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FULL ARTICLE

Measuring the impact of ride-hailing firms on urban congestion: The case of Uber in Europe

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Abstract

This paper examines the impact of Uber, the world's largest ride-hailing firm, on congestion. Drawing on data from European cities for the period 2008 through 2016, I find a negative impact of Uber on congestion. The estimated impact in the baseline regression is −3.5 percentage points, but it is higher in cities that do not impose strong regulatory restrictions to ride-hailing services. In addition, the negative impact of Uber on congestion is only statistically significant in denser cities. The Uber effect is gradual given that its impact increases over time. Finally, I find suggestive evidence that the potential endogeneity bias underestimates the negative effect of Uber on congestion.

KEYWORDS
Europe, ride-hailing firms, uber, urban congestion

JEL CLASSIFICATION
R00; R41; Q50

1 | INTRODUCTION

Uber, Lyft, and other ride-hailing firms have reshaped mobility in many cities across the globe; and, at the same time, their success has generated a considerable number of economic, social and legal controversies, including debates about working conditions, safety, quality standards and unfair competition. Hence, many cities have banned or imposed restrictions on the activity of ride-hailing firms.

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One of the main controversies concerns their impact on congestion, the focus of this present study. Urban congestion results in traffic jams that affect both drivers and pedestrians, who have to put up with increasing levels of gridlock, noise and pollution. *INRIX* and *Centre for Economics and Business Research* carried out a study in 2014 to estimate the economic impact of the delays caused by traffic jams in the UK, France, Germany, and the US (INRIX and Cebr, 2014). Congestion costs represented $200 billion in the four countries (around 0.8% of their joint GDP). Furthermore, the relationship between congestion and pollution is well-documented, with prolonged car circulation at reduced speeds having a notable effect on the emission of polluting substances (Barth & Boriboonsomsin, 2008; Beaudoin et al., 2015; Parry et al., 2007). Congestion would also seem to have a negative impact on road safety outcomes, especially for the most congested cities (Albalate & Fageda, 2021).

In this paper, I examine the impact of the largest ride-hailing firm in the world today—Uber—on urban congestion. The analysis is undertaken for cities in Europe (EU) between 2008 and 2016.

The relationship between ride-hailing firms and congestion is *a priori* unclear. On the one hand, users of ride-hailing firms may benefit from shorter waiting times, greater flexibility, and lower prices than users of traditional taxi services. Hence, congestion could increase due to demand induction (i.e., car trips, which without ride-hailing services, would not have been made). On the other hand, ride-hailing firms match passengers with drivers via websites and mobile apps so this reduces the number of unoccupied cars driving around looking for customers. Thus, the higher efficiency of ride-hailing firms to match demand with supply may reduce congestion. Finally, it is unclear whether ride-hailing firms compete with private cars, with public transit or with both.

In this regard, the limited evidence about the impact of ride-hailing firms on congestion in United States is not conclusive. Using data for a large sample of US cities, Li et al. (2016) find evidence that Uber entry has decreased congestion costs. Ward et al. (2019) find that ride-hailing services appears to cause a decline in state *per capita* vehicle registrations by 3%, but results regarding travel distances, gasoline consumption, and several air pollutants are not conclusive. Finally, case studies for San Francisco and New York provide evidence that in these large cities ride-hailing services may have worsen congestion (Anderson, 2014; Qian et al., 2020).

Here, I seek to add to this literature by providing a direct test of the impact of Uber on congestion using data of European cities between 2008 and 2016. In this regard, I examine the different effects of Uber on congestion based on the regulatory environment in which it operates. Taking into account that Uber is constrained to operate in the pre-booking segment in the considered period, I can distinguish two regulatory environments in my sample of cities; (i) a highly restrictive environment that imposes quantitative restrictions and strong qualitative requirements; and (ii) a low restrictive environment that as much only imposes some specific qualitative requirements. Thus, I exploit the variability in the regulatory environment in which Uber operates to capture the intensity in the use of its services. I should expect a more intense use of Uber services in those cities where the regulatory environment imposes less restrictions.

I also examine whether the different effects of Uber on congestion are based on the relatively levels of public transport provision, income and population density. In particular, the impact of Uber could be higher in denser cities given that density is a strong predictor of the probability of Uber entry and it can be expected that denser cities have a better endowment of public transportation.

One potential threat to my identification strategy is that Uber presence may be correlated with the previous levels of congestion in the city. To deal with this concern, I include city specific time trends so that I control for the fact that each city may have its own linear time trend. Furthermore, I apply a propensity score matching procedure so that I pair treated and control observations that have similar levels of congestion and similar values of the covariates in the initial year of the considered period. Finally, I apply an event study analysis in which I capture the effect of Uber over time.

Another potential threat to my identification strategy is that Uber entry may be correlated with unobserved time varying factors that also have an influence on congestion. To deal with this potential endogeneity bias, I use a subsample based on cities that are eventually treated. The potential endogeneity bias for this subsample should be more modest given that such bias would be related with the time of entry and not with the decision of entry or not. Furthermore, I apply an instrumental variables procedure using as main instrument the regulatory environment for Uber alike services that it is in force in the sample cities.

I find a negative and significant impact of Uber on congestion, an outcome that is consistent across all regressions in the empirical analysis. The estimated impact in the baseline regression is 3.5 percentage points. In addition, I find that less restrictions on Uber lead to a stronger negative impact on congestion. In highly restrictive environments, the impact of Uber is weak. In contrast, such impact is significant when it operates in a regulatory environment that does not impose quantitative restrictions nor strong qualitative requirements. Furthermore, I find that the negative impact of Uber on congestion is only statistically significant in denser cities where the presence of Uber is most common. Finally, I find suggestive evidence that the potential endogeneity bias underestimate the negative effect of Uber on congestion.

The rest of this paper is organized as follows. In the next section, I review the main mechanisms that may explain the relationship between Uber and congestion. Then, I provide details about the regulatory environment in which Uber operates in Europe. After that, I explain the empirical equation that I estimate and discuss my identification strategy. In the following section, I outline the sample used and provide relevant information about the data employed in the empirical analysis. Then, I present the results of the econometric estimates. The last section is devoted to the discussion and concluding remarks.

2 | CONGESTION AND RIDE-HAILING SERVICES: BACKGROUND

Uber could affect congestion through different mechanisms. Several studies have found evidence that the arrival of ride-hailing services has led to a substitution effect away from traditional taxi services. For example, Wallsten (2015) and Brodeur and Nield (2018) find fewer taxi trips as Uber grows in New York City, Contreras and Paz (2018) find that ride-hailing firms have reduced taxi ridership in Las Vegas and Berger et al. (2018) found that taxi drivers experienced a relative decline in earnings due to Uber's entry into a new US market. Outside the US, Nie (2017) finds that Uber entry has reduced taxi ridership in Shenzhen, while Chang (2017) shows that it has reduced the number of operating miles of taxi drivers in Taiwan. Thus, we may expect that the arrival of ride-hailing services will have a strong impact on the for-hire car with drivers' sector (including traditional taxi and ride-hailing services).

In this regard, Uber's presence could have a negative effect on congestion. Ride-hailing firms may promote an increase in the efficiency of the for-hire car with drivers' sector with the consequent decrease in congestion.

Uber services imply the use of a technology that efficiently matches demand and supply. Indeed, the use of apps to match demand with supply should reduce the cruising externality associated with empty cars looking for customers. In this regard, Cramer and Krueger (2016) examine the efficiency of ride-hailing services by comparing the vehicle utilization rate of UberX drivers and taxi drivers in five major urban areas in the US. Similarly, Kong et al. (2020) compare the vehicle utilization rate of Didi (a Uber alike service) and taxi services in Chengdu (China). Both studies find that the vehicle utilization rate of ride-hailing services is higher than that of taxi services. The entry of Uber and other ride-hailing firms may incentivize taxi firms to use similar apps for their own services. In Europe, examples of taxi-hailing apps include MyTaxi (now Free Now) and Taxify (now Bolt).

Another potential mechanism that might have an influence on congestion by means of promoting efficiency is the dynamic price-system (surge pricing) used by ride-hailing services (Chen & Sheldon, 2015; Cohen et al., 2016). In contrast to traditional taxi services where prices are usually the same for both peak and off-peak hours, ride-hailing firms charge higher prices in periods of excess demand and lower prices in periods of excess supply. Higher peak-hour prices could deviate demand to off-peak periods.

Therefore, we can expect a negative effect of Uber's presence on congestion should it significantly promote greater efficiency in the entire for hire car with drivers sector. Indeed, ride-hailing firms may have increased the utilization of vehicles due to the use of online apps and surge prices that match more efficiently demand and supply.

Furthermore, there may be a substitution effect away from private cars as it is found in the study by Ward et al. (2019). Hence, we can expect a negative effect of Uber's presence on congestion if this substitution effect is relevant.

However, ride-hailing firms may also lead to an increase in the size of the for-hire car with drivers sector. Uber users may benefit from shorter waiting times, greater flexibility, and lower prices (particularly in periods of less demand) than users of taxi services. Hence, the size of the for-hire car with drivers sector could increase due to demand induction.

Thus, we can expect a positive effect of Uber's presence on congestion if it promotes an increase of the size of the for-hire car with drivers' sector.

In addition, there may be a substitution effect away from public transportation. Thus, we could expect an increase in congestion due to Uber's presence if this substitution effect is relevant. Evidence on this line for United States is inconclusive. Hall et al. (2018) find evidence that Uber may complement public transit, especially in larger cities. The positive effect of Uber on public transit might lie in the fact that it helps overcome the "last-mile problem" attributable to the fixed routes and fixed schedules of public transit services. Nelson and Sadowsky (2019) find that the positive effect of Uber on public transit largely disappeared with the entry of Lyft. They attribute this result to the fact that price competition between the two firms appears to have made making the whole trip with one of them more attractive.

Taken together, Uber's presence will have a negative effect on congestion if the increased efficiency it promotes and the replacement effect of private cars is more relevant than demand induction and the public transport substitution effect. This is the main hypothesis that we test in the empirical analysis.

Furthermore, the effect of Uber on congestion should be greater in cities where the intensity in the use of its services is higher. We can expect that the intensity in the use of Uber is higher in those cities that impose fewer regulatory restrictions to ride-hailing firms. Furthermore, our data clearly shows (see details below) that Uber's presence is more common in denser cities. Finally, Uber could be more popular in less affluent cities given its ability to charge lower prices than traditional taxi services.

In addition to identifying Uber's net effect on congestion, the empirical analysis also tests the hypothesis that Uber's effect on congestion should be stronger in cities that impose fewer regulatory restrictions and in denser and less affluent cities.

A substitution effect from public transport to Uber alike services should be less relevant in cities with more public transport options. Thus, we may expect better outcomes of Uber's presence in terms of congestion in those cities with a higher endowment of public transport infrastructures. This is another hypothesis that is tested in the empirical analysis.

In short, I examine Uber's net effect on congestion and the potential heterogeneous impacts according to city's attributes and the regulatory environment in which it operates.

3 | REGULATORY ENVIRONMENT OF THE HIRED CARS WITH DRIVER SECTOR

Table 1 provides the list of cities used in the empirical analysis. The sample includes 130 cities from 19 different countries in the European Union and United Kingdom adding up 1162 observations. The time span covered is from 2008 to 2016. Figure 1 provides a map with the cities included in the analysis differentiating between cities with Uber entry and cities with no Uber entry in the considered period.

TABLE 1 Cities included in the sample

City	Country
Vienna	Austria
Antwerp, Brussels, Charleroi, Gent, Liège	Belgium
Brno, Prague	Czech Republic
Copenhagen	Denmark
Helsinki, Tampere	Finland
Avignon, Bordeaux, Grenoble, Lille, Lyon, Marseille, Montpellier, Nantes, Nice, Paris, Rennes, Rouen, Saint-Étienne, Strasbourg, Toulon, Toulouse, Tours	France
Berlin, Bielefeld, Bochum, Bonn, Bremen, Cologne, Dortmund, Dresden, Duesseldorf, Duisburg, Essen, Frankfurt, Hamburg, Hannover, Karlsruhe, Leipzig, Mannheim, Muenster, Munich, Nuremberg, Stuttgart, Wuppertal	Germany
Athens, Thessaloniki	Greece
Budapest	Hungary
Dublin	Ireland
Bari, Bologna, Brescia, Cagliari, Catania, Florence, Genoa, Milan, Modena, Naples, Padova, Palermo, Parma, Pescara, Reggio Emilia, Rome, Taranto, Torino, Verona	Italy
Amsterdam, Eindhoven, Rotterdam, The Hague, Utrecht	Netherlands
Bydgoszcz, Cracow, Gdansk, Katowice, Lodz, Lublin, Poznan, Szczecin, Warsaw, Wroclaw	Poland
Lisbon, Porto	Portugal
Bucharest	Romania
Bratislava	Slovakia
Alicante, Barcelona, Bilbao, Córdoba, Las Palmas, Madrid, Málaga, Murcia, Palma de Mallorca, Sevilla, Valencia, Valladolid, Zaragoza	Spain
Gothenburg, Stockholm	Sweden
Belfast, Birmingham, Bournemouth, Brighton, Bristol, Cardiff, Coventry, Edinburgh, Glasgow, Hull, Leeds, Leicester, Liverpool, London, Manchester, Newcastle, Nottingham, Preston, Reading, Sheffield, Southampton, Stoke-on-Trent, Swansea	United Kingdom

Notes: The time span covered is from 2008 to 2016. The sample includes 130 cities from 19 different countries accumulating a total of 1162 observations.

I exploit the variability in the regulatory context for Uber alike services in Europe to capture the intensity in the use of Uber services. I should expect a more intense use of Uber services in those cities where the regulatory environment imposes less restrictions.

In this regard, the number of licences available for ride-hailing firms may be capped, while technical requirements on drivers, cars and the service to weaken competition are frequently imposed (Rienstra et al., 2015).

The study of Frazzani et al. (2016) prepared for the European Commission provides detailed information about the regulation of the hired cars with driver sector in all EU member states up to 2016. The regulation of ride-hailing firms like Uber present two common features across EU: (i) the driver obligation to perform the service based on a prior reservation (for a pre-arranged fixed fare); and (ii) the driver obligation to return to the place of business after each ride, except if there is a prior reservation. The main purpose of these two obligations is to avoid ride-hailing firms picking up passengers on the street. In the period considered, the only exception is in Northern Ireland where since 31 May 2016, ride-hailing firms are able to ply for hire in certain areas of Belfast. Thus, competition is in theory restricted to the pre-booked segment although the waiting times may be so low in some countries that competition between taxis and Uber alike services may be *de facto* very intense.

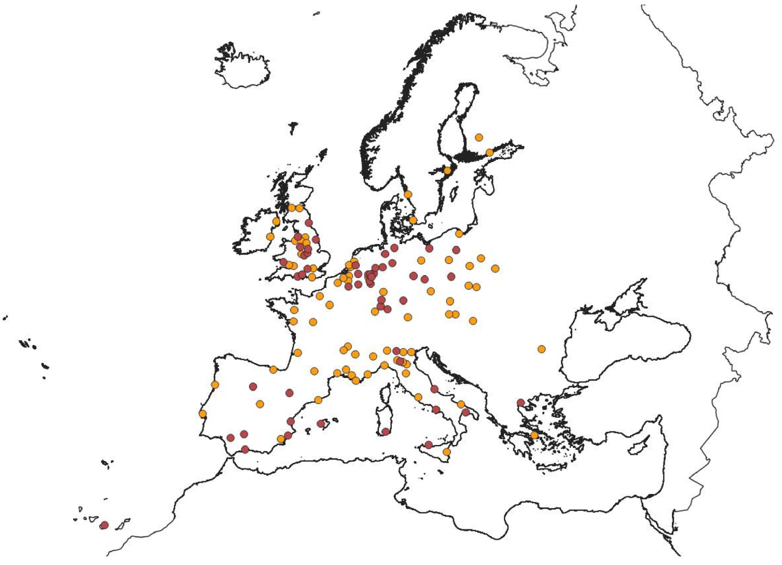

FIGURE 1 Map of the sample cities
Note: Yellow circles mark treated cities (ie; cities with Uber entry) and red circles mark control cities (ie; cities with no Uber entry)

Furthermore, almost all EU Member States regulate the for-hire car with drivers' sector at the national level, except Belgium and the United Kingdom. In other countries, the national legislation is supplemented by regional legislation and local regulation. However, the regulation is mainly based on national legislation for the period considered even in semi-federal states like Spain. While cities within a country may impose or relax the regulatory restrictions set at the national level, I did not identify a different regulatory environment between cities from the same country (with the exception of Belgium).

Table 2 provides the details of the regulatory environment for ride-hailing firms on all countries for which I have at least one city in my sample. While I can distinguish three regulatory environments, the activity of Uber should be particularly constrained in a regulatory environment that imposes quantitative restrictions and strong qualitative requirements.

Some countries impose quantity restrictions so that the licences for Uber alike services may be capped in function of different parameters like the population of the city or the number of taxi licences. The imposition of quantitative restrictions is always accompanied with strong specific qualitative requirements like minimum price and time of the trip in Belgium, financial plan and credit line in Denmark, minimum pre-booking time in Greece, obligation to have a garage in Italy, obligation to keep the contract with the passenger in the vehicle in Germany and Spain or to have a car rental contract in Portugal.

Second, some countries do not impose quantitative restrictions, but they impose specific qualitative requirements like financial standing of drivers or technical requirements of vehicles. Finally, some countries do not impose quantitative restrictions and ride-hailing firms are subject to the same qualitative requirements than taxi services.

Table 2 also shows the total number of cities included in the sample for each country and the number of cities with Uber services in at least some year of the considered period. In very restrictive environments, Uber is only offering services in the largest cities of the country. This is the case for example of Germany and Spain. The only exception would be Italy with a large number of cities with Uber services in 2014. However, in many cases these are services that were offered by Uberpop (that do not use professional drivers) that were banned in 2015. In less restrictive environments, Uber's expansion goes beyond the most populated cities. This is the case for example in Poland, the UK or especially France.

Table 2 also reports information on the regulation for taxi services. In all countries, taxi drivers must pass official exams and other qualitative requirements may include financial capability and medical fitness. The need to pass official exams implies that, in some countries, the regulation may be stricter for taxi services than for ride-hailing firms.

TABLE 2 Regulatory environment for ride hailing firms

Country	Quantitative restrictions	Specific qualitative requirements	Total number of cities/Uber cities[a]	Taxi regulations
Austria	NO	Professional qualification test; 3 years of driving experience Financial guarantee (EUR 18,400 per vehicle)	1/1	Fixed fares
Belgium	YES (Brussels)	Professional card, morality conditions, the professional qualification and the creditworthiness of the applicant. Suitability of the vehicle In Brussel and Walloon region, minimum 3 hours and EUR 90	5/2	Quantitative restrictions (Brussels and Wallonia) and maximum fares (all regions)
Cezch Republic	NO	Contract with client prior but not immediately before the commencement of the service	2/2	Quantitative restrictions (Prague) and maximum fares
Denmark	YES	Financial plan, credit line of EUR 7000, presentation of a business plan, need to prove that there is demand for the service, experience as professional driver	1/1	Quantitative restrictions and maximum fares
Finland	NO	NO	2/2	Quantitative restrictions and maximum fares
France	NO	Professional card, training + exam Financial standing, technical requirements for vehicles (minimum length and height, or hybrid vehicles)	17/17	Quantitative restrictions and maximum fares
Germany	YES	Professional card, obligation to receive orders at the place of business, obligation to keep contract with the passenger	22/5	Quantitative restrictions (except Berlin and Hamburg) and fixed fares
Greece	Only travel agencies and car rental	No criminal records, payment of taxes and social security, financial standing, parking spaces, minimum 6 hours pre-booking.	2/1	Quantitative restrictions and minimum fares
Hungary	NO	Licence as dispatch affiliation centre, financial standing, licensed taxi drivers	1/1	Fixed fares (Budapest)
Ireland	NO	NO	1/1	Maximum fares
Italy	YES	Professional card, registered office, garage in the municipality which issued the licence, booking must be performed at the place of business, obligation to perform a specific service	19/13	Quantitative restrictions and maximum fares
Netherlands	NO	Professional card	5/3	Maximum fares
Poland	NO	No criminal offence, not be barred from performing business activities, certificate of	10/7	Maximum fares

TABLE 2 (Continued)

Country	Quantitative restrictions	Specific qualitative requirements	Total number of cities/Uber cities[a]	Taxi regulations
		professional competence, financial standing (EUR 9,000 for the 1st vehicle, EUR 5,000 for the others), capacity to demonstrate that the vehicle used are at disposal, agreement made in writing at the business premises		
Portugal	YES	Car rental contracts or licensed taxi drivers	2/2	Quantitative restrictions and minimum fares
Romania	NO	Professional card	1/1	Quantitative restrictions and maximum fares
Slovakia	NO	NO	1/1	NO
Spain	YES	Residence in the area of the licence, physical fitness, no criminal records, compliance with social security and tax rules, minimum size of vehicle fleets, technical specifications for the vehicles (i.e., minimum size, and minimum engine power), a copy of the contract must be in the vehicle	13/4	Quantitative restrictions and minimum fares
Sweden	NO	NO	2/2	NO
United Kingdom	NO	NO	23/12	Quantitative restrictions (except London) and maximum fares

Notes: [a] In this column, I show the number of cities in my sample and the number of cities with Uber services in at least some year of the considered period. UberPop services have been banned in Brussels (2014), Netherlands (2014), Flemish region (2016), Germany (2015), Romania (2015) and Italy (2015). Bans for Uber pop services imply the imposition of professional drivers as a qualitative restriction. The hire for car sector was completely liberalized in France until October 2014. Uber stopped its activities in Budapest in August 2016 and in Madrid from December 2014 to March 2016.

Bearing this in mind, some countries impose stringent regulations like quantitative restrictions or fixed fares to taxi services. In this regard, a cap in the number of licenses is imposed for taxi services in all countries where ride-hailing services are also subject to stringent regulations. Regarding the countries where ride-railing firms only need to meet some specific qualitative requirements, we may find cases where taxi services are not subject to strict regulations (Poland, Wallonia) and others where taxi services are subject to quantitative restrictions (France, Prague) or fixed fares (Austria, Budapest). Finally, a liberal environment for ride-hailing firms usually implies a liberal environment for taxi services (Ireland, the Netherlands, Slovakia, Sweden, London). However, quantitative restrictions are imposed in Finland, Romania and United Kingdom (except London).

Figure 2 shows the number of cities with Uber presence in at least one year of the considered period according to the different regulatory environment in which it operates. A strict regulatory context for Uber alike services is almost always associated with a strict regulation for taxi services. In contrast, the regulation of taxi services is more flexible in around a third of the cities where the regulation for Uber is also more flexible. Note that the sample does not include cities highly liberal in the regulation of taxi services but with a strong regulation in terms of ride-hailing services.

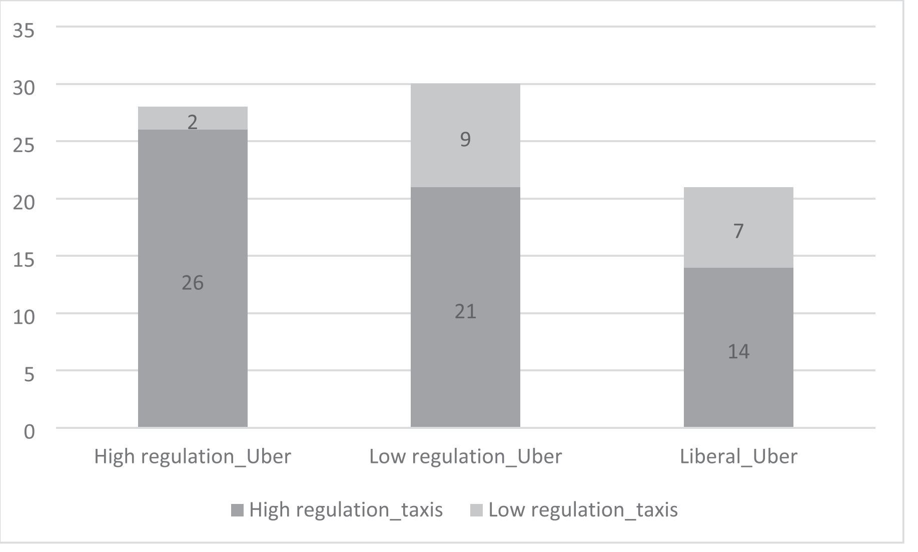

FIGURE 2 Regulatory environment for cities with Uber services
Note: This figure shows information for cities with Uber services in at least one year of the considered period. High regulation_Uber means that Uber services are subject to quantitative restrictions and strong qualitative requirements. Low regulation_Uber means that Uber services are subject to some specific qualitative requirements and Liberal_Uber means that Uber is not subject to quantitative restrictions nor specific qualitative requirements. High regulation_taxis means that taxi services are subject to quantitative restrictions and Low regulation_taxis means that taxi services are not subject to quantitative restrictions. The figure provides the number of cities with Uber presence according to the different regulatory environment in which it operates

4 | EMPIRICAL IMPLEMENTATION

4.1 | The model

I estimate the following equation for city *c* in year *t*:

$$\log(Congestion)_{ct} = \beta_1 D^{Uber}{}_{ct} + \beta_2 \log(Density)_{ct} + \beta_3 \log(Income)_{ct} + \beta_4 Rail\_length_{ct} + \beta_5 \log(Cars\ per\ inhabitant)_{ct}$$
$$+\beta_6 \log(rain)_{ct} + \lambda' \text{City} + \gamma' \text{Year} + \delta' \text{City X Year} + \varepsilon_{ct}, \tag{1}$$

where all the continuous variables without zero values are transformed using logarithms, so that the influence of outliers is reduced and parameter estimates can be interpreted as elasticities.

The dependent variable (*Congestion*) measures the additional time as a percentage that a vehicle needs for any trip in the city compared to a situation characterized by free traffic flow. Data have been obtained from TomTom (https://www.tomtom.com/en_gb/trafficindex).

To identify the impact of Uber, I use a dummy variable that takes a value of one if Uber offers any of its services (UberX, UberBlack, UberPop, etc.) in the city, and 0 otherwise. The dates of entry and exit of Uber have been obtained from local newspapers and from Uber's own press releases.

As control variables, I take into account different attributes of cities as potential drivers of congestion. The appropriate spatial unit of analysis is the city given that Uber entry in the core city of the urban area does not necessarily imply its entry in all municipalities within the urban area. Thus, control variables used refer to the most disaggregated spatial unit possible based on data availability.

First, I include the population density that is measured by the number of inhabitants per square kilometre at the city level. The relationship between urban density and congestion is unclear as denser cities are characterized by a lower number of vehicle/kilometres travelled but traffic is concentrated in fewer points (Ewing et al., 2014, 2018; Sarzynski et al., 2006; Su, 2010). Data for population have been obtained from Eurostat, while data for the size of the city in terms of square kilometres have been collected from city councils' websites.

Second, I also consider the income by incorporating the regional GDP per capita (*Income* variable). The income variable is the GDP *per capita* at the NUTS 3 level. The relationship between income and congestion is again unclear. Although a positive relationship seems to make sense as the number of car trips in richer cities is typically higher, it is also true that richer cities have better infrastructures (including roads and different types of public transportation) that could mitigate congestion. Data for this variable have been obtained from Eurostat.

The quality of public transportation networks is also taken into consideration. Since comparable data for urban buses are not available, I incorporate a comprehensive measure of the urban rail systems in terms of total kilometres of rail lines per square kilometre (*Rail_length* variable), which includes metro, light trains, trams, and local trains. This variable captures an important source of variability in my sample as we may find cities with a dense network of metro lines and cities with no rail services available. A recent review by Beaudoin et al. (2015) suggests that better public transportation options can help in reducing congestion, with the magnitude of such effects being specific of each particular location. Data for this variable have been obtained from Urban rail (http://www.urbanrail.net/), World Metro database (http://mic-ro.com/metro/table.html) and operators' websites.

I also consider a variable that measures the number of registered cars per inhabitant. Data for this variable have been obtained from Eurostat and it is at the NUTS 2 level. We may expect more congestion in cities with more cars per inhabitant. This variable has the limitation that the geographic unit with available data focuses on the surrounding region and not the city.

The amount of precipitation (*Rain* variable) at the city level is also included as a regressor. Data is for the precipitation sum with unit 0.01 Precipitation (mm) and it have been obtained from Tank et al. (2002). We may expect more congestion in more rainy cities.

All regressions include city fixed effects and year fixed effects. Most regressions also include the interaction between city and year fixed effects. In this regard, the estimation of a city fixed effects model implies the identification of changes from one period to another because it is based on the within-transformation of the variables as deviations from their average. Therefore, it is the most appropriate method to evaluate the effect of Uber on congestion. Note also that city fixed effects control for omitted, time-invariant factors correlated with the variables of interest. Furthermore, I add year dummies to control for yearly effects that are common to all cities. Finally, I include city specific time trends so that I control for the fact that each city may have its own linear time trend.

4.2 | Identification strategy

Some potential threats may distort the identification of the impact of Uber on congestion. The dummy variable for Uber exploits the variability between cities with and without Uber services, but it does not capture the intensity of Uber use that can differ substantially from one city to another with Uber services. Furthermore, Uber entry may be correlated with the levels of congestion in the city. Finally, Uber entry may be correlated with unobserved time varying factors that also have an influence on congestion.

To capture the intensity of Uber use, I examine the different effects of Uber on congestion based on the regulatory environment in which Uber is operating. We could expect that the intensity of use of Uber is higher in those cities that impose less restrictions to ride-hailing firms.

Another potential threat to my identification strategy is that the treatment (Uber presence) may be correlated with the explanatory variables and with the previous levels of congestion in the city. To deal with this concern, I include city specific time trends so that I control for the fact that each city may have its own linear time trend.

Furthermore, I apply the logic of differences in differences with matching that is a common methodology employed within the treatment evaluation framework (see Angrist & Pischke, 2009; Gertler et al., 2016 for details). Indeed, to identify the causal effect of the treatment status on outcomes we need to compare comparable cities. Thus, I apply a propensity score matching procedure and re-estimate Equation (1) with the observations that have common support. Matching procedures eliminate possible bias by pairing observations in the treated cities (with Uber services in at least one year of the considered period) with control cities (with no Uber services in any year of the considered period) having similar characteristics.

Following Rosenbaum and Rubin (1983), I first estimate the probability of being treated, conditional on pre-existing characteristics that may differ between groups using a logit model, to obtain a propensity score for each observation. Using data for the first year of the period considered, the first step of the matching procedure implies to estimate an equation where the dependent variable is a dummy variable that takes the value one for treated cities (cities with Uber entry in some year of the considered period). As covariates, I consider all control variables and congestion. This is the matching equation that I estimate for city *c*:

$$\mathrm{D^{treated}}_{\mathrm{c}} = \beta_1 log(Congestion)_{\mathrm{c}} + \beta_2 \log(Density)_{\mathrm{c}} + \beta_3 \log(Income)_{\mathrm{c}} + \beta_4 Rail\_length_{\mathrm{c}} + \beta_5 \log(Cars\ per\ inhabitant)_{\mathrm{c}} + \beta_6 \log(rain)_{\mathrm{c}} + \varepsilon_{\mathrm{c.}} \quad (2)$$

In a second step, I match the observations in the treated and control groups with respect to the propensity score, using the first nearest neighbour algorithm. This algorithm matches treated observations with the control observations that have the closest propensity score. Then, I drop all the observations without common support and re-estimate Equation (1) using the reduced matched sample.

Furthermore, I also reframe the Equation (1) in which the Uber dummy variable is now defined as $\sum_{k=-3}^{3} Uberct$ so that equals 1 if Uber enters in the city *k* years from year *t*. This definition implies that $\mathrm{k} = 0$ represents the first year following the entry of Uber, $\mathrm{k} = -1$ is the year prior to treatment and $\mathrm{k} = 1$ is the year after treatment. With this event study analysis, I can examine the timing of the Uber effects after treatment, and I can test for parallel trends between treated and control cities before treatment. I choose three years before and after treatment because only two cities in my sample have Uber services for more than three years after the initial year of arrival.

Finally, I apply two different strategies to deal with the potential endogeneity bias that could come from unobservable factors correlated with congestion and Uber's decision to entry. First, I use a subsample based on cities that are eventually treated cities excluding the city-specific time trends as suggested by Borusyak and Jaravel (2020). The potential endogeneity bias for this subsample should be modest given that such bias would be related with the time of entry and not with the decision of entry or not.

Furthermore, I apply an instrumental variables procedure. As main instrument, I use a regulation index that captures the regulatory environment that is in force in each city (see Table 2 for the details in each country). This regulation index takes the value 1 when Uber operates in a regulatory environment that imposes quantitative restrictions and strong specific qualitative requirements. It takes the value 2 when Uber operates in a regulatory environment that only imposes some specific qualitative requirements. Finally, it takes the value 3 when Uber operates in a regulatory environment that does not impose either quantitative restrictions or specific qualitative requirements.

Uber's expansion strategy is focused on offering services in all cities, at least to all those that have a sufficiently large dimension such as those included in the sample analysed here. In this regard, one of Uber's marketing slogans is: “We don't choose cities, cities choose us”. Uber first enters some of the most populated cities. Apart from the first selected cities, the subsequent Uber's expansion has been quite widespread in those countries where its activity is not very restricted by regulation and it is limited to the largest cities in countries where regulatory restrictions are high. Thus, the regulatory environment is clearly one of the main drivers of the Uber presence beyond the characteristics of cities. In this regard, I did not identify substantial differences between cities within the same country. Regulatory restrictions are generally aimed to protect taxi drivers as there is a correlation between the regulations imposed to taxi services and the regulations imposed to Uber alike services. So I do expect that the regulatory environment is exogenous to city level conditions.

Given that I estimate a city-fixed effects model, this instrument captures the within variation that comes from the imposition of qualitative restrictions in a few countries that had previously a liberalized environment for ride-hailing services. Hence, I cannot use different levels of regulation to examine the exogeneity of the instrument through the overidentification test of all instruments. Hence, I consider an additional instrument to be able to run such test. This additional instrument is the total airport traffic serving the surrounding area of the city (data come from Eurostat). I expect that the popularity of Uber services (and hence the probability of entry) is higher in those cities with bigger airports as visitors that come to the city by plane are potential users of for-hire car with driver services. *A priori*, it could be that the total amount of airport traffic has a direct effect on urban congestion. However, the congestion variable is based on time calculations of millions of trips per each city. While some specific corridors that connect the core-city with the airport may be congested at peak-hours, I do not expect that this has a relevant effect on the indicator of congestion.

Finally, estimates may present problems of heteroscedasticity and temporal autocorrelation in the error term. The Breusch-Pagan/Cook-Weisberg test shows heteroscedasticity problems so that standard errors are robust to heteroscedasticity. Likewise, the Wooldridge test for autocorrelation in panel data reveals that a problem of serial autocorrelation may exist so that I allow for an arbitrary variance–covariance structure by computing the standard errors in clusters by city to correct for autocorrelation in the error term both at the cross-sectional and temporal levels (Bertrand et al., 2004).

5 | DATA

The empirical analysis considers cities in several countries of the European Union for which I have available congestion data. My sample includes information for 130 cities from 19 different countries adding up 1162 observations.[1]

Entry and exit dates for Uber have been obtained from local newspapers and Uber's own press releases. Congestion data are taken from the TomTom traffic index (https://www.tomtom.com/en_gb/trafficindex). Following Shi et al. (2016), congestion measures can be broken down into three general categories: density-based, travel time-based and travel speed-based. The TomTom congestion index belongs to this second category. Rather than relying on theoretical models or simulations, TomTom obtains real data on drivers' travel time from its anonymous customers in all cities where it is active. TomTom includes in its analysis local roads, arterials and highways, based on actual GPS based measurements for each city.

The congestion index is built by establishing first a baseline of travel times during uncongested, free flow conditions across each road segment in each city. Then, average travel times per hour across the entire year per every vehicle in the entire network of the city are calculated. TomTom does not specify the number of car trips involved in the calculation of the congestion index, but they specify the kilometres of GPS data from actual driven trips used to calculate it. For example, in London were 1,190,918,306 in 2016. Thus, several million trips per year are used to build the congestion index.

This information is compared against free flow periods to derive extra travel time. This free traffic flow time is based upon the contemporaneous year during off-peak hours (usually at night). Hence, the congestion index represents the measured amount of extra travel time experienced by drivers across the entire year in the city due to traffic conditions. For example, a congestion level of 36% corresponds to 36% extra travel time for any trip, anywhere in the city, at any time compared to what it would be in local free flow conditions.[2]

These data for congestion refer to a mean annual average value for the entire city. Congestion during peak hours is higher. Figure 3 shows the box-plot of the average measure of congestion that I use and the same indicator of congestion but only in peak hours. The data available for congestion in peak hours is for 2016 and includes just 90 out

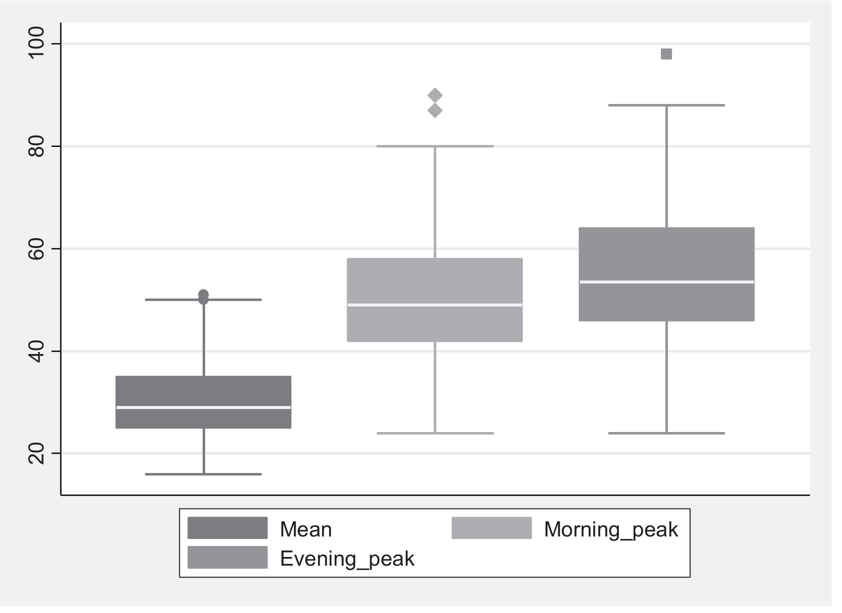

FIGURE 3 Box-plot of congestion indicators

TABLE 3 Descriptive statistics of the variables included in the empirical analysis

Variable	Geographical unit of analysis	Mean	St. Deviation
Congestion (percentage of additional travel time in comparison to a free-flow situation)	City	24.624	7.995
D^{Uber} (Dummy variable)	City	0.143	0.350
Density (number of inhabitants per square km)	City	3648.618	3180.727
Income (euros per inhabitant)	NUTS 3	29215.6	11101.06
Rail length (number of kms of rail lines per square km)	City	0.235	0.307
Rain (amount of precipitation -mm)	City	72123.78	24200.63
Cars per inhabitant (Number of registered cars per 1000 inhabitants)	NUTS 2	501.89	74.803

of the 130 cities in the sample but they are still useful to illustrate differences between average congestion and congestion in peak hours. Mean values for the average measure of congestion are about 30% of extra-travel time in relation to free-flow conditions, while that the mean values in the morning and evening peaks are about 50% and 55% respectively. Furthermore, the variability across cities is lower for average congestion in comparison to congestion in peak hours.

Table 3 shows the descriptive statistics of the variables used in the empirical analysis, while that Table 4 shows the correlation matrix of those variables. In this regard, the correlation between the different explanatory variables is low except for the variables of density and rail length. However, results of unreported regressions excluding one or the other variable does not distort its individual identification.

Figure 4 show the evolution taken by Uber services. In EU, Uber started its operations in Paris in 2011 and in London in 2012. A handful of cities started to operate Uber services in 2013. Uber underwent a remarkable

TABLE 4 Correlation matrix of the variables used in the empirical analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Congestion (1)	1						
D^{Uber} (2)	0.14	1					
Density (3)	0.22	0.19	1				
Income (4)	0.02	0.22	0.19	1			
Rail_length (5)	0.08	0.11	0.54	0.15	1		
Rain (6)	−0.04	0.02	−0.01	0.02	0.03	1	
Cars per inhabitant (7)	−0.06	−0.02	−0.04	−0.13	−0.08	−0.03	1

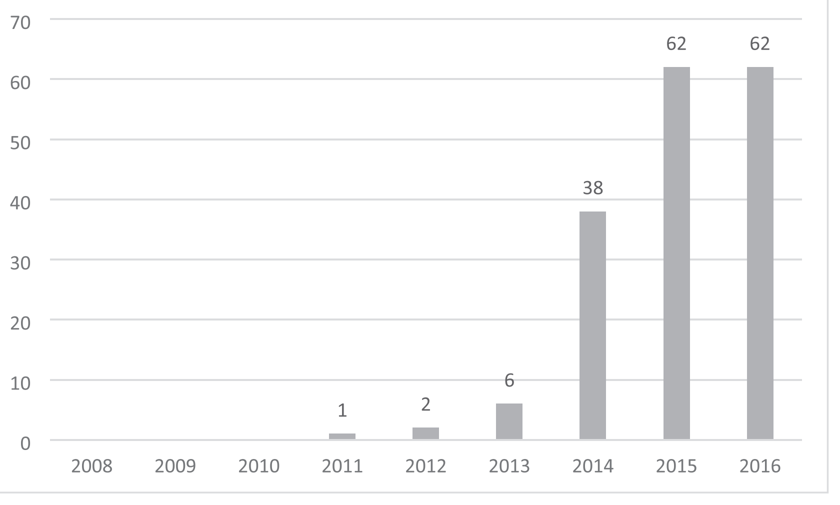

FIGURE 4 Evolution of the number of cities with Uber services
Note: The sample include 130 cities

expansion from 2014 onwards but about half the cities in the sample were not operating Uber services at the end of the period considered here.

Figure 5 shows the evolution taken by the mean levels of congestion in all cities of the sample. It is worth mentioning the high persistence that characterize the evolution of congestion with relatively small changes for the entire period considered. Bearing this in mind, we can differentiate between three periods. An increase in congestion from 2008 to 2010, a decrease in congestion in 2011–2012 and an increase in congestion from 2013. Thus, the expansion of Uber in Europe coincides with a period of increased congestion.

Figure 6 shows the evolution of congestion in treated cities. This figure is centred on the year of arrival of Uber in the city and shows the evolution of congestion three years before and three years after the arrival of Uber. I build four different groups of treated cities based on the year of arrival of Uber. For all groups of treated cities, there is an increase in congestion after the arrival of Uber. Thus, data suggest that there is an increase in congestion in the last years of the considered period regardless Uber is present or not in the city. The question that I want to disentangle in the following section is if Uber has contributed to moderate or to accelerate the increase in congestion in treated cities in comparison to control cities.

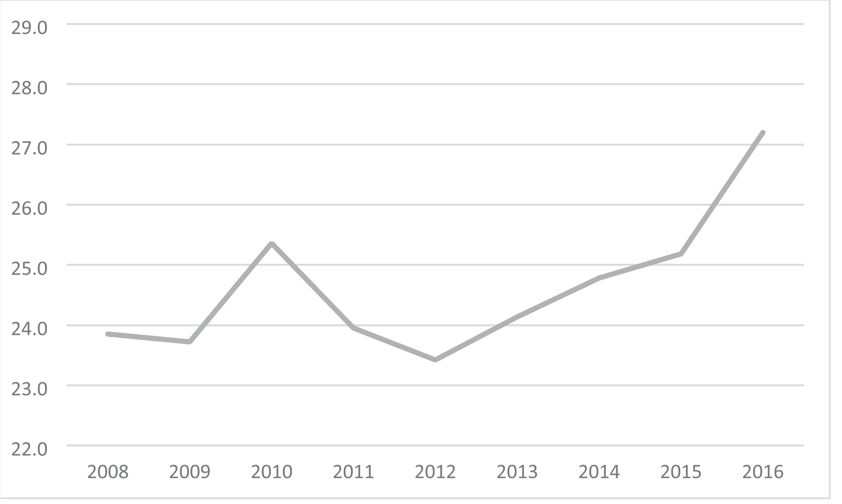

FIGURE 5 Evolution of congestion (Percentage extra-travel time in relation to free-flow conditions) in all cities

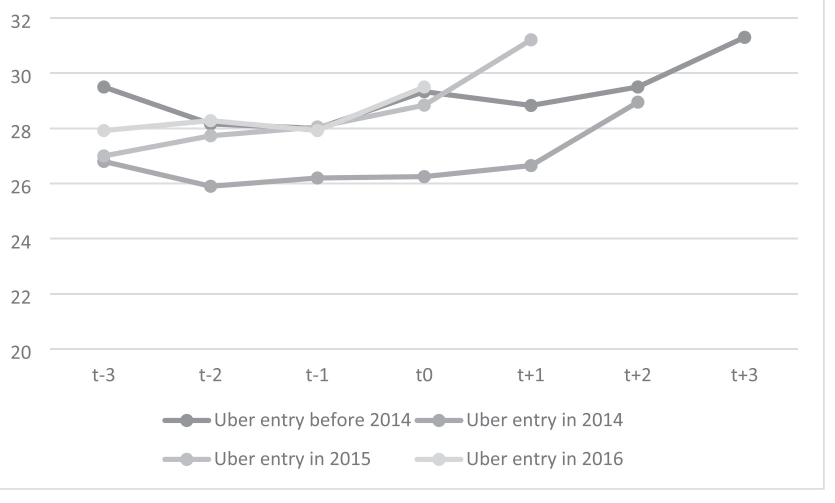

FIGURE 6 Evolution of congestion (Percentage extra-travel time in relation to free-flow conditions) in treated cities
Note: This figure is centered on the year of arrival of Uber in the city (to) and shows the evolution of congestion three years before and three years after the arrival of Uber. I build four different groups of treated cities based on the year of arrival of Uber

6 | ESTIMATION AND RESULTS

In this section, I report and discuss the results of the estimates. Table 5 shows the results of the estimates by inserting additional controls one-by-one. In the case of the controls, I find that congestion is higher in richer and more rainy cities. Furthermore, congestion is lower in those cities with a denser rail network.

In the case of the Uber variable, I find a negative impact of Uber on congestion. The dummy for Uber services is negative and statistically significant in all regressions. The negative impact of Uber is −3.5 percentage points when

TABLE 5 Estimation results (baseline regression with different controls)

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)—2010 omitted
D^{Uber}	−0.045 (0.011)***	−0.046 (0.011)***	−0.036 (0.011)***	−0.036 (0.010)***	−0.036 (0.010)***	−0.035 (0.011)***	−0.034 (0.011)***
Log (Density)	-	0.219 (0.176)	0.225 (0.167)	0.200 (0.169)	0.200 (0.169)	0.216 (0.168)	0.278 (0.199)
Log (Income)	-	-	0.569 (0.092)***	0.541 (0.092)***	0.541 (0.092)***	0.506 (0.102)***	0.547 (0.105)***
Rail_length	-	-	-	−0.144 (0.067)**	−0.144 (0.067)**	−0.144 (0.065)**	−0.151 (0.008)*
Log (Rain)	-	-	-	-	0.036 (0.013)***	0.036 (0.013)***	0.045 (0.015)***
Log (Cars per inhabitant)	-	-	-	-	-	0.191 (0.245)	0.223 (0.269)
Intercept	−28.931 (2.210)***	−38.268 (1.501)***	−14.956 (3.758)***	−13.720 (3.828)***	−13.720 (3.828)***	−14.360 (3.954)***	−23.408 (3.977)***
City fixed effects	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES
City X Year fixed effects	YES	YES	YES	YES	YES	YES	YES
R^2	0.64	0.65	0.66	0.67	0.67	0.67	0.67
Observations	1162	1162	1162	1162	1162	1162	1033

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

considering all controls. Such impact is remarkable given its statistical significance and the high persistence in the evolution of the mean levels of congestion across cities in my sample (see Figure 5). Note that the coefficient of the Uber variable is slightly higher without controls. In particular, the impact gets slightly reduced when adding the income variable.

Given that 2010 looks like an outlier for congestion data, I also run the regression with all controls but excluding 2010 from the analysis. Results of the Uber variable are similar to those obtained in the regressions that use the entire sample.

In Table 6, I show the results of the first step in the matching procedure. Using data for the first year of the considered period, results reported in this table come from a regression in which the dependent variable is a dummy variable that takes the value one for treated cities (cities with Uber entry in some year of the considered period). As covariates, I consider all control variables and congestion.

Results in Table 6 show that the main predictor of Uber entry is population density given that it is the only variable that it is statistically significant. The probability of Uber entry is higher in denser cities.

Table 7 reports the mean t-test differences between treated and control cities when I consider the full sample and when I consider the matched sample in the baseline period. In the entire sample, treated cities are denser, richer and have a better endowment of urban rails than control cities. In the matched sample, differences between treated and control cities are smaller than in the entire sample and those differences are not statistically significant

TABLE 6 Determinants of the probability of being treated

Log (Congestion)	0.806 (0.659)
Log (Density)	0.795 (0.346)***
Log (Income)	−0.013 (0.465)
Rail_length	−0.013 (0.465)
Log (Rain)	0.539 (0.596)
Log (Cars per inhabitant)	0.043 (1.454)
Intercept	−14.671 (11.666)
R^2	0.09
Observations	130

Notes: Standard errors in parentheses (robust to heterocedasticity).
Statistical significance at 1% (***), 5% (**), 10% (*).

TABLE 7 Mean T-tests of variables used in the empirical analysis in 2008

	All sample			Matched sample		
Sample	**Control**	**Treated**	**T-test**	**Control**	**Treated**	**T-test**
Congestion	22.52	24.70	−1.34	22.52	23.33	−0.48
Density	2385.23	4376.27	−3.57***	2385.23	3225.45	−2.57**
Density[a]	2385.23	4376.27	−3.57***	1417.89	2054.43	−1.11
Income	26403.92	30062.03	−1.95**	26403.92	27207.84	−0.52
Rail length	0.15	0.27	−2.24**	0.15	0.22	−1.51
Rain	73784.9	75566.2	−1.25	73784.9	75593	−0.39
Cars per inhabitant	490.31	487.45	0.21	490.31	492.88	−0.20
Observations	51	79	-	51	51	-

Note: [a] The matched sample here makes reference to the procedure when density is the only covariate used in the first step. In all other cases, all covariates and congestion are used as covariates in the first step.

TABLE 8 Estimation results (matched sample)

	All sample (I)	Matched sample - all variables (II)	Matched sample - density (III)
D^{Uber}	−0.035 (0.011)***	−0.041 (0.013)***	−0.042 (0.015)***
Controls	ALL	ALL	ALL
City fixed effects	YES	YES	YES
Year fixed effects	YES	YES	YES
City X Year fixed effects	YES	YES	YES
R^2	0.67	0.66	0.68
Observations	1162	913	745

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

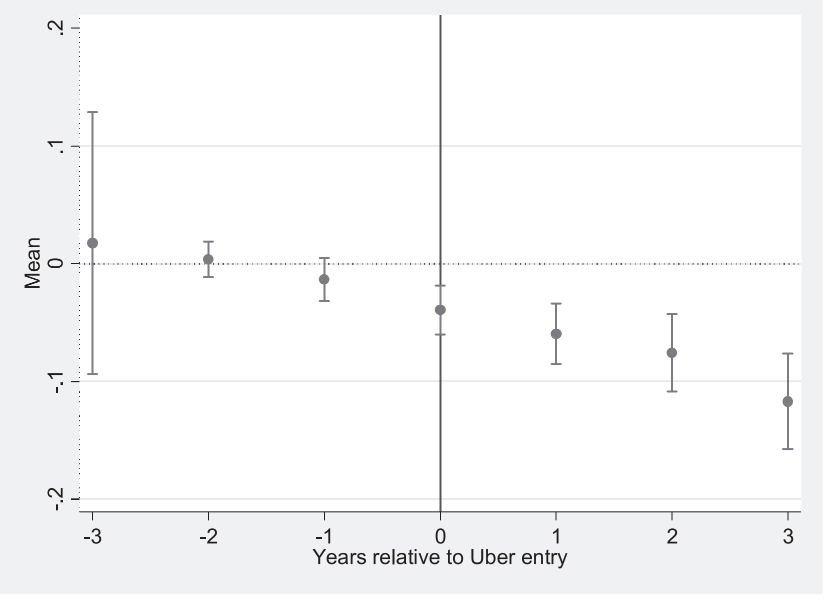

FIGURE 7 Impact of Uber on congestion over time
Note: This figure shows the main results of the event study analysis in which the treatment variable is based on dummies for 3 years before and 3 years after the entry of Uber in the city. I also show the 95% confidence interval based on standard errors that are clustered at the city level. Coefficients of Uber variables: $Uber_{ut-3}$: 0.017 (0.011), $Uber_{ut-2}$: 0.003 (0.015), $Uber_{ut-1}$: −0.011 (0.018), $Uber_{ut-0}$: −0.039 (0.020)*, $Uber_{ut+1}$: −0.059 (0.025)**, $Uber_{ut+2}$: −0.075 (0.032)**, $Uber_{ut-3}$: −0.117 (0.040)***

for all variables except for the density variable. Keeping this in mind, I also implement the matching procedure using density as single covariate in the first step to be able to build a matched sample with comparable treated and control cities in terms of population density (see Table 7).

Table 8 shows the results of the regressions using the matched sample. In column (2), I show the results of regressions when the first step of the matching procedure includes as covariates all controls and congestion. In column (3), I show the results of regressions when the first step of the matching produce includes just population density as covariate. The coefficient of the Uber variable remains negative and statistically significant in both

TABLE 9 Estimation results (regressions that deal with the potential endogeneity bias)

	D^{Uber} as exogenous regressor—all sample (I)	D^{Uber} as exogenous regressor—treated cities (II)	Instrumental variables regression (III)—all sample	Instrumental variables regression (IV)—all sample
D^{Uber}	−0.039 (0.014)***	−0.033 (0.010)***	−0.108 (0.055)**	−0.103 (0.033)***
Controls	ALL	ALL	ALL	ALL
City fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
R^2	0.29	0.30	0.26	0.27
Observations	1162	703	1162	1162
Partial R^2 *–instruments*	-	-	0.043	0.117
F-test - instruments	-	-	45.87***	67.59***
Underidentification test (Anderson canon. Corr. LM statistic)	-	-	44.493***	79.316***
Sargan-Hansen (overidentification test of all instruments)	-	-	-	0.012

Notes: Standard errors in parentheses (robust to heterocedasticity and clustered at the city level). Statistical significance at 1% (***), 5% (**), 10% (*). Instrument for D^{uber} in (III): Regulation_index. Instruments for D^{uber} in (IV): Regulation_index and airport traffic. The Instrumental variables regression does not allow adding city X year fixed effects.

regressions. The magnitude of the effect is very similar to that found in the regression that uses the entire sample although slightly higher (−4.1/−4.2 percentage points).

Figure 7 plots the results of the regression based on the event study analysis in which I capture the effect of Uber over time using dummies for three years before and three years after the arrival of Uber in each city.

The coefficients of the variables for one-year, two-year and three-year lags of the Uber variable are not statistically significant. Thus, there is not a different pre-trend between treated and control cities that could bias my results. In contrast, the coefficients of the Uber variable since the arrival of Uber are negative and statistically significant. The magnitude of the negative impact of Uber on congestion is increasing over time so that I find evidence that the negative impact of Uber on congestion is gradual.

Table 9 shows the results of the estimates that deal with the potential endogeneity bias that could come from unobservable factors correlated with congestion and Uber's decision to entry. In column (2), I show the results when the Uber dummy variable is treated as an exogenous covariate and the entire sample is used as in previous regressions. In column (3), I show the results when I use a subsample based on cities that are eventually treated cities. In columns (4) and (5), I apply an instrumental variables procedure where the dummy variable for Uber is treated as endogenous. In column (4), the instrument for Uber is the index variable that capture the regulatory environment for ride-hailing services that is in force in the city. In column (5), I use the regulation index and the airport traffic variables as instruments for Uber presence.

When using the subsample based on cities that are eventually treated, I find a similar impact of Uber on congestion as that found in previous regressions that used the entire sample.

The instrument based on the regulation index passes the strength tests (F-test of the first-stage regression higher than 10 and under-identification test) and it also passes the exogeneity test when adding the airport traffic as instrument (Sargan-Hansen of overidentification test of all instruments). Taking this into account, the negative impact of Uber on congestion is higher than that found in previous regressions. This result holds when using just the

TABLE 10 Estimation results (Uber effects based on regulatory environment)

	Restrictive high (I)	Restrictive low (II)
D^{Uber} X *Restrictive_high*	0.032 (0.017)*	-
D^{Uber} X *Restrictive_low*	-	−0.055 (0.022)***
D^{Uber}	−0.048 (0.015)***	−0.027 (0.010)***
$D^{Uber} + (D^{Uber}$ X *Interaction term*)	−0.015 (0.012)	−0.077 (0.022)***
Controls	ALL	ALL
City fixed effects	YES	YES
Year fixed effects	YES	YES
City X Year fixed effects	YES	YES
R^2	0.67	0.67
Observations	1162	1162

Notes: Standard errors in parentheses (robust to heterocedasticity and clustered at the city level). Statistical significance at 1% (***), 5% (**), 10% (*). By restrictive high, I mean a regulatory environment that imposes quantitative restrictions and strong qualitative requirements. By restrictive low, I mean a regulatory environment that does not impose quantitative restrictions nor strong qualitative requirements.

regulation index as instrument and when using both the regulation index and the airport traffic jointly as instruments.

However, it must be recognized that the instruments are imperfect. While the instruments pass the suitability tests, the regulation index variable may be correlated with other regulations that impact congestion and the airport traffic variable may be correlated with city-level conditions. Hence, the instrumental variables regressions provide suggestive evidence that the potential endogeneity bias underestimate the magnitude of the negative impact of Uber on congestion.

Overall, I find that the net effect of Uber on congestion is negative taking into account that different opposing forces may be playing a simultaneous role. To this point, I examine below the different effects of Uber based on the regulatory environment in which it operates and city attributes.

In Tables 10 and 11, I show the results of these additional regressions. In column (2) of Table 10, I show the results when the interaction is between the dummy variable for Uber services and a dummy variable that takes the value one when the regulatory environment imposes quantitative restrictions and strong qualitative requirements. In column (3) of Table 10, I show the results when the interaction is between the dummy variable for Uber services and a dummy variable that takes the value one when the regulatory environment does not impose quantitative restrictions nor strong qualitative requirements.

I find that less restrictions on Uber lead to a stronger negative impact on congestion. Indeed, I find that Uber does not have an impact on congestion when it operates in a regulatory environment that imposes quantitative restrictions and strong qualitative requirements. If Uber must operate in a highly restrictive environment, it is not surprising that its impact is weak because the intensity of use of its services should be modest at least in comparison with less restrictive regulatory environments. In contrast, the impact of Uber on congestion is negative and statistically significant when it operates in a regulatory environment that does not impose quantitative restrictions nor strong qualitative requirements. In such a context, the negative impact of Uber on congestion is −7.7 percentage points.

In Table 11, I examine the different effects of Uber based on the length of the rail network, population density and income. In columns (2) and (3), I show the results when the interaction is between the dummy variable for Uber services and a dummy variable that takes the value 1 when the length of rail lines is above and below the mean sample, respectively. In columns (4) and (5), I show the results when the interaction is between the dummy variable for

TABLE 11 Estimation results (Uber effects based on rail length, density and income)

	Rail_length above mean (I)	Rail_length below mean (II)	Density above mean (III)	Density below mean (IV)	Income above mean (V)	Income below mean (VI)
D^{Uber} X *Rail_length above mean*	−0.011 (0.019)	-	-	-	-	-
D^{Uber} X *Rail_length below mean*	-	0.015 (0.017)	-	-	-	-
D^{Uber} X *Density above mean*	-	-	−0.012 (0.021)	-	-	-
D^{Uber} X *Density below mean*	-	-	-	0.012 (0.021)	-	-
D^{Uber} X *Income above mean*	-	-	-	-	0.009 (0.020)	-
D^{Uber} X *Income below mean*	-	-	-	-	-	−0.009 (0,020)
D^{Uber}	−0.030 (0.013)**	−0.043 (0.015)***	−0.027 (0.018)	−0.039 (0.013)***	−0.039 (0.017)**	−0.030 (0.012)**
D^{Uber} + (D^{Uber} X *Interaction term)*	−0.041 (0.016)***	−0.027 (0.013)**	−0.039 (0.013)***	−0.027 (0.018)	−0.030 (0.012)**	−0.039 (0.017)**
Controls	ALL	ALL	ALL	ALL	ALL	ALL
City fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
City X Year fixed effects	YES	YES	YES	YES	YES	YES
R^2	0.67	0.67	0.67	0.67	0.67	0.67
Observations	1162	1162	1162	1162	1162	1162

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

Uber services and a dummy variable that takes the value 1 when population density is above and below the mean sample. In columns (6) and (7), I show the results when the interaction is between the dummy variable for Uber services and a dummy variable that takes the value 1 when income *per capita* is above and below the mean sample.

Previous literature does not examine the potential heterogeneous effects of Uber according to city's attributes. Only the study of Hall et al. (2018) find that Uber complements public transport in big cities and replace it in small cities. A substitution effect from public transport to Uber alike services could counteract other positive effects of Uber on congestion. Such substitution effect should be less relevant in cities with better public transport options. Thus, we may expect that the negative impact of Uber on congestion is higher in cities with better public transport infrastructures.

In the matching analysis implemented previously, I found that population density is the main city attribute that explains the probability of Uber entry. Indeed, Uber entry is more likely in denser cities. If Uber leads to a reduction in congestion, the effect should be greater in cities where Uber's presence is most common. In addition, the availability of different public transport options can be expected to be greater (as shown by the high correlation between the variables of density and rail length) in denser cities. Thus, we may expect that the negative impact of Uber on congestion is higher in denser cities.

One of the reasons that may explain the popularity of Uber alike services in comparison to taxi services is the possibility to charge lower prices, particularly in periods of less demand. Hence, Uber may be more popular in less affluent cities. If the intensity in the use of Uber services is higher in less affluent cities and Uber reduces congestion, the negative impact of Uber on congestion could be higher on those less affluent cities.

I find that the negative impact of Uber on congestion is stronger in denser and poorer cities and in those cities with a larger urban rail network. However, differences according to the rail length and income are modest from a statistical point of view. The differential impact is particularly relevant in terms of density given that Uber does not have an effect in cities with a density below the mean sample, but it has a negative and significant impact in cities above the mean sample. Denser cities are most affected by Uber's presence, whose technology implies a more efficient match between demand and supply.

Furthermore, the potential shift from public transportation to Uber (if any) may be more modest in denser cities as it is found in Hall et al. (2018). The higher differential impact of Uber, albeit modest from a statistical point of view, for cities with a larger urban rail network goes along this line.

However, a caveat must be mentioned in relation to the stronger impact of Uber on denser cities. The indicator of congestion is based on average levels of congestion. In denser cities, congestion at peak-hours may be particularly high and my data do not allow me to identify Uber's effect on peak-hour congestion.

7 | DISCUSSION AND CONCLUDING REMARKS

This paper has examined the impact of Uber, the world's largest ride-hailing firm, on urban congestion in Europe. I find a negative impact of Uber presence on congestion, an outcome that is consistent across all regressions in the empirical analysis. The estimated impact in the baseline regression is −3.5 percentage points, but it is higher in cities that do not impose strong regulatory restrictions to ride-hailing services. In addition, the negative impact of Uber on congestion is only statistically significant in denser cities. The Uber effect is gradual given that its impact increases over time. Finally, I find suggestive evidence that the potential endogeneity bias underestimates the negative effect of Uber on congestion.

Results of my analysis suggest that the impact of Uber on congestion can be explained by the changes that has promoted on the for-hire car with drivers' sector (including traditional taxi and ride-hailing services). The increase in the efficiency of the for-hire car with drivers' sector have not been offset with an increase of its size.

In Europe, ride-hailing firms may have promoted an increase in the utilization of vehicles due to the use of online apps and surge prices that match more efficiently demand and supply. Indeed, ride-hailing firms may have contributed to reduce the cruising externality associated with empty cars looking for customers. Given that traditional taxi services may be forced to use similar apps and similar price-settings to compete with ride-hailing firms, such efficiency effect could be relevant for the entire for-hire car with drivers' sector. A potential substitution effect away from private cars could also have an influence on the positive outcomes of Uber's presence in terms of congestion. Furthermore, the potential substitution effect away from public transportation does not seem to be relevant in the context of my data, particularly for denser cities.

While I find clear evidence about the negative impact of Uber on congestion for European cities in the period 2008–2016, this does not mean that the impact of ride-hailing firms on congestion must be always negative. First of all, my results should be interpreted as short-term impacts given that for most cities the arrival of Uber is in 2014 or later. Furthermore, my congestion measure is based on average levels of congestion so that I cannot identify the specific impact of Uber on congestion in peak-hours. Second, the substitution effect away from public transportation may be more relevant in other contexts where the public transportation network is worse in comparison to the European cities of my sample.

Finally, my results suggest that the effect of Uber on congestion depends upon the regulatory environment in which it operates. My analysis is based on cities and a period in which Uber is constrained to operate in the pre-booking segment. Thus, it is uncertain the impact of Uber on congestion in a fully liberalized environment in which ride-hailing firms may pick up passengers on the streets.

To conclude, many different matters—and not just their impact on congestion—need to be taken into consideration when evaluating the most adequate regulatory response to the arrival of ride-hailing firms in a city. Bearing this mind, my analysis suggests that congestion is not a major concern to justify the imposition of strict regulatory restrictions to ride-hailing services in Europe.

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ENDNOTES

[1] Data for some cities are not available for all years of the considered period.

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

REFERENCES

Albalate, D., & Fageda, X. (2021). On the relationship between congestion and road safety in cities. *Transport Policy*, *105*, 145–152. https://doi.org/10.1016/j.tranpol.2021.03.011

Anderson, D. N. (2014). “Not just a taxi”? For-profit ridesharing, driver strategies, and VMT. *Transportation*, *41*, 1099–1117. https://doi.org/10.1007/s11116-014-9531-8

Angrist, J. D., & Pischke, J. S. (2009). *Mostly harmless econometrics*. New York: Princeton University Press. https://doi.org/10.1515/9781400829828

Barth, M., & Boriboonsomsin, K. (2008). Real-world carbon dioxide impacts of traffic congestion. *Transportation Research Record: Journal of the Transportation Research Board*, *2058*, 163–171. https://doi.org/10.3141/2058-20

Beaudoin, J., Farzin, Y. H., & Lin Lawell, C. Y. (2015). Public transit investment and sustainable transportation: A review of studies of transit's impact on traffic congestion and air quality. *Research in Transportation Economics*, *52*, 15–22. https://doi.org/10.1016/j.retrec.2015.10.004

Berger, T., Chen, C., & Frey, C. B. (2018). Drivers of disruption? Estimating the Uber effect. *European Economic Review*, *110*, 197–210. https://doi.org/10.1016/j.euroecorev.2018.05.006

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics*, *119*, 249–275. https://doi.org/10.1162/003355304772839588

Borusyak, K., & Jaravel, X. (2020). Revisiting event study designs. University of Harvard Working Paper.

Brodeur, A., & Nield, K. (2018). An empirical analysis of taxi, Lyft and Uber rides: Evidence from weather shocks in NYC. *Journal of Economic Behavior and Organization*, *152*, 1–16. https://doi.org/10.1016/j.jebo.2018.06.004

Chang, H.-H. (2017). The economic effects of Uber on taxi drivers in Taiwan. *Journal of Competition Law and Economics*, *13*, 475–500.

Chen, M. K., & Sheldon, M. (2015). Dynamic Pricing in a Labor Market: Surge Pricing and Flexible Work on the Uber Platform. Unpublished results.

Cohen, P., Hahn, R., Hall, J., Levitt, S., & Metcalfe, R. (2016). Using Big Data to estimate consumer surplus: The case of Uber. *NBER Working Papers* 22627: 1–42.

Contreras, S. D., & Paz, A. (2018). The effects of ride-hailing companies on the taxicab industry in Las Vegas, Nevada. *Transportation Research A: Policy and Practice*, *115*, 63–70.

Cramer, J., & Krueger, A. B. (2016). Disruptive change in the taxi business: The case of Uber. *American Economic Review: Papers and Proceedings*, *106*, 177–182. https://doi.org/10.1257/aer.p20161002

Ewing, R., Hamidi, S., Gallivan, F., Nelson, A. C., & Grace, J. B. (2014). Structural equation models of VMT growth in US urbanised areas. *Urban Studies*, *51*, 3079–3096. https://doi.org/10.1177/0042098013516521

Ewing, R., Tian, G., & Lyons, T. (2018). Does compact development increase or reduce traffic congestion? *Cities*, *72*, 94–101. https://doi.org/10.1016/j.cities.2017.08.010

Frazzani, S., Grea, G., & Zamboni, A. (2016). Study on passenger transport by taxi, hire car with driver and ridesharing in the EU. Report prepared for the European Commission. URL at: https://ec.europa.eu/transport/sites/transport/files/2016-09-26-pax-transport-taxi-hirecar-w-driver-ridesharing-final-report.pdf

Gertler, P. J., Martinez, S., Premand, P., Rawlings, L. B., & Vermeersch, C. M. J. (2016). *Impact evaluation in practice*. Washington, DC: Inter-American Development Bank and World Bank.

Hall, J. D., Palsson, C., & Price, J. (2018). Is Uber a substitute or complement for public transit? *Journal of Urban Economics*, *108*, 36–50. https://doi.org/10.1016/j.jue.2018.09.003

INRIX and Cebr. (2014). *The future economic and environmental costs of gridlock in 2030: An assessment of the direct and indirect economic and environmental costs of idling in road traffic congestion to households in the UK, France, Germany and the USA*. London: INRIX and Ceber.

Kong, H., Zhang, X., & Zhao, J. (2020). Is ridesourcing more efficient than taxis? *Applied Geography*, *125*, 102301. https://doi.org/10.1016/j.apgeog.2020.102301

Li, Z., Hong, Y., & Zhang, Z. (2016). Do on-demand ride-sharing services affect traffic congestion? Evidence from Uber entry. Available at SSRN: https://ssrn.com/abstract=2838043

Nelson, E., & Sadowsky, N. (2019). Estimating the impact of ride-hailing app company entry on public transportation use in major US urban areas. *The B.E. Journal of Economic Analysis & Policy*, *19*, 1–21.

Nie, Y. M. (2017). How can the taxi industry survive the tide of ridesourcing? Evidence from Shenzhen, China. *Transportation Research Part C: Emerging Technologies*, *79*, 242–256. https://doi.org/10.1016/j.trc.2017.03.017

Parry, W. H., Walls, M., & Harrington, W. (2007). Automobile externalities and policies. *Journal of Economic Literature*, *45*, 373–399. https://doi.org/10.1257/jel.45.2.373

Qian, X., Lei, T., Xue, J., Lei, Z., & Ukkusuri, S. V. (2020). Impact of transportation network companies on urban congestion: Evidence from large-scale trajectory data. *Sustainable Cities and Society*, *55*, 1–13. https://doi.org/10.1016/j.scs.2020.102053

Rienstra, S., Bakker, P., & Visser, J. (2015). International comparison of taxi regulations and Uber. KiM Netherlands Institute for Transport Policy Analysis Technical Report.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*, 41–55. https://doi.org/10.1093/biomet/70.1.41

Sarzynski, A., Wolman, H. L., Galster, G., & Hanson, R. (2006). Testing the conventional wisdom about land use and traffic congestion: The more we sprawl, the less we move? *Urban Studies*, *43*, 601–626. https://doi.org/10.1080/00420980500452441

Shi, Q., Abdel-Aty, M., & Lee, J. (2016). A Bayesian ridge regression analysis of congestion's impact on urban expressway. *Accident Analysis and Prevention*, *88*, 124–137. https://doi.org/10.1016/j.aap.2015.12.001

Su, Q. (2010). Travel demand in the US urban areas: A system dynamic panel data approach. *Transportation Research Part a*, *44*, 110–117.

Tank, K., Wijngaard, J. B., Konnen, G. P., Bohm, R., Demaree, G., Gocheva, A., … Petrovic, P. (2002). Daily dataset of 20th-century surface air temperature and precipitation series for the European Climate Assessment. *International Journal of Climatology*, *22*, 1441–1453. https://doi.org/10.1002/joc.773

Wallsten, S. (2015). The competitive effects of the sharing economy: How is Uber changing taxis? Unpublished results.

Ward, J. W., Michalek, J., Azevedo, I. L., Samaras, C., & Ferreira, P. (2019). Effects of on-demand ridesourcing on vehicle ownership, fuel consumption, vehicle miles traveled, and emissions per capita in U.S. States. *Transportation Research Part C: Emerging Technologies*, *108*, 289–301. https://doi.org/10.1016/j.trc.2019.07.026

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Resumen. Este documento explora el impacto de Uber, la mayor empresa de servicios de reserva de taxis del mundo, en la congestión de tráfico. A partir de datos de ciudades europeas para el período 2008 a 2016, se encontró un impacto negativo de Uber en la congestión de tráfico. El impacto estimado en la regresión de referencia es de –3,5 puntos porcentuales, pero es mayor en las ciudades que no imponen fuertes restricciones normativas a los servicios de reserva de taxis. Además, el impacto negativo de Uber en la congestión de tráfico sólo es estadísticamente significativo en las ciudades más densas. El efecto de Uber es gradual, ya que su impacto aumenta con el tiempo. Por último, se encontró evidencia que sugiere que el sesgo potencial de endogeneidad subestima el efecto negativo de Uber sobre la congestión de tráfico.

抄録: 本稿では、世界最大の配車サービス会社であるUberの渋滞への影響を検討する。2008~2016年の欧州の都市のデータから、Uberが渋滞に悪影響を与えていることを発見した。ベースライン回帰で推定した影響は、–3.5%ポイントであるが、配車サービスに強い規制を課していない都市ではもっと高い値がみられる。さらに、渋滞に対するUberの負の影響は、人口密度の高い都市においてのみ統計的に有意である。Uberの影響は、時間の経過とともに大きくなるものであり、徐々に拡大するものである。また、潜在的な内生性バイアスが、Uberの渋滞に対する負の効果を過小評価することを示唆するエビデンスが認められる。

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