AN EMPIRICAL ANALYSIS OF UBER FARES: EVIDENCE FROM MADRID

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ABSTRACT

Ride-hailing is an emerging service that is transforming door to door mobility in urban areas. Users can easily request a ride through a smartphone app that informs them of the pickup time, the location of the vehicle, and the fare that they will pay in advance. Even though it is well know that Uber implements a dynamic pricing approach depending mostly on supply, demand and competition with other services, there is still little empirical evidence on the main drivers explaining the fare strategy of the company. Using 10-month data from the Uber's Application Programming Interface (API) in the city of Madrid, this research studies the evolution and trends experienced by Uber fares in terms of several explanatory variables. It also explores the main differences between Uber and taxi fares.

The results indicate that trip distance, day of the week, origin and destination of the trip, and rain precipitation have a statistically significant impact on Uber fares. The findings also show that on average, Uber fares are lower than taxi fares, with the exception of particular hours of the day. The analysis also demonstrates that Uber fares slightly decreased during taxi strikes.

1. INTRODUCTION

Information and Communication Technologies (ICT) are radically changing mobility habits as they help connect customers to services through smartphone applications. These apps have important advantages to riders in terms of information, availability, and payment systems. Taking advantage of ICT, ride-hailing is one of the emerging mobility options that is revolutionizing door to door mobility services.

Users can easily request a ride through a smartphone app that informs them of the pickup time, the location of the vehicle, and the fare that they will pay in advance. The app also facilitates the payment to the user.

Uber, Lyft, Cabify, and Didi Chuxing are examples of ride-hailing companies offering their services through smartphone apps. The popularity of these companies is rising due to their availability, convenience, and quality of service compared to traditional taxi systems (Rayle et al., 2016; Shokoohyar et al., 2020). As a consequence of that, traditional cabs, threatened by ride-hailing apps, have set strikes and demonstrations all around the globe to protest for what they consider unfair competition.

One of the main differences between ride-hailing and taxi services is that ride-hailing platforms freely adjust their fares using real-time dynamic algorithms (K. Chen & Sheldon, 2015), while taxi fares are fixed and generally regulated. That means that ride-hailing fares automatically increase when demand is higher than the supply of drivers within a specific area. Dynamic pricing is also called "surge pricing", and it is an automated system based on the simple principles of demand and supply conditions. Thus, passengers pay a higher fare for rides during times of high demand. When fares applied sharply increase due to high demand conditions, users are generally informed prior to requesting a ride.

The aim of this study is to explain and understand fare patterns by ride-hailing operators. To that end, we collected data from one of the most popular ride-hailing companies worldwide, Uber, so as to conduct an econometric model to explain Uber fares as a function of several exogenous variables. The research exploits supply data from Uber rides collected in the city of Madrid from September 2018 to June 2019, which were obtained by the Uber's Application Programming Interface (API).

This paper contributes to the state of the art on transportation networking companies (TNCs) in three main aspects. First, we analyse the fares applied by a ride-hailing operator over a long period of time (ten months), to explore the evolution of Uber fares according to several variables. Some previous studies are based on simple simulation approaches (Pepić, 2018), or online surveys to riders (Smart et al., 2015), but did not examined prices actually offered to ride-hailing customers. Other contributions have focused on fare supply during short periods (days or weeks), or special events (L. Chen, n.d.; Hall et al., n.d.; Jiao, 2018; Shokoohyar et al., 2020), but they lack insight from longer timespans, which is important to obtain robust conclusions on the patterns followed by ride-hailing fares. Second, we compare Uber and taxi fares using real data about prices. And third, due to some particular characteristics of the case study, we study to what extent taxi strikes impact on Uber fares.

The paper is structured as follows. After this introductory part, the state of the art and practice concerning ride-hailing services is provided.

A description of the main characteristics of Uber and taxi services in the city of Madrid (Spain) is then presented. This is followed by the description of the data set, their descriptive statistics and the model specification used for this research. The main findings on the evolution of Uber fares and the comparison between Uber and taxi prices are presented. The last section draws the main conclusions and new research avenues.

2. RIDE-HAILING DEMAND AND SUPPLY: SCIENTIFIC BACKGROUND

The scientific literature devoted to ride-hailing has increased in the past few years in parallel with the increasing adoption of these services worldwide. Despite the limited amount of empirical data available up to date, many contributions have been conducted in different research areas regarding ride-hailing, namely: individuals' adoption and frequency of use of these services, estimates of ride-hailing effects, and knowledge of ride-hailing supply. It is worth noticing that nowadays, the majority of research pieces are focused on specific countries, such as the US and China (see comments by e.g. (Mohamed et al., 2019)), with only a few analyses conducted in other geographical areas.

The first group of contributions has modelled individuals' adoption and frequency of use of ride-hailing, both at the individual and trip level as noted by (Lavieri & Bhat, 2019). These papers conduct econometric models to identify the explanatory factors determining the use of these services . For instance, many research works have concluded that ride-hailing users tend to be young people, are familiar with new technologies, and have a higher level of education (see e.g. (Alemi et al., 2018; Rayle et al., 2016; Wang & Mu, 2018)). Furthermore, it has been found that wealthy individuals and residents of urban areas are more likely to adopt ride-hailing services (Alemi et al., 2018; Goodspeed et al., 2019; Lavieri & Bhat, 2019; Tirachini & del Río, 2019; Yu & Peng, 2019). These papers are typically based on the information collected through questionnaires or geo-located trips provided by ride-hailing operators.

The second group of contributions is aimed at approaching the effects of ride-hailing services on the performance of urban sustainability indicators. For instance, there is evidence that the irruption of ride-hailing services has resulted in an increase of road congestion (see, e.g., (Clewlow & Mishra, 2017; Erhardt et al., 2019; Gehrke et al., 2018; Wenzel et al., 2019)). Regarding the impact on other transport modes, many authors such as (Nie, 2017), (Shaheen et al., 2016), or (Henao, 2017) have found out that transport demand of ride-hailing has been mainly captured from taxi services and, to a lesser extent, public transport. Among the positive effects of ride-hailing, we can mention the improvement of road safety (Peck, 2017) and the encouragement of car-free styles (Jin et al., 2018).

Other aspects such as the real impact of ride-hailing on car ownership decisions remain unanswered, with contributions concluding positive (see e.g. (Gong & Song, 2017)), negative (e.g., (Gehrke et al., 2018)) or even neutral effects (e.g. (Rayle et al., 2016)).

Again, these research works generally use information from surveys or geo-located trips.

Finally, the third group of contributions focuses on the supply side of ride-hailing. Given the scarcity of empirical data and the unfeasibility to get large amounts of information from e.g. questionnaires, these papers have often obtained data through Application Programming Interfaces (APIs) provided by operators. For instance, (Cramer & Krueger, 2016) analysed the utilization rate for Uber drivers versus taxi drivers in five major US cities. They concluded that ride-hailing drivers present a significantly higher fraction of their time and share of miles driven with a passenger in their car. (Berger et al., 2018) examined how the irruption of ride-hailing impacted the taxi supply and found a noticeable decline in taxi drivers' earnings, but not in their level of labour supply. Similarly, for the case of Spain, (Akimova et al., 2020) found that the irruption of ride-hailing companies in this country had a significant negative impact on the profitability of the traditional taxi companies in Madrid and Barcelona. Additionally, (Brodeur & Nield, 2018) studied the influence of weather conditions on ride-hailing demand in NYC, concluding that ride-hailing trips increase by 19% when it rains.

Price is a key factor generally considered when analysing ride-hailing supply. For instance, (Shokoohyar et al., 2020) studied a 13-day database collected from the Uber and Lyft APIs to determine to what extent weather conditions influence ride fares, trip duration, and pick-up waiting time in the city of Philadelphia. They found a statistically significant positive effect of extreme weather conditions on ride-hailing fares during weekdays, and a negative impact during weekends due to the lower demand experienced those days compared to normal weather conditions. By exploiting a randomly-drawn Uber dataset from several US cities, (K. Chen & Sheldon, 2016) studied how driver-partners on the ride-hailing platform respond to the dynamic pricing of trips and concluded that drivers tend to drive longer and provide more trips at times with high surge prices.

Despite the increasing attention devoted to the study of ride-hailing services, the current literature has some gaps that have motivated this research. As can be observed, there is a need in the current literature to analyse the evolution of ride-hailing fares during longer periods of time to capture for instance monthly variations. While previous contributions have focused on short timespans, longer periods may allow e.g. exploring potential seasonal effects on ride-hailing fares and obtaining more robust conclusions on their change over time. Additionally, competition between ride-hailing companies and taxis should be explore more in depth.

While previous contributions such as (Akimova et al., 2020) have focused on the impact on earnings, from the supply side, it should be interesting to compare the evolution of fares in ride-hailing services versus the prices applied by taxis, their direct competitors. In this respect, (Smart et al., 2015) found that, for the case of Los Angeles, Uber rides were cheaper by a considerable measure compared to taxis. While this result is based on an online survey to riders, comparing ride-hailing and taxi fares through more massive datasets would provide additional and useful insight.

Finally, given the direct competition between taxi cabs and ride-hailing services, there is a lack of evidence on how an event concerning the taxi supply (e.g. strikes in the taxi sector) impacts on ride-hailing services.

3. THE CASE STUDY OF MADRID CITY

This section provides a brief description of the case study selected to analyse the trends and evolution followed by ride-hailing fares, and their comparison with prices in the taxi sector. Madrid is the capital of Spain and its most populated city, with a total of 3.3 million inhabitants and a metropolitan area comprising 6.5 million inhabitants. The city has two main ring highways (M-30 and M-40), which absorb a significant share of intra-city trips made by private vehicles. In recent decades, Madrid has experienced rapid growth, and a suburbanization process, so many residents and jobs are moving from the city center (districts inside the M-30 ring) to outer neighbourhoods or municipalities within the Madrid metropolitan area.

Mobility in Madrid is characterized by a strong presence of public transport modes. According to the last Metropolitan Mobility Survey (Consorcio Regional de Transportes de Madrid, 2019), there are 7.9 million trips on average in a working day in the city: 36.1% of trips are made on foot, while private transport and private vehicle trips account for, respectively, 33.8% and 26.3% of the trips. Minority options (taxi, ride-hailing companies, bicycle, motorcycle, etc.) represent 3.4% of urban trips.

Ride-hailing services started to operate in Spain in the city of Madrid in September 2014, with the irruption of Uber. At that time, Uber drivers did not have any license, which was against Spain’s transport legislation, so the service was forced to stop offering rides in the country, therebay ceasing all its activities in December 2014. In order to fulfil with all legal requirements, Uber drivers got VTC licenses and the company’s activities resumed in Madrid in March 2016. It was followed shortly after by the Spanish company Cabify, also offering ride-hailing services. Demand for Uber and Cabify rides sharply increased and extended to other Spanish cities, which caused severe opposition from the taxi sector throughout the country.

The taxi sector reacted with hostility to this new competitor due to a negative impact on their economic profitability. Taxi drivers complained that ride-hailing companies did not pay taxes in Spain, did not comply with labour legislation in the country, and benefited from being allowed to change their fares freely. As a consequence of that, demonstrations and strikes from the taxi sector have been common in recent years in Spain, particularly in Madrid. In February 2016, there was the first march of taxi drivers against ride-hailing services. In January 2019, taxi drivers blocked access to the main road in the city for days and even caused violent incidents (Akimova et al., 2020).

Some particular characteristics can be pointed out in the ride-hailing and taxi sectors in Spain. For instance, unlike other countries such as the United Kingdom or the US, where ride haling services are almost fully liberalised, the number of VTC licenses in Spain is currently limited by the government. Furthermore, since 2018 VTC licences are regulated at the regional level, but ride-hailing drivers can occasionally offer their services in any city of the country, depending on the specific demand needs. By contrast, taxi licences in Spain are limited and regulated at the municipal level, and taxi drivers can only offer their services in the specific city where the licence is awarded. It is also worth noticing that most local governments in Spain have suspended the launch of new taxi licenses for decades. As a result, the number of taxi licences in many cities (and particularly in Madrid) have remained almost constant for more than 20 years (Vassallo et al., 2018), mainly due to the pressure of taxi drivers to keep or increase the prices of their licences in the secondary market. According to the Ministry of Transportation (Ministerio de Fomento, 2020), as of March 2020, there were 63,917 taxi licenses and 16.450 VTC licenses in Spain. In the case of Madrid, there were 15,665 taxi licenses and 8,375 VTC licenses, what makes Madrid one of the Spanish cities with the highest ratio of VTC licenses per taxi licenses.

As noted above, Uber and Cabify are the two most widespread ride-hailing services in Spain. Nevertheless, this paper only focuses on Uber services, data due to the lack of data available for the case of its competitor Cabify.. In Spain, Uber provides three different services, namely UberX, UberBlack, and UberVan. UberX is by far the most popular and demanded Uber product, UberBlack is the premium service (Hughes & MacKenzie, 2016; Jiao, 2018) and UberVan is a service for groups of up to 6 people. Uber fares are determined by multiple factors, namely the base fare, the price per kilometre, the price per minute, and the “surge pricing” factor, which is the output of the dynamic algorithm (Ngo, 2015).

Taxi fares in the city of Madrid are set by the City Council, and are determined according to trip distance, trip duration, day of the week, and time of the day (BOAM Boletín Oficial Del Ayuntamiento de Madrid - Núm. 8546, 2018). It should be noted that trips departing or arriving at the airport have a special fare scheme when the origin or destination is located within the inner districts (inside the M30 ring road). In those cases, a fixed fare of €30 is applied regardless of any other trip characteristics.

There are four components which determine Uber and taxi fares in Madrid in 2019 (BOAM Boletín Oficial Del Ayuntamiento de Madrid - Núm. 8546, 2018; Jimenez, 2019): i) a starting fee, which is fixed no matter the duration or length of the ride; ii) fare per minute; iii) fare per kilometre; and iv) minimum fare, which is a minimum fare for each service to reimburse drivers for short rides. This fare, only applied in the case of Uber rides, is charged when the cost of the ride is below €3.50. Taxi services do not include the "minimum fare" component, but the starting fee applied is significantly higher when compared to Uber rides (the starting fee of Uber X is 0.40€ and the starting fee of the taxi is 2.50€ or 3.10€ depending if it is working day or not and depending on the hour of the day in which the ride was requested). In addition to these four components, Uber applies dynamic pricing in its rides when the demand is particularly higher than the supply of drivers.

4. DATA DESCRIPTION

This section presents the data used to explore the trends and evolution followed by ride-hailing fares, and their comparison with prices in the taxi sector. Multiple sources and type of information were employed . Regarding the prices offered by ride-hailing, we collected the information through Uber's Application Programming Interface (API). This tool allows collecting real-time information of requested rides by controlling the latitude and longitude coordinates (origin and destination point) sent by the script developed by the authors of this paper. As noted above, prices applied by Cabify, the other ride-hailing company operating in Spain, were not available and consequently it was not possible to include this company in the analysis.

For the purpose of collecting information on ride-hailing prices, the authors defined 10 locations throughout the city, which were used as origins and destinations of the requested rides. These locations were selected with the aim to homogeneously cover the whole city (see Figure 1), including both inner and outer neighbourhoods (inside and outside the M-30 ring, respectively). We also included special locations such as Madrid-Barajas airport and Atocha train station, with a high demand for ride-hailing and taxi trips in the city. These locations defined a network with 90 potential origins-destinations in Madrid, but we had to subsequently reduce the combinations in a noticeable way (see comments below). The data were requested to the API and stored at 1-hour intervals from September 1st 2018 to June 9th 2019. Figure 1 shows all routes considered in the analysis.

From the service models offered by Uber in Madrid, we focus on UberX rides because it is the most popular Uber service (Hughes & MacKenzie, 2016; Jiao, 2018). The following information was collected from each ride requested in the Uber API: fare, trip distance, trip duration, and the time the ride was requested (year, month, day, and hour). Uber fare indicates the cost of the ride shown by the app. Trip distance and trip duration indicate the trip distance and duration for a given origin and destination, respectively.

It is worth noticing that trip duration reported by the Uber API is based on real traffic conditions, therefore It can be considered a proxy of road congestion in the city.

In order to capture changes in ride fares over time, we included categorical variables controlling for time-related variables for requested rides, namely month, day of the week and hour (time of day). The analysis also controls for potential differences in ride fares depending on the origin and destination of the requested trip. Consequently, we may expect that rides within the city center would be cheaper, given that ride-hailing supply is generally higher in this area of the city.

Therefore, a categorical variable was created to control for the location of the origin and destination of each, particularly whether they are inside or outside of M30, Madrid's inner ring highway.

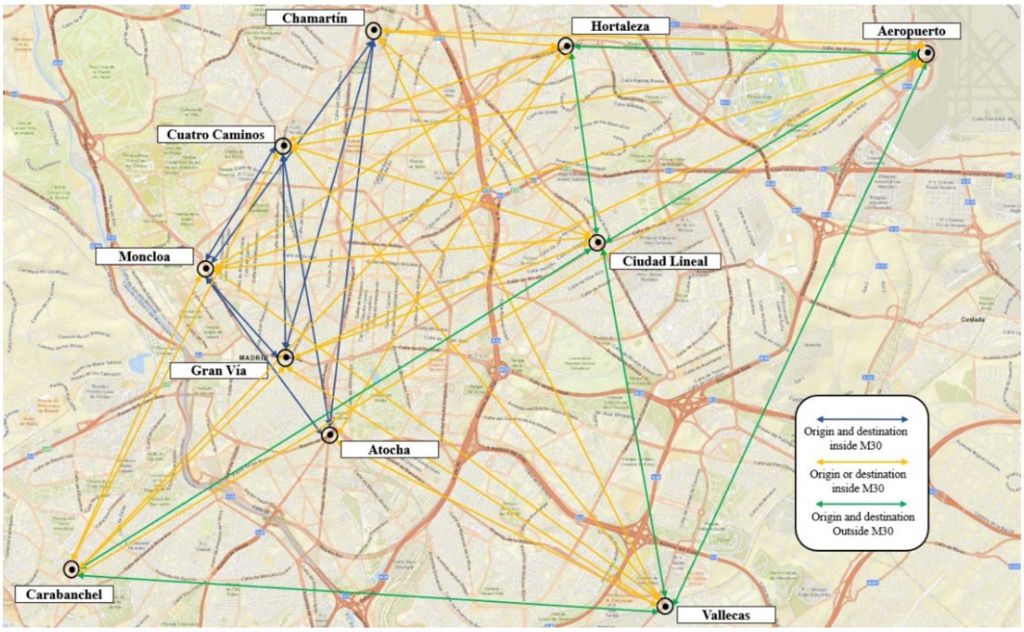

Fig. 1 – Routes selected

In addition to these variables, we also included further information regarding the taxi sector. Firstly, taxi fares were calculated for each ride, following the regulation of the Madrid City Council (BOAM Boletín Oficial Del Ayuntamiento de Madrid - Núm. 8546, 2018) and based on the information collected through the Uber API regarding trip distance, trip duration, type of day, and time of day hour of each trip. This step allowed us to estimate taxi fares and calculate the difference between the prices applied by UberX and taxi services for each specific ride.

The analysis also considers taxi strikes that happened during the period of analysis, in order to control for special events affecting the transport supply of its main competitor. We included a categorical variable capturing the days of strike in Madrid between September 1st 2018 and June 9th 2019.

During the period analysed in this research, there have been taxi strikes for 20 days. Nevertheless, it should be pointed out that a few additional strikes happened in the taxi sector in Madrid in 2018, before the time period covered by the research.

The analysis incorporates weather conditions since they could influence the Uber dynamic pricing and affect ride fares, as found by (Shokoohyar et al., 2020). We collected data on rain precipitation (measured in millimetre) on a 1-hour interval. This variable was obtained from the State Meteorological Agency (AEMET), Ministry of Agriculture, Food, and Environment.

Once the information needed for the research has been collected, a first exploratory analysis of the sample was conducted. It revealed that ride prices for many OD pairs keep constant over time and equals the minimum fare, as explained before. Therefore, these OD combinations were not valid for the purpose of the research so the sample was reduced to 40 OD pairs. A total of 277,840 valid requested rides were finally included in the analysis. Descriptive statistics of the final data sample can be observed in Table 1.

Variables	**Typology**	**Summary statistics**		**Units**
Uber fare (FARE)	*Continuous*	*Mean*	*20.6*	*€*
		Median	*20.0*	*€*
		Max	*149.0*	*€*
		Min	*5.0*	*€*
		SD	*7.6*	*€*
Trip distance (DIST)	*Continuous*	*Mean*	*12.7*	*km*
		Median	*12.3*	*km*
		Max	*36.4*	*km*
		Min	*2.2*	*km*
		SD	*4.8*	*km*
Travel time (TTIME)	*Continuous*	*Mean*	*1161*	*seconds*
		Median	*1140*	*seconds*
		Max	*3180*	*seconds*
		Min	*360*	*seconds*
		SD	*311*	*seconds*
Day of week (DAY)	*Categorical*	*Working days**	*127,760*	
		Saturday, Sunday and holidays	*150,080*	
Taxi fare	*Continuous*	*Mean*	*25.1*	*€*
		Median	*25.0*	*€*
		Max	*66.0*	*€*
		Min	*7.0*	*€*
		SD	*7.22*	*€*
Taxi strike (STRIKE)	*Categorical*	*Strike**	*934*	
		No Strike	*276,906*	
Origin/destination of the ride	*Categorical*	*(1) Origin and destination inside M30**	*27,786*	

Variables	Typology	Summary statistics		Units
(SPAT)		*(2) Origin inside and destination outside M30*	*83,348*	
		(3) Origin outside and destination inside M30	*83,347*	
		(4) Origin and destination outside M30	*83,359*	
Rain precipitation (PREC)	*Continuous*	*Mean*	*0.33*	*mm*
		Median	*0.00*	*mm*
		Max	*91.00*	*mm*
		Min	*0.00*	*mm*
		SD	*2.50*	*mm*
Difference	*Continuous*	*Mean*	*-4.5*	*€*
		Median	*-5.0*	*€*
		Max	*107.0*	*€*
		Min	*-17.0*	*€*
		SD	*3.9*	*€*

Table 1 – Summary statistics of explanatory variables

As exploratory analysis, Figure 2 shows Uber fare behaviour per day, hour, and strike event. Uber fares vary around the day and hour.

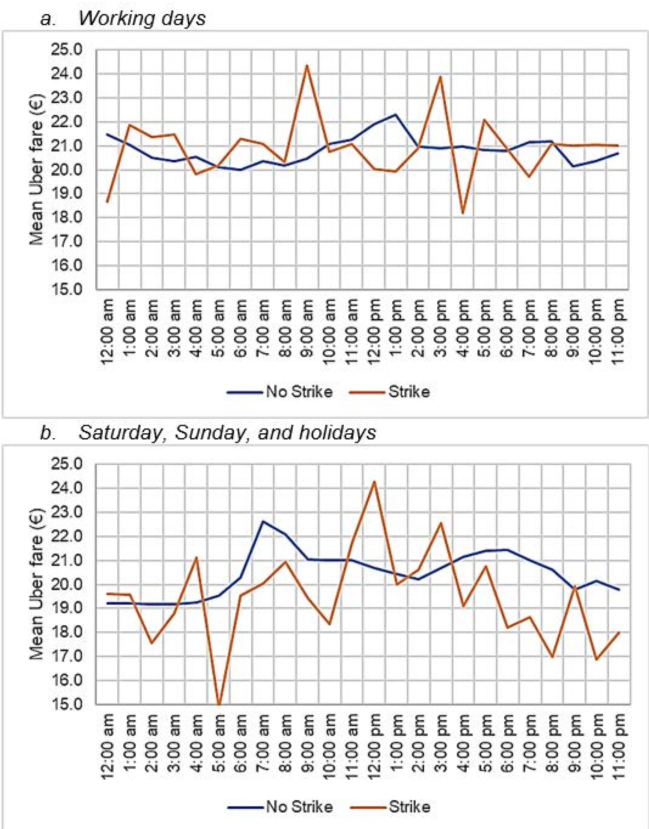

Fig. 2 – Mean Uber fare behavior

5. METHODOLOGY

In order to explore the evolution and trends followed by fares applied in the ride-hailing sector, we adopted a generalized linear model (GLM) framework. The dependent variable to be modelled is the fare applied by Uber services. Nevertheless, the paper also provides some insight regarding differences in terms of prices offered by Uber and taxi services.

GLM is a widely statistical technique used when the response distribution of the dependent variable is non-normal (Oliveira et al., 2018). It is made up of three components: random component, a linear predictor, and a link function. The random component consists of a response variable with independent observations that can be defined by a probability density function of the exponential family (Agresti, 2015). In this case, the Uber fare showed to follow a gamma distribution (k=7.145, θ=0.345) and therefore we used the natural log function, g(μ_i)=ln(μ_i) as a link function. Additionally, a linear predictor relates parameters with the explanatory variables using a linear combination defined as:

$$\ln(Y) = \beta_0 + \Sigma_j \beta_j X_j + \varepsilon \tag{1}$$

In our case, the set of explanatory variables Xj includes: trip distance, trip duration, month of the year in which the ride was requested, day of the week, hour of the day, taxi strike, origin/destination of the ride and rain precipitation, as can be seen in Equation 2:

$$\ln(FARE) = \beta_0 + \beta_1 DIST + \beta_2 TTIME + \beta_3 STRIKE + \beta_4 PREC + \beta_5 DAY + \beta_6 SPAT + \Sigma_i \beta_i MONTH_i + \Sigma_j \beta_j HOUR_j + \Sigma_{k,j} \beta_k DAYxHOUR_j \tag{2}$$

where:

- FARE is the dependent variable to be modelled, Uber fare.
- DIST is the trip distance of the requested ride.
- TTIME is the trip duration of the requested ride.
- STRIKE is a dummy variable that equals 1 when there is taxi strike and 0 otherwise.
- PREC is the rain precipitation, measured in mm.
- DAY is a dummy variable that indicates the day of the week. It equals 1 for non-weekdays (Saturday, Sunday, or holidays), and 0 otherwise (weekdays).
- SPAT is a categorical variable that controls for the location of the origin and destination of each particular ride, as detailed in Table 1.
- $MONTH_i$ is a set of dummy variables reporting the month (i) in which the ride is requested.
- $HOUR_j$ is a set of dummy variables reporting the hour of the day (j) in which the ride was requested.
- $DAYxHOUR_j$ indicates the interaction between DAY and $HOUR_j$ variables.

- B_k is a vector of coefficients to be estimated. The coefficient of variables indicates that when a specific explanatory variable X_i increases by one unit, holding all other predictors constant, the rate ratio (RR) increases by $e^{\beta i}$.

As can be observed, five explanatory variables used in the model are categorical (STRIKE, DAY, SPAT, MONTH, HOUR), so choosing a base reference is needed to explain the modelling results properly. This enables us to determine whether Uber fares are statistically significant when compared to the base reference. For instance, the base reference of STRIKE is when there is taxi strike. The base reference of DAY is working days. Regarding the SPAT variable, the base reference is the ride whose origin and destination is inside the M-30 highway. June 2019 is taken as the base reference of MONTH. Finally, 11:00 p.m. to 12:00 a.m. is considered as the base reference of HOUR. Base references chosen in each case can be observed in Table 1.

6. RESULTS

This section summarizes the main findings of the analyses conducted in this study. Prior to conducting the analyses, we studied potential multicollinearity problems in the sample.

Trip distance and trip duration variables were highly correlated with each other according to multicollinearity tests (Gujarati & Porter, 2009). Therefore, we decided to include only trip distance.

6.1 Uber fares

The results of the model explaining Uber fares are presented in Table 2. The signs of the modelling coefficients and their statistical significance are in line with the expected results.

All explanatory variables are statistically significant and, therefore, the p-value is accepted.

The model confirms the significant impact (with a level of 99% confidence from a statistical point of view) of the variables: trip distance, day of the week, location of the origin/ destination of the ride, and rain precipitation level. The taxi strike variable was significant with a level of 90% confidence.

The trip distance variable is positive and statistically significant, thus indicating that longer distances are associated to higher Uber fares as seems reasonable. According to the modelling results, Uber prices increase by €1.07 for each additional kilometre. Additionally, the variable controlling for the location of the origin and destination of the rides has positive and statistically significant coefficients. This means that coeteris paribus Uber fares decrease when both the trip origin and destination are inside the M-30 ring road.

This result seems reasonable due to the greatest supply density of Uber drivers in the city centre. Some detailed results are provided by the model. When the trip origin takes place inside the M-30 ring and the destination is located outside the M-30, Uber fares increase by 31.6% compared to the base reference. Price rises are lower when the trip origin is outside the M30 and the destination is inside it (+24.2%), and when both the origin and destination of the trip are outside M-30 (+23.2%), compared to the base case.

Variable	Estimate	Std. error	t value	p-value
(Intercept)	*1.929*	*0.0027*	*721.975*	*0.000*
DIST	*0.068*	*0.0001*	*752.292*	*0.000*
STRIKE	*-0.009*	*0.0056*	*-1.696*	*0.090*
DAY	*0.046*	*0.0032*	*14.637*	*0.000*
SPAT_2	*0.274*	*0.0013*	*205.554*	*0.000*
SPAT_3	*0.217*	*0.0013*	*165.084*	*0.000*
SPAT_4	*0.209*	*0.0016*	*134.629*	*0.000*
PREC	*0.003*	*0.0001*	*21.267*	*0.000*

AIC: 1,365,072
Null deviance: 39,791.3 on 277,839 degrees of freedom
Residual deviance: 5,982.7 on 277,777 degrees of freedom
Wald test: 0.0288

Table 2 – Modelling results

Day of the week also evidences to have a significant influence on prices offered by Uber services. The coefficient sign for this variable is also positive and statistically significant (see Table 2). According to the modelling results, coeteris paribus, Uber fares increase by 4.8% on Saturdays, Sundays, and holidays, compared to weekdays.

The influence of the time of day on Uber fares is also analysed (see Figure 3a). The model estimates conclude that, on average, Uber fares decrease by 2.3% from 12:00 p.m. to 5:00 a.m., compared to the base reference (from 11:00 p.m. to 12:00 a.m.). As expected, Uber fares increase on average by 9.5% from 6:00 to 9:00 a.m., coinciding with the morning peak hour. This result may be related to the higher demand and traffic congestion typically observed in this period (Gramaglia et al., 2016; Vassallo et al., 2012). The model also shows that, on average, Uber fares increase by 3.2% from 3:00 p.m. to 9:00 p.m. The afternoon peak hour, which in Madrid happens from 5 p.m. to 7 p.m., is included within that time frame. Fare rises in the afternoon peak hour are significantly lower than in the morning peak hour. Periods not mentioned above were not found statistically significant in the model.

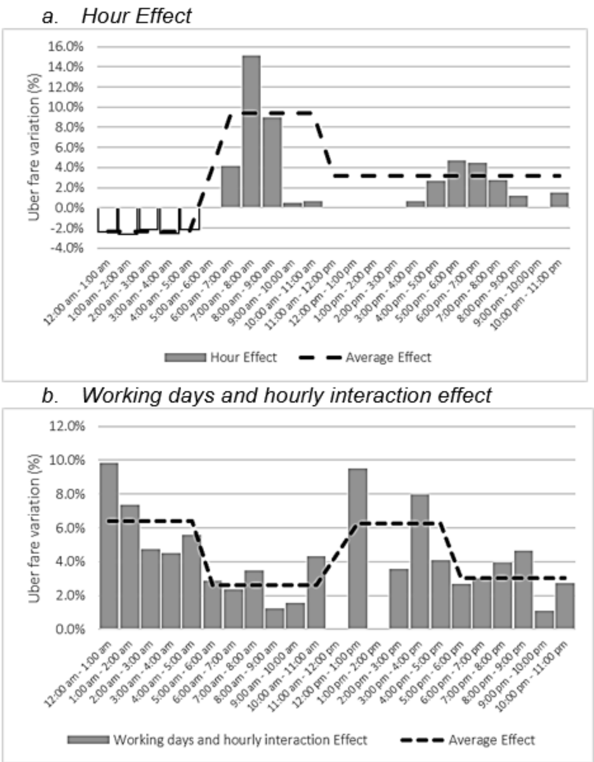

Fig. 3 – Effect generated by the hour to Uber fare

Furthermore, we analysed the day of the week and the hour interaction. This is motivated by the fact that the change in Uber prices at e.g. late hours may be significantly different during weekdays and non-weekdays. As previously mentioned, Uber fares are higher on Saturday, Sunday, and holidays compared to working days. However, the modelling results make it clear that this effect changes quite a lot throughout the day (see Figure 3b). We can identify two time periods when the fare rise is significantly noticeable: from midnight to 4.00 a.m., due to the high demand of people getting back home from night leisure activities (dinner, party, etc.); and from noon to 4.00 p.m., coinciding with the weekend dinner time in Spain. In these two periods, Uber fares increase around 6% according to the modelling results.

Concerning the Taxi strike variable, we obtain a negative statistically significant coefficient with 90% confidence. This result indicates that Uber fare decreases during taxi strikes. According to the modelling results, Uber fares drops by 0.94% compared to the base scenario (no taxi strike). This result appears to be surprising since we may expect that Uber had taken advantage of the taxi strike situation to rise the fares. The explanation we found to this empirical result is that Uber decided to use taxi strikes to capture new clients by maintaining, or even reducing, their usual fares rather than by rising prices. This fact was possible from the supply perspective since, as mentioned above, VTC licences can easily move across different cities of Spain during special occasions or events.

Finally, we found that weather conditions may influence the Uber dynamic pricing and affect the ride fare, which is in line with (Shokoohyar et al., 2020). The coefficient obtained for the rain precipitation variable is positive and statistically significant, and sates that Uber fare increases by 0.3% when rain per hour increases by 1 mm. This is likely due to the higher traffic congestion generally observed during rainy times and, therefore, longer trip duration.

6.2 Comparison of prices offered by Uber and Taxi Services

Furthermore, Uber and taxi fares are also compared. In this analysis we excluded airport trips departing/arriving within the M30 ring because taxi fares for these routes are fixed irrespective of the destination. The difference between the two fares is around €4.5 on average. In general, our findings suggest that taxi fares are higher than Uber ones in all types of day: working days, Saturday, Sunday, and holidays. This result confirms the hypothesis proposed by (Pepić, 2018), who obtained similar results regarding taxi and ride-hailing prices on the basis of a simulation approach.

We found that fare differences are higher in working days, from 10:00 p.m. to 6:00 a.m., compared to the rest of the day (see Figure 4a). This is mainly due to the fact that Uber reduces its fares in this period of time. In leisure days (Saturday, Sunday, and holidays), the trend is similar throughout the whole day (see Figure 4b) with the exception of the midnight period. A t-test was conducted to check whether there is a statistically significant difference between the means of Uber and taxi fares. We found evidence to believe that the difference is lower than 0. This result implies that, for the case of Madrid, Uber prices are lower, in a statistically significant way, than taxi prices.

Finally, we also analyse whether there is a significant fare difference depending on the hour of the day and day of the week. We found that in working days, there is statistical evidence that their means are significantly different except from mid overnight (1:00 a.m. to 4:00 a.m.), late morning (10:00 a.m. to noon), and early evening (from 6:00 p.m. to 7:00 p.m.). Therefore, the analysis suggests that Uber and taxi fares are similar only during these periods. Regarding leisure days (Saturday, Sunday and holidays), there is statistical evidence that Uber prices are significantly lower than taxi fares except from mid-late (9:00 a.m. to 11:00 a.m.) and mid-afternoon (2:00 p.m. to 4:00 p.m.). These findings mean that Uber and taxi fares are only similar during leisure days in these specific periods.

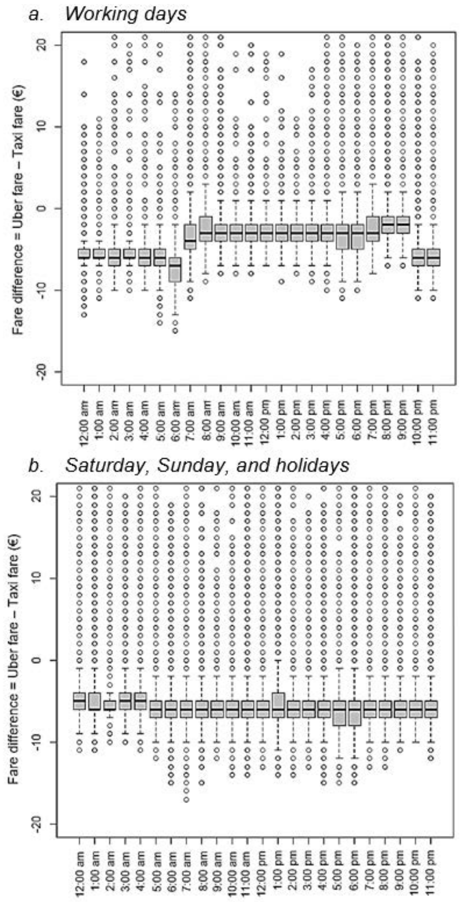

Fig. 4 – Uber and taxi fare difference behaviour

7. CONCLUSIONS

This study explores the evolution and trends experienced by ride-hailing prices, according to different explanatory variables: trip distance, the time the ride was requested (year, month, day and hour), origin/destination of the ride, weather conditions and taxi strikes. To that end, we applied an econometric specification using 10-month data (from September 2018 to June 2019) for Madrid obtained from the Uber's API. In addition, the paper explores the differences between Uber and taxi fares.

The results indicate that trip distance, the time the ride is requested, the origin/destination of the ride and rain precipitation significantly increase the fares offered by Uber. Particularly, Uber prices tend to increase during rainy conditions, but decrease in areas with higher service supply, such as the city centre. The modelling results show significant differences in Uber prices throughout the day. Uber fares increase significantly during the weekday morning peak hour (+9.5%) and, to a lower extent, during mid-afternoon and mid-evening (+3.2%) coinciding with the afternoon peak hour. By contrast, Uber prices significantly drop overnight (-2.3%). In addition to this, it is worth noticing that Uber fares are significantly higher during leisure days, likely due to the higher demand of leisure trips observed in this type of days.

Additionally, the results from this research show that Uber may have taken advantage of taxi strikes to capture new clients through fare reductions since, according to the model results, violent strikes conducted by the taxi sector coincided with a small decrease in Uber prices. This was possible from the supply side because the Spanish legislation makes possible to transfer ride-hailing supply licences across cities for high demand periods.

This research also found that, at least for the case of Madrid, Uber prices are on average significantly lower than taxi fares, with the exception of particular times of day within off-peak hours. The results suggest that taxi fares are around €4.5 higher than Uber in any type of day: working days, Saturday, Sunday, and holidays.

Some aspects can be pointed out for further research. Extending the analysis conducted in Madrid to other geographical areas (e.g. American cities) would provide broader insight. While the ride-hailing sector is regulated and the number of ride-hailing licenses are limited in Spain, this is not the case in many other cities. Additionally, studying the reasons motivating individuals' choices towards ride hailing and taxi adoption would be of the greatest interest to understand users' behaviour.

ACKNOWLEDGMENTS

The authors would like to thank the Comunidad de Madrid (CM), which has funded the project Y2018/EMT-4818 (Co-Mov/CM). The project has been also co-funded by the European FEDER and FSE funds.

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