Dinner at Your Door: How Delivery Platforms Affect Workers and Firms

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Abstract

This paper studies the impacts of online-delivery platforms on workers and firms. I leverage unique data that links restaurants and workers on a large delivery platform in Brazil with employer-employee data. I exploit the staggered roll-out of the delivery platform across regions in Brazil and use a matched event-study design to estimate the effects of the platform on restaurants' labor demand and workers' labor market outcomes. I find that the average restaurant that adopts the platform substitutes one-to-one in-house waiters for outsourced platform workers. Restaurants that do not adopt the platform downsize and are more likely to shut down. These effects impact negatively the earnings and employment of restaurant workers over time. However, the earnings gains for gig workers outweigh the losses of restaurant workers. The evidence in this paper sheds light on who are the winners and losers of online-delivery platforms.

Keywords: Outsourcing, Informality, Gig Economy, Displacement

JEL Codes J24, J31, J42, J53, L24.

1 Introduction

Technological change has been a topic of extensive debate in economics. While technological advancements can lead to job losses in certain sectors, they can simultaneously generate new tasks and occupations, thereby reshaping labor demand (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu et al., 2024). Simultaneously, technology reshapes how consumers behave, affecting demand for various goods and services (Bakos, 1997; Dolfen et al., 2023). Several industries provide clear examples of how technological change simultaneously affects labor and product markets. The rise of e-commerce, driven by companies like Amazon, has shifted the retail sector toward online operations, leading to changes in job composition and forcing retailers to close (Chava et al., 2024). Streaming services have revolutionized media consumption patterns, altering the landscape of the film, music and television industries (Aguiar and Waldfogel, 2018). Meanwhile, the growth of digital banking and fintech has led to a reduction in traditional bank teller jobs but increased demand for professionals skilled in cybersecurity and software development (Jiang et al., 2021). While the labor and product market impacts of technological change are commonly discussed separately, they often overlap. However, to date, limited empirical evidence exists to explain how these two forces interact in practice and how it may affect workers.

In the service sector, online delivery platforms have allowed restaurants to expand their markets geographically while potentially replacing in-house dining for delivery services. Advocates of the gig economy argue that these platforms provide workers with flexibility and grant opportunities for workers with low outside options, while critics argue that they replace "good" jobs for others with lower wages and higher insecurity. Understanding how delivery platforms affect workers in traditional employer-employee jobs as well as gig workers is crucial for examining the broader impact that these new rising technologies have on welfare and inequality, as well as for guiding policymakers who are responsible for regulating these online platforms. However, empirically measuring these effects is challenging, both because technological adoption and gig workers are not observable in standard datasets and because the adoption of new technology is a strategic decision that may correlate with productivity or demand shocks at the firm level.

This paper studies the winners and losers of the adoption of online-delivery platforms for workers in Brazil. The Brazilian context provides a perfect setting to study the impact of online-delivery platforms on workers. First, Brazil has a substantial restaurant sector, representing approximately 4 percent of formal employment, and a large pool of gig economy workers, with 1.5 million people engaged in this sector (IBGE, 2022). Additionally, Brazil's significant levels of informality and unemployment create conditions where delivery platforms may provide essential opportunities for workers with limited outside options. Second, the online-delivery platform market in Brazil is highly concentrated, with around 80 percent of the market controlled by a single platform. This allows for an in-depth study of the industry through the lens of a single app.

These factors make Brazil an ideal case for understanding how online platforms affect workers.

I overcome the challenges that previous literature has faced, by combining an identification strategy that exploits the staggered roll-out of online-delivery platforms throughout the country, with a novel dataset that allows to match adopting restaurants and app workers, from the largest online-delivery platform in Brazil, to administrative employer-employee data. The empirical strategy relies on matching adopting firms—and their workers—in locations where platforms are available to those in regions where no online-platforms were available at the time. By assuring that no platforms were available for the control group, I am able to bypass the endogeneity of the adoption decision. The data allows me to identify the date of adoption of an online-delivery platform and to follow the workers of adopting restaurants and app workers over time.

I start by deriving a stylized framework that illustrates the potential effects of online-delivery platforms on the labor demand of restaurants. The model illustrates the two different channels through which this technology can affect the demand for in-house workers at adopting restaurants. First, platforms can impact the labor demand by changing the product demand for restaurants which is reflected through a change in the revenue per worker and the size of the service sector (waiters and delivery workers)—the product demand effect—. Second, delivery apps can change the relative productivity of delivery workers with respect to potentially substitutable in-house workers, such as waiters—the outsourcing effect—. Under this framework, differences in the impact of delivery platforms on labor demand across locations are driven by heterogeneities in the product demand effect across these regions. I follow the urban literature and extend the model to microfound the product demand through a consumer search model and show that the app can can reduce consumer search costs for adopters but increase it for non-adopters (Vitali, 2022; Goldmanis et al., 2010).

I then move to study empirically the effect of the adoption of online-delivery platforms on the labor demand of restaurants. I first document that restaurants that enroll on a delivery app are larger and pay higher wages to all their workers—as measured by their AKM firm fixed effects— (Abowd et al., 1999). I use a matched difference-in-difference design that compares restaurants that adopt an online-delivery platform to observationally similar restaurants located in regions where no platform is available at the time. The identifying assumption is that matched treated and control restaurants would have trended similarly in terms of their labor demand in absence of the adoption of the platform. I find that restaurants that adopt an app reduce on average their number of in-house workers by 6 percent five quarters after adoption. This decline in size is fully explained by service workers (waiters and formal delivery workers) who are substituted one-to-one by outsourced app drivers. In contrast, the number of cooks remains stable after adoption, suggesting that the outsourcing effect dominates the product demand effect for the average adopting restaurant.

The effects of app adoption on labor demand are heterogeneous across the wage setting of firms and regions. I find that higher paying restaurants decrease a larger portion of their in-house workforce compared to low-paying restaurants (8 percent vs 4 percent) after five quarters of adoptions. These differences are once again driven by waiters that are being replaced by outsourced workers, while cooks are non-affected at both groups of adopting restaurants. In line with theoretical models of outsourcing, the estimates are consistent with the outsourcing effect being stronger for high-paying restaurants (Bilal and Lhuillier, 2022), while there is no evidence of differential product demand effect for high and low paying restaurants.

Does this mean that the product demand effect is irrelevant across all restaurants? Motivated by the model, I answer this question by studying heterogeneous effects of adoption on restaurants located in areas with high and low density of restaurants. Consistent with apps reducing consumer search costs, I find that restaurants located in areas with low density of restaurants increase their total workforce by 6 percent more than restaurants in areas with high density of restaurants. This increase in size in restaurants located in low-dense areas is driven by an increase in the number of cooks, while waiters remain constant. Taken together, the results suggest that the product demand effect is relevant for restaurants in low dense areas (Overby and Forman, 2015; Kitchens et al., 2018; Couture et al., 2021).

Online-delivery platforms may not only affect restaurants that adopt these technologies, but can also influence the product demand of non-adopting restaurants. To examine the indirect effects of platforms on the labor demand of non-adopters, I focus on sudden, large increases in the share of restaurants adopting the platform within a 1-kilometer radius of non-adopters. In line with these platforms crowding out demand of non-adopting restaurants (Chava et al., 2024), I find evidence that these apps also have an impact on restaurants that don't adopt these technologies. Specifically, restaurants that do not adopt located near a significant share of adopters are 5 percentage points more likely to close five quarters after the shock. These spillovers also have an impact in the intensive margin in the short-run. Non-adopting restaurants decrease their size 3.5 percent, but conditional on survival, recover by quarter 5 after the shock.

Proven that online-delivery platforms change the labor demand of both adopting and non-adopting restaurants, I leverage the granularity of my data and study the effect that these apps have on restaurant sector workers' employment and earnings. Following the job displacement and outsourcing literature (Goldschmidt and Schmieder, 2017; Jacobson et al., 1993; Bertheau et al., 2023), I define a worker as treated if their employer enrolls on an online-delivery platform and match them to a control restaurant worker in a location where no app is available. I find that treated workers suffer a modest earnings (and employment) loss of only 1.5 percent five quarters after their employer adopts the app. The main mitigating factor of this loss is that treated workers find a new job at a quick pace. That is, 75 percent of treated workers have found a new job by quarter 5 after their former employer adopts an online-delivery platform. Remarkably, these new jobs are also in the formal sector and not in the gig economy.

In contrast, workers at non-adopting restaurants experience a more significant earnings loss compared to those at restaurants that adopt the app. Five quarters after a large share of nearby restaurants adopt the app, workers at non-adopting restaurants see their earnings decrease by 6.6 percent. This group also faces a greater risk of displacement, as many non-adopting restaurants close. Consequently, their probability of remaining employed drops more sharply—five quarters after the shock, they are 3.8 percentage points less likely to be employed compared to the control group.

The reduce form estimates indicate that online-delivery platforms have a persistent impact on the earnings of in-house workers at adopting restaurants and spillovers towards workers at non-adopting restaurants. However, it is possible that the earnings gains by app workers outweigh the earnings loss by in-house workers. To assess the overall impact of online-delivery platforms on workers earnings I compute the present value net gains (or losses) per adopting restaurant for in-house workers at adopting restaurants, workers affected by spillovers and app workers. Using the reduced form estimates, I find that in-house workers at adopting restaurants and workers at affected by spillovers lose earnings equivalent to 6.9 and 18.5 percent of the pre-platform wage-bill of adopting restaurants respectively.

To assess the potential gains from delivery platforms for gig workers, I contrast the earnings that they make on the platform with their potential outside option. To do this, I separate app workers in two groups. Those who were employed in the formal sector before working on the platform (and were not laid-off)—23 percent of the app workers—and those who did not have a formal employment when starting to work on the app—77 percent—. For the first group, I leverage the granularity of my data to define the per hour gains of the app as the wage per hour earned on the app versus the wage per hour that these workers were earning the quarter prior to working on the platform (their outside option). When considering their outside option, I find that app workers that were employed in the formal sector before working on the app gain 1.8 percent of the pre-platform wage-bill of adopting restaurants.

The second group, those who did not have a formal employment previous to working on the app, propose a heavier challenge as their outside option is not observable in my data. I propose different scenarios of outside options for individuals who were not working in the formal sector prior to becoming gig workers. If all non-formal gig workers were unemployed before working on the app (outside option equal to 0), these workers would gain 40.1 percent of the pre-platform wage-bill of adopting restaurants. In the other extreme, if all non-formal gig workers were employed and making the same hourly wage as the average formal worker, the gains of these workers would represent 6.02 percent of the pre-adoption wage bill. A more realistic scenario is likely somewhere in the middle of these two extremes. When using the estimated earnings of non-formal workers using the Brazilian household survey (PNAD-C), I find that the net earnings gain of these workers per adopting restaurant is 27.6 percent of the pre-platform wage bill of these firms. When summing up the earnings gains and losses of all groups using these estimates, I find that the total wage effect of the delivery platform per adopting restaurant represents a 4 percent increase of the pre-platform wage bill.

This paper contributes to several strands of literature. First, it integrates online-delivery platforms into the broader literature on technological adoption. One strand of this literature focuses on the impact of technology in labor markets, particularly the substitutability between workers and technology and the shifts in worker tasks (Autor et al., 2003; Acemoglu and Autor, 2011). From a theoretical perspective, Acemoglu et al. (2024) presents a framework that shows how technological change can affect labor through changes in productivity, automatization or creation of new tasks. Firms play a crucial role in the diffusion of technologies making the analysis of firm level adoption particularly relevant (Corn, 1957; Mokyr, 2003; Bloom et al., 2016) [1]. In parallel, another strand examines how technology can influence product demand by enabling firms to reach new markets and alter consumption patterns (Bakos, 1997; Dolfen et al., 2023). Studying eBay, Dinerstein et al. (2018) shows that search ranking algorithms play a significant role in reducing consumer search frictions. More related to the setting covered in this paper, Zheng et al. (2023) shows that a query recommender system on online-delivery platforms increase the probability that customers place a food order [2]. Typically, these two dimensions of technological impact—labor and product demand—are studied independently. This paper bridges the gap by proposing a simple framework that decomposes the effects of technological adoption on labor demand into the effect on the product demand and productivity margin. It then offers empirical evidence of how a technology that influences both margins—online-delivery platforms—impacts workers.

Second, this paper relates to a growing literature that studies the consequences of domestic outsourcing on workers. Most of the micro level evidence has focused on outsourcing events where workers transfer from an outsourcing firm to a firm that offers outsourcing services (Goldschmidt and Schmieder, 2017; Daruich and Kuntze, 2024) or temporary work agencies (Deibler and Commission, 2023; Drenik et al., 2023). A majority of these papers have found an outsourcing

[1] A growing literature has focused on firm-level technological changes to study the skill-demand. Cite Aghion finds that firms that invest more in R&D pay a lower college premium. Bøler (2015) presents evidence that firms with a higher R&D presence are associated with a larger skill-ratio. Using a framework closer to mine, Lindner et al. (2022) quantifies the contribution of firm-level technological change to skill demand in the presence of imperfect competition in the labor market and show that skill-biased technological changes change both the skill and ratio and premium.

[2] Fang et al. (2024) finds that search tools in e-commerce increased customers orders and expenditures by looking at a large e-commerce platform in China. Filippas et al. (2023) finds that advertisement on digital platforms can steer consumers to sellers with a greater capacity.

"penalty" due to wage differentials between in-house and outsourced workers (Dube and Kaplan, 2010; Goldschmidt and Schmieder, 2017; Drenik et al., 2023; Guo et al., 2024). Due to data limitations in standard datasets, a struggle of this literature, has been to identify outsourced and in-house workers simultaneously [3]. This has limited the ability to study the level of substitution between outsourced workers and in-house workers in core occupations of firms. This paper overcomes this challenge by studying a technology that enables to outsource workforce and observing the both in-house and outsourced workers after the adoption of the technology.

Finally, this paper relates to the burgeoning literature that seeks to understand the rapid growth of alternative work arrangements (Katz and Krueger, 2019), and more specifically the gig economy (Harris and Krueger, 2015; Garin et al., 2023, 2024). In the US, the gig economy has been found to smooth consumption (Koustas, 2018) and alleviate the negative effects of job displacement (Jackson, 2022). Closer to this paper, Abraham et al. (2024) use tax records to study the effects of the introduction of online ride-sharing platforms on the employment and earnings of taxi drivers in the US. The authors describe that the introduction of ride-share apps in a local labor market increased the number of new self-employed drivers but decreased the number of incumbent taxi drivers. Similarly, Berger et al. (2018) use American Community Survey (ACS) to show that the entry of uber in the US reduced the earnings of taxi drivers by 10 percent.

I extend this literature in several ways. First, I expand the literature by studying the effects of online-delivery platforms on workers. Online-delivery platforms represent a significant share of the gig economy [4]. Online-delivery platforms are a technology that are adopted by establishments and allow them to transform their workforce while impacting the demand for their product—differing from ride-sharing platforms that compete directly with self-employed workers. Therefore, the adoption of this technology involves three parties: the workers at the establishments that adopt the technology, the workers at the establishments that don't adopt and the gig workers. This paper also extends the literature by providing a more complete overview of the winners and losers of the gig economy, focusing on the impact that delivery platforms have on both workers in formal jobs and gig workers. By matching data from a large gig firm with administrative employer-employee records, I am able to follow workers and firms over time, overcoming common issues associated with survey and tax data (Garin et al., 2024). Lastly, I expand previous literature by studying the effects of the gig economy in a middle-income country where gig jobs may provide a safety net due to significant levels of informality and unemployment (Ulyssea, 2018). In particular, I show that the main benefits of online-delivery platforms are driven by

[3] An exception this is Drenik et al. (2023) that finds that temporary work agencies earn a 50 percent wage premia respect to in-house workers.

[4] In the context of this paper, Brazil, delivery platforms represented 40 percent of the gig economy workforce in 2022 (IBGE). Try to find how much they represent in the US.

workers that do not hold a formal job before working on the app[5].

2 Theoretical Framework

This section presents a theoretical framework that illustrates the different mechanisms through which online-delivery platforms can affect the labor demand of restaurants. The model is a wage posting model following Card et al. (2018) with three labor factors: cooks (C), waiters (ω) and delivery (D). The restaurant faces an upward labor supply curve for all three types of labor.

Waiters and delivery drivers compose what I define as service workers in restaurants (S). Cooks and service workers are complements in a production function that has constant returns to scale. Waiters an delivery drivers are related through a constant elasticity of substitution function (CES) with elasticity of substitution σ. Restaurants compete in a competitive monopolistic market and therefore face a downward sloping demand curve for the good they produce[6].

Firms Profit Maximization Problem Restaurants must choose between between the three types of labor. Within a market l restaurants post wages for waiters and cooks and choose the number of delivery workers solving the following profit maximization problem:

$$\max_{W_{j\omega},W_{jC},D} P_{jl}Y_j - W_{j\omega}\omega_j - W_{jC}C_j - W_D D_j$$

subject to

$$\begin{aligned} Y_j &= T_j C_j^{\alpha} S_j^{1-\alpha} \\ S &= [\theta\omega^{\rho} + (1-\theta)D^{\rho}]^{\frac{1}{\rho}} \\ ln(\aleph_j) &= \lambda_j + \beta\, ln(W_{j\aleph}) \\ P_{jl} &= P_{0jl}Y^{-\frac{1}{\epsilon}} \end{aligned}$$

Where $\sigma = (1-\rho)^{-1}$, and $\aleph = \{C, \omega, D\}$. That is, each firm faces their own labor supply for all three types of labor, where λ contains firm specific amenities as well as macroeconomic shifters. β represents the labor supply elasticity which is assumed to be the same for all types of labor[7]. Lastly, each firm faces a negatively sloped demand curve for the good they produce with product demand elasticity of $\epsilon > 1$. The demand curve contains a firm (and location) specific product demand shifter P_{0j}, that allows for firms to set different prices for the same quantities.

[5]This potentially contrasts with developed countries where non-wage benefits such as flexibility have a significant value for workers (Chen et al., 2019, 2020; Angrist et al., 2021).

[6]This condition, in combination with the fact that firms face a negative product demand and a positive labor supply curve ensure that firms won't want to grow infinitely.

[7]This assumption implies that the difference between the quantities demanded (and effectively hired) of both types of labor will be a function of the output elasticities and relative productivities of each type of labor.

The first order conditions yield the following wage equations for in-house cooks and waiters (disregarding the j notation for simplicity):

$$W_\omega = \underbrace{\frac{\beta}{1+\beta}}_{\text{Markdown}} \underbrace{\frac{\epsilon-1}{\epsilon}\frac{R}{S}\,\theta\,(1-\alpha)\,\left(\frac{\omega}{S}\right)^{\rho-1}}_{\text{MRPL}} \tag{1}$$

$$W_C = \frac{\beta}{1+\beta}\frac{\epsilon-1}{\epsilon}\frac{R}{C}\,\alpha \tag{2}$$

Where R represents the revenue of the firm. The wage equation illustrates the typical wage in a monopsonistic setting (Manning, 2011), where the markdown is a function of the labor supply elasticity and the marginal revenue product of labor is a function of the output elasticity and the relative productivities of each type of labor.

Impact of online-delivery platforms Under this setting, the introduction of online-delivery platforms will have two main effects. First online-delivery platforms increase the relative productivity of delivery workers respect to waiters—a decrease in θ and makes the delivery workers de-facto competitive (i.e. restaurants become price takers for delivery workers). The increase in the productivity of delivery workers represents the increasing returns to scale that online-delivery platforms have by specializing in delivery services[8]. I call this increase in relative productivity the *outsourcing effect*.

Second, the introduction of online-delivery platforms may allow adopters to access new markets that may have been unaccessible ex-ante. Yet delivery platforms may also substitute or crowd-out in-house dinning (in favor of delivery) in markets that were already accessible to the restaurant having a net zero—or potentially negative—impact on the total demand of goods produced by the restaurant. Ultimately, the effect on product demand is uncertain and can depend on several characteristics such as the location of the firm and the baseline competition that it was facing. Through the lens of the model, a change in demand would be reflected in a shift in P_{0jl}. I call this potential shift in demand the *product demand effect* [9].

Comparative Statics By comparing the number of in-house workers hired before and after the adoption of online-delivery platforms, one is able to decompose the change in labor demand for

[8]A micro-foundation of the comparative advantages of firms that provide outsourcing services can be found in Bilal and Lhuillier (2022)

[9]One could also think of a model with two goods produced by restaurants: in-house goods and delivery goods. In such a model, online-delivery platforms could increase delivery goods at the expense of in-house goods depending on the level of substitutability between both types of products. Yet it could still be the case that delivery platforms allow restaurants to access new markets, expanding their visibility and allowing for positive spillovers between delivery and in-house goods. That is, in a model with two goods, the effect of the product demand effect would still be uncertain.

waiters as follows:

$$\Delta\, ln(\omega) = \frac{\beta\sigma}{\beta+\sigma}\left[\underbrace{\underbrace{\Delta\, ln(V_S)}_{\substack{\Delta\text{ Revenue p/}\\ \text{Service Worker}}} + \frac{1}{\sigma}\underbrace{\Delta\, ln(S)}_{\substack{\Delta\text{ Service Sector}\\ \text{Size}}}}_{\textit{Product demand effect}} + \underbrace{\underbrace{\Delta\, ln(\theta)}_{\substack{\Delta\text{ relative productivity}\\ \text{waiters}}}}_{\textit{Outsourcing Effect}}\right] \tag{3}$$

Notice that the change in the number of in-house waiters will depend on the product demand effect and the outsourcing effect. The effect on product demand can be decomposed in the change of revenue per service worker and an additional term which reflects the relative change of the service sector size after adopting the platform. This second term is scaled by the level of substitutability of waiters and delivery drivers. That is if waiters and delivery drivers are complements $\sigma \longrightarrow 0$, then the increase in the number of delivery drivers should increase the number of waiters hired by the firm. In contrast, as $\sigma \longrightarrow \infty$, waiters do not benefit from the overall increase in the number delivery drivers, making this second term irrelevant. Taken together, equation (3) gives guidance on the forces behind the impact that the adoption of delivery platforms have on the demand for in-house waiters. On the one hand, the outsourcing effect will most certainly drive waiters down. The product demand effect is uncertain and could drive waiters up or down, likely depending on certain characteristics of the adopters such as their location.

The impact of the adoption of delivery platforms on the number of in-house cooks hired is expressed as follows:

$$\Delta\, ln(C) = \beta\, \underbrace{\Delta\, ln(V_C)}_{\substack{\Delta\text{ Revenue p/}\\ \text{Cook}}} \tag{4}$$

The change in the number of in-house cooks will depend on the change in the revenue per cook at the firm. That is, because the output elasticity of cooks is not affected by the adoption of the app (i.e., cooks are equally complementary to waiters and to deliver drivers), the change in the number of cooks will be solely determined by the change in their marginal productivity[10].

[10]Importantly, if online-delivery platforms retain all the additional rents generated by the adoption of the platform, even if the demand increases the revenue per cook may not change. In other words, the revenue per cook reflects the gains in the marginal revenue of productivity of cooks net of the costs of the app.

And underlying feature of the model is that any difference in the effect of app adoption in labor demand of either waiters or cooks between restaurants in different locations $l's$ will depend on the differential product demand effect that the app has in each $l's$. In Appendix XXX, I extend the framework to provide a micro-foundation of the product demand effect through a consumer search model to illustrate how firm location can influence the product demand effect of online-delivery platforms.

3 Setting & Data

Online delivery platforms operate as intermediaries in a contractual relation between restaurants, consumers and workers. Figure 1 illustrates this relationship: consumers order through the app some good from a restaurant. The app then is in charge of coordinating the delivery by assigning the task to a worker. Under this contractual relation, the establishment is only in charge of producing/selling the good, while the worker usually operates as an independent contractor. When a consumer orders a good, the app offers the task to app workers that are logged on at the time and are relatively close to the establishment. The first app worker that accepts the task will get the assingment and earn a fee that is a function of the distance covered, the time spent on the task and additional bonuses that may be present at the time.

To work on an online-delivery platform in Brazil, individuals must go through a background check, and must have a smartphone. Deliveries can be done by bike, motorbike or car[11]. There is no additional requirement for the app worker to own the mean of transportation that they use[12]. App workers are usually paid once per week by the platforms. Through the lens of the Brazilian law, delivery workers are considered independent contractors and therefore do not have social security contributions covered by the platform. This also implies that app workers are not entitled to benefits such as maternity leave, paid vacations. App workers are also not covered by the federal minimum wage which only apply to formal employees. Online-delivery platforms workers must pay income taxes on their earnings as long as their monthly earnings exceeds a minimum threshold applicable to all self-employed (in 2023, this threshold was approximately equivalent to 2 minimum wages). When app workers earn above the threshold, 10 percent of their earnings are subject to self-employed tax[13].

Since 2018, online delivery platforms have been growing in relevance in the Brazilian market. This growth was propelled during the Covid-19 pandemic that incentivized restaurants to offer

[11] A vast majority of the deliveries are done through motorbikes. In my sample, 81 percent of app workers and 87 percent of deliveries are done through motorbikes. In contrast, bicycles represent 11 percent of deliveries (16 percent of workers) and cars represent 2 percent of deliveries and 3 percent of workers.

[12] Anecdotical evidence shows that a significant share of workers that deliver using bicycles use the public shared bicycle system available in their cities (CITE SOME ARTICLE).

[13] This contrast with ridesharing workers who have 60 percent of their earnings taxable. More details can be found: https://istoedinheiro.com.br/imposto-de-renda-motorista-entregador-2024/

a reliable alternative to in-house dining. In the present, over 250 apps dedicated to deliveries operate in the country[14]. This has lead Brazil to represent close to 50 percent of the total number of deliveries in Latin America.

For the context of this paper, I focus on a large online-delivery platform that operates in Brazil. This app has been operating as an app in the country since 2018 and has enrolled over 100,000 establishments. The app operates in all major cities in Brazil and has a relevant share of the market. The app offers two main types of services to establishments: (1) delivery services, where consumers order through the app and the app is in charge of coordinating the delivery of the order; (2) marketplace services, where consumers order through the app and establishments are in charge of delivering the ordered good. The app charges a fee for both services, but the fee varies depending on the service provided [15].

3.1 Data

App data The app data is provided by a large online-delivery platform app in Brazil. This data includes information on the establishments that are enrolled in the app, the drivers that work on the app and the orders that are made through the app between 2018—the start of the operations of the platform—and 2021. Importantly, both the establishment data and the worker level data have a unique identifier that allows me to link these two datasets to administrative employer—employee data from Brazil (RAIS).

The establishment panel data from the app has information on the establishments that are offering delivery services through the delivery platform. Specifically, this data contains information per establishment and month of the number of hours that app workers worked for that establishment and if the share of revenue obtained through the app using delivery services was above 50 percent [16].

The worker level panel data from the app contains information per worker and month on the number of deliveries that the driver made, the number of hours that the driver worked—and the number of hours that they have been logged in on the app—, the distance they covered during the period, and the earnings the driver made on the app. Thease earnings are separated by tips, main earnings and bonuses. It also includes information on the the municipality in which the driver mostly operated during the period, as well as main modality of transportation (i.e. bike,

[14] These applications have extended to other sectors beyond restaurants, such as groceries, convenience stores and pharmacies. For anecdotal evidence, see: https://portal.fgv.br/artigos/boom-plataformas-delivery-brasil-e-suas-consequencias-peculiares

[15] The app also operates with two sets of delivery drivers: (1) app workers, who are independent contractors. These workers are paid by delivery and represent the vast majority of workers on the app; (2) OL workers, who are formally employed by an intermediary firm and receive a wage independently of their deliveries. These workers are usually hired by firms that operate with several different apps and represent a minority of the workers of the app. For the purpose of this paper, I only consider app workers as the unit of analysis.

[16] Recall that the app offers two types of services: delivery services and marketplace services.

motorbike or car)[17].

Employer-Employee Data: RAIS The other main data source is the administrative employer-employee data from Brazil called *Relação Anual de Informações Sociais* (RAIS) [18]. Employers are required to submit yearly reports to the federal government detailing all formal job contracts established in the previous year[19]. This information is used to calculate various benefits for both workers and firms. Compliance with this reporting requirement is high, as incomplete submissions result in substantial penalties. Importantly, this dataset allows to follow workers over time and includes the universe of formal workers and their employers—establishment—from 2003 to 2021. The data contains information on the worker, such as the average monthly wages, hours hired, occupation, age, gender, education and race. Each worker is identified through their unique tax identifier: *Cadastro de Pessoas Físicas* (CPF). On the employer side, the data includes information on the industry of the employer and the location of the establishment. Each establishment is identified through their unique tax identifier: *Cadastro Nacional de Pessoas Jurídicas* (CNPJ). All reported wages are deflated to 2018 Reais. I restrict to employment spells where the worker worked at least 2 months and made at least 20 reais per month (approximately 5 USD at the time)[20].

4 Research Design

This section discusses the research design to estimate the causal effect of online-delivery platforms on restaurants labor demand and workers labor market outcomes. Section 4.1 presents the research design to study the impact of online-delivery apps on establishments that enroll on the app. Section 4.2 presents the research design to study the spillover effects of neighbors enrolling on the app. Finally, Section 4.3 presents the empirical strategy to study the impact of employer enrollment on the app on the labor market outcomes of restaurant workers.

4.1 Research Design: Adopting Establishments

This section provides an empirical strategy that allows to estimate the reduced form impact of enrollment on the app on restaurants labor demand. To do so, I leverage the staggered rollout of the app throughout Brazil. The app started operating in 2018 and extended its operations in the country every year. This gives place to quasi-experimental variation on app availability from the firms perspective. That is, depending on the location of the establishment, at a certain period in

[17]The data also includes the type of contract. That is, if the individual was an app worker or OL.

[18]This data has been used in several other settings such as to study the impact of trade on labor market concentration (Felix, 2022), the impact of the minimum wage on inequality (Edgel et al., 2023), and racial pay difference (Gerard et al., 2021), between others.

[19]Formal employment represented 62 percent of all employment in 2023 in Brazil.

[20]The vast majority of workers earn above the minimum wage (see Figure A15). Yet it is possible, that some may earn less due to low hours, suspensions or leaves.

time, some restaurants had the possibility of enrolling on online-delivery platforms, while others did not. Figure A12 shows the staggered roll-out of the app in Brazil. The app started operations in 2018 in the largest cities (mostly located in the Southeast region of Brazil). As the app grew in popularity in the following years, it expanded its operations to other regions of the country without a clear geographic pattern [21].

Matching Restaurants at locations where the app enrolled earlier may differ from restaurants where the app never entered. To ensure comparability between treated and control restaurants, I use a matching algorithm. I start by considering the pool of treated restaurants that, at the time of their adoption of the platform, generated more than 50 percent of their revenue through the app using the delivery services[22]. At the time of enrollment, treated restaurants must be located in microregions where the app has above 50 percent of the market share of the online-delivery platform industry. To ensure a balanced sample, I further limit it to restaurants that had been open for at least two years before the quarter prior to enrolling on the app and were treated at least five quarters before the end of my sample period.

To build an appropriate comparison group, I use a matching procedure [23]. The potential control group of establishments corresponds to restaurants that are located in labor markets where no online-delivery platform technology had been available up to the time of treatment—and the app doesn't enter up to five quarters after treatment[24]. Each treated restaurant is matched to a potential control restaurant that belongs to the same cell the quarter prior to treatment. A Control restaurant belongs to the same cell as firm j if they have been open for at least two years the quarter prior to treatment, belong to the same quartile of firm size, quartile of average earnings, and median of share of restaurants within a radius of 1km (with respect to the total restaurants in their microregion). Within each cell, treated and control restaurants are paired based on their propensity score, where propensity score is estimated using a logit model that predicts the probability of being treated based on log firm size in quarters $[t-8, t-1]$, log average earnings in the quarters $[t-4, t-1]$, firm age, share of waiters, average tenure, age of workers, share of female workers and average hours of workers.

[21]To operate in a microregion, the app must fulfill two requirements: (i) it must have a set of client restaurants that are willing to use the service, and (ii) it must have a large enough force of drivers that allow to offer the service during all business times. Both of these requirements take time to achieve and can explain why the app did not extend the business across the entire country all at once.

[22]Restaurants are defined as the establishments that have a the two-digit *Classificação Nacional de Atividades Econômicas* (CNAE) code of 56. This includes: "Restaurants and other food and beverage services" and "Catering services, buffet, and other prepared food services"

[23]similar empirical strategies have been used to study worker substitutability (Jäger and Heining, 2022), the effect of merger and acquisitions (Arnold, 2019), the effect of outsourcing (Goldschmidt and Schmieder, 2017; Daruich and Kuntze, 2024) between others.

[24]By only considering firms that are never treated during the entire period as control groups, I ensure that I don't include "forbidden controls" (Borusyak et al., 2024).

Given the high volatility of the restaurant sector (Parsa et al., 2011, 2021), matching on lagged size and earnings captures control restaurants that are following similar trends as the treated establishments. However, matching on lagged outcomes may rise concerns regarding mean reversion post-treatment. I therefore, do not target average earnings in three quarters of the pre-period and show that treated and control restaurants have similar trends even in these non-targeted moments.

Econometric Framework I estimate the causal effect effect of restaurant enrollment on the labor demand of establishment j estimating the following event-study model on the matched sample of treated and control establishments:

$$Y_{\{j,i\}t} = \beta_0 + \alpha_{\{j,i\}} + \delta_t + \sum_{k=-7}^{k=5} \theta_k \mathbf{1}\{t = t^*(j) + k\} + \sum_{k=-7}^{k=5} \beta_k \mathbf{1}\{t = t^*(j) + k\} \times Treated_{\{j,i\}} + \epsilon_{\{j,i\}t} \quad (5)$$

Where Y_{jt} is the outcome of interest (e.g., average wages, establishment size) for restaurant j in time t. α_j are establishment fixed effects, and δ_t are quarter-year fixed effects. $Treated_j$ is a dummy variable indicating if the establishment j enrolls on the app, while $t^*(j)$ indicates the date in which the restaurant first enrolled on the app[25]. $\mathbf{1}\{t = t^*(j) + k\}$ are the event-study indicators that reference the time relative to treatment date. The main coefficient of interest is β_k which captures the causal effect of establishment enrollment on the app on the outcome of interest. The event study indicators are normalized relative to β_{-2}. Therefore, the coefficients β_k for $k \geq 0$ capture the effect of the restaurant enrolling on the app on outcome y_{jt}, k quarters after the enrollment relative to two quarters prior to enrollment. Standard errors ar clustered at the establishment level.

Identification The key identifying assumption of this model is that, in the absence of the treatment, the differences in the outcomes of interest between treated and control establishments would have remained constant (the parallel trend assumption). This is potentially a strong assumption as the decision of an establishment to enroll on the app is a strategic decision that could be correlated with both potential outcomes and past trends. For instance, restaurants may decide to enroll if they face a negative demand shock. In this case, wages or employment at enrolling restaurants may decrease in absence of the app which would lead to a downward bias of the estimates. Alternatively, if firms decide to enroll based on a positive shock that allows them to expand the size of the firm, the estimates would be biased upwards.

To address this concern, treated restaurants are matched to control restaurants located in microregions where no platform is available. Therefore, under the parallel trends assumption, the

[25]In the matched sample, control restaurants are assigned the treatment date of their matched treated pair.

control restaurants propose a suitable counterfactual in a scenario where enrollment on the app is not a possibility. To enhance the likelihood of the parallel trends assumption's validity, I leverage the detailed nature of my data. First, restaurants are matched based on their average wages, size, composition and number of restaurants in surrounding areas. Second, I compare the outcomes for treated and control restaurants the quarters prior to the treated establishments adoption of the app in Figure 4. Both earnings and size trend similarly in the pre-treatment period. This is true even for moments that are not targeted in the matching procedure (e.g., average wages in quarters -7 to -4).

However, a potential concern is that the enrollment of the treated group may incentivize competing restaurants within their market to enroll on the app as well. Through the lens of the model, this would impact potential outcomes through the spillover term in the post-treatment period. Figure A13 shows that this is not the case as there is no discrete change in the likelihood of adoption of restaurants within 1km of a treated firm after treatment.

The research design relies on comparing establishments in different microregions across the country. An additional potential threat to identification could be if microregions are exposed to different shocks over time. This is particularly concerning in the period studied as the country faced the Covid-19 pandemic during 2020 and 2021. To alleviate this concern I present results for a set of restaurants that are treated at the beginning of 2019 and therefore are not affected by the pandemic. I additionally present results controlling for state-date fixed effects (which absorb state-specific Covid policies), and show that the individual level treatment effects are unsensitive to the Covid cases reported in the municipality of the treated establishment (Chauvin, 2021).

4.2 Research Design: Spillovers

To capture the spillover effects I define a set of firms that are affected by a sudden large increase in the number of neighboring restaurants that enroll on the app. First, I restrict potential treated restaurants to: (i) restaurants that at the time of treatment had never adopted the app before, (ii) restaurants that have at least 5 restaurants within a 1km radius, (iii) restaurants that don't belong to a multi-establishment firm where other establishments have already enrolled on the app. Restriction (i) is intended to capture non-adopting restaurants at the moment of treatment [26]. Restriction (ii) assures that the treated restaurants are exposed to a minimum of competition, while restriction (iii) is intended to exclude firms that may be exposed to potential within-firm spillovers generated by other adopting establishments.

I compute for each potential treated establishment j, the share of restaurants within 1km that are enrolled on the app in each quarter (χ_{jt}), and calculate the difference in this share between quarter t and quarter $t-1$. That is: $\Omega_{jt} = \chi_{jt} - \chi_{jt-1}$. Treated restaurants are defined as the estab-

[26]No restriction is imposed on posterior probability of adopting the app to avoid conditioning on an outcome.

lishments that belong to the top 5 percentile of the distribution of Ω. When several observations of the same establishment belong to the top 5 percentile, I only keep the first event. Appendix Figure A14 plots the distribution of Ω. The mean of Ω is 0.01, while the top 5 percentile has a mean of 0.11 (standard deviation of 0.04). Treated establishments are matched to control establishments using the same procedure as in the enrollment analysis. Finally, I estimate the same event-study model as in Equation (5).

4.3 Research Design: Workers

This section provides an empirical strategy that allows to estimate the causal effect of online-delivery platforms on restaurant workers labor market outcomes. The first step to this estimation is to construct a control group. Workers who work in restaurants that do and do not enroll on the app may differ in various dimensions. Furthermore, firms that enroll on the app may differ from firms that do not enroll in the app, and these differences may spillover to workers by affecting their potential outcomes. Similar to the establishment level analysis, I build my control group using a matching algorithm where the pool of control workers are located in labor markets where no online-delivery platform technology is available at the time of treatment (and up to five quarters after treatment).

Matching To construct an appropriate comparison group, I use a matching procedure. I start by considering the pool of treated workers as those whose employer enrolls on the app. I restrict to workers who are treated up to December 2020 such that I can observe at least 4 quarters after treatment. I additionally impose that these workers must have at least two quarters of tenure [27]. For each cohort (quarter X year) of treated workers, the potential control group corresponds to all the restaurant workers that work during the same date in a micro-region where no online-delivery platforms were available previous to the date and for the subsequent 5 quarters after treatment.

Each treated worker is then matched to a control worker the quarter previous to treatment. Workers are matched exactly on gender, occupation, quartile of firm size, quartile of average earnings of the firm and median of the share of restaurants (in the microregion) within a 1km radius[28]. I use a one-to-one matching using a caliper algorithm (Stepner and Garland, 2017)[29]. I use earnings in $t^* - 3$ to $t^* - 1$ (with a bandwidth of ± 200 BRL),age (with a bandwidth of ± 2 years) and tenure (with a bandwidth of ± 1 quarter).

[27] Tenure restrictions are commonly used in the job displacement literature (e.g., Jacobson et al., 1993; Schmieder et al., 2023; Bertheau et al., 2023). This restriction is imposed to measure outcomes for workers with a certain degree of attachment to the firm.

[28] Occupations are based on the 6 digit CBO code (Classificacao Brasileira de Ocupacoes). I define four groups of occupations: waiters, cooks, administrative and other. More details on the construction of these four categories is available in Appendix XX.

[29] Workers are matched without replacement within each cohort of treatment.

Econometric Framework & Identification I estimate the effect of employer enrollment on restaurant workers labor market outcomes by estimating Equation (5) on workers. Under this specification, Y_{it} is the outcome of interest (e.g., earnings, employment) for individual i in time t. α_i are worker fixed effects, δ_t are quarter-year fixed effects. I additionally control for a quadratic in age. *Treated* is a dummy variable indicating if the employer of individual i enrolls on the app, while $t^*(i)$ indicates the date in which the employer enrolled on the app. $\mathbf{1}\{t = t^*(i) + k\}$ are the event-study coefficients that reference the time relative to treatment date. The main coefficient of interest is β_k which captures the effect of employer enrollment on the app on the outcome of interest. The event study indicators are normalized relative to β_{-1}. Therefore, the coefficients β_k for $k \geq 0$ capture the effect of the employer enrolling on the app on outcome y_{it}, k quarters after the enrollment relative to the quarter before the employer enrolled on the app. Standard errors ar clustered at the worker level.

Likewise the establishment level analysis, the research design for workers relies on the parallel trend assumption. Although an employer's decision to enroll in the app is likely exogenous to the worker, it is not feasible to test this identifying assumption directly. A potential concern is that the employer's decision to enroll in the app could correlate with potential worker-level shocks. To maximize the likelihood of the validity of the parallel trends assumption workers are matched based on age, tenure, gender, occupation, and quartile of firm size to control workers in labor markets where the app is unavailable. The latter re-enforces the strength of the control group as a suitable counterfactual, as their employers are not able to enroll in the app despite potential similar trends. Second, I compare the outcomes for treated and control workers in the quarters prior to the employer's enrollment in the app, as shown in Figure 9. Both earnings and employment outcomes are similar in trends and levels in the quarters preceding treatment, even for periods not targeted by the matching algorithm (e.g., quarters -7 to -3).

5 Impact of Online-Delivery Platforms on Restaurants Labor Demand

This section discusses the impact that online-delivery platforms have on restaurants labor demand. Section 5.1 presents summary statistics and descriptive evidence for treated and control establishments, Section 5.2 discusses the main results of the event study analysis, Section 5.3-5.5 discuss effects by occupation, restaurant pay policy and density of restaurants. Finally, Section 5.6 presents some robustness checks and Section 5.7 studies potential spillover effects of the adoption of the app by competitors.

5.1 Summary Statistics & Descriptive Evidence

Column (1) and Column (2) of Table 1 present a snapshot of the characteristics of the matched control and treated restaurants in 2017—the year prior to the entry of the app—, respectively.

Workers at treated and control restaurants average 11 years of formal education—slightly less than complete high-school— and earn approximately 1,500 BRL per month (in real terms of 2018). Workers at control establishments have slightly higher tenure (2.6 years vs 1.4 years at treated establishments) and are also slightly older (33.4 years vs 32.5 years at treated establishments). Both treated and control restaurants predominantly hire brazilian, full-time workers (97 percent) and have a similar share of female workers (59 percent). These restaurants have an average size of 11 workers and waiters represent approximately 50 percent of their workforce.

Column (3) displays a snapshot of the characteristics for all potential treated restaurants in 2017. Overall, these establishments have similar characteristics to the matched treated and control restaurants in terms of average education of their workers, tenure, average age, share of brazilian, female and full-time workforce. However, matched treated restaurants are slightly larger than the average of potential treated restaurant (11 workers vs 9 workers) and pay slightly higher average wages.

Lastly, column (4) provides a snapshot of all restaurants in 2017. Compared to the matched treated and control restaurants, the average restaurant in 2017 was smaller, employing an average of 7 workers compared to 11 in the matched groups. Interestingly, while the average restaurant in 2017 paid slightly lower average wages than the matched treated restaurants (1,530 BRL vs. 1,438 BRL-2018), these wages were still significantly above the minimum wage of 971 BRL-2018. This, along with the fact that restaurants in Brazil predominantly employ full-time workers, contrasts with other countries, such as the US, where part-time work and tips are key components of restaurant sector employment cite(some paper). Figure A15 shows the distribution of wages for workers at treated and control firms in $t^* - 1$ and shows that there is no evidence of bunching around the national minimum wage.

Figure 2 panel (a) plots the distribution of the AKM firm fixed effects for restaurants that at some point enroll on the app and restaurants that never enroll on the app using the method pioneered by Abowd et al. (1999) [30]. Restaurants that adopt the app have on average 8 log points higher AKM firm fixed effects. This suggests that firms that enroll on the app have a wage-setting policy such that they pay higher wages to all the workers. Interestingly, AKM firm fixed effects also have predictive power for the intensive margin. Figure 2 panel (b) shows that there is a positive correlation between the AKM firm fixed effects and the number of hours app drivers work for each restaurants.

Figure 3 presents trends of total hours hired for the matched establishments that enroll on the app. Panel (a) shows that total hours of in-house workers reduced by 27.6 percent between $t^* - 2$ and $t^* + 5$. Only a part of this decrease is compensated by outsourced app workers. When account-

[30] Gerard et al. (2021) have tested the validity of AKM model in Brazil. Appendix XX presents details on the sample construction and AKM estimation.

ing for app workers, total hours worked at the establishment decrease by 21.3 percent. Panel (b) shows that as an establishment enrolls on the app, they increasingly rely more on app workers. App workers represent 2.4 percent of the total hours worked at the establishment the month of enrollment. This share increases over time and reaches 7.5 percent after 5 quarters of enrollment. Both of these patterns suggest a replacement between in-house workers and app workers after app adoption. However, understanding the effect of app enrollment on labor demand requires a comparison with a counterfactual scenario. I present in the next sections the results of the event study analysis.

5.2 Main Results: Effect of Enrollment on the App

Trajectories of treated and control restaurants Figure 4 panel (a) shows the trajectories for log average wages paid to employees at treated and control restaurants. Both groups exhibit similar trends in earnings in the quarters prior to treatment. Average wages for both groups are mostly stable between $t^* - 7$ and $t^* - 2$. Wages present a sharp decrease between $t^* - 1$ and t^* of approximately 17 log points for treated establishments and 13 log points for control establishments. This pattern suggests that treated establishments may start making adjustments the quarter prior to enrollment in the app—which motivates using $t^* - 2$ as baseline in the event study analysis. Following enrollment on the app, differences in wages between treated and control establishments remain fairly constant over time.

Panel (c) reports the trends for log firm size—as considered by workers formally hired (in-house) by the establishment—at treated and control restaurants. Both groups show similar trends (and levels) in size in the quarters prior to treatment. As with wages, firm size for both types of establishments remain mostly stable between quarters $t^* - 7$ and $t^* - 2$ and suffer a large decrease between $t^* - 1$ and t^*. Firm size decreases by approximately 10 log points for treated establishments and 9 log points for control establishments during that period. In contrast to wages, the size of treated and control establishments persistently diverge after enrollment up to five quarters after the event. After five quarters of enrollment, treated establishments are on average 7 log points smaller than control establishments.

Figure A16 illustrates the trends for the extensive margin of restaurants[31]. Five quarters after the event, approximately 12 percent of the restaurants in the sample have closed, highlighting the high turnover in the sector. The average difference between the two groups at the extensive margin appears marginal, with treated restaurants being 1.5 percent more likely to close after five quarters. To investigate these patterns more formally, I next present the estimated results for the regression model.

[31] By construction, restaurants cannot close prior to the event. The outcome measured in this figure is closure (after opening) and thus can only differ from 0 in the post-period.

Effect of App Enrollment on Size and Hours Figure 4 Panel (b) presents the estimated β_k from Equation 5 for log firm size and shows that treated restaurants decrease the number of in-house workers after adopting the app and that this effect is persistent. After 5 quarters of enrollment, the number of in-house workers at treated firms decrease by 6 percent.

Figure 5 shows the estimated effect of app adoption on the log number of hours worked by in-house workers (red line) and the log number of hours including app workers (blue line) [32]. Consistent with a decrease in the intensity of in-house labor, the results show that treated restaurants reduce the number of hours worked by in-house workers by 7.6 percent after 5 quarters of app adoption. This decrease in in-house hours is entirely compensated the hours worked by outsourced workers. The number of hours worked at the establishment when including app workers is essentially unchanged five quarters after enrollment.

Taken together, these results suggest that restaurants adopting the app are decreasing their labor demand for in-house workers and replacing in-house labor with app delivery drivers. However, to study the relative importance of each component shown in Equations (3) and (4), we must focus on the effects by occupation, which I discuss in the next section.

Effect of App Enrollment on Wages Figure 4 Panel (d) plots the effects of enrollment on the app on average wages paid at the restaurants. Average wages at treated firms decrease by 2.8 percent the quarter prior to enrollment, suggesting that firms may adjust wages prior to enrollment. The decrease in average wages persists during the post-enrollment period. Average wages are on average 2 percent lower between $t^* + 1$ and $t^* + 4$ for treated establishments and only seem to recover in $t^* + 5$.

The wage level effects are smaller in absolute terms compared to the effects found for establishment size. The disparity between wage and size effect could be associated with two main factors. First, treated restaurants may be changing their composition of occupations as they reduce their size. If lower-paid jobs are being replaced at a higher rate than high-paid jobs by outsourced app workers, then the effect of adoption on average wage of in-house workers would be smaller the effect on firm size [33]. Second, employment may be elastic such that a relatively *smaller* change in wages is needed to decrease a *larger* amount of labor hired. To untangle these two components, I zoom in on the impact of app adoption on the labor demand of cooks and waiters separately [34].

[32]App worker hours are measured as the time an app driver is dedicating to deliver food from a specific establishment.

[33]For instance, if cooks are on average paid more than waiters, a decrease in θ could yield a smaller effect on average wages at the firm level

[34]A model that allows for worker heterogeneity could also explain the disparity between wages and size through a change in the type of workers (more or less productive)—conditional on the occupational structure of the establishment. Figure A17 panel (a) plots the effect of app enrollment on the average worker fixed effects at the establishment and finds a null effect. Figure A17 panel (b) leverages the matched design to construct establishment level treatment effects for average worker fixed effects following Schmieder et al. (2023). The figure plots these treatment effects on

5.3 *Effects by Occupation*

This section presents treatment effects of adoption on labor demand for in-house cooks and waiter separately. I start by studying the change in the overall service sector (that is, all workers that are not cooks including app workers). Figure A18 provides evidence that the total hours hired of service workers (including app workers) remains essentially unaffected five quarters after app adoption. Through the lens of equation (3), the null effect on the size of the service sector indicates that changes in the number of waiters will only be a reflection of changes in the revenue of the firm and the relative productivity of waiters.

Table 2 presents difference-in-difference estimates for cooks and waiters using the methodology developed by Borusyak et al. (2024). Column (1) reports the causal effect of adoption of the online delivery platform on the number of waiters. Treated restaurants decrease the number of in-house waiters by 5.4 percent after adoption. Column (2) reports the changes in the number of cooks after app adoption. Enrollment on the app has a sharp 0 effect on the demand for cooks.

The null effect on cooks has two important implications. First, the adoption of online delivery platforms has no impact on the revenue of the average restaurant. Furthermore, the null effect on the revenue combined with the zero effect on total service workers implies that changes in the number of waiters are a reflection of the relative productivity between waiters and delivery workers—the outsourcing effect. Taken together, column (1) and column (2) suggest that the adoption of online-delivery platforms allow the average restaurant to shift their business from in-house dinning to delivery services without a clear effect on the product demand of the goods produced by the adopting restaurants.[35].

Column (3) reports the effect of app adoption on the wages of waiters. On average, the wages of waiters decrease by 2.25 percent after app adoption. A direct implication of the model presented in Section (2) is that the labor supply elasticity can be recovered from the following ratio:

$$\beta = \frac{\Delta\ ln(\aleph)}{\Delta\ ln(W_{\aleph})} \tag{6}$$

Using this ratio and my estimations for number of waiters and wages, the implied labor supply elasticity for waiters is 2.43. This is on the higher end of what has been found in other empirical studies (e,g., Card et al., 2018; Manning, 2021), indicating that the labor market for waiters is

average worker fixed effects on firm fixed effects and finds a flat 0 discarding the app enhancing sorting.

[35] A model where restaurants produce two substitutable separate goods (in-house dining and delivery services) that use different types of workers could also explain the patterns. In such a model all the effect would be driven by changes in consumer demand as there would be no room for the outsourcing effect. Importantly, this type of model would predict a strong negative correlation between the effect on the number of waiters and the intensity of app sales by the restaurant. In Figure A20 I plot the establishment level treatment effects on the number of waiters and the hours of app workers used by the restaurant and do not find evidence of a negative correlation.

fairly competitive. This is not surprising taking into account that the restaurant sector is usually considered a sector with close-to-null rent-sharing (Card et al., 2016).

Column (4) reports the effect of app adoption on the wages of cooks. Consistent with the null effect on labor demand for cooks, the effect on wages is not statistically different from 0. In summary, the results suggest that the outsourcing effect dominates for the average firm, leading to a decrease in the number of waiters, while the number of cooks remains unaffected. I now explore heterogeneities across restaurants that allow to potentially isolate the outsourcing effect from the product demand effect.

5.4 *Effects by Establishment Pay Premium*

Up to the moment, the analysis has centered around the *average* treatment effect of app adoption on the labor demand of restaurants. However, it is possible that the returns to adoption are heterogenous depending on the wage setting of the firm. Several models of outsourcing suggest that higher paying firms will be more likely to substitute in-house workers to outsourced workers in order to decrease labor costs (Bilal and Lhuillier, 2022; Spitze, 2022)[36].

To test this, Figure 6 plots the effects on firm size of adoption of the app by median of AKM firm fixed effects. Panel (a) shows that high AKM firms decrease their in-house labor more than low AKM firms. Five quarters after adoption, high paying firms decrease their in-house size by approximately 4 log points more than low paying firms. Panel (b) of Figure 6 shows that the change in total hours (including app workers) is not significantly different from 0 after 5 quarters of adoption for either high are low AKM restaurants—although the difference in total hours between high and low AKM restaurants is significant.

Table 4 presents the results for waiters and cooks separately. Column (1) shows that low AKM firms decrease the number of waiters by 3.5 log points after enrollment, while Column (3) reports that high AKM firms decrease the number of waiters by 6.2 log points, suggesting that high paying firms outsource a larger portion of their workforce [37].

However, it is still possible that the product demand effect is different across high and low AKM firms. This would be the case if firms that face an ex-ante large market for their product have a relatively smaller increase in their market as they adopt the app. To test this, I start by plotting the effects of adoption on total hours hired in the service sector by AKM firm fixed effects.

[36]Notice that the model proposed in Section 2 does not model selection into the app and so does include this feature. Introducing a fixed cost to the app could give a similar prediction to those found in the literature. However, in that case the mechanism compared to Bilal and Lhuillier (2022) would be different as in their case high-paying firms select into outsourcing due to the differences between the cost of outsourced workers and the cost of in-house workers that have a positive sloped labor supply.

[37]These findings are consistent with what has been found empirically in other settings such as Germany and Argentina, where higher paying firms have larger incentives to outsource to avoid paying higher rents to all their workers (Goldschmidt and Schmieder, 2017; Drenik et al., 2023).

Figure A19 shows that the total hours hired by service workers are unaffected in restaurants with both high and low pay premium. With that result in hand, it is possible to once again interpret the effects on the number of waiters as a reflection of the outsourcing effect and the change in revenue at adopting firms. Column (2) and Column (4) of Table 4 show that the number of cooks is not significantly different from 0 for both high and low AKM firms, suggesting that there is no significant impact in the revenue of both high and low paying firms. Taken together these results suggests that the difference between high and low paying restaurants is due to the outsourcing effect being higher for high paying restaurants compared to the restaurants that have a lower pay policy.

5.5 *Effects by Restaurant Density*

As of now, the estimates show limited impact of the product demand effect after adoption. However, it is possible that impact on the demand of goods is more salient in firms located in certain regions. Under the assumption of a constant outsourcing effect across regions, the difference in the effect of app adoption on in-house labor between high and low density areas will be a reflection of differences in the product demand effect. Consumer search models often predict that the agglomeration of establishments is a reflection of the demand externalities and distance to the average consumer (Vitali, 2022; Leonardi and Moretti, 2023).[38] In such models, as online-delivery platforms decrease transportation costs for consumers, the demand for restaurants at further distances from the average consumer—and therefore located in areas with less density of restaurants—should increase more respect to restaurants located in more central areas (or with more density of restaurants). [39]

In this section I explore heterogeneous effects of delivery platform adoption on labor demand for restaurants located in areas with high and low density of restaurants. To define restaurant density, I start by geocoding the universe of formal restaurants in Brazil between 2017 and 2021.[40] For each restaurant, count the number of nearby restaurants that are within 1 kilometer radius of the establishment. Define this number as τ_{jt}. I then calculate quartiles per micro-region and year of τ and define restaurants located in high-density areas if their τ_{jt} is above the median the quarter before they adopt the delivery platform.[41]

[38]Appendix XX provides an extension to the model presented in Section 2 where I microfound the product demand of restaurants through a consumer search model. In that model, density of restaurants will be a reflection of the quality of restaurants in the are—demand externalities— and the distance to the average consumer in the region.

[39]Another way of thinking about this is that restaurants that had a lower demand for their goods previous to delivery platforms, have more to gain from the these apps as they can expand to new markets. In the contrast, restaurants that faced a higher baseline demand previous to the adoption of an online-delivery platform is less likely to benefit as much from expanding to new markets. In contrast, the latter are more likely to face a crowd out from in-house dining to demand for delivery which would yield a net 0 effect on the demand of the restaurant.

[40]Formality here is defined as a restaurant reporting their workers to RIAS.

[41]Appendix XX describes taken to geo-locate the restaurants in Brazil and the share of restaurants I was able to

The next step is to study if there are heterogeneities in the outsourcing effect across locations. Although ex-ante there are no strong reasons to presume that the number of restaurants surrounding would have an impact on the outsourcing effect, I take two steps to ensure that the outsourcing effect is constant across high and low density areas. First, I compare the share of wage bill and hours that delivery workers represent respect to total service workers in high and low density areas.[42] Figure A21 shows that by quarter 5, both the share of wage bill and hours that delivery workers represent respect to total service workers is essentially the same across restaurants located in high and low dense areas suggesting that location is independent of the outsourcing effect. Second, to ensure that the distribution of firm pay premium across high and low dense areas is similar, I re-weight treated restaurants located in areas with lower density following the methodology pioneered by DiNardo et al. (1996)—DFL estimator—.

I proceed to plot the effects of adoption on firm size and total hours (including app workers) by density of restaurants. Figure 7 panel (a) shows that restaurants in high dense areas reduce their in-house labor substantially more than restaurants located in less dense areas. Restaurants located in high dense areas decrease their in-house labor by approximately 8 percent five quarters after adopting the app. In contrast, restaurants located in less dense areas do not change their in-house labor after adopting the app. Panel (b), shows large difference in the effect of total of hours, when accounting for app workers. Total hours at restaurants located in areas with high density of restaurants are essentially unchanged while hours for at restaurants located in less dense areas increase by 6 percent after 5 quarters of the adoption of the app.

Table 3 presents the results for waiters and cooks separately. Column (1) shows that the number of waiters at restaurants in high dense areas decreases by 7.1 percent after the adoption of the app. In contrast, column (3) reports that the effect on the number of waiters at restaurants located in areas with less density of restaurants is not significantly different from 0. Consistent with the overall effect on hours, the number of cooks is not significantly different from 0 for restaurants in located in areas with more density of restaurants (column 2), while the cooks increase 3.6 percent for restaurants located in areas with less density of restaurants (column 4) suggesting an overall increase in the demand of the latter group after adoption of the platform.

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geo-locate per year.

[42]The CES production function presented in Section 2 implies that differences across locations in the ratio of the wage bill and the ratio of hours of delivery workers to in-house service workers should identify the ratio of productivities between the two types of workers:

$$\left[\Delta_H\, ln\left(\frac{\text{WB }\omega}{\text{WB }S}\right) - \Delta_L\, ln\left(\frac{\text{WB }\omega}{\text{WB }S}\right)\right] - \rho\left[\Delta_H\, ln\left(\frac{\omega}{S}\right) - \Delta_L\, ln\left(\frac{\omega}{S}\right)\right] = \Delta_H\, ln\left(\frac{\theta}{1-\theta}\right) - \Delta_L\, ln\left(\frac{\theta}{1-\theta}\right)$$

Where H and L define areas with high and low density of restaurants respectively. Ideally one would want to see if the percentage difference (between pre and post adoption) in wage bills and hours between delivery workers and in-house workers is the same across high and low dense areas. However, the sparsity of data on delivery workers in the pre-adoption period makes this analysis unfeasible.

Taken together, the results presented in this section suggest that online-delivery platforms have different impacts on the product demand of restaurants depending on the location of these restaurants. These heterogenous effects are reflected in the overall impact on labor demand. Importantly, these results suggest that online-delivery platforms may provide an alternative path for restaurants to expand their business without having to locate in central areas or benefit from the demand externalities that accompany agglomeration (Vitali, 2022; Leonardi and Moretti, 2023).

5.6 Robustness

In this section I explore the sensitivity of the results to several robustness checks. First, following the recent difference-in-difference literature with staggered treatment, Figure A22 show that the main results are robust to using the estimator proposed by Borusyak et al. (2024). This is not surprising, as the control establishments are collected from regions where treatment is not available, and therefore ar never treated in my setting (Roth et al., 2023).

The period of consideration overlaps with the COVID-19 pandemic. This raises the concern that the results could be mainly driven by firms that adopt the app to cope with the pandemic. In this case, the negative impact of enrollment on the app, could be primarily related to a response to the pandemic than to the app itself. Indeed, if firms that were most negatively exposed by the pandemic are the most responsive to the app, the external validity of the results could be limited. To address this concern, I take three routs. First, leveraging the the matching strategy, I plot in Figure A23 the establishment level treatment effects on size and the change in the number of covid cases per capita in the post period.[43] The figure shows that treatment effects on size are not correlated with increases in covid cases. Second, I estimate the effect of enrollment on the app on firm size for establishments that are treated until 5 quarters prior to the pandemic and compare the estimates to restaurants treated during the pandemic. Figure A24 shows that if anything, the effects on in-house size are more negative for establishments treated in the pre-covid period. Lastly, I leverage within state variation in app availability and consider a specification that includes state-year fixed effects to control for state-specific policies that may have affected restaurants during Covid (Chauvin, 2021). Figure A25 shows that the results are non-sensitive to the inclusion of these fixed effects.

An additional concern regarding the external validity of my estimates is related to the relatively high levels of informality in Brazil compared to other developed countries such as the US and Canada. If restaurants that adopt the app hire a large set of their workers informally, it is possible that part of the changes in labor demand are not observed in my data (which only covers formal workers). To understand the potential implications of this, I estimate the share of

[43]I constructed the establishment level treatment effects following Schmieder et al. (2023). See Appendix XX for details.

formal workers in the restaurant sector in each municipality using the 2010 Brazilian census (the latest census available). I then separate my matched sample in above and below the median of the share of formal workers—based on the share of informal workers of their municipality. Figure A26 shows that restaurants located in municipalities with below the median informality, decrease their in-house size by approximately 9 percent after 5 quarters of adoption. In contrast, restaurants located in municipalities with high informality in the sector, decrease their formal labor by just 2 percent, suggesting that these restaurants may be adjusting their informal (unobserved) labor instead. If anything, these results suggest that the main results are conservative estimates of the effect of app adoption on labor demand. When considering the overall effect of the app on workers in Section 7, I will consider the possibility of the adoption of the delivery platform affecting informal workers as well.

5.7 Indirect Effect of Online-Delivery Platforms on Non-Adopting Restaurants

Online-delivery platforms can have an impact on restaurants labor demand that goes beyond those that adopt these apps. Specifically, if establishments that start selling goods through online-delivery platforms crowd out demand for thee restaurants that do not adopt such platforms, the labor demand of non-adopting restaurants could be affected (Chava et al., 2024). [44] Importantly understanding the impact that online-delivery platforms have on non-adopting restaurants is crucial to understand the overall impact of these platforms on workers in the sector.

Following the discussion in Section 4.2 I define an event for non-adopters as a large sudden increase in the share of restaurants within a 1 kilometer radius that adopt the online-delivery platform. Figure 8 Panel (a) presents the estimated treatment effects of this event on log firm size of non-adopters. The estimates show that firm size decreases 3 percent on impact. However, this negative effect on firm size is not persistent over time. Five quarters after the event, the effect on firm size is essentially null. [45]. Figure A27 panel (a) shows the trends on closure for treated and control establishments. Restaurants that are exposed to neighbors adoption are approximately 5 percent more likely to close after 5 quarters of the event respect to control establishments. Figure 8 Panel (b) shows that the average wages of non-adopters decrease by 2 percent after 5 quarters of the event. Taken together these results suggest that restaurants that adopt online-delivery platforms may be crowding out the demand for non-adopters, leading to a decrease in their size and average paid wages. [46] I now proceed in the next section to investigate the impact that the

[44]The model presented in Appendix XX highlights that the adoption of online-delivery platforms can have an impact in the market that goes beyond those who adopt. Specifically, the 'spillover' term in Equation A9 implies that as the share of neighbors that have enrolled on the app increases, the consumer search costs associated with the product of restaurant j will increase, leading to an impact on its demand.

[45]Appendix Figure A28 shows that the results are similar when considering restaurants slightly further away, such as those within a radius of 2 kilometers using a donut design.

[46]Figure A27 panel (b) shows that approximately 7 percent of the ex-ante non-adopting restaurants adopt the

adoption of online-delivery platforms has on workers in the restaurant sector.

6 Restaurant Workers

The results presented in Section 5 provide evidence that restaurants replace in-house waiters with outsourced delivery workers, potentially leading to a persistent negative effect on workers earnings. Yet the magnitude of this impact on workers will ultimately depend on the extent to which workers are able to find alternative employment and the quality of these new jobs. I now proceed to study the effects that restaurants adoption of online-delivery platforms has on restaurant workers labor market outcomes. Section 6.1 presents summary statistics and discusses the main results of the event study analysis, Section 6.2 presents the event study analysis for spillovers on workers.

6.1 Main Results: Effect of Employer Enrollment on the App

Summary Statistics Table 5 presents summary statistics for matched treated workers (Column 1), matched control workers (Column 2) and all potential treated workers—including those did not match— (Column 3) the quarter prior to treatment. Matched treated and control workers earn on average 1,500 BRL-2018 per month, work full-time, have 11 years of formal education and are 33 years old. The sample of matched workers is composed by 60 percent of female workers. In terms of occupations, 65 percent of the matched workers are waiters, 18 percent are cooks, and the remaining 17 percent are other types of workers. The average tenure of matched workers is 3.7 years. When comparing to all potentially treated workers (column 3), the matched workers have lower earnings (1,501 vs 1,788 BRL-2018), have a slightly higher share of female workers and of waiters.

Trajectories of Treated and Control Workers Figure 9 panel (a) presents the earnings trajectories for treated and control workers. Both groups of workers present similar levels in terms of their earnings in the prior to treatment. Following the employers adoption of the app, treated workers experience a slightly stronger negative impact on their formal sector earnings compared to the control group that persists 5 quarters after the event [47]. Specifically, treated workers experience a decrease of 11.3 percent in their earnings the quarter after the event, while control workers experience a decrease of 9.7 percent. The decline in earnings is persistent, as treated workers earnings decrease 37.1 percent five quarters after the event, while control workers earnings decrease by 35.4 percent.

Panel (c) reports the trends of formal employment for treated and control workers. Similar to

delivery platform after 5 quarters of the event.

[47] Given that control workers are also required to have 2 quarters of tenure at the moment of the event — but do not have any tenure requirements after the event —, some may experience a decline in earnings post event due to non-employment.

earnings, both treated and control workers present a negative and persistent trend in terms of their employment. Five quarters after the event, treated workers experience a slightly stronger negative impact on their formal employment compared to the control group (32.7 percent vs 31 percent decrease). To further investigate these patterns, I next presents the estimated results for the regression model.

Earnings & Employment Figure 9 Panel (b) presents the estimated β_k from Equation (5) for total monthly earnings in the formal sector. The quarter following the employers adoption of the app, treated workers earnings are reduced by 20 BRL-2018 — approximately 1.5 percent of their pre-event average earnings. This slightly negative impact on earnings is persistent 5 quarters after the event (although the estimates become noisier in the fifth quarter)[48]. Panel (c) presents the estimated treatment effects for employment. The estimates show that treated workers experience a small negative impact on their formal employment after the event. Workers whose employer adopts the delivery platform experience a negative impact of 1.5 percentage points on their probability of being employed in the formal sector. This negative impact is persistent 5 quarters after the event [49].

Figure A30 panel (a) presents the cumulative likelihood of leaving their pre-event establishment (either to another firm or to non-employment). Workers whose employer adopts the delivery platform have a higher likelihood of leaving the firm after the event. Specifically, these workers are 2 percent more likely to leave their employer the quarter after the event. The cumulative likelihood increases over time, as workers are 6 percent more likely to leave their employer 5 quarters after their employer adopts the app. These estimates are the worker side reflection of Figure 4 panel (b) which reported the same patterns when estimating the effect of app adoption on in-house firm size. Taken together with the employment effects of employer adoption of the platform reported in Figure 9 panel (d), these results suggest that a significant share of restaurant workers leave their job as their employer adopts the app, but are able to find a new formal job relatively quickly after the event. Figure A30 panel (b) confirms this. Approximately 75 percent

[48]For context, the negative earnings effect of mass-layoffs in Brazil es estimated to be 40 percent (Britto et al., 2022). In Germany, workers who are exposed to a domestic outsourcing event (and remain employed) lose approximately 5 percent of their earnings the year after the event (Goldschmidt and Schmieder, 2017). In Italy, outsourced workers lose 23 percent percent of their pre-outsourced earnings after the event, effect which is mostly driven by the loss of formal employment (Daruich and Kuntze, 2024).

[49]Figure A29 panel (a) shows treatment effects of employers adoption of the app for workers log earnings (which conditions on employment). These estimates show that conditional on employment, treated workers earnings reduce by approximate 3 percent after five quarters of the event. Figure A29 panel (b) reports estimates on log monthly earnings after dropping pairs of workers where the treated workers is not employed but the control is. The underlying assumption is that is that the control worker is a *complier*. That is, a worker which if they're employer would have adopted the app, they would have been non-employed as well (Lee, 2009). By dropping these compliers from the sample, I can evaluate evaluate the effect of app adoption among the *always takers*—those who remain employed even after adoption of the app. The results essentially do not change after conditioning on always takers.

of the workers that leave their employer are working at a new employer the fifth quarter after the event. This dynamic, likely explains why workers earnings are not as negatively affected as one would expect from the firm level analysis.

Transition to App Work The richness of the data allows me to measure if workers whose employer adopt the delivery platform are more likely to transition to work as gig delivery drivers themselves. That is, this would allow to understand if part of the negative impact on earnings is compensated by the new income generated by working on the app. Figure A31 presents the estimated treatment effects for the likelihood of working on the delivery platform. Following the quarter of the employers adoption of the platform, workers are 0.1 percent more likely to work on the platform. The likelihood of transition to app work slightly increases over time such that 5 quarters after the event, treated workers are 0.4 percent more likely to work on the app. The small impact on transition to app work suggests that waiters in the restaurant sector are being replaced by a different set of workers and not being outsourced themselves to a new employer. The characteristics of these gig workers are explored in Section 7.

6.2 Indirect Effect of Online-Delivery Platforms on Workers

To fully capture the costs and the benefits of online-delivery platforms on workers, one must also consider the impact that these platforms have on workers that are not directly employed by restaurants that adopt these platforms. Section 5.7 discussed the spillovers that the adoption of the platform of nearby restaurants has on non-adopting restaurants. Yet is unclear what the total effect of these spillovers is on workers at these non-adopting establishments. For instance, the set of workers affected by negative spillover shocks might differ from those impacted by the employer's adoption of the app, which could result in different effects on their earnings and employment. This could be the case if non-adopting firms have a lower pay policy (as suggested in Figure 2) or different occupations are affected beyond waiters.

Figure 10 panel (a) presents the estimated results of Equation (5) on total earnings for workers who are employed at non-adopting restaurants that are exposed to a sharp increase in the share of nearby restaurants on the platform as defined in Section 4.2. The results show that workers at non-adopting restaurants experience a negative impact on their earnings after the event that is larger than those experienced by workers at restaurants that indeed do adopt the platform. Workers at non-adopting restaurants suffer a 3 percent decrease in their earnings the quarter after the event. This effect is persistent and increases to 6.6 percent five quarters after the event. Panel (b) presents the estimated treatment effects for employment. The results show that workers at non-adopting restaurants also experience a negative impact on their formal employment after the event. Workers at non-adopting restaurants are 2.3 percentage points less likely to be employed in the formal sector the quarter following the event. This negative impact is persistent 5 quarters after the event and increases to 3.8 percentage points.

The stronger impact on earnings and employment is driven the large fraction of non-adopting restaurants closing. Figure A32 plots the differences in the effects for workers whose employer (the quarter prior to the event) eventually closes and those for whom the employer remains open. Panel (a) shows that workers that were working at restaurants (the quarter prior to the event) that did not eventually closed see their earnings decrease by approximately 2.6 percent five quarters after the event. These workers represent 92 percent of the matched sample and the effects on this group follows closely the effects of delivery platforms on in-house workers that were affected directly by their employer adopting the platform. In contrast, workers whose employer at t*-1 eventually closes —8 percent of the matched sample— suffer a 37 percent decrease in their earnings five quarters after the event. This effect is largely driven by the extensive margin as these workers are 40 percent less likely to be employed five quarters following the event.

Taken together, these results suggest that online-delivery platforms have an impact on formal employment and earnings that goes beyond the direct effects that they have on workers at restaurants that adopt these platforms. The spillover effects at non-adopting restaurants are larger than the direct effects of employer adoption due to restaurant closure. Although understanding the exact mechanisms through which these spillovers operate in the product market exceed the scope of this paper, a search cost model like the one proposed in Section A1 could provide a potential explanation. In this model, the spillovers of the adoption of platforms of nearby restaurants on workers at non-adopting restaurants could be driven by a crowding out effect in the product market. Through the lens of the model, this would imply that as nearby restaurants adopt the platform, consumers suffer a higher search cost when searching for non-adopting restaurants. This increase in search costs would lead to a subsequent decrease in demand for the product of non-adopting restaurants, which decreases the demand for labor at these restaurants. Importantly, a complete overview of winners and losers of online-delivery platforms must take into account not only the direct effect of the app on workers at adopting restaurants, but also the spillovers that these platforms may have on workers at non-adopting restaurants. The next section discusses the trade-offs of the online-delivery platforms, by also taking into account informal workers in the restaurant sector and the app workers.

7 Winners & Losers

To study the total effect of online-delivery platforms on workers earnings, I propose the following the accounting exercise per adopting restaurant:

$$\underbrace{\pi_{\text{app}}}_{\substack{\text{Total Wage-Bill Effect}\\\text{App}}} = \underbrace{\pi_{\text{in-house}}}_{\substack{\text{Wage-Bill Effect}\\\text{In-House Workers}}} + \underbrace{\pi_{\text{spillovers}}}_{\substack{\text{Wage-Bill Effect}\\\text{Spillovers}}} + \underbrace{\pi_{\text{app-workers}}}_{\substack{\text{Wage-Bill Effect}\\\text{App-Workers}}} \tag{7}$$

Where wage bill effects is the sum of total earnings effects on each group of workers times the average number of workers affected per adopting restaurant. As of now, I have discussed that the adoption of online-delivery platforms has a slightly negative impact on the earnings of in-house restaurant workers and a stronger negative effect on the earnings of workers at non-adopting restaurants. Table 6 summarizes the per adopting firm wage bill effect of both components. Column (1) shows the total earnings lost by in-house restaurant workers per adopting restaurant each quarter after the restaurant enrolls adopts the delivery platform. The cumulative discounted present value loss five quarters after adopting the app is 3,681 BRL (2018-Reais). This is equivalent to 6.3 percent of the average wage-bill of adopting restaurants before they start offering deliveries through a platform. Column (2) reports the effects for the same group, but net of social security contributions. As discussed in Section 3, considering net wages is particularly relevant when comparing gains and losses of the delivery platforms as app workers are not required to pay these contributions. When netting out contributions, the effect on in-house workers represents 5.9 percent of the pre-app wage bill of adopting restaurants.

Column (3) considers the effect on informal in-house workers. These workers are not observed directly in my data and so I rely on additional data sources to estimate this effect. I start by estimating the share of informal workers in the restaurant sector at each municipality using the 2010 Brazilian census (latest census available). I estimate that the average restaurant in my sample has 25 percent of informal workers. I then estimate the ratio informal wages to formal wages in the restaurant sector for each state-quarter using the Brazilian household survey (PNAD-C) which provides information representative at the state level. I estimate that informal restaurant workers in my sample earn on average 70 percent of the wages of formal workers. I assume that the wage effect on informal workers represents the same impact (in percentage of their pre-event earnings) as for formal workers. Using my estimates from the census and PNAD-C I then input to each adopting restaurant, the corresponding number of informal workers and the average wage effect on these informal workers. Column (3) shows that the effects on informal workers represent 1.4% of the wage-bill of adopting restaurants previous to the adoption of the platform.[50]

Column (4) reports the effect of spillovers per adopting restaurant. To estimate a per adopting restaurant spillover effect I re-scale the worker level spillover point estimates by the estimated effect of a spillover event on neighbors adoption. This provides a per worker effect in units of

[50]For all the columns of the table, the pre-adoption wage-bill is calculated considering informal workers as well.

nearby restaurants adoption (χ). I then multiply this re-scaled coefficient by the average χ in my sample. Finally, I multiply the re-scaled per worker effect by the average size of restaurants in Brazil between 2018 and 2021 to get a per firm adopting restaurant measure of spillovers.[51] The cumulative discounted present value loss of spillovers per adopting restaurant is 8,693 BRL (2018-Reais), which is equivalent to 15 percent of the pre-adoptiong wage bill of restaurants. When netting out contributions, these number reduces to 13.7 percent (Column 5). In Column 6, I consider the informal workers affected by spillovers following the same methodology as discussed previously. The effect on informal workers represents 3.4 percent of the wage-bill of adopting restaurants previous to the adoption of the platform.

The analysis of total effect of online-delivery platforms requires to study the impact that these platforms have on the earnings of app workers as well. This task is particularly challenging for several reasons. First a non-trivial share of app workers may be employed in the informal sector or unemployed prior to working on the app—and consequently are not visible in RAIS. I start by describing the trends and characteristics of app workers in my sample. Figure A33 panel (a) presents the trends of formal employment for workers before and after they start working on the app. Overall, app workers have a low-attachment to the formal sector. Seven quarters before their first delivery on the app, 29 percent of drivers held a formal job. This number decreases to 22 percent at the moment of their first delivery, and displays a slight recovery after 5 quarters where 24 percent of the drivers hold a formal job.

Table 7 summarizes the main characteristics and the performance of platform workers in my sample. Column (1) shows a snapshot of the characteristics of app workers the first quarter that they worked on the delivery platform. [52] The average platform worker was 29 years old and had 11 years of education. App workers are also predominantly non-black and men. Those who are formally employed when working on the platform have close to 2 years of tenure in their formal job, mostly work full-time and earn average monthly wages of approximately 1,500 BRL (1.57 times the minimum wage in 2018). Column (2) and Column (3) show the performance on the app for drivers who the quarter prior to working on the platform (for the first time) held a formal job (formal workers app workers) and for workers who did not hold a formal job prior to working on the app (non-formal workers app workers), respectively. On average, non-formal app workers earn 13 percent more than formal app workers on the platform per month (646 BRL-2018 vs 571 BRL-2018). This is explained by non-formal workers working more hours (35hs vs 30hs), spending more time logged on the app (76hs vs 62hs), doing more deliveries (92 vs 78), and covering more distance (480 kilometers vs 426 kilometers)[53].

[51] For full details see Appendix XXX.

[52] Demographic characteristics are only available for workers who at some point in their career held a formal job.

[53] The average driver spends slightly more than half of the time they are logged on the app without actually doing a delivery.

To estimate the impact of online-delivery platforms on app workers, I must consider not only the earnings they get from the app but also their potential outside options and potential costs of working on the app (such as gas, maintenance of vehicle, etc.). I take estimates from the previous studies in Brazil that calculate the average maintenance cost for app drivers in Brazil (Callil and PINCAÇO, 2023). [54]. To calculate the outside options of app workers, I start by separating app workers in two groups: (i) workers who the quarter prior to working on the app held a formal job (and were not laid-off), and (ii) workers who did not hold a formal job the quarter prior to working on the app, or held a formal job but were laid-off the quarter prior (or the first quarter) to their first spell on the platform. For the first group of platform workers, I take a conservative approach and define the outside option as the per hour wage they held the quarter prior to working on the app. The implicit assumption, is that these workers could have continued to earn the same wage if they had not started working on the platform. For workers who did not hold a formal employment prior to working on the platform, I estimate each workers outside option as the outside option of formal app workers in their municipality and quarter multiplied by the ratio of informal/unemployed to formal wages in their state-quarter found in PNAD-C. [55]

A limitation of my data is that I do not observe which worker delivered for each restaurant at each moment in time and therefore I can not compute the exact wage bill generated for app workers by each restaurant. I instead observe the earnings that each app worker makes per hour at each month/municipality and the total number of hours that restaurants used delivery services from the app at each month/municipality. I overcome this limitation by calculating the average per hour earnings of app workers in each month and municipality (weighted by the number of hours each platform worker worked in that month-municipality) and multiply per hour wage by the number of hours each restaurant utilizes delivery platforms. [56]

Table 6 Column (7) reports the average wage bill per adopting restaurant of app workers that held a formal job prior to working on the platform. These app workers made on average a cumulative present discounted value of 5,080 (BRL-2018), equivalent to 8.7 percent of the pre-platform wage bill of restaurants. Column (8) presents the total wage bill net of the opportunity costs and transportation/maintenance cost for the same group of workers. When considering the pre-platform wage per hour as the opportunity cost for these workers, the cumulative present discounted value decreases to 1,195 (BRL-2018)—equivalent to 2.1 percent of the pre-app wage

[54]The estimated maintenance cost for motorcycle delivery drivers is 3.7 BRL-2018 per hour worked

[55]I only consider men between 18 and 65 years of age, and exclude the agricultural sector. The average ratio of informal/unemployed to formal wages in my sample is 0.32.

[56]I define the per hour wage on the app for each worker as the total earnings they made in a month divided by 1.15 times the total hours they worked on the app that month. That is, I allow for an additional 15% of time to be idle/non-productive time. This is the mid point of what has been used in other studies in Brazil following the same type of workers (Callil and PINCAÇO, 2023).

bill. [57].

Table 6 Column (9) reports the app wage bill, per adopting restaurant, that workers that did not hold a formal employment (or were laid-off) the quarter prior to working on the app get each quarter after a restaurant adopts the platform. The per firm cumulative present discounted wage bill generated by the app for these non-formal workers is equivalent to 25,169 (BRL-2018)–equivalent to 43.3 percent of the average pre-app wage bill of adopting restaurants. Column (10) presents the wage-bill effects for the same group of workers when accounting for their transportation/maintenance costs and their outside option as estimated using the PNAD-C. The cumulative present discounted value of the app for these workers is 15,647 (BRL-2018)—equivalent to 26.9 percent of the pre-app wage bill of adopting restaurants.

Taken together, when considering the total effect of the delivery platform on workers wages, I find that the platform generates a wage-bill surplus of 4.5 percent of the average pre-platform wage bill of restaurants. Put differently, the gains of the platform for app workers (net of their costs of working on the app) are 18.5 percent larger than the direct and indirect impact that the platform has on restaurant workers both hired formally and informally. Although the outside options estimated through PNAD-C provide a reasonable benchmark, it is possible that gig workers may have outside options that are not completely accounted for in survey data. Figure 11 displays the total effect of the app as a function of the outside option of non-formal app workers (expressed as a ratio of their wages to the wages of formal workers—Φ—). The figure highlights a few interesting scenarios. First, if app workers that did not hold a formal job prior to working on the platform were unemployed (outside option of 0), then the total wage-bill surplus of the app would be equivalent to 12.5 percent of the pre-platform wage bill of restaurants. On the other extreme, if all non-formal app workers had the same outside option as formal workers, then the delivery platform would generate a wage-bill deficit of 12.4 percent. The break-even point is when the outside option of non-formal workers is 0.5 times the outside option of formal workers. In this case, the app generates a wage-bill surplus of 0.

Limitations & Discussion The approach taken to study the cost and benefits of the app is centered around the partial-equilibrium impact of the app and does not consider the potential re-allocation effects that the app may have. For instance, the app may act as a stepping stone for non-formal workers (Booth et al., 2002; Jahn and Rosholm, 2014) who may be able to enter the formal sector after working on the app. In-house workers displaced by outsourced app drivers may re-allocate to other types of firms (Dustmann et al., 2022) affecting their long-term career

[57]Figure A33 panel (b) shows trends for formal and app earnings for app workers that held a formal job the quarter prior to working on the app. Consistent with the app allowing individuals to smooth consumption over time, formal workers receive a negative income shock in the months prior to their first delivery on the app. Similar results have been found in the US (e.g., Koustas, 2018; Jackson, 2022)

paths—something that the time-frame of my data does not allow to measure—. These potential general equilibrium effects are beyond the scope of this paper, but are important avenues for future research to further understand the overall impact of online-delivery platforms on the labor market. Furthermore, the exercise presented in the section only considers the monetary value created (and destroyed) by delivery platforms but does not consider other non-pecuniary aspects such as amenities that may affect the total welfare impact of these apps. In particular, if app workers have a high valuation for flexibility, then the gains of platform for app workers may go beyond those I presented in this section (Mas and Pallais, 2020). Additionally, although the app studied in this paper is the largest in Brazil and represents a large share of the delivery market, it is also possible that gig drivers work on multiple apps at the same time (Caldwell and Oehlsen, 2023), or combine app worker with other types of non-formal worker, something that my analysis can not account for. In this case, if these workers are able to generate these additional income sources due to the flexibility of the app, the earnings effect of the app on formal workers could be underestimated. In contrast, if working on the app limits the possibilities of finding other jobs, it is possible that the effect of the platform on app workers may be overestimated.

8 Conclusion

References

Abowd, John M., Kramarz, Francis and Margolis, David N. (1999). 'High Wage Workers and High Wage Firms', *Econometrica* 67(2), 251–333.
URL: *http://doi.wiley.com/10.1111/1468-0262.00020*

Abraham, Katharine G., Haltiwanger, John C., Hou, Claire Y., Sandusky, Kristin and Spletzer, James. (2024), 'Driving the Gig Economy'.
URL: *https://www.nber.org/papers/w32766*

Acemoglu, Daron and Autor, David. (2011), Skills, Tasks and Technologies: Implications for Employment and Earnings, *in* 'Handbook of Labor Economics', Vol. 4, Elsevier, pp. 1043–1171.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0169721811024105*

Acemoglu, Daron, Kong, Fredric and Restrepo, Pascual. (2024), 'Tasks At Work: Comparative Advantage, Technology and Labor Demand'.
URL: *https://www.nber.org/papers/w32872*

Aguiar, Luis and Waldfogel, Joel. (2018), 'Platforms, Promotion, and Product Discovery: Evidence from Spotify Playlists'.
URL: *https://www.nber.org/papers/w24713*

Angrist, Joshua D, Caldwell, Sydnee and Hall, Jonathan V. (2021). 'Uber versus taxi: A driver's eye view', *American Economic Journal: Applied Economics* 13(3), 272–308. Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203-2425.

Arnold, David. (2019). 'Mergers and acquisitions, local labor market concentration, and worker outcomes', *Local Labor Market Concentration, and Worker Outcomes (October 27, 2019)* .

Autor, David H., Levy, Frank and Murnane, Richard J. (2003). 'The Skill Content of Recent Technological Change: An Empirical Exploration*', *The Quarterly Journal of Economics* 118(4), 1279–1333.
URL: *https://doi.org/10.1162/003355303322552801*

Bakos, J. Yannis. (1997). 'Reducing Buyer Search Costs: Implications for Electronic Marketplaces', *Management Science* 43(12), 1676–1692. Publisher: INFORMS.
URL: *https://pubsonline.informs.org/doi/abs/10.1287/mnsc.43.12.1676*

Berger, Thor, Chen, Chinchih and Frey, Carl Benedikt. (2018). 'Drivers of disruption? Estimating the Uber effect', *European Economic Review* 110, 197–210.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0014292118300849*

Bertheau, Antoine, Acabbi, Edoardo Maria, Barceló, Cristina, Gulyas, Andreas, Lombardi, Stefano and Saggio, Raffaele. (2023). 'The Unequal Consequences of Job Loss across Countries', *American Economic Review: Insights* 5(3), 393–408.
URL: *https://pubs.aeaweb.org/doi/10.1257/aeri.20220006*

Bilal, Adrien and Lhuillier, Hugo. (2022). 'Outsourcing, Inequality and Aggregate Output'.

Bloom, Nicholas, Sadun, Raffaella and Van Reenen, John. (2016), *Management as a Technology?*, Vol. 22327, National Bureau of Economic Research Cambridge, MA.

Booth, Alison L, Francesconi, Marco and Frank, Jeff. (2002). 'Temporary jobs: stepping stones or dead ends?', *The economic journal* 112(480), F189–F213.

Borusyak, Kirill, Jaravel, Xavier and Spiess, Jann. (2024), 'Revisiting Event Study Designs: Robust and Efficient Estimation'. arXiv:2108.12419 [econ].
URL: *http://arxiv.org/abs/2108.12419*

Britto, Diogo G. C., Pinotti, Paolo and Sampaio, Breno. (2022). 'The Effect of Job Loss

and Unemployment Insurance on Crime in Brazil', *Econometrica* 90(4), 1393–1423. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA18984.
URL: *https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA18984*

Bøler, Esther Ann. (2015). 'Technology-skill complementarity in a globalized world'.

Caldwell, Sydnee and Oehlsen, Emily. (2023). 'Gender, Outside Options, and Labor Supply: Experimental Evidence from the Gig Economy'.

Callil, Victor and PINCAÇO, Monise. (2023), 'Mobilidade Urbana e Logística de Entregas: Um Panorama Sobre o Trabalho de Motoristas e Entregadores Com Aplicativos'.

Card, David, Cardoso, Ana Rute, Heining, Joerg and Kline, Patrick. (2018). 'Firms and Labor Market Inequality: Evidence and Some Theory', *Journal of Labor Economics* 36(S1), S13–S70. Publisher: The University of Chicago Press.
URL: *https://www.journals.uchicago.edu/doi/10.1086/694153*

Card, David, Cardoso, Ana Rute and Kline, Patrick. (2016). 'Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women', *The Quarterly journal of economics* 131(2), 633–686.

Chauvin, Juan Pablo. (2021), Why does COVID-19 affect some cities more than others? Evidence from the first year of the pandemic in Brazil, Technical report, IDB Working Paper Series.

Chava, Sudheer, Oettl, Alexander, Singh, Manpreet and Zeng, Linghang. (2024). 'Creative Destruction? Impact of E-Commerce on the Retail Sector', *Management Science* 70(4), 2168–2187.
URL: *https://pubsonline.informs.org/doi/10.1287/mnsc.2023.4795*

Chen, Kuan-Ming, Ding, Claire, List, John A. and Mogstad, Magne. (2020), 'Reservation Wages and Workers' Valuation of Job Flexibility: Evidence from a Natural Field Experiment'.
URL: *https://www.nber.org/papers/w27807*

Chen, M. Keith, Chevalier, Judith A., Rossi, Peter E. and Oehlsen, Emily. (2019). 'The Value of Flexible Work: Evidence from Uber Drivers', *Journal of Political Economy* 127(6), 2735–2794. Publisher: The University of Chicago Press.
URL: *https://www.journals.uchicago.edu/doi/abs/10.1086/702171*

Corn, Hybrid. (1957). 'An Exploration in the Economics of Technological Change', *Econometrica* 25(4), 501–522.

Couture, Victor, Faber, Benjamin, Gu, Yizhen and Liu, Lizhi. (2021). 'Connecting the Countryside via E-Commerce: Evidence from China', *American Economic Review: Insights* 3(1), 35–50.
URL: *https://www.aeaweb.org/articles?id=10.1257/aeri.20190382*

Daruich, Diego and Kuntze, Martino. (2024). 'The Consequences of Domestic Outsourcing on Workers: New Evidence from Italian Administrative Data'.

Deibler, Daniel Mark and Commission, Federal Trade. (2023). 'How Does Outsourcing Affect Remaining Workers, Firms, and Inequality? Evidence from Germany's Hartz Reforms'.

DiNardo, John, Fortin, Nicole M. and Lemieux, Thomas. (1996). 'Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach', *Econometrica* 64(5), 1001–1044. ISBN: 0012-9682;1468-0262;.

Dinerstein, Michael, Einav, Liran, Levin, Jonathan and Sundaresan, Neel. (2018). 'Consumer Price Search and Platform Design in Internet Commerce', *American Economic Review* 108(7), 1820–1859.
URL: *https://www.aeaweb.org/articles?id=10.1257/aer.20171218*

Dolfen, Paul, Einav, Liran, Klenow, Peter J., Klopack, Benjamin, Levin, Jonathan D.,

Levin, Larry and Best, Wayne. (2023). 'Assessing the Gains from E-Commerce', *American Economic Journal: Macroeconomics* 15(1), 342–370.
URL: *https://www.aeaweb.org/articles?id=10.1257/mac.20210049*

Drenik, Andres, Jäger, Simon, Plotkin, Pascuel and Schoefer, Benjamin. (2023). 'Paying outsourced labor: Direct evidence from linked temp agency-worker-client data', *Review of Economics and Statistics* 105(1), 206–216.

Dube, Arindrajit and Kaplan, Ethan. (2010). 'Does Outsourcing Reduce Wages in the Low-Wage Service Occupations? Evidence from Janitors and Guards', *ILR Review* 63(2), 287–306.
URL: *https://journals.sagepub.com/doi/10.1177/001979391006300206*

Dustmann, Christian, Lindner, Attila, Schönberg, Uta, Umkehrer, Matthias and Vom Berge, Philipp. (2022). 'Reallocation effects of the minimum wage', *The Quarterly Journal of Economics* 137(1), 267–328.

Edgel, Danny, Houde, Jean-François, Newberry, Peter and Seim, Katja. (2023). 'The Impact of Distance in Retail Markets', *AEA Papers and Proceedings* 113, 229–233.
URL: *https://pubs.aeaweb.org/doi/10.1257/pandp.20231066*

Fang, Lu, Chen, Yanyou, Farronato, Chiara, Yuan, Zhe and Wang, Yitong. (2024), 'Platform Information Provision and Consumer Search: A Field Experiment'.
URL: *https://www.nber.org/papers/w32099*

Felix, Mayara. (2022). 'Trade, Labor Market Concentration, and Wages'.

Filippas, Apostolos, Horton, John J and Urraca, Diego. (2023). 'Advertising as Coordination: Evidence from a Field Experiment'.

Garin, Andrew, Jackson, Emilie and Koustas, Dmitri K. (2024), 'New Gig Work or Changes in Reporting? Understanding Self-Employment Trends in Tax Data'.
URL: *https://www.nber.org/papers/w32368*

Garin, Andrew, Jackson, Emilie, Koustas, Dmitri and Miller, Alicia. (2023), The Evolution of Platform Gig Work, 2012-2021, Technical Report w31273, National Bureau of Economic Research, Cambridge, MA.
URL: *http://www.nber.org/papers/w31273.pdf*

Gerard, François, Lagos, Lorenzo, Severnini, Edson and Card, David. (2021). 'Assortative Matching or Exclusionary Hiring? The Impact of Employment and Pay Policies on Racial Wage Differences in Brazil', *American Economic Review* 111(10), 3418–3457.
URL: *https://pubs.aeaweb.org/doi/10.1257/aer.20181596*

Goldmanis, Maris, Hortaçsu, Ali, Syverson, Chad and Emre, Önsel. (2010). 'E-Commerce and the Market Structure of Retail Industries', *The Economic Journal* 120(545), 651–682.
URL: *https://academic.oup.com/ej/article/120/545/651-682/5089706*

Goldschmidt, Deborah and Schmieder, Johannes F. (2017). 'The rise of domestic outsourcing and the evolution of the German wage structure', *The Quarterly Journal of Economics* 132(3), 1165–1217. Publisher: Oxford University Press.

Guo, Naijia, Li, Duoxi and Wong, Michael B. (2024). 'Domestic Outsourcing and Employment Security'.

Harris, Seth D and Krueger, Alan B. (2015). 'A Proposal for Modernizing Labor Laws for Twenty-First-Century Work: The "Independent Worker"', *The Hamilton Project* Discussion Paper 2015-10.

Jackson, Emilie. (2022). 'Availability of the Gig Economy and Long Run Labor Supply Effects for the Unemployed'.

Jacobson, Louis S., LaLonde, Robert J. and Sullivan, Daniel G. (1993). 'Earnings Losses of Displaced Workers', *The American Economic Review* 83(4), 685–709. Publisher: American Economic Association.
URL: *https://www.jstor.org/stable/2117574*

Jahn, Elke J and Rosholm, Michael. (2014). 'Looking beyond the bridge: The effect of temporary agency employment on labor market outcomes', *European Economic Review* 65, 108–125.

Jiang, Wei, Tang, Yuehua, Xiao, Rachel (Jiqiu) and Yao, Vincent. (2021), 'Surviving the Fintech Disruption'.
URL: *https://www.nber.org/papers/w28668*

Jäger, Simon and Heining, Jörg. (2022). 'How Substitutable Are Workers? Evidence from Worker Deaths'.

Katz, Lawrence F. and Krueger, Alan B. (2019). 'The Rise and Nature of Alternative Work Arrangements in the United States, 1995–2015', *ILR Review* 72(2), 382–416. Publisher: SAGE Publications Inc.
URL: *https://doi.org/10.1177/0019793918820008*

Kitchens, Brent, Kumar, Anuj and Pathak, Praveen. (2018). 'Electronic Markets and Geographic Competition Among Small, Local Firms', *Information Systems Research* 29(4), 928–946. Publisher: INFORMS.
URL: *https://pubsonline.informs.org/doi/abs/10.1287/isre.2017.0754*

Koustas, Dmitri K. (2018). 'Consumption Insurance and Multiple Jobs: Evidence from Rideshare Drivers'.

Lee, David S. (2009). 'Training, Wages, and Sample Selection: Estimating Sharp Bounds on Treatment Effects', *The Review of Economic Studies* 76(3), 1071–1102.
URL: *https://doi.org/10.1111/j.1467-937X.2009.00536.x*

Leonardi, Marco and Moretti, Enrico. (2023). 'The Agglomeration of Urban Amenities: Evidence from Milan Restaurants', *American Economic Review: Insights* 5(2), 141–157.
URL: *https://pubs.aeaweb.org/doi/10.1257/aeri.20220011*

Lindner, Attila, Muraközy, Balázs, Reizer, Balazs and Schreiner, Ragnhild. (2022). 'Firm-level technological change and skill demand'. Publisher: Centre for Economic Performance, London School of Economics and Poiltical ....

Manning. (2011), Imperfect Competition in the Labor Market, *in* 'Handbook of Labor Economics', Vol. 4, Elsevier, pp. 973–1041.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0169721811024099*

Manning. (2021). 'Monopsony in Labor Markets: A Review', *ILR Review* 74(1), 3–26.
URL: *http://journals.sagepub.com/doi/10.1177/0019793920922499*

Mas, Alexandre and Pallais, Amanda. (2020). 'Alternative work arrangements', *Annual Review of Economics* 12, 631–658. Publisher: Annual Reviews.

Mokyr, Joel. (2003). 'Thinking about technology and institutions', *Macalester International* 13(1), 8.

Overby, Eric and Forman, Chris. (2015). 'The Effect of Electronic Commerce on Geographic Purchasing Patterns and Price Dispersion', *Management Science* 61(2), 431–453.
URL: *https://pubsonline.informs.org/doi/10.1287/mnsc.2014.1977*

Parsa, HG, Gregory, Amy, Terry, Michael et al. (2011). 'Why do restaurants fail? Part III: An analysis of macro and micro factors'.

**Parsa, HG, Kreeger, Jeff C, van der Rest, Jean-Pierre, Xie, Lijjia'Karen' and Lamb, Jack-

son. (2021). ‘Why restaurants fail? Part V: Role of economic factors, risk, density, location, cuisine, health code violations and GIS factors’, *International Journal of Hospitality & Tourism Administration* 22(2), 142–167.

Roth, Jonathan, Sant’Anna, Pedro HC, Bilinski, Alyssa and Poe, John. (2023). ‘What’s trending in difference-in-differences? A synthesis of the recent econometrics literature’, *Journal of Econometrics* 235(2), 2218–2244.

Schmieder, Johannes F., von Wachter, Till and Heining, Jörg. (2023). ‘The Costs of Job Displacement over the Business Cycle and Its Sources: Evidence from Germany’, *American Economic Review* 113(5), 1208–1254.
URL: *https://www.aeaweb.org/articles?id=10.1257/aer.20200252*

Spitze, Scott. (2022). ‘The Equilibrium Effects of Domestic Outsourcing’.

Stepner, Michael and Garland, Allan. (2017), ‘CALIPMATCH: Stata module for caliper matching without replacement’.
URL: *https://econpapers.repec.org/software/bocbocode/s458342.htm*

Ulyssea, Gabriel. (2018). ‘Firms, Informality, and Development: Theory and Evidence from Brazil’, *American Economic Review* 108(8), 2015–2047.
URL: *https://pubs.aeaweb.org/doi/10.1257/aer.20141745*

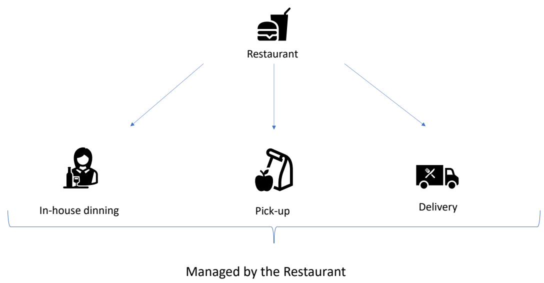
Vitali, Anna. (2022). ‘Consumer search and firm location: theory and evidence from the garment sector in uganda’, *Job market paper* .

Zheng, Shuang, Tong, Siliang, Kwon, Hyeokkoo Eric, Burtch, Gordon and Li, Xianneng. (2023). ‘Recommending What to Search: Sales Volume and Consumption Diversity Effects of a Query Recommender System’, *SSRN Electronic Journal* .
URL: *https://www.ssrn.com/abstract=4667778*

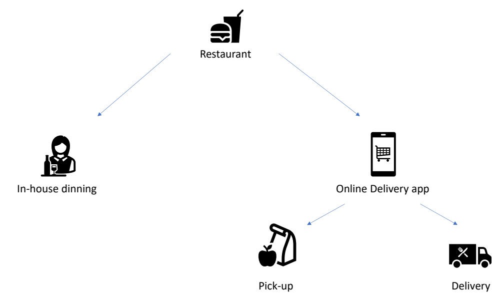
Figures

Figure 1: Restaurant Structure before and after online-delivery platforms

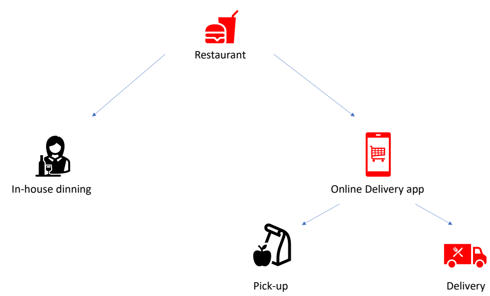
(a) Restaurant Structure Previous to Online Delivery Platforms



(b) Restaurant Structure After Online Delivery Platforms



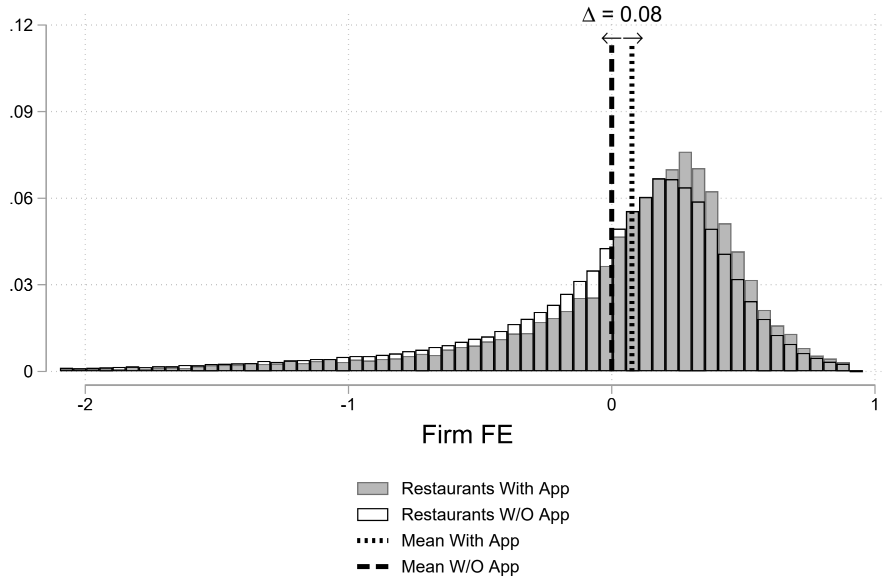
(c) Main Relationship Studied in the Paper



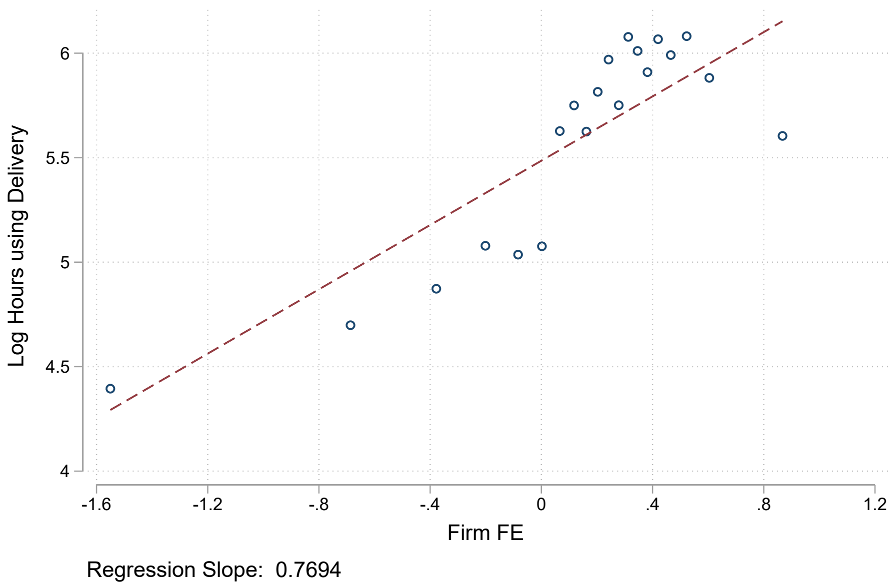
Notes: The figure illustrates the structure of restaurants before and after the adoption of online-delivery platforms. Panel (a) shows the structure of restaurants before the adoption of online-delivery platforms. When not enrolled on delivery platforms, restaurants usually operate in-house dinning, pick-ups and deliveries (if offered). Panel (b) and panel (c) show the structure of restaurants after the adoption of online-delivery platforms. When restaurants start offering services through online-delivery platforms, these platforms often take over the pick-up and deliveries of the restaurants. In this paper I focus on the impact of online-delivery platforms that offer delivery services, as highlighted in red in panel (c).

Figure 2: AKM Firm FE and usage of the App

(a) Distribution of AKM firm FE for Adopters and Non-Adopters



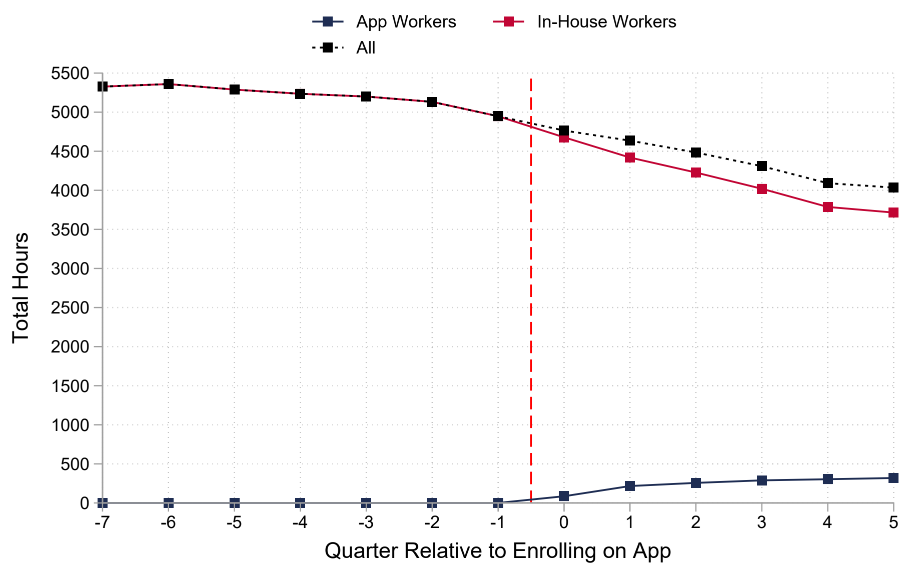
(b) Intensive Margin of App and AKM Firm FE



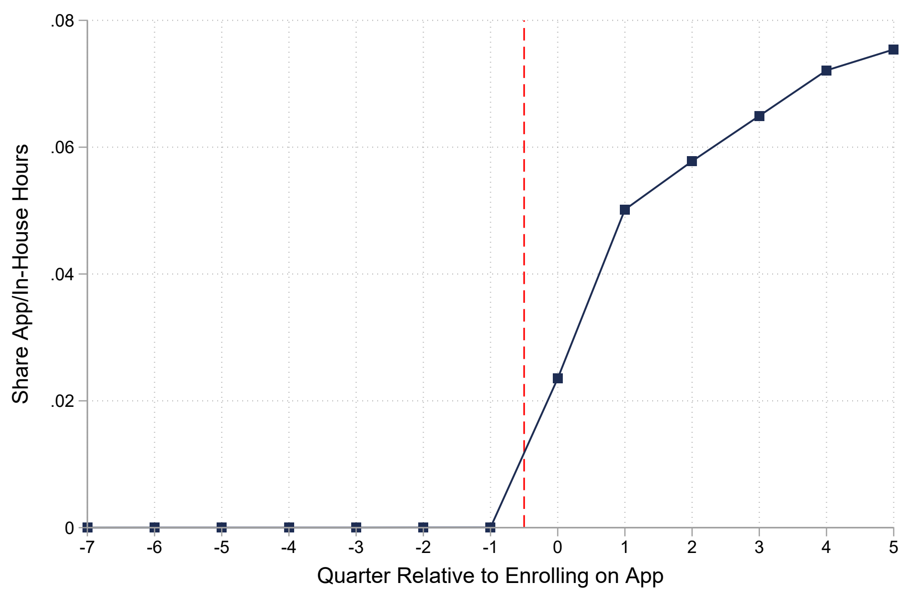
Notes: Panel (a) reports the histogram of AKM workplace effects for restaurants in Brazil. It plots the selection into offering deliveries through an online platforms. The figure plots the histogram of AKM firm effects for restaurants that at some point in time offered deliveries through the delivery app and restaurants that never offered services through the app. The distributions fo AKM firm effects are normalized such that the average workplace effect in the group of firms that never offered services through online delivery platforms is zero. The distribution for restaurants that offer services through the platform is shifted to the right by 8 log points, indicating that firms with higher wage policies for formal workers are more likely to offer services through the app. Panel (b) plots a binned scatter plot of the logarithm of the total hours reported in my sample that app workers worked as delivery drivers through the app for restaurants, plotted against the AKM firm effects of restaurants that offer services through the app (slope is 0.77; SE XXX). The hours worked at each firm through the delivery platform cover the years 2018 to 2021. Estimated firm effects are restricted to those restaurants in the largest connected set that, at any point in my sampling window, offered services through delivery platforms. The AKM specification was estimated using data from RAIS between the years 2012 and 2018. Restaurants are defined as establishments that have a CNAE two digit code equal to 56.

Figure 3: Trends in hours Hired for In-House and App Workers

(a) Total Hours by Type of Labor



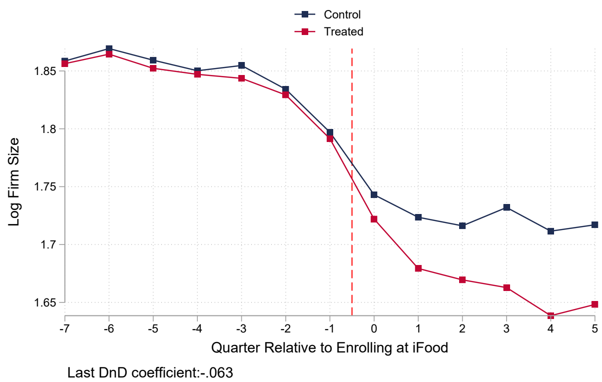
(b) Share of Outsourced Labor



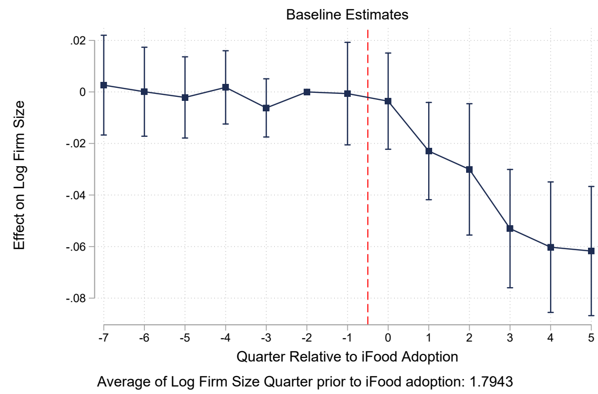
Notes: Panel (a) reports the total hours per quarter hired by restaurants that offer delivery services through the platform and match to a control restaurant. The red line reports the average quarterly hours for workers hired formally by these restaurants (in-house workers). The blue line reports the average quarterly hours that delivery platform workers worked for these restaurants (app workers). The solid black line is the sum of in-house workers and app workers hours. Panel (b) shows the share of average quarterly hours that delivery platform workers contributed to these restaurants, relative to the total hours worked by both in-house employees and app workers. The x-axis reflects the quarter relative to the first quarter in which each restaurant offered delivery services through the platform for the first time.

Figure 4: Size and Wages of Restaurants that Adopt and Do Not Adopt Online-Delivery Platforms

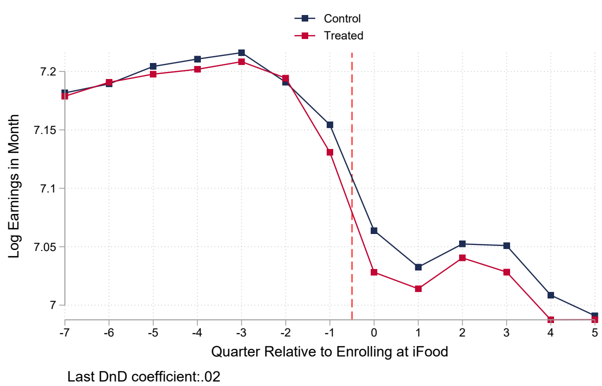
(a) Log Size of Restaurants



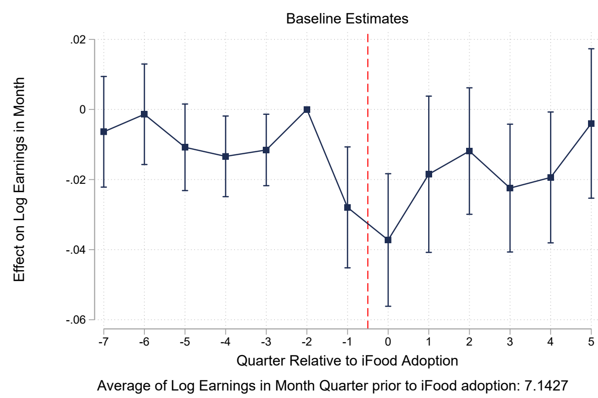
(b) Event-Study Estimates on Log Size of Restaurants



(c) Avg. Wages Paid by Restaurants

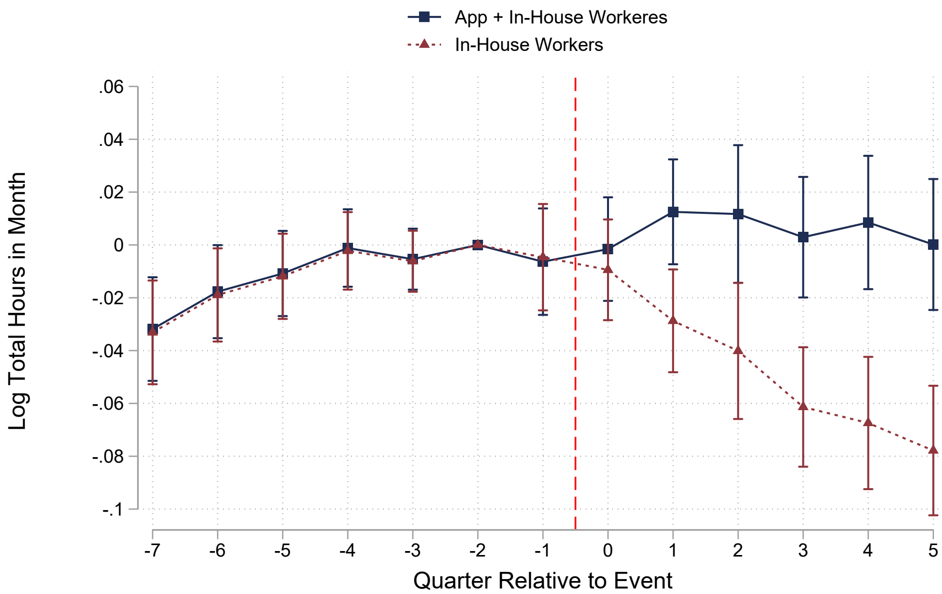


(d) Event-Study Estimates on Avg. Wages Paid by Restaurants



Notes: Panel (a) and Panel (c) reports the trajectories of the logarithm of the size of the restaurants—as measured by the number of workers hired in a quarter— (Panel a) and wages as measured by the average wages paid by a restaurant in a quarter (Panel c) of restaurants that offer delivery services through the online platform and their matched-controls. Panel (b) and Panel (d) report the corresponding event-study estimates obtained after fitting equation (5) on log restaurant size (Panel b) or average wages paid at the establishment (panel d). The x-axis reflects the quarter relative to the first quarter in which each restaurant offered delivery services through the platform for the first time. Quarter 0 is the quarter when the treated restaurant starts offering delivery services through the platform. A formal worker is defined to be employed in a month if they have at least one day of work recorded in RAIS. Quarterly size is constructed by taking the average of the number of workers hired each month in the quarter by the establishment after applying the restrictions described in Section 3. Average quarterly wages are constructed by taking the quarterly average of all wages reported in RAIS by the establishment in the corresponding quarter. Wages are expressed in real terms (2018 CPI). Standard errors are clustered at the establishment level.

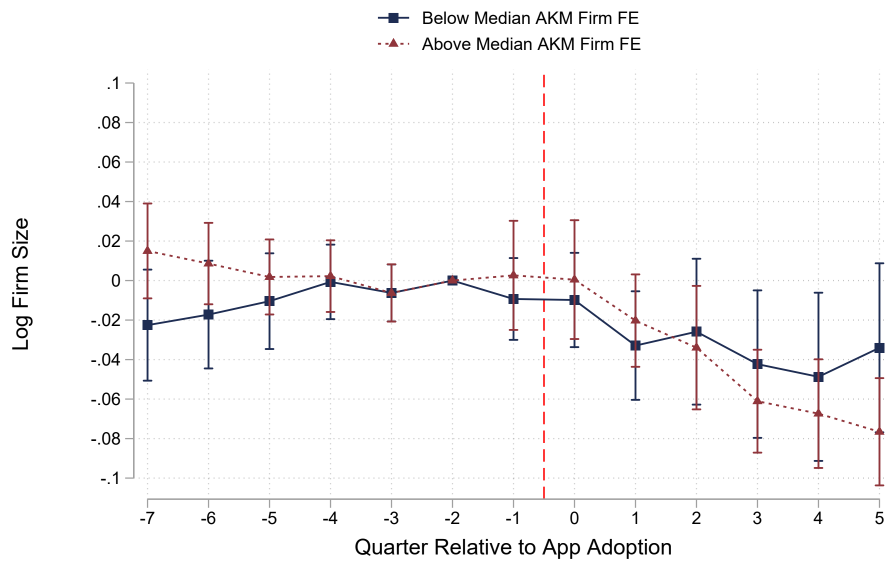
Figure 5: Effect of App adoption on Hours Worked with and without App



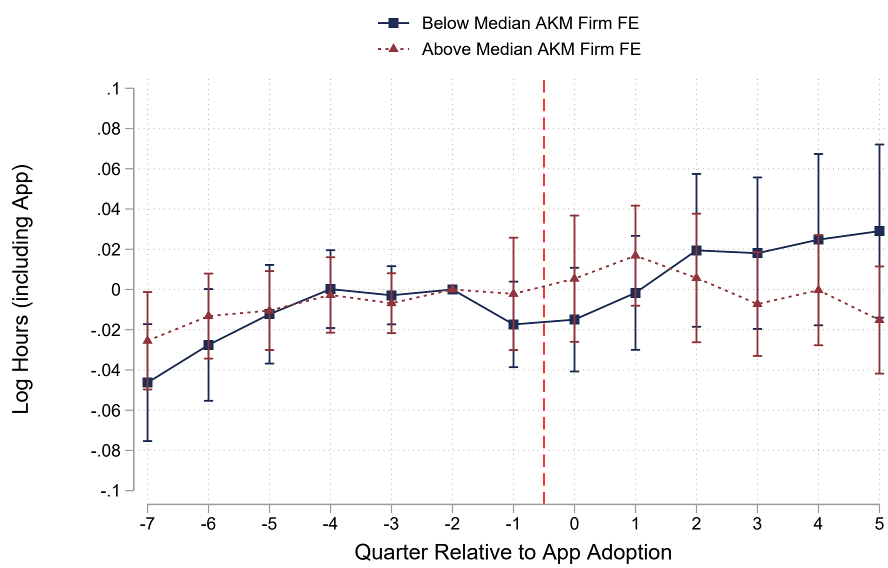
Notes: This figure reports the corresponding event-study estimates obtained after fitting equation (5) on log total hours hired quarterly for workers hired formally (the red dashed line) and log total hours hired quarterly when accounting for formal workers and platform workers (the solid blue line). The x-axis reflects the quarter relative to the first quarter in which each restaurant offered delivery services through the platform for the first time. Quarter 0 is the quarter when the treated restaurant starts offering delivery services through the platform. Standard errors are clustered at the establishment level.

Figure 6: Effect of Platform Adoption on Restaurant Size and Total Hours Hired by Firm AKM

(a) Log Firm Size



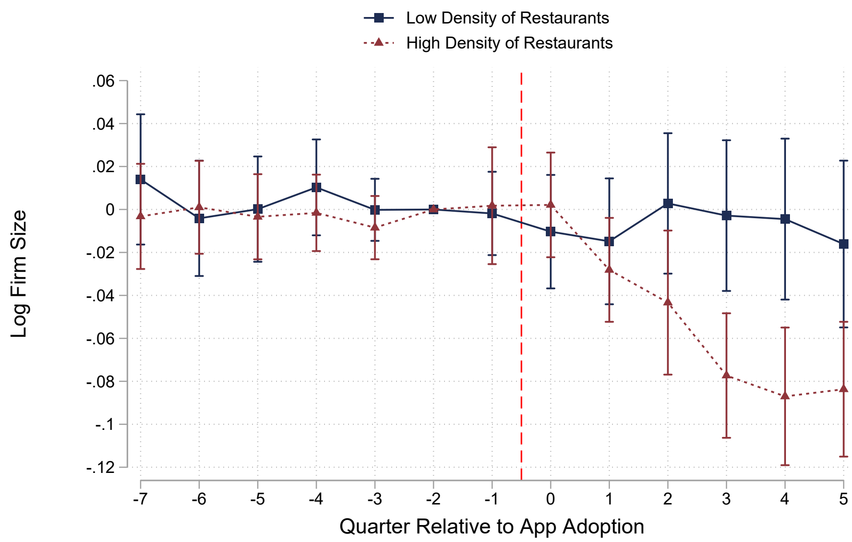
(b) Log Total Hours Hired



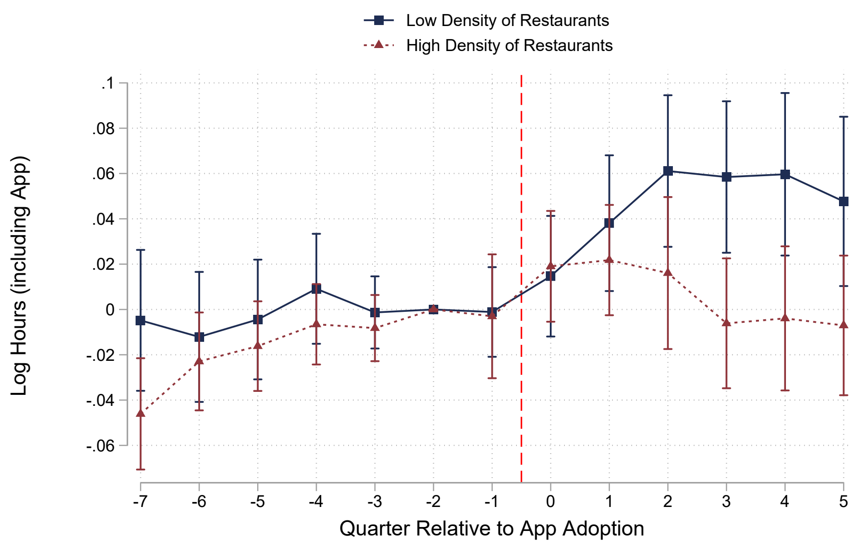
Notes: Panel (a) reports the corresponding event-study estimates obtained after fitting equation (5) on log restaurant size as defined by the average number of formal workers hired by the establishment. A formal worker is defined to be employed in a month if they have at least one day of work recorded in RAIS. Quarterly size is constructed by taking the average of the number of workers hired each month in the quarter by the establishment after applying the restrictions described in Section 3. The red dashed line reports the estimates for restaurants that are above the median of AKM firm effects. The solid blue line reports the estimates for restaurants that are below the median of AKM firm effects. The median of AKM firm effects is calculated using the AKM firm effects of all treated and control restaurants that match that belong to the largest connected set. When a restaurant does not have an AKM firm effect, I input the firm effect of their matched pair. The AKM specification was estimated using data from RAIS between the years 2012 and 2018. Panel (b) reports the corresponding event-study estimates obtained after fitting equation (5) on log total hours hired in the quarter when accounting for workers hired formally and workers working through the platform. The x-axis reflects the quarter relative to the first quarter in which each restaurant offered delivery services through the platform for the first time. Quarter 0 is the quarter when the treated restaurant starts offering delivery services through the platform. Standard errors are clustered at the establishment level.

Figure 7: Effect of App Adoption on Restaurant Size and Total Hours Hired by Restaurant Density

(a) Log Firm Size



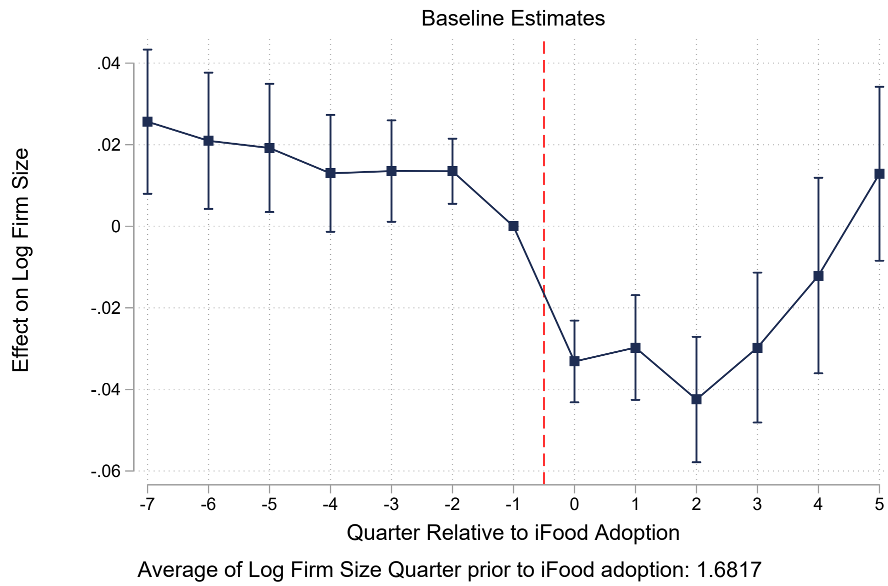
(b) Log Total Hours Hired



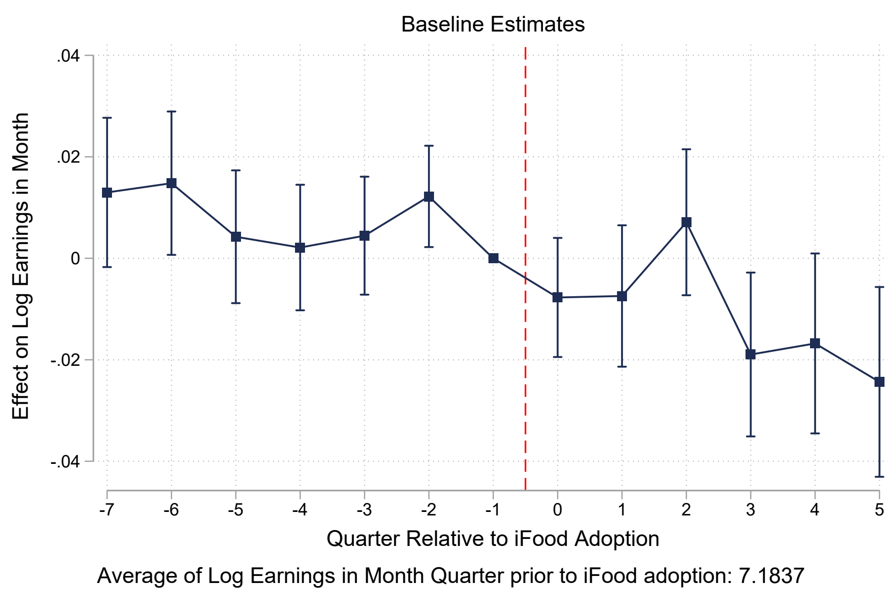
Notes: Panel (a) reports the corresponding event-study estimates obtained after fitting equation (5) on log restaurant size as defined by the average number of formal workers hired by the establishment. A formal worker is defined to be employed in a month if they have at least one day of work recorded in RAIS. Quarterly size is constructed by taking the average of the number of workers hired each month in the quarter by the establishment after applying the restrictions described in Section 3. The red dashed line reports the estimates for restaurants that are above the median of restaurant density within their microregion. The solid blue line reports the estimates for restaurants that are below the median of restaurant density within their microregion. Restaurant density is calculated as the number of restaurants that are located in a 1 kilometer radius of each restaurant (τ). The median of restaurant density is calculate using the distribution of τ corresponding to the microregion of each restaurant in each quarter. The density assigned to each restaurant corresponds to the τ calculated using the quarter prior to the first quarter in which the treated restaurant of the pair started offering delivery services through the platform. Panel (b) reports the corresponding event-study estimates obtained after fitting equation (5) on log total hours hired in the quarter when accounting for workers hired formally and workers working through the platform. The x-axis reflects the quarter relative to the first quarter in which each restaurant offered delivery services through the platform for the first time. Quarter 0 is the quarter when the treated restaurant starts offering delivery services through the platform. Standard errors are clustered at the establishment level

Figure 8: Spillover Effects of App Adoption on Non-Adopting Restaurants

(a) Log Firm Size



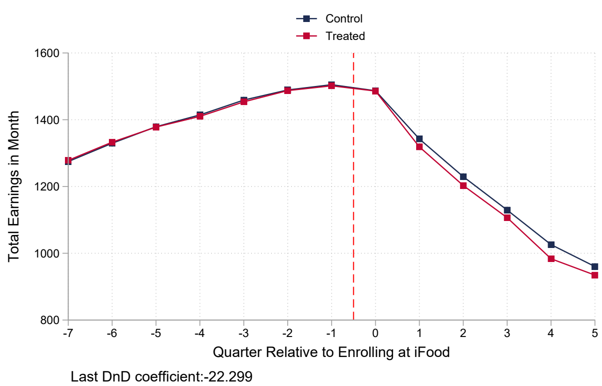
(b) Log Avg. Monthly Wages



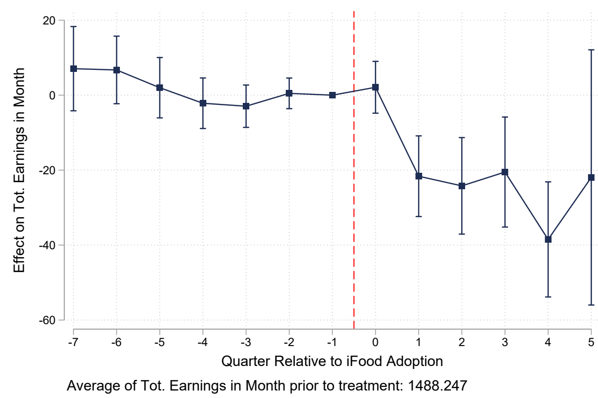
Notes: This figure reports .

Figure 9: Earnings and Employment of In-House Restaurant Workers After the Employer Adopts the Platform

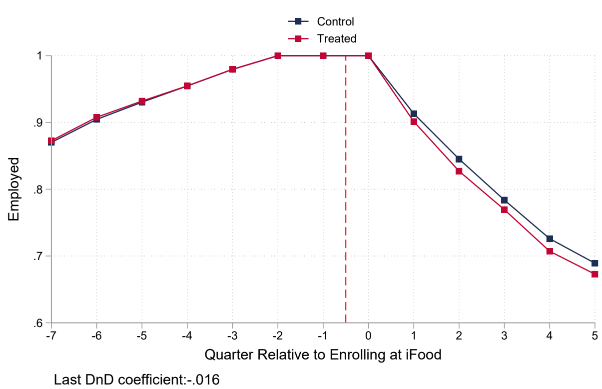
(a) Total Earnings



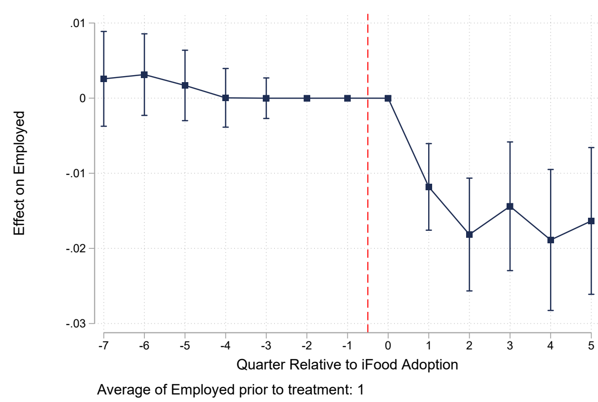
(b) Event-Study Estimates on Total Earnings



(c) Employment



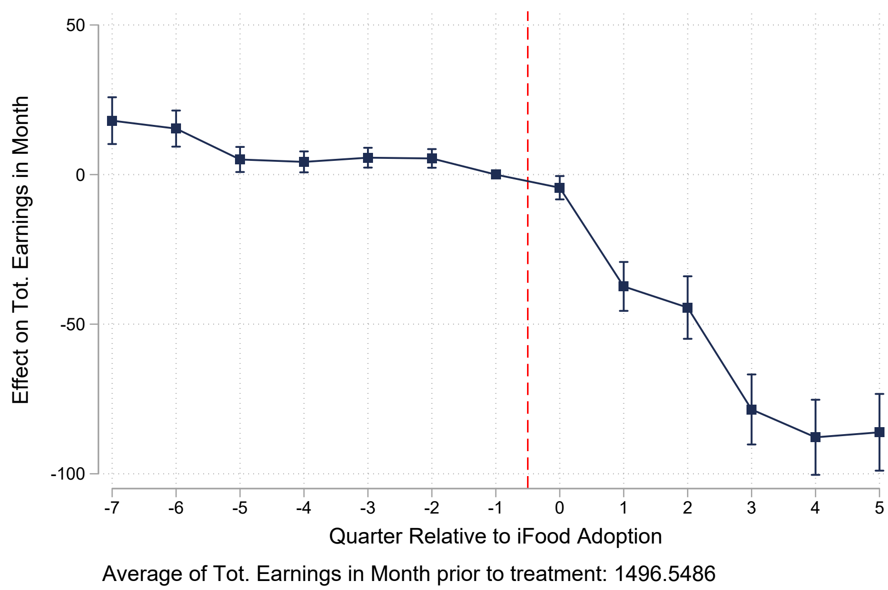
(d) Event-Study Estimates on Employment



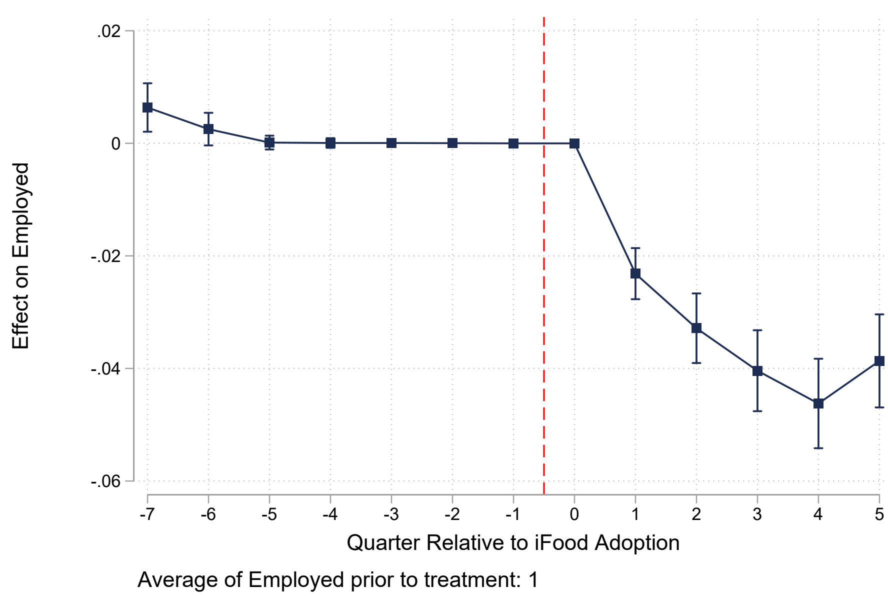
Notes:

Figure 10: Spillover Effects of App Adoption on Restaurant Workers

(a) Total Monthly Earnings

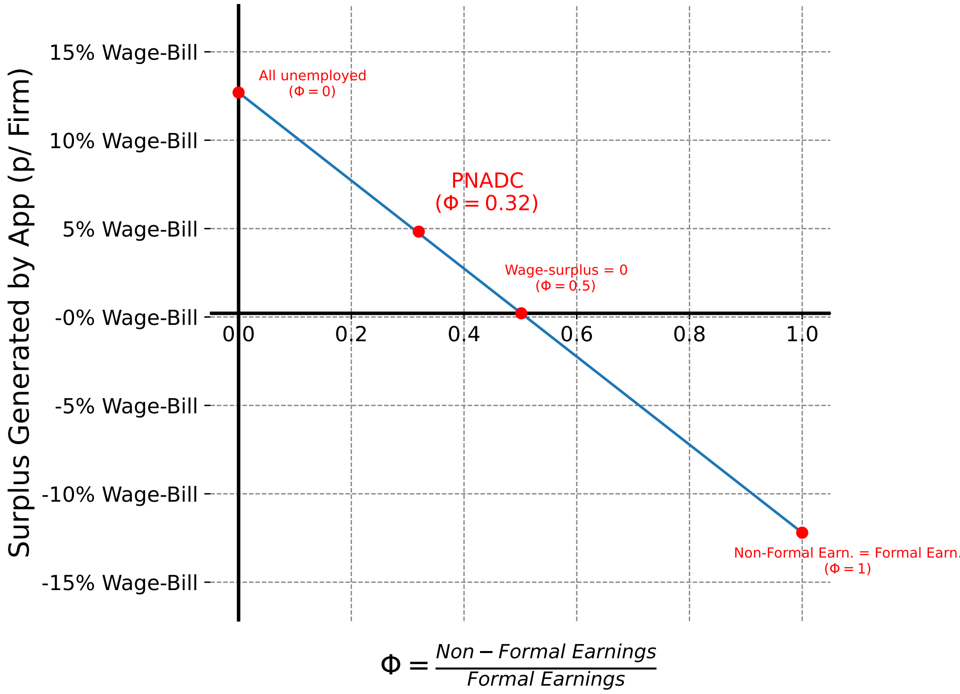


(b) Employment



Notes: This figure reports .

Figure 11: Total Wage Bill Gains from App adoption



Notes: This figure reports

Tables

Table 1: Summary Statistics for Treated and Control Restaurants

	(1) Matched Control	(2) Matched Treated	(3) Potential Treated	(4) All Restaurants
Years of Education	11.02	11.29	11.29	11.01
	(1.38)	(1.27)	(1.43)	(1.62)
Tenure (in years)	2.58	1.43	1.25	2.04
	(1.78)	(1.92)	(1.90)	(2.43)
Monthly Wage (2018 - R$)	1,483.81	1,530.43	1,477.52	1,438.13
	(412.83)	(571.16)	(553.56)	(507.57)
Age	33.38	32.48	32.71	34.95
	(7.02)	(6.94)	(7.68)	(8.42)
Share of Brazilians	1.00	0.99	0.99	0.99
Female	0.59	0.59	0.59	0.60
Hours	43.10	43.05	43.18	43.09
	(2.75)	(3.05)	(2.81)	(3.02)
Full-Time	0.97	0.97	0.97	0.97
Establishment Size	11.34	11.50	9.12	7.36
	(24.75)	(22.83)	(42.77)	(34.84)
Share of Waiters	0.48	0.50	0.49	0.49
	(0.32)	(0.31)	(0.35)	(0.36)
Number of Establishments	7,836	14,862	57,962	296,263

Notes:

Table 2: Effect of App Adoption on Labor Demand per Occupation

	(1) Number of Waiters	(2) Number of Cooks	(3) Log Wage Waiters	(4) Log Wage Cooks
(Diff-in-Diff)	-0.2845***	0.0001	-0.0225***	-0.0112
	(0.0567)	(0.0255)	(0.0063)	(0.0081)
Mean Dependent Variable prior to App Enrollment	5.2062	2.0368	7.1397	7.2294
Observations	363,129	363,129	289,424	207,408

Notes:

Table 3: Effect of App Adoption on Labor Demand per Occupation & Restaurant Density

	Panel A: Restaurants at High Density Areas		**Panel B: Restaurants at Low Density Areas**	
	(1)	(2)	(3)	(4)
	Number of Waiters	Number of Cooks	Number of Waiters	Number of Cooks
Dif-in-Diff	-0.3867***	-0.0247	-0.0990	0.0695*
	(0.0691)	(0.0324)	(0.1032)	(0.0386)
Mean Dependent Variable prior to App Adoption	5.3931	2.0888	4.6975	1.9286
Observations	232,545	232,545	105,887	105,887

Notes:

Table 4: Effect of App Adoption on Labor Demand per Occupation & Restaurant Density

	Panel A: Above Median of AKM Firm FE		**Panel B: Below Median of AKM Firm FE**	
	(1)	(2)	(3)	(4)
	Number of Waiters	Number of Cooks	Number of Waiters	Number of Cooks
Dif-in-Diff	-0.3809***	0.0140	-0.1276*	-0.0273
	(0.0727)	(0.0324)	(0.0656)	(0.0302)
Mean Dependent Variable prior to App Adoption	6.0611	2.2369	3.6061	1.6845
Observations	236,494	236,494	120,848	120,848

Notes:

Table 5: Summary Statistics for Treated and Control Workers

	(1) Matched Treated Workers	(2) Matched Control Workers	(3) Potential Treated Workers
Years of Education	11.06	10.92	11.42
	(1.89)	(2.18)	(2.05)
Avg Tenure (in years)	3.69	3.69	2.91
	(1.35)	(1.35)	(1.58)
Avg Monthly Earnings (in 2018-R$)	1,502	1,505	1,789
	(393)	(382)	(1,475)
Age	32.52	32.58	33.14
	(9.99)	(9.96)	(11.10)
Share of Brazilians	0.99	1.00	0.99
Female	0.59	0.59	0.51
Hours	41.29	43.12	41.69
	(6.95)	(3.22)	(6.66)
Share of Black Workers	0.07	0.05	0.06
Delivery	0.01	0.01	0.01
Admin	0.04	0.04	0.12
Kitchen	0.19	0.19	0.18
Waiters	0.65	0.65	0.48
Other	0.11	0.11	0.21
Number of Workers	19,402	15,281	132,861

Notes:

Table 6: Total Wage Bill Effect of App Adoption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	In-House Restaurant Workers (Formal)		In-House Restaurant Workers (Informal)	Spillovers (Formal)		Spillovers (Informal)	App Workers (From Formal Sector)		App Workers (From Non-Formal Sector)	
	Gross Wage	Net Wage		Gross Wage	Net Wage		Wage Bill App	Wage Bill App Net of Opportunity Cost & Transportation Costs	Wage Bill App	Wage Bill App Net of Opportunity Cost & Transportation Costs
Quarter 0	64.6	44.4	10.5	-108.3	-101.8	-25.0	330.2	88.2	1494.2	966.7
Quarter 1	-664.1	-622.5	-147.6	-905.2	-835.7	-204.8	770.8	189.6	3660.8	2319.0
Quarter 2	-743.1	-695.8	-165.0	-1108.3	-1023.8	-250.9	868.9	198.9	4317.2	2672.1
Quarter 3	-629.9	-590.2	-140.0	-2027.3	-1861.2	-456.1	1075.7	269.4	5290.5	3324.9
Quarter 4	-1182.0	-1087.8	-258.0	-2430.9	-2230.2	-546.5	1110.6	259.9	5547.8	3426.9
Quarter 5	-673.9	-633.9	-150.3	-2493.1	-2282.2	-559.2	1115.1	233.3	5820.2	3530.6
Cumulative PDV	-3681.5	-3449.0	-818.0	-8693.5	-7986.9	-1957.1	5080.6	1195.7	25169.1	15647.2

Notes:

Table 7: Summary Stats for App Workers

	Summary Stats	Performance on the App	
	App Workers	Worker Formal Before App	Worker Non-Formal Before App
	(1)	(2)	(3)
Demographics:			
Age	29.5		
	(8.0)		
Female	0.1		
Monthly Earnings in Formal Job (Unconditional)	358.5		
	(867.4)		
Monthly Earnings in Formal Job (Conditional on Employment)	1583.9		
	(1176.1)		
Weekly Hours in Formal Job	41.7		
	(6.5)		
Tenure in Formal Job (in Years)	2.2		
	(2.9)		
Education (Years)	11.6		
	(1.7)		
Full Time	0.9		
Black	0.1		
Brazilian	1.0		
Workers in RAIS at some point	0.6		
Performance on App:			
Monthly Earnings (Tips)		10.2	11.2
		(19.0)	(20.8)
Monthly Earnings (Trip)		571.2	646.6
		(727.3)	(810.5)
Monthly Earnings (Promotions)		51.7	47.8
		(92.2)	(88.7)
Monthly Hours Online		62.0	75.9
		(62.9)	(73.0)
Monthly Hours Worked		30.1	34.9
		(36.8)	(41.6)
Monthly Total Deliveries		79.5	91.8
		(104.4)	(117.3)
Monthly Total Distance (KMs)		425.9	480.0
		(593.5)	(660.0)
Number of Workers	624,141	143,996	480.145

Notes:

A1 Extension: Product Demand (ADD A TERM THAT DEFINES HOW MUCH THEY CAN TRANSMIT THE COST OF THE APP TO CONSUMERS)

I now extend the model to provide a micro-foundation of the product demand curve. The model builds on consumer search models that allow for demand externalities across firms in the same location (Vitali, 2022). Under such framework, Appendix XXX shows that the product demand can be expressed as the following:

$$P_{jl} = P_{0jl}\, Y_j^{-\frac{1}{\epsilon}}$$

$$P_{jl} = \underbrace{(S\Lambda)^{\frac{1}{\epsilon}}}_{\text{Macro Context}} \quad \zeta_{jl} \left[\underbrace{\sum_{j'=1}^{N_l} \exp\left(\epsilon\ \psi_{l j'}\right)}_{\text{Quality in } l} \right]^{\frac{1}{\epsilon}\left(\alpha\frac{1}{\epsilon}-1\right)} \quad \left[\underbrace{\frac{1}{C_{jl}}}_{\text{Search costs}} \right]^{\frac{1}{\epsilon}} Y_j^{-\frac{1}{\epsilon}} \tag{A8}$$

$$C_{jl} = ln\left(\underbrace{\tau_1\ g_1(\|z - z_l\|)}_{\text{Avg. Distance}}\right) + ln\left(\underbrace{\tau_2\ g_2\left(App_l, \frac{N_l}{ar_l}\right)}_{\text{Spillovers}}\right) - ln\left(\underbrace{\tau_3\ g_3\left(App_{jl}, \|z - z_l\|\right)}_{\text{Direct Effect}}\right) + \iota_{jl} \tag{A9}$$

This parametrization of the demand curve decomposes the demand for a restaurants good in three elements: (i) an overall macro-context that affects all restaurants in the economy, (ii) a positive demand externality that increases the demand for the good produced by the restaurant as the quality of the goods produced by the other neighboring restaurants in the location increases (Leonardi and Moretti, 2023), and (iii) a search cost term that negatively impacts demand. The latter is a function of the distance between the average consumer and the location of the restaurant—$g_1(.)$—, a firm specific idiosyncratic shock (ι_{jl}), and two factors that are directly affected by online-delivery platforms: the direct effect of adoption, and the spillovers due to other neighboring restaurants adopting the app.

The direct effect captures how the adoption of a delivery platform will impact the demand for the restaurant. This impact will be governed by the function $g_3(.)$ which will depend on the distance of the location to the average restaurant. Following the previous discussion on the undetermined sign of the product demand effect, the partial derivative $\frac{\partial g_3}{\partial App_{jl}}$ will depend on the the value of $||z - z_l||$[58]. That is for restaurants that are closer to the average consumer, the enrollment on the app may substitute in-house dinning for delivery conveying in a zero or even negative product demand effect (depending on the elasticity of substitution of these two margins). In contrast, for restaurants that are further away from the average consumer, the adoption of the app will likely allow them to access new markets which can lead to a positive product demand effect.

The spillover, on the other hand, captures the impact of other restaurants in the location adopting the app on the demand of the restaurant j. The function $g_2(.)$ depends on the density of restaurants in location l. When no online-delivery platforms are adopted by nearby competitors this term reflects competition within the location. Conditional on the number of competitors in the location, as more nearby neighbors adopt online-delivery platform the demand for firm j decreases due to neighboring restaurants absorbing a higher share of the demand in l. That is, $\frac{\partial g_2}{\partial App_l} > 0$.

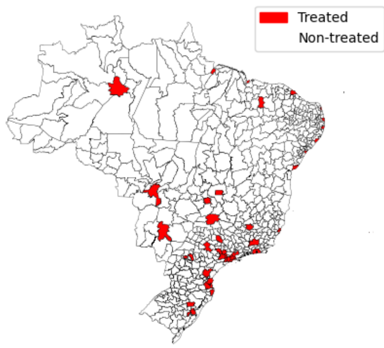
Equation (A8) also entails the agglomeration forces that arise from search costs. Firms benefit from the overall quality of their neighbours and will concentrate in locations where the distance to the average consumer is smaller. These forces however will be mitigated by the overall density of restaurants in the location that increase the firm specific search cost conditional on searching in that location. Put differently, regions that have a high density of restaurants must be either close to a large share of consumers, must have a high a concentration of high quality restaurants, or both, such that location externalities dominate the firm-specific search costs. In summary, under this framework, the introduction of online-delivery platforms reduces search costs for adopting restaurants that are further away from the average consumer, and increases search costs for non-adopting restaurants[59].

[58]The cross-derivative $\frac{\partial^2 g_3}{\partial App_{jl} \partial ||z - z_l||}$ is always positive, as the returns to the app increase with the distance of the restaurant to the average consumer.

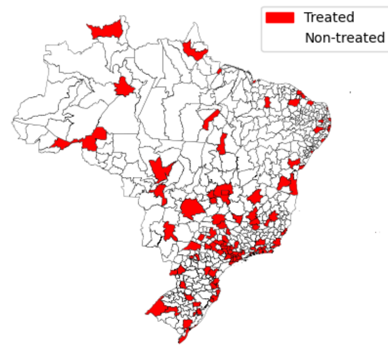
[59]Given the positive impact on adopters product demand and the negative impact on non-adopters demand, one may be tempted to think that all restaurants should adopt. Although modelling selection into adoption is beyond the scope of this paper, a large enough fixed cost could limit financially constrained restaurants from adoption. Similarly, high enough variable costs may discourage low profit margin restaurants to adopt.

Figure A12: Roll-out of the App

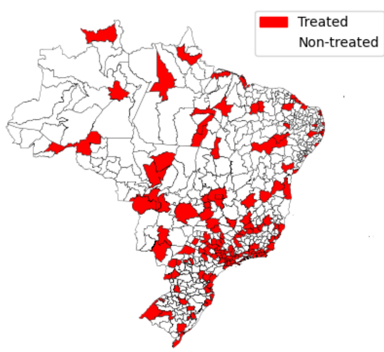
(a) 2018



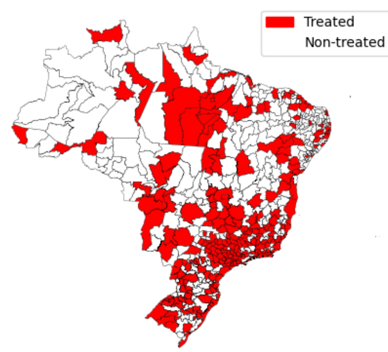
(b) 2019



(c) 2020

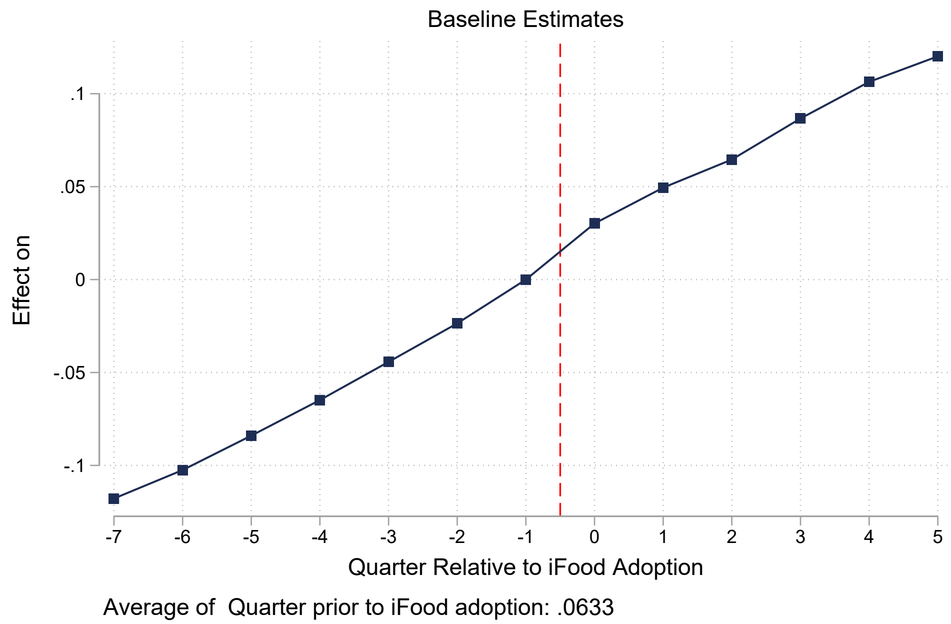


(d) 2021



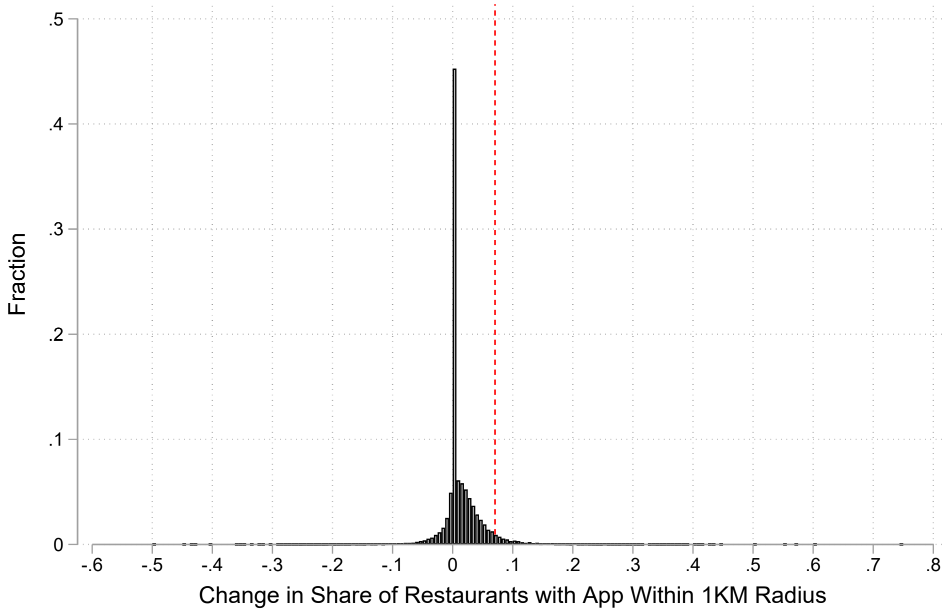
Notes:

Figure A13: Restaurants within 1 Kilometer Adopting the App



Notes: This figure reports

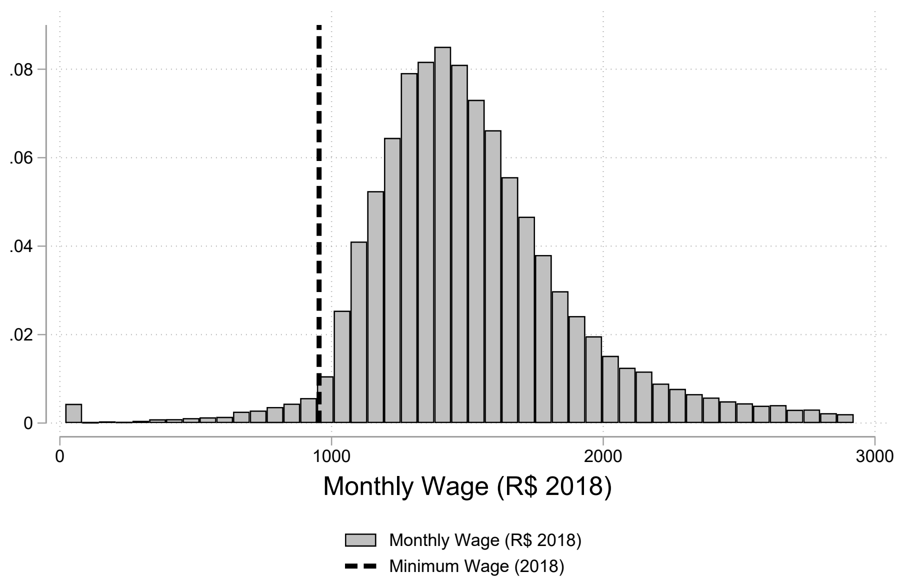
Figure A14: Distribution of Ω



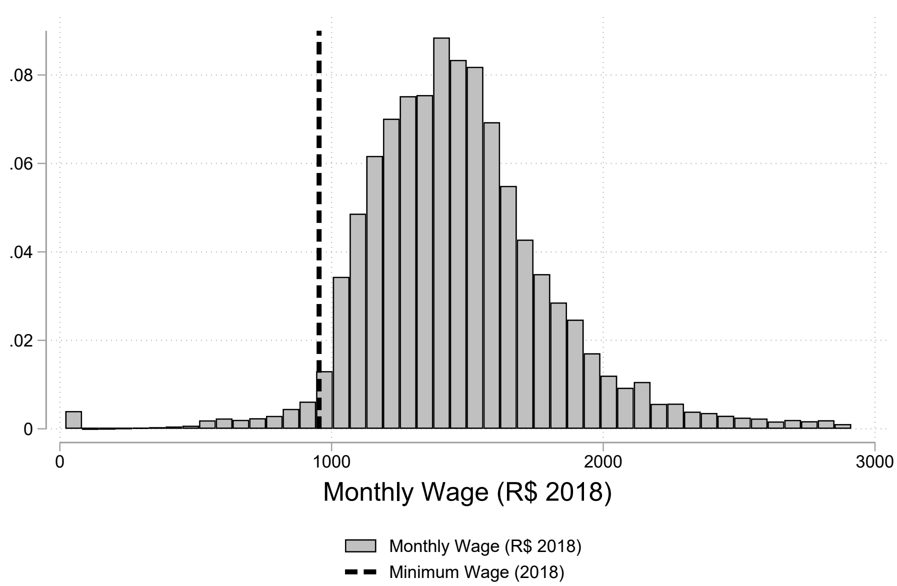
Notes: This figure reports

Figure A15: Distribution of Wages Matched Treated and Control

(a) Matched Treated

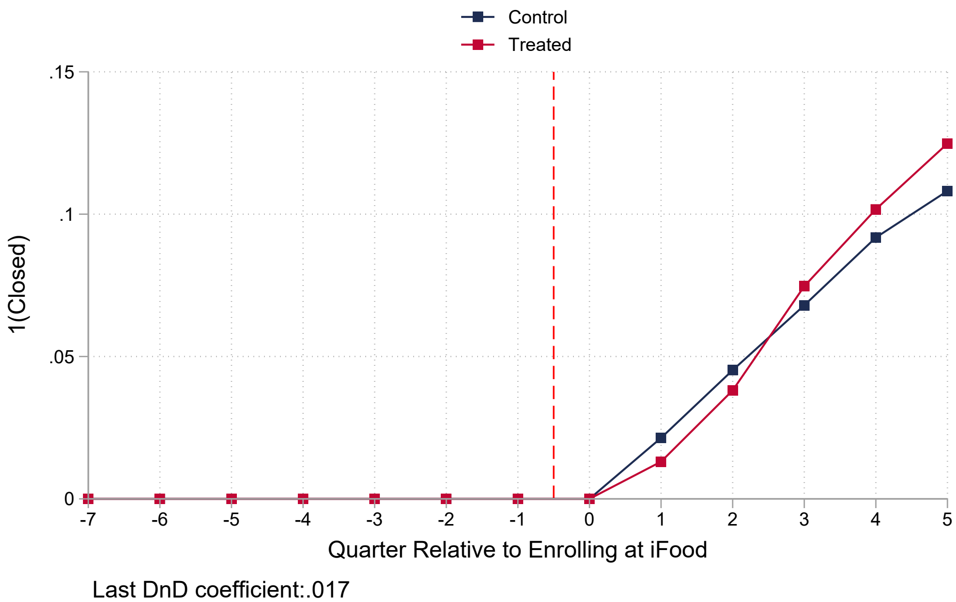


(b) Matched Control



Notes: This figure reports .

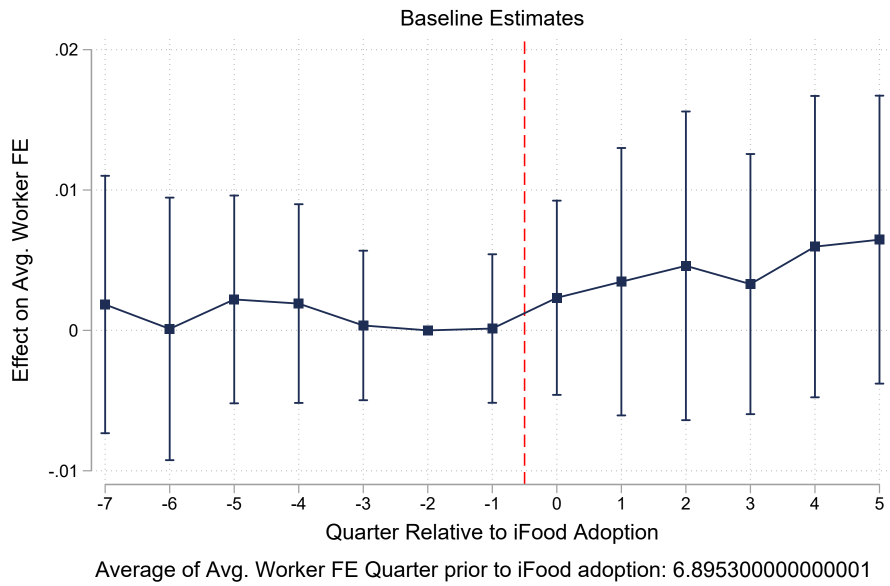
Figure A16: Trends in Closure for Treated and Control Restaurants



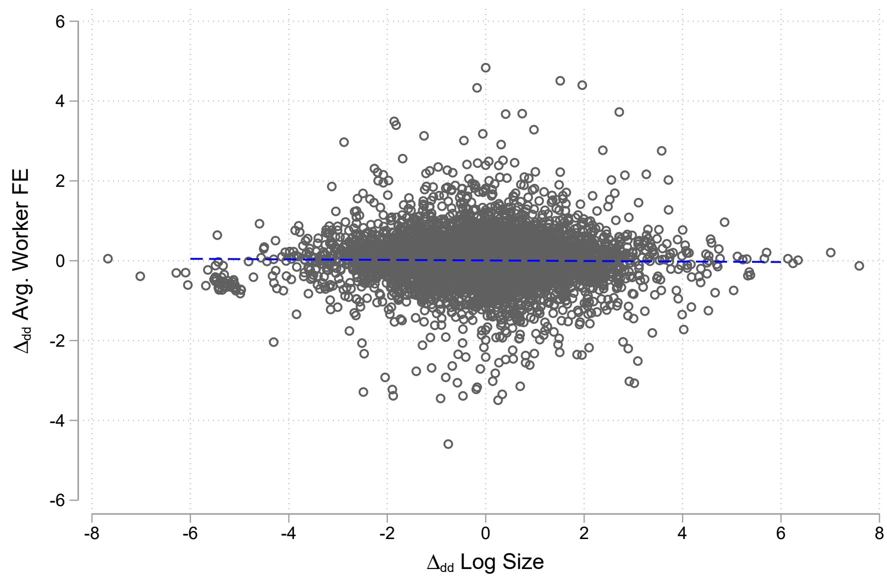
Notes: This figure reports

Figure A17: Effect of App Adoption on Avg. Worker Fixed Effects at Restaurants

(a) Avg. AKM Worker Fixed Effects

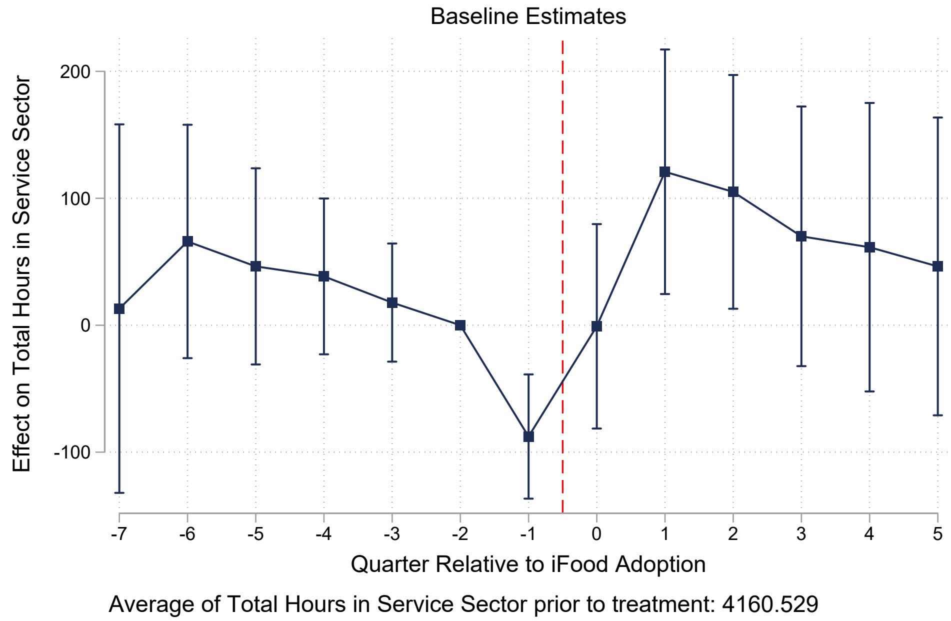


(b) Relation Between Log Size Treatment Effects and Avg. AKM Worker Fixed Effects



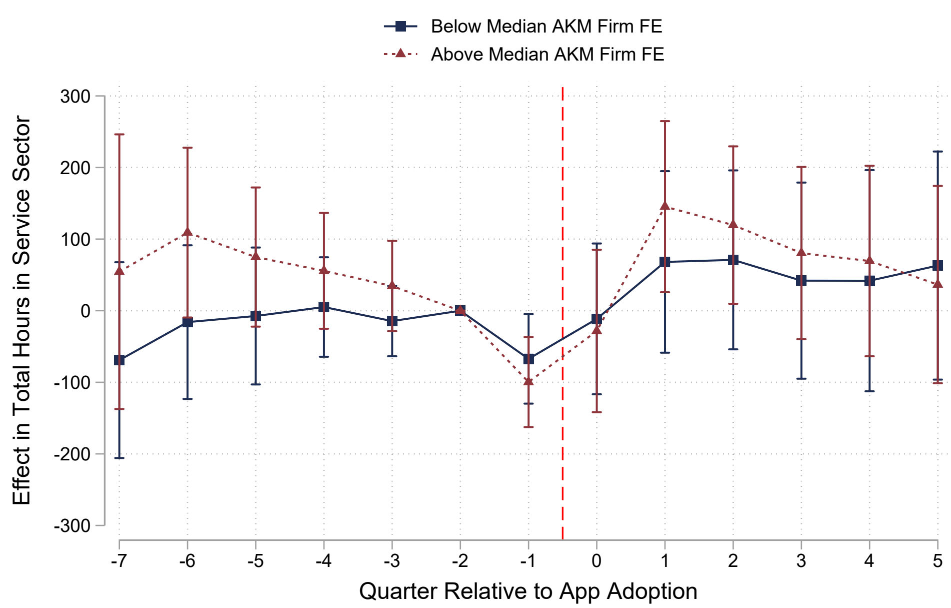
Notes: This figure reports .

Figure A18: Effect of App Adoption on Total Hours for Service Workers



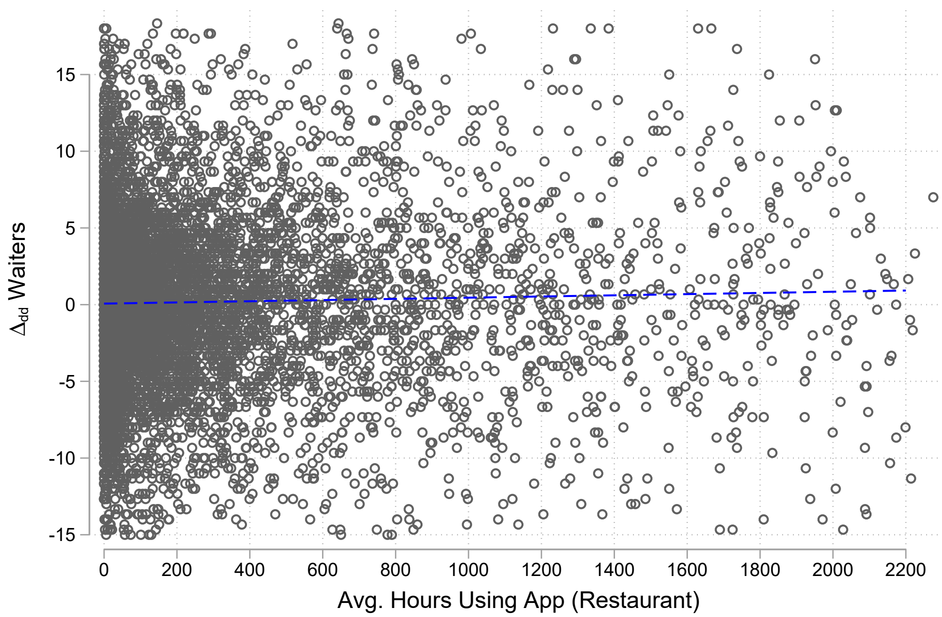
Notes: This figure reports

Figure A19: Effect of App Adoption on Total Hours for Service Workers by AKM Firm Fixed Effects



Notes: This figure reports

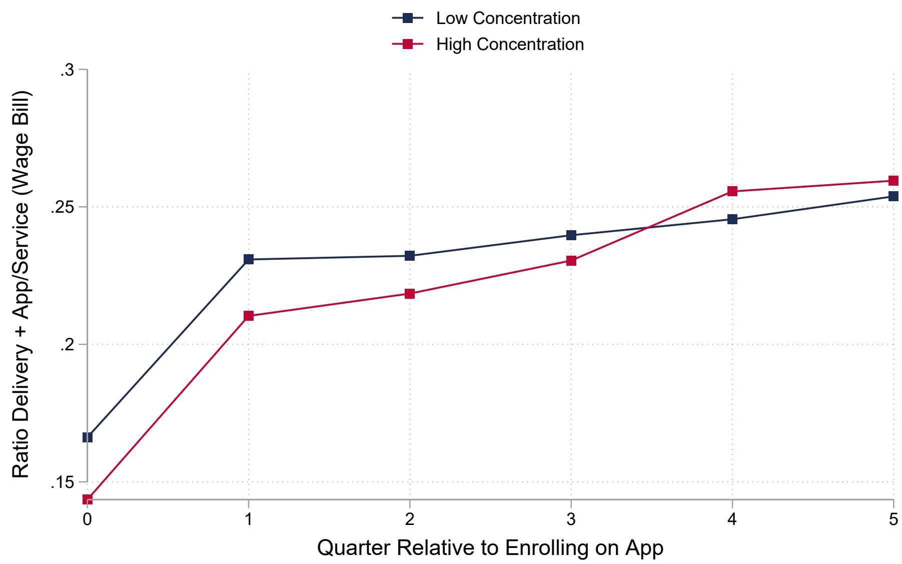
Figure A20: Relation Between Establishment Level Treatment Effect on Number of Waiters and Usage of Delivery Platform by Restaurants



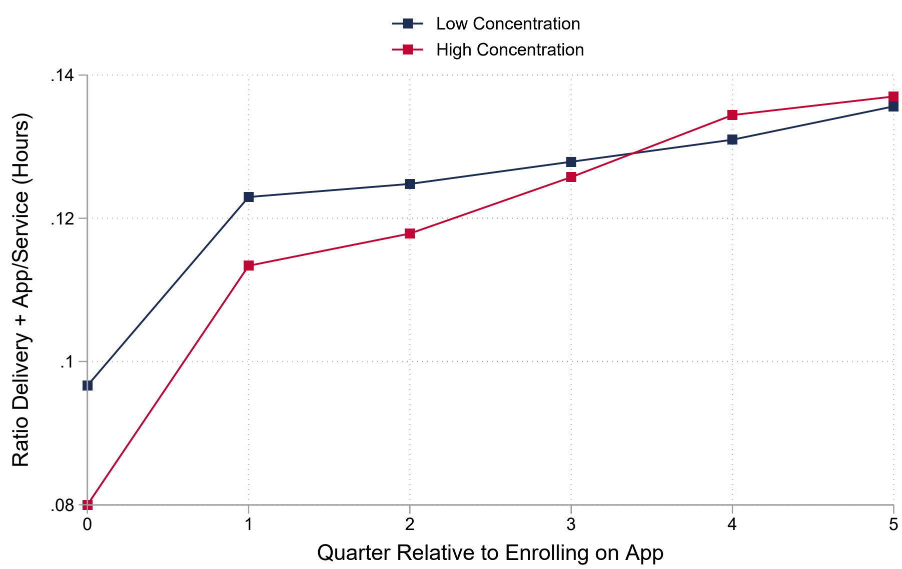
Notes: This figure reports

Figure A21: Ratio of Delivery Workers and Service Workers at Treated Establishments by Density

(a) Wage Bill



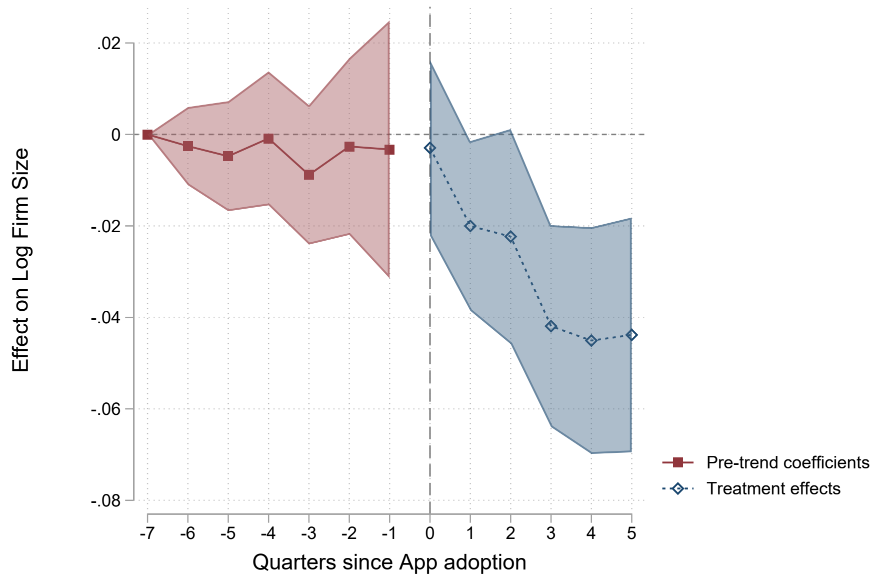
(b) Hours



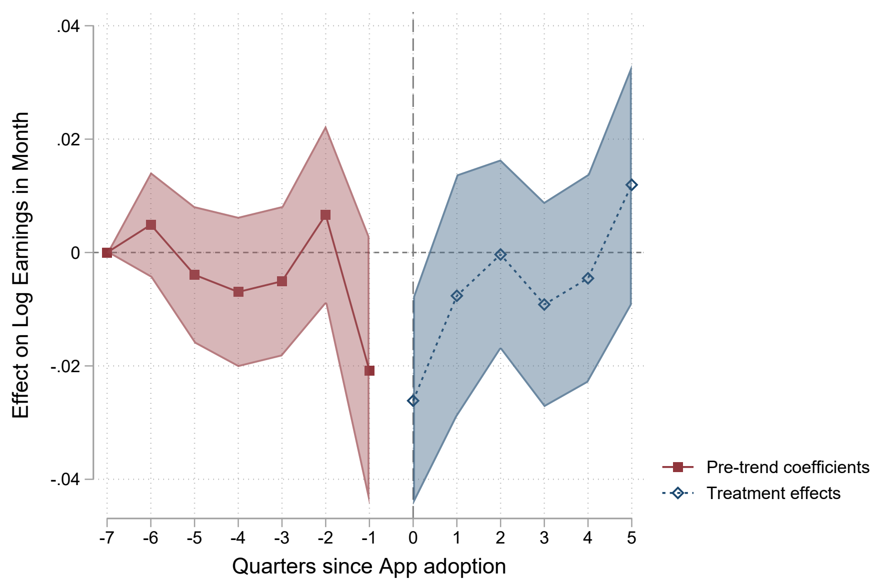
Notes: This figure reports .

Figure A22: Effect of Adopting the App using Borusyak et al. (2024) estimator

(a) Log Firm Size



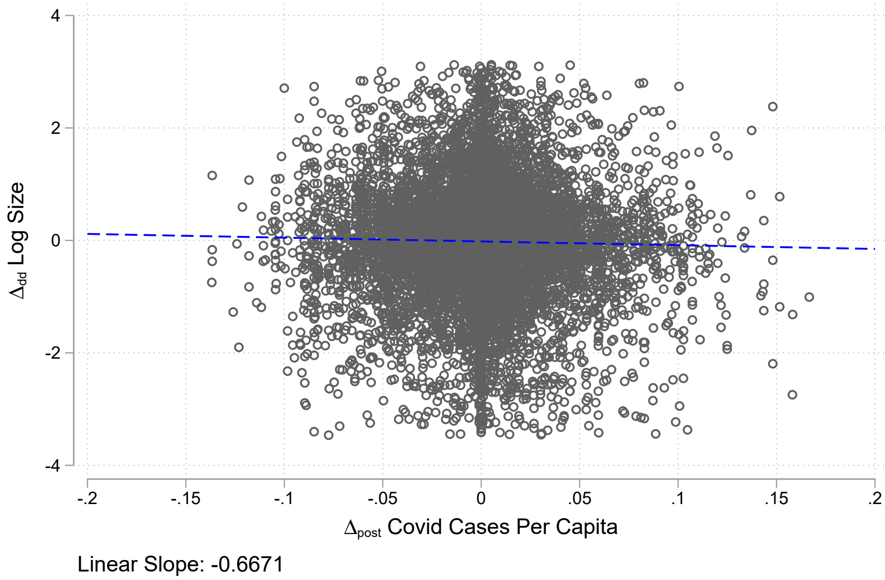
(b) Log Monthly Wages



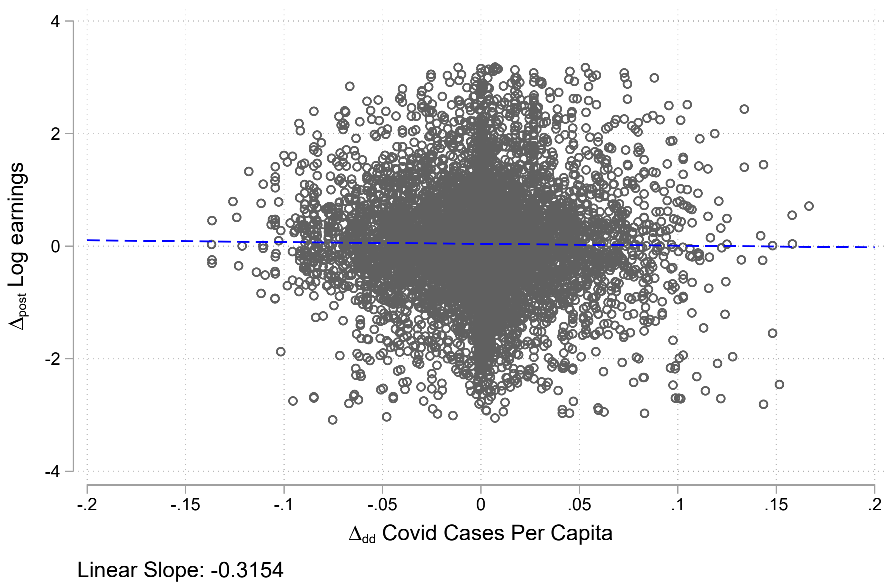
Notes: This figure reports .

Figure A23: Establishment level treatment effect and Covid Case

(a) Log Firm Size

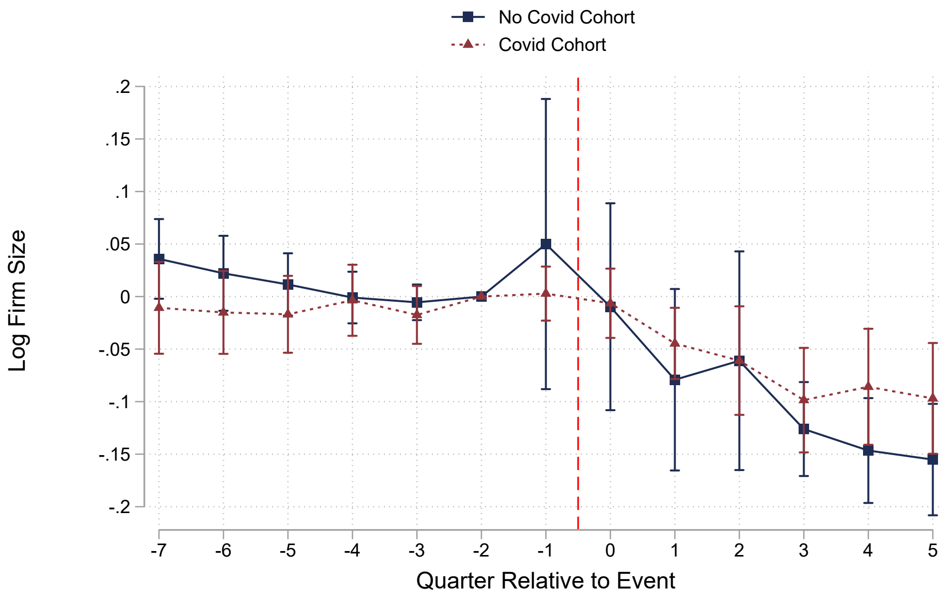


(b) Log Monthly Wages



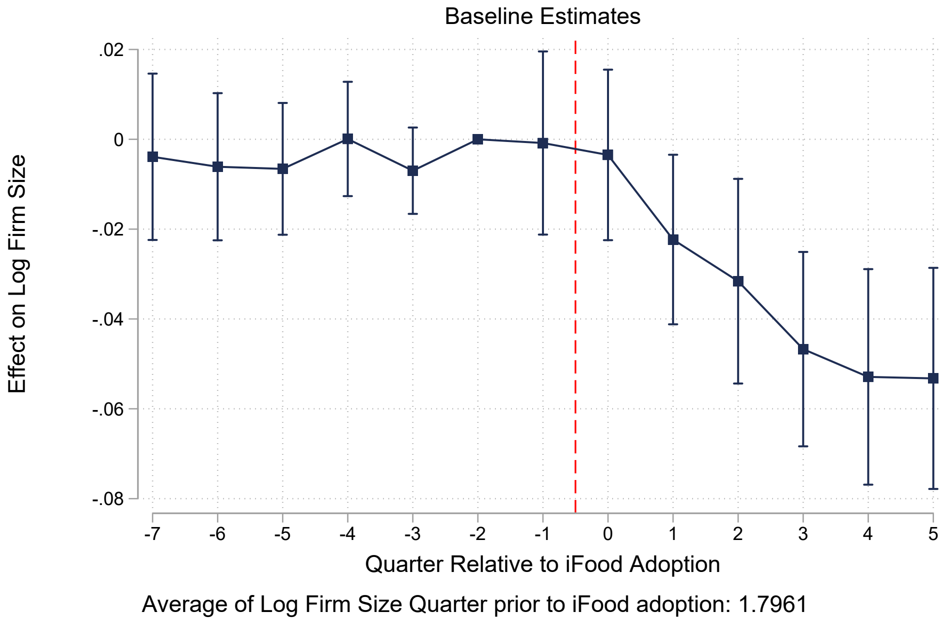
Notes: This figure reports .

Figure A24: Effect of App Adoption on Log Firm Size by Covid-19 period



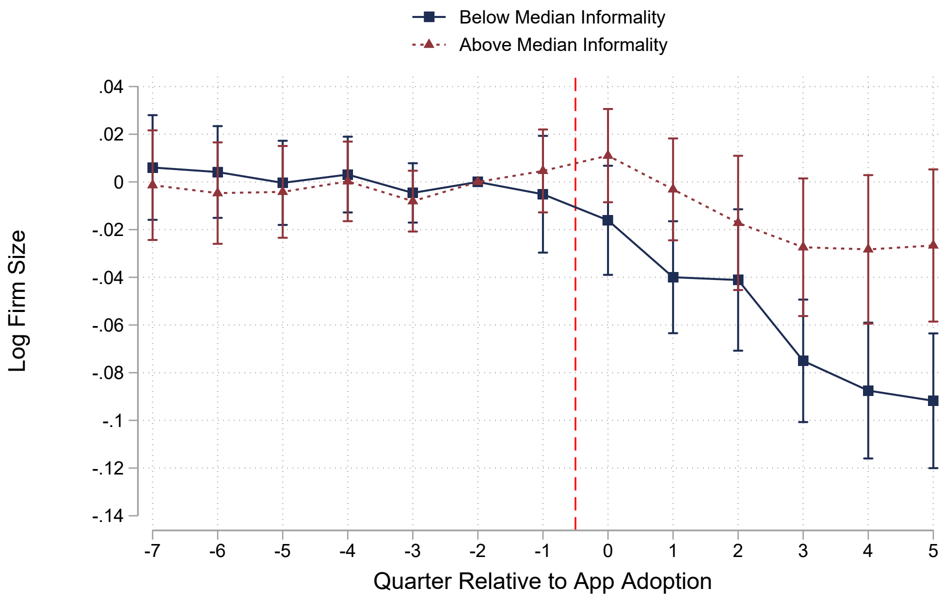
Notes: This figure reports

Figure A25: Effect of App Adoption on Log Firm Size with State-Year Fixed Effects



Notes: This figure reports

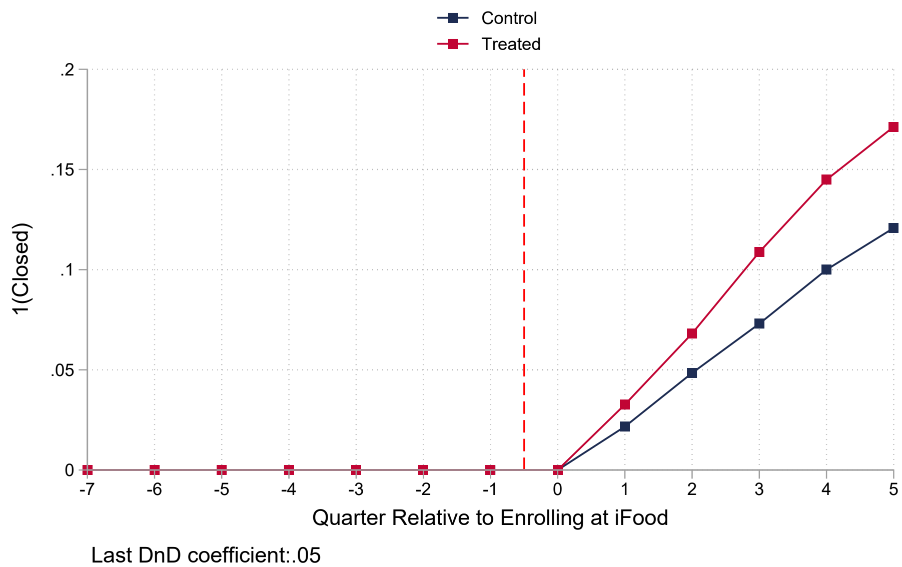
Figure A26: Effect of App Adoption on Log Firm Size By Informality of the Municipality of the Establishment



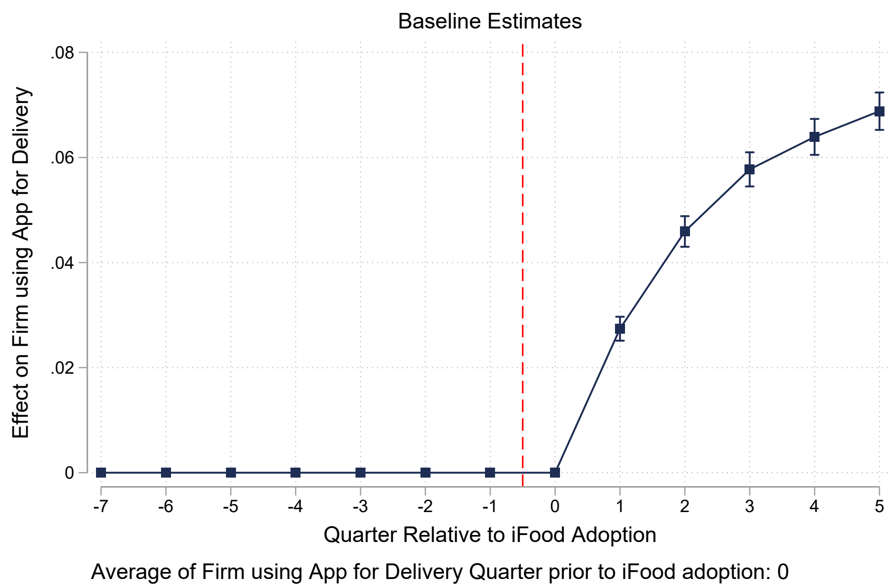
Notes: This figure reports

Figure A27: Spillover Effects of App Adoption on Non-Adopting Restaurants Closure and App Adoption

(a) Closure



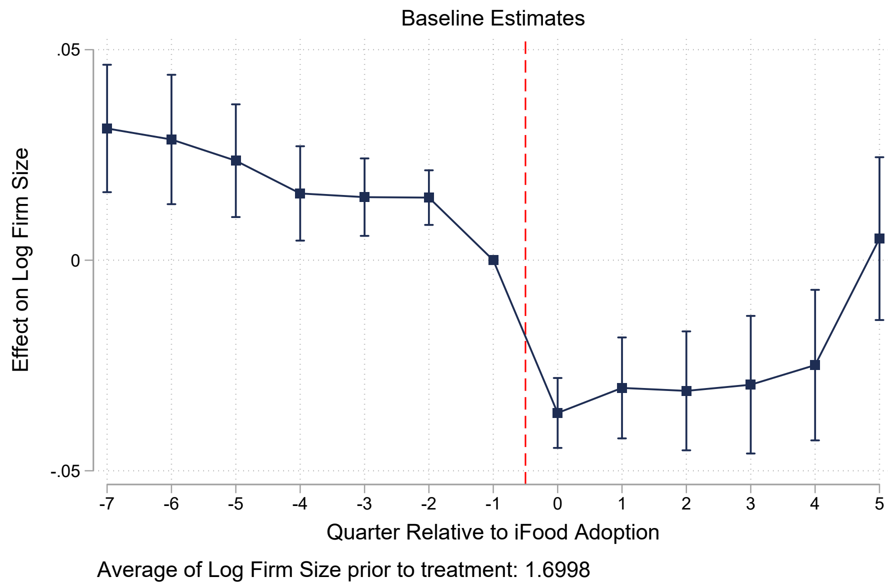
(b) Likelihood of App Adoption



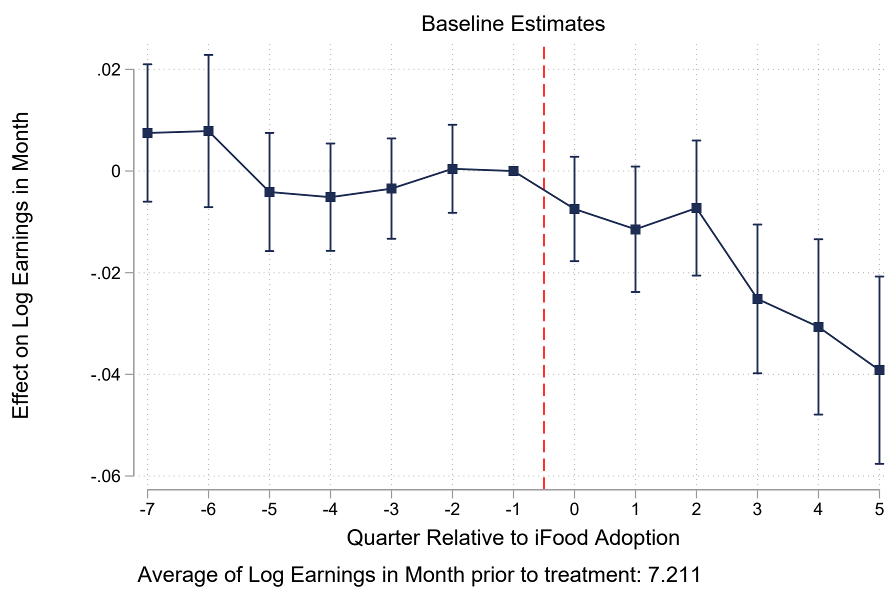
Notes: This figure reports .

Figure A28: Spillover Effects of App Adoption on Non-Adopting Restaurants (2KM)

(a) Log Firm Size



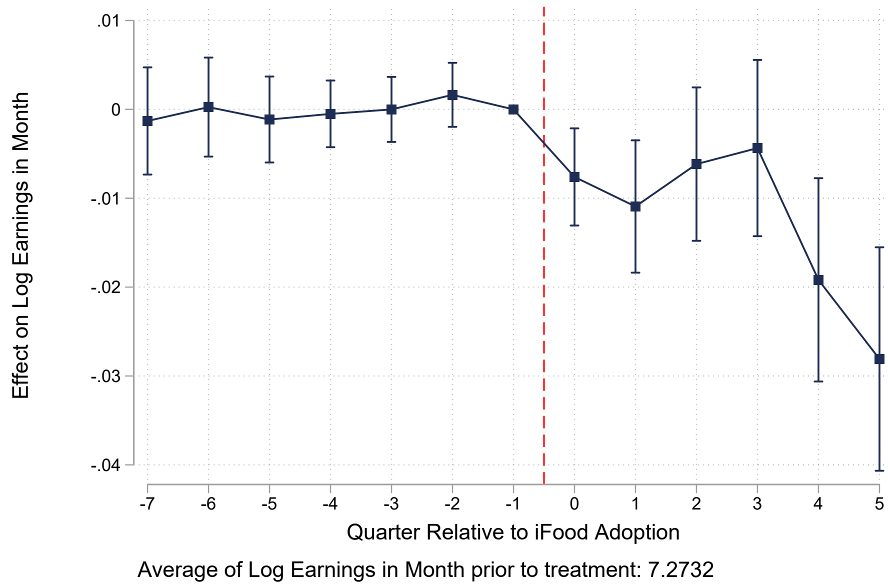
(b) Log Avg. Monthly Wages



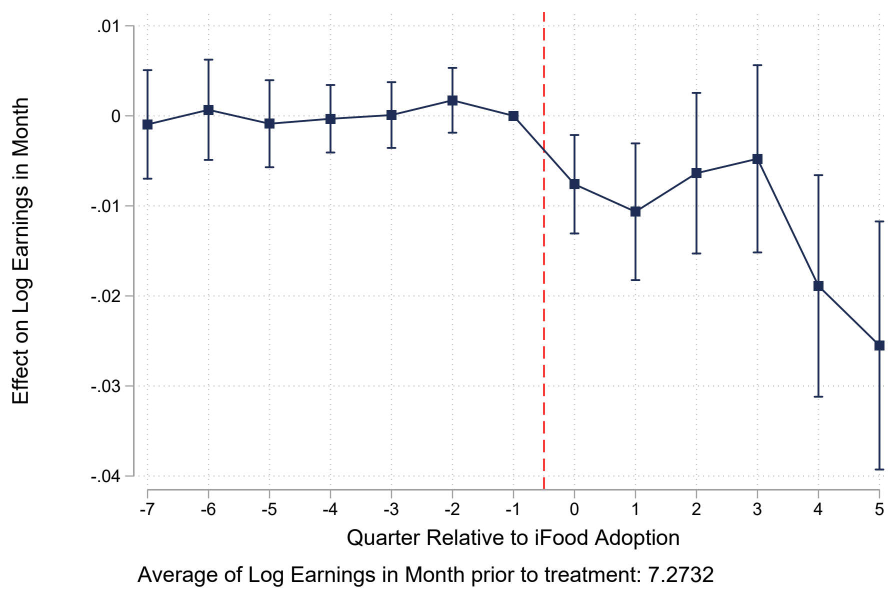
Notes: This figure reports .

Figure A29: Effect of Employer App Adoption on Restaurant Workers Log Earnings

(a) Log Firm Size



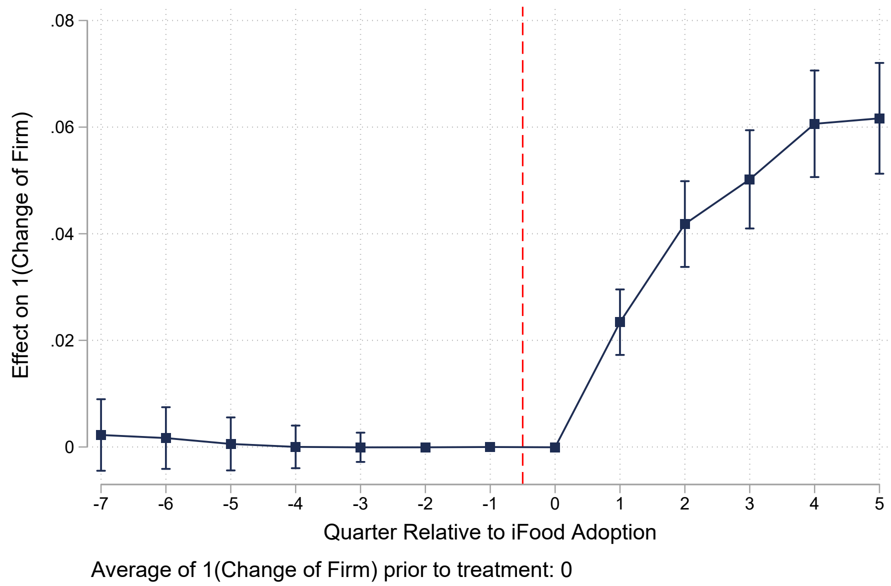
(b) Always Takers (Lee, 2009)



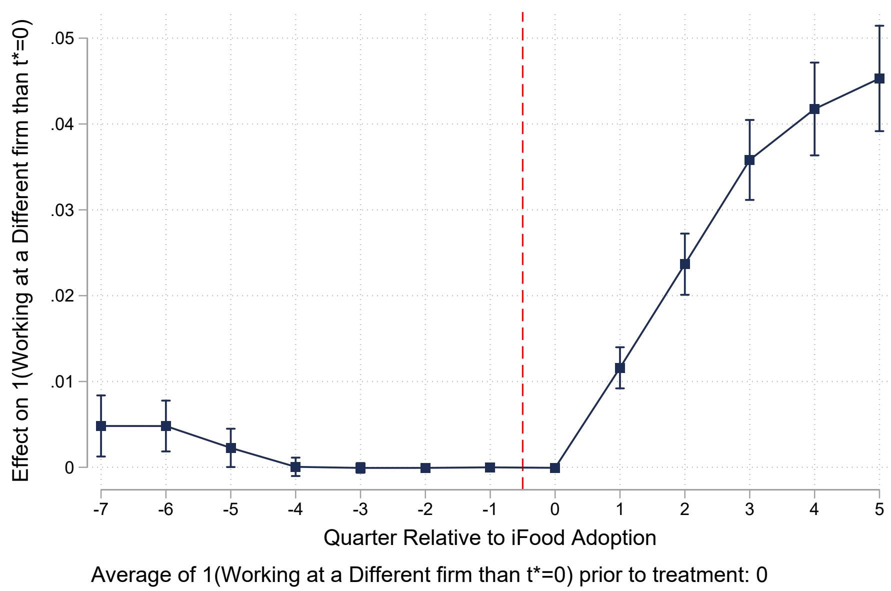
Notes: This figure reports .

Figure A30: Effect of Employer App Adoption on Worker Probability of Changing Firm

(a) Likelihood of Leaving Employer from t*=0 (Non-Employment or New-Employer)

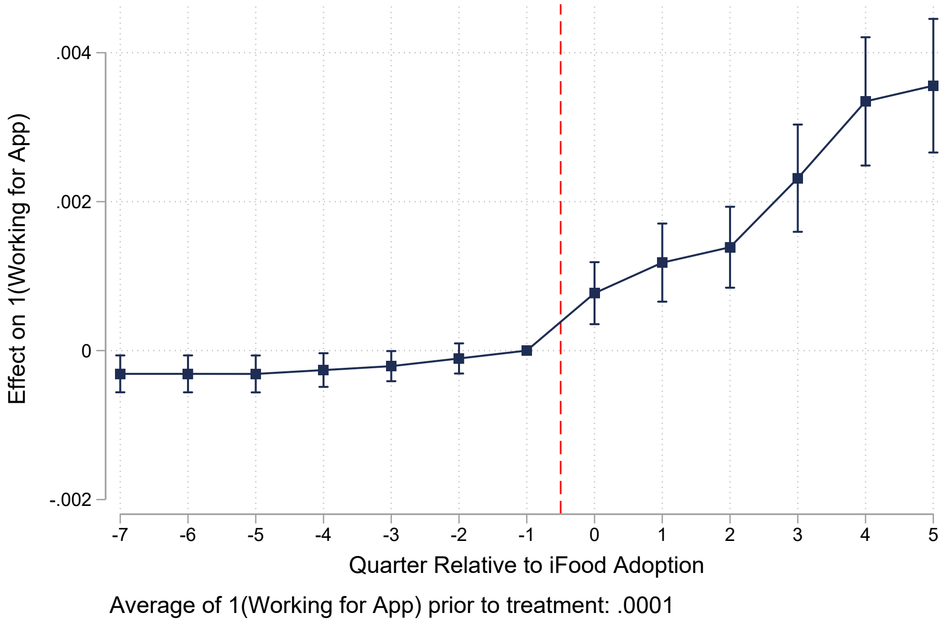


(b) Likelihood of Working for a different Employer than t*=0



Notes: This figure reports .

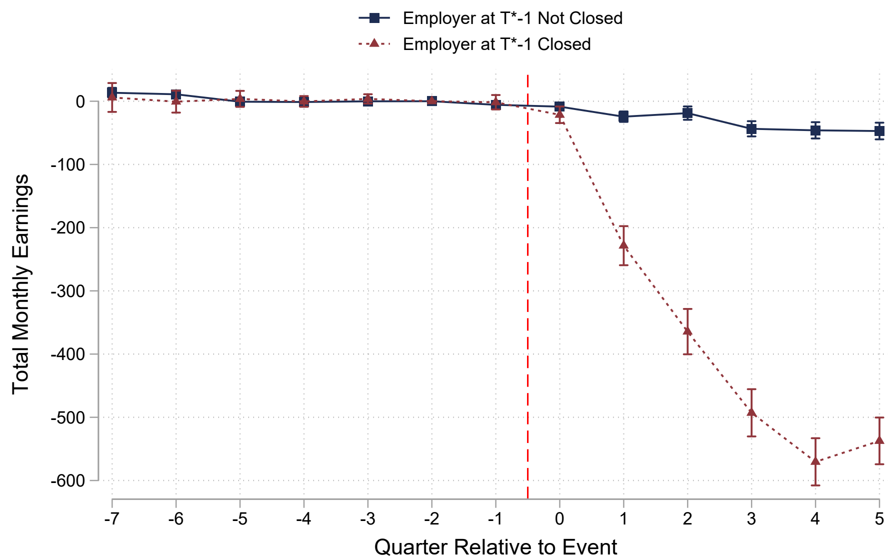
Figure A31: Effect of Employer App Adoption on Worker Probability for Delivery Platform



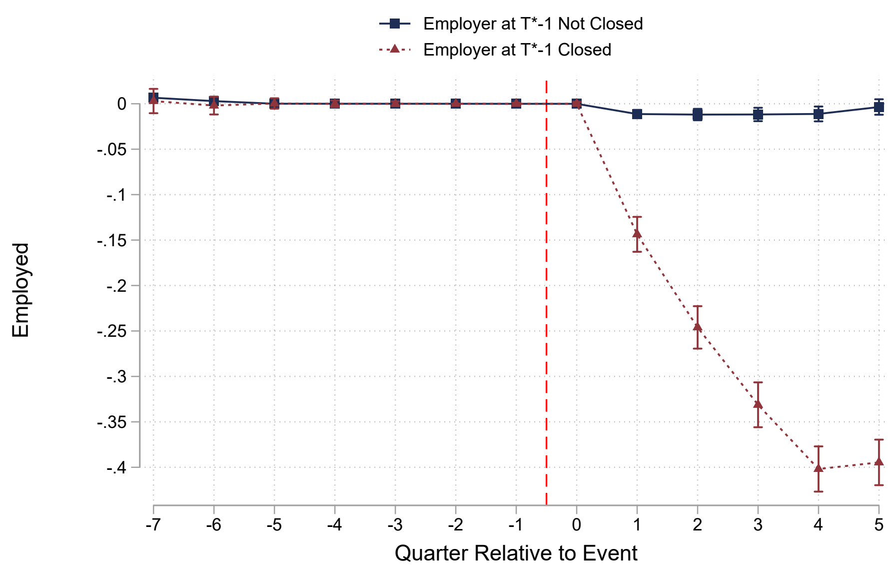
Notes: This figure reports

Figure A32: Spillover Effects of Nearby Restaurants Adoption of Delivery Platforms on Workers by Employer Closure

(a) Total Earnings



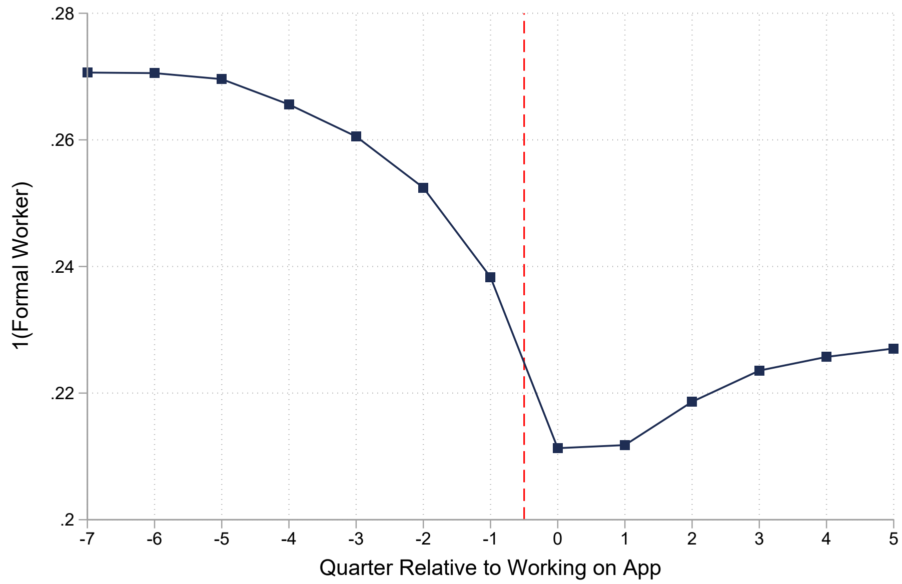
(b) Employment



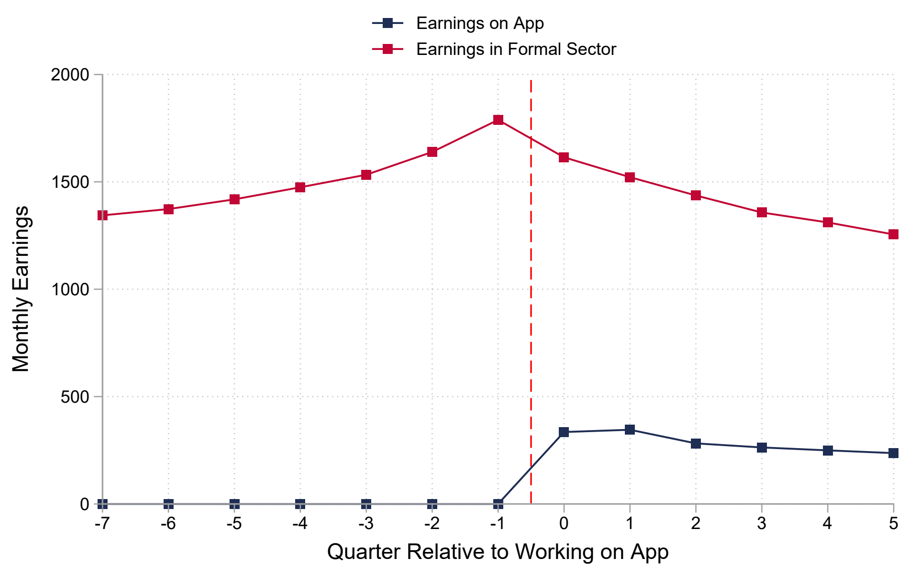
Notes: This figure reports .

Figure A33: Trends of Formal Employment and Earnings for App Workers

(a) Formal Employment



(b) Total Earnings Conditional on Worker Employed in $t^* - 1$



Notes: This figure reports .