# Effects of the entry of food delivery apps in the restaurant industry: evidences from Brazil

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# Introduction

- Food delivery apps have become very popular in recent years;
- Additional strength during the COVID-19 pandemic;
- Consumers: benefit -> convenience; cost -> delivery fee.
- Restaurants: benefit -> larger demand; costs -> more competition, adaptation to delivery (more cooks and fewer waiters?)

# Introduction – main questions

- 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?

# Introduction – main questions

- iFood: pioneer and largest delivery app in Brazil.
- Evolution of employment from 2014 to 2021.
- 12 Brazilian cities; 790 areas.
- Sample corresponding to 21% of all restaurants within the country.

# Literature

- Many consumer side studies: Lee et al., 2017; Gupta, 2019; Cho et al., 2019; Ray et al., 2019, Tandon et al., 2021; Seghezzi et a., 2021.

- Mostly qualitative studies about the supply side: Meenakshi and Sinha, 2019; Khan, 2020; Veldhoven et al., 2021; Kumar and Kaur, 2021.

- Pigatto et al. (2017) analyses meal delivery services in the Brazilian context and shows the rapid growth of firms and operations volume.

- 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. 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.

# Literature

- Cohen et al. (2016) used individual-level observations to estimate the consumer surplus involved with the use of the Uber car-sharing App. They find very a large positive effect on consumer surplus.

- Collison (2020) uses Visa Inc.'s individual-level credit and debit transactional data of purchases in American restaurants. He finds that 30-50 cents of every dollar spent on online food delivery services are incremental, and the rest is diverted away from brick-and-mortar sales.

# Data

- iFood  provided monthly data on the list of restaurants that were using the platform.

- We used the CNPJ to match the restaurants with the employment records from RAIS (Ministry of Labor).

- We also used the Receita Federal (Internal Revenue Services)records to find the complete list of active restaurants in the cities analyzed.

- Final sample: 35.366 restaurants
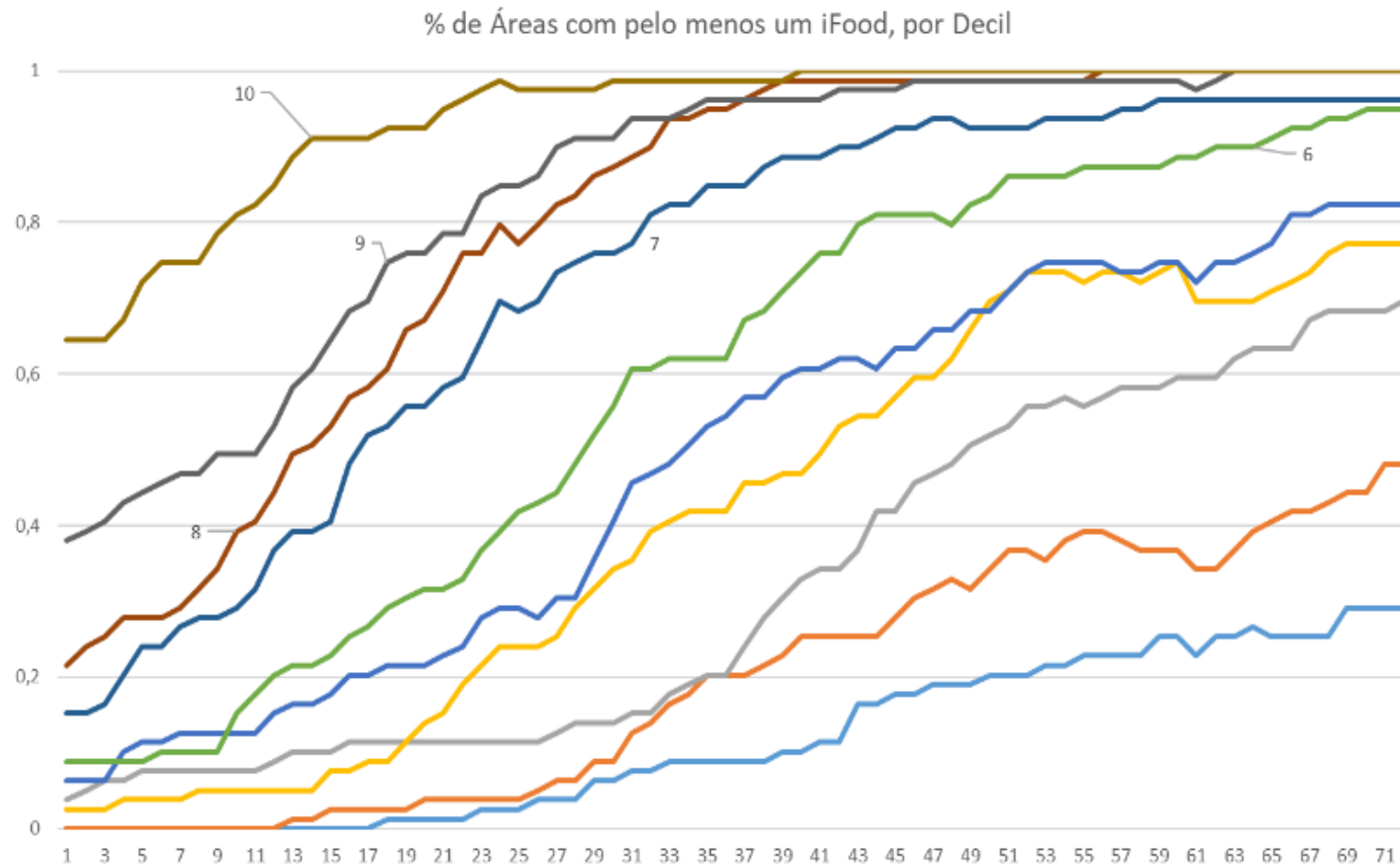
# Share of restaurants with meal delivery in the sample
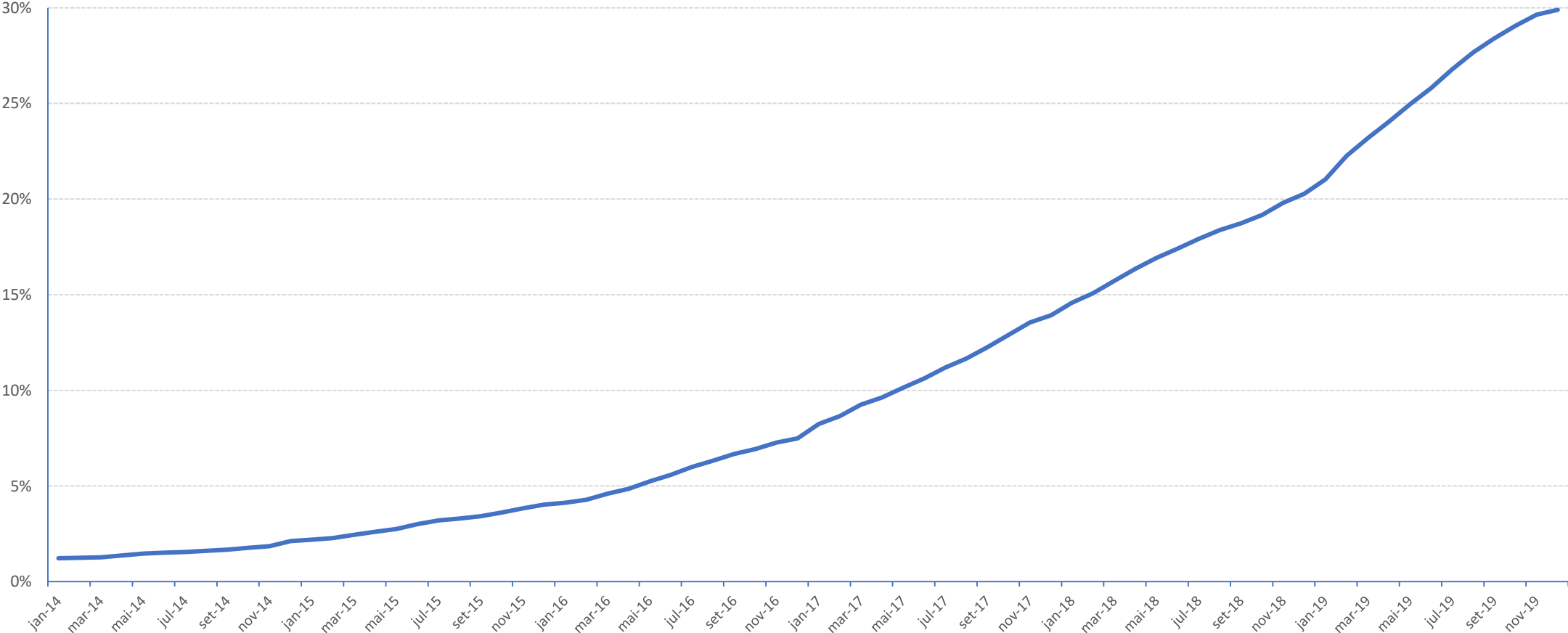
# Restaurant Openings and Closures in the cities studied
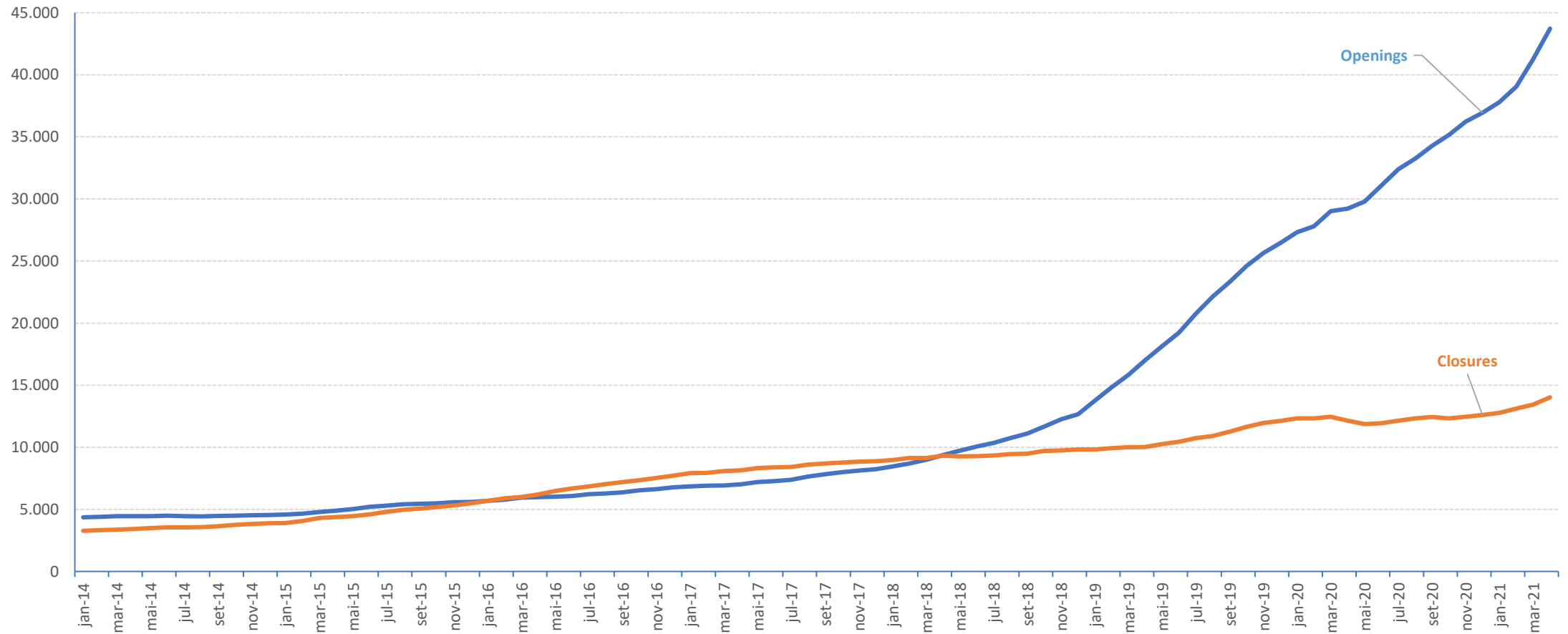
# Share of areas with at least one meal-delivering restaurant, by area decile



% de Áreas com pelo menos um iFood, por Decil

# Econometric model I: openings and closings per area

$$\ln(Outcome_{a,t}) = f(Trend, Covid19, Share\_iF)$$

- *Outcome: the sum of openings (or closings) on the 12-month period ending in month t.*
- *Trend* – time trend
- *Covid19* – dummy variable for March 2020 to May 2021
- *Share_iF* – share of restaurants in area *a* adopting the iFood app in month *t*

# Meal delivery and new restaurant openings

| | (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 |

# Restaurant openings

- In levels, Covid19 and Share_iF 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.

- 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.

# Meal delivery and the closing of restaurants

| | (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 |

# Restaurant closings

- Overall rate of growth of restaurant closures varies between 1.24% and 1.63% per month.

- Areas with more restaurants using the platform see more restaurant closings but, on the margin, a higher share of restaurant using iFood decreases the rate of closure over time.

- There are more closings during the lock down months, but with a lowering rate of closings during these months.

- Triple interaction is not significant.

# Openings and closings - summary

These exercises indicate that the existence of meal-deliverers is associated with an increase in the rate of openings and with a decrease on the rate of closings, suggesting a positive net effect on the industry as a whole.

# Employment per area

|  | (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 $\times$ 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 |

# Establishment level analysis

- Goal is to compare the job evolution of restaurants that deliver meals with those that do not deliver.

- A staggered diff-in-diff approach where adopting the iFood app is the treatment.

- However, the decision of using the app is highly endogenous.

- IV approach to the problem.

- Wooldridge (2002) suggests to estimate the model in three steps.

# 3 steps estimation

1. Estimate the probability of joining the platform:
$$P\left(iFood_{i,a,t}\right) = f\left(X_{i,a,t}, Z_{a,t}\right)$$

2. Use the probability estimated in the first step as instrument:
$$\langle iFood, Trend * iFood \rangle = G(\hat{P}_{i,a,t}, X_{i,a,t}, Z_{a,t})$$

3. Use the predicted value from 2, to estimate the model:
$$ln(Emp_{i,a,t}) = \beta_0 + \beta_1 Trend + \beta_2 \widehat{iFood} + \beta_3 (\widehat{Trend * iFood})$$

# First step – probit model

| | Todos | Grandes | Médios | Pequenos |
|---|---|---|---|---|
| Intercepto | −1.9363*** | −1.8767*** | −2.0684*** | −2.0921*** |
| | (0.0065) | (0.0078) | (0.0135) | (0.0257) |
| Tempo | 0.0068*** | 0.0057*** | 0.0114*** | 0.0097*** |
| | (0.0001) | (0.0002) | (0.0002) | (0.0005) |
| Share_iFood$_{t-1}$ | 3.9500*** | 3.9775*** | 3.6885*** | 3.7127*** |
| | (0.0173) | (0.0214) | (0.0348) | (0.0580) |
| Share_Salão$_{t-1}$ | −0.1777*** | −0.1927*** | −0.1589*** | −0.1842*** |
| | (0.0048) | (0.0060) | (0.0092) | (0.0170) |
| Idade | −0.0015*** | −0.0011*** | −0.0034*** | −0.0030*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0001) |
| Salário_Médio_Relativo | 0.1498*** | 0.1241*** | 0.2302*** | 0.3190*** |
| | (0.0044) | (0.0052) | (0.0097) | (0.0187) |
| AIC | 1049683.8672 | 688800.0403 | 273945.0380 | 79848.2488 |
| BIC | 1049757.8536 | 688871.3048 | 274011.5297 | 79906.9250 |
| Log verossimilhança | −524835.9336 | −344394.0202 | −136966.5190 | −39918.1244 |
| Observações | 1674579 | 1063851 | 480197 | 130531 |

# Characteristics of restaurants using iFood

- The probability of adopting meal delivery increases with time;
- The share of meal-delivering restaurants in the area is positively associated with the probability of adoption;
- The share of meal-serving occupations has a negative effect;
- The age of the restaurants shows a negative coefficient.
- 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.

# Third step – IV regressions

| | 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 |

# Effect of iFood on employment

- The overall trend in employment in the sector in the cities covered by this study is negative, with less intensity in larger cities.

- The dummy *iFood* shows that restaurants that adopt the app are smaller.

- The comparison with meal-delivering restaurants to themselves, before the adoption of the system, and to restaurants that never adopted meal delivering shows positive effects on the employment rate of growth, for all city sizes.

# Brazilian restaurant industry

- There was 1,283,234 jobs in 2019, with 35.1% in restaurants that used the iFood app.

- There were 450,415 workers in iFood restaurants and 832,819 in non-iFood ones.

- Non-iFood restaurants have a rate of decrease in employment of -0.43% and iFood ones have an increase of (0,0056-0,0043=) 0.13%.

# Aggregate effects

- Jobs lost in non-iFood restaurants during a month:

  832,819 x (-0.0043)= 3.581

- For the iFood group, we have on average

  (450,415 x 0.0013=) 586, jobs created or saved

- Net effect of 2,996 jobs lost per month in the restaurant business.

# Conclusions

- The iFood app had a positive effect on the opening of new restaurants, but less so during the pandemic years.
- It had a negative effect on the closure of restaurants.
- Evidence of a positive impact on the number of businesses in the sector, but smaller during the COVID19 pandemic months.

# Conclusions

- More traditional and older establishments and with more workers working as waiters have a lower probability of joining the platform.

- Significant network effect: restaurants located in regions with more delivery having a higher chance of also adopting the delivery app.

- **Non-iFood restaurants decreased employment while iFood restaurants increased employment during the sample period, but not enough to offset the general trend of decreasing employment in the indutry.**