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Post-entry rivalry: The immediate impact of the Uber application on door-to-door taxi rides

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Post-entry rivalry: The immediate impact of the Uber application on door-to-door taxi rides [1]

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[1] All opinions expressed here are personal and do not represent CADE's official position.

This is a work by the Department of Economic Studies (DEE)

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1. Introduction

The purpose of this work is to evaluate the immediate economic impact of the introduction of the **Uber** application in the Brazilian cities of São Paulo, Rio de Janeiro, Belo Horizonte, and the Federal District during the first semester of 2015, more specifically, concerning the effects on the number of taxi rides hired by means of the cell phone applications **99taxis** and **Easy Taxi**. The central issue is to determine whether the ride-sharing services hired by means of the **Uber** application have been offering any degree of substitution or exercising any kind of rivalry with the taxi rides hired by means of the cell phone applications **99taxis** and **Easy Taxi**.

As discussed in Esteves (2015), taxi rides and ride-sharing services may be classified as services offered in the individual passenger transportation market (both public and private). For the purposes of this empirical work, the semantic discussion of whether or not the services offered by the **Uber** application are ride-sharing services or taxi rides is completely irrelevant, even because the expected outcome from this exercise is exactly to provide an empirical answer to that question.

The hypotheses to be developed to address the issue – substitutability between the services offered by the **Uber** application and taxis – may be obtained from the very arguments of the disputing parties, that is, cab drivers and owners of taxi permits, and the company **Uber**. Cab drivers and owners of taxi permits maintain that the **Uber** application operates directly in the taxi rides market, offering a perfect replacement for the services already provided by the regulated market. The company **Uber** maintains, in turn, that its main competitors are private vehicles. These are, of course, extreme situations, since convex combinations of these two propositions may be built – for example, **Uber** competing only with a certain fraction of the taxi rides operated in the door-to-door segment.[2]

In an attempt to shed light on the discussion, this work provides an empirical exercise based on commonly used techniques in laboratory experiments with *control* and *treatment groups*. The fact that the **Uber** application operates in a smaller number of Brazilian capitals as compared to the taxi applications **99taxis** and **Easy Taxi** provides an interesting possibility to identify the

[2] Esteves (2015) provides a discussion on the characteristics of the taxicab markets and their different segments.

competitive effects. Such identification is reinforced by the fact that the **99taxis** and **Easy Taxi** applications started to consolidate their operations in the market even before the effective entry of the **Uber** application.[3]

Our strategy to identify the competitive effects was designed as follows: (i) we chose a period of time when the taxi ride applications **99taxis** and **Easy Taxi** already operated and the **Uber** application did not operate (or operated in an incipient and statistically irrelevant way). We therefore selected the month of October 2014, hereinafter called *Pre-Entry period*; (ii) we chose a period of time when the entry of the **Uber** application could already exert some competitive effect. We therefore selected the month of May 2015, hereinafter called *Post-Entry period*; (iii) we chose a group of cities where the **Uber** application did not operate in either of the selected periods. This group is called *control group*, and is formed by the cities of Porto Alegre and Recife; (iv) we chose a group of cities where **Uber** did not operate (or operated in a very incipient way) during the *Pre-Entry period*, but operated with more intensity during the *Post-Entry period*. This group is called *treatment group*, and is formed by the cities of São Paulo, Rio de Janeiro, Belo Horizonte, and the Federal District.

The competitive effect was inferred on the sum of the number of rides hired by means of the **99taxis** and **Easy Taxi** applications for each of the analyzed periods, that is, October 2014 (*Pre-Entry period*) and May 2015 (*Post-Entry period*). The information on the number of rides was obtained by means of official letters sent directly to the abovementioned companies. The information on the rides corresponded to the sum of all rides for each hour of the day (one-hour intervals, totaling 24 intervals) for each of the 31 days of each of the analyzed periods.

Considering the hypothesis of rivalry between the ride-sharing services hired by means of the **Uber** application and the taxi rides hired by means of the taxi applications **99taxis** and **Easy Taxi**, there would be corroboration in case the *treatment group* presented weaker performance (in terms of rides) than that observed for the *control group*. In short, the *treatment group* performance between the *Pre-Entry period* and the *Post-Entry period* would be statistically weaker than the performance observed for the *control group* within the same

[3] Market entry and consolidation is, for purposes of this work, a quantitative and statistical phenomenon, that is, it takes into account the quantities of marketed goods and services. As a result, it does not necessarily bear any relation with the date the companies are organized before the Corporate Taxpayers Registry of the Ministry of Finance (CNPJ).

time period. Such counterfactual exercise was individually performed by each of the cities of the *treatment group*, being the *control group* always formed by the cities of Porto Alegre and Recife.

The results obtained do not provide any evidence that the number of taxi rides hired in the *treatment group* cities (with the presence of the **Uber** application in the *Post-Entry period*) presented a weaker performance than those of the *control group* (without the presence of the **Uber** application in the *Post-Entry period*). In terms of empirical exercises applied to the antitrust policy, that means that we cannot even assume (at least in the periods analyzed herein) the proposition that the services rendered by the **Uber** application were (until May 2015) in the same relevant market as the services rendered by the taxi ride applications **99taxis** and **Easy Taxi**. In addition, it is not possible to overlook the possibility that the entry of the **Uber** application in the Brazilian individual passenger transportation market was almost exclusively fostered by the expansion and diversification of that market, that is, by satisfying a restrained demand, until then not satisfied by the services offered by the taxicabs.

In other words, the analysis of the studied period, which is **Uber's** entry and consolidation in some capitals, showed that the application, rather than absorbing a relevant portion of the taxi rides, actually conquered, for the most part, new clients, who did not use the services of taxicabs before. That means, in short, that so far **Uber** has not "appropriated" a considerable part of the taxi clients or significantly compromised the taxi drivers' business, but created a new demand instead.

We should underscore that the results obtained here must be interpreted with caution. First, none of the companies or business models (taxi and ride-sharing applications) analyzed here have reached the stage of product cycle maturity. For example, in the periods considered, some of the services in **Uber's** portfolio had not even been introduced in the Brazilian market. In short, the fact that the services provided by the **Uber** application are not within the same relevant market today as the services provided by the **99taxis** and **Easy Taxi** applications does not eliminate the possibility of them being part of the same relevant market in the future. In addition, considering the experience in other places where **Uber's** services portfolio is already strongly consolidated, we can expect that at some point the expansion of the application in Brazil will be supported, at least in part, by means of an interchange between ride-sharing services and taxi rides.[4]

Second, we should stress that, differently from laboratory-controlled experiments, our *control groups* (cities with **Uber** in the *Post-Entry period*) and *treatment groups* (cities without **Uber** in the *Post-Entry period*) are not selected from a random sampling design, even because **Uber's** decision to start operating in a certain city is not random. That has statistical implications that require additional caution, which will be discussed throughout this work.

This article comprises five sections, including this introduction. The second section is dedicated to presenting the methodological aspects and the empirical strategy of this exercise. The third section is dedicated to presenting the databases used herein. The fourth section is dedicated to presenting the results of the empirical exercise. The fifth and last section is dedicated to the conclusions and final considerations.

2. Methodology and empirical strategy

As mentioned in the introduction, our strategy to identify the competitive effects was designed as follows:

- **Step 1:** We chose a period of time when the taxi ride applications **99taxis** and **Easy Taxi** already operated and the **Uber** application did not operate (or operated in an incipient and statistically irrelevant way). We therefore selected the month of October 2014, hereinafter called *Pre-Entry period*;

- **Step 2:** We chose a period of time when the entry of the **Uber** application could already exert some competitive effect. We therefore selected the month of May 2015, hereinafter called *Post-Entry period*;

[4] Some news stories published in the North-American media report that the New York (NY) cab drivers have lost about 25%-30% of their rides to the **Uber** application. In the case of the city of San Francisco (CA), the competitive effects would have been even bigger. However, we should note that such information is not supported by official statistics (which does not mean they are wrong). Unfortunately, the availability of empirical studies on this subject in the literature is still very limited and incipient, which is yet another reason for the readers to be cautious when interpreting the available results and wait until the specialized literature grows, becomes more diversified in terms of alternative data an empirical methods, and offers evidence that may serve as input for the authorities and public policy managers to make decisions.

- **Step 3:** We chose a group of cities where the **Uber** application did not operate in either of the selected periods. This group is called *control group*, and is formed by the cities of Porto Alegre and Recife;

- **Step 4:** We chose a group of cities where **Uber** did not operate (or operated in a very incipient way) during the *Pre-Entry period*, but operated with more intensity during the *Post-Entry period*. This group is called *treatment group*, and is formed by the cities of São Paulo, Rio de Janeiro, Belo Horizonte, and the Federal District.

Based on the information above, we may specify and estimate the following regression model with the purpose of calculating a possible competitive effect resulting from the entry of the **Uber** application in the *treatment group* cities.

$$lnQ_t = \alpha + \beta t + \gamma T + \delta tT + \varepsilon_t \quad [1]$$

$$\varepsilon_t \sim N(0, \sigma^2)$$

Where lnQ_t is the number of taxi rides hired in period *t* (specified in logarithmic terms); *t* is a dummy variable with value equal to zero when the rides happen in the *Pre-Entry period* and equal to one when they happen in the *Post-Entry period*; *T* is a dummy variable with value equal to zero when the rides happen in *control group* cities and equal to one when they happen in *treatment group* cities; Greek characters α, β, γ and δ are parametric constants to be estimated based on the data; and ε_t is a stochastic error term with average zero and constant variance.

The model specified by equation [1] is known in the specialized literature as difference-in-differences model.[5] Differences in performance between the *control* and *treatment groups* between the *Pre-Entry* and *Post-Entry periods* are captured by means of the parametric constant, which multiplies the interaction term *tT*. Please note that the interaction term will only equal one when the taxi rides happen in the *Post-Entry period* and in the *treatment group* cities, that is,

[5] Khandker, Koolwal and Samad (2010) provide a bibliographical survey and a quite detailed and satisfactory discussion of that kind of technical literature, commonly referred as “impact assessment.” The discussion on the difference-in-differences techniques is found in chapter five of the manual. Finally, a digital version of the manual may be obtained free of charge in the World Bank website.

where a possible competitive effect of the **Uber** application would happen. A negative and statistically significant sign for constant δ would corroborate the proposition that ride-sharing overlaps the same relevant market of taxi rides, that is, that the **Uber** application exercises rivalry with the taxi applications **99taxis** and **Easy Taxi**.

It is necessary to discuss in further detail the propositions of the model reported by equation [1]. One implicit proposition of the model is that all regressors (independent or explanatory variables) on the right side of the equation are exogenous, that is, the regression model errors do not bear any relation with the explanatory variables. Should this really happen, the model of equation [1] could be estimated by the ordinary least squares method (OLS) without much difficulty. However, as already mentioned in the introduction, differently from laboratory-controlled experiments, our *control groups* (cities with **Uber** in the *Post-Entry period*) and *treatment groups* (cities without **Uber** in the *Post-Entry period*) are not selected from a random sampling design (which would entail the exogeneity of the regressors), even because **Uber's** decision to start operating in a certain city is not random.

The available solutions to address the issue are limited, and, depending on the available data, little trivial. This work attempted to address such problem and sought to reduce as far as possible the bias of the variable omitted from the model, favoring the inclusion of additional regressors that could explain the variability of the taxi ride numbers, but that also bore some relation with **Uber's** decision as to whether or not to operate in that specific market – mainly variables determined by the system in an exogenous way, that is, regressors that bore some relation with **Uber's** decision to participate in the market, but that **Uber** could not manipulate or exert any influence on.

Even considering such precautions, it is not possible to state that such kind of solution may have completely addressed the problem and eliminated each and every estimate bias for parametric constant δ. Therefore, due caution is recommended in the interpretation of the results presented throughout this work.

3. Database and additional methodological aspects

The main data used in this work were directly collected from the companies responsible for the taxi applications **99taxis** and **Easy Taxi**. The data was obtained by means of official letters issued by CADE's General Superintendence (SG) and Department of Economic Studies (DEE).

The following information was requested in order to develop this work: the sum of all taxi rides hired by means of the application from October 1st to 31, 2014 and from May 1st to 31, 2015. The information on the daily rides was also separated and reported by one-hour intervals, that is, the sum of rides from 00h01-01h00 on October 1st, 2014; between 01h01-02h00 on October 1st, 2014 … and between 23h01-24h00 on October 31, 2014; and between 00h01-01h00 on May 1st, 2015; between 01h01-02h00 on May 1st, 2015 … and between 23h01-24h00 on May 31, 2015. With that information it was possible to control the heterogeneity of the number of rides hired by means of applications according to the time of the rides, days of the week, and days of the month.

In addition, as mentioned in the previous section, the fact that the *treatment group* cities are not randomly determined requires additional explanatory variables to be found that may determine in an exogenous way **Uber's** participation in the *treatment group* cities. The fact that we work with daily city data (with the possibility of monthly aggregations) in a very recent historic event reduces even more the number of available variables that could serve that purpose.

In this respect, we have collected information on the private vehicles fleet in each of the cities of the *control* and *treatment groups* for both periods analyzed, that is, October 2014 and May 2015. That information is consolidated based on the licensed vehicles records of the State Departments of Traffic (DETRAN), available in a consolidated way at the National Transit Department (DENATRAN). The central argument to use such variable is that it would be of fundamental importance for **Uber's** decision to participate in a given city, considering that, as the company itself suggests, private cars are its main competitors. Accordingly, the biggest the number of competitors, the biggest the ability to secure market by offering the replacement service. Clearly the private vehicles fleet of a certain location is an exogenous variable to the **Uber** application.

Since the private vehicles fleet may also exert influence on the number of taxi rides, disregarding its participation on the left side of equation [1] could potentially entail an omitted variable problem, biasing, therefore, the estimation of the parametric constant δ.

An additional explanatory variable to be considered in the empirical exercise was the initial fare (*bandeirada*), regular fare for ordinary taxis in each of the cities, for each of the analyzed periods of time (October 2014 and May 2015). These fares were collected in articles published in the main local newspapers (online versions) of each of the *control* and *treatment group* cities.

The central argument to use such variable is that it would be of utmost importance for **Uber's** decision to participate in a certain city, considering that, as suggested by taxi drivers and taxi permit owners, **Uber's** goal is to enter the taxi market in order to offer a perfect, unregulated replacement. Accordingly, the fare that is exogenously determined by the regulatory authority would be a key parameter for **Uber's** decision to enter a certain market.

Since the initial fare certainly exerts influence on the number of taxi rides, disregarding its participation on the left side of equation [1] could also potentially entail an omitted variable problem, also biasing the estimation of theparametric constant δ .

Finally, considering the confidentiality of the information provided by the companies, this work will not report any descriptive statistics, not even in the aggregate, which would facilitate identification of the data amongst competitors. The only figures reported throughout the work will be therefore the estimates of the parametric constants of the regression models.

4. Results

In this section we will report the empirical results about the post-entry immediate impact of the **Uber** application on the taxi rides hired by means of cell phone applications for the geographic markets of São Paulo, Rio de Janeiro, Belo Horizonte, and the Federal District, considering the geographic markets of Recife and Porto Alegre always as counterfactuals, or *control group*.

As already discussed in the previous sections, we will use the econometric method of estimation by means of the difference-in-differences model, where the identification of the effects is made by the intertemporal comparison of *treatment* and *control groups*, or more specifically by means of the econometric estimate of parameter δ of the regression function specified by equation [1].

As mentioned above, the application of these methods with *control* and *treatment groups* not randomly selected may create potential estimate biases. In this respect, we tried to address the problem with an increased specification (larger number of regressors) of equation [1]. The additional regressors include fixed effects for cities, a dummy variable for each of the days of the month, a dummy variable for each of the days of the week, a dummy variable for each hourly interval of the rides, in addition to the variables private vehicles fleet (in logarithmic specification) in the city/period, and initial fare in the city/period.

The empirical exercise is separately conducted for each of the cities of the *treatment group* (São Paulo, Rio de Janeiro, Belo Horizonte, and the Federal District), being the *control group* always the cities of Porto Alegre and Recife.

4.1 Treatment Group 1: City of São Paulo

Table 1 reports the results obtained for the empirical exercise involving the city of São Paulo.

Table 1. Difference-in-Differences Model, Treatment Group 1: City of São Paulo

Regressor	Model 1	Model 2	Model 3	Model 4
Uber Effect	-0.032 (0.125)	-0.028 (0.118)	0.001 (0.101)	0.035 (0.054)
fleet log	0.809 (0.021)***	0.809 (0.020)***	0.806 (0.017)***	0.831 (0.010)***
regular initial fare (R$)	0.450 (0.356)	0.412 (0.336)	0.350 (0.288)	0.200 (0.153)
time variable	0.093 (0.035)***	0.095 (0.033)***	0.129 (0.028)***	0.149 (0.015)***
city dummy	Yes	Yes	Yes	Yes
day of month dummy	No	Yes	Yes	Yes
day of week dummy	No	No	Yes	Yes

hour dummy	No	No	No	Yes
number of observations	4,462	4,462	4,462	4,462
F-Snedecor statistics	1,372	223	271	1,262
estimated R^2 in OLS	0.52	0.53	0.54	0.83

Notes: (i) Dependent variable: log of the number of rides in city *i*, in hour interval *h*, on the day of the week *d*, on the day of the month *m,* on year *t*; (ii) estimate by means of robust regression to eliminate outliers effects, as suggested in LI (1985); (iii) estimate conducted by means of the statistical package Stata; (iv) the control group is formed by the taxi rides in the cities of Recife and Porto Alegre for the same periods; (v) levels of statistical significance: p-value 0.01(***); p-value 0.05 (**); p-value 0.10 (*); (vi) standard errors in parenthesis; (vii) all models include intercept; (viii) the reported R^2 value was obtained by means of OLS equivalent regression, since Stata's robust regression estimator does not report that statistics.

Our difference-in-differences econometric model is estimated based on four different versions, where the second column of table 1 reports the simplest version – with fewer regressors – and the fifth and last column presents the results obtained based on model 4, which, in our view, is the most complete model and with less likelihood of presenting omitted variable bias. This may be verified based on the R^2 statistics of each of the models: while model 1 presents an R^2 of 52%, model 4 presents an R^2 of 83%.

Our main focus must be the value of the coefficient estimated for the "Uber Effect" variable, which, in terms of regression function [1], represents the coefficient δ of the interaction variable tT, which captures the desired effect.

The first line of results of table 1 provides the values of the estimated parameters for each model. Right below, in parenthesis, we find the respective standard error estimates. None of the estimated coefficients presents a value statistically different from zero, that is, it is not possible to infer, in any of the four models, that the performance (in terms of logarithm of the number of taxi rides) of the **99taxis** and **Easy Taxi** applications has been lower in the city of São Paulo, as compared, in the same period, with the performance of the *control group* cities, where the **Uber** application did not operate in the *Post-Entry period*.

4.2 Treatment Group 2: City of Rio de Janeiro

It may be observed in table 2 that the results obtained for the coefficient of the "Uber Effect" variable for the city of Rio de Janeiro are practically identical to those observed for the city of São Paulo (that is, insignificant), except for model 4, which presents a coefficient with positive and statistically significant value.

The positive and statistically significant value of the coefficient for model 4 suggests that the performance of the **99taxis** and **Easy Taxi** applications was even more satisfactory in the city of Rio de Janeiro than in the cities of Recife and Porto Alegre (15.37% higher).[6] However, the most conservative interpretation for this case is that there is no effect, since the statistical significance only appears in one of the four estimated econometric models. In addition, should we adopt an excessively strict criterion for statistical significance, a p-value of 0.01 (***), none of the four parameters would be characterized as statistically significant.

Table 2. Difference-in-Differences Model, Treatment Group 2: City of Rio de Janeiro

Regressor	Model 1	Model 2	Model 3	Model 4
Uber Effect	0.096 (0.116)	0.109 (0.113)	0.106 (0.107)	0.143 (0.063)**
fleet log	0.577 (0.140)***	0.587 (0.138)***	0.594 (0.129)***	0.743 (0.077)***
regular initial fare (R$)	0.408 (0.332)	0.379 (0.326)	0.363 (0.306)	0.111 (0.182)
time variable	0.099 (0.031)***	0.096 (0.030)***	0.112 (0.028)***	0.144 (0.017)***
city dummy	Yes	Yes	Yes	Yes
day of month dummy	No	Yes	Yes	Yes
day of week dummy	No	No	Yes	Yes

6 That result is obtained from the formula ($exp^{0.143}$−1)*100

hour dummy	No	No	No	Yes
number of observations	4,462	4,462	4,462	4,462
F-Snedecor statistics	529	80	83	528
Estimated R^2 in OLS	0.288	0.302	0.323	0.749

Notes: (i) Dependent variable: log of the number of rides in city *i*, in hour interval *h*, on the day of the week *d*, on the day of the month *m*, on year *t*; (ii) estimate by means of robust regression to eliminate outliers effects, as suggested in LI (1985); (iii) estimate conducted by means of the statistical package Stata; (iv) the control group is formed by the taxi rides in the cities of Recife and Porto Alegre for the same periods; (v) levels of statistical significance: p-value 0.01(***); p-value 0.05 (**); p-value 0.10 (*); (vi) standard errors in parenthesis; (vii) all models include intercept; (viii) the reported R^2 value was obtained by means of OLS equivalent regression, since Stata's robust regression estimator does not report that statistics.

4.3 Treatment Group 3: Federal District

The issue of positive and statistically significant coefficients appears again in the case of the Federal District. In this case, such result appears in all four econometric models proposed. However, the case of the Federal District presented an additional limitation: the variable private vehicles fleet (specified in logarithmic terms) suffered omission on account of perfect collinearity with other regressors (or a linear combination of regressors) of the model.

The problem is that when we omit the variable *fleet log* from the regression models for the cities of São Paulo and Rio de Janeiro, we also find positive and statistically significant coefficients. That suggests that the omission of the *fleet log* variable seems to tend to positively bias the coefficient of interest and respective standard errors. In short, considering the analysis of other cities' data, we may infer that the coefficients of the "Uber Effect" variable in table 3 may be biased.

It is not possible to assert that, if the problem could be solved by the use of a Proxy variable for the *fleet log*, such coefficient values would still remain positive and statistically significant. In addition, we should note that in none of our exercises (which include several other unreported empirical exercises) did we obtain a parameter estimate with negative and statistically significant sign. Finally, we should underscore that our hypothesis test lies on the alternative hypothesis that $H_A : \delta < 0$, that is, we are testing whether the effect of the "Uber Effect" variable coefficient is negative, against the hypothesis that the parameter is non-negative. In short, once again we did not find empirical evidence that would provide support to the hypothesis that the "Uber Effect" on the taxi rides was negative.

Table 3. Difference-in-Differences Model, Treatment Group 3: Federal District

Regressor	Model 1	Model 2	Model 3	Model 4
Uber Effect	0.271 (0.056)***	0.275 (0.054)***	0.296 (0.046)***	0.231 (0.028)***
fleet log	-	-	-	-
regular initial fare (R$)	0.447 (0.403)	0.481 (0.385)	0.409 (0.326)	0.173 (0.205)
time variable	0.112 (0.039)***	0.106 (0.038)***	0.149 (0.032)***	0.161 (0.020)***
city dummy	Yes	Yes	Yes	Yes
day of month dummy	No	Yes	Yes	Yes
day of week dummy	No	No	Yes	Yes
hour dummy	No	No	No	Yes
number of observations	4,439	4,439	4,439	4,439
F-Snedecor statistics	2,360	373	453	1,030
Estimated R^2 in OLS	0.672	0.676	0.683	0.875

Notes: (i) Dependent variable: log of the number of rides in city *i*, in hour interval *h,* on the day of the week *d*, on the day of the month *m*, on year *t*; (ii) estimate by means of robust regression to eliminate outliers effects, as suggested in LI (1985); (iii) estimate conducted by means of the statistical package Stata; (iv) the control group is formed by the taxi rides in the cities of Recife and Porto Alegre for the same periods; (v) levels of statistical significance: p-value 0.01(***); p-value 0.05 (**); p-value 0.10 (*); (vi) standard errors in parenthesis; (vii) all models include intercept; (viii) the reported R^2 value was obtained by means of OLS equivalent regression, since Stata's robust regression estimator does not report that statistics.

4.4 Treatment Group 4: City of Belo Horizonte

Last, for the city of Belo Horizonte we found very similar results to those obtained for the city of Rio de Janeiro, that is, all coefficients are statistically equal to zero, except for Model 4, where the sign is positive and statistically significant.

Table 4. Difference-in-Differences Model, Treatment Group 4: City of Belo Horizonte

Regressor	Model 1	Model 2	Model 3	Model 4
Uber Effect	0.078 (0.061)	0.087 (0.059)	0.082 (0.054)	0.096 (0.030)***
fleet log	-	-	-	-
regular initial fare (R$)	0.430 (0.345)	0.390 (0.331)	0.364 (0.302)	0.152 (0.173)
time variable	0.108 (0.034)***	0.106 (0.032)***	0.128 (0.029)***	0.154 (0.017)***
city dummy	Yes	Yes	Yes	Yes
day of month dummy	No	Yes	Yes	Yes
day of week dummy	No	No	Yes	Yes
hour dummy	No	No	No	Yes
number of observations	4,462	4,462	4,462	4,462
F-Snedecor statistics	217	37	44	576
Estimated R^2 in OLS	0.134	0.150	0.178	0.710

Notes: (i) Dependent variable: log of the number of rides in city *i*, in hour interval *h*, on the day of the week *d*, on the day of the month *m*, on year t; (ii) estimate by means of robust regression to eliminate outliers effects, as suggested in LI (1985); (iii) estimate conducted by means of the statistical package Stata; (iv) the control group is formed by the taxi rides in the cities of Recife and Porto Alegre for the same periods; (v) levels of statistical significance: p-value 0.01(***); p-value 0.05 (**); p-value 0.10 (*); (vi) standard errors in parenthesis; (vii) all models include intercept; (viii) the reported R^2 value was obtained by means of OLS equivalent regression, since Stata's robust regression estimator does not report that statistics.

The difference from the city of Rio de Janeiro is that, just as the case of the Federal District, the “fleet log” variable was eventually omitted as well, due to a perfect collinearity with other regressors (or a linear combination of regressors) of the model. In short, it is not possible, again, to assert that, if the problem could be addressed by the use of a Proxy variable for the “fleet log” variable, such coefficient values would still remain positive and statistically significant. However, we should once again underscore that in none of our exercises did we obtain an estimate with negative and statistically significant sign for such coefficient, and that our hypothesis test lies on the alternative hypothesis that $H_A : \delta < 0$. In short, also for the city of Belo Horizonte we did not find any empirical evidence that would corroborate the hypothesis that the “Uber Effect” on the taxi rides was negative.

5. Conclusions

The purpose of this article was to evaluate the immediate economic impact of the introduction of the **Uber** application in the Brazilian capitals of São Paulo, Rio de Janeiro, Belo Horizonte, and in the Federal District during the first semester of 2015. Our strategy was to attempt to identify the effects of the **Uber** application competition on the number of taxi rides hired by means of the cell phone applications **99taxis** and **Easy Taxi**. In short, this work tried to determine whether the ride-sharing services hired by means of the **Uber** application offered any degree of substitution or exerted any kind of rivalry with the taxi rides hired by means of the cell phone applications **99taxis** and **Easy Taxi** during the period under analysis.

We used a methodology of impact assessment by means of intertemporal comparison of *control* and *treatment groups*, more specifically by using models known in the specialized literature as difference-in-differences models. The fact that the **Uber** application operates in a smaller number of Brazilian capitals as compared to the taxi applications **99taxis** and **Easy Taxi** provided the possibility to identify the competitive effects. Such identification is reinforced by the fact that the **99taxis** and **Easy Taxi** applications started to consolidate their operations even before the effective entry of the **Uber** application in the market. The cities of São Paulo, Rio de Janeiro, Belo Horizonte, and the Federal District formed the *treatment group*, while the cities of Porto Alegre and Recife served as *control group* cities.

The results obtained do not provide any evidence that the number of taxi rides hired in the cities of the *treatment group* (with the presence of the **Uber** application in the *Post-Entry period*) had a weaker performance than those of the *control group* (without the presence of the **Uber** application in the *Post-Entry period*). In terms of empirical exercises applied to the antitrust policy, that means that we cannot even assume (at least in the periods analyzed herein) the proposition that the services rendered by the **Uber** application were (until May 2015) in the same relevant market as the services rendered by the taxi ride applications **99taxis** and **Easy Taxi**. In addition, it is not possible to overlook the possibility that the entry of the **Uber** application in the Brazilian individual passenger transportation market was almost exclusively fostered by the expansion and diversification of that market, that is, by satisfying a restrained demand, until then not satisfied by the services offered by the taxicabs.

In other words, the analysis of the studied period, which is **Uber's** entry and strengthening in some capitals, showed that the application, rather than absorbing a relevant portion of the taxi rides, actually conquered, for the most part, new clients, who did not use the services of taxicabs before. That means, in short, that so far **Uber** has not "appropriated" a considerable part of the taxi clients or significantly compromised the taxi drivers' business, but created a new demand instead.

It is worth noting that the results obtained must be interpreted with due caution, for the reasons discussed to exhaustion in the introduction and throughout this work. On the other hand, the study brought a relevant empirical contribution for the analysis of the individual passenger transportation market and for the very discussion on mobility and urban planning policies, namely: a high number of families uses private cars every day, not only due to the limitations imposed by the low substitutability provided by the collective passenger transportation network, but also due to the low substitutability offered by the taxi services to a segment of consumers that is not to be neglected.

The preliminary evidence reported herein suggests that we are facing the creation of a new market. Considering the experience registered in other geographic markets, where the ride-sharing services are already consolidated, the rivalry between the ride-sharing services and taxi rides is expected to grow over time, creating different kinds of substitutability in different niches of consumers, that is, a competitive situation experienced each day by the vast majority of the economic agents.

6. Bibliography

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