NEREUS
Núcleo de Economia Regional e Urbana
da Universidade de São Paulo
The University of São Paulo
Regional and Urban Economics Lab

EFFECTS OF THE ENTRY OF FOOD DELIVERY APPS IN THE RESTAURANT INDUSTRY: EVIDENCE FROM BRAZIL

Carlos R. Azzoni
Rodrigo M. S. Moita
Mateus Rodrigues
Marina Merlo
Arthur Fisch

TD Nereus 02-2023
São Paulo
2023

Effects of the entry of food delivery apps in the restaurant industry: evidence from Brazil[1]

Carlos R. Azzoni, NEREUS – The University of Sao Paulo Regional and Urban Economics Lab, Department of Economics, University of Sao Paulo, Brazil, cazzoni@usp.br

Rodrigo M. S. Moita, Department of Economics, University of Sao Paulo, Brazil, rodmoita@usp.br

Mateus Rodrigues, Graduate Student, Sao Paulo School of Economics, Fundação Getúlio Vargas, mateus.rodrigues@fgv.edu.br

Marina Merlo, iFood Public Policy, Ph. D. Student, Department of Political Science, University of São Paulo, marina.merlo@ifood.com.br

Arthur Fisch, Public Sector Politics and Economics Research Center, Fundação Getúlio Vargas, arthur.fisch@fgv.org.br

Abstract

Food delivery apps have become popular in recent years, with additional strength during the COVID-19 pandemic. Do these apps benefit new and more suit to delivery restaurants at the cost of harming more traditional non-delivery ones? What is the net impact on the restaurant industry as a whole? This paper investigates these questions by analyzing the impact of the major meal delivery app in the Brazilian restaurant industry. We analyze the effects of the app's introduction on the opening and closure of restaurants and employment in the restaurant business. The app positively affected opening new restaurants, but less so during the pandemic years. It also had a negative effect on the rate of closure of restaurants, implying a net positive impact on the industry as a whole. But, again, this effect is smaller during the COVID19 pandemic. Also, restaurants increased their employment when they joined the delivery platform. At the same time, restaurants that remained out of the platform decreased their employment during the same period. The net effect of the delivery app on employment in the restaurant industry is positive but not enough to offset the general negative trend of decreasing employment.

Keywords: food delivery apps, restaurant industry

1. Introduction

Ordering meals from home or office became popular during the Covid-19 Pandemic, but the practice grew consistently well before that. From the consumer point of view, the conveniences involve a more extensive selection of restaurants and food types since traffic and parking are not relevant issues and time-saving. These conveniences come at a price, including the cost of delivery (packing and freight) and the loss of some food properties in transportation. For the restaurants, delivering enlarges the pool of potential clients. However, it might imply some cost-

[1] Preliminary version. Please do not quote

incurring adaptations in the production process, such as creating or expanding a packing department, assembling and managing the delivery service or joining a meal delivery platform. Eventually, it involves a change in the job structure within the restaurant, with more cooks and fewer waiters, for example.

The question arises about the effect of meal delivery on the restaurant industry. If a significant number of consumers substitute meals delivered for meals produced at home, there would be an enlargement of the pool of clients, resulting in an overall increase in the restaurant activity. This quantity effect must balance against a possible price effect coming from a foreseeable increase in the final cost of meal resulting from adaptations necessary in the production process to allow for meal delivery. The effects are expected to be different for restaurants that deliver than those that do not. One would expect that the former would face an increase in activity, both because of the larger pool of clients to dispute with competitors and the possibility of stealing clients from non-delivering competitors. As not all restaurants wish or can adopt meal delivery, the question arises about the consequences for restaurants operating traditionally. In principle, one could expect a reduction in their activity, with shrinkage of their market share. If there is just a substitution of deliverers for non-deliverers, the net effect on the business would be null. The answer to what the aggregate effects are rests on the combination of all these effects.

Other effects might be at play in this scenario. Even if deliverers face increases in their activity, it might not imply that they achieve better financial results. The profit margin could decrease because of the increased costs involved in delivering the meals. There are complaints from the Brazilian national association of restaurants about the fees charged by the existing delivery apps. Other controversial aspects involve labor issues with the delivery employees, typically working without a labor contract and facing non-traditional working hours. Several proposals are under discussion in the national congress to regulate the activity, imposing stricter rules for its operations.

To the best of our knowledge, no study has addressed the impacts of the introduction of food delivery apps on the restaurant industry. As the literature review below shows, only some aspects of food delivery were considered, mainly consumer choices. This paper provides the first assessment of the effects of the introduction of food delivery apps on restaurant activity levels, based on evidence from Brazil. We examine the effects of the largest meal delivery service - iFood - on restaurant activity[2] from 2014 through 2021. We analyze the evolution of openings and closures of restaurants and employment in the restaurant sector across 790 areas within 12 Brazilian cities, corresponding to 21% of all restaurants in the country. With a rich set of establishment-level data, we compare the evolution of these variables from the moment the restaurant starts delivering meals with the previous evolution of the same restaurant, and with restaurants that never delivered meals. We found that the presence of restaurants delivering meals is associated with an increase in the rate of openings and a decrease in the rate of closings in the areas and with the net creation of jobs.

The paper is organized into four sections, besides this introduction. Section 2 provides a brief review of the literature; section 3 presents the data used, describing its richness and limitations; section 4 describes the econometric models estimated and their results, both at the area and establishment levels. Finally, section 5 presents the conclusions of the study.

[2] See Pigatto et al. (2017) for more information on the Brazilian food delivery scenario.

2. Literature

The literature is more abundant in exploring the consumer side, examining the factors behind consumer's decision to order food, loyalty, brands, etc. (Lee et al., 2017; Gupta, 2019; Cho et al., 2019; Ray et al., 2019, Tandon et al., 2021; Seghezzi et a., 2021). The point of view of restaurants is less covered, with only a few studies, most qualitative (Meenakshi and Sinha, 2019; Khan, 2020; Veldhoven et al., 2021; Kumar and Kaur, 2021). Assessing the impacts of engaging in meal delivery on the economic performance of restaurants is new to the literature. Gupta (2019) analyzes the impact of two startups in food delivery in the Indian case, but only qualitatively. The COVID-19 pandemic prompted interesting situations to compare restaurants' financial performance before and after its beginning, such as Song et al. (2021) for the US, and Kim et al. (2021), for China. Dano and Chopra (2021) examine the effects of commission rates charged by delivery services in the United Arab Emirates in the context of the pandemic. Alvarez-Palau et al. (2021) used data from the largest delivery services in Barcelona, Spain, to build a Monte Carlo simulation model to estimate the necessary number of orders to reach economic profitability across the three options.

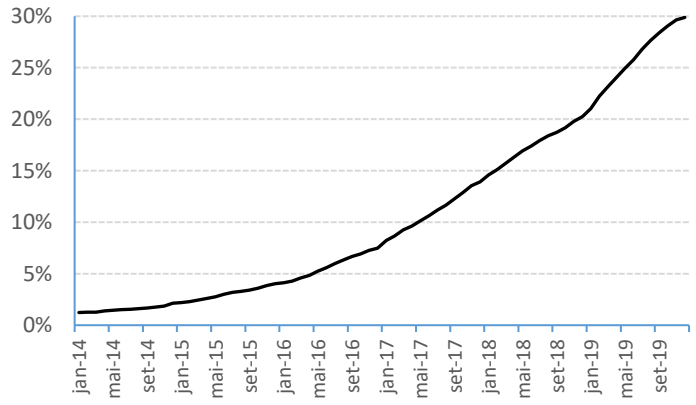
The gradual engagement of restaurants with meal delivery precedes the pandemic, and its effect in regular times is still to be determined. Hirschberg et al. (2016) provide information on the growth of this market in 16 countries. Pigatto et al. (2017) analyze the evolution of meal delivery services in the Brazilian context and shows the rapid growth of firms and operations volume. However, the impact of this innovation on the performance of firms is still an open question. Dolsen et al. (2021) used US credit card data to assess the effects of e-commerce in general through consumer surplus between 2007 and 2017. They estimate that e-commerce was responsible for a 1% boost of over $1,000 per household per year, with a substitution effect of local merchants for merchants available online but not locally. Kim et al. (2021) use the economic census to associate the introduction of electronic commerce and the performance of all Japanese firms. They found that e-commerce is positively associated with firms' productivity and higher wages.

These studies generally cover e-commerce and are not specific to the restaurant industry. Cohen et al. (2016) used individual-level observations to estimate the consumer surplus involved with using the Uber car-sharing App. Although they come to impressive positive numbers, a proper evaluation would also involve considering the supply side to check what the net surplus would be. Kim et al. (2021) analyzed sales data of 86,507 small- and medium-sized firms in nine Chinese cities restricted to the COVID-19 situation. They found positive impacts in operational characteristics and brand effects. Veldhoven et al. (2021) compared financial data of 49 Belgian restaurants before and after joining a delivery service and found substantial improvements in liquidity but less so in profitability and solvency. Although their data allow assessing the effects of engagement in meal delivery, the sample is too small to allow any conclusions. Collison (2020) uses Visa Inc.'s individual-level credit and debit transactional data of purchases in American restaurants between 2014 and 2017. Using difference-in-differences analysis, he finds that 30-50 cents of every dollar spent on online food delivery services are incremental. The rest is diverted away from brick-and-mortar sales. However, the level of cannibalization of brick-and-mortar restaurant sales increased with time. He verifies an increase in restaurants' revenues but a decrease in profitability.

3. Data

We work with establishment-level data on restaurants belonging to 12 Brazilian cities, representing 15.3% of the population and 21% of restaurants in the country in 2021[3]. The sample includes the two largest cities, Sao Paulo and Rio de Janeiro, five state capitals and four medium-size cities from different parts of the country, and the nation's capital, Brasília. The final sample includes 35.366 restaurants with two or more employees in all months and operating at least for 24 consecutive months. As of 05/2021, almost 50% of restaurants in the country belonged to the meal delivery platform considered in the study. Figure 1 shows the evolution of the share of restaurants delivering meals in the sample. It reveals that the meal delivery service enrollment was minimal in the initial years and increased consistently even before the pandemic.

Figure 1 – Share of restaurants with meal delivery in the sample



Source: RAIS, Ministry of Labor, and iFood data

Table 1 shows that restaurants in the two groups present some important differences. Regarding the number of jobs, those that deliver present 14 jobs/restaurant, and the comparison group, 11. The share of employment in kitchen occupations is larger, and the percentage in table-serving occupations is lower in restaurants that do not deliver meals. Wage levels, on the other hand, are similar across groups.

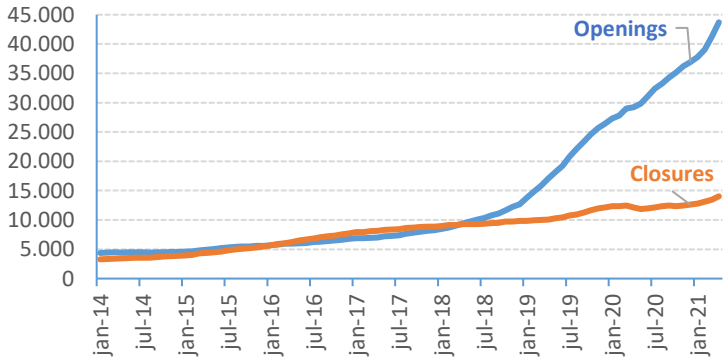
Besides following the evolution of jobs, we also considered restaurant openings and closures in the period, based on the records of the National Revenue Service (Receita Federal do Brasil). Figure 2 shows the evolution of both variables in the period. The market area for restaurants tends to be spatially restricted, given the transportation effort involved (distance, consumer time). Therefore, it is necessary to work at a more disaggregated level than the city, especially the large ones. We divided the cities in the sample into 790 areas, based on the weighting areas used by the official statistics office (IBGE) in the population census.

[3] Data from the Ministry of Labor, RAIS – Relação Anual de Informações Sociais, a mandatory report for all firms legally established in the country.

Table 1 – Descriptive statistics

	Never Delivered	Delivered at some point in time
# Restaurants	22.898	12.468
Jobs/Restaurant		
Average	11	14
Median	7	8
Minimum	1	1
Maximum	1.337	454
St-Deviation	19	19
% kitchen occupations	23,62%	20,99%
% serving tables	37,16%	40,28%
Average wage/Restaurant		
Average	1.640	1.648
Median	1.476	1.476
Minimum	0	0
Maximum	11.206	17.494
St-Deviation	646	631
% Wage bill in kitchen	24,59%	22,81%
% Wage bill in table-serving	34,52%	38,19%

Figure 2 – Restaurant Openings and Closures in the cities studied



Source: Receita Federal do Brasil

4. The econometric model

4.1. Area level analysis

The first exercise considers each of the 790 areas as the unity of analysis. We start by verifying if the presence of delivery restaurants in the area affects the opening of new restaurants.

4.1.1. Openings and closures of restaurants

Given the small number of startups in a month, we use the sum of new restaurants over 12-month periods. We estimate the following equation:

$$\ln\left(Openings_{a,t}\right) = f(Trend, Covid19, Share\_iF\ ) \qquad (1)$$

Where the variable *Openings*$_{a,t}$ indicates the sum of new restaurant openings in area *a* in the 12-month period ending in month *t*. The variable Trend is a time trend, intended to measure the rate of new restaurant openings. The share of restaurants in area *a* adopting meal delivery in the month t is $Share\_iF_{a,t}$. Since the pandemic increased the interest in meal delivery, especially during the lockdown times, we include the dummy *Covid*19 to differentiate the period March 2020 to May 2021 from the previous months. As we will see on Table 2, we included the interaction of those variables. Our main purpose here is to see how the trend of opening new restaurants is affected by the share of restaurants on iFood in the area and the Covid months affected this trend.

The overall monthly rate of growth varies between 2.14% and 2.75%, depending on the variables included in the regression. Models (1) to (5) show the effects of controlling for the pandemic months (Covid19), the share of restaurants on iFood. Our analisys will focus on the full model (6). The coefficients for Covid19 and Share_iF show that, in levels, these variables reduce restaurant openings. Both interactions of Trend with Covid19 and Share_iF show that the rate of openings increased during the pandemic months and with a higher share of restaurants using the app. However, the triple interaction*, Trend* x *Covid19* x *Share_iF*, shows that the rate of openings increases with the share using the app, but this number is still positive but significantly smaller during the lockdown months.

Table 2 – Meal delivery and new restaurant openings in the areas

	(1)	(2)	(3)	(4)	(5)	(6)
Trend	0.0275***	0.0249***	0.0255***	0.0233***	0.0232***	0.0214***
	(0.0003)	(0.0005)	(0.0006)	(0.0003)	(0.0003)	(0.0006)
Covid19				0.4679***	−0.2295***	−0.1516
				(0.0139)	(0.0770)	(0.2424)
Share-iF$_{t-12}$		2.4876***	0.1841			−4.0987***
		(0.1687)	(0.7237)			(1.2061)
Trend × Covid19					0.0086***	0.0099***
					(0.0010)	(0.0032)
Share-iF$_{t-12}$ × Covid19						3.7379**
						(1.7280)
Trend × Share-iF$_{t-12}$			0.0257***			0.1072***
			(0.0076)			(0.0164)
Trend × Share-iF$_{t-12}$ × Covid19						−0.1031***
						(0.0228)
Obs	71808	62016	62016	71808	71808	62016
R^2	0.8263	0.8515	0.8518	0.8422	0.8424	0.8607
Adj R^2	0.8243	0.8495	0.8498	0.8404	0.8406	0.8588
F	413.7673	429.5250	429.9444	463.8061	463.8338	459.9454

Obs: Area fixed effects included. Errors clustered by area. Significance levels: *** 1%, ** 5% and * 10%

We performed the same exercise for the closure of restaurants, substituting *Closures*$_{a,t}$ for $Openings_{a,t}$. The variable *Closures*$_{a,t}$ is the sum of the number of restaurants closed in area *a* in the 12-month period ending in month *t*. The explanatory variables are the same as in Equation (1). As the results in Table 3 reveal, the overall rate of growth of restaurant closures is also positive, with coefficient values between 1.24% and 1.63% per month, depending on the specification. Column (3) shows that areas with more restaurants using the platform see more

restaurant closings but, on the margin, a higher share decreases the rate of closures over time. The results in column (5) are similar, with more closings during the lock down months, but with a lowering rate of closings during these months. Finally, column (6) shows a similar result to model (3), with no difference on the rate of closure between the regular and the lockdown months, as shown by the non-significant triple interaction.

In summary, these exercises indicate that the existence of meal-deliverers is associated with an increase in the rate of openings and a decrease in the rate of closings, suggesting a positive net effect on the industry. As we have no information on the profitability of restaurants, this positive effect does not allow the conclusion that the financial performance of the restaurant industry improves as the share of food-deliverers in the areas increases. However, it is an indirect indicator that entrepreneurs spot new opportunities in areas with a more intense presence of food-deliverers. One should consider that the areas are not homogeneous, and profitable opportunities are not randomly distributed across them. Although the fixed effects take part of this problem into account, this result should be taken with care. In the analysis at the restaurant level to be performed below, we treat this problem explicitly.

Table 3 – Meal delivery and the closures of restaurants in the areas

	(1)	(2)	(3)	(4)	(5)	(6)
Trend	0.0150***	0.0133***	0.0124***	0.0163***	0.0163***	0.0138***
	(0.0002)	(0.0005)	(0.0005)	(0.0003)	(0.0003)	(0.0006)
Covid19				−0.1433***	0.2197*	0.2304
				(0.0147)	(0.1173)	(0.2812)
Share-iF$_{t-12}$		0.1019	4.0581***			4.1002***
		(0.1594)	(0.7368)			(0.9642)
Trend × Covid19					−0.0045***	−0.0058
					(0.0015)	(0.0036)
Share-iF$_{t-12}$ × Covid19						0.4176
						(1.9105)
Trend × Share-iF$_{t-12}$			−0.0441***			−0.0509***
			(0.0076)			(0.0124)
Trend × Share-iF$_{t-12}$ × Covid19						0.0113
						(0.0245)
Obs	71808	62016	62016	71808	71808	62016
R^2	0.8122	0.8174	0.8185	0.8141	0.8142	0.8199
Adj R^2	0.8100	0.8149	0.8161	0.8120	0.8121	0.8175
F	376.2695	335.2770	337.3491	380.6355	380.3170	338.9066

Obs: Area fixed effects included. Errors clustered by area.
Significance levels: *** 1%, ** 5% and * 10%

4.1.2. Number of jobs

We now move on to consider the number of jobs in the restaurant industry in the areas. In this case, data constraints limit the analysis to the period Jan/2014 through Dec/2019. Figure 3 shows the share of areas with at least one meal deliverer in the period considered in the study, by deciles of job numbers per area. It reveals that enrollment in meal delivering occurred pace wise in all area sizes, and that smaller areas are latecomers in having their first restaurant doing delivery. The combined information in Figures 1 and 3 indicate that the period of analysis is adequate to verify the impacts of meal delivering on the restaurant industry, since the adoption of the system was minimal in the initial months and increased consistently over time. It also

suggests that city size might be a possible source of heterogeneity, which led us to split the analysis for three different city sizes.

A word of warning is necessary about the nature of the data used. There is no information on the volume of meals, revenue, profit or any other activity variable representing restaurant activity, except for the number of jobs. Our data includes only workers with a formal labor contract with the employer, rending a number of benefits such as 13 months of wage payments, additional payment during holidays, etc. In the Brazilian economy as a whole, only 60% of employees have such a type of contract, but this share is probably much higher in the restaurant industry. This data limitation would be a problem if the share of formal jobs differed for deliverers and non-deliverers, which does not seem probable. Unfortunately, there is no information available.

Another caveat is that our measure of activity, number of jobs, could be affected by the adoption of meal delivery. For example, a restaurant could end serving meals in the store to concentrate on meal delivering, which could affect the number of employees utilized. It would also change the type of occupations hired (e.g. fewer waiters, more cooks. Contrary to the previous limitation (formal jobs only), this weakness of our measure of activity is more probable to affect deliverers and non-deliverers differently. Part of this problem is taken into account in our estimations by the inclusion of the share of employees in kitchen occupations in each restaurant, as we show below.

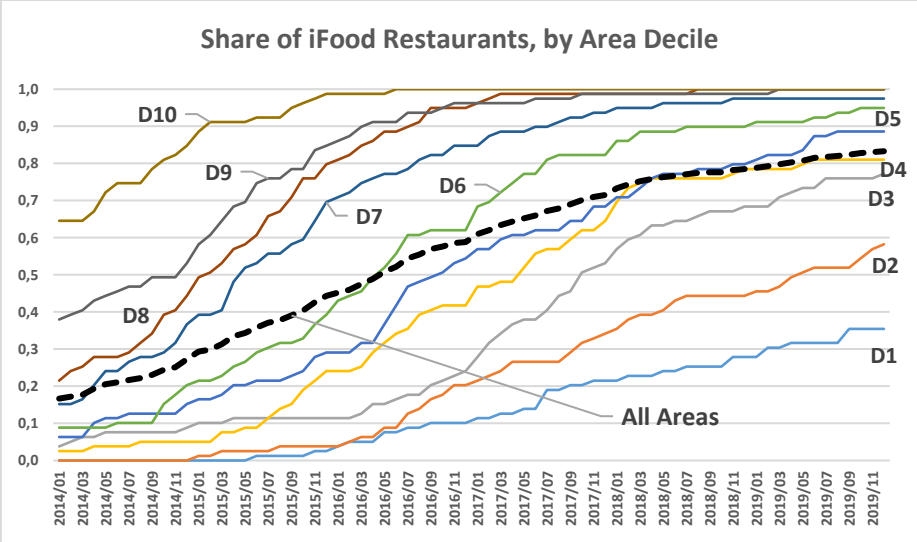
An important additional issue with our data is that we have no information on the previous engagement of the restaurants with meal delivery, either with an internal service or with other delivery apps. Consequently, our results are limited to the effects of the delivery service we are dealing with in the calculations. However, this particular service is a pioneer in Brazil, and, besides being the most important quantitatively, started much earlier than the competitors did (Pigatto et al. 2017). This increases the chances that the engagement of restaurants with delivery apps started with iFood. Another limitation is that we have no information on the self-services provided by the restaurants at the moment of engagement with iFood. Although not typical of the Brazilian's food habits, there were some experiences in particular sectors, such as pizza and Chinese food delivery, but restricted to large cities. Anyhow, these are limitations that must be considered in analyzing the results.

We first estimate the model in Equation (2), in which employment levels are associated with the share of meal-delivering restaurants in the area.

$$\ln(Emp_{a,t}) = h(Trend, Sh\_iFood) \qquad (2)$$

In which $Emp_{a,t}$ is the number of employees in area a in the month t. As Column (1) in Table 4 show, the overall monthly rate of employment growth in the restaurant business was 0.14%. The share of meal-delivering restaurants in each region is positively associated with the level of restaurant employment (Columns 2 and 3) in that region, and negatively related with the rate of growth in employment (Column 3). But this last result is only marginally significant.

Figure 3 – Share of areas with at least one meal-delivering restaurant, by area decile



Source: iFood Database and Receita Federal

Table 4 – Presence of meal delivery and jobs in restaurants in the areas

	(1)	(2)	(3)
Trend	0.0014*	−0.0001	−0.0001
	(0.0007)	(0.0012)	(0.0011)
Share_iFood		0.4560**	0.7933***
		(0.1680)	(0.2448)
Trend × $\mathrm{Sh}_i Food$			−0.0057*
			(0.0026)
Obs	56880	56880	56880
R^2	0.9662	0.9668	0.9668
Adj R^2	0.9657	0.9663	0.9663
F	1997.6527	2028.2167	2027.4055

Obs: Area fixed effects included. Errors clustered by area.
Significance levels: *** 1%, ** 5% and * 10%

4.2. Establishment level analysis

In this sub-section, we consider the impact of meal delivery on restaurants, comparing the job evolution of restaurants before and after they started delivering meals. Restaurants that never delivered meals are also in the comparison group. As the descriptive statistics suggest, there might be a selection bias for restaurants adopting meal delivery. Therefore, when analyzing the impacts of this mode of meal provision, attention must be devoted to this problem.

Since the delivery adoption is not random, we use instrumental variables to control for the resulting endogeneity of the decision to enter the platform. Following Wooldridge (2002), we estimate the model in three steps. In the first step, we use a Probit model to estimate the probability of a restaurant joining the platform:

$$P(iFood_{i,a,t}) = f(X_{i,a,t}, Z_{a,t}) \quad (3)$$

$P(iFood_{i,a,t})$ indicates the probability that restaurant *i*, located at area *a*, to deliver meals through the platform at time t. $iFood$ is a dummy variable that has value 0 for every month before the beginning of the service in the restaurant; and $iFood_{i,a,t} = 1$ for all months after that. $X_{i,a,t}$ is a vector of characteristics of the restaurant, and $Z_{a,t}$ is a vector of characteristics of the area in which the restaurant is located, both at period t.

As Figure 3 indicates, the number of restaurants adopting meal delivery grows with time, especially in cities with a smaller number of restaurants. As there is a learning process about how the delivery system works, entrepreneurs accumulate information over time. To capture that aspect, we include the variable *Trend* in the estimation. To account for the fact that the proximity to other restaurants also facilitates learning about the positive and negative aspects of meal delivery, we include the share of meal-delivering restaurants in the area one month before each restaurant starts delivering meals. As the adaptation to meal delivery depends on the nature of the meals prepared by restaurants, it is expected that not all types of restaurants could adopt delivery. Traditional and sophisticated restaurants could face more barriers to adopting the system. This behavior could reflect a conservative attitude or even menus less adaptable to delivery. To account for those aspects, we include the share of employees involved in activities associated with serving meals in the restaurants (maîtres, waiters), the age of the restaurant (years since establishment), and the relative level of wages paid. Higher relative wages might reflect a more sophisticated composition of occupations (more maîtres, for example) or higher payments to well-trained employees in the same occupations (waiters receiving higher payments).

Table 5 presents the results. Since Figure 3 shows that meal delivery adoption differs across city sizes, we estimate the model for all restaurants and for those in three different city sizes. The probability of adopting meal delivery increases with time, more intensively in medium then small and large cities. The share of meal-delivering restaurants in the area is positively associated with the probability of adoption and has the most intense effect. The share of meal-serving occupations reduces the probability of adopting meal delivery, and the age of the restaurants shows negative coefficients, as expected. It seems that older and more sophisticated restaurants tend to present a slow reaction to the innovation represented by meal delivery apps. The positive sign of the relative wage indicates that restaurants concerned with recruiting good employees and retaining them with higher compensations are more prone to adopt meal delivery.

Table 5 – First step estimation – Probit model

	All Cities	City sizes		
		Large	Medium	Small
Intercept	-1.9363*** (0.0065)	-1.8767*** (0.0078)	-2.0684*** (0.0135)	-2.0921*** (0.0257)
Trend	0.0068*** (0.0001)	0.0057*** (0.0002)	0.0114*** (0.0002)	0.0097*** (0.0005)
Sh_iFood $_{t-1}$	3.9500*** (0.0173)	3.9775*** (0.0214)	3.6885*** (0.0348)	3.7127*** (0.0580)
Sh_Waiters$_{t-1}$	-0.1777*** (0.0048)	-0.1927*** (0.0060)	-0.1589*** (0.0092)	-0.1842*** (0.0170)
Age	-0.0015*** (0.0000)	-0.0011*** (0.0000)	-0.0034*** (0.0000)	-0.0030*** (0.0001)
Relative wage	0.1498*** (0.0044)	0.1241*** (0.0052)	0.2302*** (0.0097)	0.3190*** (0.0187)
AIC	1019683.9	688800.0	273945.0	79848.2
BIC	1049757.8	688871.3	274011.5	79906.9
Log Likelihood	-524835.9	-344394.0	-136966.5	-39918.1
# Obs	1674579	1063851	480197	130531

In the second step, we use the estimated probability calculated in the first step as an instrument, together with other exogenous variables, to have the IV equations we use as a second step:

$$\langle iFood, Trend * iFood \rangle = G(\hat{P}_{i,a,t}, X_{i,a,t}, Z_{a,t}) \qquad (4)$$

The results from the second step are in Tables 6 and 7, in the Appendix. Finally, in the third step, we use the predicted values calculated in the second step to estimate the equation of interest:

$$ln(Emp_{i,a,t}) = \beta_0 + \beta_1 Trend + \beta_2 \widehat{iFood} + \beta_3 (\widehat{Trend * iFood}) \qquad (5)$$

Table 8 shows the result of the third step. The overall trend in employment in the sector in the cities covered by this study is negative, reflecting a reduction in the number of employees per restaurant, with less intensity in larger cities. The dummy *iFood* shows that restaurants that adopt the app are smaller.

The comparison of meal-delivering restaurants to themselves, before the adoption of the system, and to restaurants that never adopted meal delivery shows positive effects on the employment rate of growth, for all city sizes. The effect is smaller in medium-sized cities.

Table 8 – Third step results: effect on of using the app on employment

	All	Large	Medium	Small
Trend	−0.0043***	−0.0035***	−0.0060***	−0.0052***
	(0.0003)	(0.0004)	(0.0003)	(0.0005)
iFood	−0.2140**	−0.3591***	0.2726	−0.0472
	(0.0971)	(0.1221)	(0.1982)	(0.2913)
Trend × iFood	0.0056***	0.0063***	0.0016	0.0061
	(0.0012)	(0.0016)	(0.0025)	(0.0037)
Obs	1674579	1063851	480197	130531
R^2	0.8670	0.8763	0.8455	0.8418
Adj R^2	0.8641	0.8737	0.8420	0.8384
F	302.1618	334.6301	244.9746	244.6297

Obs: Restaurants fixed effects included. Monthly dummies plus a dummy for the year 2019 and the city of Cuiaba are included. Errors clustered by area.
Significance levels: *** 1%, ** 5% and * 10%

Using the numbers from the column 'All', we can quantify the iFood effect on jobs in the restaurant business all over the country. There were 1,283,234 jobs in 2019, with 35,1% in restaurants that used the iFood app. Hence, there were 450,415 workers in iFood restaurants and 832,819 in non-iFood ones. Since the model is log-level, we can interpret the estimated coefficients as percentage rates. Non-iFood restaurants have a rate of decrease in employment of -0.43% and iFood establishments have an increase of (0,0056-0,0043=) 0.13%. If we multiply the stock of workers by the rate of change of non-iFood restaurants we have an average of (832,819 x (-0.0043)=) 3.581 jobs lost in the restaurant industry during a month of the sample period. For the iFood group, we have on average (450,415 x 0.0013=) 586 jobs created or saved. We then have a net effect of 2.996 jobs lost per month in the restaurant business.

This result indicates that the negative effects imposed on restaurants that resisted adopting delivery were not offset by the positive effects on those that delivered meals to their clients through the app. This does not mean that profitability in the sector increased in parallel, for delivering meals required investments in equipment (packing) and personnel, as well adding the cost of delivery to the production costs.

5. Conclusions

This paper analyzes the effects of the introduction of a major food delivery app on the Brazilian restaurant industry. The results show that the app had a positive effect on the opening of new restaurants, but less so during the pandemic years. It also had a negative effect on the closure of restaurants, showing evidence of a positive impact on the number of businesses in the sector. But, again, this effect is smaller during the COVID19 pandemic.

We find evidence that the types of restaurants that join the platform are different from the ones that do not join. More traditional and older establishments with more workers working as waiters have a lower probability of joining the platform. We also find a significant network effect, with restaurants located in regions with more delivery having a higher chance of also adopting the delivery app.

Finally, restaurants increased their employment when they joined the delivery platform. At the same time, restaurants that remained out of the platform decreased their employment during the same period of time. The effect of the delivery app on employment on the restaurant industry is positive but not large enough to offset the general trend of decreasing employment in the industry.

References

Alvarez-Palau, E. J.; Calvet-Liñán, L.; Viu-Roig, M.; Gandouz, M.; Juan, A. A. (2021). Economic profitability of last-mile food delivery services: Lessons from Barcelona. Research in Transportation Business & Management, 100659, ISSN 2210-5395,

Cho, M; Bonn, M. A. Li, J. (2019) Differences in perceptions about food delivery apps between single-person and multi-person households. International Journal of Hospitality Management, Volume 77, Pages 108-116, ISSN 0278-4319

Cohen, P.; Hanh, R.; Hall, J.; Levitt, S.; Metcalfe, R. (2016) Using Big Data to Estimate Consumer Surplus: The Case of Uber. NBER Working Paper 22627. DOI 10.3386/w22627

Collison, J. (2020). The Impact of Online Food Delivery Services on Restaurant Sales. Department of Economics, Stanford University, Honors Thesis. https://web.stanford.edu/~leinav/teaching/Collison.pdf Visited Jan-18-2022

Dano, D. R.; Chopra, A. (2021). Impact of Delivery Apps Commission Rates on U.A.E Restaurants. *2021 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE)*, 2021, pp. 273-278, doi:0.1109/ICCIKE51210.2021.9410736

Dolfen, P.; Einav, L.; Klenow, P. J.; Klopack, B.; Levin, J. D.; Levin, L.; Best, W. (2021) Assessing the Gains from E-Commerce. NBER Working Paper 25610; http://www.klenow.com/assessing-gains-ecommerce.pdf

Gupta, M. (2019). A Study on Impact of Online Food delivery app on Restaurant Business special reference to zomato and swiggy. International Journal of Research and Analytical Reviews, Volume 6, Issue 1, Jan-March, ISSN 2348 –1269, Print ISSN 2349-5138

Hirschberg, C.; Rajko, A.; Schumacher, T.; Wrulich, M. (2016) The changing market for food delivery. McKinsey &Company, Telecommunications November 2016. http://dln.jaipuria.ac.in:8080/jspui/bitstream/123456789/2874/1/The-changing-market-for-food-delivery.pdf Assessed Jan-18-22

Hyoung Ju Song, Jihwan Yeon, Seoki Lee, Impact of the COVID-19 pandemic: Evidence from the U.S. restaurant industry, International Journal of Hospitality Management, Volume 92, 2021, 102702,ISSN 0278-4319, https://doi.org/10.1016/j.ijhm.2020.102702.

Khan, M. A. (2020) Technological Disruptions in Restaurant Services: Impact of Innovations and Delivery. Journal of Hospitality & Tourism, Volume:44 issue: 5, pages:715-732 https://doi.org/10.1177/1096348020908636. Published February 26

KIM Y. G.; KWON, H. U. & FUKAO, K.; IKEUCHI, K. (2021). "E-Commerce, Firm Performance and Economic Dynamism: Empirical analysis using the Economic Census (Japanese)," Discussion Papers 21016, Research Institute of Economy, Trade and Industry (RIETI). https://ideas.repec.org/p/eti/rdpsjp/21016.html. Visited Jan 20, 2022

Kim, J., Kim. J., Wang, Y. (2021) Uncertainty risks and strategic reaction of restaurant firms amid COVID-19: Evidence from China. International Journal of Hospitality Management Volume 92, January 2021, 102752

Kumar, P.; Kaur, H. (2021) Determinants of e-commerce adoption: a literature-derived model for developing nations. International Journal of Business Information SystemsVol. 37, No. 2 Published Online:May 26, 2021pp 182-199

Lee, Eun-Yong; Lee, Soo-Bum; Jeon, Yu Jung Jennifer (2017). Factors influencing the behavioral intention to use food delivery apps, Social Behavior and Personality: an international journal, Volume 45, Number 9, 2017, pp. 1461-1473(13)

Meenakshi, N.; Sinha, A. (2019). Food delivery apps in India: wherein lies the success strategy? Strategic Direction, ISSN: 0258-0543 Issue publication date: 11 July 2019

Pigatto, G.; Machado, J. G. C. F.; Negreti, S. S.; Machado, L. M. (2017) Have you chosen your request? Analysis of online food delivery companies in Brazil British Food Journal Vol. 119 No. 3, 2017 pp. 639-657

Ray, A.; Dhir, A; Bala, P. K.; Kaur, P. (2019) Why do people use food delivery apps (FDA)? A uses and gratification theory perspective. Journal of Retailing and Consumer Services, Volume 51, Pages 221-230, ISSN 0969-6989, https://doi.org/10.1016/j.jretconser.2019.05.025.

Seghezzi, A., Winkenbach, M. and Mangiaracina, R. (2021), "On-demand food delivery: a systematic literature review", The International Journal of Logistics Management, Vol. 32 No. 4, pp. 1334-1355. https://doi.org/10.1108/IJLM-03-2020-0150

Tandon, A.; Kaur, P.; Bhatt, Y.; Mäntymäki, M.; Dhir, A. (2021) Why do people purchase from food delivery apps? A consumer value perspective, Journal of Retailing and Consumer Services, Volume 63, 2021, 102667, ISSN 0969-6989

Wooldridge, J. M. (2002) Econometric Analysis of Cross Section and Panel Data, MIT Press, 2002.

Z. Van Veldhoven, P. Aerts, S. L. Ausloos, J. Bernaerts and J. Vanthienen, "The Impact of Online Delivery Services on the Financial Performance of Restaurants," *2021 7th International Conference on Information Management (ICIM)*, 2021, pp. 13-17, doi: 10.1109/ICIM52229.2021.9417153.

Appendix – second step IV tables

Table 6 – Second step estimation - dependent variable: dummy iFood

	All cities	Large cities	Medium cities	Small cities
Trend	0.0010***	0.0011***	0.0007***	0.0009***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
January	0.0002	0.0008*	−0.0002	−0.0006
	(0.0004)	(0.0005)	(0.0006)	(0.0014)
February	−0.0004	0.0007	−0.0019***	−0.0018
	(0.0005)	(0.0006)	(0.0006)	(0.0013)
March	0.0001	0.0007*	−0.0005	−0.0006
	(0.0003)	(0.0004)	(0.0005)	(0.0012)
April	−0.0004	0.0003	−0.0009	−0.0025**
	(0.0003)	(0.0004)	(0.0005)	(0.0010)
May	−0.0000	0.0007*	−0.0007	−0.0027**
	(0.0003)	(0.0004)	(0.0005)	(0.0014)
June	−0.0003	0.0000	−0.0005	−0.0016*
	(0.0002)	(0.0003)	(0.0004)	(0.0009)
August	−0.0008***	−0.0007***	−0.0010*	−0.0003
	(0.0002)	(0.0003)	(0.0005)	(0.0008)
September	−0.0013***	−0.0008**	−0.0028***	−0.0006
	(0.0003)	(0.0003)	(0.0005)	(0.0009)
October	−0.0016***	−0.0011***	−0.0027***	−0.0026**
	(0.0003)	(0.0004)	(0.0006)	(0.0010)
November	−0.0013***	−0.0005	−0.0030***	−0.0044***
	(0.0004)	(0.0004)	(0.0007)	(0.0011)
December	−0.0017***	−0.0006	−0.0043***	−0.0054***
	(0.0004)	(0.0004)	(0.0007)	(0.0016)
Dummy 2019	0.0025	0.0062***	−0.0089**	−0.0130*
	(0.0018)	(0.0019)	(0.0038)	(0.0075)
Dummy Cuiabá 2018	0.0059			0.0050
	(0.0055)			(0.0069)
Estimated iFood	0.8163***	0.8487***	0.7885***	0.6216***
	(0.0391)	(0.0451)	(0.0776)	(0.1478)
Obs	1674579	1063851	480197	130531
R^2	0.7022	0.7056	0.7003	0.6932
Adj R^2	0.6958	0.6994	0.6936	0.6865
F	109.2362	113.1027	104.1491	103.4447

Table 7 – Second step estimation - dependent variable: Trend x dummy iFood

	All cities	Large cities	Medium cities	Small cities
Trend	0.0444	0.0504	0.0298	0.0398
	(0.0278)	(0.0317)	(0.0402)	(0.0743)
January	0.0287	0.0378	0.0486	0.0604
	(0.1444)	(0.1778)	(0.2828)	(0.5157)
February	0.0211	0.0643	−0.0304	0.0144
	(0.1960)	(0.2694)	(0.2545)	(0.4942)
March	0.0232	0.0335	0.0293	0.0420
	(0.1210)	(0.1531)	(0.2195)	(0.3861)
April	0.0059	0.0214	0.0061	−0.0291
	(0.1078)	(0.1299)	(0.2113)	(0.3606)
May	0.0161	0.0439	−0.0095	−0.0533
	(0.1239)	(0.1642)	(0.1782)	(0.4102)
June	−0.0110	0.0025	−0.0178	−0.0690
	(0.0870)	(0.1086)	(0.1572)	(0.3343)
August	−0.0398	−0.0397	−0.0512	−0.0226
	(0.0947)	(0.1065)	(0.2106)	(0.3265)
September	−0.0832	−0.0497	−0.1803	−0.0686
	(0.1108)	(0.1357)	(0.2289)	(0.2913)
October	−0.1046	−0.0720	−0.1897	−0.1685
	(0.1352)	(0.1650)	(0.2456)	(0.4067)
November	−0.1011	−0.0469	−0.2152	−0.2874
	(0.1522)	(0.1746)	(0.2944)	(0.4463)
December	−0.1033	−0.0396	−0.2641	−0.2746
	(0.1677)	(0.1887)	(0.3062)	(0.5843)
Dummy 2019	0.2315	0.4758	−0.5578	−0.6863
	(0.8974)	(0.9667)	(1.9814)	(3.3855)
Dummy Cuiabá 2018	0.2644			0.2120
	(2.0376)			(2.6464)
Estimated iFood	−7.6214	−3.7049	−15.9227	−21.5766
	(13.7940)	(16.2026)	(29.6269)	(39.5872)
Estimated Trend $\times iFood$	0.8554***	0.7775***	1.0641**	1.1490*
	(0.2227)	(0.2484)	(0.4577)	(0.5901)
Obs	1674579	1063851	480197	130531
R^2	0.6517	0.6509	0.6615	0.6523
Adj R^2	0.6442	0.6435	0.6539	0.6447
F	86.7056	87.9624	87.0868	85.9076