Congestion in highways when tolls and railroads matter: Evidence from European cities

Miquel-Àngel Garcia-López[*†]
Universitat Autònoma de Barcelona and *Institut d'Economia de Barcelona*

Ilias Pasidis[*‡]
Institut d'Economia de Barcelona

Elisabet Viladecans-Marsal[*§]
Universitat de Barcelona and *Institut d'Economia de Barcelona*

June 2021

Abstract: Using data from the 545 largest European cities, we study whether the expansion of their highway capacity provides a solution to the problem of traffic congestion. Our results confirm that in the long run, and in line with the 'fundamental law of highway congestion', the expansion in cities of lane kilometers causes an increase in vehicle traffic that does not solve urban congestion. We disentangle the increase in traffic due to the increases in coverage and in capacity. We further introduce road pricing and public transit policies in order to test whether they moderate congestion. Our findings confirm that the induced demand is considerably smaller in cities with road pricing schemes, and that congestion decreases with the expansion of public transportation.

Key words: congestion, highways, Europe, cities
JEL classification: R41, R48

[*]We are grateful to the comments provided by the Editor, two anonymous referees, Gabriel Ahlfeldt, Jan Brueckner, Gilles Duranton, Ricardo Flores-Fillol, Jordi Jofre-Monseny, Stephan Heblich, Jos van Ommeren, Stef Proost, Albert Solé-Ollé, Matthew Turner, and participants of the 2020 UEA (virtual), 2019 ITEA (Paris). Finally, we are grateful to Marta MJ, Joel MG and Maria MG for excellent research assistance. Special thanks to Jordi Martin i Oriol for sharing the UNECE data. We acknowledge funding from Generalitat de Catalunya (2017SGR-796 and 2017SGR-1301), Ministerio de Ciencia e Innovación (RTI2018-097401-B-I00 and PID2019-108265RB-I00), the Xarxa de Referència d'R+D+I en Economia Aplicada and the UB Urban Economics Chair.

[†]Corresponding author. Department of Applied Economics, Universitat Autònoma de Barcelona, Edifici B, Facultat d'Economia i Empresa, 08193 Cerdanyola del Vallès, Spain (e-mail: miquelangel.garcia@uab.cat; phone: +34 93 581 4584; website: https://miquelangelgarcialopez.wordpress.com).

[‡]John M. Keynes 1-11, 08034 Barcelona, Spain (e-mail: ipasidis@gmail.com; phone: +34 93 403 4646).

[§]Department of Economics, Universitat de Barcelona, John M. Keynes 1-11, 08034 Barcelona, Spain (e-mail: eviladecans@ub.edu; phone: +34 93 403 4646; website: https://elisabetviladecansmarsal.com).

1. Introduction

Road congestion remains one of the most pressing issues in urban areas all over the world. Although the five most congested cities are located in developing countries, recent data indicate that they are followed by Rome, Paris and London, which all present higher values than some large US cities[1] (INRIX, 2019). In the case of Rome, for example, 166 hours are lost per driver due to congestion per year. Evidence is growing that traffic congestion has many negative consequences related to employment (Hymel, 2009), pollution and health (Green et al., 2020, Simeonova et al., 2020, Requia et al., 2018) and road fatalities (Pasidis, 2019). All in all, the current cost of road congestion in Europe is estimated to be over 270 billion euro per year (about 1% of its GDP).

Several different options exist for addressing congestion in cities. One of the most common policies has been to expand highway capacity. At times when politicians intend to foster economic growth, the increase in investment in road transportation has an important impact as a countercyclical fiscal policy (Leduc and Wilson, 2017). However, one of the main criticisms levelled at the expansion of an intrametropolitan highway network is that this policy may not generate any real improvements in accessibility and in economic growth; the evidence shows that, in the long term, these investments may simply relocate economic activity and leave congestion levels unchanged (Duranton et al., 2020).

One of the reasons for the inability of these policies to reduce urban congestion is the induced demand effect, also known as the 'fundamental law of highways congestion' (Downs, 1962, 1992). As a result of the new demand induced by the added road capacity, the travel speed (as a measure of congestion) on an expanded highway reverts to its level prior to its expansion. The induced demand phenomenon has undergone extensive empirical testing; however, the evidence is not conclusive for either short-run or long-run analyses (for an overview, see Hymel, 2019). Many of the earlier studies lack a good identification strategy for explaining the causal links between the increase in highway capacity and its impact on vehicle traffic. Interesting exceptions are the papers by Duranton and Turner (2011) and Hsu and Zhang (2014), which show an elasticity of traffic with respect to highway lane miles of approximately one for both US and Japanese urban areas. A unit elasticity suggests that increasing capacity supply does not reduce traffic congestion, not even partially.

In this paper we test the 'fundamental law of highway congestion' for 545 metropolitan areas of the EU28 countries during the period 1985—2005. We think that adding new evidence for those cities is an interesting contribution for several reasons. First, we are working with a much bigger sample of cities, compared to the cited papers, and this can also be considered a contribution in a continent where running country analysis is complicated because some of the countries are really small. Second, European cities (as the Japanese ones) are more compact than most US cities, and they are also characterized by a lower degree of car-dependency and the widespread use of

[1]Taking into account the commute delay attributable to congestion delay, the 10 most congested cities in the world in 2019 were Bogotá, Rio de Janeiro, Mexico City, Istanbul, Sao Paulo, Rome, Paris, London, Boston and Chicago (INRIX, 2019).

public transportation[2]. So, we think that this setting might add new insights to understand how the law performs. Third, taking into account the fact that the EU Regional and Cohesion Funds have funded a considerable portion of the immense highway network development in the last few decades, we think that having results for the European cities is also an important feature in terms of policy implications.

This analysis for the whole of Europe is methodologically challenging because we need to assemble data for many cities of different countries and for a long period. The difficulty is even greater to overcome several identification issues in order to properly estimate the causal effect. The first contribution of this paper is that we combine GIS data for a variety of historical data of transportation networks in Europe in order to obtain unbiased estimates. A second contribution is that we break down the effect of the highway expansion to the capacity effect (number of lanes) and the coverage effect (length of the network). Finally, our third contribution is that we are able to study the heterogeneity of the effects based on the existence of other policies that target congestion in cities. To see whether these policies affect congestion, we first control for the road pricing policies, and then take into account the availability of public transportation (railroads and subways) connecting some city centers with their suburbs. Our average results indicate that, in line with the evidence from the US and Japan, for the European cities there is an induced demand effect for both the capacity and coverage expansion. However, we find that this induced demand is considerable smaller in cities with road pricing schemes, and that congestion falls with public transportation expansions.

It is important to note that, due to the lack of data on travel (demand) speeds, a more direct measure of congestion used in other studies that analyse one city or small group of cities (Adler and van Ommeren, 2016, Bauernschuster et al., 2017, Adler et al., 2020, Russo et al., 2021), we estimate the effect of highway expansion on travel (demand) quantity. We follow the same approach than the closest works to ours, Duranton and Turner (2011) and Hsu and Zhang (2014), which face the same limitation of not being able to access to travel speed data for a big sample of cities and a long period of time.

The remainder of the paper is organized as follows. In Section 2, we begin by describing our data on congestion and highways in European cities and how we process them. Then in Section 3, we discuss our estimation approach and in Section 4 we present the results. In Section 5 we include congestion pricing and the availability of public transportation in cities in the analysis. Finally, we present the main conclusions in Section 6.

2. Congestion and highways in Europe

We use the Functional Urban Area (FUA) (formerly known as Larger Urban Zone (LUZ)), defined by the European Commission (Urban Audit Project) and the OECD as the unit of observation. In

[2] According to OECD data, the average urban population density in the European metropolitan areas in 2011 was 718 persons per km^2, compared to only 282 in the US. OECD and Eurostat statistics indicate for the same year that car use in Europe was some 42% lower than in the US. Also Europe is the world's leader in public transit systems: two thirds of the large European cities have subways compared with only a third in the US (Gonzalez-Navarro and Turner, 2018).

common with the Metropolitan Statistical Area in the US, the FUA consists of a central city (with at least 50,000 inhabitants) and a commuting zone (made up of all municipalities with at least 15% of their employed residents working in the city. The final dataset includes 545 FUAs covering the whole geography of Europe (29 countries)[3].

2.1 Congestion in Europe

We use data from the Road Traffic Censuses conducted by the United Nations Economic Commission for Europe (UNECE). These censuses contain traffic and inventory information on the main highways in Europe (E-Road network) at a very detailed geographical level (road segments) for every five years from 1985 to 2005[4]. Specifically, we obtain information on the annual average daily traffic (AADT), the length (km) and the number of lanes of each segment for the years 1985, 1995 and 2005.

Table 1: Highway congestion in European cities, 1985–2005

	1985	1995	2005	1985–1995	1995–2005	1985–2005
Annual average daily traffic (vehicles) - FUA	15,900	21,358	27,020	34.3%	26.5%	69.9%
	(15,318)	(19,237)	(21,837)			
Vehicle kilometers traveled ('000 km) - FUA	2,673	3,603	4,586	34.8%	27.2%	71.6%
	(3,959)	(4,722)	(5,426)			
VKT for the top 10 FUAs with population over 1 million ('000 km)						
London (UK)	57,435	62,633	66,830	9.1%	6.7%	16.4%
Madrid (ES)	21,754	20,737	39,644	-4.7%	91.2%	82.2%
Ruhrgebiet (DE)	20,326	28,405	29,964	39.7%	5.5%	47.4%
Frankfurt (DE)	24,217	27,500	28,810	13.6%	4.8%	19.0%
West Midlands (UK)	25,282	25,578	28,608	1.2%	11.8%	13.2%
Berlin (DE)	13,610	20,425	24,930	50.1%	22.0%	83.1%
München (DE)	18,386	19,747	23,111	7.4%	17.0%	25.7%
Amsterdam (NL)	10,969	22,204	22,304	102%	0.5%	103 %
Hamburg (DE)	17,212	22,548	22,169	31.0%	-1.7%	28.8%
Manchester (UK)	16,368	19,421	21,231	18.7%	9.3%	29.7%
VKT for the bottom 10 FUAs population over 1 million ('000 km)						
Leipzig (DE)	4,632	5,849	6.954	26.3%	18.9%	50.1%
Napoli (IT)	3,526	5,877	5,798	66.7%	-1.3%	64.5%
Torino (IT)	1,774	5,272	5,289	197%	0.3%	198%
Porto (PT)	1,081	3,443	5,125	218%	48.8%	374%
Sofia (BG)	2,745	3,495	5,039	27.3%	44.2%	83.6%
Ostrava (CZ)	902	1,227	3,825	36.0%	212%	324%
Krakow (PL)	1,732	2,127	3,753	22.8%	76.5%	117%
Katowice (PL)	1,012	1,856	3,708	83.5%	99.8%	267%
Gdansk (PL)	1,419	1,591	2,806	12.1%	76.4%	97.7%
Bucuresti (RO)	738	1,051	2,135	42.5%	103%	189%

Notes: FUA's values are averages. Standard deviations in parenthesis.

To measure traffic congestion, we use the well-known indicator 'vehicle kilometers traveled' (VKT), that is, the kilometers traveled by motor vehicles on the highway network. We first compute its value at the segment level by multiplying the length of each highway segment (km)

[3] 34 cities have not been considered in the final sample due to the lack of congestion data.

[4] Unfortunately, more recent censuses for 2010 and 2015 do not cover all European countries, only some of them.

with its AADT. Then, we compute the VKT at the FUA level by summing the values for all highway segments located within each FUA. Unfortunately, information about travel speeds is not available and, as a result, we measure congestion in terms of quantity.

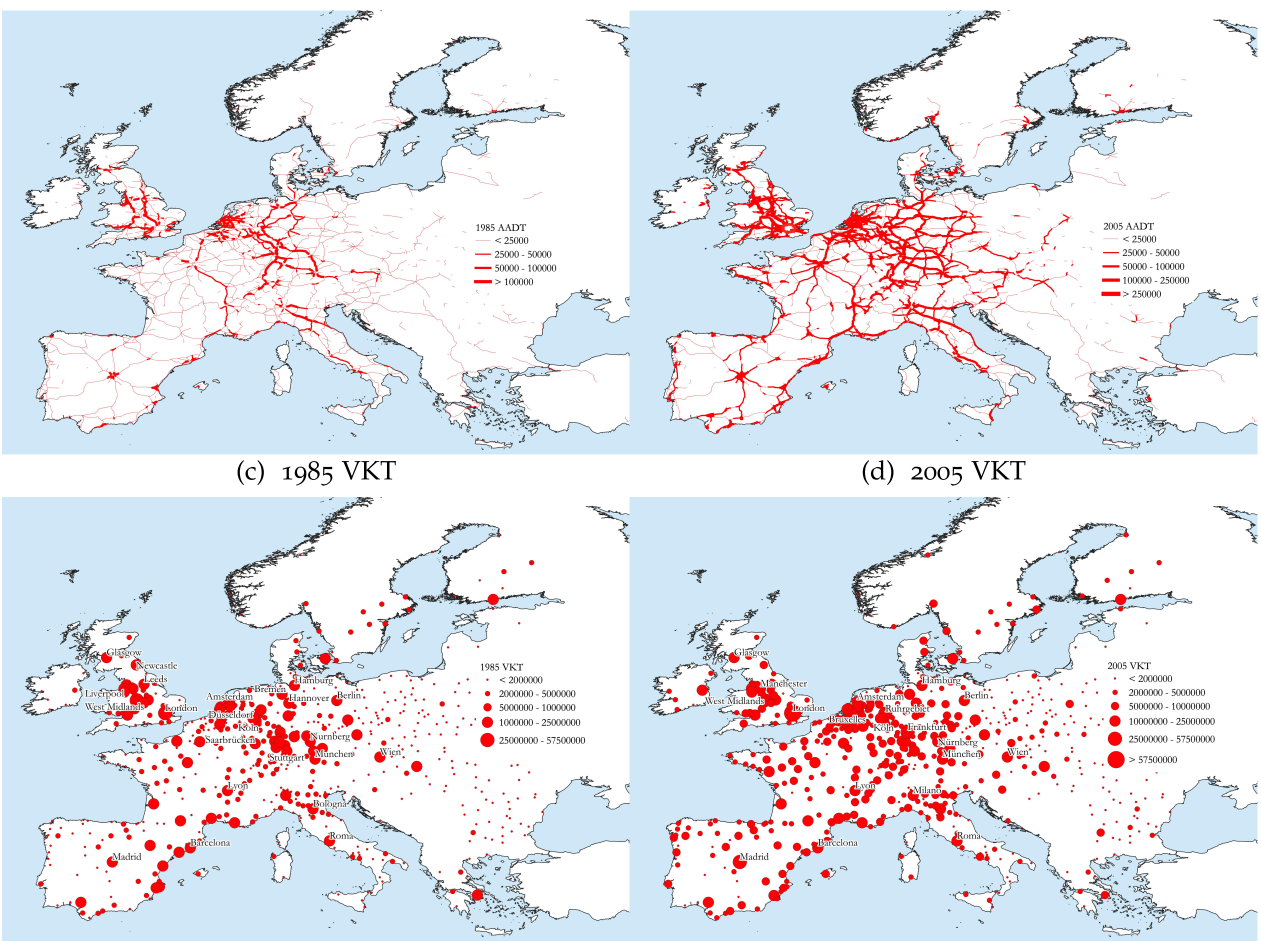
Table 1 reports the computations of these indicators for our sample of 545 European cities: Average values for both AADT and VKT, and individual VKT values for the top 10 and the bottom 10 cities with population over 1 million inhabitants. Regarding the AADT, an average European city in 2005 had 15,900 vehicles passing any point of the highway network. Between 1985 and 2005, the number of vehicles increased by 70%. Figures 1a and 1b show that the increase of the AADT was a general feature in all Europe.

VKT figures in Table 1 and Figures 1c and 1d also show high levels of traffic on highways and a growth between 1985 and 2005. On average, motor vehicles traveled 2.7 and 4.6 million km in 1985 and 2005, respectively. Focusing on the most populated cities, the top 10 cities had VKT values above the 20 million km. Their traffic grew with rates ranging from 13% in West Midlands (UK) to 103% in Amsterdam (NL). The cities with lowest VKT had values in 2005 between 2 million km (Bucuresti, RO) and almost 7 million km (Leipzig, DE). All these cities experienced significant increases in their traffic levels, between 50% (Leipzig, DE) and more than 300% (Ostrava, CZ; Porto, PT).

Figure 1: Highway congestion in Europe

(a) 1985 AADT

(b) 2005 AADT



(c) 1985 VKT

(d) 2005 VKT

2.2 *Highways in Europe*

To measure the size of the highway network, we compute the so-called 'lane kilometers'. First, we multiply the length (km) of each highway segment with the number of lanes. Then, we sum the resulting values for segments located within each city. As above mentioned, the UNECE Road Traffic Censuses also provide information on segment length and lanes.

Table 2 presents the main characteristics of the highway network in 1985, 1995 and 2005 in Europe and in our sample of 545 cities. Of the more than 74,000 km of European highways in 2005, almost half of them were located in FUAs. Between 1985 and 2005, the network more than doubled. Figure 2a shows the evolution of the highway network in Europe between 1985 and 2005.

Table 2: Highways in European cities, 1985–2005

	1985	1995	2005	1985–1995	1995–2005	1985–2005
Total length (km) - Europe	28,196	52,077	74,219	84.7%	74.2%	163%
Total length (km) - FUA	14,747	23,070	35,328	56.4%	53.1%	140%
Average length (km) - FUA	127 (106)	139 (107)	184 (146)	9.4%	32.3%	44.9%
Average number of lanes - FUA per direction	1.6 (0.9)	1.9 (1.0)	2.1 (1.2)	18.7%	10.5%	31%
Average Lane kilometers - FUA	1,666 (1,441)	1,762 (1,501)	1,884 (1,575)	5.8%	6.9%	13.1%

Notes: Standard deviations in parenthesis.

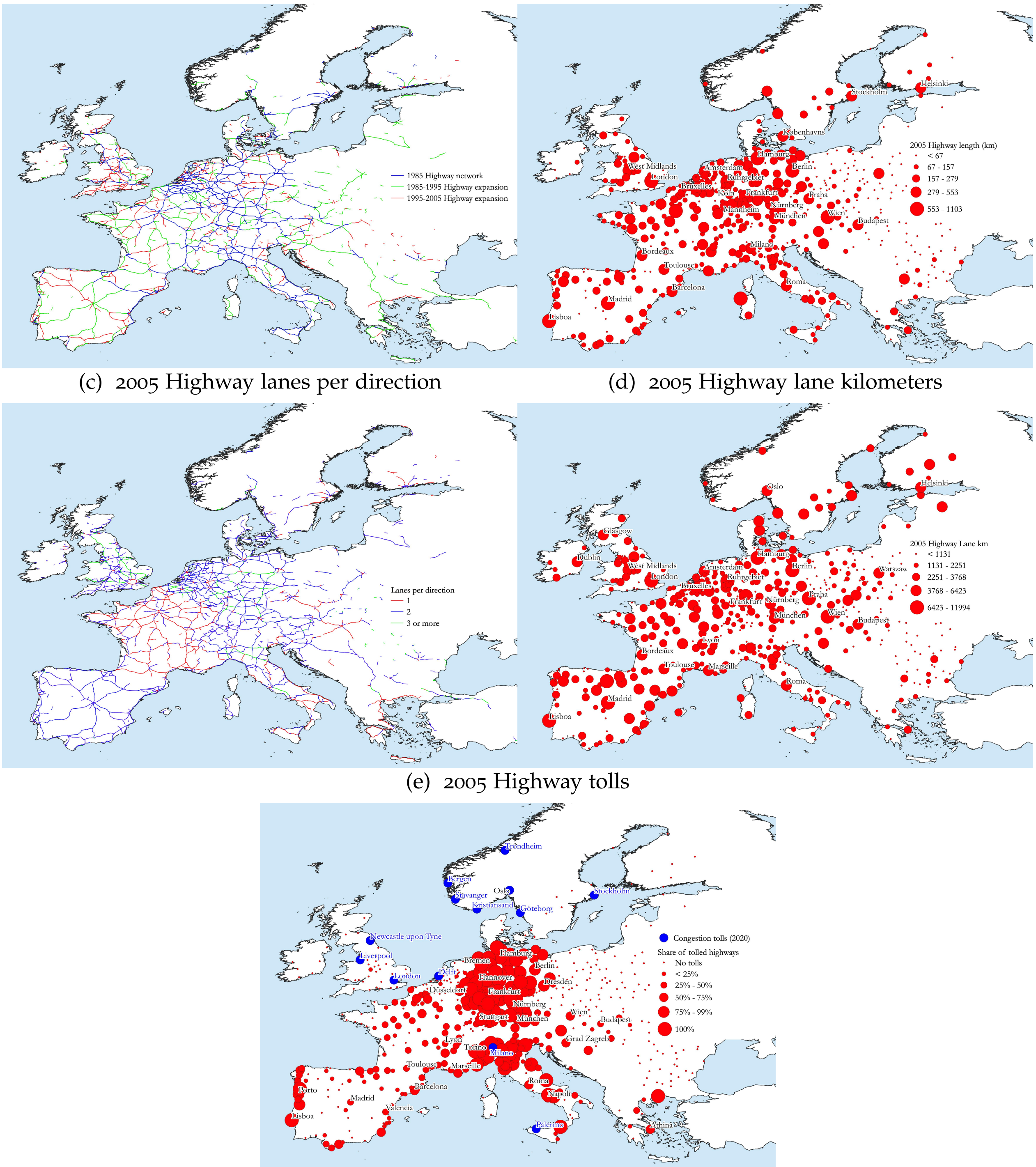
Table 2 also reports average computations for the 545 FUAs and shows that highways were extended both in terms of their coverage and their capacity. First, the length of the highway network of an average FUA increased from 127 to 184 km (a 45%) between 1985 and 2005. Second, the average number of lanes per direction also increased from 1.6 to 2.1 in 20 years. As a result, the number of lane kilometers of the average FUA increased from 1,666 in 1985 to 1,884 km in 2005. The high standard deviations of these three variables (in parenthesis) and their related maps in Figures 2b, 2c and 2d indicate that the European cities show a high degree of heterogeneity.

Figure 2e shows a categorization of the share of tolled highway kilometers in the 545 FUAs. In 2005[5], an average city had a 25% of tolled highways. However, our sample includes cities without tolls (285) and with tolls (260). Among the latter, 77 cities have tolls in all their highways.

According to Albalate and Bel (2012), tolls in Europe are mostly used to finance construction and maintenance costs of highways. However, more recently some cities have adopted congestion pricing policies -the so-called urban tolls- in order to reduce the impact of traffic (congestion, noise and pollution). Figure 2e shows the 14 cities that, according to `https://www.urbanaccessregulations.eu`, apply 'congestion prices' in 2020.

[5]Unfortunately, only the 2005 UNECE Road Traffic Census provide this kind of information at the highway segment level.

Figure 2: Highways in Europe



(a) Evolution of the highway network, 1985-2005

(b) 2005 Highway length

(c) 2005 Highway lanes per direction

(d) 2005 Highway lane kilometers

(e) 2005 Highway tolls

3. Empirical strategy

3.1 *Pool, panel and first-difference*

In this section, we introduce the empirical framework used to estimate the effect of the highway network expansion on the level of congestion. Increasing the supply of highways is expected to lower the cost of motor vehicle use in the short run because of the increase in the overall highway capacity in a city, which decreases traffic congestion. However, this reduction in the major component of the cost of motor vehicle use might affect the travel decisions of individuals regarding the mode and quantity of travel. The 'fundamental law of highway congestion' suggests that the long term average effect of increasing the supply of roads will be that induced demand will bring the level of congestion back to its initial level (or even to a higher level).

To empirically study the role played by highways improvements on highway congestion, we index cities by i and years by t, and estimate the following equation:

$$\begin{aligned}\ln(\text{VKT}_{it}) = \beta_0 + \beta_1 \times \ln(\text{Lane km}_{it}) \\ + \beta_2 \times \ln(\text{Population}_{it}) + \beta_3 \times \text{Socioeconomy}_{it} \\ + \beta_4 \times \text{Geography}_i + \beta_5 \times \text{History}_i + \epsilon_{it}\end{aligned} \tag{1}$$

where VKT_{it} refers to the vehicle kilometers traveled and measures the kilometers traveled by motor vehicles in the highway network. The main explanatory variable is Lane km_{it} and refers to the number of highway lane kilometers. Population_{it} is the number of inhabitants from official population censuses provided by the DG REGIO of the European Commission. Socioeconomy_{it} is a vector of characteristics including income, proxied by GDP; unemployment rate; and industrial composition, proxied by the shares of employment in manufacturing, in financial and business services, and in non-market services. Since there are no data available at the FUA level, all three variables are computed using data from the NUTS3 in which the FUA is located. Geography_i includes controls for physical geography such as total land area (km^2); a suburbanization index, which is the share of the central city area; the altitude (meters), elevation range (meters), and the terrain ruggedness index computed *a la* Riley et al. (1999) using the Digital Elevation Model over Europe (EU-DEM)[6]; and the logarithm of the distance (m) to the closest coast from the centroid of the central city. Finally, History_i adds two types of historical controls. First, dummy variables for historical major cities in 814, 1000, 1200, 1450 and 1850[7]. Second, three controls for more recent history (the 20th century): The logarithms of the decennial levels of population between 1960 and 1980.

With data describing a panel of cities, we can partition ϵ_{it} into permanent (δ_i) and time-varying (η_{it}) components. By so doing, we can remove all time-invariant city effects by estimating Equation (1) using city fixed-effects (Equation (2)) or its first-difference version (Equation (3)):

$$\begin{aligned}\ln(\text{VKT}_{it}) = \beta_1 \times \ln(\text{Lane km}_{it}) \\ + \beta_2 \times \ln(\text{Population}_{it}) + \beta_3 \times \text{Socioeconomy}_{it} + \delta_i + \eta_{it}\end{aligned} \tag{2}$$

$$\begin{aligned}\Delta\ln(\text{VKT}_{it}) = \beta_1 \times \Delta\ln(\text{Lane km}_{it}) \\ + \beta_2 \times \Delta\ln(\text{Population}_{it}) + \beta_3 \times \Delta\text{Socioeconomy}_{it} + \Delta\eta_{it}\end{aligned} \tag{3}$$

where Δ is the first-difference operator.

[6]The original GIS raster maps are available in https://www.eea.europa.eu/data-and-maps/data/copernicus-land-monitoring-service-eu-dem.

[7]These dummies are computed using information from the Digital Atlas of Roman and Medieval Civilizations (DARMC, http://darmc.harvard.edu) and from Bairoch et al. (1988).

3.2 *Instrumental variables*

When the random element of traffic congestion is uncorrelated with highways, we can estimate Equations (1), (2) and (3) by ordinary least squares (OLS). However, highway lane kilometers are expected to be endogenous to vehicle kilometers traveled because of reverse causation (e.g., congestion fostering highway expansion), measurement error (e.g., highways mismeasured because some may have just opened or are about to be opened) and omitted variables (e.g., geography, amenities or economic structure leading to more highways).

To address concerns of endogeneity, we rely on IV estimations (limited-information maximum likelihood, LIML). We use the digital vector maps created or used by Garcia-López (2019) to built instruments based on the ancient road and railroads in Europe: The main and secondary roads during the Roman Empire (McCormick et al., 2013), the main trade routes in the Holy Roman Empire in the 15th century (Ciolek, 2005), the postal roads in 1810 according to A. Arrowsmith's map[8], and the railroad network in 1870 (Marti-Henneberg, 2013). Figures A.1 and A.2 in Appendix A.1 shows their location in Europe and Barcelona, respectively.

Since, by definition, these historical instruments are *time-invariant*, we follow Baum-Snow (2007) and Garcia-López (2012, 2019) and adopt a 'shift-share' approach *a la* Bartik (1991) using each historical (rail)road as the 'share' component and the evolution of the highway network as the 'shift' component. Specifically, we compute each *time-variant* historical instrument by multiplying its historical length (in km) by the fraction of the highway network kilometrage in each country completed at each year and excluding each city's own contribution.

As common sense suggests, historical transportation networks may be relevant because modern networks are not built in isolation from them. On the contrary, it is easier and cheaper to build new infrastructures close to old infrastructures. Duranton and Turner (2011, 2012), Garcia-López (2012) or Garcia-López et al. (2015), among others, show that the stocks of historical (rail)roads are indeed highly correlated with the stocks of modern transportation networks in the US, Barcelona and Spain, respectively.

We econometrically test the relevance of each *time-variant* historical (rail)road in Appendix A.2. Specifically, Table A.1 shows OLS results when we regress the highway lane kilometers on the length of each ancient (rail)road (km) following a pooled strategy (columns 1 to 3, Equation (A.1)) and panel fixed-effect strategy (columns 4 and 5, Equation (A.2)). We also follow a first-difference strategy regressing the changes in the highway lane kilometers on changes in the length of each ancient (rail)road (km) (columns 6 and 7, Equation (A.3)), and adding the lag of VKT while controlling for geography, history and country fixed-effects (columns 8 and 9) or for FUA fixed-effects (columns 10 and 11). According to Murray (2006), valid instruments should have significant effects on modern highway lane kilometers and high First-Stage F-statistics. First-stage results show that both Roman roads and the 1870 railroads predict the congestion level when we follow a pooled regression strategy (columns 1 and 2). However, when we use a panel fixed-effect and first-difference regressions (columns 4, 6, 8 and 10), only the Roman roads predict both the levels and the changes in the highway lane kilometers. Results also show First-Stage F-statistics

[8] See the David Rumsey Map Collection (`http://www.davidrumsey.com`) for the original paper maps.

are near or above Stock and Yogo (2005)'s critical values, in particular when only Roman roads are used as instrument.

Our *time-variant* historical instrument also needs to be exogenous. As Garcia-López (2019) explains in detail, its 'shift' element is exogenous because, by construction, it refers to the length of the highway network that would have existed in each year had governments allocated highway construction uniformly across Roman roads within the countries. The 'share' component, the length of Roman roads, may also be exogenous because Roman roads were not built to anticipate the current traffic congestion levels in European cities. On the contrary, they were built to achieve military, administrative, and commercial goals between different parts of the Roman Empire (Garcia-López et al., 2015, Garcia-López, 2019). However, since geography and history have influenced both the evolution of European cities and its transportation networks, the exogeneity of the Roman instrument hinges on controlling for those characteristics as in the pooled regression strategy (Equation (1)). Alternatively, we can add city fixed-effects as in Equation (2) or estimate a first-difference regression as in Equation (3).

4. Does the fundamental law of highway congestion apply in Europe?

4.1 Main results

The fundamental law of highway congestion has been confirmed in the US (Duranton and Turner, 2011) and Japan (Hsu and Zhang, 2014). In this section, we investigate whether this (more than) proportional increase in congestion levels when highways are expanded also applies in Europe.

Table 3 reports OLS and LIML results in columns 1 to 5 and 6 to 7, respectively, when we regress the log of vehicle kilometers traveled on the log of highway lane kilometers. In columns 1 and 6, we follow a pooled strategy and estimate Equation (1) without control variables. In columns 2 and 7, we add all control variables. Columns 3 to 5 and 8 to 10 show results when we follow a fixed panel strategy and estimate Equation (2) gradually adding time-variant explanatory variables: the log of lane kilometers in columns 3 and 8, the log of population and year fixed-effects in columns 4 and 9, and socioeconomic controls in columns 5 and 10. Table 3 also reports first-stage statistics for the LIML regressions (which use the log of the *time-variant* length of Roman roads as instrument), and all of them are near or above Stock and Yogo (2005)'s critical values.

The estimated OLS coefficient of interest is positive and significantly different from zero in all specifications and shows that a 1% increase in the log of lane kilometers increases the vehicle kilometers traveled between 0.7 (column 5) and 0.8% (column 2). After addressing concerns of endogeneity, LIML counterparts in columns 7 to 10 show a higher impact of highways on congestion between 1.2 and 1.6%, respectively.

Appendix B provides additional results following a pooled strategy. In Table B.1, we estimate Equation (1) for each year: 1985, 1995 and 2005. OLS and LIML results are between 0.8-0.9 and 1.3-1.8, respectively, and are not statistically different from their counterparts in Table 3. In Table B.2, we show that the estimated coefficient of interest is quite stable when we gradually add explanatory variables to the pooled regression.

Table 3: The effect of highways on traffic congestion, OLS and IV results

Dependent variable:	ln(VKT)									
	OLS results					IV results				
	Pool		Panel			Pool		Panel		
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
ln(Lane km)	1.072[a]	0.831[a]	1.315[a]	0.686[a]	0.695[a]	2.077[a]	1.558[a]	2.710[a]	1.285[a]	1.205[a]
	(0.036)	(0.034)	(0.099)	(0.097)	(0.097)	(0.271)	(0.272)	(0.598)	(0.337)	(0.314)
ln(Population)		0.815[a]		-0.080	-0.048		0.545[c]		0.097	0.101
		(0.223)		(0.363)	(0.364)		(0.283)		(0.363)	(0.364)
Geography		✓					✓			
History		✓					✓			
Socioeconomy		✓			✓		✓			✓
Country fixed-effects		✓					✓			
FUA fixed-effects			✓	✓	✓			✓	✓	✓
Year fixed-effects		✓		✓	✓		✓		✓	✓
Adjusted R^2	0.60	0.89	0.31	0.70	0.71					
First-Stage F-statistic						22.88	12.01	16.15	19.90	19.79
Instrument						ln(Km of Roman r.)		ln(Km of Roman roads)		

Notes: 1,635 observations (545 cities × 3 decades (1985-2005)) in each regression. Geography controls include the logarithm of the FUA area, a suburbanization index, which is the share of the central city area, the mean and range of FUA elevation, the mean surface ruggedness for each FUA and the logarithm of the distance to the closest coast from the central city centroid. History includes the logarithms of FUA population in 1960, 1970 and 1980, and dummy variables for historical major cities in 814, 1000, 1200, 1450 and 1850. Socioeconomic characteristics are the log of the GDP, the share of employment in manufacturing, the share of employment in finance and business services, the share of employment in non-market services, and the unemployment rate. Robust standard errors are clustered by FUA and are in parenthesis. [a], [b] and [c] indicates significant at 1, 5, and 10 percent level, respectively.

We also perform a set of robustness checks in Table C.1 of Appendix C. First, to address endogeneity concerns about the population variable (Duranton and Turner, 2011), in Panel A we follow the pooled strategy and estimate Equation (1) instrumenting the population variable with two time-invariant instruments: the average temperature and the average precipitation of the FUA. In column 1 we only instrument population, in column 2 we simultaneously instrument the two endogenous variables. In both cases, the associated First-Stage statistics are above and close to the Stock and Yogo (2005)'s critical values, respectively. Furthermore, the OLS and LIML results are in line with those in columns 2 and 7 of Table 3[9].

Second, we are worried that some country specific shocks may have affected both the evolution of highways and congestion at the country level. To allow the countries to have different time trends, in Panel B we follow the panel fixed-effect strategy and estimate Equation (2) adding country-specific linear trends in columns 3 and 4. Both OLS and LIML results hold. To test for the possible impact of the European Union integration process, we have introduced a time dummy to control for the year in which each country was part of the EU. The results remained the same.

[9]There is a considerable increase of the lane kilometer coefficient in column 2. However, it is important to note that in column 1, where we just instrument the population variable, the estimated coefficient for lane kilometers is very similar to the one we obtain when we do not instrument any variable (Table 3 column 2). This makes us confident that when we do not instrument the population variable, we are not biasing the results of lane kilometers. This is similar to what Duranton and Turner (2011) explain when studying the possible endogeneity of the population variable.

Third, another potential concern is that the increase in highway traffic and the highway development are both affected by the supply of other roads that are not classified as highways[10]. In Panel C, we estimate Equation (2) adding the length of secondary roads and the length of local roads as explanatory variables. Since these two additional variables are also endogenous, we instrument them in column 6 using the *time-variant* lengths of the 15th c. trade routes during the Holy Roman Empire and of the 1810 post routes[11]. The related First-Stage F-statistic is near the Stock and Yogo (2005)'s critical value. Results for the lane kilometers are not statistically different from those in columns 2 and 7 of Table 3. Interestingly, the expansion of secondary roads decreases highway congestion, but the effect is quite small (0.02-0.03).

Finally, we also test for the functional form of the effect under study. One might expect that the effect of highway expansion on traffic congestion depends crucially on the extent of the highway network in each city. In Panel D, we add the square of the log of lane kilometers. Results show that this quadratic term is not statistically significant and its value is very close to zero. Furthermore, the estimated coefficient for lane kilometers is in line with previous results.

Table 4: The effect of highways on traffic congestion, OLS and IV results: First-difference

Dependent variable:	Δln(VKT)									
	OLS results					IV results				
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Δln(Lane km)	0.632^a	0.633^a	0.638^a	0.520^a	0.243^a	1.190^a	1.177^a	1.249^a	1.104^b	1.138^a
	(0.103)	(0.103)	(0.103)	(0.092)	(0.063)	(0.328)	(0.361)	(0.375)	(0.438)	(0.306)
Lagged ln(VKT)				-0.161^a	-1.057^a				-0.131^a	-0.874^a
				(0.020)	(0.048)				(0.039)	(0.088)
Δln(Population)		0.044	0.065	0.407	-0.066		-0.050	-0.051	0.139	-0.138
		(0.355)	(0.366)	(0.262)	(0.279)		(0.353)	(0.351)	(0.257)	(0.166)
Geography				✓					✓	
History				✓					✓	
ΔSocioeconomy			✓	✓	✓			✓	✓	✓
Country fixed-effects				✓					✓	
FUA fixed-effects					✓					✓
Adjusted R^2	0.32	0.32	0.33	0.41	0.80					
First-Stage F-statistic						23.58	22.01	21.26	14.12	16.22
Instrument						Δln(Km of Roman roads)				

Notes: 1,090 observations (545 cities × 2 first-difference periods) in each regression. Geography controls include the logarithm of the FUA area, a suburbanization index, which is the share of the central city area, the mean and range of FUA elevation, the mean surface ruggedness for each FUA and the logarithm of the distance to the closest coast from the central city centroid. History includes the logarithms of FUA population in 1960, 1970 and 1980, and dummy variables for historical major cities in 814, 1000, 1200, 1450 and 1850. Socioeconomic characteristics are the log of the GDP, the share of employment in manufacturing, the share of employment in finance and business services, the share of employment in non-market services, and the unemployment rate. Robust standard errors are clustered by FUA and are in parenthesis. ^{a}, ^{b} and ^{c} indicates significant at 1, 5, and 10 percent level, respectively.

Now we change our empirical strategy and follow the first-difference approach by estimating

[10]We use data of secondary and local roads provided by the EC DG-REGIO (for more details, see Stelder, 2016).

[11]We build these instruments using the 'shift-share' approach explained in Section 3.2. The length of each historical (rail)road is the 'share' component and the evolution of the country transportation network (excluding each city's own contribution) is the 'shift' component.

Equation (3). Table 4 presents OLS and LIML results in columns 1 to 5 and 6 to 10, respectively. Columns 1 to 3 and 6 to 8 show results when we gradually add time-variant explanatory variables: Only the change in lane kilometers (columns 1 and 6), adding the change in population (columns 2 and 7) and including the changes in socioeconomic controls (columns 3 and 8). Since all time-invariant factors drop out of Equation (3), we add geography, history and country dummies as control variables in columns 4 and 9, and add FUA fixed-effects in columns 5 and 10. Moreover, we also add the logarithm of the lagged vehicle kilometers traveled in columns 4-5 and 9-10. Table 4 also reports first-stage statistics for the LIML regressions (which use the log of the *time-variant* change in the length of Roman roads as instrument), and all of them are above Stock and Yogo (2005)'s critical values.

Results for the OLS regressions show elasticities of the change in lane kilometers ranging between 0.2 in the most demanding specification (column 5) and 0.6 in the *pure* first-difference specification (column 3). After instrumenting lane kilometers with the *time-variant* Roman road instrument, LIML results for the different specifications are quite stable and show an elasticity around 1.2%. Both OLS and LIML results are in line with those using pooled and panel fixed-effect approaches in Table 3.

The fundamental law of highway congestion states that a capacity expansion of highways produces a (more than) proportional increase in highway congestion levels. LIML results when using pooled, panel and first-difference empirical strategies confirm that this law also applies in European cities. Focusing in our preferred specification in column 10 of Table 3 that follows a panel fixed-effect estimation, a 1% increase in the highway lane kilometers increases the vehicle kilometers traveled by 1.2%. This elasticity is slightly higher than the one obtained by Duranton and Turner (2011) for the US (1.02) and almost the same than the estimated by Hsu and Zhang (2014) for Japan (1.24).

A qualifier is important here. While the previous conclusions apply for the point estimates, the picture is mixed when we take into account their confidence intervals. For the case of the pooled results, their IV estimated coefficients are statistically higher than 1, indicating that highway expansions cause a more than proportional increase in travel quantity (VKT). However, panel and first-difference results report IV point estimates that are not statistically different from 1 and, in most cases, from 0.7, indicating a (less than) proportional increase in VKT. In other words, when we consider confidence intervals, it is not totally clear whether the fundamental law applies. We explore this question in more detail in Section 5.2, in which we introduce the effects of public transportation that, in the case of the European cities, we consider a more robust and not biased specification.

4.2 Coverage and capacity effects

A highway network can be extended by increasing the number of lanes, that is, its 'capacity'. Another way is extending the length of existing routes or creating new ones, that is, increasing the 'coverage' of the highway network. After confirming that the fundamental law apply to European cities, we now turn our attention to study whether the effect of an increase in highway provision is related to a 'coverage effect' and/or to a 'capacity effect'.

Based on previous main results, we depart from our preferred panel fixed-effect approach to estimate an equation that consider both the length of the highway network and the average number of highway lanes[12]:

$$\begin{aligned}\ln(\text{VKT}_{it}) = & \beta_{1a} \times \ln(\text{Km of highways}_{it}) \\ & + \beta_{1b} \times \text{Average number of lanes}_{it} \\ & + \beta_2 \times \ln(\text{Population}_{it}) + \beta_3 \times \text{Socioeconomy}_{it} + \delta_i + \eta_{it}\end{aligned} \tag{4}$$

It is important to notice that these two variables are also endogenous and, as a result, need to be instrumented. For the case of the length of highways, Garcia-López (2019) shows that historical (rail)roads and, in particular, Roman roads, are good predictors of this variable. Table A.2 of Appendix A.3 reports first-stage OLS results when we regress the log of km of highways on the log of km of our *time-variant* historical (rail)roads conditional on controls. In column 1, we separately include the four old (rail)roads and find that only Roman roads has a positive and significant effect. In column 2, we only include the Roman roads and confirm its effect. In both cases, the First-Stage F-Statistic is near Stock and Yogo (2005)'s thresholds.

As shown by Garcia-López (2012), Garcia-López et al. (2015) and Garcia-López et al. (2017a,b), the location of modern highways is also related to the location of historical (rail)roads. In fact, when mapping these old (rail)roads we realize that most of them are located very close to each other (see, for example, the case of Barcelona in Figure A.2). This could mean that, conditional on the geography, building additional lanes is easier and cheaper in those highway segments where we also find more old (rail)roads in parallel. Based on this idea, we instrument the average number of highways lanes with the average number of historical (rail)roads[13]. Column 3 of Table A.2 shows first-stage results when we consider the average number of *all* historical (rail)roads. In column 4, we separately consider the average number of *each* historical (rail)road. In both cases, estimated coefficients are positive and significant. The related First-Stage F-Statistics are above the Stock and Yogo (2005)'s thresholds.

Table 5 reports LIML results of estimating different specifications of Equation (4). First, we separately consider the logarithm of the highway length (column 1) and the average number of lanes (columns 2 and 4). Later, we jointly include both variables in columns 3 and 5. Since both variables are expected to be endogenous, we instrument them with the above mentioned instruments: The length of historicals (rail)roads (columns 1, 3 and 5), the average number of all historical (rail)roads (columns 2 and 3), and the average number of each historical (rail)road (columns 4 and 5). These LIML results show positive effects of extending highway routes and increasing lanes. In particular, our preferred results in column 3 indicate that doubling the highway network, either by increasing the highway length by 100% or by building one additional lane in all highway segments, causes a 114% and a 212% growth in the vehicle kilometers traveled, respectively. These elasticities confirm both the coverage and capacity effects, being the latter more important. In Appendix D we confirm these results using the log of the number of lanes as explanatory variable.

[12]We consider the number of lanes in each highway segment and compute the average for each city.

[13]For each year and highway segment, we compute the number of historical (rail)roads that are located in parallel less than 1 kilometer. Then, we compute the average for each city.

Table 5: The effect of highways on traffic congestion, IV results: Length and lanes

Dependent variable:	ln(VKT)				
Instrumenting:	Length [1]	Lanes [2]	Both [3]	Lanes [4]	Both [5]
ln(Km of highways)	2.293[a] (0.561)		1.146[a] (0.288)		1.287[a] (0.208)
Number of lanes		2.117[a] (0.493)	2.198[a] (0.369)	2.702[a] (0.513)	2.540[a] (0.333)
ln(Population)	-0.557 (0.895)	1.226[a] (0.363)	0.162 (0.400)	1.137[a] (0.421)	-0.019 (0.398)
Socioeconomy	✓	✓	✓	✓	✓
FUA fixed-effects	✓	✓	✓	✓	✓
Year fixed-effects	✓	✓	✓	✓	✓
First-Stage F-statistic	11.52	26.29	7.65	11.78	8.47
Instruments	ln(Roman roads)		ln(Roman roads)		ln(Roman roads)
		Number of all historical (rail)roads		Numbers of each historical (rail)road	

Notes: 1,635 observations (545 cities × 3 decades (1985-2005)) in each regression. Socioeconomic characteristics are the log of the GDP, the share of employment in manufacturing, the share of employment in finance and business services, the share of employment in non-market services, and the unemployment rate. Robust standard errors are clustered by FUA and are in parenthesis. [a], [b] and [c] indicates significant at 1, 5, and 10 percent level, respectively.

5. Do tolls and public transportation matter?

Compared with US cities, there are at least two prominent features in European cities: The use of tolls, and the massive investment in public transportation, in particular, in railroads. In this section, we study whether these two characteristics affect the fundamental law of highway congestion.

5.1 Tolls

As discussed in Section 2.2, in 2005 almost half of the cities included in our sample had tolls (260 out of 545) and, on average, these tolls affected 25% of the highway network. To analyze the role of these tolls, we depart from the panel fixed-effect approach to estimate an equation that includes the interaction of our main explanatory variable:

$$\begin{aligned} \ln(\text{VKT}_{it}) = {} & \beta_1 \times \ln(\text{Lane km}_{it}) \\ & + \beta_2 \times \ln(\text{Lane km}_{it}) \times \text{Tolls}_i \\ & + \beta_3 \times \ln(\text{Population}_{it}) + \beta_4 \times \text{Socioeconomy}_{it} + \delta_i + \eta_{it} \end{aligned} \tag{5}$$

Table 6 show results for Equation (5). In column 1, we interact lane kilometers with a dummy for cities with tolled highways. In column 2, the interaction variable is a dummy for cities with 25% or more of tolled highways. Finally, we directly interact lane kilometers with the share of tolled highway segments in columns 3. Results are essentially identical and show that (1) highway improvements increase congestion, (2) the effect is smaller in cities with tolls, and (3) fundamental law is mainly related to cities without tolls or with a low percentage of tolled highways. In particular, and focusing on our preferred specification in column 3 (using a continuous interaction), a 1% increase in lane kilometers increases congestion by 1.9% in cities without tolls and by only 0.3% (=1.9-1.6) in cities with tolls in all their highways (100% share of tolled highways). Some simple computations show that the fundamental law applies to cities with a share of tolled highways below 56%. These results can be regarded as novel evidence in line with recent literature suggesting that the solution to traffic congestion is the adoption of 'congestion' pricing policies (Santos, 2004, de Palma et al., 2006, Winston and Langer, 2006, Leape, 2006, Eliasson and Mattsson, 2006).

Table 6: The effect of highways on traffic congestion, IV results: Tolls and interactions

Dependent var.:	ln(VKT)			
Interacting:	All tolled cities	Above 25% tolls cities		Share of tolled highways
	[1]	[2]		[3]
ln(Lane km)	1.903^a	2.106^a	ln(Lane km)	1.894^a
	(0.560)	(0.743)		(0.629)
ln(Lane km) ×Dummy tolls	-1.203^b	-1.454^b	ln(Lane km) ×Share tolls	-1.598^b
	(0.527)	(0.685)		(0.785)
ln(Population)	-0.020	-0.063	ln(Population)	-0.049
	(0.276)	(0.284)		(0.281)
Socioeconomy	✓	✓	Socioeconomy	✓
FUA fixed-effects	✓	✓	FUA fixed-effects	✓
Year fixed-effects	✓	✓	Year fixed-effects	✓
First-Stage F-stat	11.18	7.62	First-Stage F-stat	4.50
Instruments	ln(Km of Roman roads)	ln(Km of Roman roads)	Instruments	ln(Km of Roman roads)
	ln(Roman)×Tolls	ln(Roman)×25% Tolls		ln(Roman)×Share tolls

Notes: 1,635 observations (545 cities × 3 decades (1985-2005)) in each regression. Socioeconomic characteristics are the log of the GDP, the share of employment in manufacturing, the share of employment in finance and business services, the share of employment in non-market services, and the unemployment rate. Robust standard errors are clustered by FUA and are in parenthesis. ^{a}, ^{b} and ^{c} indicates significant at 1, 5, and 10 percent level, respectively.

Finally, in Appendix E we follow an alternative empirical strategy based on estimating Equation (2) for two subsamples: Cities with tolls vs. without tolls. Results reported in Table E.1 confirm that highway tolls mitigate the induced demand effect of highway expansions.

Two additional qualifiers are important here. First, the above results assume that tolls in Europe are exogenous to traffic because, as discussed in Section 2.2, at that period they were mostly used to finance construction and maintenance costs of highways (Albalate and Bel, 2012). Additionally, only 14 of our 545 cities have recently adopted 'congestion' pricing policies in order to reduce the impact of traffic (congestion, noise, pollution, ...), and, when we do not consider them in the analysis, the results hold. However, it might still be that endogeneity is not fully addressed if governments allocate tolls in those highway segments with most traffic. Therefore, the above results should be read with caution.

Second, if we consider the confidence intervals as in Section 4.1 for the lane kilometers coefficient in column 3, there is small probability that the coefficient could be 0.89 (below 1 indicating a less than a proportional impact). What is clear is that, considering the confidence intervals, the toll road impact is always negative and significantly different from zero. In the next section, we study this question in detail by also controlling for the effect of the supply of public transportation.

5.2 *Public transportation*

Now we turn our attention to public transportation and, in particular, the railroad network. In Europe, it was mainly built during the 19th and 20th centuries and nowadays there are more than 225,000 km of rail lines. At the FUA level, the network expanded from 32,000 to 52,000 km between 1985 and 2005. On average, the network increased more than 60%, from 59 to 96 km. Some examples of the more recent railroad expansion are the construction of the Regional Express Rail (RER) network in Paris (Garcia-López et al., 2017a,b) or the introduction of the high-speed rail in Germany (Ahlfeldt and Feddersen, 2018), Spain (Albalate et al., 2017) and the UK (Heblich and Simpson, 2018).

We study the effect of railroads[14] on congestion by estimating a version of Equation (2) which includes the length of railroads as explanatory variable:

$$\begin{aligned}\ln(\text{VKT}_{it}) = {} & \beta_1 \times \ln(\text{Lane km}_{it}) \\ & + \beta_2 \times \ln(\text{Km of railroads}_{it}) \\ & + \beta_3 \times \ln(\text{Population}_{it}) + \beta_4 \times \text{Socioeconomy}_{it} + \delta_i + \eta_{it}\end{aligned} \tag{6}$$

Since the stock of railroads may also depend on the level of highway congestion, now we have to deal with an additional endogenous variable. To do so, we follow Garcia-López (2019), which shows that the 1870 railroad network is a good predictor of the length of modern railroads. Table A.3 of Appendix A.4 reports first-stage OLS results when we regress the log of km of railroads on the log of km of our *time-invariant* historical (rail)roads conditional on controls. In column 1, we separately include the four old (rail)road networks and find that only the 1870 railroads has a positive and significant effect. In column 2, we only include the 1870 railroad network and confirm its effect. In both cases, the First-Stage F-Statistic is near Stock and Yogo (2005)'s thresholds.

Column 1 of Table 7 reports LIML results when we estimate Equation (6). They confirm the positive effect of lane kilometers on travel quantity. If we consider the confidence interval, as in Section 4.1, the IV point estimate is now significantly higher than 1, indicating that highway expansions cause a more than proportional increase in VKT. As a result, when we estimate a more complete empirical specification, which includes the supply of public transportation, we confirm that the fundamental law of highway congestion applies in European cities (with more than proportional effects).

On the other hand, the results for railroads are also very interesting. Their estimated coefficients in all three columns of Table 7 are significant and, more important, negative. They indicate that the supply of public transportation (railroads) directly moderate highway congestion in terms of (travel) quantity. In particular, a 1% increase in the length of the railroad network decreases congestion (VKT) by 0.5%.

[14]Unfortunatley, there is no data available for all the cities and the period of our analysis on public buses.

Subways are important in the largest European cities because a high proportion of their mobility is based on this transportation mode (Gonzalez-Navarro and Turner, 2018). In our sample, 32 cities have a subway network within their cores and connecting with their suburbs. The subway network of the average city had 52 km in 2011 and it represented around 14% of the total railroad length. To study whether subways also matter for congestion, we estimate Equation (6) including the interaction[15] between the railroad length and the share of subways. Column 2 shows LIML results when we only instrument lane km and railroad length. Our preferred specification in column 3 reports LIML estimates when the interaction term is also instrumented. In this case, results confirm (1) the fundamental law of highway congestion (with a VKT elasticity above 1) and (2) the above mentioned negative effect of railroads on congestion. Furthermore, the negative estimated coefficient for the interaction term shows that (3) the more important the subways in the railroad network, the higher the reduction of congestion. In particular, a 1% increase in the length of the railroad network decreases congestion by 0.6% in a city without subways, by 0.8% in a city with the average share of subways (14%), and by 1.3% in a city where subways are 50% of the total railroad network.

Table 7: The effect of highways on traffic congestion, IV results: Public transportation

Dependent variable:	ln(VKT)		
		Interacting with the share of subways	
	[1]	[2]	[3]
ln(Lane km)	2.208^{a}	1.408^{a}	1.407^{a}
	(0.531)	(0.324)	(0.344)
ln(Km of railroads)	-0.533^{b}	-0.488^{b}	-0.562^{b}
	(0.270)	(0.240)	(0.268)
ln(Km of railroads) ×Share of subways		-0.660^{c}	-1.384^{c}
		(0.393)	(0.760)
ln(Population)	-0.605	-0.351	-0.394
	(1.048)	(0.513)	(0.564)
Socioeconomy	✓	✓	✓
FUA fixed-effects	✓	✓	✓
Year fixed-effects	✓	✓	✓
Share of subways		✓	✓
First-Stage F-stat	4.98	3.31	2.12
Instruments	ln(Km of Roman roads)	ln(Km of Roman roads)	ln(Km of Roman roads)
	ln(Km of 1870 railroads)	ln(Km of 1870 railroads)	ln(Km of 1870 railroads)
			ln(1870 Rail)×% Subways

Notes: 1,635 observations (545 cities × 3 decades (1985-2005)) in each regression. Socioeconomic characteristics are the log of the GDP, the share of employment in manufacturing, the share of employment in finance and business services, the share of employment in non-market services, and the unemployment rate. Robust standard errors are clustered by FUA and are in parenthesis. ^{a}, ^{b} and ^{c} indicates significant at 1, 5, and 10 percent level, respectively.

In summary, the above results point out that railroads serve to free up highway capacity by taking drivers off the highways and putting them in trains. These findings are in contrast to those of Duranton and Turner (2011), who find no effect of public transit on congestion. However, their

[15]We use an empirical strategy based on an interaction term (instead of directly using the length of the subway network as explanatory variable) because, unfortunately, we only have GIS maps and data for subways in 2011.

empirical evidence is based on regular buses, which are as prone to traffic congestion as motor vehicles. On the contrary, our findings are in line with those of Anderson (2014), Adler and van Ommeren (2016), Bauernschuster et al. (2017), Adler et al. (2020) and Russo et al. (2021), who find that public transit generates large congestion relief benefits.

6. Conclusions

In this paper, we provide evidence that the 'fundamental law of highway congestion' holds for the cities of Europe, but also that well designed public policies can moderate this congestion. We use data for the 545 largest European cities to estimate the elasticity of a measure of congestion with respect to highway expansion. The results indicate that this elasticity is in the range close to 1. This suggests that expansion of the highway network induced the demand for car travel, and so, on average, the level of congestion remained roughly unchanged in the period 1985-–2005. In other words, we show that investments in highways did not effectively relieve traffic congestion. We also break down the type of expansion into coverage (the network length) and capacity (number of lanes); we find that both effects were significant in explaining the increase in traffic especially the capacity effect. Controlling further for road pricing and public transportation policies, our results indicate that cities with these policies in place suffer less congestion.

It is important to note that in this paper we estimate the effect of capacity on travel quantity, rather than travel speed which would had been a preferred measure. This is the measure used by other papers on congestion analyses (see, for example, Adler and van Ommeren, 2016, Adler et al., 2020, Bauernschuster et al., 2017, Russo et al., 2021). In those papers the analysis is done for one city (Rome or Rotterdam) or, in the case of Bauernschuster et al. (2017), for the 5 largest cities in Germany. Unfortunately, these data are not available for all the cities and the period we use in our analysis. Our measure of congestion is the indicator 'Vehicles kilometers traveled' (VKT) which is a good approach for the travel demand quantity. This indicator is also the one used in the papers more related to what we do with also a big sample of cities from which obtaining speed data information is not possible. This is the case of Duranton and Turner (2011) (for 228 MSA in the US) and Hsu and Zhang (2014) (for 189 urban employment areas in Japan).

The increase in traffic that we show could be related to many different reasons as changes on individual's behavior in their daily activities, migration of people and economic activity or increases on commercial transportation. Understanding those mechanisms would had also been a very interesting exercise. However, due to the sample of cities we use (more than 500 cities from 28 different countries) it is not feasible to assemble the data we would need to test for all these possible mechanisms.

These findings have major implications for transportation policies, given the persisting severity of traffic congestion in worldwide urban areas where the reduction of car use has become a priority. Only a few cities have established congestion charges, and public transport systems are under financial pressure. It is clear that there is great deal of scope for the design of good policies. Related to our results, it is well known that public acceptance of road pricing schemes is very low. People are not willing to pay in order to be able to drive and, on the other hand, the evidence seems to show that this policy might be regressive. A good way to proceed would be to introduce urban tolls and use the revenues obtained to improve public transportation.

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Appendix A. Historical roads and railroads in Europe

A.1 Maps

Figure A.1: Historical roads and railroads in Europe

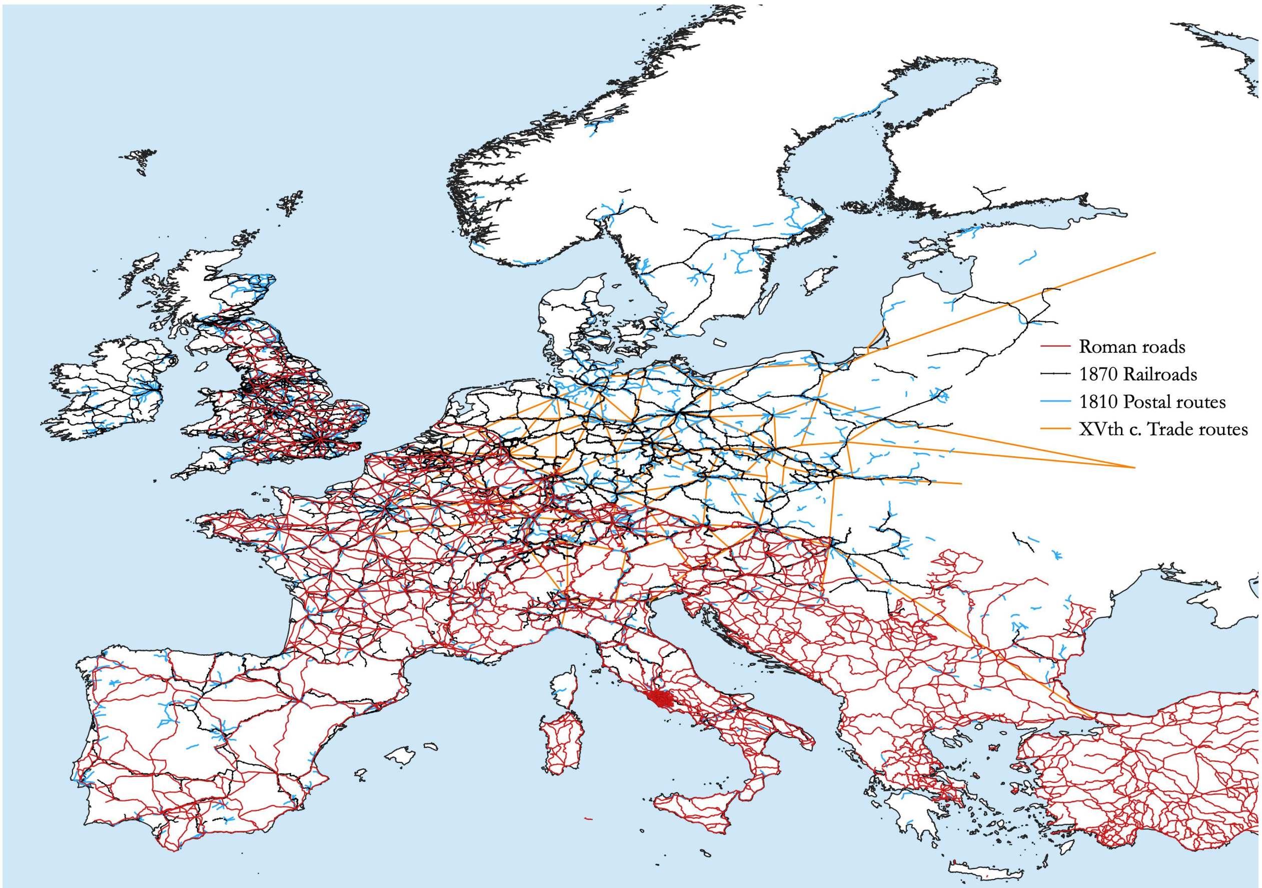
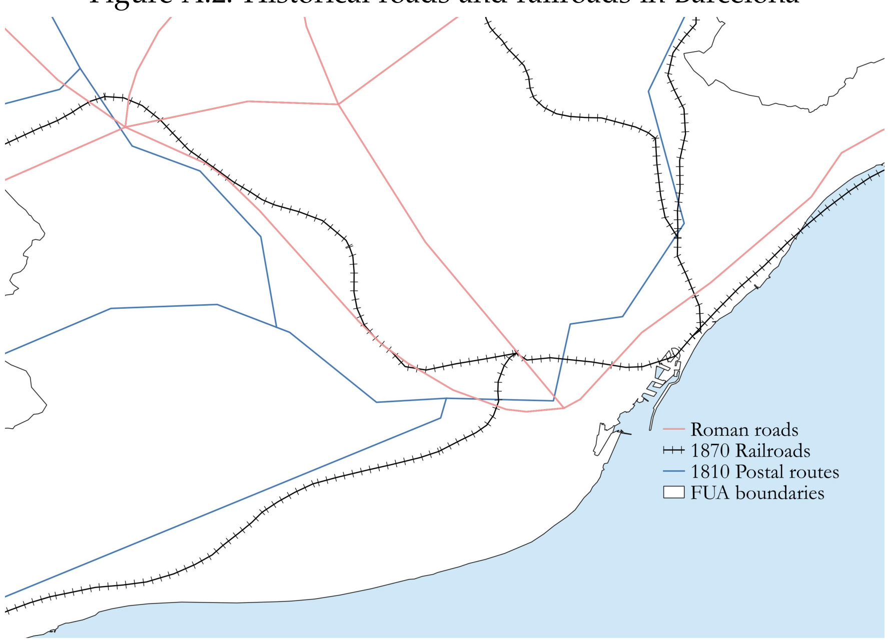


Figure A.2: Historical roads and railroads in Barcelona



A.2 *First-stage results for highway lane kilometers*

To econometrically test the relevance of each *time-variant* historical (rail)road, we estimate the following first-stage equations and show their results in Table A.1:

$$\begin{aligned}\ln(\text{Lane km}_{it}) = \gamma_0 + \gamma_1 \times \ln(\text{Historical (rail)road km}_{it}) \\ + \gamma_2 \times \ln(\text{Population}_{it}) + \gamma_3 \times \text{Socioeconomy}_{it} \\ + \gamma_4 \times \text{Geography}_i + \gamma_5 \times \text{History}_i + \epsilon_{it}\end{aligned} \tag{A.1}$$

when we follow a pooled regression approach (Equation (1)). Results are in columns 1 to 3.

$$\begin{aligned}\ln(\text{Lane km}_{it}) = \gamma_1 \times \ln(\text{Historical (rail)road km}_{it}) \\ + \gamma_2 \times \ln(\text{Population}_{it}) + \gamma_3 \times \text{Socioeconomy}_{it} + \delta_i + \eta_{it}\end{aligned} \tag{A.2}$$

when we follow a panel fixed-effect approach (Equation (2)). Results are in columns 4 and 5.

$$\begin{aligned}\Delta\ln(\text{Lane km}_{it}) = \gamma_1 \times \Delta\ln(\text{Historical (rail)road km}_{it}) \\ + \gamma_2 \times \Delta\ln(\text{Population}_{it}) + \gamma_3 \times \Delta\text{Socioeconomy}_{it} + \Delta\eta_{it}\end{aligned} \tag{A.3}$$

when we follow a first-difference approach (Equation (3)). Results are in columns 6 to 11.

Table A.1: Historical (rail)roads and modern highway lane kilometers, OLS results: First-stage

Dependent variable:	ln(Lane km)						Δln(Lane km)					
	Pool			Panel			First-Difference					
	[1]	[2]	[3]	[4]	[5]		[6]	[7]	[8]	[9]	[10]	[11]
ln(Roman roads)	0.026^a	0.025^a	0.025^a	0.037^a	0.038^a	Δln(Roman roads)	0.034^a	0.034^a	0.028^a	0.028^a	0.034^a	0.034^a
	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)		(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
ln(15th c. trade routes)	0.002											
	(0.007)											
ln(1810 post routes)	0.011											
	(0.008)											
ln(1870 railroads)	0.029^a	0.027^a		0.008		Δln(1870 railroads)	0.006		0.002		0.011	
	(0.008)	(0.008)		(0.008)			(0.008)		(0.008)		(0.011)	
ln(Population)	✓	✓	✓	✓	✓	Δln(Population)	✓	✓	✓	✓	✓	✓
Socioeconomy	✓	✓	✓	✓	✓	ΔSocioeconomy	✓	✓	✓	✓	✓	✓
Geography	✓	✓	✓			Geography			✓	✓		
History	✓	✓	✓			History			✓	✓		
Country fixed-effects	✓	✓	✓			Country fixed-effects			✓	✓		
FUA fixed-effects				✓	✓	FUA fixed-effects					✓	✓
						Lagged ln(VKT)			✓	✓	✓	✓
Year fixed-effects	✓	✓	✓	✓	✓	Year fixed-effects	✓	✓	✓	✓	✓	✓
First-Stage F-Statistic	5.22	10.36	12.01	10.55	19.79	First-Stage F-Statistic	11.13	21.26	7.92	14.12	8.44	16.22

Notes: 1,635 observations (545 cities × 3 decades (1985-2005)) in pooled and panel regressions (columns 1 to 5) and 1,090 observations (545 cities × 2 periods) in first-difference regressions (Columns 6 to 11). Geography controls include the logarithm of the FUA area, a suburbanization index, which is the share of the central city area, the mean and range of FUA elevation, the mean surface ruggedness for each FUA and the logarithm of the distance to the closest coast from the central city centroid. History includes the logarithms of FUA population in 1960, 1970 and 1980, and dummy variables for historical major cities in 814, 1000, 1200, 1450 and 1850. Socioeconomic characteristics are the log of the GDP, the share of employment in manufacturing, the share of employment in finance and business services, the share of employment in non-market services, and the unemployment rate. Robust standard errors are clustered by FUA and are in parenthesis. ^{a}, ^{b} and ^{c} indicates significant at 1, 5, and 10 percent level, respectively.

A.3 *First-stage results for highway length and number of lanes*

Table A.2: Historical (rail)roads and modern highway length and lanes, OLS results: First-stage

Dependent variable:	ln(Km of highways)			Number of lanes	
	[1]	[2]		[3]	[4]
ln(Km of Roman roads)	0.043[a]	0.050[a]	Number of all historical (rail)roads	0.119[a]	
	(0.015)	(0.015)		(0.023)	
ln(Km of 15th c. trade routes)	-0.017[b]		Number of Roman roads		0.183[a]
	(0.007)				(0.040)
ln(Km of 1810 post routes)	0.011		Number of 15th c. trade routes		0.174[a]
	(0.010)				(0.046)
ln(Km of 1870 railroads)	0.010		Number of 1810 post routes		0.097[b]
	(0.010)				(0.049)
			Number of 1870 railroads		0.157[a]
					(0.046)
ln(Population)	✓	✓	ln(Population)	✓	✓
Socioeconomy	✓	✓	Socioeconomy	✓	✓
FUA fixed-effects	✓	✓	FUA fixed-effects	✓	✓
Year fixed-effects	✓	✓	Year fixed-effects	✓	✓
First-Stage F-Statistic	5.15	11.52	First-Stage F-Statistic	26.29	11.78

Notes: 1,635 observations (545 cities × 3 decades (1985-2005)) in each regression. Socioeconomic characteristics are the log of the GDP, the share of employment in manufacturing, the share of employment in finance and business services, the share of employment in non-market services, and the unemployment rate. Robust standard errors are clustered by FUA and are in parenthesis. [a], [b] and [c] indicates significant at 1, 5, and 10 percent level, respectively.

A.4 *First-stage results for modern railroads*

Table A.3: Historical (rail)roads and modern railroads, OLS results: First-stage

Dependent variable:	ln(Kilometers of railroads)	
	[1]	[2]
ln(Kilometers of Roman roads)	-0.019	
	(0.012)	
ln(Kilometers of 15th c. trade routes)	0.006	
	(0.013)	
ln(Kilometers of 1810 post routes)	0.011	
	(0.020)	
ln(Kilometers of 1870 railroads)	0.308[a]	0.311[a]
	(0.083)	(0.075)
ln(Population)	✓	✓
Socioeconomy	✓	✓
FUA fixed-effects	✓	✓
Year fixed-effects	✓	✓
First-Stage F-statistic	5.75	17.41

Notes: 1,635 observations (545 cities × 3 decades (1985-2005)) in each regression. Socioeconomic characteristics are the log of the GDP, the share of employment in manufacturing, the share of employment in finance and business services, the share of employment in non-market services, and the unemployment rate. Robust standard errors are clustered by FUA and are in parenthesis. [a], [b] and [c] indicates significant at 1, 5, and 10 percent level, respectively.

Appendix B. Additional results

Table B.1: The effect of highways on traffic congestion, OLS and IV results: Years

Dependent variable:	ln(VKT)					
	OLS results			IV Results		
	1985	1995	2005	1985	1995	2005
	[1]	[2]	[3]	[4]	[5]	[6]
ln(Lane km)	0.904^a	0.813^a	0.768^a	1.832^a	1.310^a	1.844^a
	(0.043)	(0.039)	(0.040)	(0.342)	(0.225)	(0.264)
Population	✓	✓	✓	✓	✓	✓
Geography	✓	✓	✓	✓	✓	✓
History	✓	✓	✓	✓	✓	✓
Socioeconomy	✓	✓	✓	✓	✓	✓
Country fixed-effects	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.88	0.90	0.88			
First-Stage F-statistic				11.92	11.89	14.11
Instrument				ln(Km of Roman roads)		

Notes: 545 observations in each regression. Geography controls include the logarithm of the FUA area, a suburbanization index, which is the share of the central city area, the mean and range of FUA elevation, the mean surface ruggedness for each FUA and the logarithm of the distance to the closest coast from the central city centroid. History includes the logarithms of FUA population in 1960, 1970 and 1980, and dummy variables for historical major cities in 814, 1000, 1200, 1450 and 1850. Socioeconomic characteristics are the log of the GDP, the share of employment in manufacturing, the share of employment in finance and business services, the share of employment in non-market services, and the unemployment rate. Robust standard errors are clustered by FUA and are in parenthesis. ^{a}, ^{b} and ^{c} indicates significant at 1, 5, and 10 percent level, respectively.

Table B.2: The effect of highways on traffic congestion, OLS and IV results: Gradual

Dependent variable:	ln(VKT)									
	OLS results					IV Results				
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
ln(Lane km)	0.969^a	0.752^a	0.896^a	0.882^a	0.831^a	1.480^a	1.617^a	1.519^a	1.529^a	1.558^a
	(0.026)	(0.031)	(0.033)	(0.033)	(0.034)	(0.150)	(0.313)	(0.233)	(0.256)	(0.272)
Population		✓	✓	✓	✓		✓	✓	✓	✓
Geography			✓	✓	✓			✓	✓	✓
History				✓	✓				✓	✓
Socioeconomy					✓					✓
Country fixed-effects					✓					✓
Adjusted R^2	0.797	0.830	0.852	0.855	0.887					
First-Stage F-statistic						29.51	13.04	15.89	12.82	12.01
Instrument						ln(Km of Roman roads)				

Notes: 1,635 observations (545 cities $\times$ 3 decades (1985-2005)) in each regression. Geography controls include the logarithm of the FUA area, a suburbanization index, which is the share of the central city area, the mean and range of FUA elevation, the mean surface ruggedness for each FUA and the logarithm of the distance to the closest coast from the central city centroid. History includes the logarithms of FUA population in 1960, 1970 and 1980, and dummy variables for historical major cities in 814, 1000, 1200, 1450 and 1850. Socioeconomic characteristics are the log of the GDP, the share of employment in manufacturing, the share of employment in finance and business services, the share of employment in non-market services, and the unemployment rate. Robust standard errors are clustered by FUA and are in parenthesis. ^{a}, ^{b} and ^{c} indicates significant at 1, 5, and 10 percent level, respectively.

Appendix C. Robustness checks

Table C.1: The effect of highways on traffic congestion: Robustness checks

Dependent variable:	ln(VKT)										
Robustness:	Panel A: Instrumenting pop			Panel B: Linear trends			Panel C: Other roads			Panel D: Non-linearity	
	IV	IV		OLS	IV		OLS	IV		OLS	IV
	[1]	[2]		[3]	[4]		[5]	[6]		[7]	[8]
ln(Lane km)	0.723^a	2.312^a	ln(Lane km)	0.695^a	1.206^a	ln(Lane km)	0.686^a	1.444^a	ln(Lane km)	0.713^a	1.230^a
	(0.062)	(0.534)		(0.097)	(0.314)		(0.098)	(0.394)		(0.033)	(0.165)
						ln(Km second. roads)	-0.021^b	-0.029^b	(ln(Lane km))^2	-0.029	-0.262
							(0.010)	(0.011)		(0.020)	(0.21)
						ln(Km local roads)	0.013	-0.012			
							(0.011)	(0.020)			
ln(Population)	✓	✓	ln(Population)	✓	✓	ln(Population)	✓	✓	ln(Population)	✓	✓
Socioeconomy	✓	✓	Socioeconomy	✓	✓	Socioeconomy	✓	✓	Socioeconomy	✓	✓
Geography	✓	✓	FUA fixed-effects	✓	✓	FUA fixed-effects	✓	✓	FUA fixed-effects	✓	✓
History	✓	✓	Year fixed-effects	✓	✓	Year fixed-effects	✓	✓	Year fixed-effects	✓	✓
Country fixed-eff.	✓	✓	Country trend	✓	✓						
Year fixed-effects	✓	✓									
Adjusted R^2			Adjusted R^2	0.71		Adjusted R^2	0.71		Adjusted R^2	0.83	
First-Stage F-stat	12.06	4.66	First-Stage F-stat		19.79	First-Stage F-stat		5.30	First-Stage F-stat		3.71
Instruments		ln(Roman)	Instruments		ln(Roman)	Instruments		ln(Roman)	Instruments		ln(Roman)
	Temperature, Precipitation						ln(1810 Post), ln(15th c. Trade)				ln(Rom)×ln(Rom)

Notes: 1,635 observations (545 cities × 3 decades (1985-2005)) in each regression. Geography controls include the logarithm of the FUA area, a suburbanization index, which is the share of the central city area, the mean and range of FUA elevation, the mean surface ruggedness for each FUA and the logarithm of the distance to the closest coast from the central city centroid. History includes the logarithms of FUA population in 1960, 1970 and 1980, and dummy variables for historical major cities in 814, 1000, 1200, 1450 and 1850. Socioeconomic characteristics are the log of the GDP, the share of employment in manufacturing, the share of employment in finance and business services, the share of employment in non-market services, and the unemployment rate. Robust standard errors are clustered by FUA and are in parenthesis. ^{a}, ^{b} and ^{c} indicates significant at 1, 5, and 10 percent level, respectively.

Appendix D. Coverage and capacity effects using the log of lanes

Table D.1: The effect of highways on traffic congestion, IV results: Log of lanes

Dependent variable:	ln(VKT)				
Instrumenting:	Length	Lanes	Both	Lanes	Both
	[1]	[2]	[3]	[4]	[5]
ln(Km of highways)	2.293[a]		1.103[a]		1.170[a]
	(0.561)		(0.323)		(0.189)
ln(Number of lanes)		3.659[a]	3.514[a]	4.302[a]	4.062[a]
		(0.894)	(0.665)	(0.761)	(0.507)
ln(Population)	✓	✓	✓	✓	✓
Socioeconomy	✓	✓	✓	✓	✓
FUA fixed-effects	✓	✓	✓	✓	✓
Year fixed-effects	✓	✓	✓	✓	✓
First-Stage F-statistic	11.52	23.70	5.08	12.90	9.23
Instruments	ln(Roman roads)		ln(Roman roads)		ln(Roman roads)
		ln(Number of all historical (rail)roads)		ln(Numbers) of each historical (rail)road	

Notes: 1,635 observations (545 cities × 3 decades (1985-2005)) in each regression. Socioeconomic characteristics are the log of the GDP, the share of employment in manufacturing, the share of employment in finance and business services, the share of employment in non-market services, and the unemployment rate. Robust standard errors are clustered by FUA and are in parenthesis. [a], [b] and [c] indicates significant at 1, 5, and 10 percent level, respectively.

Appendix E. An alternative approach to analyze the role of tolls

As an alternative, but also complementary approach to the one developed in Section 5.1 to analyze the role of tolls, we consider an empirical strategy based on subsamples. Specifically, in Table E.1 we split our sample of cities and run separate regressions. First, in columns 1 and 2 we compare cities without tolls (285) with cities with tolls (260). Second, in columns 3 and 4 we compare cities with less than 25% of tolled highways (343) with cities with 25% or more of tolled highways (202). All LIML results point out in the same direction: The effect of lane kilometers on VKT is higher in cities without tolls or with less than 25% of tolled highways than in cities with tolls or with more than 25% of tolled highways. Furthermore, LIML results show that the fundamental law is only related to cities without tolls or with less than 25% of tolled highways, with elasticities of 1.13 and 1.34, respectively. As a whole, these results confirm the ones obtained using an empirical strategy based on interactions (Section 5.1).

Table E.1: The effect of highways on traffic congestion, IV results: Tolls and subsamples

Dependent variable:	ln(VKT)			
	Without vs. With tolls		Below vs. Above 25% tolled highways	
	without [1]	with [2]	below [3]	above [4]
ln(Lane km)	1.132^{c}	0.856^{a}	1.335^{b}	0.589^{c}
	(0.680)	(0.328)	(0.529)	(0.328)
ln(Population)	✓	✓	✓	✓
Socioeconomy	✓	✓	✓	✓
FUA fixed-effects	✓	✓	✓	✓
Year fixed-effects	✓	✓	✓	✓
Observations	855	780	1029	606
FUA	285	260	343	202
First-Stage F-statistic	4.82	11.16	7.72	9.44
Instrument	ln(Km of Roman roads)	ln(Km of Roman roads)	ln(Km of Roman roads)	ln(Km of Roman roads)

Notes: Socioeconomic characteristics are the log of the GDP, the share of employment in manufacturing, the share of employment in finance and business services, the share of employment in non-market services, and the unemployment rate. Robust standard errors are clustered by FUA and are in parenthesis. ^{a}, ^{b} and ^{c} indicates significant at 1, 5, and 10 percent level, respectively.