut} + \beta_{14}\text{Time\_trend}_{t} + \beta_{15}\text{Log(Median\_age)} + \varepsilon,\end{gathered} \tag{3}$$

$$\begin{gathered}\text{Log (Casualties)}_{ut} =\alpha + \beta_1\text{Log (Population)}_{ut} + \beta_2\text{Log (Density)}_{ut}\\ + \beta_3\text{Log (Unemployment)}_{ut} + \beta_4\text{Log (GDP per capita)}_{ut} + \beta_5\text{Log (City/Metropolitan)}_{ut}\\ + \beta_6\text{Log (Rain)}_{\mathbf{ut}} + \beta_7\text{Metro}_{ut} + \beta_8\text{Tram}_{ut} + \beta_9\text{Local\_train}_{ut} + \beta_{10}\text{Log (Bus)}_{ut}\\ + \beta_{11}\text{Log (percentage highways over total network)}_{u} + \beta_{12}\text{Parking\_commercial}_{ut}\\ + \beta_{13}\text{Parking\_residential}_{ut} + \beta_{14}\text{Time\_trend}_{t} + \beta_{15}\text{Log (Median\_age)} + \varepsilon,\end{gathered} \tag{4}$$

where all the continuous variables without zero values were transformed using logarithms, so that the influence of outliers was reduced and parameters could be interpreted as elasticities.

The dependent variable in Equation (1) is the mean level of congestion in the urban area. This variable measures, in percentage terms, the additional time a vehicle takes to make any trip in the city in congested conditions compared to conditions of free traffic flow. Speed measurements were used to compute travel times on individual road segments and over entire networks. A weighting was then applied, taking into account the number of measurements, with busier and primary roads being assigned a greater weight. Data were obtained from TomTom (https://www.tomtom.com/en_gb/trafficindex). Note that the congestion variable provides average values that may hide substantial differences between peak and off-peak periods.

The dependent variables in Equations (2) and (3) are the number of accidents with victims on urban roads and the sum of the number of deaths and hospitalized injuries from accidents on urban roads, respectively. Data were obtained from the annual statistical report from the Spanish General Directorate of Traffic. In this regard, the annual statistical report from the Spanish General Directorate of Traffic makes a clear distinction between safety statistics for urban roads and safety statistics for interurban roads. Our analysis relied exclusively on safety statistics for urban roads.

The figures in these reports provide information about accidents on urban roads at the provincial level (NUTS 3 level). In order to obtain figures corresponding to the urban area level, we firstly calculated the proportion of the population of each urban area in relation to the total urban population in the province. Then, we calculated the total number of accidents and casualties in each urban area by multiplying the total number of accidents and casualties on urban roads in the province by the weight of the population of the urban area over the total urban population of the province. In most cases, the population of each urban area represents the province's total urban population.

The main focus of this article is to examine the role of transport policy measures. Next, we describe the policies considered in our empirical analysis as the set of transport policy variables. Firstly, we included different variables that captured the network length of public transportation modes. We considered the number of kilometers of metro, tram, and bus lines providing services in the urban area. We also considered the number of local train lines that connect the core-city with the other municipalities in the urban area. Given that public transportation may work as a substitute for private vehicles, we can expect a negative effect of these variables on congestion. In theory, more public transportation infrastructure and services should make the alternative modes more attractive for car drivers. More public transportation infrastructure should be associated with better and more efficient public transportation, which should affect the relative generalized cost of transportation in favor of the mass modes. Hence, the expected number of trips by car is expected to diminish, but it is unclear—as explained in the literature review—what the expected effect is for road safety outcomes a priori. On the one hand, all public transportation options are theoretically safer alternatives to private vehicles, and a negative effect on congestion could lead to a lower exposure to accidents given the reduction in the number of vehicles on urban roads. On the other hand, less congestion may lead to faster average speeds—as justified in the literature review—with a consequent negative effect in terms of road safety.

As a result, our first hypothesis to test is described below (H1).

Hypothesis 1. *A better public transportation infrastructure (endowment) is negatively correlated with congestion and road fatalities and casualties.*

Data for these variables were obtained from the annual report on metropolitan transport published by the Spanish Ministry of Environment, the annual report on transport and logistics published by the Spanish Ministry of Transport, and the websites of the Metropolitan Transport Agencies. Note that data for bus lines were only available for 17 urban areas, such that regressions that include bus lines as an explanatory variable had a smaller sample size. In the sample of 17 urban areas, variability in most variables was substantially reduced and it is a standard statistical rule that results are more robust with larger sample sizes. Thus, our baseline regression did not consider the variable of bus lines as an explanatory variable.

Secondly, we also considered a variable that captures the quality of private transportation, with a variable on the quality of urban roads: the percentage of highways over total roads in the metropolitan area. We can expect a road network of higher quality to have a negative effect on both congestion and on road safety outcomes. High-quality roads are expected to affect the relative generalized cost of transportation in favor of private transportation with respect to the public mass alternative, as well as to promote higher mean speeds. Data for this variable were obtained from TomTom (https://www.tomtom.com/en_gb/trafficindex). However, a major limitation of this variable is that information was only available for 2016. Given this limitation, we did not consider this variable in our baseline regression. Nevertheless, it allowed us to test our second hypothesis, described below (H2).

Hypothesis 2. *Better roads promote both congestion and road fatalities and casualties.*

Thirdly, we also considered transport policies that are not associated with the supply of infrastructure or services, but with the regulation of mobility. For this reason, we included two dummy variables that capture the regulation of parking spaces in the core-city of the urban area. On the one hand, we considered a dummy variable for those urban areas where there are commercial parking areas, i.e., where there is a charge per unit of time during a maximum period of time. On the other hand, we considered another dummy variable that denotes with 1 the cities and years in which there are mixed-use parking areas or resident only parking zones, which are zones that are typically more advantageous for residents (low price or free) but less so for visitors. We would expect both variables to have a negative effect on congestion such that, as with the public transportation variables, their correlation with road safety outcomes is not clear a priori. Stricter parking regulations are considered a second-best option and an alternative to road pricing, given that they increase the generalized cost of the private trip in a similar manner. The coefficients associated with these variables should be interpreted with respect to the reference category, which is the absence of these parking regulations. Data for these variables were obtained from the city councils and their municipal ordinances.

Therefore, we tested as a third hypothesis (H3) the role of parking regulations as described below.

Hypothesis 3. *Stricter parking regulations reduce congestion and improve road safety outcomes.*

Our models included other control variables. For instance, we considered different characteristics of the urban areas that may have an influence on both congestion and road safety outcomes according to theory or to past empirical literature. Firstly, we included the population at the urban level. In this regard, according to the literature, we can expect a positive relationship between population and congestion [83,84]. Since there is a high correlation between the number of vehicles and trips and population, it is straightforward to theoretically expect a positive relationship with congestion. As is usual in road safety studies, we estimated a negative binomial model in the analysis of the determinants of accidents and casualties, so that the population variable served as an exposure variable for interpreting the results in terms of rates per capita. As an exposure variable, the coefficient of the population variable in Equations (2) and (3) was restricted to 1.

We also included two variables to capture the population density of the main city and its surrounding region: population density of the urban area and the proportion of the core-city population over the total population of the urban area. The relationship between urban density and congestion is unclear in the literature, as denser cities are characterized by a lower number of vehicle/kilometers traveled but their traffic is concentrated in fewer points [85–88]. Given that the relationship between congestion and density is not clear a priori, the expected sign of these variables is not clear in the regressions of Equations (2) and (3).

In addition, we considered two variables related to income levels and economic cycle: the province's GDP per capita and the unemployment rate in the urban area. The relationship between income and congestion is again unclear. While a positive relationship might be theoretically expected due to the higher number of car trips in richer urban areas, it is also true that richer areas have better infrastructure that could mitigate congestion. The sign of these variables in Equations (2) and (3) is, similarly, unclear. On the one hand, the road accident fatality rate could rise along with income due to greater risk exposure [89] but, on the other hand, the relationship between income and the road accident fatality rate could be negative due to better infrastructure and attitudes in richer urban areas [90]. Note that the unemployment variable may capture the role of the economic cycle highlighted in previous literature [91] or the level of income in the urban area, but it might also imply a lower exposure to accidents for those who do not need to commute daily to/from the workplace.

In the equations for the determinants of road safety outcomes, we also include the median age of the population in each urban area, although the sign of this variable is not clear a priori. On the one hand, older drivers may be more vulnerable to the consequences of accidents [92], while, on the other, younger drivers may take more risks [93].

Data to build all the aforementioned control variables were obtained from the Spanish Statistics Institute (INE).

As an additional explanatory variable, we included the number of rainy days to account for traffic conditions. Although worse driving conditions should lead to more risk exposure, it was also theoretically argued the existence of a sort of Peltzman's offsetting behavior [94], which could lead to lower numbers of trips in rainy conditions and more careful driving, which on aggregate could compensate for the negative effects of adverse weather. Data for this variable were obtained from the Spanish Weather Agency (AEMET).

Finally, we considered a time trend to control for common time-shocks for all urban areas.

The empirical literature on road safety considers count models like the negative binomial distribution method as the preferred regression method to estimate the determinants of accidents, fatalities or casualties [13,95–98]. In this regard, the advantage of the negative binomial distribution method is that it explicitly models the dependent variable as the number of occurrences and it accounts for the non-normality distribution of variables. Thus, we cannot jointly estimate the three equations as a system of seemingly unrelated regression equations because the equation for congestion is estimated using the ordinary least squares method while the equations for safety performance are estimated using the negative binomial distribution method.

Note also that we considered the pooled model as the most suitable panel data model for our purposes. The fixed-effects model cannot be used in the context of our data because such a model only captures the within variation of the data. Most of the policy variables have low or even null within variation; thus, we could not identify properly their effects with a fixed-effects model. The random-effects model could be inconsistent if random effects are correlated with the rest of covariates. Taking this into account, we run regressions with the random-effects model and results for the congestion equation were very similar to those obtained using the pooled model. However, the equations for safety did not converge to any value when using the negative binomial model with random effects. Hence, the pooled model was our preferred regression method. However, it must be recognized that a limitation of the analysis is that the lack of within variation of the most relevant variables prevents estimating the equations using the fixed-effects method.

4. Results

Figures 1 and 2 show the evolution of mean levels of congestion and road safety outcomes in the period considered. Accident numbers are reported in a separate figure, given that they are much higher than those for casualties and congestion.

Data show a high persistence in the evolution of congestion and casualties per capita. However, we can identify a declining trend for 2008–2012 and an increasing trend for 2013–2017, although a significant reduction in congestion was reported in 2017. The trend is clear for increasing accidents per capita, particularly from 2010 onward. Having said this, as in the case of congestion records, a reduction in accidents per capita was identified for 2017.

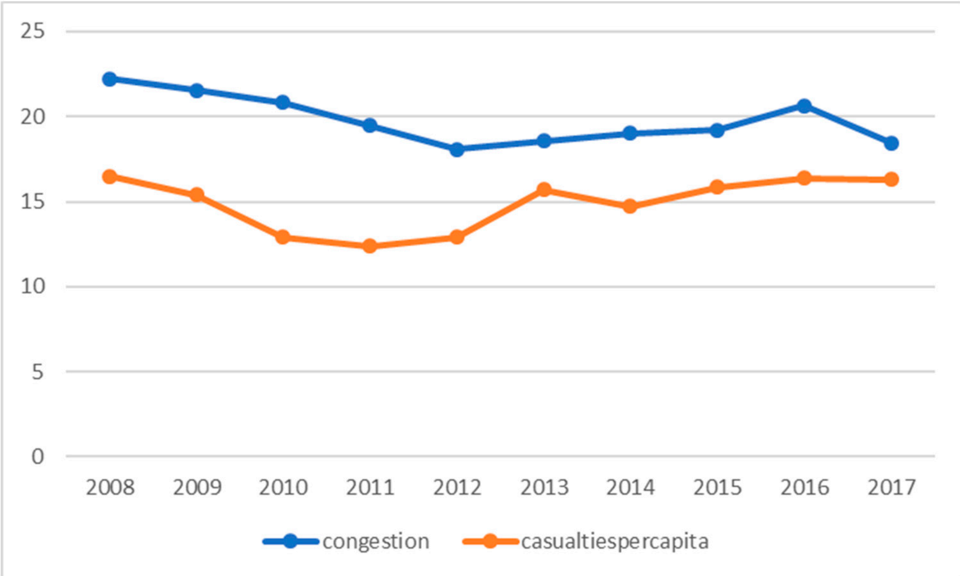

Figure 1. Evolution of congestion and casualties per capita. Note: Congestion is the percentage of extra travel time in comparison to a free-flow situation. Casualties per capita are the number of injuries hospitalized and fatalities per 100,000 inhabitants.

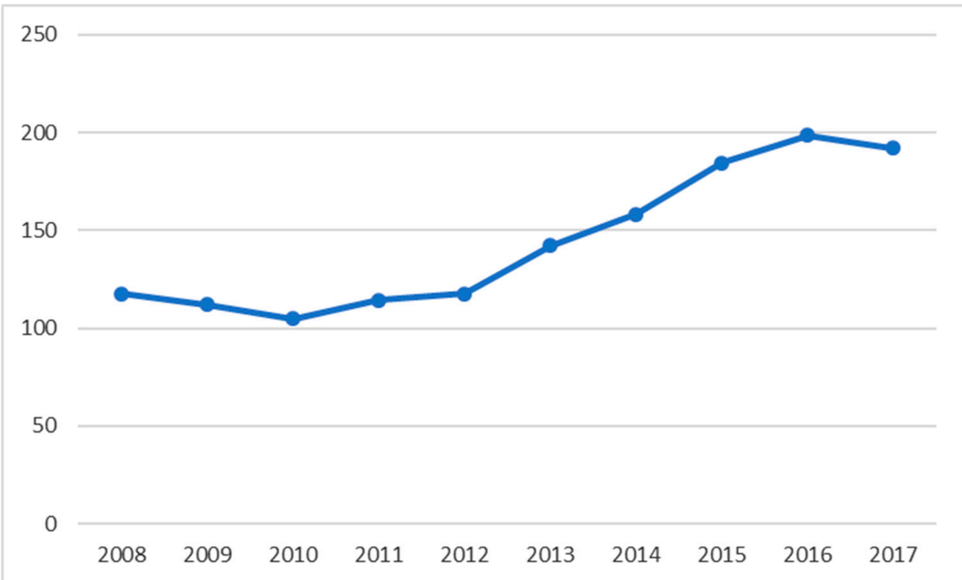

Figure 2. Evolution of accidents per capita. Note: Accidents per capita are the number of accidents with victims per 100,000 inhabitants.

Whatever the case, the numbers for the three indicators considered in these figures were high for each year of the period considered. Specifically, additional travel time in comparison to a free-flow scenario was close to 20% in all years, while the number of casualties per 100,000 inhabitants was close to 15 and the number of accidents per 100,000 inhabitants was more than 100 in all years. Thus, these results confirm that both congestion and accidents on urban roads are serious problems that need to be addressed by the public authorities responsible for urban mobility. Table A1 (Appendix A) provides details of mean values for all explanatory variables of the empirical analysis of each urban area considered in our sample.

Table 1 shows the results for the regressions that considered congestion as the dependent variable. We used the ordinary least squares (OLS) method, and standard errors were robust to heteroscedasticity and clustered at the urban level to account for any autocorrelation problem. In column (I), we show the results when considering only the characteristics of urban areas as explanatory variables. In column (II), we show the results when adding the policy variables (except for the bus and highway variables which, as discussed, present limitations that might distort the results for the other variables). The regression reported in column (II) is our baseline regression. In column (III), we added the variable for the percentage of highways over the total network of urban roads. In column (IV), we added the variable for the number of kilometers of bus lines.

Table 1. Estimation results (congestion, ordinary least squares (OLS)). GDP—gross domestic product.

	Dependent Variable: Log (Congestion)			
Variables	*(I)*	*(II)*	*(III)*	*(IV)*
Log (Population)	0.16 (0.05) ***	0.27 (0.06) ***	0.22 (0.05) ***	0.41 (0.07) ***
Log (Density)	0.01 (0.08)	0.07 (0.10)	0.08 (0.09)	−0.06 (0.09)
Lo g(Unemployment)	−0.01 (0.14)	−0.09 (0.12)	−0.03 (0.09)	0.02 (0.13)
Log (GDP per capita)	−0.59 (0.24) **	−0.43 (0.29)	−0.30 (0.22)	−0.93 (0.28) ***
Log (City/Metropolitan)	−0.09 (0.17)	0.12 (0.15)	0.12 (0.12)	−0.16 (0.16)
Log (Rain)	*0.05* *(0.09)*	*0.07* *(0.09)*	*0.02* *(0.06)*	*0.17* *(0.08)* **
Metro	-	−0.001 (0.0005) **	−0.0006 (0.0005)	−0.0006 (0.0007)
Tram	-	−0.001 (0.001)	−0.001 (0.001)	−0.0005 (0.001)
Local Train	-	0.001 (0.01)	0.008 (0.009)	−0.001 (0.009)
Bus	-	-	-	−0.12 (0.03) ***
Percentage highways over total road network	-	-	−0.20 (0.05) ***	-
Parking_commercial	-	−0.27 (0.10) ***	−0.27 (0.08) ***	−0.28 (0.11) **
Parking_residential	-	−0.39 (0.08) ***	−0.38 (0.06) ***	−0.16 (0.11)
Time_trend	−0.01 (0.005) ***	−0.01 (0.007) *	−0.01 (0.006) **	−0.01 (0.009)
Intercept	1.01 (0.52) *	−0.77 (1.10)	−0.88 (0.86)	−2.03 (1.10) *
R^2	0.34	0.44	0.52	0.56
N	249	249	249	169

Notes: Standard errors in parentheses (robust to heteroscedasticity and clustered at the metropolitan level). Statistical significance at 1% (***), 5% (**), and 10% (*).

As expected, we found that congestion is worse in larger urban areas. However, the coefficient was lower than 1 which means there is no evidence of a superlinear relationship, i.e., a higher population does not lead to a more than proportional increase in congestion. Furthermore, we found less congestion in richer urban areas; however, this result did not hold when we added public policy variables as explanatory factors. We did not find a relevant influence of variables linked to the population density of the city and its surrounding region. Overall, congestion seems to be of particular concern in relatively large and poor urban areas. It should also be noted that we found a negative time trend in the period considered, although this does not mean that current levels of congestion are not high. We also found that the variable of rain was generally not statistically significant except for model IV, where it was positive and statistically significant at 5%.

We found a negative and significant effect of metro and bus lines on congestion, which supports H1. Note that these two public transportation options may be particularly relevant to improving mobility within the core-city of the urban area. The result for metro lines did not hold in the reduced sample that considered bus lines as an explanatory variable. However, the reduced sample excluded the smaller urban areas without a metro line, which weakened the variability of the metro variable. Furthermore, metro and bus line variables were highly correlated which could distort the individual identification of each variable. Taking into account these caveats, our results suggest that a larger network of public transportation modes, which improves mobility within the core-city, leads to a reduction in congestion. This result is in line with previous analyses [39,52,55]. In our sample, bus lines do seem to play a role in congestion mitigation, contrary to Reference [39], which found bus transit mileage to increase congestion costs in the US, but is in line with Reference [56], which suggested the opposite result by finding congestion relief due to bus transit in Australia. This mixed result of the literature might be explained by the fact that exclusive lanes and frequent bus stops might produce delays and intermittent bottlenecks on the road, what may offset part of the benefits of mode shift.

In contrast, we did not find a relevant effect for tram lines, rejecting H1 for this public transport mode. Note that the number of passengers that can be channeled through trams is much lower than via the metro. Furthermore, trams are a more rigid transportation option in comparison to buses; thus, they may cause congestion on adjacent streets. We did not find a relevant effect for local trains either. Local trains may substantially improve mobility between the core-city and other municipalities in the urban area, but it seems that such an improvement is not relevant in terms of congestion.

Furthermore, we found less congestion when the percentage of highways over the total roads in the urban area was higher. Recall here that an important limitation of this variable is that information was only available for 2016, although the actual variability of the highways variable in the period considered is likely to be modest. The effect of high capacity seems to surpass, on average, the induced demand for private transportation, at least for some time. This result does not support H2 for congestion.

Finally, we found a negative effect for variables related to the regulation of parking spaces, although these results did not hold for residential areas when we considered the reduced sample that included bus lines as an explanatory factor. In comparison to public transportation, the regulation of parking spaces is a cheap way to reduce levels of congestion in the urban area. This supports H3 for congestion.

Table 2 shows the results of regressions for road safety outcomes. Columns (I) to (IV) show the results when the dependent variable was the number of accidents, while columns (V) to (VIII) show the results when the dependent variable was the number of casualties. We followed the same logic as for the congestion regressions. We firstly present the results considering only the characteristics of the urban areas as explanatory factors, and then we added the policy variables, considering specifications (II) and (IV) as the baseline regressions given the limitations of the bus and highway variables.

The estimation was made using the negative binomial method. Note that we used population as an exposure variable; thus, we effectively estimated the ratio of accidents to population. Standard errors were robust to heteroscedasticity and clustered at the urban level to account for any autocorrelation problem.

We found similar results for both accidents and casualties; thus, when we did not identify any differences in the outcomes of the two dependent variables, we expressed them collectively as safety outcomes.

Table 2. Estimation results (road safety, negative binomial).

	Dependent Variable: Log (Accidents)				*Dependent Variable: Log (Casualties)*			
Variables	*(I)*	*(II)*	*(III)*	*(IV)*	*(V)*	*(VI)*	*(VII)*	*(VIII)*
Log (Density)	−0.32	0.18	0.18	0.22	−0.32	0.15	0.15	0.20
	(0.22)	(0.14)	(0.08) **	(0.10) **	(0.20)	(0.14)	(0.14)	(0.12) *
Log (Unemployment)	−0.36	−0.08	−0.09	0.22	−0.46	−0.17	−0.17	0.09
	(0.31)	(0.18)	(0.13)	(0.19)	(0.28) *	(0.15)	(0.15)	(0.15)
Log (GDP per capita)	−1.91	−0.30	−0.37	0.45	−2.17	−0.45	−0.51	0.26
	(0.93) **	(0.54)	(0.24)	(0.57)	(0.70) ***	(0.41)	(0.44)	(0.49)
Log (City/Metropolitan)	0.69	0.92	0.91	0.66	0.69	0.91	0.90	0.57
	(0.38) *	(0.21) ***	(0.14) ***	(0.31) **	(0.35) **	(0.21) ***	(0.21) ***	(0.28) **
Log (age)	5.35	3.01	2.86	4.61	5.35	2.87	2.77	4.52
	(1.59) ***	(1.21) ***	(0.87) ***	(0.93) ***	(1.54) ***	(0.92) ***	(0.84) ***	(0.88) ***
Log (Rain)	0.06	0.18	0.21	−0.15	0.02	0.12	0.14	−0.21
	(0.13)	(0.05)	(0.10) **	(0.21)	(0.11)	(0.11)	(0.10)	(0.16)
Metro	-	−0.004	−0.004	−0.004	-	−0.004	−0.004	−0.003
		(0.0009) ***	(0.0007) ***	(0.0009) ***		(0.0008) ***	(0.0008) ***	(0.0008) ***
Tram	-	−0.004	−0.004	−0.003	-	−0.003	−0.003	−0.002
		(0.005)	(0.002)	(0.003)		(0.004)	(0.004)	(0.003)
Local Train	-	−0.04	−0.05	−0.05	-	−0.05	−0.05	−0.05
		(0.01) ***	(0.009) ***	(0.01) ***		(0.01) ***	(0.01) ***	(0.01) ***
Bus	-	-	-	−0.12	-	-	-	−0.13
				(0.05) **				(0.05) ***
Percentage highways over total road network	-	-	0.11				0.07	-
			(0.06) *	-	-	-	(0.15)	
Parking_commercial	-	−0.35	−0.34	−0.27	-	−0.38	−0.38	−0.23
		(0.15) **	(0.14) ***	(0.16) *		(0.15) ***	(0.14) ***	(0.16)
Parking_residential	-	−0.42	−0.42	−0.39	-	−0.39	−0.39	−0.30
		(0.18) **	(0.13) ***	(0.32)		(0.16) ***	(0.15) ***	(0.29)
Log (population) - exposure	1	1	1	1	1	1	1	1
Time_trend	−0.03	0.004	0.007	−0.02	−0.05	−0.009	−0.007	−0.02
	(0.01)	(0.01)	(0.01)	(0.01) *	(0.01) ***	(0.01)	(0.009)	(0.01) ***
Intercept	−28.27	−23.35	−22.60	−28.06	−28.15	−22.47	−21.97	−27.24
	(6.04) ***	(4.54) ***	(2.95) ***	(3.27) ***	(6.28) ***	(3.78) ***	(3.48) ***	(3.51) ***
Wald test (joint sign.	56.93 ***	909.83 ***	361.25 ***	-	81.86 ***	2276.21 ***	2915.43 ***	-
N	249	249	249	169	249	249	249	169

Notes: Standard errors in parentheses (robust to heteroscedasticity and clustered at the metropolitan level). Statistical significance at 1% (***), 5% (**), and 10% (*). Population was used as an exposure variable.

We found poorer safety outcomes when the proportion of the population of the core-city over the total population of the urban area was higher. Thus, accidents and causalities seem to be higher in bigger cities taking into account that the population of the entire urban area was used as an exposure variable. Similar to the congestion regressions, road safety outcomes were better in richer urban areas, although this result did not hold when we added the policy variables. Furthermore, population density of the urban area was not relevant for road safety outcomes, just as for congestion. Also, notable was the (modest in statistical terms) negative time trend found. Accidents and casualties seem to be more closely associated with older generations because the variable of median age was positive and statistically significant in regressions that considered both accidents and casualties as the dependent variable. Finally, we did not find a statistically significant effect of the variable for rain.

Overall, results for the control variables were similar for congestion and safety outcomes, taking into account that the coefficient of the population variable was freely estimated in the regressions for congestion and restricted to 1 in the regressions for safety outcomes.

More importantly, we found clear evidence that a larger network of metro, buses, and local trains has a negative and significant effect on safety outcomes. This supports H1 also for road safety outcomes. Thus, a better endowment of metro and buses leads to less congestion and fewer accidents and casualties. This means that, despite the complex relationship between congestion and accidents, policies aimed at improving connectivity through metro and bus lines are helpful in reducing the magnitude of the problem linked to both negative externalities. Results for local trains suggest that mobility between the core-city and the other municipalities is relevant in terms of safety but not in terms of congestion. Recall that our variable of congestion measured the mean level of congestion;

thus, it could be that local trains are helpful in reducing congestion in peak periods, but this is an effect that our aggregate measure of congestion was not able to capture.

As with the congestion regressions, trams do not seem to improve road safety outcomes. Overall, the contribution of trams to improving urban mobility seems to be modest, at least for the sample of urban areas considered in our empirical analysis. Thus, H1 is completely refuted in our analysis for trams.

We found a positive significant effect for the variable of the percentage of highways over the total roads in the urban area when the dependent variable was the number of accidents. Such a variable was not statistically when we considered the number of casualties as a dependent variable. It seems that the quality of the road infrastructure may be helpful in reducing congestion (refuting H1) but not in improving safety outcomes. Of course, the average speed of vehicles should be higher on highways than on other roads within the urban area. This may explain why we did not find a significant negative influence of highways on safety outcomes.

Finally, we found that the regulation of parking spaces is effective in improving safety outcomes, confirming H3, although this result did not hold in the regression with the reduced sample that included bus lines as an explanatory factor. Parking regulations are an alternative to road pricing in the fight against congestion and which, according to our results, also seem to be an effective road safety policy. This result is in line with some previous analyses [85,86].

Overall, we found support for hypotheses 1—except for trams—and 3, while results for H3 offered mixed conclusions regarding the role of private road quality.

Finally, recall that we had to implement an assignment methodology based on the population of the urban areas and provinces to obtain accident and casualty data at the urban area level. This assignment methodology was only relevant for those provinces that had more than one urban area. Hence, we estimated additional regressions to account for any potential distortion of the assignment methodology. We report in Appendix A (Tables A2 and A3) the results of the estimation of Equations (1), (2), and (3) for a subsample with provinces having just one urban area. Results of these additional regressions were similar to previous ones, particularly for the baseline regressions. In this reduced sample, we confirm that a larger network of metro and buses and stricter parking regulations may improve both congestion and safety outcomes, while a denser network of local trains may be helpful in improving safety outcomes.

5. Discussion

In this paper, we examined different public transport policies aimed at reducing urban congestion but which may also have indirect effects in terms of accidents and casualties. Although the relationship between congestion and safety is complex, we found evidence that the greater network length of different public transportation options and stricter parking regulations may contribute positively to reducing both types of negative externality.

Our results deliver important recommendations for transportation policies in the form of a package that needs to be considered for the mitigation of congestion and road safety outcomes. According to our results, such a package must include soft and hard transportation policies. Among the hard policies, in particular, we found that a better endowment of public transport modes that improve mobility within the core-city of the urban area, such as metro and buses, may be effective in containing both congestion and accidents. Among soft measures, we found that a stricter regulation of parking spaces through the implementation of commercial and mixed-use areas is also effective in reducing congestion and accidents. While some policies, such as speed limits, may have contradictory results for both types of negative externalities, we identified different policies that may improve the performance of urban areas in terms of congestion and safety.

The result for the regulation of parking spaces is particularly relevant. Investments in public transportation require huge amounts of resources, and the development or expansion of the metro network may not be viable in many urban areas. In contrast, the implementation of parking regulation policies may be a cost-effective measure to reduce both congestion and accidents and one that is more readily accepted by the public than the introduction of congestion charges.

Furthermore, we found evidence that not all public transportation options have relevant effects for the negative externalities considered in this study. In particular, trams do not seem to be effective at reducing either congestion or accidents. Given that the resources needed to develop tram lines are substantial, a careful pre-analysis of any proposed tram line should be made.

We also found that local train systems aimed at improving mobility between the core-city and the municipalities of the urban areas are effective at containing accidents but not congestion. However, our results did not exclude the possibility that local trains may be effective at reducing congestion in peak-periods. By contrast, we found that a higher percentage of highways over the total roads in the urban area leads to less congestion but not to fewer accidents. Note that highways and local trains may work as alternatives for suburban trips. Hence, local trains seem to contribute to safer suburban trips, while highways help increase the speed of such trips. In this regard, note that the expansion of both the highway and local train networks is expensive, and many of the urban areas considered in this analysis already have mature networks of highways and local trains.

Overall, we found that the promotion of certain modes of public transportation and the implementation of stricter parking regulations may contribute to making cities more sustainable, both in terms of the time spent traveling and the probability of being affected by an accident. However, this empirical analysis is not free of limitations, which should be underlined calling for caution in the interpretation of our results. Firstly, our results on the relationship of policies and road safety must be considered as correlations, given the impossibility of having an identification strategy able to call for strict causality in our framework. Secondly, the sample was relatively small, especially when we included the bus network variable. Thirdly, the within variation of the main variables of the analysis was limited (or even null). This prevented us from including urban area fixed effects that would allow us to control for unobservable factors that do not vary over time. Finally, some relevant policies to improve urban mobility like congestion tolls or low-emission zones could not be examined because none of the urban areas implemented them in the considered period. These are some areas that may pave the road to improve the analysis in further research.

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Appendix A

Table A1. Mean values in 2008–2017. N/A—not available.

Metropolitan Area	Congestion (%)	Accidents (Number)	Casualties (Number)	Population ($\times 10^3$)	City/ Metropolitan (%)	GDP per Capita (Index)	Density (per km^2)	Age (Median)	Un-Employment (%)	Bus (kms)	Metro (kms)	Train (lines)	Tram (kms)	Highways (%)	Parking (Index)
A Coruña	26	259	45	413	0.6	0.9	551	44	16	267	0	0	7	1	2
Alicante	17	760	92	462	0.7	0.8	1303	40	23	729	0	3	41	3	2
Barcelona	28	14,150	782	4900	0.3	1.2	1867	41	18	18,015	120	14	29	4	2
Bilbao	15	1004	86	1000	0.3	1.2	680	45	15	27,214	44	3	6	4	2
Cartagena	14	167	21	234	0.9	0.8	402	39	26	N/A	0	0	0	4	2
Cádiz	19	832	58	260	0.5	0.7	1090	41	31	4219	0	2	0	5	2
Córdova	16	631	86	361	0.9	0.7	192	41	35	N/A	0	0	0	2	2
Gijón	23	523	45	301	0.9	0.9	575	47	20	194	0	9	0	3	2
Granada	26	690	56	548	0.4	0.7	565	39	33	2022	0	0	0	1	1
Las Palmas	25	312	46	635	0.6	0.9	815	41	33	N/A	0	0	0	2	2
Madrid	21	11,285	1159	6600	0.5	1.4	836	40	17	25,205	285	10	36	6	2
Murcia	17	443	55	619	0.7	0.8	516	38	24	N/A	0	3	2	2	2
Málaga	23	1105	123	848	0.7	0.7	549	40	29	4190	3	2	0	4	2
Oviedo	19	546	47	315	0.7	0.9	335	45	17	194	0	9	0	3	1
Palma	25	1552	106	674	0.6	1.0	333	39	20	776	9	0	0	3	2
Pamplona	15	182	43	368	0.5	1.2	218	40	14	413	0	0	0	2	2
SC Tenerife	26	611	75	494	0.4	0.8	726	41	29	N/A	0	0	15	3	0
San Sebastián	13	962	79	335	0.6	1.3	872	44	10	507	0	1	0	3	2
Santander	19	87	15	385	0.5	0.9	564	43	16	N/A	0	3	0	3	2
Sevilla	22	2372	126	1400	0.5	0.8	309	39	28	3137	16	3	2	2	1
Valencia	21	2833	429	1700	0.5	0.9	952	41	23	3231	132	6	20	4	2
Valladolid	18	358	65	426	0.7	1.0	368	43	16	544	0	0	0	3	2
Vigo	18	387	93	545	0.5	0.8	405	43	21	N/A	0	0	0	3	2
Vitoria	12	556	41	268	0.9	1.5	168	42	14	299	0	0	12	3	2
Zaragoza	18	959	167	758	0.9	1.1	275	42	17	N/A	0	1	13	4	2

Table A2. Estimation results (congestion, OLS). Subsample with provinces having one metropolitan area.

	Dependent Variable: Log (Congestion)		
Variables	*(I)*	*(II)*	*(III)*
Log (Population)	0.18 (0.09) *	0.21 (0.08) **	0.29 (0.16) *
Log (Density)	0.06 (0.07)	0.07 (0.08)	0.01 (0.08)
Log (Unemployment)	0.01 (0.10)	−0.01 (0.12)	0.05 (0.18)
Log (GDP per capita)	−0.34 (0.27)	−0.36 (0.28)	−0.62 (0.55)
Log (City/Metropolitan)	−0.11 (0.16)	−0.06 (0.22)	−0.11 (0.17)
Log (Rain)	−0.17 (0.07) **	−0.15 (0.09)	−0.10 (0.10)
Metro	−0.001 (0.0005) **	−0.001 (0.0005) **	−0.001 (0.0007) **
Tram	0.001 (0.005)	0.002 (0.005)	0.006 (0.009)
Local Train	0.001 (0.01)	−0.001 (0.01)	−0.006 (0.02)
Bus			−0.05 (0.03) **
Percentage highways over total road network		−0.08 (0.14)	
Parking_commercial	−0.19 (0.11) *	−0.20 (0.10) *	−0.21 (0.12)
Parking_residential	−0.17 (0.11)	−0.17 (0.12)	−0.09 (0.21)
Time_trend	−0.02 (0.005) ***	−0.02 (0.006) ***	−0.01 (0.008) *
Intercept	1.01 (1.40)	0.28 (1.70)	−0.19 (2.11)
R^2	0.69	0.69	0.75
N	170	170	110

Notes: Standard errors in parentheses (robust to heteroscedasticity and clustered at the metropolitan level). Statistical significance at 1% (***), 5% (**), and 10% (*).

Table A3. Estimation results (road safety, negative binomial). Subsample with provinces having one metropolitan area.

	Dependent Variable: Log (Accidents)			***Dependent Variable: Log (Casualties)***		
Variables	***(I)***	***(II)***	***(III)***	***(IV)***	***(V)***	***(VI)***
Log (Density)	0.16 (0.14)	0.12 (0.10)	0.13 (0.12)	0.13 (0.15)	0.10 (0.10)	−0.004 (0.11)
Log (Unemployment)	−0.01 (0.19)	−0.18 (0.17)	0.20 (0.09) **	−0.11 (0.18)	−0.27 (0.11) **	0.12 (0.08)
Log (GDP per capita)	0.35 (0.46)	0.29 (0.30)	0.98 (0.41) ***	0.04 (0.39)	0.0006 (0.35)	0.59 (0.31) *
Log (City/Metropolitan)	0.94 (0.24) ***	1.07 (0.20) ***	0.24 (0.25)	0.93 (0.28) **	1.06 (0.15) ***	−0.16 (0.21)
Log (age)	0.29 (1.28)	2.38 (1.56)	4.40 (1.38) ***	1.11 (1.41)	2.99 (1.06) ***	5.91 (1.16) ***
Log (Rain)	0.35 (0.13) ***	0.37 (0.13) ***	−0.09 (0.07)	0.21 (0.10) **	0.24 (0.09) ***	−0.14 (0.09) *
Metro	−0.003 (0.0008) **	−0.001 (0.0009) *	−0.002 (0.001) **	−0.002 (0.0007) ***	−0.001 (0.0007) *	−0.0007 (0.001)
Tram	−0.01 (0.007) **	−0.009 (0.007)	−0.007 (0.01)	−0.01 (0.007) **	−0.007 (0.007)	−0.01 (0.01)

Table A3. *Cont.*

	Dependent Variable: Log (Accidents)			*Dependent Variable: Log (Casualties)*		
Variables	*(I)*	*(II)*	*(III)*	*(IV)*	*(V)*	*(VI)*
Local Train	−0.05 (0.02) **	−0.05 (0.01) ***	−0.05 (0.03)	−0.04 (0.02) *	−0.04 (0.02) **	−0.04 (0.03)
Bus	-	-	−0.21 (0.05) ***	-	-	−0.30 (0.04) ***
Percentage highways over total road network	-	−0.70 (0.17) ***	-	-	−0.65 (0.21) ***	-
Parking_commercial	−0.61 (0.26) ***	−0.56 (0.17) ***	−0.37 (0.18) **	−0.61 (0.25) ***	−0.56 (0.24) **	−0.32 (0.18) *
Parking_residential	−0.68 (0.20) ***	−0.66 (0.18) ***	−0.66 (0.18) ***	−0.60 (0.20) ***	−0.59 (0.22) ***	−0.54 (0.13) ***
Log (population) - exposure	1	1	1	1	1	1
Time_trend	0.03 (0.01) **	0.01 (0.01)	−0.01 (0.01)	0.06 (0.01)	−0.01 (0.01)	−0.05 (0.01) ***
Intercept	−13.99 (4.20) ***	−23.55 (5.50) ***	−26.32 (4.36) ***	−16.28 (5.21) ***	−24.96 (4.25) ***	−30.64 (3.79) ***
Wald test (joint sign.	3193.93 ***	327.20 ***	-	1858.31 ***	17,631.78 ***	-
N	170	170	170	170	170	110

Notes: Standard errors in parentheses (robust to heteroscedasticity and clustered at the metropolitan level). Statistical significance at 1% (***), 5% (**), and 10% (*). Population was used as an exposure variable.

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