Meal Delivery and the Local Restaurant Industry

Carlos R. Azzoni * Rodrigo M. S. Moita † Mateus Rodrigues ‡

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Abstract

Meal deliveries have increased in recent years, particularly during the COVID-19 pandemic. Does it benefit suit-to-delivery restaurants at the cost of harming non-delivery ones? What is the net impact on the restaurant industry as a whole? This paper investigates the effects of the major meal delivery app in the restaurant industry of the two largest Brazilian cities, São Paulo and Rio de Janeiro, comprising 30,757 restaurants. We estimate a staggered difference-in-differences model using restaurant-level information for 2011-2018 in 500 areas of the two cities. We analyze the effects of the app's introduction on the openings and closures of restaurants and the number of restaurant jobs at the area level and discover that meal delivery was associated with increased restaurant openings and closures, with a more substantial impact on openings, leading to a net positive impact on the industry. The net effect on the industry's activity level, as measured by the number of jobs, is also positive. The estimated average effect per area and year is the creation of 94 jobs (between 38 and 150, with a 5% confidence interval) and the opening of 1.4 (0.5–2.2) and closure of 0.7 (0.3–1.2) establishments. The aggregate effect over the two cities represents a yearly increase of 0.15% in the number of restaurants and 3.3% in the number of jobs. We also find strong evidence of network effects.

Keywords: Meal delivery apps, local restaurant industry.

*NEREUS — The University of Sao Paulo Regional and Urban Economics Lab, Department of Economics, University of Sao Paulo, Brazil, cazzoni@usp.br

†Department of Economics, University of Sao Paulo, Brazil, rodmoita@usp.br

‡Sao Paulo School of Economics, mateus.rodrigues@fgv.edu.br

1 Introduction

Ordering meals from home or the office became commonplace during the COVID-19 pandemic but had grown consistently before then. From the consumer's point of view, the process saved time and allowed for a greater choice of restaurants and food types (since traffic and parking were not an issue). Such convenience comes at a price, however, namely, the cost of delivery (packing and freight) and the loss of some food properties in transportation. For restaurants, home delivery enlarges the pool of potential clients. On the other hand, it may incur costly adaptations to the production process, such as creating or expanding a packing department, assembling and managing the delivery service, or joining a meal delivery platform. It may also involve changes in the job structure within restaurants (e.g., more cooks and fewer waiters) (Bauer and Guerrico 2022; Das and Ghose 2019).

The ultimate effects of meal delivery on the restaurant industry have yet to be determined. If a significant number of consumers substitute delivered meals for home-cooked meals, the pool of clients is likely to enlarge, resulting in an overall increase in restaurant activity. This quantity effect must be balanced with a possible price effect, for instance, a foreseeable growth in the final cost of meals resulting from adaptations necessary in the production process that allow for meal delivery. The effects are expected to be different for restaurants that deliver than those that do not. One would imagine that the former would face an increase in activity because of the larger pool of potential clients and the possibility of stealing clients from non-delivering competitors[1].

As not all restaurants wish or are able to deliver meals, a question arises about the consequences for restaurants operating traditionally. In principle, one might expect a reduction in their activity, with a market share shrinkage. If there were simply a substitution of deliverers for non-deliverers, the net effect on the business would be null. The aggregate effects are a combination of all these factors.

Other aspects might be at play. Even if deliverers face increased activity, it might not imply better financial results. The profit margin could decrease because of the increased cost of meal delivery[2]. Other aspects involve labor issues with the delivery employees, typically working without contracts or traditional hours[3]. None of these aspects are considered in the present study. We concentrate on the industry's activity under the existing regulations in the period

[1] Dolfen et al. (2023) document a rapid growing share of e-commerce in the United States, with most of the gains accruing to merchants available online but not locally. Higher income consumers have gained more, along with consumers in more densely populated counties. Kim et al. (2021) find that Chinese fine dining restaurants had lower sales than casual dining, fast casual, and fast food restaurants during the pandemic. Li and Wang (2020) analyze the possible substitution or complementarity between meal-delivery platforms and restaurants' own takeout or dine-in channels in Chicago. They conclude that delivery platforms increase restaurants' takeout sales and create positive spillovers to customer dine-in visits, with fast food chains benefiting the most.

[2] The Brazilian national association of restaurants have complained about the fees charged by the delivery apps, for example.

[3] The Brazilian Congress has introduced motions to regulate activity and impose stricter rules for its operations.

under discussion.

As the literature review below shows, only some aspects of food delivery are considered, mainly consumer choices. The present study assesses the effects of introducing food delivery apps on restaurant activity levels based on evidence from Brazil. Studies of e-commerce in the local retail industry reveal that it has had a negative impact, as out-of-region suppliers have substituted local establishments (Bauer and Guerrico 2022; Chava et al. 2022; Chun et al. 2020; Vitt 2017). However, the restaurant industry is different, as local demand must be matched by local supply by the nature of the product being delivered. Therefore, the results of the introduction of meal delivery are not entirely clear.

We examine the effects of the largest meal delivery service – iFood[4] -— on restaurant activity from 2011 through 2018. We analyze the evolution of employment and the number of openings and closures in the restaurant industry across 500 areas in São Paulo (300) and Rio de Janeiro (200), which contain 13.6% of the establishments and 21.4% of the jobs in the Brazilian restaurant industry. With a rich set of establishment-level data, we compare the evolution of openings and closures and the number of jobs before and after the first restaurant starts delivering meals through the iFood platform in the area. The estimated average effect per area is the creation of 94 jobs per year (between 40 and 147, with a 5% confidence interval) and the opening of 1.4 (0.5–2.2) and closure of 0.7 (0.2–1.3) establishments. The aggregate effect over the two cities in the period is a yearly increase of 0.15% in the number of establishments and 3.3% in the number of jobs in the restaurant industry.

We contribute to the literature by presenting a study of the impact of meal delivery on restaurant employment on a fine geographical scale[5]. This is important because, except for a few starred establishments, the market area of a restaurant is geographically restricted. Thus, the competition between delivering and non-delivering establishments occurs within a limited neighborhood within cities, especially in large ones. We use data that identifies the exact month the first restaurant in each area started delivering meals and compare the number of jobs before and after. As we compare the outcomes before and after delivery begins in the areas, it is necessary to consider the timing of the first occurrence of meal delivery. Therefore, we use a staggered difference-in-differences approach since the areas start delivering meals at different times. Moreover, we account for network effects by considering the share of restaurants using the app in the respective areas. The results show evidence of a positive and relevant effect. Additionally, we estimate the effects on employment and the openings and closures of restaurants in the areas. The scant literature on the subject does not cover this dimension. Finally, we provide evidence from two large cities in a developing country, unlike the few studies that deal with developed economies.

The present study is organized into four subsequent sections. Section 2 provides a brief literature review; Section 3 presents the data, describing its richness and limitations; Section 4 describes

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

[5] Muller and Neumann (2023) estimate the entrance of meal delivery platforms at the metropolitan area level.

the econometric models used and their results; and Section 5 presents the conclusions.

2 Literature review

The engagement of restaurants with meal delivery preceded the pandemic. Hirschberg et al. (2016) provide information on the growth of this market in 16 countries, while Pigatto et al. (2017) analyze the evolution of meal delivery services in the Brazilian context, showing the rapid growth of firms and the volume of their operations. However, the impact of this innovation on firms' performance is still an open question. The literature on meal delivery is abundant on the consumer side; it examines the factors behind food ordering decisions, loyalty, brands, and so on (Cho et al. 2019; Gupta 2019; E.-Y. Lee et al. 2017; Ray et al. 2019; Seghezzi et al. 2021; Tandon et al. 2021). Frederick and Bhat (2022) review the literature on consumer attitudes toward ordering food and develop a conceptual model. The viewpoint of restaurants has been less well-researched, and most of the studies have been qualitative (Khan 2020; Kumar and Kaur 2021; Meenakshi and Sinha 2019; Van Veldhoven et al. 2021).

Many studies examine e-commerce in general. Chun et al. (2020) analysis of 30 billion credit card transactions at the county level in the United States concludes that e-commerce has led to a 2.5% reduction in average retail employment. Bauer and Guerrico (2022) also note a decline in the number of establishments and jobs as a result of e-commerce. Dolfen et al. (2023) use United States credit card data to assess the effects of e-commerce in general through the 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 online but not locally. YoungGak et al. (2021) employ the economic census to examine the correlation between electronic commerce with the performance of all Japanese firms and conclude that e-commerce positively correlates with productivity and higher wages. Cohen et al. (2016) use individual-level observations to estimate the consumer surplus of the Uber car-sharing app, though, while the numbers are impressive, a more realistic evaluation would consider the supply side to check the net surplus. Kim et al. (2021) analyze the sales data of 86,507 small and medium-sized firms in nine Chinese cities under COVID-19 restrictions, finding a positive impact on operational characteristics and brand effects. Alcedo et al. (2022) investigate e-commerce in 47 economies during COVID-19 using credit card data and observe an increase in the share of online transactions on consumption; they also point to signs of dissipation over time. However, they identify a longer-lasting shift to digital in the case of retail and restaurants.

The present study contributes to the strand of the literature that analyzes platforms, or two-sided markets, and network effects. Significant early research in this area includes Rochet and Tirole (2003) and Armstrong (2006). The strand considers platforms where consumers and firms meet. Network externalities play a vital role in these markets, as platform strategies must take them into account. Jullien et al. (2021) provide a recent and comprehensive review of the relevant literature.

Studies on the impact of engagement in meal delivery on the economic performance of restaurants are scarce. Gupta (2019) offers a qualitative analysis of the effects of two startups in food delivery in India. The COVID-19 pandemic prompted before-and-after examinations of restaurants' financial performance; for example, Song et al. (2021) for the United States 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, while Alvarez-Palau et al. (2022) use data from the largest delivery services in Barcelona to build a Monte Carlo simulation model to estimate the number of orders needed for profitability across three options. Yost et al. (2021) follow the survival strategies of a United States restaurant chain, and Yang and Han (2021) analyze the impact of the pandemic on the hospitality industry and how it responded to the crisis. The authors suggest that food delivery might trigger the growth of firms and increase demand for managerial-level jobs. Ding et al. (2021) study 6,700 firms across 61 economies in the context of the pandemic, indicating that the drop in stock returns was milder for firms that were more financially secure before 2020. Kim et al. (2020) investigate the effect of nine epidemic events on the value of United States restaurants. Van Veldhoven et al. (2021) compare the financial data of 49 Belgian restaurants before and after joining a delivery service, finding substantial improvements in liquidity but not in profitability or solvency. Although their data allow for the effects of engagement in meal delivery, the sample is too small to come to any firm conclusions.

Collison (2020) uses Visa's individual-level credit and debit transactional data regarding 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 were incremental, with the remainder diverted away from brick-and-mortar sales. However, the level of cannibalization of brick-and-mortar restaurant sales increased over time. He verifies an increase in restaurant revenues but a decrease in profitability. Li and Wang (2020) conclude that on-demand delivery in the Chicago metropolitan area benefits restaurants that use online platforms (especially fast food chains). Muller and Neumann (2023) show that big meal-delivery platforms do not affect food-preparation employment, negatively impact dine-in service workers, and increase the number of delivery workers in American cities. Bermeo et al. (2023) analyze the effects of meal delivery on restaurants' revenues in the State of Paraiba, in the Northeast of Brazil, and its capital city, Joao Pessoa, during the COVID-19 pandemic. They used the difference-in-differences method to compare restaurants that used a delivery platform before the pandemic with those that started using it during the restriction period imposed by the authorities. They concluded that restaurants with previous experience with the platform performed better than those that started using the mechanism later.

3 Data

3.1 Data sources

The present study uses data from various sources. The number of employees per restaurant derives from a yearly report produced by the Ministry of Labor[6]; we use the number of employees in December of each year. We restrict the analysis to establishments classified with the SIC codes (CNAE): 5611201 ("Restaurants and similar") and 5611203 ("Snack bars, tea houses, juice bars, and similar"). The Federal Revenue Service (Receita Federal) provides information on the date of openings and closures of firms. From the iFood database, we identify the restaurants using the platform, with details about the month they joined. We merge the databases using firm tax IDs. The study period is 2011-2018, that is, it begins one year before the first firm joined the iFood (platform or app hereafter) in 2012, so we have a period in the database with no firms on the platform. As this specific platform is the pioneer in food delivery apps in Brazil, it is safe to say that food delivery before 2012 existed only for few pizza and Chinese food restaurants[7].

Both RAIS and the Federal Revenue Service databases contain details of the firms and their addresses, including the ZIP codes. We use a supplementary source of identification of the location of the restaurants to allocate the firms to districts and weighting areas[8]. The latter are aggregations of census tracts with similar socioeconomic and demographic characteristics. The official census office uses them to ensure that the survey samples represent the city's population. The official statistics office (IBGE) provided the shapefiles of the areas, both at the weighting area level and the more aggregated district level. Our database comprises firms with identifiable locations only.

The dummy variable app_{it} indicates the year t in which firm i joined the food delivery app:

$$app_{it} := \mathbf{1}\{t \geq \underline{t} \text{ and } app_i = 1\}. \tag{1}$$

Firms with SIC Code 5611201 – "Restaurants and similar" – , encompassing brick-and-mortar establishments, are identified with a dummy variable, as they are used as a control in the model. The openings and closures of restaurants are identified with dummy variables relative to the year the openings and closures occurred. The database is aggregated at the weighting area and year level by summing the number of restaurants, the number of restaurants using the app, employment, openings, and closures.

We calculate the share of establishments using the platform in the weighting area ("area," hereafter) and year from app_{it}. We create a dummy variable D_{at} identifying whether area a

[6] RAIS – Relação Anual de Informações Sociais (Yearly Report on Social Information).
[7] See Pigatto et al. (2017).
[8] *"Qual é o CEP?"*.

had joined the app in period t, defined as:

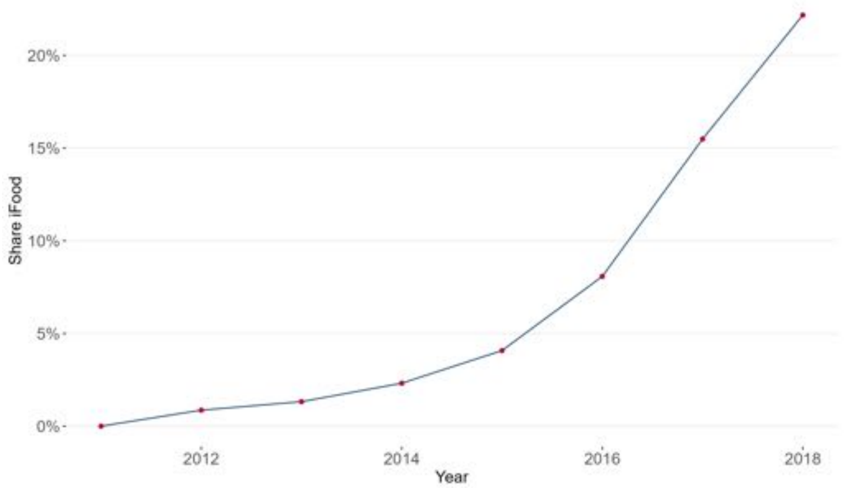
$$D_{at} := \mathbf{1}\left\{t \geq \min\left\{t \in T : \sum_{i \in a} app_{it} > 0\right\}\right\} \tag{2}$$

Where $T := \{2011, 2012, \ldots, 2018\}$. We use D_{at} to assign the weighting areas to the groups for the identification strategy of our baseline results.

3.2 Descriptive statistics

We use establishment-level data from restaurants in 500 districts in São Paulo and Rio de Janeiro (the two largest cities in Brazil)[9]. These cities comprised 13.6% of the establishments and supply 21.4% of the jobs in the restaurant industry in 2018 (the last year of the period under study). The sample covers 30,757 restaurants and 178,331 jobs, of which 22.2% of the former and 32.6% of the latter used the food delivery app that year. Figures 24–27 in the Appendix present the spatial dispersions of restaurants and employment in 2011 and 2018, and Figures 28–31 display the location of openings and closures between 2011 and 2018. The app's adoption as a meal delivery platform began in 2012 and has evolved gradually since then, as Figures 1 and 2 reveal.

Figure 1: Share of meal-delivering restaurants in the sample

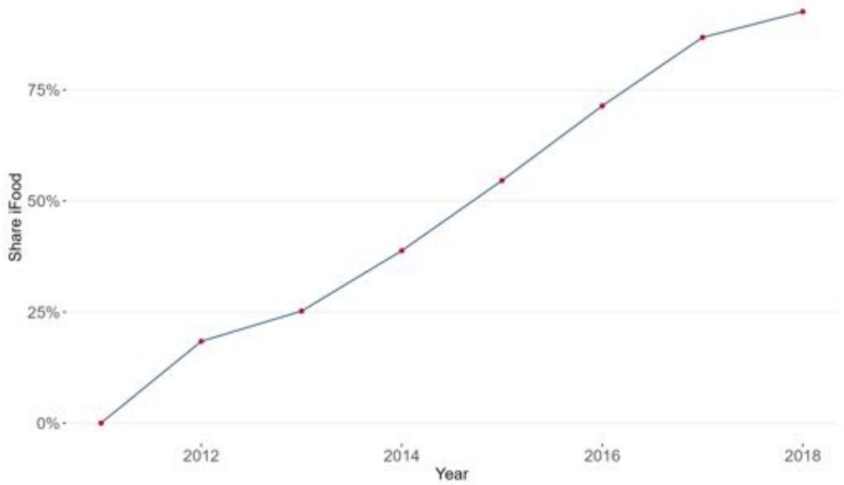


Notes: The figure displays the share of meal-delivering restaurants in the sample from 2011 to 2018.

Table 1 provides descriptive statistics at the area level. Comparing the results for all areas, there is a large dispersion regarding all the variables, suggesting that the areas are heterogeneous across different dimensions. One dimension that captures these differences is the type and composition of the restaurants. Areas with a higher proportion of full-service cloth-and-table restaurants than fast-food and snack bars (High share, in Table 1) have, on average, more jobs, openings, and closures. This indicates that their potential outcomes depend on the relative

9 From the original number of 200 weighting areas in Rio de Janeiro and 310 in São Paulo, the sample selection procedure resulted in a dataset comprising 191 and 309 weighting areas, respectively.

Figure 2: Share of meal-delivering areas in the sample



Notes: This figure displays the share of areas that already have at least one meal-delivery restaurant in each year from 2011 to 2018.

number of restaurants in the areas. This stylized fact provides evidence for using the share of restaurants as a covariate in the baseline model.

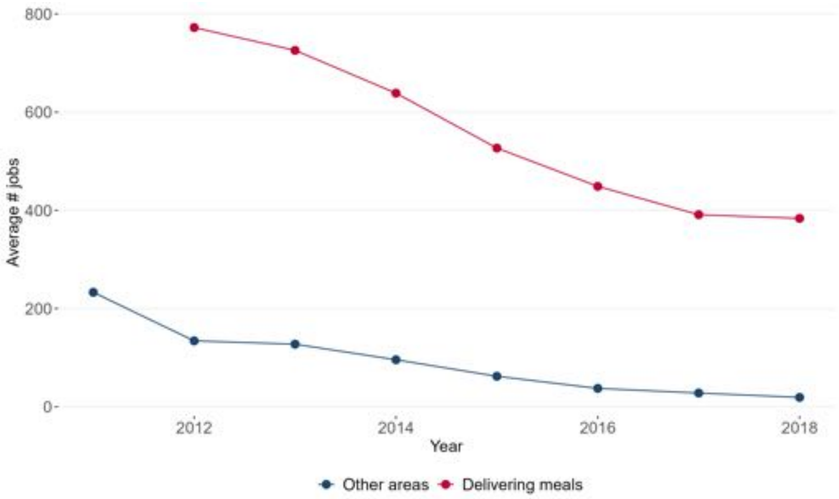
Table 1: Descriptive statistics per area

Variable	All areas		Low share		High share	
	Mean	SD	Mean	SD	Mean	SD
Jobs	302.00	661.71	74.59	119.19	529.39	1078.21
Openings	2.82	4.82	1.34	1.77	3.59	6.36
Closures	1.04	2.04	0.58	1.01	1.05	2.30
Share of restaurants	0.35	0.16	0.16	0.07	0.56	0.14
App share	0.06	0.09	0.05	0.08	0.08	0.11

Notes: This table shows mean and satandard deviations of the outcomes for different types of areas. An area is of type "High share" if it is in the fourth quartile of the distribution of the average share of restaurants at the area level. Similarly, an area is classified as "Low share" if it is in the first quartile of the distribution.

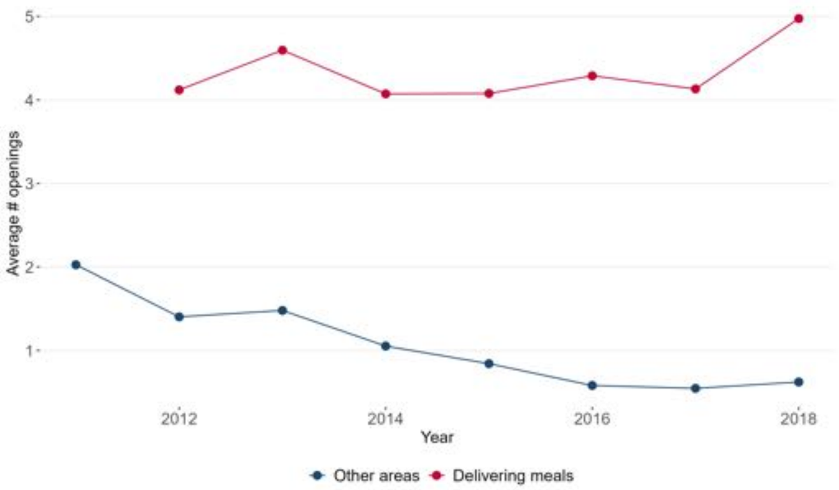
Figures 3, 4, and 5 show the evolution of the average number of jobs, openings, and closures by year for two types of areas: the ones in which at least one restaurant is using the app (labeled delivering meals), and the ones in which none is using it. There is a decreasing trend in the number of jobs in restaurants in both, revealing a characteristic of the restaurant industry in the cities. The evolution in the number of new restaurants per area is stable in meal delivery areas and negative in others. The trend in closures of restaurants increases in meal delivery areas and decreases in others. Although there are level differences, we check the parallel trend assumption later on in the study.

Figure 3: Evolution of the average # of jobs by type of area



Notes: This figure displays the average number of jobs by area type from 2011 to 2018. The red line represents the areas that already have at least one meal-delivery restaurant in each year, and the blue one represents the complementary set of areas.

Figure 4: Evolution of the average # of openings by area type



Notes: This figure displays the average number of openings by area type from 2011 to 2018. The red line represents the areas that already have at least one meal-delivery restaurant in each year, and the blue one represents the complementary set of areas.

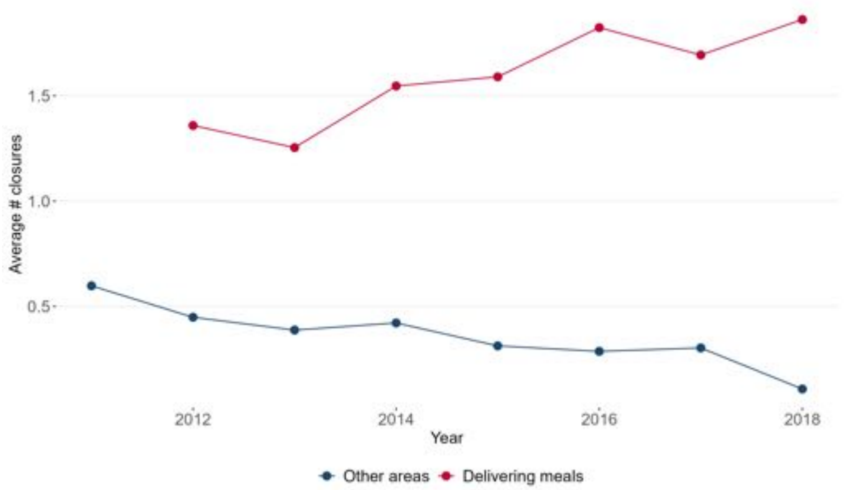
4 Methodology and results

4.1 Classic difference-in-differences

We begin the econometric analysis with a classic differences-in-differences model, given by:

$$y_{at} = \alpha_a + \mu_t + \beta D_{at} + \varepsilon_{at} \tag{3}$$

Figure 5: Evolution of the average # of closures by area type



Notes: This figure displays the average number of closures by area typerom 2011 to 2018. The red line represents the areas that already have at least one meal-delivery restaurant in each year, and the blue one represents the complementary set of areas.

Where y_{at} is one of the outcomes of interest (jobs, openings, or closures) for area a in period t, α_a is an area fixed effect, and μ_t is a period fixed effect. The coefficient β gives the effect of the app.

An area enters the treated group from the year its first restaurant joins the platform. Areas whose restaurants never join the platform or have not yet joined form the group of control areas. As the previous section indicates, the treatment happens in distinct periods for different areas. Table 2 shows the average treatment effects for jobs, restaurant openings, and closures (all negative and statistically significant). This preliminary result indicates that adopting meal delivery reduces the restaurant industry's activity: fewer than 10.7 jobs per year per area and fewer than 0.75 new restaurants per year. However, the number of closures is lower, at 0.14 per year per area. Similar results are presented by Muller and Neumann (2023) for Chicago's restaurant industry (and many other studies on the impact of e-commerce; see the Literature section). However, as the first restaurant joins the platform at different moments in different areas, this exercise is inadequate in the present case. The group of treated and control areas changes over time, and this must be considered to allow for precise identification of the treatment's effect. Therefore, to properly assess the effect of meal delivery on the area's restaurant activity, we use the method proposed by Callaway and Sant'Anna (2021), that is, the doubly robust difference-in-differences estimator, which is our baseline model.

Since we have a staggered adoption setting, the classic difference-in-differences framework does not retrieve the average treatment effect on the treated (ATT), as Callaway and Sant'Anna (2021) show. This occurs because the estimated β is a weighted average of effects given by three area comparisons: earlier versus later treated, treated versus untreated, and later versus earlier treated. The latter comparison biases the estimate for β since it compares areas presently receiving the treatment with areas that have already received the treatment. This happens

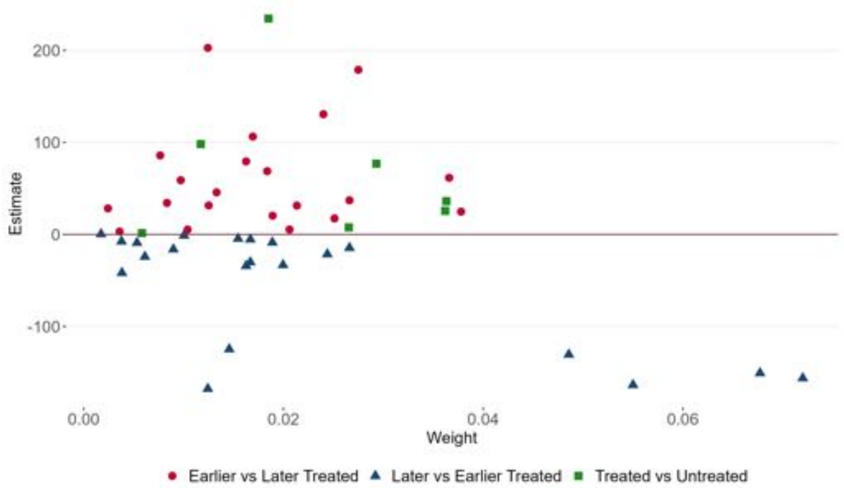
Table 2: Classic difference-in-differences estimates

Outcome	Estimated effect	95% CI inf.	95% CI sup.
Jobs	-10.67	-38.49	17.15
Openings	-0.75	-1.19	-0.31
Closures	-0.14	-0.31	0.02

Notes: This table displays the results of the classic difference-in-differences estimates for each outcome, following the specification (3), along with the respective 95 % confidence intervals. Standard errors are clustered at the district level, where a district is a collection of areas defined by IBGE.

because the treatment, or the restaurants' adoption of the delivery platform, increases over time for the areas, and an earlier area entrant ends up having a larger treatment effect than a later entrants. To illustrate the problem, we show in Figures 6, 7, and 8 the Goodman-Bacon (2021) decompositions. They indicate that large-weight improper comparisons produce the negative effects shown in Table 2.

Figure 6: Goodman-Bacon decomposition for jobs

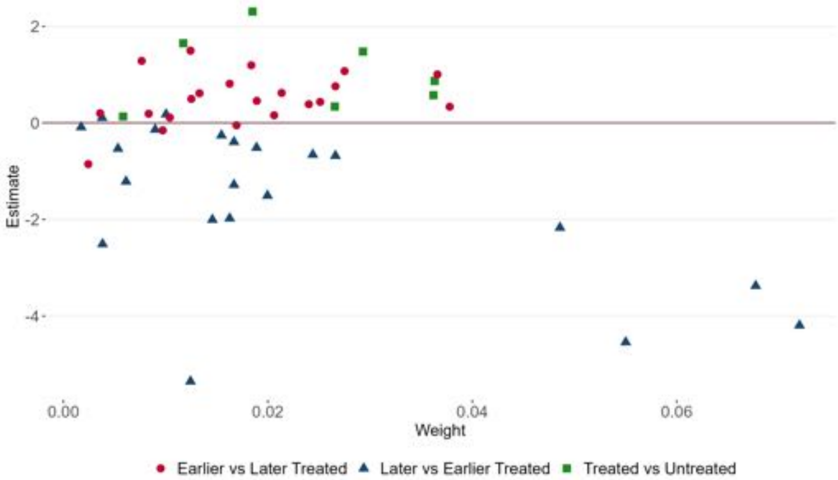


Notes: This figure presents the decomposition of the effects on jobs from Table 2, following Goodman-Bacon (2021). Each point represents a comparison group of one of the following types: earlier versus later treated, later versus earlier treated, and treated versus untreated.

We aggregate those decompositions in Table 3. The classic difference-in-differences estimator puts almost half the weight on comparisons between later and earlier treated groups, which have a large negative effect. Therefore, the canonical approach leads to biases in estimating the actual treatment effect.

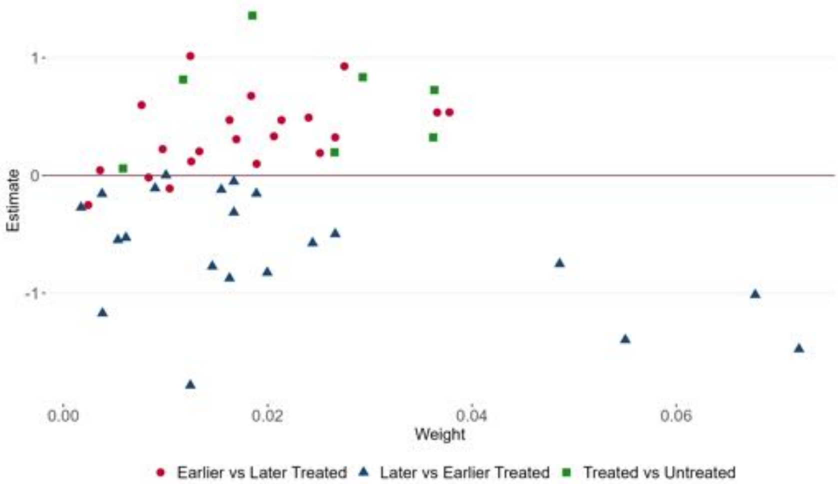
Even with this limitation, we continue the exercise by performing event studies for the effect of the treatment on jobs, openings, and closures (Figures 9, 10, and 11). For openings and closures, there is no effect before treatment and an increasing effect after the treatment. The latter occurs because other restaurants in the area may join the platform after the treatment. For jobs, there is a slightly negative effect before the treatment, which might be related to the

Figure 7: Goodman-Bacon decomposition for openings



Notes: This figure presents the decomposition of the effects on openings from Table 2, following Goodman-Bacon (2021). Each point represents a comparison group of one of the following types: earlier versus later treated, later versus earlier treated, and treated versus untreated.

Figure 8: Goodman-Bacon decomposition for closures



Notes: This figure presents the decomposition of the effects on closures from Table 2, following Goodman-Bacon (2021). Each point represents a comparison group of one of the following types: earlier versus later treated, later versus earlier treated, and treated versus untreated.

inadequacy of the method in a staggered adoption setting.

4.2 Staggered difference-in-differences estimator

This section presents the results obtained using the doubly robust difference-in-differences estimator proposed by Callaway and Sant'Anna (2021)[10]. We use a conditional parallel trends

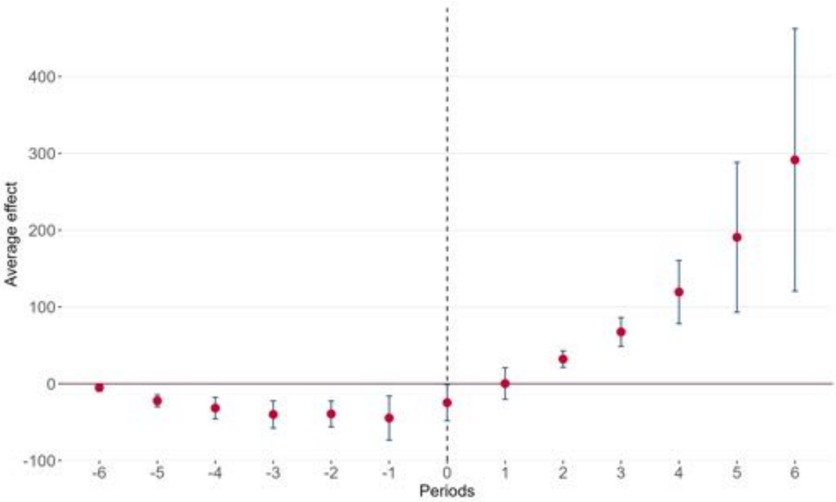
[10] One of the assumptions of Callaway and Sant'Anna (2021) model is the irreversibility of the treatment. This is true for most of the areas. However, a few areas eventually leave the platform. As the authors highlight, this assumption can be interpreted as if units do not forget about the treatment experience.

Table 3: Aggregate Goodman-Bacon decompositions

Comparison	Jobs		Openings		Closures	
	Estimate	Weight	Estimate	Weight	Estimate	Weight
Earlier vs Later Treated	63.00	0.37	0.60	0.37	0.42	0.37
Later vs Earlier Treated	-95.03	0.47	-2.45	0.47	-0.87	0.47
Treated vs Untreated	61.96	0.16	1.02	0.16	0.63	0.16

Notes: This table aggregates the results displayed in Figures 6, 7, and 8, showing the weighted average of the estimates for each group and its respective weight, which is determined by the share of observations within the group.

Figure 9: Event study for jobs



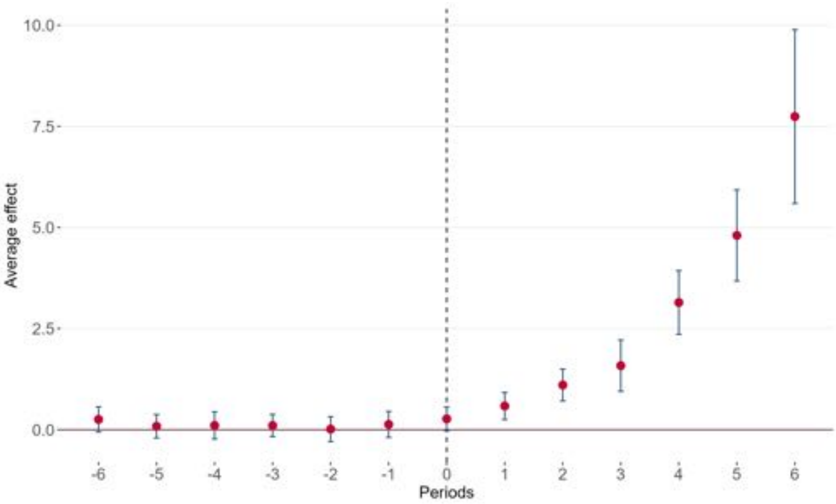
Notes: In this figure, each point represents an estimate of the coefficients of a dynamic difference-in-differences model, with the outcome of interest being the number of jobs. The error bars display the 95% confidence interval, and standard errors are clustered at the district level.

assumption, selecting as a covariate the share of full-service restaurants in the area in 2011, which is a pre-treatment period and does not, therefore, create a bad control problem. The establishments in the present study include full-service table-and-cloth restaurants, as well as fast-food, snack bars, and other types of food-serving firms. The share of full-service restaurants in the area works as a control variable because these establishments are larger and have more employees than the fast food type. Therefore, areas with a larger share of table-and-cloth restaurants have larger establishments and are similar in this dimension. Figures 12, 15, and 18 show that controlling for the share of restaurants guarantees the parallel trend assumption.

Table 4 displays the overall numbers for the food delivery effect on employment, openings, and closures of restaurants. These numbers refer to a typical area's yearly average effect from 2011

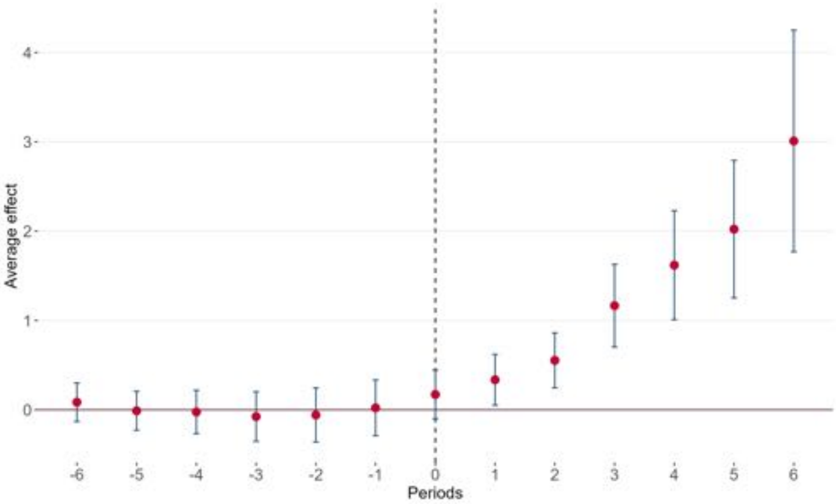
This is plausible in the present setting since it is reasonable to suppose that the use the delivery platform permanently affects the dynamics of the treated areas. As robustness, we drop those areas from the sample. As Table 6 and Figures 32–40 in the Appendix indicate, the results are almost the same relative to the baseline sample.

Figure 10: Event study for openings



Notes: In this figure, each point represents an estimate of the coefficients of a dynamic difference-in-differences model, with the outcome of interest being the number of openings. The error bars display the 95% confidence interval, and standard errors are clustered at the district level.

Figure 11: Event study for closures



Notes: In this figure, each point represents an estimate of the coefficients of a dynamic difference-in-differences model, with the outcome of interest being the number of closures. The error bars display the 95% confidence interval, and standard errors are clustered at the district level.

to 2018. The numbers are positive and significant at a 95% confidence interval. Nearly 94 jobs were created yearly in a typical area, while 0.74 restaurants closed and 1.37 restaurants opened. Compared with the previous estimation, there is an important change in the results. When the proper estimation method is applied, the results change from a negative to a positive effect of meal delivery on the area's restaurant industry. Now, the effect on jobs is positive, as are the effects on openings and closures, with the openings of new restaurants trumping the increase in closures, leading to a net increase in the number of establishments. In the previous estimation, the difference in openings and closures also led to increasing numbers of establishments, although with negative coefficients.

Table 4: Aggregate ATT estimates

Outcome	Estimated ATT	95% CI inf.	95% CI sup.
Jobs	97.58	42.37	152.79
Openings	1.42	0.59	2.25
Closures	0.77	0.23	1.31

Notes: This table displays the results of the aggregate estimates for each outcome, using the doubly robust estimator of Callaway and Sant'Anna (2021), along with the respective 95 % confidence intervals. Standard errors are clustered at the district level.

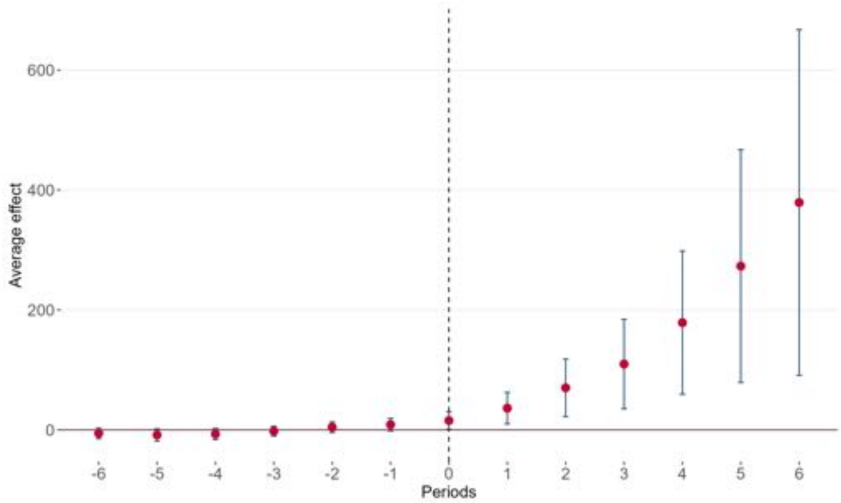
4.2.1 Effects on employment

Now we analyze the overall results in detail. Figure 12 shows the average ATT by length of exposure. There is no difference in employment by area between the treatment and the control groups before treatment. This is a significant result in that the potential selection bias of restaurants joining the platform is dealt with. Therefore, the positive effect observed does not result from areas with better growth potential joining the platform earlier than areas with less potential. The increasing average effect after the treatment may be due to a positive cumulative effect because more restaurants may join the platform over time in the area and earlier entrants may become more successful. Figure 13 supports this explanation by showing the ATT by groups of areas that join the platform in the same year, as the effect is larger for the earlier entrants. Although there is no area selection, as the restaurants accumulate experience delivering meals using the platform, they may gain a competitive advantage because they adopt better strategies than the competition. Figure 14 complements the analysis by illustrating the effect of joining the platform by year. There is a lower initial effect of almost 50 jobs per area in 2012, followed by a steady effect of nearly 100 jobs per year for each treated area.

4.2.2 Effects on restaurant openings and closures

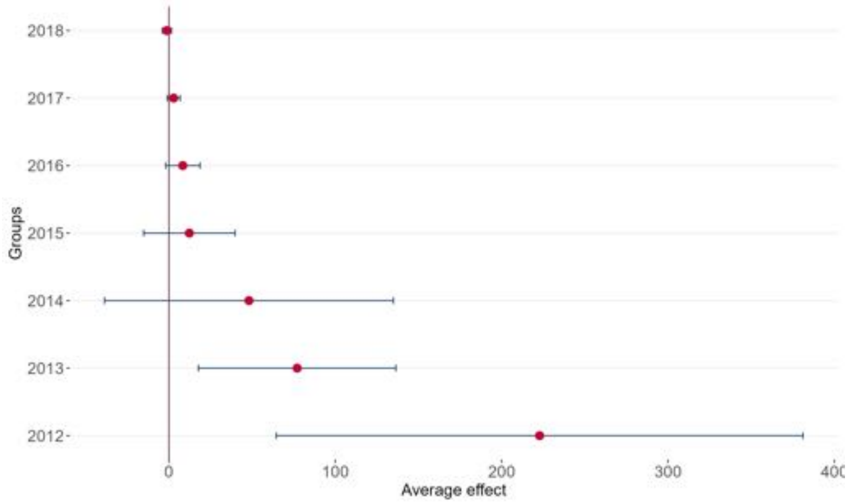
The following three figures show the impact of the app on openings. Figure 15 shows the treatment intensity by length of exposure. Again, we observe parallel trends before treatment and an increasing effect afterward. Thus, we can rule out the survival of the fittest firms driving the results since we are analyzing the entry of restaurants using the meal delivery platform. Earlier entrant areas have more openings than new ones. In Figure X, we see that earlier entrant areas also show more closings. The conclusion is that meal delivery entry in an area increases restaurant turnover, although there are more openings than closures, with a final positive net effect. Figure 16 shows the same pattern as Figure 13, with larger effects for the earlier entrant areas. By contrast, Figure 17 displays an increasing number of restaurant openings. This may represent a meal delivery-associated reduction in the cost of opening a restaurant. As new restaurants are adapted to delivering meals, it becomes easier to enter the market since they can avoid rent and other mandatory expenses associated with brick-and-mortar businesses.

Figure 12: Average effects on jobs by length of exposure



Notes: This figure illustrates the adjusted event study for jobs generated by the dynamic aggregation of the treatment effects estimated using the doubly robust estimator proposed by Callaway and Sant'Anna (2021). Error bars represent the 95% confidence intervals.

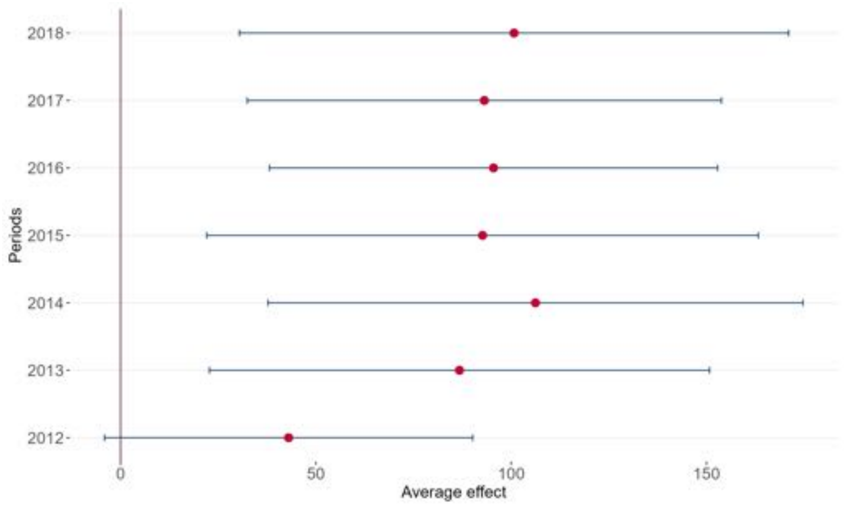
Figure 13: Average effects on jobs by group



Notes: This figure illustrates the treatment effects on jobs by group, where each group represents areas that were first treated in the same year. Treatment effects were estimated using the doubly robust estimator by Callaway and Sant'Anna (2021). Error bars depict the 95% confidence intervals.

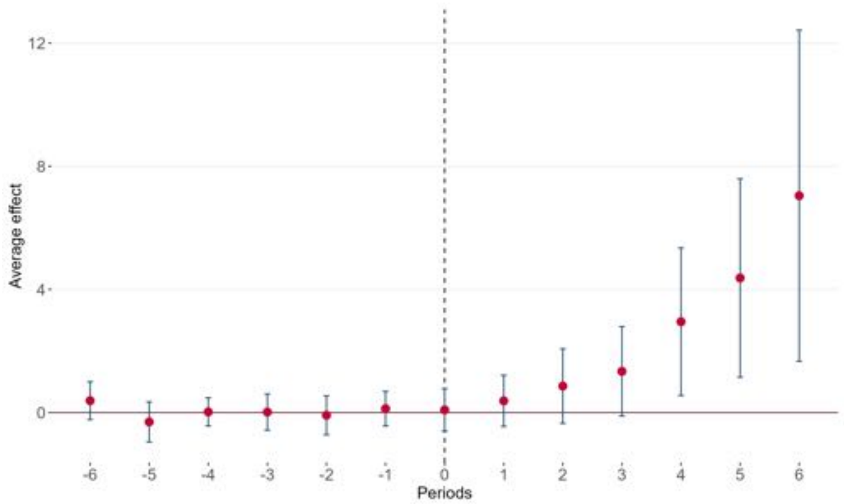
Observing the results for closures of restaurants, we verify the same effect of meal delivery as for openings, only with fewer closures. Figure 18 shows the same increasing effect over time. Areas with earlier entrants on the platform have more closures; Figure 19 shows stronger effects for earlier entrants, and Figure 20 shows an increasing effect on the treated group. These results indicate that introducing a digital platform for food delivery increases turnover in the restaurant business.

Figure 14: Average effects on jobs by period



Notes: This figure illustrates the treatment effects on jobs by calendar year, aggregating the estimates from the doubly robust estimator by Callaway and Sant'Anna (2021) across years. Error bars depict the 95% confidence intervals.

Figure 15: Average effects on openings by length of exposure

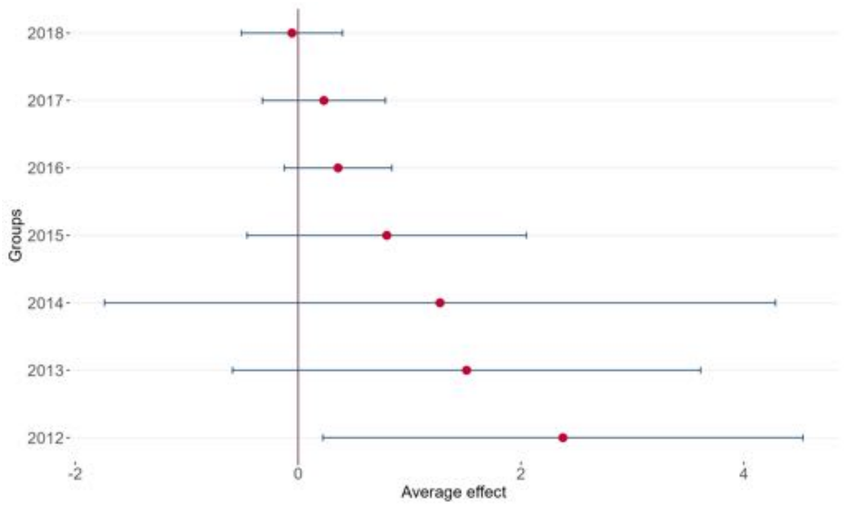


Notes: This figure illustrates the adjusted event study for openings generated by the dynamic aggregation of the treatment effects estimated using the doubly robust estimator proposed by Callaway and Sant'Anna (2021). Error bars represent the 95% confidence intervals.

4.3 Network effect

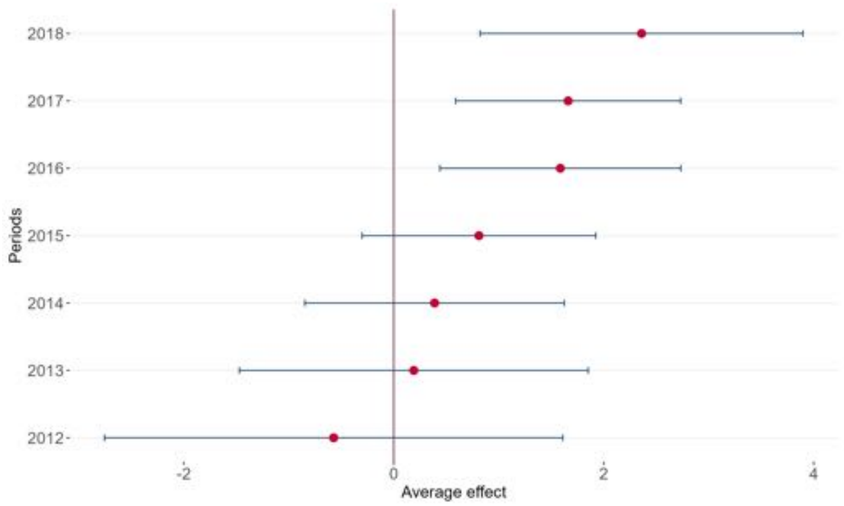
We now consider the network effect. According to the theory (Jullien et al. 2021), there are positive externalities in more restaurants and consumers joining the platform. As such, the delivery app's positive effect on business performance may increase over time. Figures X to X show an always-increasing average effect of the treatment over time for jobs, openings, and closures, possibly due to the network effect. To capture this, we estimate a model similar to the one described in Equation 3 using the share of restaurants on the platform as the explanatory

Figure 16: Average effects on openings by group



Notes: This figure illustrates the treatment effects on openings by group, where each group represents areas that were first treated in the same year. Treatment effects were estimated using the doubly robust estimator by Callaway and Sant'Anna (2021). Error bars depict the 95% confidence intervals.

Figure 17: Average effects on openings by period

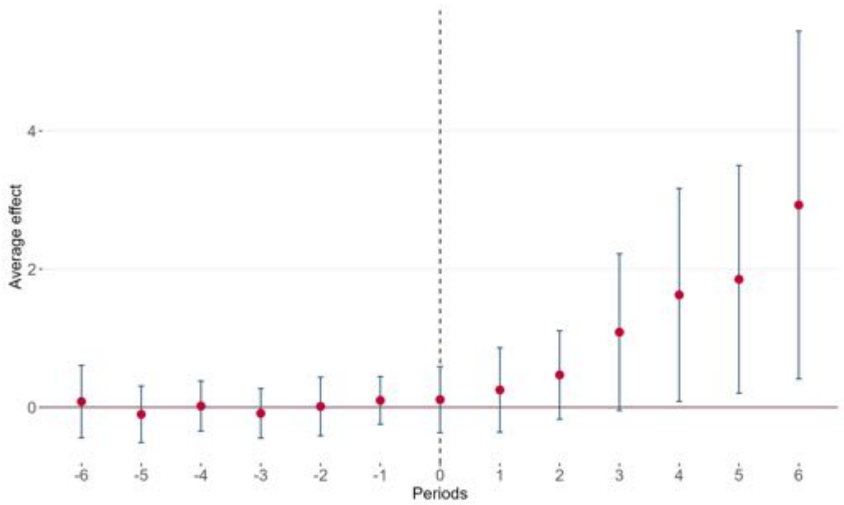


Notes: This figure illustrates the treatment effects on openings by calendar year, aggregating the estimates from the doubly robust estimator by Callaway and Sant'Anna (2021) across years. Error bars depict the 95% confidence intervals.

variable. Table 5 shows the results for the three outcomes.

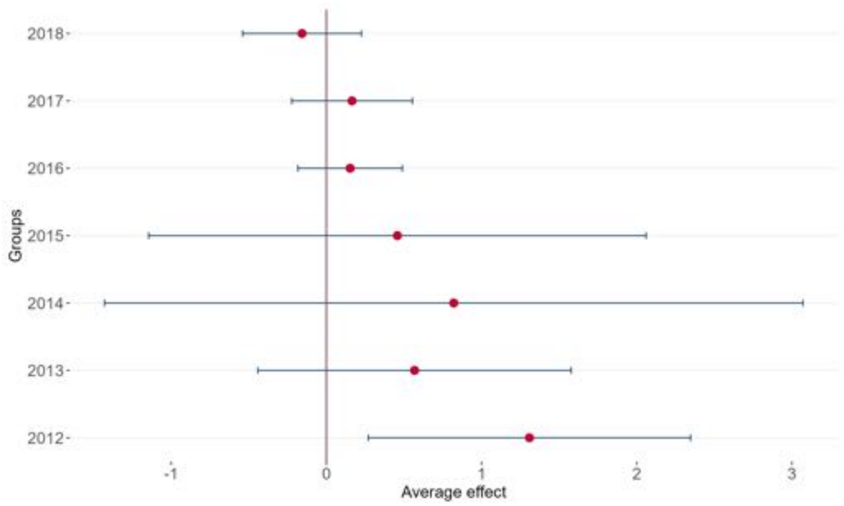
The estimated coefficients are positive, significant, and similar to those obtained using the Callaway and Sant'Anna (2021) method. Given that an average 20% of all restaurants use the app in 2018, we have a yearly increase of 60 jobs, an entry of 1.3 restaurants, and a market exit of 0.3 establishments per area. These numbers are between 30% and 50% smaller than those obtained in the previous subsection, though they are not statistically different at a 95% confidence interval.

Figure 18: Average effects on closures by length of exposure



Notes: This figure illustrates the adjusted event study for closures generated by the dynamic aggregation of the treatment effects estimated using the doubly robust estimator proposed by Callaway and Sant'Anna (2021). Error bars represent the 95% confidence intervals.

Figure 19: Average effects on closures by group

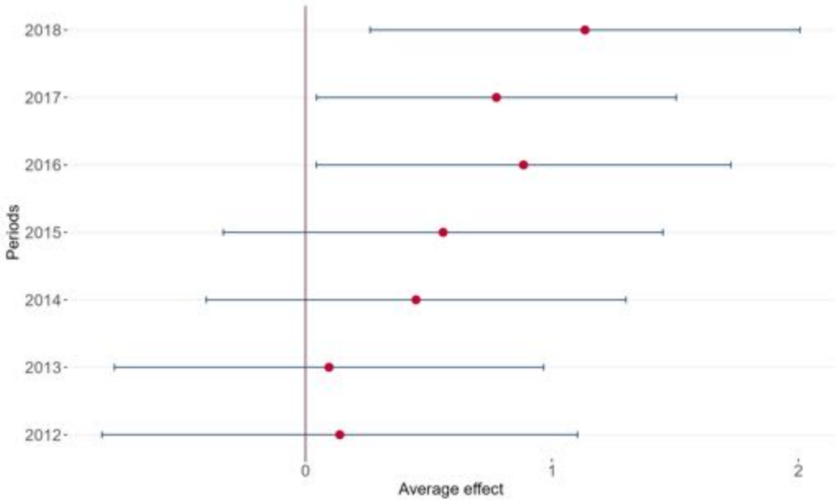


Notes: This figure illustrates the treatment effects on closures by group, where each group represents areas that were first treated in the same year. Treatment effects were estimated using the doubly robust estimator by Callaway and Sant'Anna (2021). Error bars depict the 95% confidence intervals.

4.4 Heterogeneity

Different area characteristics, such as population and area size, the number of households, and the age of restaurants, might drive the above results. Thus, we investigate how the results might change for different levels of those variables. We define two groups of areas –high and low – for each variable based on the median value. Figure 21 shows the effects on the level of jobs in the areas. The effect is positive for all groups, albeit insignificant for the more populated areas. There is no statistical difference in the effects for different area sizes and numbers of

Figure 20: Average effects on closures by period



Notes: This figure illustrates the treatment effects on closures by calendar year, aggregating the estimates from the doubly robust estimator by Callaway and Sant'Anna (2021) across years. Error bars depict the 95% confidence intervals.

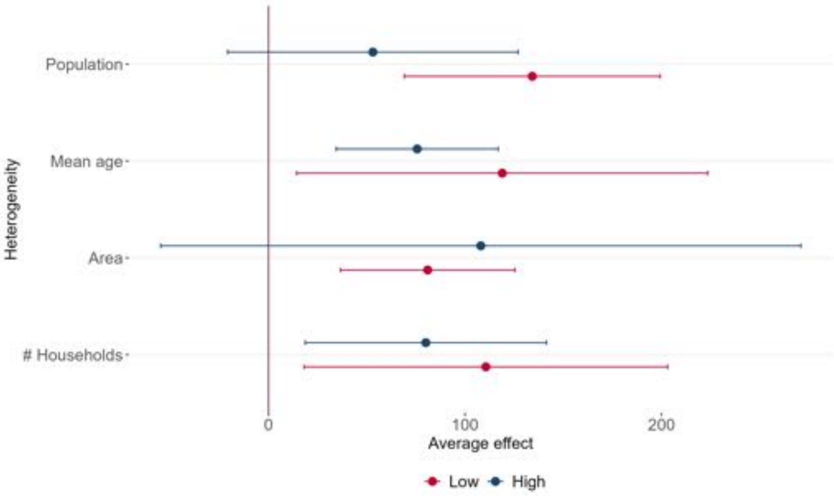
Table 5: Estimated regressions of the app share on outcomes

	Jobs	Openings	Closures
Share Platform	301.38***	6.38***	1.45**
	(109.41)	(1.46)	(0.73)
Area FE	YES	YES	YES
Year FE	YES	YES	YES
Num. obs.	4000	4000	4000
R^2	0.97	0.77	0.65
Adj. R^2	0.97	0.74	0.60

Notes: The dependent variables are the number of jobs, openings, and closures. The covariate represents the share of restaurants within the area that are members of the platform in a given year. The specification includes area and year fixed effects, and standard errors are clustered at the district level. Significance levels: $***p < 0.01$; $**p < 0.05$; $*p < 0.1$.

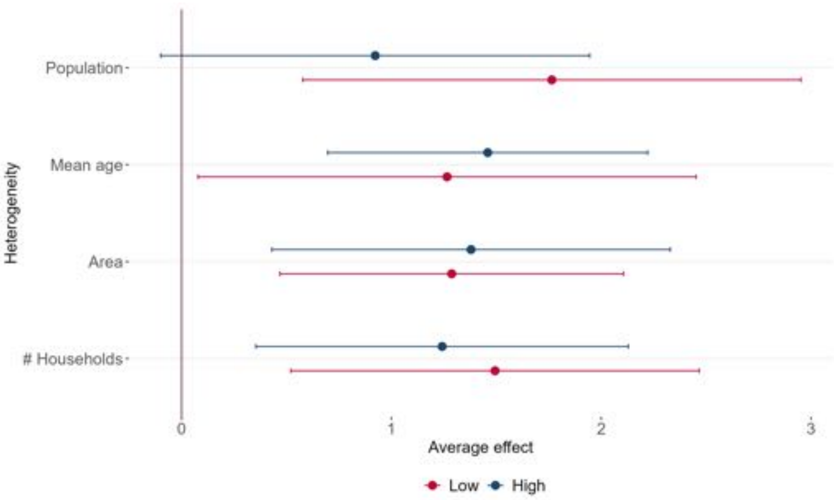
households. The effect is larger in areas with smaller populations and younger restaurants. However, except for population, the differences are close to the confidence interval limits. As the effect is insignificant for more populated areas, those with smaller populations drive the overall positive effect on jobs. The results for openings (Figure 22) and closures (Figure 23) indicate no statistical difference across different types of area. Although the effect is larger in less populated areas, the difference is not statistically significant, nor is the effect in more populated areas. Thus, the positive effects of meal delivery on restaurant activity are pervasive. However, they are marginally stronger in areas with smaller populations and non-significant in more populous ones.

Figure 21: Effects on jobs by area characteristics



Notes: This figure illustrates the treatment effects on jobs for different subsamples. Population is defined as the number of residents in permanent private households within an area. Mean age is defined as the mean age (in years) of the restaurants within an area. Area represents the total km^2 of the unit. The number of households is given by the total number of permanent private households within an area. All of these variables are derived from the aggregate results by census tract of the 2010 Brazilian Census. Error bars depict the 95% confidence intervals, and standard errors are clustered at the district level.

Figure 22: Effects on openings by area characteristics

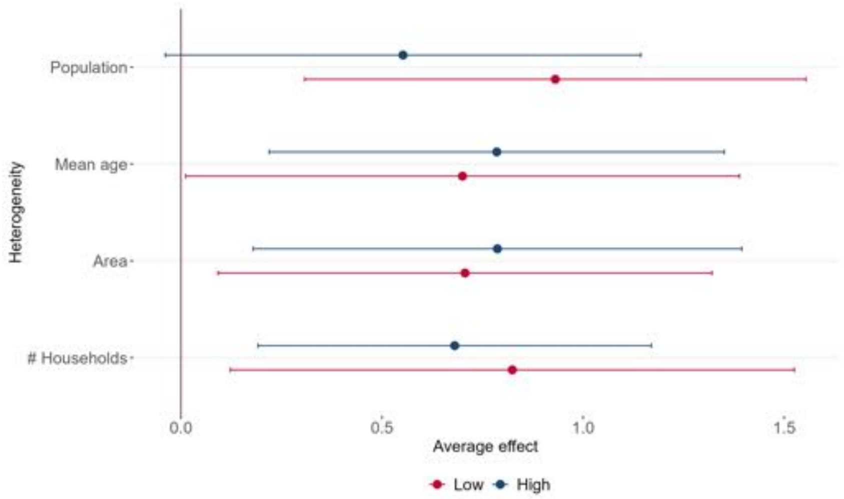


Notes: This figure illustrates the treatment effects on openings for different subsamples. Population is defined as the number of residents in permanent private households within an area. Mean age is defined as the mean age (in years) of the restaurants within an area. Area represents the total km^2 of the unit. The number of households is given by the total number of permanent private households within an area. All of these variables are derived from the aggregate results by census tract of the 2010 Brazilian Census. Error bars depict the 95% confidence intervals, and standard errors are clustered at the district level.

5 Conclusions

Although some restaurants have long been delivering meals (e.g., pizza and Chinese food outlets), the practice has increased with the introduction of online platforms that make ordering

Figure 23: Effects on closures by area characteristics



Notes: This figure illustrates the treatment effects on closures for different subsamples. Population is defined as the number of residents in permanent private households within an area. Mean age is defined as the mean age (in years) of the restaurants within an area. Area represents the total km^2 of the unit. The number of households is given by the total number of permanent private households within an area. All of these variables are derived from the aggregate results by census tract of the 2010 Brazilian Census. Error bars depict the 95% confidence intervals, and standard errors are clustered at the district level.

food more accessible for restaurants and consumers. This activity has shown intensive growth in recent years and constitutes a significant innovation in the restaurant business. Convenience comes at a cost, however, in the form of necessary adaptations of production lines and platform fees. The right balance is yet to be established, as few studies deal with the subject. In the present case, we assess the impact of meal delivery in two large Brazilian cities, encompassing more than 30,000 restaurants. We measure the effects of joining the country's leading meal delivery platform on employment and the openings and closures of restaurants.

Using the information on individual restaurants, we examine 500 areas within the two cities from 2011 (a year before the first restaurant started using the meal delivery platform) to 2018. By dealing with areas within cities, we recognize that, for most establishments, restaurant markets are spatially limited. We follow the evolution of jobs, openings, and closures of restaurants in the areas from the moment the first restaurant starts delivering meals using the app. We first use a staggered difference-in-differences method to establish the effect on the areas from the point when they begin to deliver meals at different times. This means that the composition of the control and treatment groups varies over time. We then examine the share of restaurants in the area to capture the effects of network externalities on platform use.

Our results indicate positive effects for the three variables in question. The estimated average effect per area per year—using the staggered difference-in-differences approach—is the creation of 94 jobs (between 38 and 150, with a 5% confidence interval) and the opening of 1.4 (0.5–2.2) and the closure of 0.7 (0.2–1.2) establishments. The aggregate effect over the two cities is a yearly increase of 0.15% in the number of restaurants and 3.3% in the number of jobs. We obtain slightly smaller numbers when we use the share of restaurants using the app as our main explanatory variable. Our heterogeneity analysis does not indicate that this conclusion is specific to a particular type of area. Therefore, the balance between the increased costs involved in the adoption of the delivery platform and the benefits derived seems to be positive, judging by the level of activity. This result does not include jobs related to the delivery of meals, which would have to be considered if the impact of the platform is to be comprehensively assessed.

This conclusion contrasts with previous analyzes that point to negative or null effects. Several studies on the impact of e-commerce on local activities reveal negative effects as consumers purchase from outside sources. The restaurant industry is different, however, because restaurant markets are spatially restricted, and local suppliers serve local demand. The scant literature on the issue deals with entire cities, observing negative or null effects. By examining geographically limited areas within the two cities, the present study reflects the reality of the sector. Additionally, using a staggered difference-in-differences methodology, we address a limitation of those studies that deal with constant treatment and control groups. Finally, we deal with two large cities in a developing country, contrasting with studies that concentrate on developed countries.

References

Alcedo, Joel, Alberto Cavallo, Bricklin Dwyer, Prachi Mishra, and Antonio Spilimbergo (2022). *E-commerce during COVID: Stylized facts from 47 economies.* Tech. rep. National Bureau of Economic Research.

Alvarez-Palau, Eduard J, Laura Calvet-Liñán, Marta Viu-Roig, Mariem Gandouz, and Angel A Juan (2022). "Economic profitability of last-mile food delivery services: Lessons from Barcelona". In: *Research in Transportation Business & Management* 45, p. 100659.

Armstrong, Mark (2006). "Competition in two-sided markets". In: *The RAND journal of economics* 37.3, pp. 668–691.

Bauer, Anahid and Sofia Fernandez Guerrico (2022). *Effects of e-commerce on local labor markets.* Tech. rep. Working Paper.

Bermeo, Caren Gabriela Castillo, Alessio Tony Cavalcanti de Almeida, and Hilton Martins de Brito Ramalho (2023). "Impact assessment of the digitization of restaurants and snack bars in the state of Paraiba-Brazil". In: *Revista Economica do Nordeste* 54.2, pp. 72–89.

Callaway, Brantly and Pedro HC Sant'Anna (2021). "Difference-in-differences with multiple time periods". In: *Journal of econometrics* 225.2, pp. 200–230.

Chava, Sudheer, Alexander Oettl, Manpreet Singh, and Linghang Zeng (2022). "Creative Destruction? Impact of E-Commerce on the Retail Sector". In: *NBER Working Paper* w30077.

Cho, Meehee, Mark A Bonn, and Jun Justin Li (2019). “Differences in perceptions about food delivery apps between single-person and multi-person households”. In: *International Journal of Hospitality Management* 77, pp. 108–116.

Chun, Hyunbae, Hailey Hayeon Joo, Jisoo Kang, Yoonsoo Lee, et al. (2020). *Diffusion of E-Commerce and Retail Job Apocalypse: Evidence from Credit Card Data on Online Spending*. Tech. rep. Center for Economic Institutions, Institute of Economic Research ...

Cohen, Peter, Robert Hahn, Jonathan Hall, Steven Levitt, and Robert Metcalfe (2016). *Using big data to estimate consumer surplus: The case of uber*. Tech. rep. National Bureau of Economic Research.

Collison, Jack (2020). “The impact of online food delivery services on restaurant sales”. In: *Department of Economics, Stanford University, Advised by Professor Liran Einav, Spring*.

Dano, Darryll Rose and Ashok Chopra (2021). “Impact of Delivery Apps Commission Rates on UAE Restaurants”. In: *2021 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE)*. IEEE, pp. 273–278.

Das, Shantashree and Debomalya Ghose (2019). “Influence of online food delivery apps on the operations of the restaurant business”. In: *International Journal of Scientific and Technology Research* 8.12, pp. 1372–1377.

Ding, Wenzhi, Ross Levine, Chen Lin, and Wensi Xie (2021). “Corporate immunity to the COVID-19 pandemic”. In: *Journal of Financial Economics* 141.2, pp. 802–830.

Dolfen, Paul, Liran Einav, Peter J Klenow, Benjamin Klopack, Jonathan D Levin, Larry Levin, and Wayne Best (2023). “Assessing the gains from e-commerce”. In: *American Economic Journal: Macroeconomics* 15.1, pp. 342–370.

Frederick, Dsouza Prima and Ganesh Bhat (2022). “Customer Perception Towards Online Food Delivery Services-Development of Conceptual Model”. In: *International Journal of Case Studies in Business, IT, and Education (IJCSBE)* 6.1, pp. 470–505.

Goodman-Bacon, Andrew (2021). “Difference-in-differences with variation in treatment timing”. In: *Journal of Econometrics* 225.2, pp. 254–277.

Gupta, Mitali (2019). “A Study on Impact of Online Food delivery app on Restaurant Business special reference to zomato and swiggy”. In: *International Journal of Research and Analytical Reviews* 6.1, pp. 889–893.

Hirschberg, Carsten, Alexander Rajko, Thomas Schumacher, and Martin Wrulich (2016). “The changing market for food delivery”. In.

Jullien, Bruno, Alessandro Pavan, and Marc Rysman (2021). “Two-sided markets, pricing, and network effects”. In: *Handbook of Industrial Organization*. Vol. 4. 1. Elsevier, pp. 485–592.

Khan, Mahmood A (2020). “Technological disruptions in restaurant services: Impact of innovations and delivery services”. In: *Journal of Hospitality & Tourism Research* 44.5, pp. 715–732.

Kim, Jaewook, Jewoo Kim, Seul Ki Lee, and Liang Rebecca Tang (2020). “Effects of epidemic disease outbreaks on financial performance of restaurants: Event study method approach”. In: *Journal of Hospitality and Tourism Management* 43, pp. 32–41.

Kim, Jaewook, Jewoo Kim, and Yiqi Wang (2021). “Uncertainty risks and strategic reaction of restaurant firms amid COVID-19: Evidence from China”. In: *International Journal of Hospitality Management* 92, p. 102752.

Kumar, Pawan and Harpreet Kaur (2021). “Determinants of e-commerce adoption: a literature-derived model for developing nations”. In: *International Journal of Business Information Systems* 37.2, pp. 182–199.

Lee, Eun-Yong, Soo-Bum Lee, and Yu Jung Jennifer Jeon (2017). “Factors influencing the behavioral intention to use food delivery apps”. In: *Social Behavior and Personality: an international journal* 45.9, pp. 1461–1473.

Li, Zhuoxin and Gang Wang (2020). “The role of on-demand delivery platforms in restaurants”. In: *Available at SSRN 3813891*.

Meenakshi, N and Anamika Sinha (2019). “Food delivery apps in India: wherein lies the success strategy?” In: *Strategic Direction* 35.7, pp. 12–15.

Muller, Michelle and Jurgen Neumann (2023). “Bring me my Meal on your Wheel-An Empirical Analysis of the Impact of Food Delivery Platforms on Local Restaurant Employment”. In.

Pigatto, Gessuir, Joao Guilherme de Camargo Ferraz Machado, Amanda dos Santos Negreti, and Lucas Miranda Machado (2017). “Have you chosen your request? Analysis of online food delivery companies in Brazil”. In: *British Food Journal* 119.3, pp. 639–657.

Ray, Arghya, Amandeep Dhir, Pradip Kumar Bala, and Puneet Kaur (2019). “Why do people use food delivery apps (FDA)? A uses and gratification theory perspective”. In: *Journal of retailing and consumer services* 51, pp. 221–230.

Rochet, Jean-Charles and Jean Tirole (2003). “Platform competition in two-sided markets”. In: *Journal of the european economic association* 1.4, pp. 990–1029.

Seghezzi, Arianna, Matthias Winkenbach, and Riccardo Mangiaracina (2021). “On-demand food delivery: A systematic literature review”. In: *The International Journal of Logistics Management* 32.4, pp. 1334–1355.

Song, Hyoung Ju, Jihwan Yeon, and Seoki Lee (2021). “Impact of the COVID-19 pandemic: Evidence from the US restaurant industry”. In: *International Journal of Hospitality Management* 92, p. 102702.

Tandon, Anushree, Puneet Kaur, Yogesh Bhatt, Matti Mäntymäki, and Amandeep Dhir (2021). “Why do people purchase from food delivery apps? A consumer value perspective”. In: *Journal of Retailing and Consumer Services* 63, p. 102667.

Van Veldhoven, Ziboud, Paulien Aerts, Sanne Lies Ausloos, Jente Bernaerts, and Jan Vanthienen (2021). "The impact of online delivery services on the financial performance of restaurants". In: *2021 7th International Conference on Information Management (ICIM)*. IEEE, pp. 13–17.

Vitt, David (2017). "Estimating the impact of e-commerce on retail exit and entry using Google Trends". In: *Available at SSRN 3076142*.

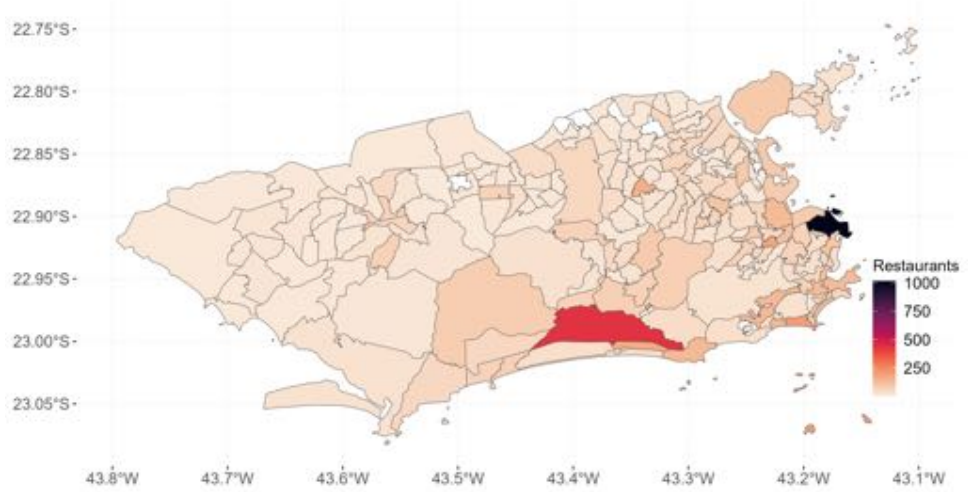
Yang, Mu and Chunjia Han (2021). "Revealing industry challenge and business response to Covid-19: a text mining approach". In: *International Journal of Contemporary Hospitality Management* 33.4, pp. 1230–1248.

Yost, Elizabeth, Murat Kizildag, and Jorge Ridderstaat (2021). "Financial recovery strategies for restaurants during COVID-19: Evidence from the US restaurant industry". In: *Journal of Hospitality and Tourism Management* 47, pp. 408–412.

YoungGak, KIM, KWON Hyeog Ug, FUKAO Kyoji, and IKEUCHI Kenta (2021). *E-Commerce, Firm Performance and Economic Dynamism: Empirical analysis using the Economic Census (Japanese)*. Tech. rep.

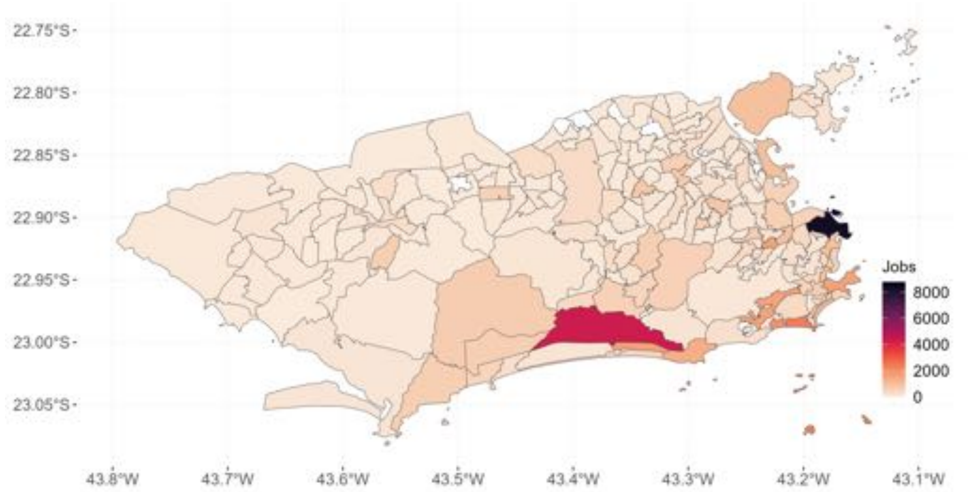
6 Appendix

Figure 24: Spatial dispersion of restaurants in Rio de Janeiro, 2018



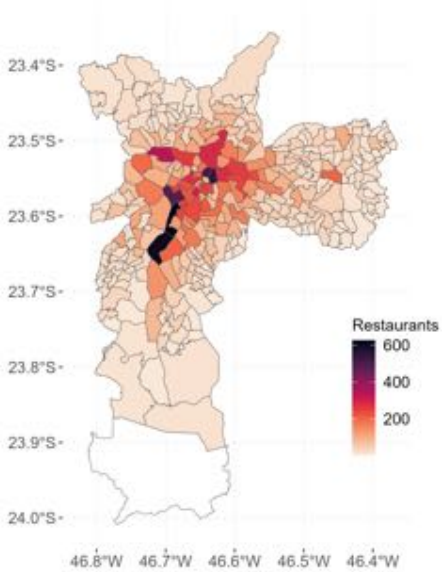
Notes: This figure illustrates distribution of the number of restaurants for the areas of Rio de Janeiro in 2018.

Figure 25: Spatial dispersion of jobs in Rio de Janeiro, 2018



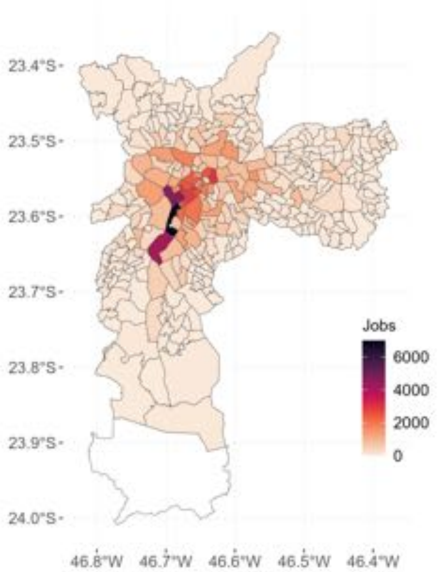
Notes: This figure illustrates distribution of the number of jobs for the areas of Rio de Janeiro in 2018.

Figure 26: Spatial dispersion of restaurants in Sao Paulo, 2018



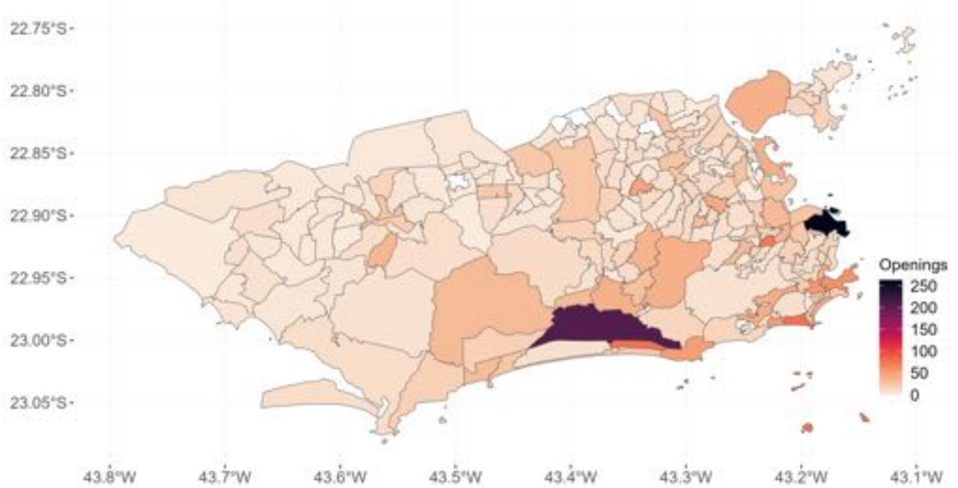
Notes: This figure illustrates distribution of the number of restaurants for the areas of Sao Paulo in 2018.

Figure 27: Spatial dispersion of jobs in Sao Paulo, 2018



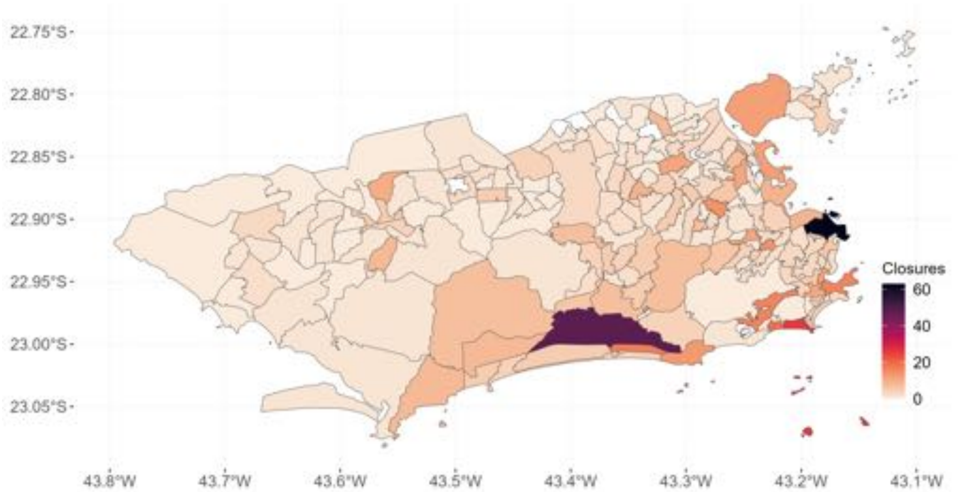
Notes: This figure illustrates distribution of the number of jobs for the areas of Sao Paulo in 2018.

Figure 28: Spatial dispersion of openings in Rio de Janeiro, 2011–2018



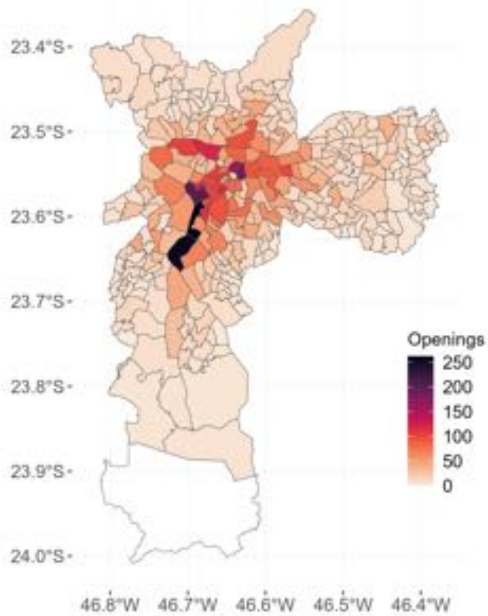
Notes: This figure illustrates distribution of the number of openings for the areas of Rio de Janeiro for the year period from 2011 to 2018.

Figure 29: Spatial dispersion of closures in Rio de Janeiro, 2011–2018



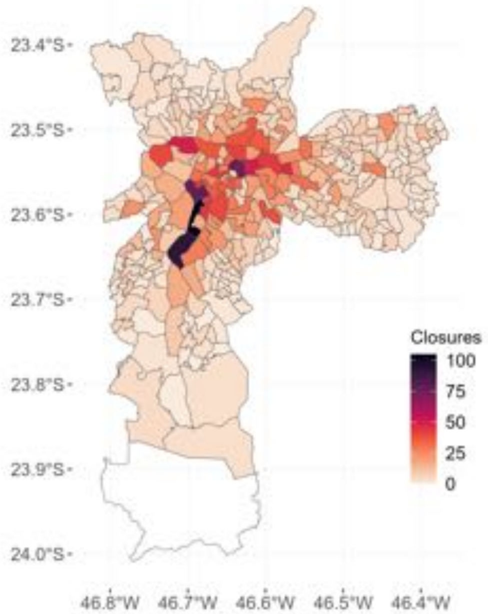
Notes: This figure illustrates distribution of the number of closures for the areas of Rio de Janeiro for the year period from 2011 to 2018.

Figure 30: Spatial dispersion of openings in Sao Paulo, 2011–2018



Notes: This figure illustrates distribution of the number of openings for the areas of Sao Paulo for the year period from 2011 to 2018.

Figure 31: Spatial dispersion of closures in Sao Paulo, 2011–2018



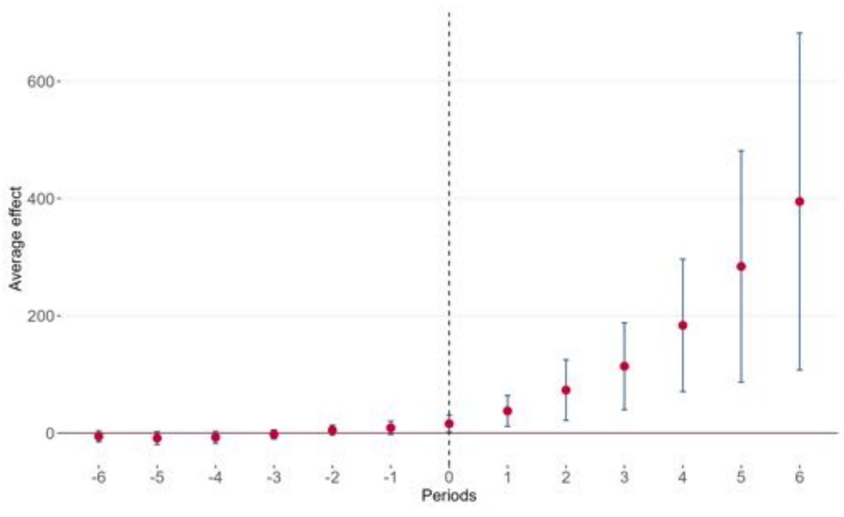
Notes: This figure illustrates distribution of the number of closures for the areas of Sao Paulo for the year period from 2011 to 2018.

Table 6: Robustness: Aggregate ATT

Outcome	Estimated ATT	95% CI inf.	95% CI sup.
Jobs	97.58	42.37	152.79
Openings	1.42	0.59	2.25
Closures	0.77	0.23	1.31

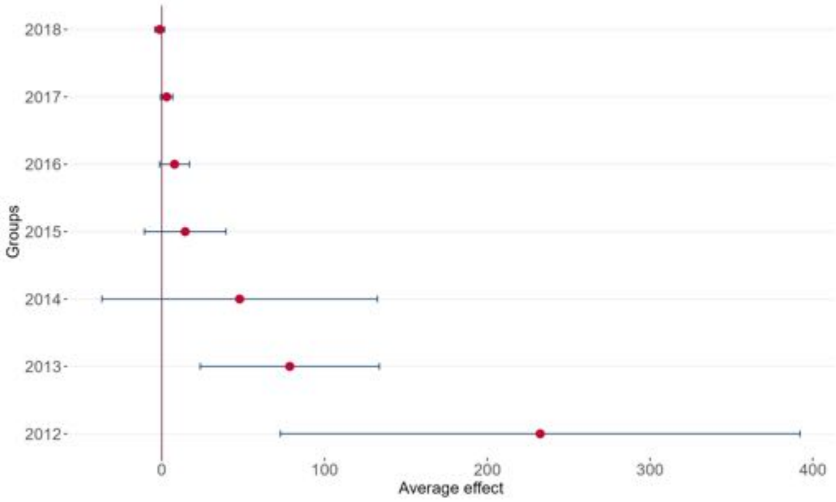
Notes: This table displays the results of the aggregate estimates for each outcome, using the doubly robust estimator of Callaway and Sant'Anna (2021), along with the respective 95 % confidence intervals. The sample was restricted to those areas that do not exhibit a reversibility of the treatment status. Standard errors are clustered at the district level.

Figure 32: Robustness: Average effect on jobs by length of exposure



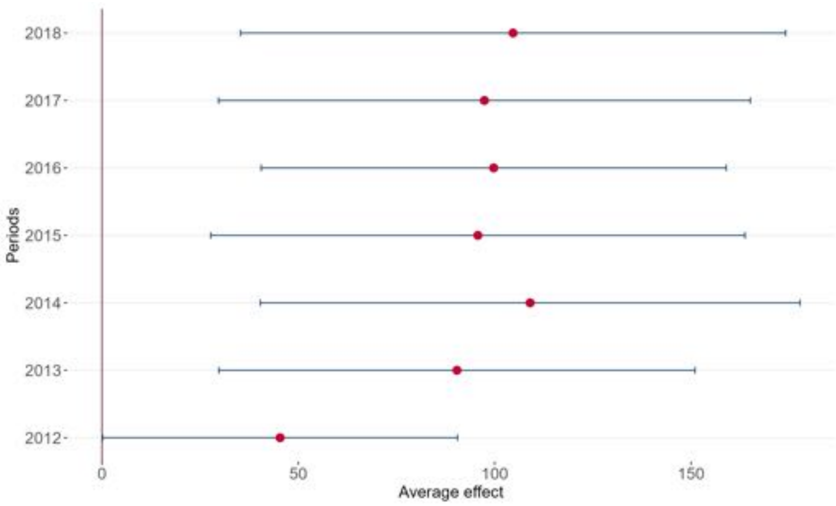
Notes: This figure illustrates the adjusted event study for jobs generated by the dynamic aggregation of the treatment effects estimated using the doubly robust estimator proposed by Callaway and Sant'Anna (2021). The sample was restricted to those areas that do not exhibit a reversibility of the treatment status. Error bars represent the 95% confidence intervals.

Figure 33: Robustness: Average effect on jobs by group



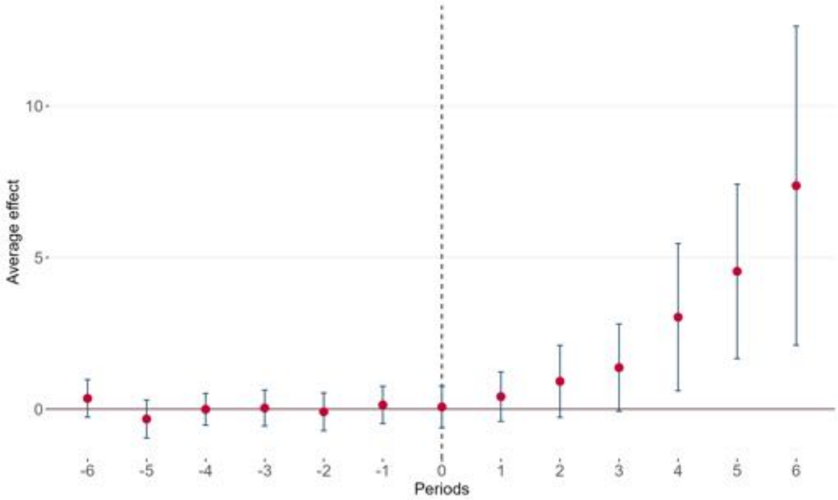
Notes: This figure illustrates the treatment effects on jobs by group, where each group represents areas that were first treated in the same year. Treatment effects were estimated using the doubly robust estimator by Callaway and Sant'Anna (2021). The sample was restricted to those areas that do not exhibit a reversibility of the treatment status. Error bars depict the 95% confidence intervals.

Figure 34: Robustness: Average effect on jobs by period



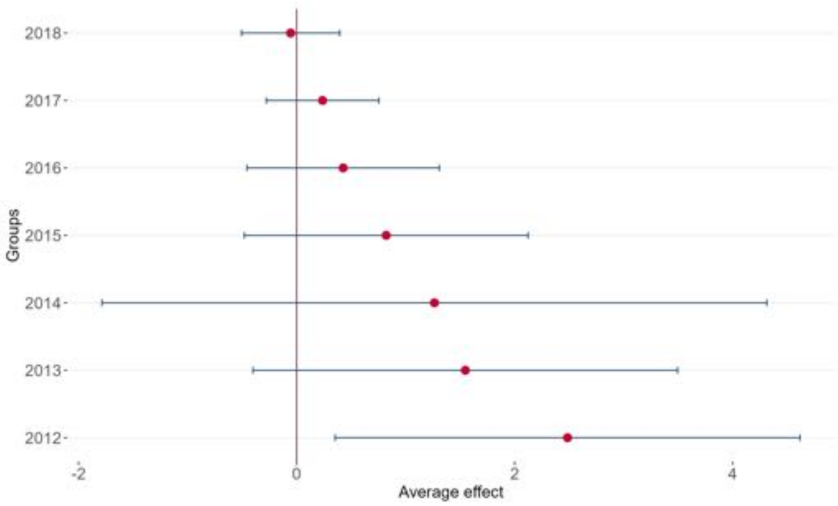
Notes: This figure illustrates the treatment effects on jobs by calendar year, aggregating the estimates from the doubly robust estimator by Callaway and Sant'Anna (2021) across years. The sample was restricted to those areas that do not exhibit a reversibility of the treatment status. Error bars depict the 95% confidence intervals.

Figure 35: Robustness: Average effect on openings by length of exposure



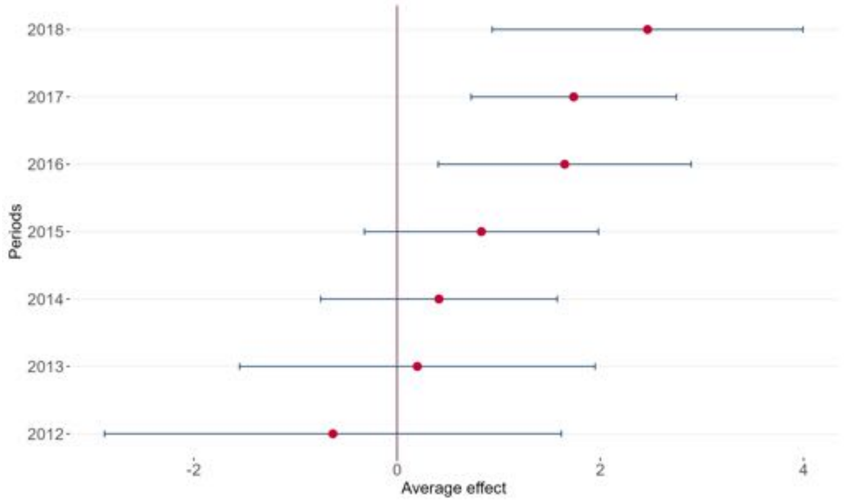
Notes: This figure illustrates the adjusted event study for openings generated by the dynamic aggregation of the treatment effects estimated using the doubly robust estimator proposed by Callaway and Sant'Anna (2021). The sample was restricted to those areas that do not exhibit a reversibility of the treatment status. Error bars represent the 95% confidence intervals.

Figure 36: Robustness: Average effect on openings by group



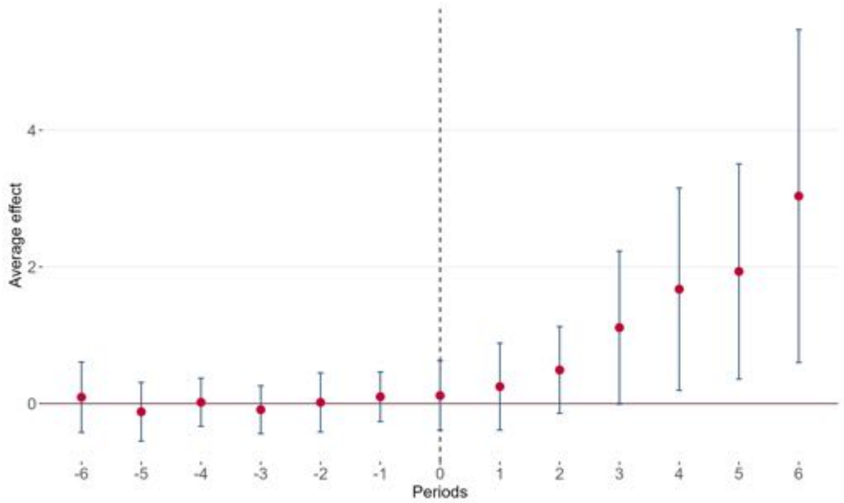
Notes: This figure illustrates the treatment effects on openings by group, where each group represents areas that were first treated in the same year. Treatment effects were estimated using the doubly robust estimator by Callaway and Sant'Anna (2021). The sample was restricted to those areas that do not exhibit a reversibility of the treatment status. Error bars depict the 95% confidence intervals.

Figure 37: Robustness: Average effect on openings by period



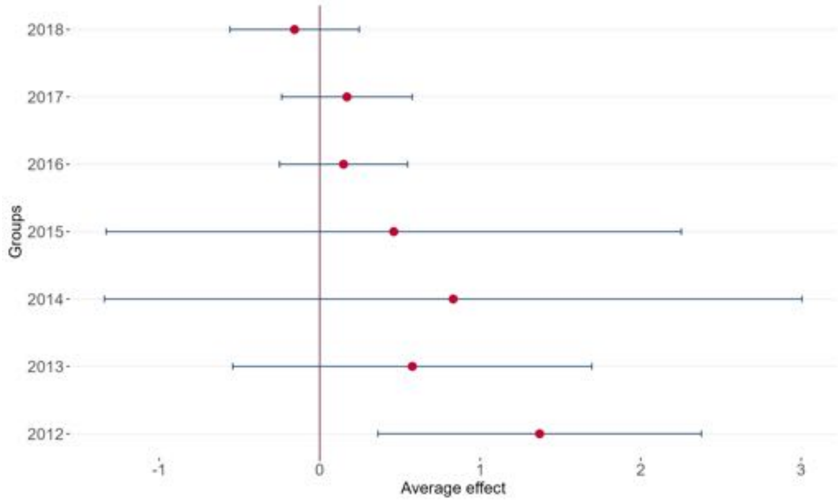
Notes: This figure illustrates the treatment effects on openings by calendar year, aggregating the estimates from the doubly robust estimator by Callaway and Sant'Anna (2021) across years. The sample was restricted to those areas that do not exhibit a reversibility of the treatment status. Error bars depict the 95% confidence intervals.

Figure 38: Robustness: Average effect on closures by length of exposure



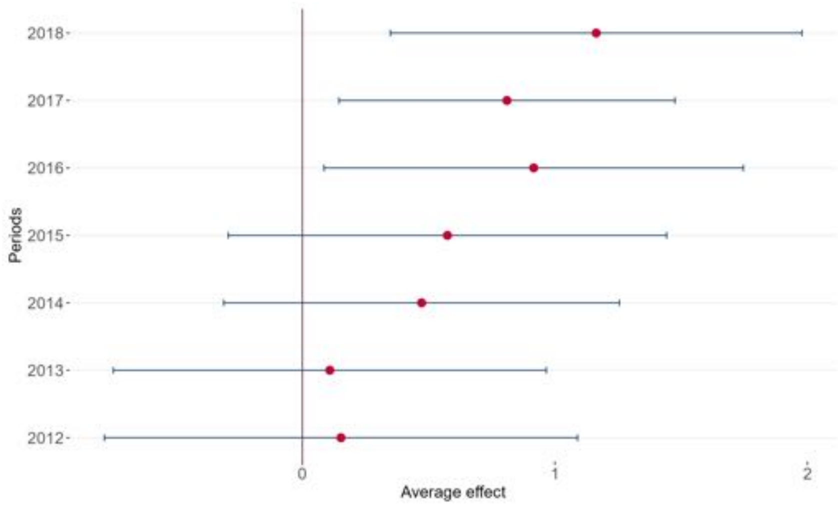
Notes: This figure illustrates the adjusted event study for closures generated by the dynamic aggregation of the treatment effects estimated using the doubly robust estimator proposed by Callaway and Sant'Anna (2021). The sample was restricted to those areas that do not exhibit a reversibility of the treatment status. Error bars represent the 95% confidence intervals.

Figure 39: Robustness: Average effect on closures by group



Notes: This figure illustrates the treatment effects on closures by group, where each group represents areas that were first treated in the same year. Treatment effects were estimated using the doubly robust estimator by Callaway and Sant'Anna (2021). The sample was restricted to those areas that do not exhibit a reversibility of the treatment status. Error bars depict the 95% confidence intervals.

Figure 40: Robustness: Average effect on closures by period



Notes: This figure illustrates the treatment effects on openings by calendar year, aggregating the estimates from the doubly robust estimator by Callaway and Sant'Anna (2021) across years. The sample was restricted to those areas that do not exhibit a reversibility of the treatment status. Error bars depict the 95% confidence intervals.