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A note on the impact of Uber on Brazilian taxi drivers' earnings

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Contents

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Abstract · **Resumo**

This article assesses the impact of Uber arrival on the hourly earnings of Brazilian taxi drivers. Microdata information from a national survey is used to build a longitudinal database that allows the estimation of these impacts through models in generalized differences in differences and in triple differences. The results indicate that Uber's services did not have a significant impact on the hourly earnings of taxi drivers in Brazil. The article provides some explanations for these results, but, concludes that this evidence supports the idea that Uber, in short run, has spread the market to new consumers.

1. Introduction

Although several studies show that net impacts on the labor market of sectors affected by new technologies are usually positive, i.e., an increase in the number of employees, there is a shared concern with its impact on the incumbent sector, particularly with the creation/elimination of employment. For example, Bessen (2015) shows that the number of banking sector employees increased despite the proliferation of Automatic Teller Machines (ATM), and Basker, Foster, and Klimek (2017) show that the number of employees per gas station increased after the implementation of self-service pumps in the United States. Despite this evidence, resistance to changes by some of the workers in incumbent sectors is significant.

In this sense, the current expansion of technology companies associated with "Sharing Economy" has reignited the debate about the impact of innovations on

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the labor market. Although some have created so far non-existent markets, others have reached traditional sectors in the economy, such as car rentals (Getaround), the accommodation sector (Airbnb), and urban transport (Lyft and Uber). In general, these technology companies use applications capable of linking potential suppliers and consumers through georeferencing, thus reducing costs by facilitating the matching between supply and demand.

In contrast to these benefits, these new business models are accused of taking employment and profit from traditional sectors, such as the hospitality and taxi sectors. The most common argument is that applications are in a gray area of tax regulation and legislation and would therefore have advantages that make competition unfair with these traditional sectors that are regulated and pay differentiated taxes. However, the impact of these applications goes beyond the labor market, since apparently it is not only the interest of a particular group of incumbent workers and companies that is under threat; there is also strong doubt about the state regulation concerning its costs and benefits, who will benefit or be disadvantaged with such a regulation, and its impact on the allocation of resources.

This debate, which has existed since the seminal contribution of Stigler (1971), is back in full force in the case of urban transport applications, where Uber is the pioneering company and the one with most prominence. Founded in 2010 in the city of San Francisco in the United States, today it operates in more than 70 countries reaching approximately 612 cities, with a total of more than 1.5 million drivers registered. In Brazil, since its arrival in Rio de Janeiro in June 2014, Uber has already expanded business to 46 other cities and the latest information provided by the company shows that it already has more than 50 thousand drivers registered in the country.

The worldwide acceptance of Uber described in detail by Hall, Kendrick, and Nosko (2015), indicates that the regulation designed by Uber has lower social costs and appears to be more efficient than the state model, thus, their arrival into the market raises concerns for incumbent rivals, especially for taxi license owners. However, such concern seems to also affect taxi drivers, even those who do not own licenses, which does not seem to be rational, taking into account that they have earned the right to arbitrate, that is, to choose to work within the model that brings the highest earning. Perhaps an explanation for this behavior is the misinformation the drivers are exposed to. As this is a fairly recent issue, few empirical studies have dealt with the impact of car ride applications on the taxi driver job market; as far as we know, there are only three studies that address this issue.

Berger, Chen, and Frey (2018) assessed the impacts of Uber on the fifty largest cities in the United States using aggregate data per city for jobs and taxi driver incomes. As control groups they used cities without Uber and workers of similar activities, such as truck drivers and vans. Using triple differences, they found no evidence of employment reduction and found small reductions in the income of non-autonomous taxi drivers after Uber's arrival. One limitation of the work is the use of aggregate data, which implies the need to use many controls to try to mimic a random experiment, since the aggregate employment and income data by city are subject to several unobserved factors that change over time.

Chang (2017) uses microdata of Taiwan taxi drivers to asses the economic impact of Uber service on taxi drivers' business performance. His results indicate that the negative impacts of Uber became stronger after Uber had been in the market longer, it shows that Uber reduced regular taxi drivers' service revenue by approximately 12 percent in the initial year and 18 percent in the third year of entry of Uber. Moreover, his results show that taxi drivers who are the members of a taxi medallion received a stronger impact by Uber compared to their non-member counterparts. Since the data available is not longitudinal (the taxi drivers are not the same over time), he also does a great effort to control differences in drivers' characteristics that can affect their profits and revenues as well as the Uber decision to entry.

In Brazil, Esteves (2015a) used information from taxi applications with a greater market share in the country (Easy taxi and 99taxis) to assess Uber's arrival into the cities of São Paulo, Rio de Janeiro, Belo Horizonte and Porto Alegre. As a control group, the author used cities of a similar size, and found that Uber did not initially affect the number of rides performed through the taxi applications. The author concluded that Uber probably met a pent-up demand and that Uber actually expanded the service consumer market. However, by using the number of rides per hour, the author fails to capture the effects of the increase in taxi fleets using the application. That is to say, the number of rides may have held up, but it does not mean the number of taxis that generated this number remained exactly the same in the assessed period.

In this sense, it is possible to state that the literature addressing the impact of Uber on the taxi driver labor market still has some gaps. This article aims to contribute to the literature by showing empirical evidence of these impacts in Brazil following the arrival of Uber in three moments. The first includes the arrival of Uber in cities of São Paulo, Rio de Janeiro and Belo Horizonte, the second moment includes the availability of Uber X services in these cities plus Brasília and Porto Alegre, and the third moment is the arrival of Uber and the Uber X services in the cities of Goiânia, Recife, Curitiba, Salvador and Fortaleza. For this purpose, microdata from a Brazilian work survey (the Continuous PNAD) are used. This database allows the extraction of longitudinal information about the drivers, and from this, allows us to estimate models of differences in differences with controls for fixed effects (generalized differences in differences), and with controls for trend changes in other categories that are also potentially affected by Uber, such as bus drivers, van and motorcycle taxis drivers (triple differences). One of the advantages of this approach in relation to previous studies is that the use of driver information allows to control several drivers and city characteristics that could affect drivers' earnings and the decision of Uber to entry in the city urban transport market.

In addition to this introduction, the article has three other sections. The next section looks at the data and methods used to identify the impact of Uber's arrival on the taxi driver labor market. The third section contains the results and a sequence of tests to assess their robustness. At the end of the paper the main conclusions are presented, along with a short discussion on the regulation of the urban transport services.

2. Identification strategy

The data used correspond to longitudinal samples of taxi drivers who participated in the survey in three periods covering the entire national territory. The first period is between the second quarter of 2014 and the first quarter of 2015. This period, as shown in Table 1, refers to the arrival of Uber in the cities of Rio de Janeiro, São Paulo, and Belo Horizonte. The second period is between the second quarter of 2015 and the first quarter of 2016 and refers to the beginning of Uber X services in the cities of Rio de Janeiro, São Paulo, Belo Horizonte, Brasília, and Porto Alegre. The third period is between the fourth quarter of 2015 and the third quarter of 2016, which includes the arrival of Uber/Uber X in the cities of Goiânia, Recife, Curitiba, Salvador, and Fortaleza.

Taxi drivers are identified by the Occupational Classification for Household Surveys (Brazilian "COD") under code 8322, which refers to chauffeur and taxi

Table 1. Arrival of Uber and Uber X per city in Brazil

City	Uber	Uber X
Rio de Janeiro	June 2014	August 2015
São Paulo	August 2014	June 2015
Belo Horizonte	December 2014	August 2015
Brasília	February 2015	August 2015
Porto Alegre	November 2015	November 2015
Goiânia	January 2016	January 2016
Recife	February 2016	February 2016
Curitiba	March 2016	March 2016
Salvador	April 2016	April 2016
Fortaleza	April 2016	April 2016

Note: Arrival in the city of Campinas in January 2016 cannot be excluded from the control groups on the of second and third entries.

Source: Uber. https://newsroom.uber.com/brazil/fatos-e-dados-sobre-a-uber/

drivers. As the occupational classification by the PNAD does not distinguish taxi drivers from the drivers of the applications, two identification criteria were chosen for the treated group (taxi drivers). The first criterion is to exclude the autonomous drivers, since after the arrival of the application, this is also the classification of Uber drivers. The second criterion is to consider only the drivers who have been working for more than a year as car driver, that is, before Uber became part of the urban transport market. Since the effects of Uber arrival can be different on license owners or lenders when compared with employee drivers that receive wages and/or commissions, the models that use this definition includes autonomous drivers as a different treated group, that could have a different treatment effect from employee drivers. For instance, as discussed in the preview section, license renters can increase their earnings in the short run due the reduction in license rents.

The survey aims to monitor at least 20% of its sample for 5 interviews, i.e. 5 quarters. However, this purpose is not guaranteed for all activities. In the case of taxi drivers, information loss is much greater than that expected for the total sample. In this context, this study has chosen to work in each arrival of Uber with a panel of four periods. It ensures that all models have a period before and two periods after the arrival into some of the cities, which allows us to evaluate the effects of Uber for at least six months from its arrival. Besides, we decided to group the drivers from different cities in three entry periods aiming to have the largest possible group of treated drivers given the available longitudinal data.

The choice of earnings per hour as a study variable outcome is justified by the fact that the possible effects expected by Uber's arrival in the urban transport market involve both changes in income (earnings) and the hours worked. For example, a possible effect of a reduction in the number of trips (rides) would be the need to work more hours (doing more rides) to maintain an earning similar to the period prior to Uber. Otherwise, there would be a reduction in earning. In both cases of increased hours and decreased earning, there is a reduction in earnings per hour. Thus, this variable can capture both effects, although their use does not allow them to be separated.

The identification strategy consists of comparing two groups: a group that has had a specific change (treated) and another that has not (control). To identify the effects of Uber's arrival it is necessary that the exercise generates results as good as a random experiment, i.e. a natural experiment. In order to have a natural experiment it is important that the definition of who will be treated is random. In this case, the necessary conditions are that the treated group cannot choose whether they will be treated or not (self-selection), for example by moving to a place where the application started to work, and the choice of who will be treated (by Uber's arrival) cannot depend on characteristics that affect the taxi drivers' earning.

It is not possible, however, to ensure that the arrival of Uber is random, i.e., independent of factors observed and non-observed which may influence the hourly earnings of taxi drivers. While Chang (2017) only includes controls for drivers and cars characteristics since his model has only one treated city, both Esteves (2015a) and Berger et al. (2018) have drawn attention to the fact that the use of some controls is needed to give the study a random experimental nature. Esteves (2015a) used a fleet of private vehicles in circulation in the city as the control group, which according to the author, is of fundamental importance for the Uber application's decision to participate in a particular city, since private vehicles could be potential rivals of applications. Hence, the greater the number of rivals, the greater would be the ability to capture the market through the supply of a substitute service. Alternatively, Berger et al. (2018) used unemployment rates, the portion of the population with higher education, the portion of the female population, and age groups that can be possibly correlated with both the arrival of Uber and the demand for taxi services. It should be noted that such studies used aggregate data and, therefore, need many variables to control the effects of omitted variable bias on the treatment impacts.

However, this study uses information from drivers and from Uber' decision to operate in a city, which is probably associated with fixed effects of cities controlled in the estimated model. Differently form Chang (2017), a short longitudinal database is used and the need for controls are lower, since in the period of one year (four interviews), few of the characteristics likely to affect a drivers' earning will change. In other words, there is no significant change in the controls indicated in the literature, such as the fleet of vehicles, age groups, the portion of population with a completed higher education, etc. So, following this reasoning, the only aggregate control included in all estimated models is the state unemployment rate. We expect that this variable is not affected by the treatment and is capable to capture regional business cycle fluctuations that affect both the demand for urban transport services as well the supply of drivers for Uber. In addition, the estimation with four periods has some advantages well known in the literature evaluating public policies (Pischke, 2005). The inclusion of the fixed time effect model allows controlling changes common to all drivers during the period evaluated, such as overall changes in the economy, seasonal effects, and business cycle fluctuations in Brazil. Of course, this does not exclude the possibility of omissions of changes occurring in the characteristics of drivers, such as the purchase of a new vehicle; however, one year is a short period of time, so one should not expect significant changes in variables to be associated with the Uber arrival.

Considering these aspects, the first strategy to identify the impact of Uber's arrival on the taxi driver labor market is a model of generalized differences in differences, given by:

$$w_{it} = \alpha_i + \delta_t + \lambda \, Uber_{it} + \beta' X_{it} + \mu_{it} \,, \qquad (1)$$

where w_{it} is the earning per hour of a driver i in the period t; α_i are the fixed effects of drivers; δ_t are the time fixed effects; X_{it} are some individual variables and $Uber_{it}$

represents the treated cities i from the period t as indicated in Table 1. In turn, λ represents the average effect of the study on the treated group an β is a vector of coefficients to be estimated. As that there is only discrete data available, the idea of this paper is to capture the extent of the effects of Uber but not its intensity because information regarding the evolution of the company's participation in the urban transport market is not available.

The estimations also include time trends per group (treated and control groups) to control potential differences in the trends among groups, and therefore, reduce concerns about the possibility that the impacts of Uber's arrival are related to differences in the trends among the groups (violating the condition of parallel trends) are reduced. An important aspect of the identification strategy herein adopted is that it is assumed that changes in the local labor market are not caused by unobservable factors which vary in time and are correlated with Uber's choice. For example, the growth in demand for taxis due to a sporting event, such as the FIFA World Cup. In this case, the effects on earnings could reflect changes that would have occurred even if Uber had not come to operate in the city. However, such changes would affect the whole urban transport sector, including buses, vans, minibuses, as well as motorcycle taxis, since several cities included in the sample have these transportation options. This allows these activities to be used as a control group. Therefore, a more robust analysis is possible by adding one more dimension that not only enables us to assess the impacts of the application's arrival on the labor market of these activities, but also to see whether the taxi driver labor market is more sensitive than the markets of other means of transport. Thus, a model with triple differences capable of controlling these changes is given by:

$$w_{it} = \alpha_i + \delta_t + \beta_1(p_t h_i) + \beta_2(p_t d_i) + \beta_3 Uber_{it} + \beta_4' X_{it} + \mu_{it}\,, \tag{2}$$

where $p_t = 1$ when the period t occurs after treatment and is equal to zero otherwise; $d_i = 1$ when the driver is in a treated city and equal to zero otherwise; and $h_i = 1$ if the driver is in the expected more treatment sensitive group (taxi drivers or autonomous taxi drivers) and equal to zero otherwise. β_2 is the coefficient that captures the impact of the treatment in the group less sensitive to the treatment (other drivers), while β_3 is the coefficient of interest, since it captures the average differential change in w from the pre-treatment to post-treatment period for the more sensitive observations in the treatment group (taxi drivers or autonomous taxi drivers) relative to the change in w for the more sensitive observations in the untreated group.

In order to ensure greater robustness of the results, many strategies are used. Changes in specification are carried out, standard errors are estimated clustered by cities whenever is possible as suggested by Bertrand, Duflo, and Mullainathan (2004), controls for potential license renters and regional unemployment are used, and the hypothesis of parallel trends is verified by the estimation of a model with trends per group (cars × motorcycles and buses) and per treated and untreated groups, as suggested by Autor (2003).

3. Results

The results are organized into three tables and each contains models with double and triple differences for the three periods of Uber entries in Brazil. In each of them, the average treatment effects on treated groups are estimated. However, for these average treatment effects on treated to have internal validity, that is, so that one can infer about causality, it is important not to violate the condition of parallel trends, which means that the treatment effect cannot reflect differences in the trend before the treatment occurs. In order to test the possibility of parallel trends, Autor (2003) suggested the estimation of a model with interactions between the control groups and the treatment in the lags, and in the periods after the treatment (leads). The hypothesis that there is no difference in the trends is answered if it is not possible to reject the null hypothesis that the coefficients in this interaction are equal to zero. These results can be seen in Table A-2 in Appendix. In all the estimated models with different control groups, these coefficients are not statistically significant. This allows us to interpret the results found here as being effectively the treatment effects on the treated drivers.

The first arrival of Uber in Brazil coincides with the 2014 FIFA World Cup, in which the city of Rio de Janeiro was one of the host cities. Two months later the Uber started to operate in the city of São Paulo and six months later it started to operate in the city of Belo Horizonte. In all these cities the service offered was Uber Black, where the Uber drivers should have a black sedan car with a maximum of three years old of manufacturing and with air conditioning, which should always be on. Prices were higher than taxi fares and apparently the intention was to offer a service different from the regular taxis, mostly targeted to consumers with higher income.

The results presented in Table 2 in the models (1) and (3), with double-differences, show that the initial impacts of Uber's arrival in Brazil were positive, very small and not statistically significant. One possible explanation for these results is the initial lack of knowledge of the service by consumers and the fact that there were few drivers available considering the car restrictions imposed by Uber.

Models (2) and (4), with triple-differences, evaluate the differences between autonomous and employee drivers. In these models, the *Uber* coefficient refers to the impact on autonomous drivers, while the interaction $p_t * d_i$ captures the treatment effects of Uber's entry into employee drivers. The total treatment effect of Uber on treated drivers is the sum of the two coefficients. The results show that autonomous drivers, who potentially could be benefited by license prices decrease, are negatively affect by Uber´s arrival while employee drivers are positively affected.

Table 2. The effects of Uber's arrival on the hourly earnings of taxi drivers in Rio de Janeiro, São Paulo, and Belo Horizonte with double and triple differences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Uber	0.6495	-1.1161	0.2821	-0.7309	0.3450	-0.4762	0.1981	-0.4646
	(0.6707)	(1.0929)	(0.9176)	(0.7371)	(0.8144)	(0.8534)	(0.7128)	(0.7978)
$p_t * h_i$		0.8528		0.7939	-0.3602	0.0494	-0.2985	-0.0557
		(0.7306)		(0.7611)	(0.3725)	(0.4062)	(0.4319)	(0.6497)
$p_t * d_i$		0.9015		0.8236	0.3895	0.5172	0.4206	0.5573
		(0.8162)		(0.8814)	(0.6741)	(0.6999)	(0. 6831)	(0.6662)
n	143	277	62	123	489	623	160	221
R^2 within	0.0191	0.0110	0.0275	0.0073	0.0084	0.0072	0.0005	0.0042
R^2 between	0.0476	0.0002	0.0794	0.0273	0.0152	0.0040	0.0356	0.0173
R^2 total	0.0251	0.0022	0.0249	0.0233	0.0117	0.0055	0.0124	0.0151
Definition of taxi drivers	1	2	1	2	1	2	1	2
Control group	1	1	2	2	1	1	2	2

Notes: Entries are the coefficients estimated by ordinary least squares. "n" is the number of drivers. The dependent variable is the earnings per hour. All the models have controls for individual and time fixed effects. Definition of taxi drivers 1: not self-employed. Definition of taxi drivers 2: working in the activity for more than a year. Control group 1: all the cities. Control group 2: only state capitals. Standard errors shown in brackets are robust to heteroskedasticity and adjusted for cluster per driver when the control group is 1 and for cluster per city when the control group is 2 Models using definition 2 of taxi driver also include a control for non-employee. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

This result may be explained by the small proportion of autonomous taxi drivers who are license renters in Brazil that could be benefited from a rent renegotiation. A 2015 survey from Brazilian Confederation of Transporters shows that they are less than 20%. Both estimated coefficients are not statistically significant. Combining both effects results in an almost null effects since they have opposite signs and almost the same magnitude.

However, as already discussed in the previous section, the impact on earnings, as estimated in the models (1) and (3), could reflect changes that would occur even if Uber had not come into the city. Most probably, such changes would affect the sector of other means of passenger transport, like buses, vans, minibuses, and motorcycle taxis. This situation allows us to use these activities as another treated group, as well to estimate the earning differences per hour of taxi drivers affected by the arrival of Uber, compared with drivers of other means of transport and drivers from cities where the application is not operating.

Models (5) to (8) in Table 2 include interactions between the treatment, taxi drivers, and the cities. Now, the interaction $p_t * d_i$ captures the treatment effect on other means of transport, while the coefficient *Uber* captures the effect of Uber's arrival exclusively on the taxi drivers. The treatment effect on all treated groups, including taxi drivers and other means of transport, is obtained by the sum between the coefficient *Uber* and $p_t * d_i$.

The triple-differences models show a small (no more than R$0.60 per hour), positive and not statistically significant impact in the other groups. The impacts of Uber on taxi drivers' earnings appear to be negative in the model that controls for possible license owners, showing that non-license owners were not benefited from Uber entrance, however, these coefficients are also statistically not significant. When these two effects are summed to obtain the total effects in the two treated groups, the effects are close to zero. These results can be an evidence that on the first arrival in Brazil, the Uber Black service was not part of the same relevant market of the established public transport services in these cities.

It should be remembered that the interviews are quarterly, therefore, two periods after the treatment is actually six months, which can be considered a reasonable time for consumers to get to know the application and its operation. This aspect is important, particularly in relation to this Uber's first arrival in Brazil in June 2014, as Uber did not have the awareness of the public it had after and currently has.

In the second arrival, commencing in June 2015, the application was already better known, so the treatment effect is expected to be more immediate. Besides, this arrival included a more popular service, Uber X. It is a service more similar to the traditional taxi service and with lower requirements than Uber Black. In this business model, the cars could be of any model and color and should be no more than 10 years old of manufacturing. Air conditioning still a requirement, but it can remain off if it is desired by the passenger. These lower restrictions expected to increase the drivers offer, thus reducing significantly the waiting time for costumers. Moreover, the prices of this service are lower than the regular taxis most of the time, and sometimes similar or higher when the surge pricing is operating. This type of service began in June 2015 in the city of São Paulo and in August of the same year it was expanded to the cities of Rio de Janeiro, Brasília and Belo Horizonte. In November Uber started to operate in Porto Alegre already offering the service of Uber X. So, the results showed in Table 3 are the sum of the impacts of Uber Black and Uber X on other drivers´ earnings.

Models (1) to (8) shows slightly larger negative impacts when compared with the estimated for the first arrival in the cities of Rio de Janeiro, São Paulo and Belo Horizonte, when Uber Black was the only service offered by the company, nevertheless, the estimated coefficients still not statistically significant. In models (2) and (4), Uber's coefficient represents the impacts of Uber on autonomous taxi drivers, they are both negative and not statistically significant while the coefficients of employee drivers are positive. In this entry, the total impact of Uber on taxi drivers is negative (varying between BRL$1.27 and BRL$1.07), but again it is not statistically significant.

In the models (5)–(8), when triple-differences are considered, the estimated impacts for the other drivers' group are very small, varying between BRL$−0.14 and BRL$0.38. They are negative when the control group is all Brazilian cities as

Table 3. The effects of Uber X's arrival on the hourly earnings of taxi drivers in Rio de Janeiro, São Paulo, Belo Horizonte, Brasília, and Porto Alegre with double and triple differences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Uber	-0.5476	-1.7363	-1.9208	-2.4541	-0.4909	-0.4175	-0.3488	-0.9733
	(0.6821)	(1.1536)	(1.4530)	(1.4522)	(0.9657)	(0.9765)	(1.6157)	(1.5197)
$p_t * h_i$		0.9087		1.6813	-0.0247	-0.4373	0.1493	0.3143
		(0.6394)		(1.2375)	(0.5365)	(0.5560)	(1.1214)	(0.6634)
$p_t * d_i$		0.6593		1.1795	-0.7298	-0.7608	-0.3665	-0.3880
		(0.9468)		(1.5841)	(0.6471)	(0.6542)	(0.6242)	(0.5392)
n	130	289	57	130	506	665	157	221
R^2 within	0.0432	0.0171	0.0516	0.0216	0.0128	0.0107	0.0332	0.0173
R^2 between	0.0016	0.0147	0.0139	0.0477	0.0002	0.0171	0.0098	0.0273
R^2 total	0.0161	0.0000	0.0452	0.0010	0.0037	0.0003	0.0205	0.0055
Definition of taxi drivers	1	2	1	1	1	2	1	2
Control group	1	1	2	1	1	1	2	2

Notes: Entries are the coefficients estimated by ordinary least squares. "n" is the number of drivers. The dependent variable is the earnings per hour. All the models have controls for individual and time fixed effects. Definition of taxi drivers 1: not self-employed. Definition of taxi drivers 2: working in the activity for more than a year. Control group 1: all the cities. Control group 2: only state capitals. Standard errors shown in brackets are robust to heteroskedasticity and adjusted for cluster per driver when the control group is 1 and for cluster per city when the control group is 2 Models using definition 2 of taxi driver also include a control for non-employee. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

control group and positive when the control group is formed only by capitals where Uber did not operate. The overall impact on the two treated groups is negative in all models, although, once again, the impacts are not statistically significant.[1]

The last entry evaluated in this study is the arrival in the cities of Goiânia, Recife, Curitiba, Salvador and Fortaleza. In all these cities the Uber X service was offered since the arrival of Uber. The results in Table 4 show mixed signs in the coefficients.

Only the models (5) and (7), that exclude the autonomous drivers from the estimations, and the models (2) and (4), that assesses the different treatment effects for autonomous and employee drivers, show negative estimated coefficients. In the models (2) and (4) employee drivers are negatively affected while autonomous drivers are positively affected, but differently from the first and the second Uber´s entry in Brazil, in the third entry the net effect is positive, since the results show high gains for autonomous drivers. The impacts on other drivers' group showed in models (5) to (8) are also small and positive and the impact on the two groups treated is invariably positive, although these impacts, as well as the others estimated impacts, are not statistically significant. In this case, it is difficult to say if the statistical

[1]It is worth remembering that the final period of these estimates is the first quarter of 2016, therefore, are not affected by the arrival of the second urban transport applications company to Brazil, Cabify, which arrived in May 2016 in the city of São Paulo and in August 2016 in the city of Rio de Janeiro.

Table 4. The effects of Uber X's arrival on the hourly earnings of taxi drivers in Goiânia, Recife, Curitiba, Salvador, and Fortaleza with double and triple differences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Uber	0.4475	3.0086	0.8673	1.6782	-0.1725	0.5077	-0.0400	1.3451
	(0.7071)	(2.2852)	(0.5087)	(1.2879)	(0.9541)	(1.3326)	(0.7704)	(1.0804)
$p_t * h_i$		-1.2779		0.1687	0.7527	0.4373	0.5782	-0.7028
		(1.5623)		(0.7031)	(0.5483)	(0.6085)	(0.9934)	(1.2831)
$p_t * d_i$		-1.1860		-0.4594	0.7060	0.4490	0.5698	0.0766
		(1.1644)		(1.2879)	(0.7097)	(0.6918)	(0.5940)	(0.6052)
n	105	243	26	59	470	608	98	131
R^2 within	0.0564	0.0054	0.1864	0.0283	0.0205	0.0055	0.0568	0.0203
R^2 between	0.0517	0.0227	0.0188	0.0689	0.0031	0.0005	0.0001	0.0010
R^2 total	0.0142	0.0030	0.0015	0.0514	0.0029	0.0000	0.0083	0.0031
Definition of taxi drivers	1	2	1	2	1	2	1	2
Control group	1	1	2	2	1	1	2	2

Notes: Entries are the coefficients estimated by ordinary least squares. "n" is the number of drivers. The dependent variable is the earnings per hour. All the models have controls for individual and time fixed effects. Definition of taxi drivers 1: not self-employed. Definition of taxi drivers 2: working in the activity for more than a year. Control group 1: all the cities. Control group 2: only state capitals. Standard errors shown in brackets are robust to heteroskedasticity and adjusted for cluster per driver when the control group is 1 and for cluster per city when the control group is 2 Models using definition 2 of taxi driver also include a control for non-employee. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

insignificance is explained by the high variability observed in the earnings or by the small sample problems that emerges from the exclusion from the control group of the cities where Uber already operated.

Taking all these results together, it is possible to infer that they show the importance of controlling the interactions, since in some cases there are coefficient signal changes, and this indicates strong evidence of bias due to the omission of relevant variables. However, in spite of this, all coefficients are non-significant statistically in all estimated models for all of the treated parties (taxi drivers, autonomous drivers, employee drivers, other drivers, and all of them together) in the three arrival periods of the Uber in Brazil. Thus, there is strong evidence that Uber's arrival did not have a significant positive or negative effect on the earning of the workers of the passenger transport sector in Brazil, particularly the taxi drivers, even considering a potential fall in the value of medallions.

A possible explanation for these results is that the service offered by Uber attends a distinct profile of consumer. The taxi market can be divided into three segments (Esteves, 2015b): (i) the segment of taxi stands, known in international literature as taxi rank; (ii) the street segment, known as hailing; and (iii) the pre-booking segment, also known as taxi-booking or phone booking. At first sight, it would appear that applications could replace taxis in all segments, although the third segment (pre-booking) is the one most affected by Uber. However, the sample of taxi drivers used in this study does not allow distinguishing the driver's working segment. Therefore, these results can only reflect a sample composed mostly of drivers of the first and second segments.

Another explanation is the partial equilibrium of the service market. As in all segments, the service regulation imposes supply restrictions; taxi service prices are not determined by supply and demand competitive mechanisms, but are defined in the form of fares, which are usually well above marginal costs. Thus, prices above the competitive equilibrium reduce the number of potential consumers. In this sense, a rival with an analogous price and better service (Uber Black) or analogous service and lower prices (Uber X) would be used by a higher number of consumers. This is probably the group of consumers of Uber services. As the company does not have the costs of state regulation, has lower transaction costs, and is able to efficiently manage its prices through its Surge Pricing mechanism, which seeks to establish prices close to the equilibrium between supply and demand. This conclusion is similar to Esteves (2015a), who affirmed that it is not possible to rule out the possibility that the entry of Uber into the Brazilian urban transport market has been characterized, almost exclusively, by the expansion and diversification of this market, which means it has met a repressed demand that was not met by the service provided by taxi drivers until then. In other words, the application would work almost exclusively with "new" customers.

Finally, it is possible to elicit an explanation based on the dissuasive powers imposed by legislation. From this point of view, the absence of effects on the taxi driver labor market could be explained by the fact that the Uber has created an illegal market for passengers since Uber operates in a gray area of Brazilian legislation. Ultimately, this possible illegality generates insecurity for both drivers and potential consumers and can be part of the explanation for Uber's lack of impact on the Brazilian taxi driver labor market.

4. Conclusions

This study examined the impact of Uber on the labor market of urban passenger transport services in Brazil. Considering the results obtained for three periods of arrival with different control groups, different specifications, and estimations of double or triple differences, the arrival was not found to change the Brazilian taxi drivers' hourly earnings. The results corroborate with the existing literature (Esteves, 2015a; Berger et al., 2018) that the impact of Uber on the employment and earning of taxi drivers is very small and even non-existent in many cases. Nevertheless, there was and still is a lot of resistance to the application by taxi drivers, enterprises and license owners, and state authorities. Moreover, the results obtained in this study support the idea that Uber has spread the market to new consumers and, thus, the taxi services were able to keep their share of the transport market at least in the short run. On the other hand, this also indicates that there are high social costs in the current regulation model, and many potential consumers are excluded from the market.

Finally, it is worth highlighting that this study and consequently its conclusions are limited. The most relevant limitation concerns its external validity. Although models of difference in differences may have good internal validity, i.e., we can infer their causality effects on the treatment of the treated groups, the same does not occur with their external validity. In other words, the estimated effects in this study may be different in other countries or cities. In addition, an increase in periods in the future could indicate that the effects of Uber's arrival may occur distinctly in different periods, i.e., more or less significant. Certainly, new studies are necessary to validate these conclusions, especially in the long run. It is expected that due to network effects, in the long run, Uber and other transport applications have enough consumers and drivers to compete and reduce earnings of workers from any traditional public transport models. However, it is difficult to assess longer periods since these transport applications have low entry costs which allows them to expand fast in a way that is hard to build a control group since almost all comparable cities are already in the treatment group, that is, already have the service available. So, it is important that new studies are carried out, preferably with longitudinal information about the rides, taxi drivers, where they work, and of course, information about Uber itself. Thus, it will be possible to evaluate the impacts in a more detailed and complete way considering that this study has severe information restrictions and, therefore, conclusions are limited to the available information.

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Appendix.

Table A-1. Descriptive statistics

	Other drivers				Taxi drivers			
	Control city		Treated city		Control city		Treated city	
Variable	Working hours	Hourly earnings	Working hours	Hourly earnings	Working hours	Hourly earnings	Working hours	Hourly earnings
Entry 1								
Mean	46.05	6.95	46.07	7.89	48.56	8.33	50.19	10.95
Std.	11.74	4.85	10.63	3.34	15.37	6.95	13.01	7.58
Min	8.00	0.00	30.00	0.49	3.00	0.33	8.00	0.48
Max	112.00	53.57	98.00	17.86	112.00	119.05	84.00	47.62
Observations	319		27		302		66	
Entry 2								
Mean	46.06	8.18	45.22	9.13	47.00	9.85	48.72	13.22
Std.	11.76	13.98	10.2	3.31	14.00	7.51	12.44	9.47
Min	1.00	0.00	16.00	1.62	4.00	0.00	20.00	2.65
Max	105.00	452.38	77.00	30.42	105.00	71.43	84.00	7.74
Observations	330		46		324		74	
Entry 3								
Mean	44.44	8.35	43.2	9.13	43.31	10.86	48.92	9.6
Std.	10.96	6.88	5.61	3.51	13.74	9.3	11.79	4.86
Min	6.00	0.00	10.00	3.83	1.00	0.00	30.00	4.26
Max	105.00	101.19	56.00	23.81	105.00	109.13	84.00	32.47
Observations	346		19		289		21	

Notes: Working hours are weekly. Hourly earnings in Brazilian currency (BRL$). Observations are the number of drivers.

Table A-2. Parallel trends tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$t_1 * Uber$	-0.2023	0.2962	0.0061	0.0438	-0.7991	-0.4849	-1.166**	-0.2551	-0.6646	-0.3269	0.3505	0.0473
	(0.4839)	(0.6352)	(0.7317)	(0.6462)	(0.6620)	(0.7824)	(0.4636)	(0.9139)	(0.7174)	(0.6778)	(0.8132)	(0.7937)
$t_1 * Taxi$	0.1292	-0.4777	-0.3836	-0.3437	0.39950	0.2819	0.6248	-0.0117	0.1234	-0.2177	-1.9842	-1.3727
	(0.4250)	(0.4988)	(0.4662)	(0.5316)	(0.5103)	(0.4673)	(0.8113)	(0.8355)	(0.8507)	(0.6252)	(1.4448)	(0.8395)
n	489	623	160	221	506	665	157	221	470	608	98	131
Definition of taxi drivers	1	2	1	2	1	2	1	2	1	2	1	2
Control group	1	1	2	2	1	1	2	2	1	1	2	2
Arrival period	1	1	1	1	2	2	2	2	3	3	3	3

Notes: Entries are the coefficients estimated by ordinary least squares. "n" is the number of drivers. The dependent variable is the earnings per hour. All the models have controls for individual and time fixed effects. Definition of taxi drivers 1: not self-employed. Definition of taxi drivers 2: working in the activity for more than two years. Control group 1: all the cities. Control group 2: only state capitals. Arrival period 1: Rio de Janeiro, São Paulo, and Belo Horizonte. Arrival period 2: Rio de Janeiro, São Paulo, Belo Horizonte, Brasília, and Porto Alegre. Arrival period 3: Goiânia, Recife, Curitiba, Salvador, and Fortaleza. Standard errors shown in brackets are robust to heteroskedasticity and adjusted for cluster per driver when the control group is 1 and for cluster per city when the control group is 2. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.