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

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**Abstract**

Online-delivery platforms are part of a recent wave of technologies that reshape workforce composition and demand for goods. While these platforms can provide new opportunities for workers with limited outside options, they may also replace "good jobs". This paper uses unique data linking employer-employee records with restaurants and workers from a major Brazilian delivery platform, along with a matched event-study design, to estimate the impact of platform adoption on labor market outcomes. Adopting restaurants, on average, replace in-house labor hours with outsourced platform worker hours one-to-one. Workers at these restaurants experience modest earnings losses, as most displaced employees find new formal sector jobs. In contrast, non-adopting restaurants tend to downsize or shut down, with their workers facing greater earnings losses due to increased displacement risks. However, the earnings gains for gig workers outweigh the losses faced by restaurant employees. These findings offer insights into the distributional effects and trade-offs of online-delivery platforms.

**Keywords:** Outsourcing, Gig Economy, Technological Change, Displacement, Informality

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

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Technological progress profoundly affects both businesses and their employees. Most directly, innovation reshapes labor demand, displacing some jobs while creating new tasks and occupations (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu et al., 2024). However, technology also reshapes demand for various goods and services, which in turn impacts the fortunes of firms and workers (Bakos, 1997; Dolfen et al., 2023).[1] Although the labor and product market impacts of technological change are commonly discussed separately, they often overlap. In the restaurant sector, online delivery platforms such as Grubhub and Doordash, have allowed restaurants to expand the market for their products while potentially outsourcing part of their labor. Advocates of the gig economy argue that these platforms enable restaurants to grow their market and simultaneously provide workers with flexibility, while granting opportunities for low-income workers with limited outside options. Critics argue that these platform replace "good" jobs for others with lower wages and higher insecurity.[2] Understanding how delivery platforms impact both in-house employees and gig workers is crucial for assessing the broader effects of these emerging technologies on welfare and inequality, as well as for informing policymakers tasked with regulation.

Measuring the effects of delivery platforms is empirically challenging because this analysis requires information on both restaurants that adopt the technology and data on gig workers which are often not available in standard datasets. Moreover, the adoption of a new technology is a strategic decision that may correlate with productivity or demand shocks at the firm level. This selection into adoption makes it difficult to identify the causal effect of online-delivery platforms in settings where the technology is widespread.

This paper estimates the impact of delivery platforms on in-house restaurant employees and gig workers in Brazil. Using a novel dataset linking adopting restaurants and platform workers to administrative employer-employee data, I exploit the staggered roll-out of online-delivery platforms across regions to measure the causal effects of platform adoption. To account for informal workers, I supplement the data with household surveys. The empirical strategy matches adopting restaurants—and their workers—in regions with platform access to those in regions without. The results show that adopting restaurants substitute in-house non-cooking staff hours with outsourced platform worker hours, but the earnings and employment effects on restaurant workers are modestly negative, as many displaced workers reallocate to new formal jobs. Additionally, delivery platforms have spillover effects, increasing the likelihood that non-adopting restaurants reduce their size or close. However, the net earnings gains for gig workers more than offset the

[1] Several industries illustrate how technology simultaneously affects labor and product markets. E-commerce has shifted the retail sector toward online operations, altering job composition and forcing some retailers to close (Chava et al., 2024). Streaming services have transformed media consumption patterns (Aguiar and Waldfogel, 2018), while digital banking has reduced bank teller jobs but increased demand for software development professionals (Jiang et al., 2021).

[2] For arguments in favor of the gig economy, see for example this article by The Economist, October 2018. For arguments against the gig economy, see for example this article by The New York Times, January 2024.

losses for in-house restaurant workers. These effects not only impact total earnings but also potentially shift income distribution, as most gig workers were previously employed informally or unemployed.

The Brazilian context offers a particularly suitable setting to study in detail the potential winners and losers of online-delivery platforms. The restaurant industry accounts for about 4 percent of formal employment, offering a chance to assess the impact of these platforms on a large portion of the labor market. Additionally, the country has a sizable gig economy, with 1.5 million workers engaged in the sector and more than 600,000 of them working in online delivery platforms (IBGE, 2022). Brazil's high levels of informality and unemployment create conditions where delivery platforms may offer opportunities to workers with limited alternatives (Ulyssea, 2020).

I start by deriving a stylized model that illustrates the potential effects of online-delivery platforms on the labor demand of restaurants. The model highlights two channels through which the adoption of the technology influences demand for in-house workers. First, there is an *outsourcing effect*, where the platform increases the productivity of delivery workers relative to substitutable in-house workers, such as waiters, similar to a skill-biased technological change. However, beyond the impact on the marginal rate of transformation between waiters and delivery drivers, the platform creates a *product demand effect* by reducing search costs, which can increase overall demand for restaurant meals and, in turn, boost restaurant employment.[3] I propose a microfoundation of the product demand effect through a consumer search model and show that restaurants located in less dense areas (or suburbs) are more likely to benefit from the platform's expanded customer base. The overall impact of the platform on in-house employment and earnings is thus ambiguous, depending on the relative strength of these two forces across different locations. Importantly, the shift in the product demand curve not only affects adopters but can have spillover effects on nearby non-adopting restaurants by crowding out demand for their goods.

Next, I study empirically the effect of adopting online-delivery platforms on the number of in-house workers, wages, and workforce composition. I first document that restaurants that enroll on a delivery platform are larger and pay higher wages to 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 the online-delivery platform to observationally similar restaurants located in regions where no platform is available at the time, thus mitigating concerns about selection into adoption of the technology. The identifying assumption is that matched treated and control restaurants would have trended similarly in terms of their labor demand in absence of platform adoption. Adopting restaurants reduce their number of in-house workers by 6 percent a

[3]In an extension of the model, I show how this framework maps into a model of selection into the platform similar to Bilal and Lhuillier (2022), where high paying firms are more likely to outsource workers to reduce costs.

year after adoption. This decline is fully explained by non-cooking staff hours being substituted one-to-one for outsourced platform driver hours. 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 platform adoption on labor demand for in-house workers are heterogeneous across the wage setting of firms and regions. I find that higher-paying restaurants reduce their in-house workforce by a greater margin than lower-paying restaurants (8 percent vs 4 percent) a year after the adoption of the platform. These differences are once again driven by non-cooking staff that are being replaced by outsourced workers, while cooks are non-affected at both groups of adopting restaurants. In line with models of selection into 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 between high and low paying restaurants.

Does this mean 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. Establishments in low-density areas typically experience less walk-in traffic and therefore face limited losses in in-house demand but stand to gain significantly from the platform's expanded customer base. Supporting this hypothesis, I find that restaurants in low-density regions expand their total workforce by 6 percent more than those in high-density areas. This workforce growth in low-density locations is primarily due to an increase in cooks, while the number of non-cooking staff remains unchanged. Together, these findings highlight the particular importance of the product demand effect for restaurants in less centric locations (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 demand of non-adopting restaurants. To examine the indirect effects of the platform on the labor demand of non-adopters, I focus on sudden, large increases in the share of restaurants using delivery platforms within a 1-kilometer radius of non-adopters. In line with adopting establishment crowding out demand of non-adopting restaurants (Chava et al., 2024), I find evidence that these platforms also have an impact on restaurants that don't use these technologies. Restaurants that do not adopt but are located near a significant share of adopters are 5 percentage points more likely to close a year after the shock. Importantly, these non-adopting restaurants are not on a stronger downward trend than adopters, indicating that pre-existing conditions are unlikely to explain the effects. The spillovers also have an impact on the intensive margin in the short run: Non-adopting restaurants decrease their size by 3.5 percent, but conditional on survival, recover by quarter 5 after the shock.

After showing that online-delivery platforms change the labor demand of both adopting and non-adopting restaurants, I leverage the granularity of my data to study the effect these platforms have on employment and earnings for workers in the restaurant sector. 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 in an online-delivery platform and match them to a control restaurant worker in a location where no platform is available. I find that treated workers suffer a modest earnings (and employment) loss of only 1.5 percent a year after their employer adopts the platform. The main mitigating factor of this loss is that treated workers find a new job at a quick pace: 75 percent of treated workers have found a new job by quarter 5 after their former employer adopts a delivery platform. Remarkably, these new jobs are also in the formal restaurant sector and not in the gig economy.

In contrast, workers at non-adopting restaurants experience a greater (unconditional) earnings loss compared to those at adopting restaurants. One year after a large share of nearby restaurants adopt the platform, earnings for workers at non-adopting restaurants decrease by 6.6 percent. This larger impact is due to a higher risk of displacement, as many non-adopting restaurants close. As a result, their likelihood of remaining employed drops more sharply—one year after the shock, they are 3.8 percentage points less likely to be employed than the control group.

The reduced form estimates indicate that online-delivery platforms have a persistent impact on the earnings of in-house workers at adopting restaurants and negative spillovers towards workers at non-adopting restaurants. However, the resulting earnings losses do not tell the full story. It is possible that the earnings gains for platform workers outweigh the earnings lost 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 platform workers. For restaurant workers, I also consider the impact on those hired informally (Ulyssea, 2018), imputing the number of informal workers per formal restaurant using the Brazilian Census and household survey (PNAD-C). I find that in-house workers at adopting restaurants and workers at restaurants affected by spillovers lose earnings equivalent to 7.3 and 17.1 percent of the pre-platform wage bill of adopting restaurants, respectively.

Turning to the potential gains for gig workers, I compare their platform earnings (net of maintenance and transportation costs) to their outside option. I separate workers into two groups: those employed in the formal sector before joining the platform (22 percent) and those without formal employment when starting (78 percent). For the first group, using their formal sector wage as the outside option, I find a gain equivalent to 2.1 percent of the pre-platform wage bill of adopting restaurants. The second group, without prior formal employment, presents a greater challenge, as their outside option is not directly observable. I propose different scenarios for their outside options and, using my best estimate—which is a regression-adjusted earnings estimate from the PNAD-C—find that their net earnings gain per adopting restaurant is 26.9 percent of the pre-platform wage bill. Summing the gains and losses across all groups, the total wage effect per adopting restaurant is positive and represents 6.8 percent of the pre-platform wage bill.

While earnings are a key part of worker utility, non-wage characteristics of these jobs—such as job security, flexibility, and health risks—can also significantly influence worker welfare. If gig work provides valued flexibility, the benefits to workers may extend beyond wages alone. Conversely, if these jobs entail higher health risks or lack security, they may be less desirable than other employment options. To account for these non-wage factors, I use job-to-job transitions (Sorkin, 2018) to rank how workers value gig work compared to other restaurant jobs. This method captures the broader quality of employers by considering both monetary and non-monetary job attributes. My findings reveal that app-based jobs rank in the 90th percentile among restaurant jobs in Brazil, suggesting that the welfare effects of delivery platforms may extend well beyond earnings, potentially due to the flexibility these platforms offer.

Although my analysis focuses on the impact of incumbent firms adopting online-delivery platforms, the overall effects of these platforms may also influence the entry of new firms. Delivery platforms can enable businesses to offer goods with lower capital requirements, thereby increasing the likelihood of new firm entry. However, they may also intensify competition, potentially discouraging smaller, less efficient firms from opening. I utilize data collected from the national registry of firms (Cadastro Nacional de Pessoas Jurídicas—CNPJ) combined with an event study at the microregion level to examine the effect of online-delivery platform availability on firm entry. I find that restaurants are on average 10.5 percent more likely to open following the platform's entry in a given microregion. This suggests that, if anything, focusing solely on incumbent restaurants represents a lower bound on the overall impact of these platforms on workers.

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).[4] 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).[5] 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).[6] Typically, these two dimen-

[4]Acemoglu et al. (2024) provides a synthesis of the literature and presents a framework showing how technological change can affect labor through changes in productivity, automation, or the creation of new tasks.

[5]A growing literature has focused on firm-level technological changes to study skill demand (Bøler, 2015; Aghion et al., 2019). Using a framework closer to mine, Lindner et al. (2022) show that skill-biased technological adoption changes both the skill ratio and premium.

[6]Studying eBay, Dinerstein et al. (2018) shows that search ranking algorithms play a significant role in reducing consumer search frictions. Fang et al. (2024) finds that search tools in e-commerce increased customer orders. More

sions 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 a product market channel and a labor replacement channel. It then offers empirical evidence of how a technology that influences both margins, online-delivery platforms, impacts workers.

This paper also relates to the growing literature that studies 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).[7] Previous research has examined the impact of ridesharing apps on self-employed workers (Berger et al., 2018; Abraham et al., 2024). This paper extends the literature by exploring the effects of online-delivery platforms on workers in both standard employer-employee jobs and gig roles. Unlike ridesharing platforms, which compete directly with self-employed workers, online-delivery platforms are adopted by establishments, allowing them to outsource labor while also influencing product demand.[8] By matching data from a major gig company with administrative employer-employee records, I am able to track workers and firms over time, overcoming limitations often associated with survey or tax data (Garin et al., 2024). This paper also extends the literature by studying the gig economy in a middle-income country, where gig jobs may serve as a safety net due to high levels of informality and unemployment (Ulyssea, 2018). Notably, I find that the main benefits of online-delivery platforms accrue to workers who did not hold formal jobs before joining the platform. This may contrast with developed countries, where non-wage benefits, such as flexibility, are the main driver of value for workers (Chen et al., 2019, 2020; Angrist et al., 2021).

## 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 ($W$) and delivery ($D$). Workers are defined by their occupation rather than their skill, reflecting the relatively homogeneous workforce in the restaurant sector; this approach contrasts with recent task-based models, where different skill groups can perform multiple tasks (Acemoglu et al., 2024). The fo-

related to the setting covered in this paper, Zheng et al. (2023) shows that a query recommender system on online-delivery platforms increases the probability that customers place a food order.

[7] In the US, the gig economy has been found to smooth consumption (Koustas, 2018) and alleviate the negative effects of job displacement (Jackson, 2022).

[8] Delivery platforms represent a form of domestic outsourcing that has not been studied extensively. Most micro-level evidence has focused on outsourcing events where workers transfer from an outsourcing firm to a firm offering outsourced services (Goldschmidt and Schmieder, 2017; Daruich et al., 2024) or to temporary work agencies and contract firms (Deibler, 2023; Drenik et al., 2023; Felix and Wong, 2024). Due to data limitations, there is limited evidence of the substitutability between outsourced and in-house workers in core occupations. This paper overcomes this challenge by observing both in-house and outsourced workers following the adoption of the technology.

cus of this model is to illustrate in a simplified framework how the adoption of online-delivery platforms can change the demand for in-house labor by enabling firms to outsource part of their workforce while potentially shifting the demand for their products. [9]

### *2.1 Model Setup*

The model features heterogeneous workers defined by their occupations. Cooks and waiters vary in their preferences for firms' non-wage attribute. Worker heterogeneity gives rise to imperfect competition in the labor market. Restaurants faces an upward labor supply curve for cooks and waiters which yields a monopsonistic labor market for these occupations. Unlike a competitive market where firms take wages as given, restaurants post wages for cooks and waiters and hire any worker willing to work at that wage. The labor supply of cooks and waiters is given by:

$$ln(C_j) = \lambda_{jC} + \beta\, ln(w_C) \tag{1}$$

$$ln(W_j) = \lambda_{jW} + \beta\, ln(w_W) \tag{2}$$

Where $\lambda_{j\{C,W\}}$ represents the firm specific amenities, common to all workers in the occupation. For simplicity, I assume that the labor supply elasticity ($\beta$) is common to both types of workers.[10] In contrast, delivery workers are hired in a competitive market.

Waiters and delivery drivers compose what I define as service workers ($S$). 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 $\sigma$. The relative productivity of waiters and delivery drivers is governed by the parameter $\theta$. Motivated by the fact that the presence of delivery workers prior to delivery platforms was very limited (as discussed in Section 4.2), these workers are assumed to have a productivity close to 0 in the pre-platform period. Therefore, restaurants essentially do not hire them previous to adopting a platform service. As described later in this section, the introduction of delivery platforms increases the productivity of the delivery workforce relative to waiters, implying a reduction in $\theta$.

Specifically, the production function is given by:

$$Y_j = T_j C_j^{\alpha} S_j^{1-\alpha} \tag{3}$$

$$S = [\theta W^{\rho} + (1-\theta) D^{\rho}]^{\frac{1}{\rho}} \tag{4}$$

[9]This approach more closely resembles models of skill-biased technological change (Acemoglu, 2002; Lindner et al., 2022), where new technology augments one skill. In this case, the technology is factor-augmenting for an occupation rather than a skill.

[10]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, amenities, and relative productivities of each type of labor. None of the derivations depend on this assumption.

Where the elasticity of substitution is equal to $\sigma = (1-\rho)^{-1}$ and $T_j$ reflects the Hicks netural firm specific productivity term. Restaurants compete in a competitive monopolistic market. 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. The product demand function takes the following form:

$$P_{jl} = P_{0jl} Y^{-\frac{1}{\epsilon}} \tag{5}$$

**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:

$$\max_{w_W, w_C, D} P_{jl} Y_j - w_W W - w_C C - w_D D$$

subject to (1)-(5). The first order conditions yield the following wage equations for in-house cooks and waiters (disregarding the $j$ notation for simplicity):

$$w_W = \underbrace{\frac{\beta}{1+\beta}}_{\text{Markdown}} \underbrace{\frac{\epsilon-1}{\epsilon} V_S \, \theta \, (1-\alpha) \left(\frac{W}{S}\right)^{\rho-1}}_{\text{MRPL}} \tag{6}$$

$$w_C = \frac{\beta}{1+\beta} \frac{\epsilon-1}{\epsilon} V_C \, \alpha \tag{7}$$

Where $V_S$ and $V_C$ are the revenue $R$ per service worker $S$ and per cook $C$, respectively ($\frac{R}{S}$, $\frac{R}{C}$), and $w_C$, $w_W$ are the wages of cooks and waiters. The wage equation illustrates the typical 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.

### *2.2 Impact of online-delivery platforms*

**Outsourcing Effect** Under this setting, the introduction of online-delivery platforms will have two direct effects. First delivery platforms increase the relative productivity of delivery workers respect to waiters—a decrease in $\theta$. This effect mimics closely the impact that skill-biased technology has on the production function (Lindner et al., 2022), by changing the marginal rate of transformation (MRT) of one type of occupation respect to the other. The increase in the productivity of delivery workers represents the increasing returns to scale that online-delivery platforms have by specializing in these services.[11] I call this the *outsourcing effect*.

**Product Demand Effect** The introduction of online-delivery platforms also impacts the demand for goods produced by the restaurant ($P_{0jl}$). On the one hand, the technology may enable restaurants to access new markets that were previously inaccessible. However, delivery platforms may also substitute or crowd out in-house dining (in favor of delivery) in markets already accessible to the restaurant, having a net zero—or potentially negative—impact on the total demand for the restaurant's goods. Ultimately, the effect on product demand will depend on several factors, such as the location of the firm and the baseline competition it faces. For example, restaurants in low-density areas typically have less walk-in traffic (Leonardi and Moretti, 2023) and therefore face limited losses in in-house demand but stand to gain significantly from the platform's expanded customer base. I call this potential shift in demand the *product demand effect*.[12]

**Spillovers** The product demand effect can also have spillovers on restaurants that do not adopt the technology. Empirical evidence suggests that the adoption of e-commerce crowds out demand for brick-and-mortar stores in the retail sector (Chava et al., 2024). Similarly, the adoption of online-delivery platforms may crowd out demand for nearby non-adopting restaurants. Intuitively, if delivery platforms increase the visibility of enrolled restaurants, making it more likely for customers to order food online instead of dining in, then firms previously benefiting from agglomeration externalities may experience a reduction in demand. Appendix C3 provides a microfoundation of the product demand effect through a consumer search model to illustrate how firm location and platform adoption can influence demand for goods produced by restaurants.

### 2.3 *Comparative Statics*

The changes in labor demand for in-house workers after a restaurant adopts an online-delivery platform depend on the relative magnitude of the product demand effect and the outsourcing effect. Specifically, by log-linearizing equation (6) with and without the adoption of the technology, and comparing the two, one arrives at the following expression for the change in labor demand for waiters:

$$\Delta\, ln(W) = \frac{\beta\sigma}{\beta+\sigma}\Bigg[ \underbrace{\underbrace{\Delta\, ln(V_S)}_{\substack{\Delta \text{ Revenue p/} \\ \text{Service Worker}}} + \frac{1}{\sigma}\underbrace{\Delta\, ln(S)}_{\substack{\Delta \text{ Service Sector} \\ \text{Size}}}}_{\textit{Product demand effect}} + \underbrace{\underbrace{\Delta\, ln(\theta)}_{\substack{\Delta \text{ relative productivity} \\ \text{waiters}}}}_{\textit{Outsourcing Effect}} \Bigg] \tag{8}$$

[11] A microfoundation of the comparative advantages of firms that provide outsourcing services can be found in Bilal and Lhuillier (2022).

[12] One could also consider a model with two types of goods produced by restaurants: in-house and delivery goods. In such a model, online-delivery platforms could increase demand for delivery goods at the expense of in-house goods, depending on the level of substitutability between the two types of products. In Section 6.3, I provide evidence that this model is unlikely to hold.

The effect on product demand can be decomposed into the change in revenue per service worker and an additional term that reflects the relative change in the service sector size after adopting the platform. This second term is scaled by the level of substitutability between waiters and delivery drivers.[13] Specifically, if waiters and delivery drivers are complements ($\sigma \rightarrow 0$), an increase in the number of delivery drivers should lead to an increase in the number of waiters hired by the firm. In contrast, as $\sigma \rightarrow \infty$, waiters do not benefit from the overall increase in delivery drivers, making this second term irrelevant. Taken together, equation (8) provides guidance on the forces behind the impact of delivery platform adoption on the demand for in-house waiters. On the one hand, the outsourcing effect will most certainly reduce demand for waiters. On the other, the product demand effect is uncertain, and its impact on in-house labor will depend on certain characteristics of the adopters, such as their location.

The model presented so far assumes a constant outsourcing effect across all adopting restaurants. A limitation of this assumption is that it does not account for the possibility that high-paying restaurants may selectively opt for outsourcing—an outcome highlighted in both the empirical and theoretical outsourcing literature (Goldschmidt and Schmieder, 2017; Drenik et al., 2023; Bilal and Lhuillier, 2022). In Appendix Section C2, I extend the model to allow for different tasks within the service sector and show that this framework enables a similar decomposition of the product effect and outsourcing effect while allowing high-paying establishments to select into outsourcing.

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

$$\Delta\, ln(C) = \beta \underbrace{\Delta\, ln(V_C)}_{\substack{\Delta \text{ Revenue p/} \\ \text{Cook}}} \tag{9}$$

The change in the number of in-house cooks will depend on the change in revenue per cook at the firm. Because the output elasticity of cooks is unaffected by the adoption of the platform (i.e., cooks are equally complementary to waiters and delivery drivers), the change in the number of cooks will be solely determined by the change in their marginal productivity.[14]

[13] The change in the service sector is analogous to the scale effect in Hicks' law of labor demand if the technology did not affect product demand. However, because $P_{0jl}$ is also impacted, the change in $S$ also reflects the change in product demand.

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

## 3 Setting

Online delivery platforms operate as intermediaries in a contractual relationship between restaurants, consumers, and workers. Figure 1 illustrates this relationship: consumers order a product from a restaurant through the app, which then coordinates the delivery by assigning the task to a worker. Under this arrangement, the restaurant is responsible for producing the good, while the worker typically operates as an independent contractor. When a consumer places an order, the app offers the task to workers who are logged on at the time and are near the restaurant. The first worker to accept the task receives the assignment and earns a fee based on factors such as the distance covered, time spent, and any additional bonuses available.

To work for an online delivery service in Brazil, individuals must pass a background check and own a smartphone. Deliveries can be made by bike, motorbike, or car.[15] According to Brazilian law, these workers are classified as independent contractors, meaning they are not entitled to social security contributions from the company. Consequently, they do not receive benefits such as maternity leave or paid vacations, and they are not subject to the federal minimum wage, which only applies to formal employees. Online delivery workers are required to pay income taxes on their earnings if they exceed a threshold that applies to all self-employed individuals (in 2023, this threshold was roughly equivalent to two minimum wages). Workers earning above this threshold have 10 percent of their income subject to taxation.[16]

For the context of this paper, I focus on a large online-delivery company operating in Brazil. Since it began operations, the platform has enrolled over 100,000 establishments. It operates in all major cities and holds a significant market share. The company provides two main services to businesses: (1) delivery services, where consumers order through the app and the company coordinates the delivery; and (2) marketplace services, where consumers order through the app, but the establishment handles the delivery. Fees are charged for both services, though they vary depending on the specific service provided.[17] Restaurants must provide a tax identifier and, therefore, must be formally registered with the government to offer services through the platform.

[15] The majority of deliveries are made by motorbikes. In my sample, 81 percent of workers and 87 percent of deliveries use motorbikes. Bicycles account for 11 percent of deliveries (16 percent of workers), while cars represent 2 percent of deliveries and 3 percent of workers.

[16] This is in contrast with ridesharing workers, 60 percent of whose earnings are taxable. For more details, see: this article.

[17] The company also employs two types of delivery drivers: (1) independent contractors, who are paid per delivery and make up the majority of the workforce; and (2) drivers affiliated with logistics companies, who are formally employed by an intermediary firm and receive a wage independent of their deliveries. These workers typically work for firms that collaborate with several delivery services and represent a minority of the workforce. For the purposes of this paper, I focus only on independent contractors.

## 4 Data

### *4.1 Delivery Platform Data*

The data comes from a major online-delivery company in Brazil. It includes detailed information on establishments enrolled in the app, delivery drivers working through the service, and orders placed between 2018 and 2021. Crucially, both the establishment and worker data contain unique identifiers, allowing me to link them to Brazil's administrative employer-employee database (RAIS). The establishment panel data covers businesses offering delivery through the app. Specifically, it provides monthly information on the number of hours workers spent on deliveries for each business and whether more than 50 percent of the business's revenue on the platform came from deliveries.

The worker panel data includes monthly details on each driver, such as the number of deliveries completed, hours worked and logged in, distance traveled, and earnings (broken down by tips, base earnings, and bonuses). It also tracks the primary municipality where the driver operated, the main mode of transportation used (i.e., bike, motorbike, or car), and identifies workers by their contract with the company.

**Descriptive Statistics: Platform Workers** Table B7 summarizes the main characteristics and performance of platform workers in my sample. Column (1) provides a snapshot of the characteristics of platform workers in the first quarter they worked on the delivery platform.[18] Platform workers are on average 29 years old, predominantly non-Black and male. Those who are formally employed while working on the platform have close to two years of tenure in their formal job, work full-time, and earn average monthly wages of approximately 1,500 BRL (1.57 times the minimum wage in 2018). Columns (2) and (3) show the platform performance for drivers who, in the quarter prior to starting on the platform, held a formal job (formal platform workers) and for workers who did not hold a formal job prior to working on the platform (non-formal app workers), respectively. On average, non-formal app workers earn 13 percent more than formal app workers per month on the platform (646 BRL-2018 vs. 571 BRL-2018). This is explained by non-formal workers working more hours (35 hours vs. 30 hours), spending more time logged on the platform (76 hours vs. 62 hours), completing more deliveries (92 vs. 78), and covering more distance (480 kilometers vs. 426 kilometers).

### *4.2 Employer-Employee Data: RAIS*

The other main data source is the administrative employer-employee dataset from Brazil, called *Relação Anual de Informações Sociais* (RAIS).[19] Employers are required to submit yearly

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

[19]This data has been used in several contexts, such as studying 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 differences (Gerard

reports to the federal government detailing all formal job contracts established in the previous year.[20] 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. This dataset allows researchers to follow workers over time and includes the universe of formal workers and their employers—establishments—from 2003 to 2021. The data contains information on the worker, such as average monthly wages, hours worked, occupation, age, gender, education, and race. Importantly for the restaurant sector, wages in RAIS also include tips. Each worker is identified by a 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 a unique tax identifier: *Cadastro Nacional de Pessoas Jurídicas* (CNPJ). For my analysis, I deflate wages to 2018 Reais. I restrict the sample to employment spells where the worker was employed for at least two months and earned at least 20 Reais per month (approximately 5 USD at the time).[21]

**Descriptive Statistics: RAIS** Column (1) of Table B6 reports summary statistics for restaurant workers in RAIS during 2018.[22] The average formal restaurant worker in RAIS earned 1,574 BRL in 2018, significantly above the minimum wage of 954 BRL-2018.[23] Restaurant workers are older than platform workers (35 years vs. 30) and are more likely to be female (56 percent vs. 8 percent). In terms of occupations, waiters and cooks represent 77 percent of all restaurant workers, while delivery drivers represented only 2 percent of the restaurant sector workforce during the same period. Columns (2) and (3) of Table B6 show the same statistics for the 2010 Brazilian Census. A key advantage of the census is that it allows observation of informal workers as well. Informal workers in the restaurant sector earn 37 percent less than formal workers, which could be partially driven by differences in occupations. Specifically, informal workers are more likely to be waiters and less likely to be cooks than formal workers in the restaurant sector. Importantly, the delivery sector was essentially non-existent in the restaurant sector in 2010 (1 percent of the workforce for both formal and informal workers).

et al., 2021), among others.

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

[21]The vast majority of workers earn above the minimum wage (see Figure A14). However, it is possible that some may earn less due to low hours, suspensions, or leaves.

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

[23]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.

## 5 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 5.1 presents the research design to study the impact of online-delivery platforms on establishments that enroll on the platform. Section 5.2 outlines the research design to examine the spillover effects of competitors' adoption of the platform. Finally, Section 5.3 presents the empirical strategy to study the impact of employer enrollment in the platform on the labor market outcomes of restaurant workers.

### *5.1 Research Design: Adopting Establishments*

The ideal experiment to estimate the causal effect of platform adoption on restaurants would involve random assignment of delivery services across establishments. However, this is not feasible in practice. Instead, I leverage the staggered rollout of the platform across Brazil.[24] Comparing restaurants across regions presents a trade-off. On the one hand, the staggered rollout provides quasi-experimental variation in platform availability, preventing establishments from self-selecting into the control group. Additionally, if delivery apps create spillovers for non-adopting restaurants, comparing establishments within the same region could violate the Stable Unit Treatment Value Assumption (SUTVA). On the other hand, comparing across regions may introduce confounding factors due to differences in the characteristics of establishments and their markets. To address this, I apply a matching algorithm to create a balanced sample of adopting restaurants and control establishments that did not have the option to adopt the platform.

**Matching** I start by considering the pool of treated restaurants that, at the time of adopting the platform, generated more than 50 percent of their revenue through the platform using delivery services.[25] At the time of enrollment, treated restaurants must be located in microregions where the platform holds more than 50 percent of the market share in the online-delivery industry. To ensure a balanced sample, I further limit the sample to restaurants that had been open for at least two years before the quarter prior to enrolling on the platform and were treated at least five quarters before the end of my sample period.

[24]Figure A11 shows the staggered rollout of the platform in Brazil. The platform began its operations in the largest cities (primarily in the Southeast region of Brazil). As the platform grew in popularity over the following years, it expanded its operations to other regions of the country without a clear geographic pattern. To operate in a microregion, the platform must fulfill two requirements: (i) it must have a set of client restaurants willing to use the service, and (ii) it must have a sufficiently large driver force to provide service during all business hours. Both requirements take time to meet and can explain why the platform did not extend operations across the entire country at once.

[25]The restaurants that meet this criterion represent 36 percent of all establishments that enrolled on the app between 2018 and 2021.

To build an appropriate comparison group, I use a matching procedure.[26] The potential control group of establishments includes restaurants located in labor markets where no online-delivery platform technology was available up to the time of treatment, and where the platform did not enter for at least five quarters after treatment.[27] Each treated restaurant is matched to a control restaurant within the same cell the quarter prior to treatment. A control restaurant belongs to the same cell as firm $j$ treated in quarter $t$ if it has been open for at least two years and belongs to the same quartile of firm size and average wages among restaurants in the year. Additionally, to ensure that treated and control restaurants face similar competition, both must fall either above or below the median share of restaurants within a 1-kilometer radius relative to the total number of restaurants in their microregion. Within each cell, treated and control restaurants are paired based on their propensity score, which 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 quarters $[t-4, t-1]$, firm age, share of waiters, average tenure, age of workers, share of female workers, and average hours of workers.

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 raise concerns regarding mean reversion post-treatment. Therefore, I do not match earnings in three quarters of the pre-period and show that treated and control restaurants have similar trends even in these non-targeted periods.

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

$$Y_{\{j,i\}t} = \beta_0 + \alpha_{\{j,i\}} + \delta_t + \sum_{k=-7}^{k=5} \theta_k \mathbf{1}\{t = t^*(j) + k\} + \sum_{k=-7}^{k=5} \beta_k \mathbf{1}\{t = t^*(j) + k\} \times Treated_{\{j,i\}} + \epsilon_{\{j,i\}t} \quad (10)$$

Here, $Y_{jt}$ represents the outcome of interest (e.g., average wages, establishment size) for restaurant $j$ at time $t$; $\alpha_j$ denotes establishment fixed effects, and $\delta_t$ denotes quarter-year fixed effects. $Treated_j$ is a dummy variable indicating whether establishment $j$ enrolls on the platform, while $t^*(j)$ indicates the date on which the restaurant first enrolled in the platform.[28] $\mathbf{1}\{t = t^*(j) + k\}$ represents the event-study indicators that reference the time relative to the treatment date. The main coefficient of interest is $\beta_k$, which, under the parallel trends assumption, captures the causal

[26] Similar empirical strategies have been used to study worker substitutability (Jäger and Heining, 2022), the effects of mergers and acquisitions (Arnold, 2019), and the effects of outsourcing (Goldschmidt and Schmieder, 2017; Daruich et al., 2024), among others.

[27] 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).

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

effect of establishment enrollment on the platform on the outcome of interest. The event-study indicators are normalized relative to $\beta_{-2}$. Therefore, the coefficients $\beta_k$ for $k \geq 0$ capture the effect of the restaurant enrolling on the platform on outcome $Y_{jt}$, $k$ quarters after the enrollment relative to two quarters prior to enrollment. Standard errors are clustered at the establishment level.

**Identification** The key identifying assumption of this model is that, in the absence of treatment, the differences in the outcomes of interest between treated and control establishments would have remained constant (the parallel trend assumption). This assumption may be strong, as the decision to enroll on the platform is strategic and could correlate with both potential outcomes and past trends.[29] To address this, treated restaurants are matched with control restaurants located in microregions where the platform is unavailable. By comparing restaurants in areas with and without platform access, I ensure that control restaurants are not self-selecting into treatment status. Under this framework, the parallel trend assumption can be divided into two parts: (i) treated and control restaurants share the same trends, conditional on the observables used for matching, and (ii) common trends affecting all restaurants are similar across treatment and control regions.

To enhance the likelihood of (i), I leverage the detailed nature of my data. First, restaurants are matched based on their average wages, size, composition, and the number of restaurants in surrounding areas. Second, I compare the outcomes for treated and control restaurants in the quarters prior to the treated establishments' adoption of the platform, as shown in Figure 4. Both earnings and size follow similar trends before the treated establishments adopt the platform, even for periods not directly targeted in the matching process (e.g., average wages between quarters -7 and -4).

Regarding (ii), a potential concern is that enrollment by treated restaurants could incentivize competitors in the same market to adopt the platform. If competitor adoption generates spillover effects, the estimates could reflect both direct and indirect effects. However, Figure A12 shows no discrete increase in the likelihood of nearby restaurants (within 1 km) adopting the platform after a treated firm adopts the platform. Another concern is that different microregions could be exposed to varying shocks over time, especially during the COVID-19 pandemic in 2020 and 2021. To address this, I present results for a set of restaurants that were treated at the beginning of 2019 and therefore were not affected by the pandemic. Additionally, I present results controlling for state-date fixed effects (which absorb state-specific COVID policies) and demonstrate that the individual-level treatment effects are insensitive to the number of COVID cases reported in the

[29] For example, restaurants may decide to enroll if they face a negative demand shock. In this case, wages or employment could decline at enrolling restaurants even without the platform, leading to a downward bias in the estimates. Conversely, if firms enroll after a positive shock that enables them to expand, the estimates would be biased upwards.

municipality of the treated establishment (Chauvin, 2021).

### 5.2 Research Design: Spillovers

To capture the spillover effects, I define a set of firms affected by a sudden, large increase in the number of nearby restaurants that enroll on the platform (spillover event). First, I restrict potential restaurants exposed to these events to: (i) restaurants that, at the time of the event, had never adopted the platform before; (ii) restaurants that had at least five other restaurants within a 1 kilometer radius; and (iii) restaurants that did not belong to a multi-establishment firm where at least one establishment had enrolled on the platform in another location. Restriction (i) is intended to capture non-adopting restaurants at the moment of treatment.[30] Restriction (ii) ensures that treated restaurants are exposed to a minimum level of competition, while restriction (iii) excludes firms that may be affected by within-firm spillovers generated by other adopting establishments.

For each potentially treated establishment $j$, I calculate the share of restaurants within 1 kilometer that are enrolled in the platform in each quarter ($\chi_{jt}$) 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 establishments in the top 5th percentile of the distribution of $\Omega$. When more than one observation of the same establishment falls within the top 5th percentile, I only keep the first event. Appendix Figure A13 plots the distribution of $\Omega$. The mean of $\Omega$ is 0.01, while the top 5th percentile has a mean of 0.11 (with a standard deviation of 0.04). Treated establishments are matched to control establishments using the same procedure as in the baseline analysis. Finally, I estimate the same event-study model as in Equation (10).

### 5.3 Research Design: Workers

This section provides an empirical strategy to estimate the causal effect of online-delivery platforms on restaurant workers' labor market outcomes. The first step in this estimation is to construct a control group. Workers employed in restaurants that do and do not enroll on the platform may differ in various dimensions. Furthermore, firms that enroll on the platform may differ from firms that do not, and these differences may spill over 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 is located in labor markets where no online-delivery platform technology is available at the time of treatment (and up to five quarters after treatment).

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

**Matching** I start by considering the pool of treated workers as those whose employer enrolls on the platform while they are employed at the restaurant. I restrict the sample to workers who are treated up to December 2020, allowing me to observe at least four quarters after treatment. Additionally, I impose a requirement that these workers must have at least two quarters of tenure.[31] For each cohort (quarter × year) of treated workers, the potential control group includes all restaurant workers employed during the same period in a microregion where no online-delivery platforms were available prior to the treatment date and for the subsequent five quarters after treatment.

Each treated worker is then matched to a control worker based on their characteristics the quarter prior to treatment. Workers are matched exactly on gender, occupation, firm size quartile, average firm wages (within restaurants in the year), and the median share of restaurants in the microregion within a 1 kilometer radius.[32] I use one-to-one matching with a caliper algorithm (Stepner and Garland, 2017).[33] Matching variables include 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).

**Econometric Framework** I estimate the effect of employer enrollment on restaurant workers' labor market outcomes by estimating Equation (10) on workers. Under this specification, $Y_{it}$ is the outcome of interest (e.g., earnings, employment) for individual $i$ at time $t$. $\alpha_i$ represents worker fixed effects, and $\delta_t$ represents quarter-year fixed effects. I additionally control for a quadratic in age. *Treated* is a dummy variable indicating whether the employer of individual $i$ enrolls on the platform, while $t^(i)$ indicates the date on which the employer enrolled in the platform. $\mathbf{1}\{t = t^*(i) + k\}$ represents the event-study coefficients that reference the time relative to the treatment date. The main coefficient of interest is $\beta_k$, which captures the effect of employer enrollment on the platform on the outcome of interest. The event-study indicators are normalized relative to $\beta_{-1}$ and standard errors are clustered at the worker level. Similar to the establishment-level analysis, the research design for workers relies on the parallel trend assumption. Although an employer's decision to enroll on the platform is likely exogenous to the worker, it is not feasible to test this identifying assumption directly. In Section 7.1, Figure 9 provides evidence that both targeted and non-targeted moments in the matching display parallel trends prior to treatment.

[31] 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.

[32] Occupations are based on the six-digit CBO code (Classificação Brasileira de Ocupações). I define four groups of occupations: waiters, cooks, administrative, and other. More details on the construction of these four categories are available in Appendix B8.

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

## 6 Impact of Online-Delivery Platforms on Restaurants Labor Demand

This section discusses the impact that online-delivery platforms have on restaurants' labor demand. Section 6.1 covers the main results of the event study analysis, and Sections 6.2-6.4 discuss effects by occupation, restaurant pay policy, and restaurant density. Finally, Section 6.5 examines potential spillover effects from platform adoption by competitors and Section 6.6 presents some robustness checks.

### 6.1 *Main Results: Effect of Adoption of the Platform*

**Descriptive Evidence** Columns (1) and (2) of Table 1 present a snapshot of the characteristics of the matched control and treated restaurants in 2017, 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. Columns (3) and (4) provide a snapshot of the characteristics for all potential treated restaurants (including those that didn't match) and all restaurants in Brazil, respectively. Overall, treated restaurants are larger than the average restaurant in Brazil and pay slightly higher wages.

Figure 2 panel (a) plots the distribution of the AKM firm fixed effects for restaurants that at some point enroll on the platform and those that never enroll, using the method pioneered by Abowd et al. (1999).[34] Restaurants that adopt the platform 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 that results in higher wages for all their workers. Interestingly, AKM firm fixed effects also have predictive power for the intensive margin. Figure 2 panel (b) shows a positive correlation between the AKM firm fixed effects and the number of hours platform drivers work for each restaurant.

Figure 3 presents trends in total hours hired for the matched establishments that enroll on the platform. Panel (a) shows that total hours of in-house workers decreased by 27.6 percent between $t^*-2$ and $t^*+5$. Only part of this decrease is compensated by outsourced platform workers. When accounting for app workers, total hours worked at the establishment decrease by 21.3 percent. Panel (b) shows that as an establishment enrolls on the platform, it increasingly relies on platform workers. App workers represent 2.4 percent of the total hours worked at the establishment in the quarter of enrollment. This share increases over time, reaching 7.5 percent after five quarters

[34] Gerard et al. (2021) have tested the validity of the AKM model in Brazil. Appendix D5 presents details on the AKM estimation.

of enrollment. Both of these patterns suggest a replacement of in-house workers with platform workers following platform adoption. However, understanding the effect of platform enrollment on labor demand requires a comparison with a counterfactual scenario. In the next sections, I present the results of the event study analysis.

**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 show a sharp decrease between $t^* - 1$ and $t^* + 5$ 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 platform, which motivates using $t^* - 2$ as the baseline in the event study analysis. Following enrollment in the platform, differences in wages between treated and control establishments remain fairly constant over time.

Panel (c) reports the trends for log firm size—as measured 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 remains mostly stable between quarters $t^* - 7$ and $t^* - 2$ and experiences a large decrease between $t^* - 1$ and $t^* + 5$. 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 diverges 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 A15 illustrates the trends for the extensive margin of restaurants.[35] 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 present the estimated results for the regression model in the next section.

**Effect of Platform Adoption on Size and Hours** Figure 4 panel (b) presents the estimated $\beta_k$ from Equation 10 for log firm size and shows that treated restaurants decrease the number of in-house workers after adopting the platform, and that this effect is persistent. Five quarters after enrollment, the number of in-house workers at treated firms decreases by 6 percent.

Figure 5 shows the estimated effect of platform adoption on the log number of hours worked

[35]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.

by in-house workers (red line) and the log number of hours including platform workers (blue line).[36] 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 five quarters of platform adoption. This decrease in in-house hours is entirely compensated by the hours worked by outsourced workers. The total number of hours worked at the establishment, when including platform workers, is essentially unchanged five quarters after enrollment.

In summary, these results indicate that restaurants adopting the platform are decreasing their labor demand for in-house workers and replacing in-house labor with platform delivery drivers. However, to study the relative importance of each component shown in Equations (8) and (9), we must focus on the effects by occupation, which I discuss in the next section.

**Effect of Platform Adoption on Wages** Figure 4 panel (d) plots the effects of enrollment in the platform on average wages paid at the restaurants. Average wages at treated firms decrease by 2.8 percent in the quarter prior to enrollment, suggesting that firms may adjust wages before enrolling. This decrease in average wages persists during the post-enrollment period. Average wages are approximately 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 effects 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 higher-paid jobs by outsourced platform workers, then the effect of adoption on the average wage of in-house workers would be smaller than the effect on firm size.[37] 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 platform adoption on the labor demand of cooks and waiters separately.[38]

### *6.2 Effects by Occupation*

This section presents the treatment effects of adoption on labor demand for in-house cooks and waiters separately. I start by examining the change in the overall service sector (that is, all

[36] App worker hours are measured as the time a platform driver dedicates to delivering food from a specific establishment.

[37] For instance, if cooks are on average paid more than waiters, a decrease in $\theta$ could yield a smaller effect on average wages at the firm level.

[38] 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 A16 panel (a) plots the effect of platform enrollment on the average worker fixed effects at the establishment and finds a null effect. Figure A16 panel (b) leverages the matched design to construct establishment-level treatment effects on average worker effects following Schmieder et al. (2023). The figure plots these treatment effects on average worker effects on firm effects and finds a flat 0, discarding the platform enhancing sorting.

workers who are not cooks, including platform workers). Figure A17 provides evidence that the total hours hired for service workers (including app workers) remain essentially unaffected five quarters after platform adoption. Through the lens of Equation (8), the null effect on the size of the service sector indicates that changes in the number of waiters will only reflect changes in the firm's revenue 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 adopting the online delivery platform on the number of in-house waiters hired. Treated restaurants decrease the number of in-house waiters by 5.4 percent after adoption.

As discussed in Section 4.2, the vast majority of restaurants did not hire delivery drivers prior to adopting delivery services through the app. Although the power of the analysis is limited due to the sparsity of delivery workers in the pre-treatment period, the estimates in Column (3) show that restaurants that did have delivery workers prior to adopting the app decrease the number of in-house delivery drivers by 10.5 percent.

Column (2) reports the changes in the number of cooks after platform adoption and shows that enrollment in the app has a sharp zero effect on the demand for cooks. This 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 revenue, combined with the zero effect on total service workers, implies that changes in the number of waiters reflect the relative productivity between waiters and delivery workers—the outsourcing effect. Taken together, columns (1) and (2) suggest that the adoption of online delivery platforms allows the average restaurant to shift its business from in-house dining to delivery services without a clear effect on the product demand for the goods produced by adopting restaurants.[39]

Column (4) reports the effect of platform adoption on the wages of waiters. On average, the wages of waiters decrease by 2.25 percent after platform adoption. A direct implication of the model presented in Section 2 is that the labor supply elasticity can be recovered from the following ratio:

$$\beta = \frac{\Delta\ ln(W)}{\Delta\ ln(w_W)} \tag{11}$$

Using this ratio and my estimates for the 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

[39] 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 effects 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 either a strong negative correlation or a null correlation between the effect on the number of waiters and the intensity of platform sales by the restaurant. In Figure A19, I plot the establishment-level treatment effects on the number of waiters and the hours of platform workers used by the restaurant and find evidence of a positive correlation for a set of establishments.

empirical studies (e.g., Card et al., 2018; Manning, 2021), indicating that the labor market for waiters is fairly competitive.[40]

Column (5) reports the effect of platform 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 zero. 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.[41]

### *6.3 Effects by Establishment Pay Premium*

Up to this point, the analysis has centered around the average treatment effect of platform adoption on the labor demand of restaurants. However, it is possible that the returns to adoption are heterogeneous, depending on the wage setting policy of the firm. Several models of outsourcing suggest that higher-paying firms are more likely to substitute in-house workers with outsourced workers to decrease labor costs (Bilal and Lhuillier, 2022; Spitze, 2022).[42]

To test this, Figure 6 plots the effects of platform adoption on firm size by median AKM firm 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 platform workers) is not significantly different from zero after five quarters of adoption for either high or low AKM restaurants, although the difference in total hours between high and low AKM restaurants is significant.

Table 3 panel (a) 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.[43]

However, it is still possible that the product demand effect differs between high and low AKM firms. This would be the case if firms facing a large ex-ante market for their product experience a relatively smaller increase in their market upon adopting the platform. To test this, I start by

[40] This is not surprising, given that the restaurant sector is usually considered a sector with close-to-null rent-sharing (Card et al., 2016).

[41] Column (6) reports the effect of platform adoption on the wages of delivery workers. The estimates show that the wages of delivery workers essentially do not decrease, but these estimates must be taken with caution given the small sample size.

[42] Appendix C2 extends the baseline model presented in Section 2 to allow for heterogeneous outsourcing effects by restaurant pay premium.

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

plotting the effects of adoption on total hours hired in the service sector by AKM firm effects. Figure A18 shows that the total hours hired for service workers are unaffected in restaurants with both high and low pay premiums. 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 3 panel (a) show that the number of cooks is not significantly different from zero for both high and low AKM firms, suggesting that there is no significant impact on revenue for either high- or low-paying firms. Taken together, these results suggest that the difference between high- and low-paying restaurants is due to the outsourcing effect being higher for high-paying restaurants compared to those with a lower pay policy.

### *6.4 Effects by Restaurant Density*

As of now, the estimates show limited impact of the product demand effect after adoption. However, it is possible that the impact on demand for goods is more pronounced in firms located in certain areas. Under the assumption of a constant outsourcing effect across local areas, the difference in the effect of platform adoption on in-house labor between high- and low-density areas will reflect differences in the product demand effect. Consumer search models often predict that the agglomeration of establishments reflects demand externalities and proximity to the average consumer (Vitali, 2022; Leonardi and Moretti, 2023).[44] In such models, as online-delivery platforms decrease transportation costs for consumers, the demand for restaurants further from the average consumer—and thus located in areas with lower restaurant density—should increase more than for restaurants located in more central or denser areas.[45]

In this section, I explore heterogeneous effects of delivery platform adoption on labor demand for restaurants located in areas with high and low restaurant density. To define restaurant density, I start by geocoding the universe of formal restaurants in Brazil between 2017 and 2021. For each restaurant, I count the number of nearby restaurants within a 1-kilometer radius of the establishment and define this number as $\tau_{jt}$. I then calculate quartiles for $\tau$ by micro-region and year, defining restaurants as being in high-density areas if their $\tau_{jt}$ is above the median in the quarter before they adopt the delivery platform.[46]

[44] Appendix C3 provides an extension to the model presented in Section 2 in which I microfound the product demand of restaurants through a consumer search model. In that model, the density of restaurants reflects both the quality of restaurants in the area (demand externalities) and the distance to the average consumer.

[45] Another way to think about this is that restaurants with lower demand for their goods prior to delivery platforms have more to gain from these platforms as they expand to new markets. By contrast, restaurants that had a higher baseline demand prior to adopting an online-delivery platform are less likely to benefit as much from expanding to new markets. Instead, these restaurants may experience a shift from in-house dining to delivery, resulting in a net zero effect on overall demand for the restaurant.

[46] Appendix D8 describes the steps taken to geolocate the restaurants in Brazil and the share of restaurants I was able to geolocate per year.

The next step is to study whether there are heterogeneities in the outsourcing effect across locations. Although there are no strong ex-ante reasons to presume that the number of surrounding restaurants would impact the outsourcing effect, I take two steps to ensure that the outsourcing effect remains constant across high- and low-density areas. First, I compare the share of the wage bill and hours that delivery workers represent relative to total service workers in high- and low-density areas.[47] Figure A20 shows that by quarter 5, both the share of the wage bill and hours that delivery workers represent relative to total service workers is essentially the same across restaurants located in high- and low-density areas, suggesting that location is independent of the outsourcing effect. Second, to ensure that the distribution of firm pay premiums is similar across high- and low-density areas, I re-weight treated restaurants located in areas with lower density following the methodology pioneered by DiNardo et al. (1996)—the DFL estimator.

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

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

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

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

Here, $H$ and $L$ define areas with high and low restaurant density, 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 consistent across high- and low-density areas. However, the sparsity of data on delivery workers in the pre-adoption period makes this analysis unfeasible.

In sum, the results presented in this section suggest that online-delivery platforms have varying impacts on the product demand of restaurants depending on their location. These heterogeneous effects are reflected in the overall impact on labor demand. Importantly, the results indicate that online-delivery platforms may provide an alternative path for restaurants to expand their business without needing to locate in central areas or rely on the demand externalities that accompany agglomeration (Vitali, 2022; Leonardi and Moretti, 2023).

### *6.5 Spillovers*

Online-delivery platforms can impact the labor demand of restaurants beyond those that adopt these platforms. Specifically, if establishments that start selling goods through online-delivery platforms crowd out demand for restaurants that do not adopt such platforms, the labor demand of non-adopting restaurants could be affected (Chava et al., 2024).[48] Importantly, understanding the impact of online-delivery platforms on non-adopting restaurants is crucial for assessing the overall effect of these platforms on workers in the sector.

Following the discussion in Section 5.2, 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 panels (a) and (c) show the trends in firm size and average wages for firms exposed to a spillover event and their matched pairs. Prior to the event, non-adopting firms do not appear to experience a larger negative shock than adopting restaurants (as reported in Figure 4), suggesting that restaurants are not selecting into earlier adoption based on their ex-ante trends.[49]

Figure 8 panel (b) plots the estimated treatment effects of the spillover event on the log firm size of non-adopters. The estimates show that firm size decreases by 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.[50] However, these patterns in firm size could be influenced by changes in composition due to firm closures. Figure A26 panel (a) shows the trends in closure for treated and control establishments. Restaurants exposed to a large share of neighbors adopting the technology are approximately 5 percent more likely to close within five quarters of the event compared to control establishments. Figure 8 panel (d) shows that the average wages of non-adopters decrease by 2 percent after five quarters. Taken together, these results suggest that restaurants adopting online-delivery platforms may crowd out demand for non-adopters, leading

[48] The model presented in Appendix C3 highlights that the adoption of online-delivery platforms can affect the market beyond the adopters. Specifically, the "spillover" term in Equation C35 implies that as the share of neighboring restaurants enrolled in the platform increases, the consumer search costs associated with the product of restaurant $j$ will increase, impacting its demand.

[49] Recall that I do not condition on post-event adoption of the platform. Figure A26 panel (b) shows that approximately 7 percent of the ex-ante non-adopting restaurants adopt the delivery platform within 5 quarters following the spillover event.

[50] Figure A27 shows similar results when considering an alternative group of nearby restaurants, such as those within a 2-kilometer radius using a donut design.

to a decrease in their size and average wages.

### 6.6 *Robustness*

In this section, I explore the sensitivity of the results to several robustness checks.

**Alternative Estimators** First, following the recent difference-in-difference literature with staggered treatment, Figure A21 shows 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 drawn from regions where treatment is not available and, therefore, are never treated in my setting (Roth et al., 2023).

**Covid** The period of consideration overlaps with the COVID-19 pandemic, raising the concern that the results could be driven primarily by firms that adopt the platform to cope with the pandemic. In this case, the negative impact of platform enrollment could be more related to a response to the pandemic than to the platform itself. Indeed, if firms most negatively affected by the pandemic are also the most responsive to the platform, the external validity of the results could be limited. To address this concern, I take three approaches. First, leveraging the matching strategy, I plot in Figure A22 the establishment-level treatment effects on size and the change in the number of COVID-19 cases per capita in the post-period. The figure shows that treatment effects on size are not correlated with increases in COVID-19 cases. Second, I estimate the effect of platform enrollment on firm size for establishments treated up to five quarters before the pandemic and compare the estimates to restaurants treated during the pandemic. Figure A23 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 platform availability and consider a specification that includes state-year fixed effects to control for state-specific policies that may have affected restaurants during COVID-19 (Chauvin, 2021). Figure A24 shows that the results are not sensitive to the inclusion of these fixed effects.

**Informality** An additional concern regarding the external validity of my estimates is related to the relatively high levels of informality in Brazil compared to developed countries such as the US and Canada. If restaurants that adopt the platform hire a large portion 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 formal workers in the restaurant sector in each municipality using the 2010 Brazilian census (the latest census available). I then divide my matched sample into groups above and below the median of the share of formal workers, based on the informality levels of their municipality. Figure A25 shows that restaurants located in municipalities with below-median informality decrease their in-house size by approximately 9 percent after five quarters of adoption. In contrast, restaurants 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 indicate that the main results are conservative estimates of the effect of platform adoption on labor demand. When considering the overall effect of the platform on workers in Section 8, I will account for the possibility that adoption of the delivery platform also affects informal workers.

## 7 Restaurant Workers

The results presented in Section 6 provide evidence that delivery platforms reshape labor demand, with restaurants replacing in-house waiters with outsourced delivery workers. To fully understand the labor market consequences, it is essential to examine the impact on the workers themselves. This section analyzes the impact of online-delivery platform adoption on restaurant workers' labor market outcomes, revealing how much of the decline in demand for in-house workers is borne by the workers. This analysis sets the stage for Section 8, where I assess the overall effects of delivery platforms by examining both restaurant workers affected by adoption and spillovers, as well as the impact on gig workers, providing a comprehensive view of the winners and losers. Section 7.1 presents summary statistics and the main results of the event study analysis, while Section 7.2 explores the spillover effects on workers at non-adopting establishments.

### *7.1 Main Results: Effect of Employer Adoption on the Platform*

**Summary Statistics** Table 4 presents summary statistics for matched treated workers (Column 1), matched control workers (Column 2), and all potential treated workers—including those who did not match—(Column 3) in 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 of 60 percent 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 compared to all potentially treated workers (Column 3), the matched workers have lower earnings (1,501 vs. 1,788 BRL-2018) and a slightly higher share of female workers and waiters.

**Trajectories of Treated and Control Workers** Figure 9 panel (a) presents the earnings trajectories for treated and control workers. Both groups show similar earnings levels prior to treatment. Following their employer's adoption of the platform, treated workers experience a slightly stronger negative impact on their formal sector earnings compared to the control group, which persists five quarters after the event.[51] Specifically, treated workers experience a 11.3 percent decrease in their earnings the quarter after the event, while control workers experience a 9.7 percent decrease. The decline in earnings is persistent, with treated workers' earnings decreasing by 37.1 percent five quarters after the event, while control workers' earnings decrease by 35.4 percent.

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

**Earnings & Employment** Figure 9 Panel (b) presents the estimated $\beta_k$ from Equation (10) for total monthly earnings in the formal sector. In the quarter following the employer's adoption of the platform, 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 persists five quarters after the event, although the estimates become noisier in the fifth quarter.[52] Panel (c) presents the estimated treatment effects for employment, showing that treated workers experience a small negative impact on their formal employment following the event. Workers whose employer adopts the delivery platform experience a 1.5 percentage point decrease in their probability of being employed in the formal sector, a negative impact that persists five quarters after the event.[53]

Figure A31 panel (a) presents the cumulative likelihood of workers leaving their pre-event establishment (either for 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 in the quarter following the event. This cumulative likelihood increases over time, reaching 6 percent five quarters after the employer

[51]Since control workers are also required to have two quarters of tenure at the time 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.

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

[53]Figure A30 panel (a) shows treatment effects of employer platform adoption on workers' log earnings (conditional on employment). These estimates show that, conditional on employment, treated workers' earnings decrease by approximately 3 percent five quarters after the event. Figure A30 panel (b) reports estimates on log monthly earnings after excluding pairs of workers where the treated worker is not employed but the control is. The underlying assumption is that the control worker is a *complier*—that is, a worker who, if their employer had adopted the platform, would also have been non-employed (Lee, 2009). By dropping these compliers, I can evaluate the effect of platform adoption among the *always takers*—those who remain employed even after platform adoption. The results essentially do not change after conditioning on always takers.

adopts the platform. These estimates reflect the worker-side dynamics shown in Figure 4 panel (b), which reported similar patterns when estimating the effect of platform adoption on in-house firm size. Combined with the employment effects of employer adoption of the platform shown in Figure 9 panel (d), these results suggest that a significant share of restaurant workers leave their job as their employer adopts the platform but manage to find a new formal job relatively quickly afterward. Figure A31 panel (b) supports this: approximately 75 percent of the workers who leave their employer are employed by a new employer five quarters after the event. This dynamic likely explains why workers' earnings are not as negatively affected as one might expect from the firm-level analysis.

**Transition to Delivery Platform Work** The richness of the data allows me to examine whether workers whose employer adopts the delivery platform are more likely to transition to work as gig delivery drivers themselves. This analysis helps determine whether some of the negative impact on earnings is offset by income generated from platform work. Figure A32 presents the estimated treatment effects for the likelihood of working on the delivery platform. In the quarter following their employer's adoption of the platform, workers are 0.1 percent more likely to begin working on the platform. This likelihood slightly increases over time, so that five quarters after the event, treated workers are 0.4 percent more likely to work on the platform. The small increase in transition to platform work suggests that waiters in the restaurant sector are being replaced by a different set of workers, rather than being outsourced to a new employer. The characteristics of these gig workers are explored further in Section 8.

### *7.2 Spillovers on Workers*

To fully capture the effects of online-delivery platforms on workers, it is essential to consider the impact on those who are not directly employed by restaurants that adopt these platforms. Section 6.5 discussed the spillover effects of platform adoption by nearby restaurants on non-adopting establishments, showing that non-adopting restaurants are more likely to close. Figure 10 panel (b) presents the estimated results of Equation (10) on total earnings for workers employed at non-adopting restaurants exposed to a sharp increase in the share of nearby restaurants on the platform, as defined in Section 5.2.[54] The results show that workers at non-adopting restaurants experience a negative impact on their earnings after the event, which is larger than that experienced by workers at restaurants that do adopt the platform. Workers at non-adopting restaurants suffer a 3 percent decrease in earnings the quarter after the event, with the effect persisting and increasing to 6.6 percent five quarters after. Panel (c) presents the estimated treatment effects for employment, showing that workers at non-adopting restaurants also experience a negative impact on their formal employment following the event. Specifically, these workers are 2.3 per-

[54]Panels (a) and (c) display the raw means for matched treated and control restaurants.

centage points less likely to be employed in the formal sector in the quarter following the event, with the negative impact persisting and increasing to 3.8 percentage points after five quarters.

The stronger impact on earnings and employment is driven by the large fraction of non-adopting restaurants that close. Figure A33 illustrates the differences in effects between workers whose employer (the quarter prior to the event) eventually closes and those whose employer remains open. Panel (a) shows that workers employed at restaurants that do not eventually close see their earnings decrease by approximately 2.6 percent five quarters after the event. This group represents 92 percent of the matched sample, and the effects on these workers closely mirror those on in-house workers directly affected by their employer's platform adoption. In contrast, workers whose employer at $t^*-1$ eventually closes—8 percent of the matched sample—experience a 37 percent decrease in 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 impact formal employment and earnings beyond the direct effects on workers at restaurants that adopt these platforms. The spillover effects on non-adopting restaurants are larger than the direct effects of employer adoption due to restaurant closures. Although a detailed exploration of the exact mechanisms driving these spillovers in the product market is beyond the scope of this paper, a search cost model, like the one proposed in Section C3, offers a potential explanation. In this model, the spillover effects of platform adoption by nearby restaurants on workers at non-adopting restaurants could be driven by a crowding-out effect in the product market. From the model's perspective, as nearby restaurants adopt the platform, consumers face higher search costs when looking for non-adopting restaurants. This increase in search costs would lead to a decline in demand for the products of non-adopting restaurants, subsequently reducing their demand for labor. Importantly, a complete assessment of the winners and losers from online-delivery platforms must consider not only the direct effect on workers at adopting restaurants but also the spillover effects on workers at non-adopting establishments. The next section examines the trade-offs of online-delivery platforms, factoring in platform workers.

## 8 Winners & Losers

In this section, I decompose the total effect of online-delivery services on workers' earnings. Following the discussion in Section 7, I differentiate the platform's effect into a direct effect on in-house workers at adopting restaurants, an indirect effect on restaurant workers at non-adopting establishments, and the impact on app-based delivery workers. Unlike a welfare analysis, which would require a comprehensive assessment of the platform's costs and benefits beyond financial outcomes, I focus specifically on earnings effects—an outcome that is comparable across different groups of workers. Although this approach narrows the scope of conclusions, it offers a clear view of the trade-offs online-delivery platforms pose across a key outcome of interest for workers, while minimizing assumptions about the welfare function.[55]

To study the total effect of online-delivery platforms on workers' earnings, I aggregate the earnings effects for each restaurant that adopts the delivery service.[56] Specifically, for each adopting restaurant $j$, I conduct the following accounting exercise:

$$\underbrace{\pi^{j}_{\text{app}}}_{\substack{\text{Total Wage-Bill Effect}\\ \text{App}}} = \underbrace{\pi^{j}_{\text{in-house}}}_{\substack{\text{Wage-Bill Effect}\\ \text{In-House Workers}}} + \underbrace{\pi^{k\neq j}_{\text{spillovers}}}_{\substack{\text{Wage-Bill Effect}\\ \text{Spillovers}}} + \underbrace{\pi^{j}_{\text{app-workers}}}_{\substack{\text{Wage-Bill Effect}\\ \text{App-Workers}}} \tag{12}$$

The wage bill effect is calculated as the sum of total earnings effects for each group of workers, multiplied by the average number of workers affected per adopting restaurant. So far, 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 impact on the earnings of workers at non-adopting restaurants. Table 5 summarizes the wage bill effect for each restaurant that adopted delivery services, covering both components.

Column (1) shows the total earnings lost by in-house restaurant workers each quarter after the restaurant adopts the delivery service. The cumulative discounted present value of this loss, five quarters after adoption, is 3,192 BRL (in 2018 Reais). This amount represents 5.5 percent of the average wage bill for restaurants that adopt the platform before offering deliveries through the app. Column (2) reports the effects for the same group, net of social security contributions. As discussed in Section 3, considering net wages is particularly relevant when comparing gains and losses, as app workers are not required to make these contributions. When social security contributions are excluded, the effect on in-house workers represents 5.2 percent of the pre-platform wage bill of restaurants that adopt the technology.

Column (4) reports the earnings effects of spillovers per restaurant that adopts delivery services. To estimate this, I re-scale the per-worker estimates presented in Section 7.2 by the impact of spillover events on the adoption of delivery services by nearby restaurants. This re-scaling provides a per-worker effect in units of neighboring restaurant adoption ($\chi$). I then multiply this

[55] If restaurant and gig jobs offered similar amenities, then, under a utility function that depends linearly on earnings—such as the one proposed in Section C1—differences in earnings across jobs would lead to proportional differences in welfare. A similar argument could be made if the value placed on non-pecuniary job characteristics were low compared to the marginal utility of income. While the first assumption is unlikely to hold given the differing job characteristics, the latter may be plausible given the relatively low income of the individuals studied in this setting.

[56] Summarizing the effects by restaurant provides a clear unit of analysis and enables straightforward extrapolation of results to contexts with varying intensities of platform adoption (assuming homogeneity in treatment effects).

adjusted coefficient by the average $\chi$ and the average restaurant size in my sample.[57] The cumulative discounted present value of spillovers per adopting restaurant, calculated over five quarters after starting delivery services, is -8,055 BRL (2018 Reais), which is equivalent to 13.9 percent of the pre-platform wage bill of these restaurants. When netting out contributions, the effect reduces to 12.7 percent (Column 5).

Assessing the total earnings impact of online-delivery services requires examining how they affect the income of delivery workers, which poses several challenges. A significant share of these workers may have been employed informally or unemployed before joining the platform and thus are not visible in RAIS. Generally, app workers have low attachment to the formal sector. Seven quarters before their first delivery, 29 percent of drivers held formal jobs. This drops to 22 percent at the time of their first delivery, then slightly recovers to 24 percent after five quarters.[58] Additionally, one must consider not only the earnings from deliveries but also outside options and work-related costs (e.g., gas, vehicle maintenance). I use estimates from prior studies to calculate the average maintenance cost for platform drivers in Brazil.[59]

To estimate outside options, I divide workers into two groups: (i) those who held a formal job the quarter before starting on the app and were not laid off, and (ii) those without a formal job or who were laid off the quarter prior to or during their first quarter on the platform. For the first group, I take a conservative approach, assuming their outside option is their pre-platform hourly wage, implying they could have continued earning the same wage had they not decided to work for the delivery service. For the second group, I estimate their outside option using the (regression-adjusted) average wage of formal platform workers, adjusted by the non-formal-to-formal wage ratio from PNAD-C data for their state and quarter.[60]

Table 5 Column (7) reports the average wage bill—per adopting restaurant—of platform workers who held a formal job prior to working on the platform.[61] These workers made, on average, a cumulative present discounted value of 5,080 BRL (2018), equivalent to 8.7 percent of the pre-adoption wage bill of restaurants. Column (8) presents the total wage bill, net of opportunity costs and transportation/maintenance costs, for the same group. When considering the pre-platform wage per hour as the opportunity cost for these workers, the cumulative present discounted value

[57]For full details on this re-scaling procedure, see Appendix D4.

[58]Figure A34 panel (a) presents trends in formal employment for workers before and after they start on the platform.

[59]The estimated maintenance cost for motorcycle delivery drivers is 3.7 BRL-2018 per hour worked (Callil and Pincaço, 2023).

[60]The mean ratio of informal and unemployed to formal wages is 0.32. Details are provided in Appendix D2.

[61]A limitation of my data is that I do not observe which worker delivered for each restaurant at any specific time. Instead, I observe the earnings of each worker per hour and the total number of hours that restaurants used the app's delivery services per month/municipality. Appendix D3 discusses how I estimate hourly earnings for each adopting restaurant.

decreases to 1,195 BRL (2018), equivalent to 2.1 percent of the pre-adoption wage bill.[62]

Column (9) reports the wage bill generated by the platform, per adopting restaurant, for workers who did not hold formal employment (or were laid off) the quarter before joining the app. The cumulative present discounted wage bill for these workers is 25,169 BRL (2018 Reais), equivalent to 43.3 percent of the pre-adoption wage bill. Column (10) presents the wage-bill effects for this group, accounting for transportation/maintenance costs and outside options as estimated using PNAD-C. The cumulative present discounted value for these workers is 15,647 BRL (2018), equivalent to 26.9 percent of the pre-adoption wage bill of restaurants.

Taken together, when considering the total effect of the delivery service on workers' wages, I find that the platform generates a wage-bill surplus equivalent to 11.1 percent of the average pre-adoption wage bill of restaurants. Put differently, the gains for delivery workers (net of their costs) are 62 percent larger than the combined direct and indirect impact on formal restaurant workers.

### *8.1 Limitations & Discussion*

**Informal Restaurant Workers** The effects presented so far do not account for the impact that the platform may have on workers hired informally in the restaurant sector. Workers can be hired informally either by formal restaurants—firms that have a tax identifier but may employ some workers informally (intensive margin)—or by firms that are entirely informal, meaning they do not have a tax identifier (extensive margin) (Ulyssea, 2018). To account for the intensive margin of informality, I use data from the 2010 Brazilian census and the household survey (PNAD-C) to impute the number of informal workers per restaurant.[63] I estimate that approximately 25 percent of the workforce in each restaurant is informal. Column (3) shows that the effects on informal workers at adopting restaurants represent 1.2 percent of the pre-adoption wage bill.[64] In Column (6), I estimate the impact on informal workers affected by spillovers, using the same methodology as for estimating the direct effects on in-house workers. The effect on informal workers represents 3.1 percent of the wage bill of adopting restaurants prior to adoption. When accounting for informality, the total earnings effect of the platform on workers remains positive but decreases to 6.8 percent of the pre-adoption wage bill.

However, a limitation of my data is that I cannot account for the extensive margin of informality. Specifically, I do not observe the number or size of informal firms.[65] Informal firms are likely

[62]Figure A34 panel (b) shows trends for formal and delivery earnings for app workers who held a formal job the quarter prior to working on the platform. Consistent with the platform allowing individuals to smooth consumption over time, formal workers experience a negative income shock in the months before their first delivery. Similar results have been found in the US (e.g., Koustas, 2018; Jackson, 2022).

[63]Appendix D1 provides the details of the imputation procedure.

[64]For all columns in the table, the pre-adoption wage bill is calculated including informal workers.

[65]Using data from Cadastro Nacional de Pessoas Jurídicas (CNPJ), a dataset that includes information on the start

smaller than formal firms (Ulyssea, 2018). To the extent that informal firms are also impacted by spillover effects, the negative impact of the platform may be underestimated. Specifically, if the spillover effects on non-formal firms account for 53 percent of the impact on formal firms, the total effect of the platform on workers would break even.[66]

**Alternative Outside Options** The outside options estimated through PNAD-C provide a reasonable benchmark; however, gig workers may have outside options not fully captured in survey data. Figure A35 shows the total effect of the delivery service as a function of the outside option for non-formal app workers—expressed as the ratio of their wages to formal workers' wages ($\Phi$). The figure highlights several interesting scenarios: if delivery workers without formal jobs had been unemployed (outside option of 0), the total surplus would be approximately 15 percent of the pre-adoption wage bill. Conversely, if all non-formal app workers had the same outside option as formal workers, the delivery service would generate a wage-bill deficit of 10 percent. The break-even point occurs when non-formal workers have an outside option equal to 60 percent of formal workers', resulting in a wage-bill surplus of zero.

**Amenities** The exercise presented in this section considers only the monetary value created (and destroyed) by delivery platforms, without accounting for other non-pecuniary aspects, such as amenities, that may affect the overall welfare impact of these platforms. For instance, if app workers highly value flexibility (Mas and Pallais, 2020), then the gains from the platform for these workers may exceed those presented here. Conversely, if working on the platform poses risks related to health, safety, or job security more broadly (Jarosch, 2023), the benefits of the platform for app workers may be overestimated by focusing solely on earnings. To benchmark the quality of the jobs created by the platform relative to the rest of the restaurant sector, I estimate firm (and platform) valuation using the PageRank algorithm developed by Sorkin (2018). This revealed preference measure leverages employer-to-employer transitions to quantify the value of working at an establishment ($V_j^e$).[67] Importantly, this valuation includes both pecuniary and non-pecuniary characteristics of the firm. Figure A36 shows the distribution of $V_j^e$ across all Brazilian restaurants where it was possible to estimate value (approximately 30 percent of all formal establishments).

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of operations for all formal firms in Brazil, I find that, among all formal restaurants created between 2015 and 2017, 43 percent never hire a formal employee and therefore do not appear in RAIS. This data is the same as used in Feinmann et al. (2022) and was kindly shared by the authors.

[66]This implies that if the earnings effect is the same for workers at both formal and informal firms, and if the size of informal firms is comparable to that of formal firms, there would need to be 0.53 informal firms for each formal firm affected by a spillover effect to break even. Given that the average share of informal restaurant workers in my sample is 25 percent, this scenario seems unlikely.

[67]Appendix D6 provides details on this estimation method and validation tests. Figure A37 Panel (a) shows that firm value correlates with pay policies, as measured by AKM firm effects. Higher-paying firms also have a higher $V_j^e$. Panel (b) plots this correlation for restaurants specifically. Interestingly, the correlation between firm value and AKM firm effects is strong for low-valuation restaurants but seems to weaken for highly valued restaurants, suggesting that amenities may play a larger role in the utility derived from these jobs.

The red dashed line represents the platform's value. The gig job on the platform ranks within the 90th percentile of $V_j^e$ among all formal restaurants in Brazil, implying that amenities offered by the platform (such as flexibility) may enhance workers' total welfare beyond the earnings generated by the platform.

**Firm Creation** Estimating the overall effects of delivery platforms requires considering not only the impacts on incumbent firms but also the effects on new firm entry. Anecdotal evidence suggests that delivery platforms have facilitated the entry of "dark kitchens"—establishments that operate exclusively through delivery services without in-house dining.[68] More broadly, delivery platforms may enable firms to offer goods with lower capital requirements, thereby increasing firm entry. However, they may also intensify competition, potentially discouraging smaller, less efficient firms from opening. I use data collected from the Cadastro Nacional de Pessoas Jurídicas (CNPJ) to measure firm entry. Figure A29 panel (a) shows the estimated effect of delivery platform availability on restaurant entry.[69] The data indicate that restaurants are more likely to open in each quarter after the platform becomes available in a given microregion, with an average increase in entry likelihood of 7.5 percent. Panel (b) presents the same estimates, this time weighted by the average number of workers in the restaurant sector in each microregion as of 2017. These weighted results are consistent with the unweighted estimates but show a larger effect, indicating that restaurants are 10.5 percent more likely to open after platform entry when accounting for microregion size. These findings suggest that focusing solely on incumbent firms may underestimate the total impact of delivery platforms on the labor market.

**Limitations** The approach used to assess the costs and benefits of the platform focuses on its partial-equilibrium impact and does not consider the potential reallocation effects it may induce. For instance, the platform may serve as a stepping stone for non-formal workers (Booth et al., 2002; Jahn and Rosholm, 2014), potentially enabling them to enter the formal sector after working on the platform. Alternatively, delivery platforms might redirect workers toward less advantageous career paths by sending negative signals to the market (Neumark, 2018) or by reducing their job search efforts (Le Barbanchon et al., 2024). In-house workers displaced by outsourced app drivers may also reallocate to other types of firms (Dustmann et al., 2022), potentially affecting their long-term career trajectories—an effect that the time frame of this data does not allow to measure. These potential general-equilibrium effects are beyond the scope of this paper but present important avenues for future research to better understand the overall impact of online-delivery platforms on the labor market. Additionally, although the platform studied in this paper accounts for a large share of the delivery market, gig drivers may work on multiple

[68] For a discussion of dark kitchens in Brazil, see this article from Globo in 2022.

[69] Appendix D7 discusses the empirical design used to estimate these effects and provides additional results indicating no substantial change in the composition of new entries.

platforms simultaneously (Caldwell and Oehlsen, 2023) or combine platform work with other forms of non-formal employment, which my analysis cannot account for. If workers are able to generate additional income sources due to the platform's flexibility, the earnings effect of the platform on formal workers could be underestimated. Conversely, if platform work restricts workers' opportunities to secure higher-paying jobs, the platform's effect on app workers could be overestimated.

## 9 Conclusion

Over the past fifteen years, online-delivery platforms have expanded rapidly worldwide, transforming interactions between workers and employers in the restaurant sector. This paper provides evidence on the impact of online-delivery platforms on restaurants and workers in Brazil. Utilizing a unique dataset that combines detailed administrative employer-employee records with platform worker data, I show that platform adoption profoundly affects labor demand. Specifically, adopting platforms leads to a substantial reduction in the number of waiters employed, who are replaced by gig delivery drivers. However, these workers do not experience persistent earnings losses, as they are able to reallocate to new jobs quickly. Online-delivery platforms also have spillover effects on non-adopting restaurants, indicating that restaurants adopting these platforms may crowd out demand for those that do not.

I assess the overall impact of delivery platforms by comparing the losses experienced by in-house workers with the gains of platform workers. Accounting for gig workers and informal workers in the restaurant sector, I find that the platform generates a wage-bill surplus of 6.8 percent relative to the average pre-platform wage bill of restaurants. This surplus is primarily driven by the gains of workers who did not hold formal employment prior to joining the platform.

The results presented in this paper carry significant implications for policymakers engaged in discussions about regulating these platforms. The findings demonstrate that online-delivery platforms substantially impact both traditionally employed workers and gig workers. Regulatory efforts should carefully balance the protection of traditional workers against displacement with the consideration of potential positive outcomes for gig workers. Policymakers might explore mechanisms to ensure gig workers gain access to basic protections, such as social safety nets, without diminishing the flexibility and low entry costs that make these jobs appealing to many. This consideration is particularly relevant in settings like Brazil, where gig work can serve as a critical buffer in an economy with high levels of informality and unemployment.

A limitation of this paper is its inability to capture the sources of the non-wage gains and losses that workers may experience while working on the platform. Future research should investigate the non-pecuniary aspects of gig work and how these platforms influence the overall welfare of workers. A particularly interesting direction would be to examine how delivery platforms affect workers' health and how these individuals value specific job characteristics, such as flexibility. Additionally, this paper does not address the long-term effects of the platform on workers' careers. Given the large share of informal and unemployed workers engaging with delivery platforms, future research could explore how these platforms impact the job ladder for individuals. Specifically, it would be important to determine whether these platforms serve as stepping stones for workers to enter the formal sector or if they, in fact, limit these workers' opportunities to find higher-quality jobs in the future.

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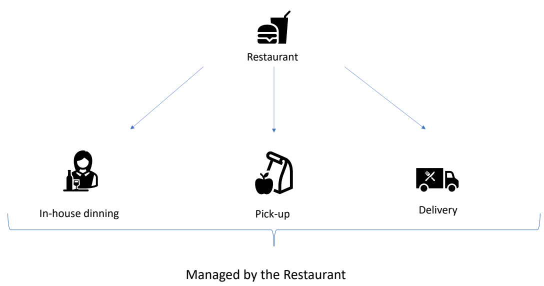
**URL:** *https://www.ssrn.com/abstract=4667778*

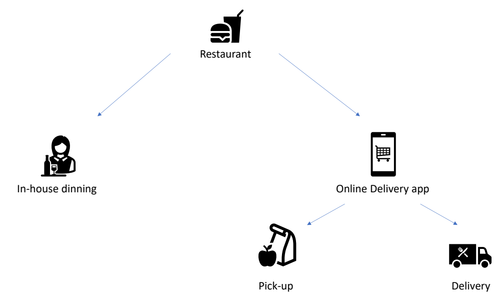
## Figures

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

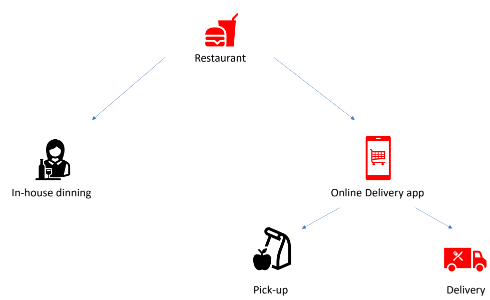
**(a)** Restaurant Structure Previous to Online Delivery Platforms




**(b)** Restaurant Structure After Online Delivery Platforms



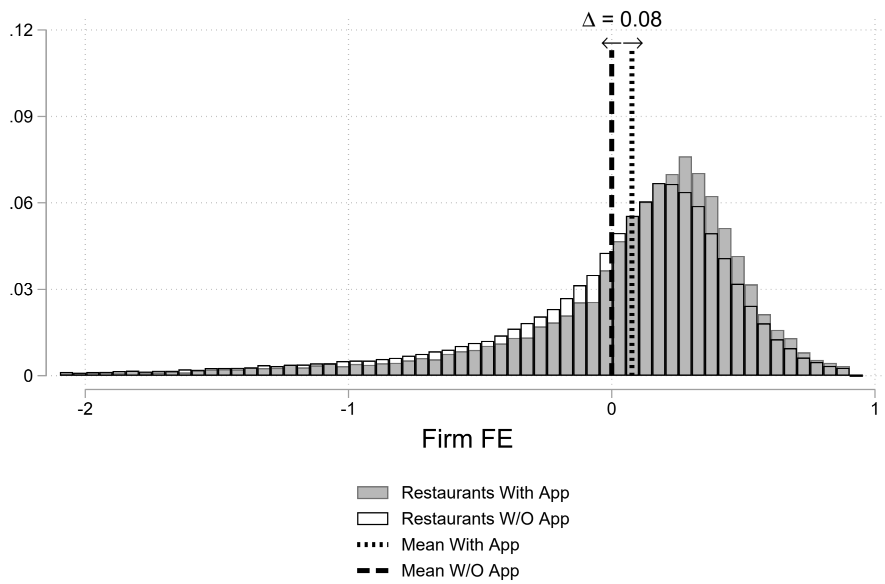

**(c)** Main Relationship Studied in the Paper



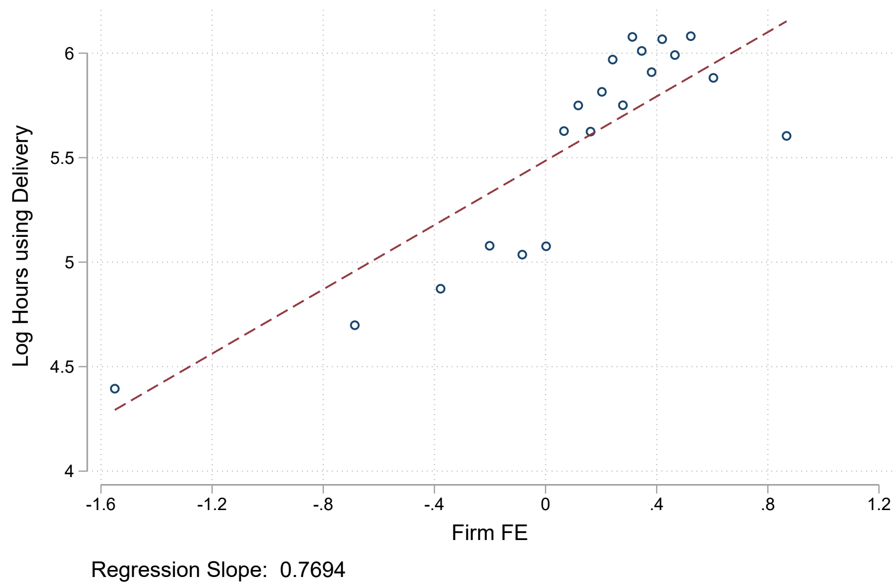

*Notes:* The figure illustrates the structure of restaurants before and after the adoption of online-delivery platforms. Panel (a) shows the structure of restaurants before the adoption of online-delivery platforms. When not enrolled in delivery platforms, restaurants usually operate in-house dinning, 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 Platform

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



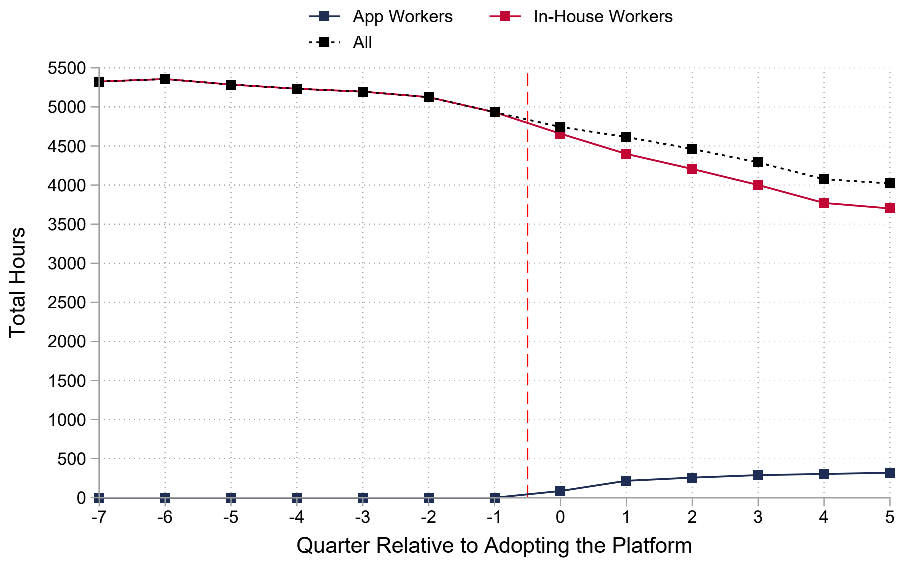

**(b)** Intensive Margin of Platform and AKM Firm FE



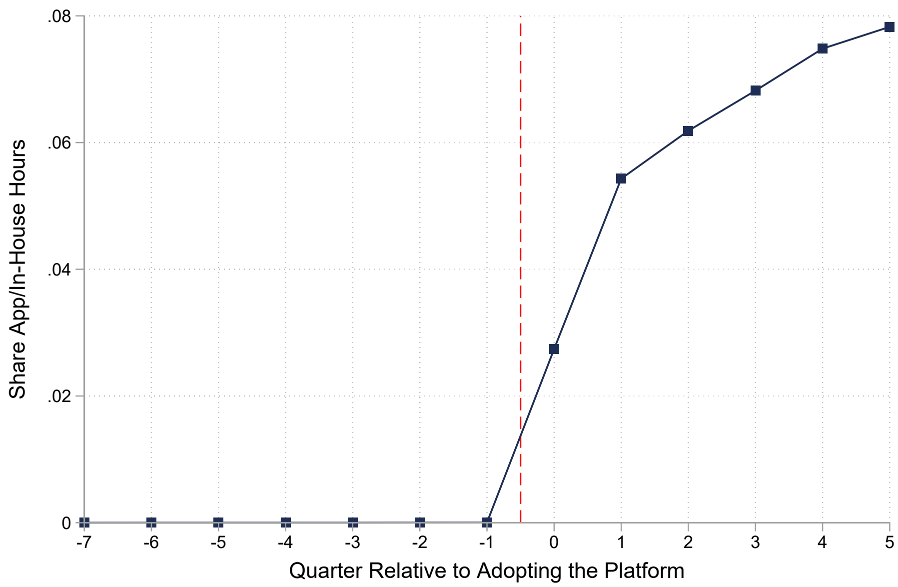

*Notes:* Panel (a) reports the histogram of AKM workplace effects for restaurants in Brazil. It plots the selection into offering deliveries through an online platforms. The figure plots the histogram of AKM firm effects for restaurants that at some point in time offered deliveries through the delivery platform 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 platform. Panel (b) plots a binned scatter plot of the logarithm of the total hours reported in my sample that platform workers worked as delivery drivers through the platform 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 establishment 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 Platform Workers

**(a)** Total Hours by Type of Labor



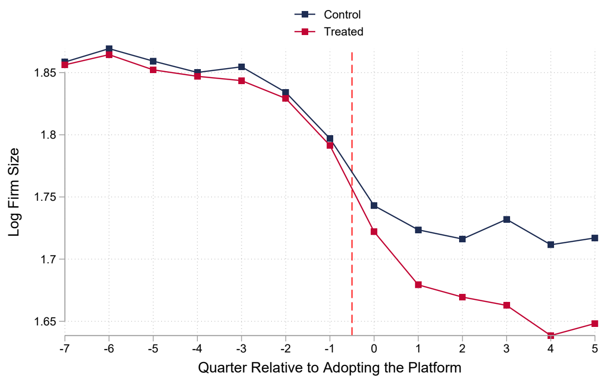

**(b)** Share of Outsourced Labor



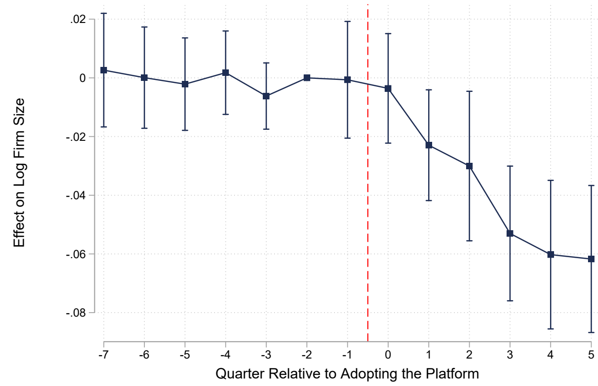

*Notes:* Panel (a) reports the total hours per quarter hired by restaurants that offer delivery services through the platform and match to a control restaurant. The red line reports the average quarterly hours for workers hired formally by these restaurants (in-house workers). The blue line reports the 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:** Effects of Online-Delivery Platform Adoption on In-House Size and Wages

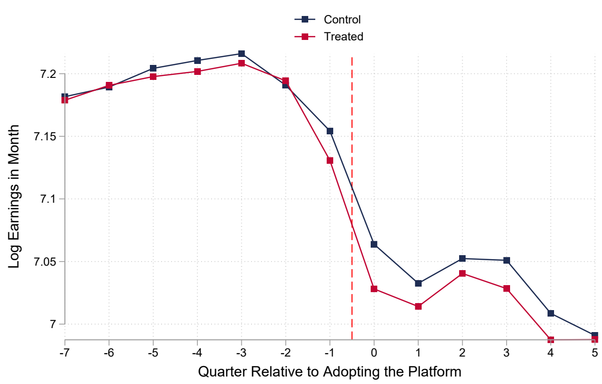
**(a)** Log In-House Size of Restaurants



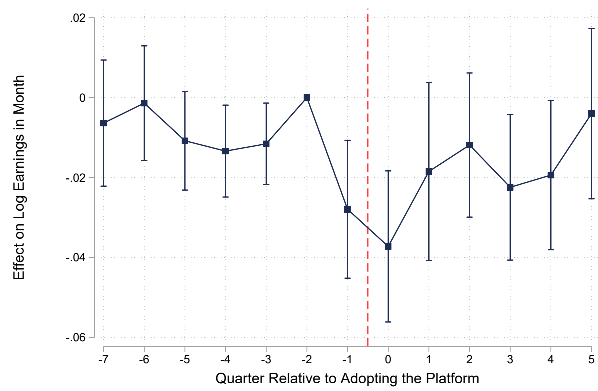

**(b)** Event-Study Estimates on Log In-House Size of Restaurants




**(c)** Avg. Wages Paid by Restaurants

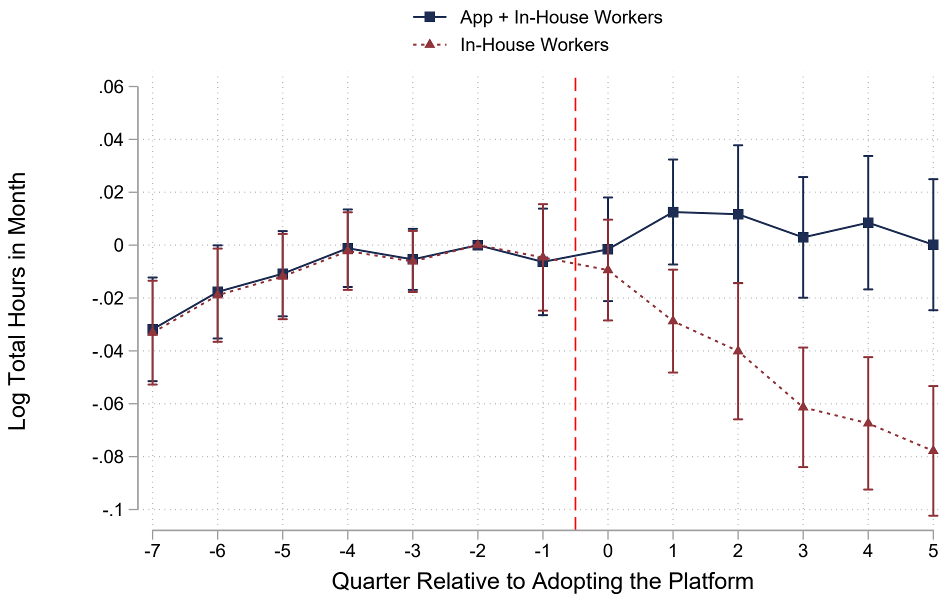



**(d)** Event-Study Estimates on Log Avg. Monthly Wages Paid by Restaurants




*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 (10) 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 quarter 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 formally each month in the quarter by the establishment after applying the restrictions described in Section 3. Average monthly wages in a quarter are constructed by taking the quarterly average of all the monthly wages reported in RAIS by the establishment in the corresponding quarter. Wages are expressed in real terms (2018 CPI). Both panels report 95% confidence intervals based on standard errors clustered at the establishment level.

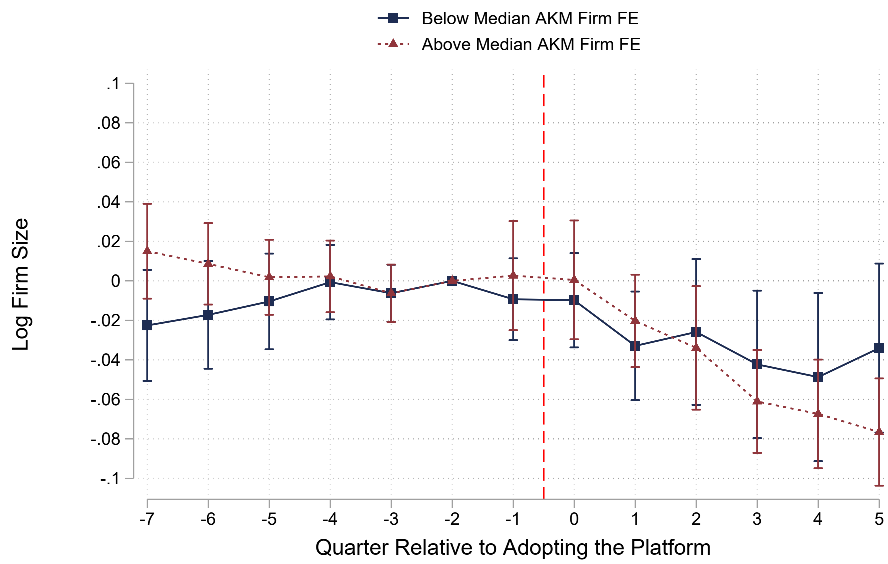
**Figure 5:** Effects of Online-Delivery Platform Adoption on Total Hours Hired



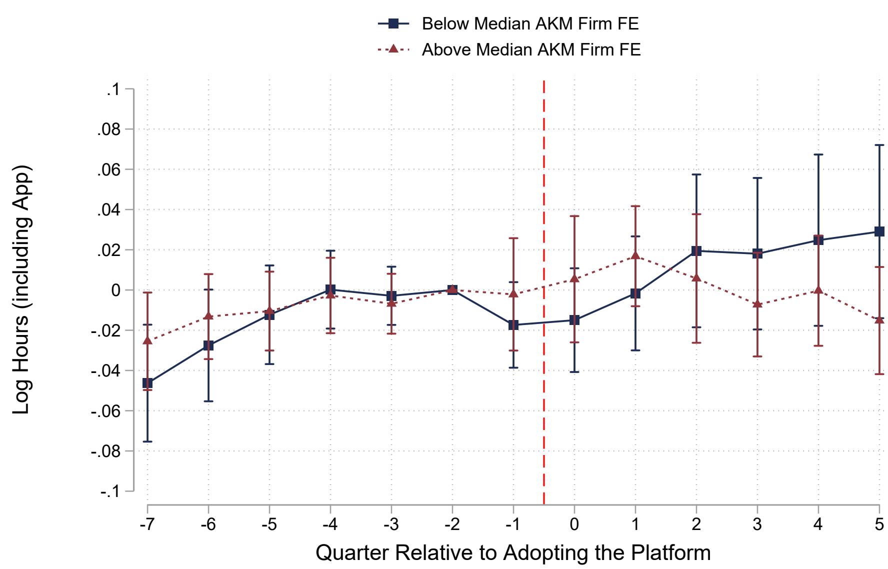

*Notes:* This figure reports the corresponding event-study estimates obtained after fitting equation (10) on log total hours hired quarterly for workers hired formally (the red dashed line) and log total hours hired quarterly when accounting for formal workers and platform workers (the solid blue line). 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. The panel reports 95% confidence intervals based on standard errors clustered at the establishment level.

**Figure 6:** Effects of Online-Delivery Platform Adoption on Total Hours Hired and In-House Size by AKM Firm Effect

**(a)** Log In-House Size of Restaurants



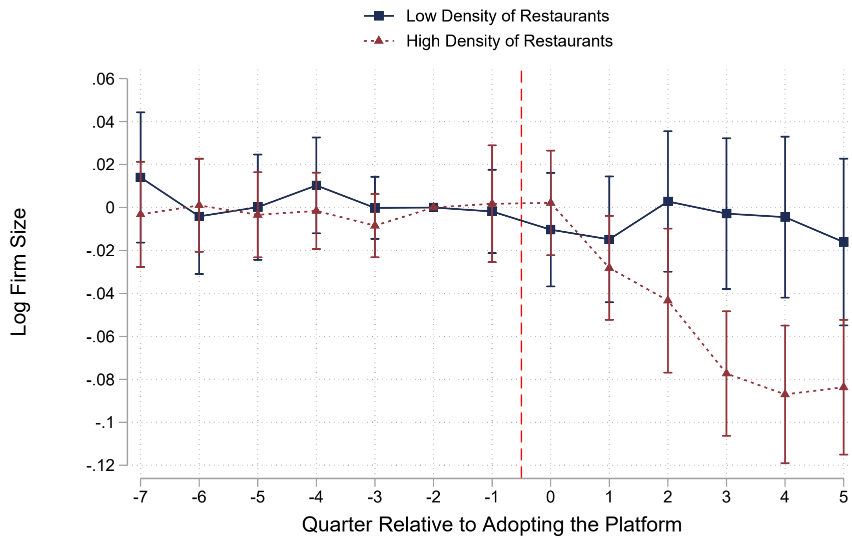

**(b)** Log Total Hours Hired



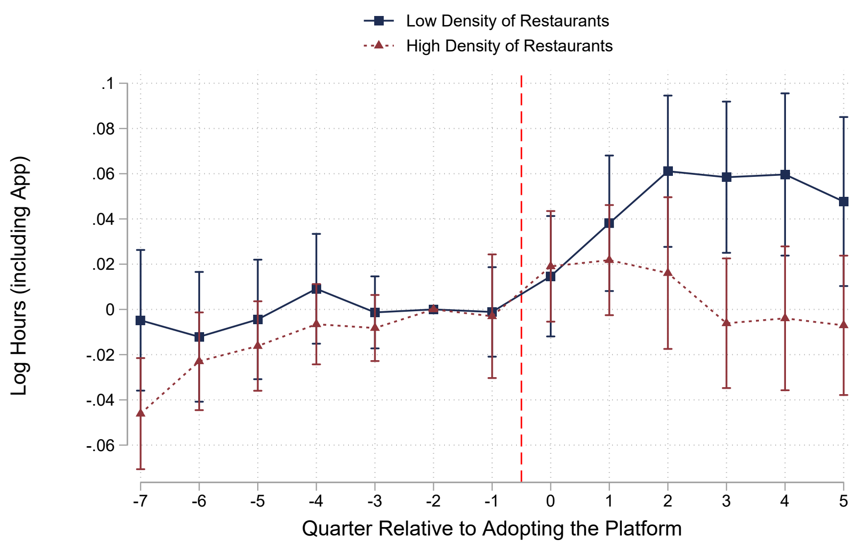

*Notes:* Panel (a) reports the corresponding event-study estimates obtained after fitting equation (10) on log restaurant size as defined by the average number of formal workers hired by the establishment. A formal worker is defined to be employed in a quarter if they have at least one day of work recorded in RAIS. Quarterly size is constructed by taking the average of the number of workers hired formally 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 (10) 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. Both panels report 95% confidence intervals based on standard errors clustered at the establishment level.

**Figure 7:** Effects of Online-Delivery Platform Adoption on Total Hours Hired and In-House Size by by Restaurant Density

**(a)** Log In-House Size of Restaurants



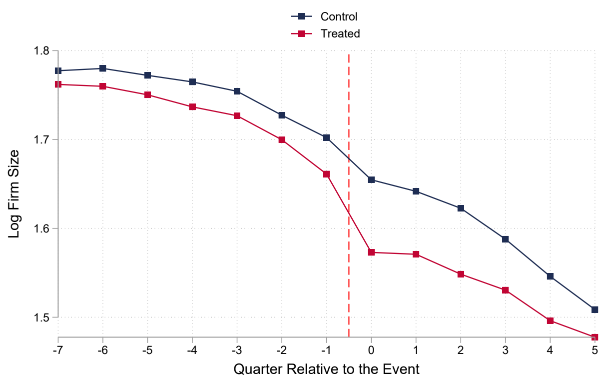

**(b)** Log Total Hours Hired



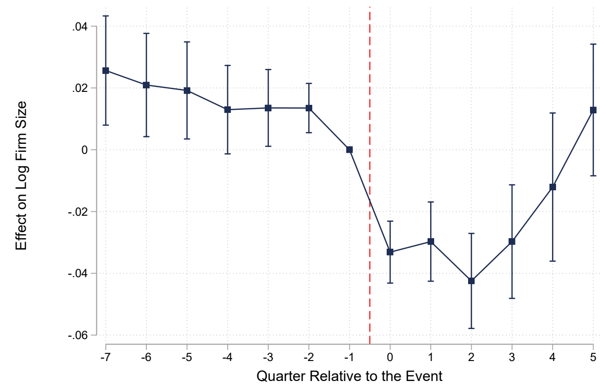

*Notes:* Panel (a) reports the corresponding event-study estimates obtained after fitting equation (10) on log restaurant size as defined by the average number of formal workers hired by the establishment. A formal worker is defined to be employed in a quarter if they have at least one day of work recorded in RAIS. Quarterly size is constructed by taking the average of the number of workers hired formally 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 ($\tau$). The median of restaurant density is calculate using the distribution of $\tau$ corresponding to the microregion of each restaurant in each quarter. The density assigned to each restaurant corresponds to the $\tau$ 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 (10) 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. Both panels report 95% confidence intervals based on standard errors clustered at the establishment level.

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

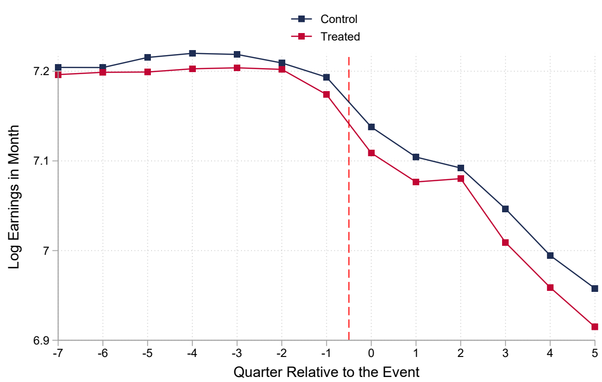
**(a)** Log In-House Size of Restaurants



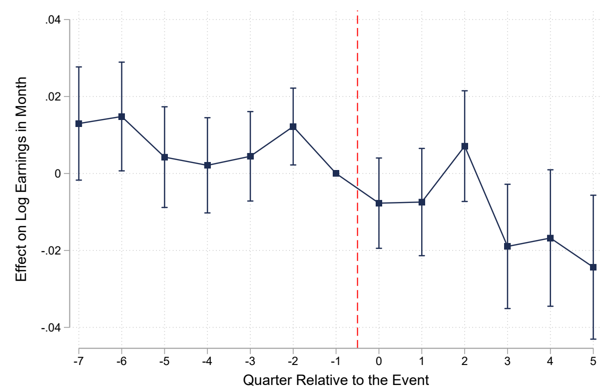

**(b)** Event-Study Estimates on Log In-House Size of Restaurants




**(c)** Avg. Wages Paid by Restaurants

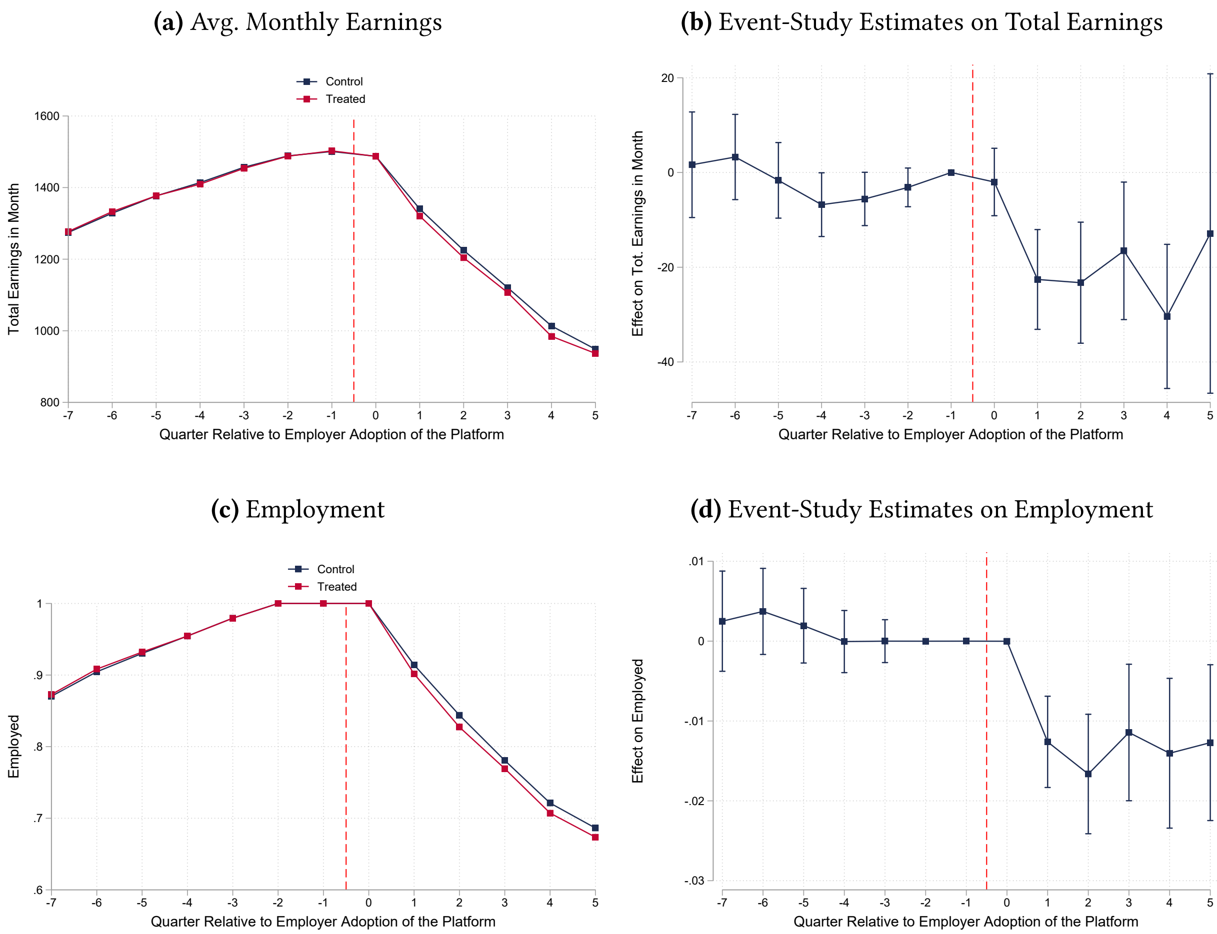



**(d)** Event-Study Estimates on Log Avg. Monthly Wages Paid by Restaurants




*Notes:* This figure reports event study estimates for restaurants that are exposed to a spillover event. A spillover event is defined as a restaurant that is exposed to a large increase in the share of restaurants within a 1 kilometer radius that start offering services through the platform. As described in Section 5.2, a large increase is defined as the top 5 percentile of the distribution of quarterly changes in the share of nearby restaurants that adopt the platform. Panel (a) and Panel (c) report 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 exposed to a spillover event and their matched-controls. Panel (b) reports the corresponding event-study estimates obtained after fitting equation (10) 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 quarter 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 formally each month in the quarter by the establishment after applying the restrictions described in Section 3. Panel (d) presents the estimates for the log average monthly wages paid at restaurants. The x-axis reflects the quarter relative to the quarter in which the spillover event occurs. Average monthly wages in a quarter are constructed by taking the quarterly average of all the monthly wages reported in RAIS by the establishment in the corresponding quarter. Wages are expressed in real terms (2018 CPI). Both panels report 95% confidence intervals based on standard errors clustered at the establishment level.

**Figure 9:** Effects of Employer Adoption of Online-Delivery Platform on Worker Earnings and Employment

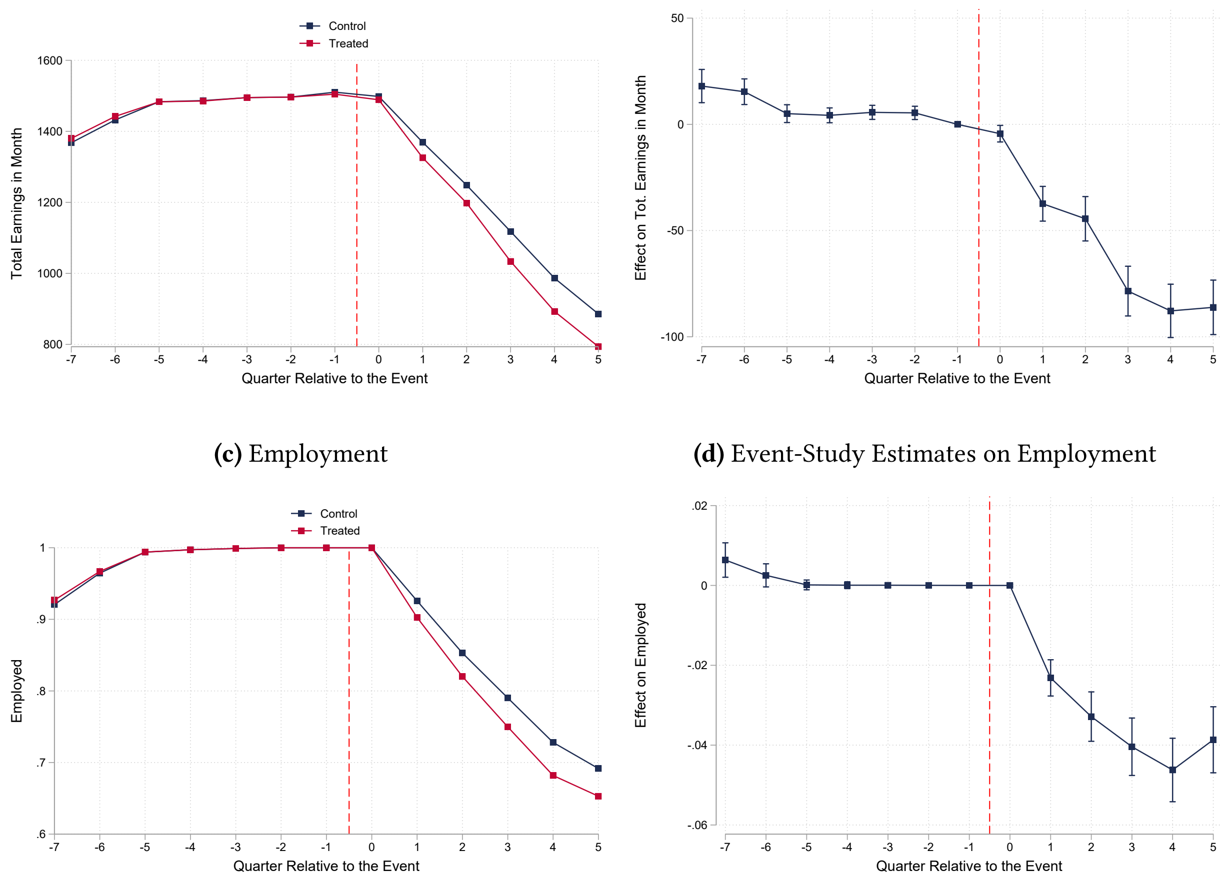



*Notes:* Panel (a) and Panel (c) reports the trajectories of total earnings and employment of restaurant workers whose employer starts offering delivery through the platform and their matched control workers. Panel (b) and Panel (d) report the corresponding event-study estimates obtained after fitting equation (10) on the quarterly average of monthly earnings (Panel b) or employment (panel d). The mean earnings for treated workers the quarter prior to treatment is 1,488 BRL-2018. Average monthly earnings reflects the quarterly average of the monthly formal wages that a worker earns in the corresponding quarter. If the worker did not hold a formal job during the period, the earnings are equal to 0. The x-axis reflects the quarter relative to the first quarter in which the employer of the treated worker offered delivery services through the platform for the first time. Quarter 0 is the quarter when the restaurant that employs the treated worker starts offering delivery services through the platform. A formal worker is defined to be employed in a quarter if they have at least one day of work recorded in RAIS. Wages are expressed in real terms (2018 CPI). Both panels report 95% confidence intervals based on standard errors clustered at the worker level.

**Figure 10:** Spillover Effects of Platform Adoption on Restaurant Workers

**(a)** Avg. Monthly Earnings **(b)** Event-Study Estimates on Total Earnings

**(c)** Employment **(d)** Event-Study Estimates on Employment




*Notes:* This figure reports event study estimates for workers who are employed at restaurants that are exposed to a spillover event. A spillover event is defined as a restaurant that is exposed to a large increase in the share of restaurants within a 1 kilometer radius that start offering services through the platform. As described in Section 5.2, a large increase is defined as the top 5 percentile of the distribution of quarterly changes in the share of nearby restaurants that adopt the platform. Panel (a) and Panel (b) reports the trajectories of total earnings and employment of restaurant workers whose employer is exposed to a spillover event and their matched control workers. Panel (b) reports the corresponding event-study estimates obtained after fitting equation (10) on on the quarterly average of monthly earnings. The mean earnings for treated workers the quarter prior to treatment is 1,496 BRL-2018. Average monthly earnings reflects the quarterly average of the monthly formal wages that a worker earns in the corresponding quarter. If the worker did not hold a formal job during the period, the earnings are equal to 0. Panel (d) presents the estimates for employment. A formal worker is defined to be employed in a quarter if they have at least one day of work recorded in RAIS. The x-axis reflects the quarter relative to the quarter in which the spillover event occurs. Wages are expressed in real terms (2018 CPI). Both panels report 95% confidence intervals based on standard errors clustered at the worker level.

## Tables

**Table 1:** Summary Statistics for Adopting and Control Restaurants

| | (1)<br>Matched Control | (2)<br>Matched Treated | (3)<br>Potential Treated | (4)<br>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*: Column 2 presents the summary statistics of the restaurants that offer delivery services through the platform and for whom I can find a matched control restaurant. These summary statistics are calculated in 2017. Potential matched control restaurants are those who in $t_j^* - 1$ do not have platform delivery services available in their microregion (and the platform does not start offering services the following five quarters). Additionally, these control restaurants must have been open for at least two years, belong to the same quartile of firm size, quartile of average earnings and median of number of restaurants within a radius of 1 kilometers (with respect to the distribution of restaurants in their corresponding microregion). A propensity score matching based on log size in $t^* - 8$ to $t^* - 1$, log average monthly wages paid in quarters $t^* - 4$ to $t^* - 1$, firm age, share of waiters, average tenure, age of workers, share of female workers and average hours of workers is conducted to assign exactly one matched control restaurant to each treated restaurant. Column 1 reports the characteristics of matched control restaurants, and Column 3 reports the summary statistics for the entire set of restaurants that offer delivery services through the platform identified in RAIS. Column 4 reports the summary statistics for all restaurants found in RAIS in 2017. Restaurants are defined as establishments that have a CNAE two digit code equal to 56. Wages are expressed in real terms (2018 CPI). All statistics are person-month-weighted, and standard deviations are reported in parentheses

**Table 2:** Effect of Platform Adoption on Labor Demand per Occupation

| | (1) Number of Waiters | (2) Number of Cooks | (3) Number of Delivery Workers | (4) Log Wage Waiters | (5) Log Wage Cooks | (6) Log Wage Delivery |
|---|---|---|---|---|---|---|
| $\beta$**(Diff-in-Diff)** | -0.3088*** | 0.0001 | -0.0162* | -0.0247*** | -0.0112 | -0.0027 |
| | (0.0581) | (0.0255) | (0.0094) | (0.0067) | (0.0081) | (0.0243) |
| Mean prior to Adoption | 5.5339 | 2.0368 | 0.1539 | 7.1397 | 7.2294 | 7.2784 |
| Observations | 363,129 | 363,129 | 363,129 | 292,984 | 207,408 | 29,466 |

*Notes*: The table reports the corresponding difference-in-difference estimates obtained after fitting equation (10) on the number of waiters (column 1), the number of cooks (column 2), the number of in-house delivery drivers (3) and their respective log wages (column 4, 5 and 6) at each establishment $j$ using the estimator from Borusyak et al. (2024). A formal worker is defined to be employed in a quarter if they have at least one day of work recorded in RAIS. Quarterly number of workers for each occupation is constructed by taking the average of the number of workers hired in that occupation formally each month in the quarter by the establishment after applying the restrictions described in Section 3. Average monthly wages in a quarter are constructed by taking the quarterly average of all the monthly wages reported in RAIS by the establishment in the corresponding quarter. Wages are expressed in real terms (2018 CPI). Standard errors clustered at the establishment level. *** is significant at the 0.01 level, ** is significant at the 0.05 level, and * is significant at the 0.1 level.

**Table 3:** Heterogeneous Effects of Platform Adoption on Labor Demand per Occupation

| | **(1)** | **(2)** | **(3)** | **(4)** |
|---|---|---|---|---|
| | **Above Median** | | **Below Median** | |
| | Number of Waiters | Number of Cooks | Number of Waiters | Number of Cooks |
| ***Panel A: Heterogeneity by AKM Firm Effects*** | | | | |
| $\beta$**(Diff-in-Diff)** | -0.4100*** | 0.0140 | -0.1452** | -0.0273 |
| | (0.0747) | (0.0324) | (0.0673) | (0.0302) |
| Mean Dependent Variable Prior to App Adoption | 6.4699 | 2.2369 | 3.7786 | 1.6845 |
| Observations | 236,494 | 236,494 | 120,848 | 120,848 |
| ***Panel B: Heterogeneity by Restaurant Density*** | | | | |
| $\beta$**(Diff-in-Diff)** | -0.4151*** | -0.0247 | -0.1161 | 0.0695* |
| | (0.0714) | (0.0324) | (0.1038) | (0.0386) |
| Mean Dependent Variable Prior to App Adoption | 5.7365 | 2.0888 | 4.9867 | 1.9286 |
| Observations | 232,545 | 232,545 | 105,887 | 105,887 |

*Notes*: Panel (a) and Panel (b) of the table report the corresponding difference-in-difference estimates obtained after fitting equation (10) on the number of waiters and the number of cooks at each establishment $j$ using the estimator from Borusyak et al. (2024). Panel (a) reports the heterogeneity by AKM firm effects. Panel (b) reports the heterogeneity by restaurant density. Columns (1) and (2) present the results for above the median of each measure, while columns (3) and (4) present the results for below the median of each measure. Restaurant density is calculated as the number of restaurants that are located in a 1 kilometer radius of each restaurant ($\tau$). The median of restaurant density is calculate using the distribution of $\tau$ corresponding to the microregion of each restaurant in each quarter. The density assigned to each restaurant corresponds to the $\tau$ calculated using the quarter prior to the first quarter in which the treated restaurant of the pair started offering delivery services through the platform. 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. A formal worker is defined to be employed in a quarter if they have at least one day of work recorded in RAIS. Quarterly number of workers for each occupation is constructed by taking the average of the number of workers hired in that occupation formally each month in the quarter by the establishment after applying the restrictions described in Section 3. Average monthly wages in a quarter are constructed by taking the quarterly average of all the monthly wages reported in RAIS by the establishment in the corresponding quarter. Wages are expressed in real terms (2018 CPI). Standard errors clustered at the establishment level. *** is significant at the 0.01 level, ** is significant at the 0.05 level, and * is significant at the 0.1 level.

**Table 4:** Summary Statistics for Workers whose Employer Adopts the Delivery Platform and Control Workers

| | (1)<br>Matched Control Workers | (2)<br>Matched Treated Workers | (3)<br>Potential Treated Workers |
|---|---|---|---|
| Years of Education | 10.92 | 11.07 | 11.42 |
| | (2.18) | (1.87) | (2.05) |
| Avg Tenure (in years) | 3.68 | 3.68 | 2.91 |
| | (1.35) | (1.35) | (1.58) |
| Avg Monthly Earnings (in 2018-R$) | 1,501 | 1,503 | 1,789 |
| | (377) | (389) | (1,475) |
| Age | 32.51 | 32.45 | 33.14 |
| | (9.96) | (9.99) | (11.10) |
| Share of Brazilians | 1.00 | 0.99 | 0.99 |
| Female | 0.59 | 0.59 | 0.51 |
| Hours | 43.13 | 41.29 | 41.69 |
| | (3.22) | (6.95) | (6.66) |
| Share of Black Workers | 0.05 | 0.07 | 0.06 |
| Delivery | 0.01 | 0.01 | 0.01 |
| Kitchen | 0.18 | 0.18 | 0.18 |
| Waiters | 0.67 | 0.67 | 0.52 |
| Other | 0.14 | 0.14 | 0.29 |
| | | | |
| Number of Workers | 15,283 | 19,610 | 132,861 |

*Notes*: Column 2 presents the summary statistics of workers working at restaurants when they start offering delivery services through the platform and for whom I can find a matched control worker. These summary statistics are calculated the quarter prior to the employers adoption of the platform, that is, $t^* - 1$. Potential matched control workers are those who in $t_j^* - 1$ are working at a restaurant that is located in a microregion where there are no platform delivery services available (and the platform does not start offering services the following five quarters). Additionally, these control workers must have the same gender, occupation as their corresponding treated worker and their employer must belong to the same quartile of wage, size and median of number of restaurants within a radius of 1 kilometers (with respect to the distribution of restaurants in their corresponding microregion). A caliper matching method based on earnings in $t^*-1$ to $t^*-4$, age and tenure is then conducted to assign exactly one matched control worker for each treated worker without replacement ((Stepner and Garland, 2017)). Column 1 reports the characteristics of matched control workers, and Column 3 reports the summary statistics for the entire set of workers that work at a restaurant that offer delivery services through the platform identified in RAIS. Restaurants are defined as establishments that have a CNAE two digit code equal to 56. Occupations are based on the 6 digit *Classificação brasileira de ocupações* (CBO). Wages are expressed in real terms (2018 CPI). Standard deviations are reported in parentheses.

**Table 5:** Total Wage Bill Effect of Platform 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 Net of Opportunity & Transportation Costs | Wage Bill App | Wage Bill Net of Opportunity & Transportation Costs |
| **Quarter 0** | -61.6 | -69.9 | -16.6 | -40.0 | -37.6 | -9.2 | 330.2 | 88.2 | 1,494.2 | 966.7 |
| **Quarter 1** | -693.4 | -651.2 | -154.5 | -307.6 | -284.0 | -69.6 | 770.8 | 189.6 | 3,660.8 | 2,319.0 |
| **Quarter 2** | -714.4 | -666.8 | -158.1 | -443.0 | -409.2 | -100.3 | 868.9 | 198.9 | 4,317.2 | 2,672.1 |
| **Quarter 3** | -507.8 | -479.8 | -113.8 | -1,225.1 | -1,124.7 | -275.6 | 1,075.7 | 269.4 | 5,290.5 | 3,324.9 |
| **Quarter 4** | -933.0 | -860.3 | -204.1 | -2,483.2 | -2,278.2 | -558.3 | 1,110.6 | 259.9 | 5,547.8 | 3,426.9 |
| **Quarter 5** | -395.6 | -381.9 | -90.6 | -3,974.7 | -3,638.6 | -891.6 | 1,115.1 | 233.3 | 5,820.2 | 3,530.6 |
| **Cumulative PDV** | -3,192.3 | -3,003.5 | -712.4 | -8,055.5 | -7,389.2 | -1,810.7 | 5,080.6 | 1,195.7 | 25,169.1 | 15,647.2 |
| **Percentage of Pre-Platform Wage Bill** | -5.5% | -5.2% | -1.2% | -13.9% | -12.7% | -3.1% | 8.7% | 2.1% | 43.3% | 26.9% |

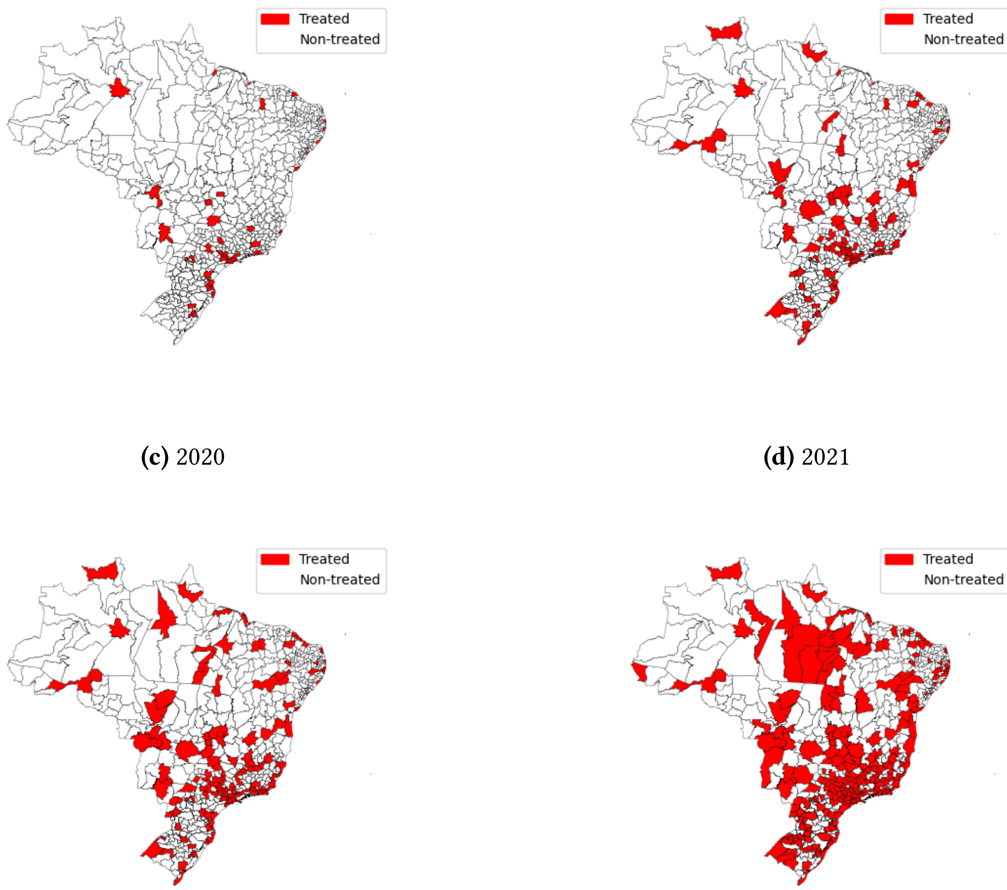
*Notes*: This table reports the estimated wage bill surplus generated by the platform for each component of equation (12). Column 1 presents the effects on in-house restaurant workers whose employer starts offering delivery services through the platform. Each quarter report the corresponding event-study estimates obtained after fitting equation (10) on monthly earnings, converting the coefficient to quarterly and multiplying it by the average firm size of restaurants that adopt the platform in $t^* - 2$. Column presents the same estimates but using the wages net of social security contributions. Column 3 presents the estimated effects for informal workers at adopting restaurants. The number of informal workers is imputed to each establishment using the average share of informal workers in the restaurant sector in each municipality estimated using the 2010 Census. The earnings of informal workers are imputed to each establishment using the ratio of informal to formal wages in the restaurant sector in each state-quarter estimated using the PNAD-C. Column 4 presents the estimated coefficients for workers that are employed at restaurants that are exposed to a spillover event. A spillover event is defined as a restaurant that is exposed to a large increase in the share of restaurants within a 1 kilometer radius that start offering services through the platform. As described in Section 5.2, a large increase is defined as the top 5 percentile of the distribution of quarterly changes in the share of nearby restaurants that adopt the platform. To estimate a per adopting restaurant effect of spillovers, the earnings effects of workers exposed to spillover events are re-scaled by the effect of spillover on restaurant adoption, multiplied by the average adoption of the platform and multiplied by the average firm size of restaurants in my sample. Column 5 and Column 6 present the net wage effect and the spillover effects on informal workers estimated using the same methodology as for in-house workers. Column 7 reports the total earnings gained by workers who held a formal job the quarter prior to working on the platform (and were not laid-off). Column 8 reports the total earnings gained for these workers net of their outside option and their transportation costs. The outside option is equivalent to the average per hour wage that workers held prior to working on the platform. Transportation costs are based on estimates from Callil and Pincaço (2023). Column 9 and 10 report the same estimates for workers that did not hold a formal job the quarter prior to working on the app. The outside option for these workers is imputed using the average wage of informal workers in the restaurant sector in each state-quarter estimated using the PNAD-C. PDV means present discounted value which was calculated using the average quarterly inflation of Brazil between 2019 and 2021 (0.012). Pre-platform wage bill is the average quarterly wage bill of restaurants that adopt the platform between $t^* - 2$ and $t^* - 7$ Wages are expressed in real terms (2018 CPI).

## Appendix

# A Appendix: Figures

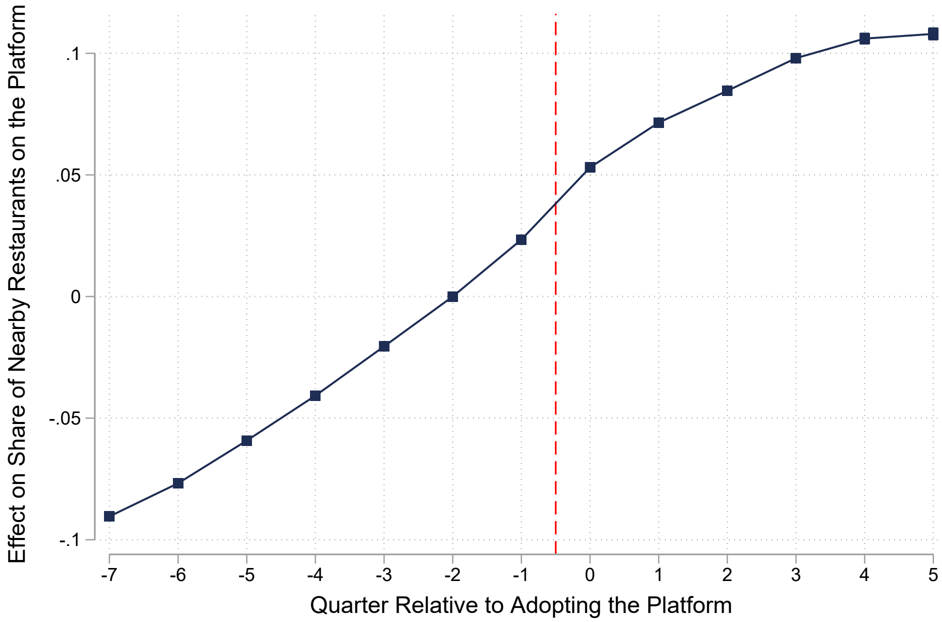
**Figure A11:** Rollout of the Platform

**(a)** 2018 **(b)** 2019 **(c)** 2020 **(d)** 2021



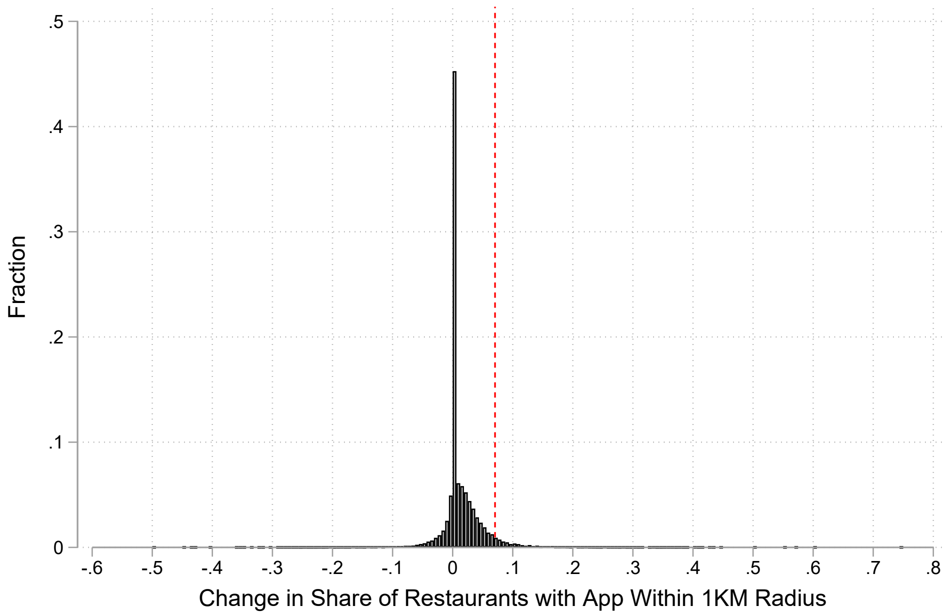

*Notes:* This figure reports the microregions in which restaurants offered services through the delivery platform in each year. Treated means that at least one establishment offered a delivery service through the platform. Panel (a) shows the presence of the platform in 2018, panel (b) in 2019, panel (c) in 2020 and panel (d) in 2021.

**Figure A12:** Restaurants within 1 Kilometer Adopting the Platform



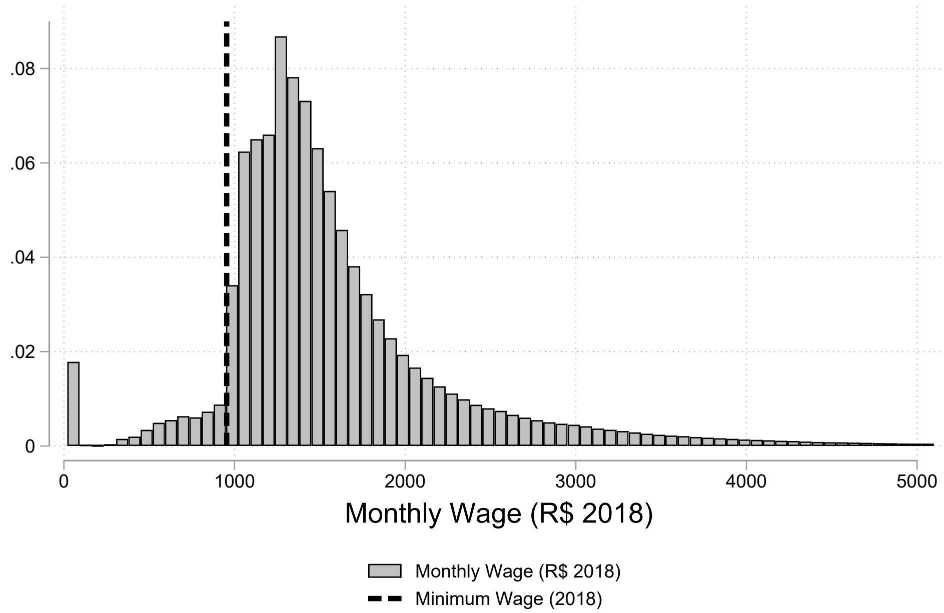

*Notes:* This figure reports the corresponding event-study estimates obtained after fitting equation (10) on the share of restaurants within a 1 kilometer radius that offer delivery services through the platform. The mean share of restaurant within 1 kilometer using the platform the quarter prior to treatment is 0.06. 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. The panel reports 95% confidence intervals based on standard errors clustered at the establishment level.

**Figure A13:** Distribution of Ω



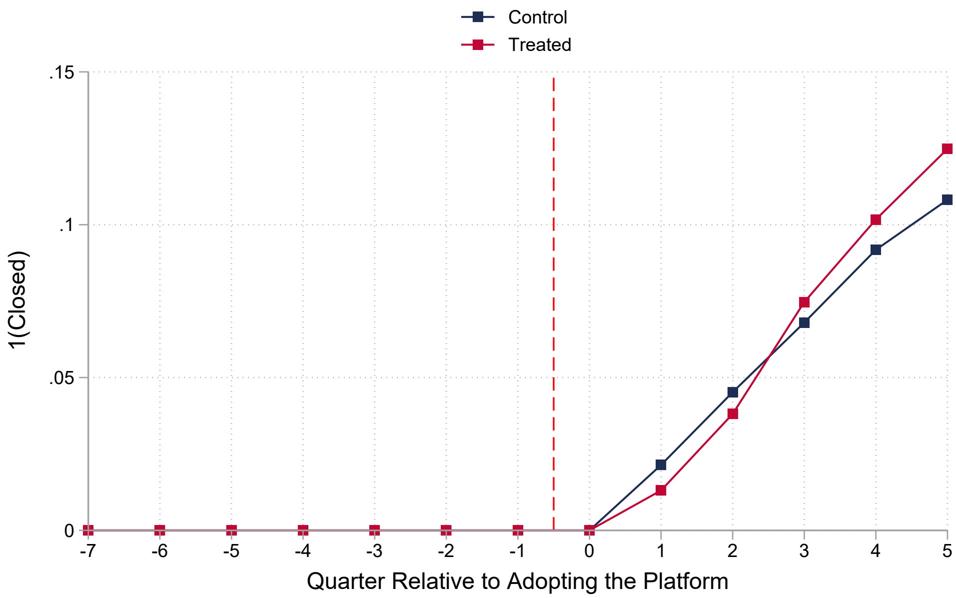

*Notes:* This figure reports the histogram of the quarterly difference in the share of restaurants that offer delivery services through the platform within a 1 kilometer radius of each restaurant (Ω). The distribution is calculated using restaurants that have at least 5 restaurants within a 1 kilometer radius. A restaurant is considered to offer delivery services through the platform if they sold at least one good through the platform using the delivery services of the platform in the quarter. The red dashed line shows the 95th percentile of the distribution. Restaurants are defined as establishments that have a CNAE two digit code equal to 56.

**Figure A14:** Distribution of Wages of Restaurant Workers (2018)




*Notes:* This figure reports the histogram of wages for restaurant workers in 2018. Restaurants are defined as establishments that have a CNAE two digit code equal to 56. The vertical black dashed line shows the minimum wage in 2018 (954 BRL). Wages are winsorized at the 99 percentile and are expressed in real terms (2018 CPI).

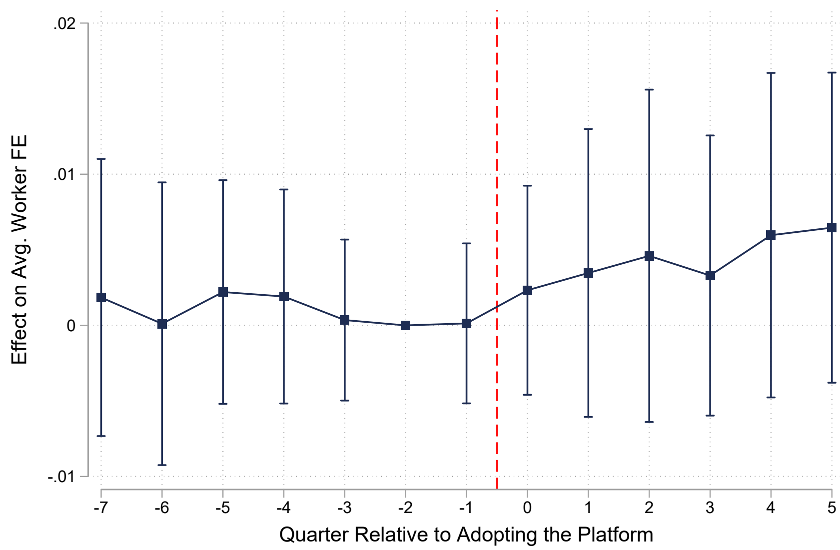
**Figure A15:** Trends in Closure for Adopting and Control Restaurants



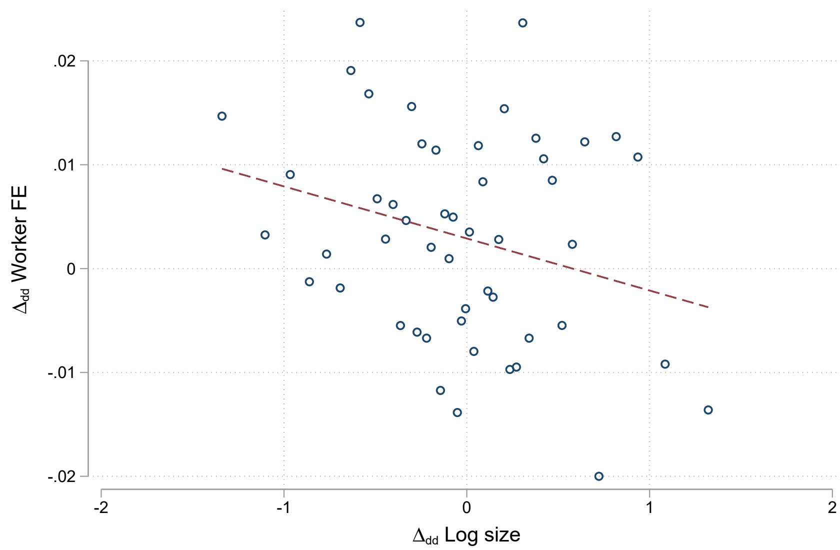

*Notes:* This figure reports the trajectories of establishment closure for matched restaurants that offered delivery services through the platform and matched control restaurants. The date of closure is defined as the last quarter in which the establishment reported having workers to RAIS (previous to the last quarter available in my sample). 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. Potential matched control restaurants are those who in $t_j^* - 1$ do not have platform delivery services available in their microregion (and the platform does not start offering services the following five quarters). Additionally, these control restaurants must have been open for at least two years, belong to the same quartile of firm size, quartile of average earnings and median of number of restaurants within a radius of 1 kilometers (with respect to the distribution of restaurants in their corresponding microregion). A propensity score matching based on log size in $t^* - 8$ to $t^* - 1$, log average monthly wages paid in quarters $t^* - 4$ to $t^* - 1$, firm age, share of waiters, average tenure, age of workers, share of female workers and average hours of workers was conducted to assign exactly one matched control restaurant to each treated restaurant. Restaurants are defined as establishments that have a CNAE two digit code equal to 56.

**Figure A16:** Effect of Platform Adoption on Avg. Worker Fixed Effects at Restaurants

**(a)** Avg. AKM Worker Fixed Effects

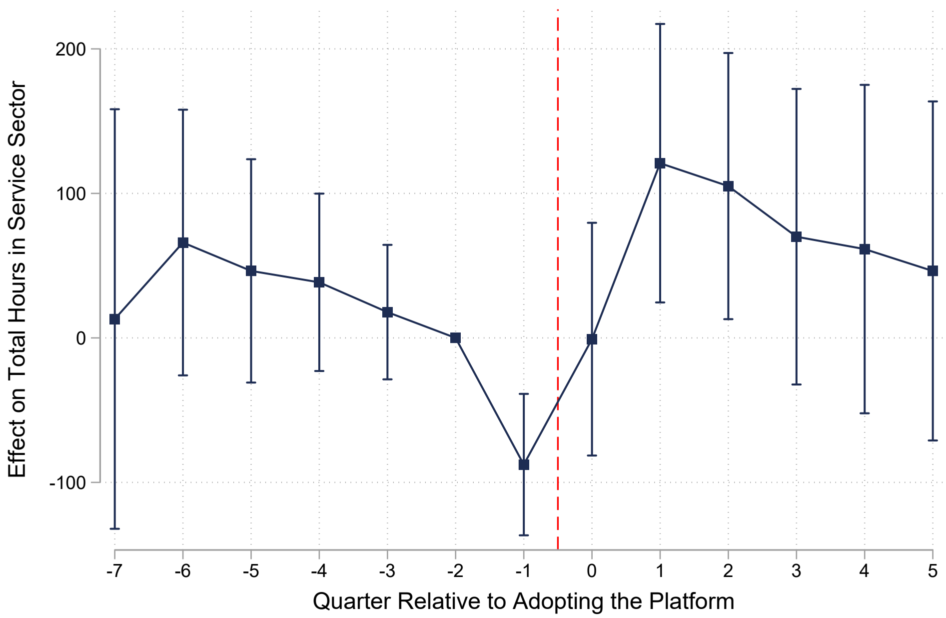



**(b)** Relation Between Log In-House Size Treatment Effects and Avg. AKM Worker Fixed Effects



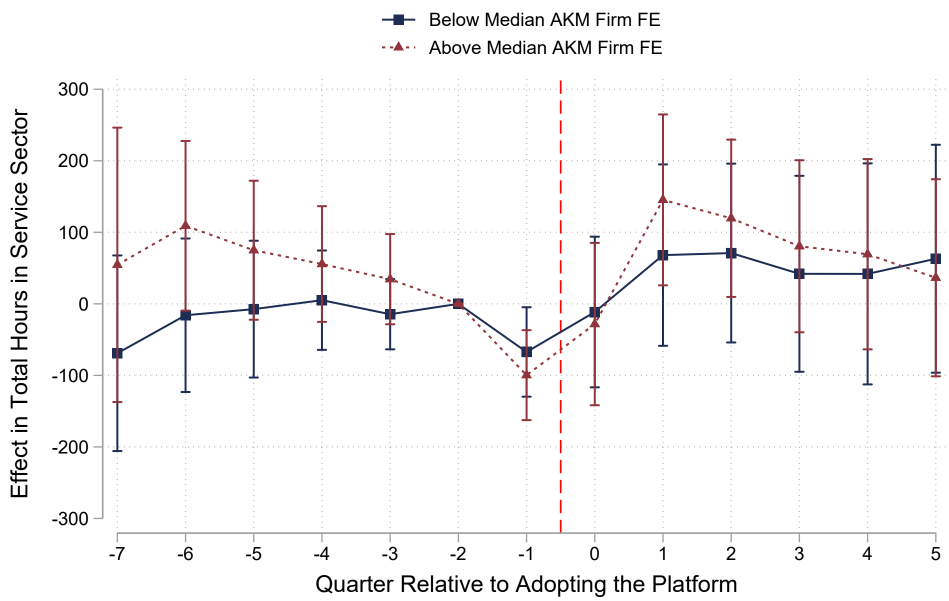

*Notes:* This figure reports the effect of the adoption of the platform on sorting at the establishment level. Panel (a) reports the corresponding event-study estimates obtained after fitting equation (10) on the average AKM worker effect at the establishment level. The x-axis reflects the quarter relative 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. The panel reports 95% confidence intervals based on standard errors clustered at the establishment level. Panel (b) displays a binscatter plot of the establishment level difference-in-difference estimates of the adoption of the platform on the average AKM worker effects plotted against the effects on log in-house establishment size (slope -0.005, SE 0.003). $\Delta_{dd}$ represents the establishment level treatment effect estimate and is equivalent to $\Delta_{dT} - \Delta_{dC}$ where $\Delta_{dT}$ and $\Delta_{dC}$ are the change before (-7 to -1 quarters) and after (0 to 5 quarters) the adoption of the platform for the treated and control establishment of the matched pair. The AKM specification was estimated using data from RAIS between the years 2012 and 2018. For workers out of the AKM sample, I imputed their worker effects using the corresponding firm effects, year effects, and age. A formal worker is defined to be employed in a quarter 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 formally each month in the quarter by the establishment after applying the restrictions described in Section 3.

**Figure A17:** Effect of Platform Adoption on Total Hours for Service Workers



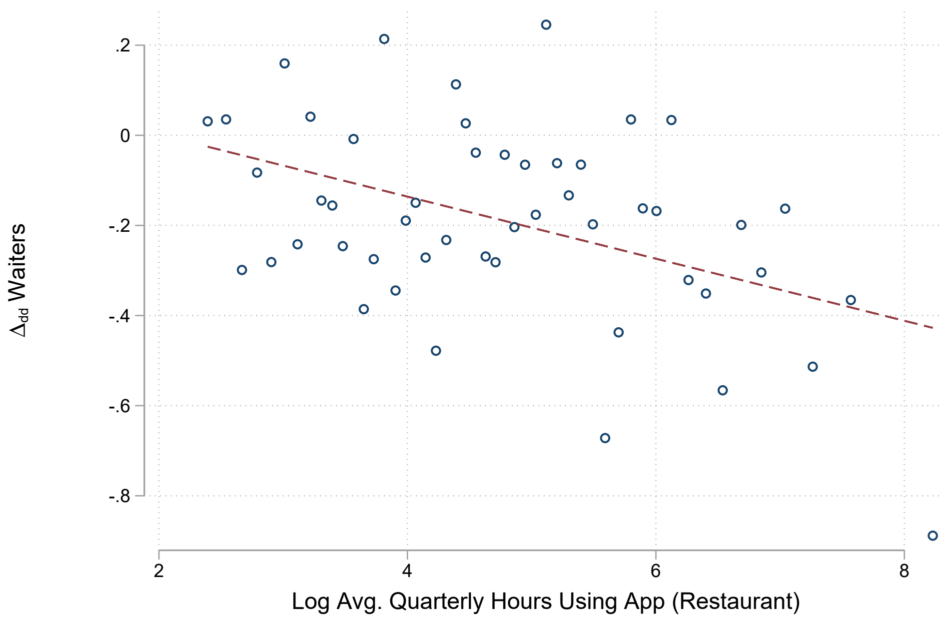

*Notes:* This figure reports the corresponding event-study estimates obtained after fitting equation (10) on the total quarterly hours hired of service workers. The average hours hired of service sector workers prior to the adoption of the platform for treated restaurants is 4,160. Service workers are defined by all workers in a restaurant that are not cooks as defined by their 6 digit *Classificação brasileira de ocupações* (CBO). Appendix Table B8 presents how occupations were classified using the CBO reported in RAIS. Service workers also include platform workers, once the restaurant starts offering delivery services 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. Total hours are defined as total hours hired in each quarter. The panel reports 95% confidence intervals based on standard errors clustered at the establishment level.

**Figure A18:** Effect of Platform Adoption on Total Hours for Service Workers by AKM Firm Effects




*Notes:* This figure reports the corresponding event-study estimates obtained after fitting equation (10) on the total quarterly hours hired of service workers. 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. Service workers are defined by all workers in a restaurant that are not cooks as defined by their 6 digit *Classificação brasileira de ocupações* (CBO). Appendix Table B8 presents how occupations were classified using the CBO reported in RAIS. Service workers also include platform workers, once the restaurant starts offering delivery services 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. Total hours are defined as total hours hired in each quarter. The panel reports 95% confidence intervals based on standard errors clustered at the establishment level.

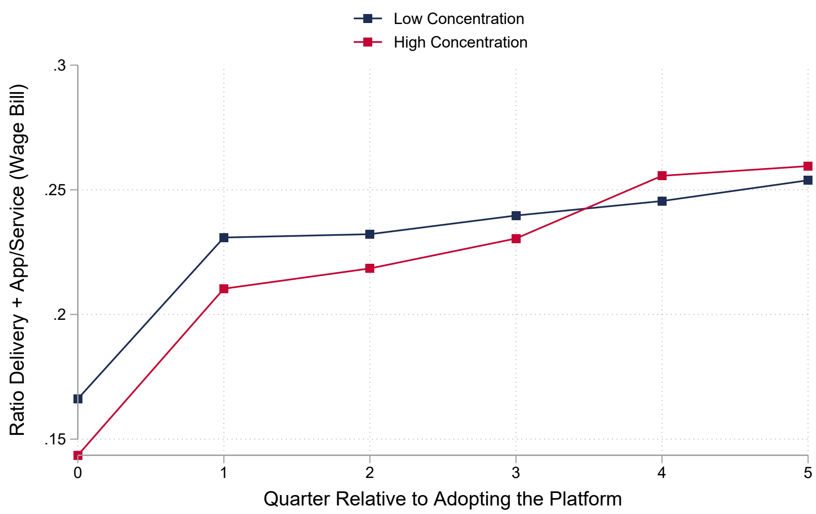
**Figure A19:** Relation Between Establishment Level Treatment Effect on Number of Waiters and Usage of Delivery Platform by Restaurants



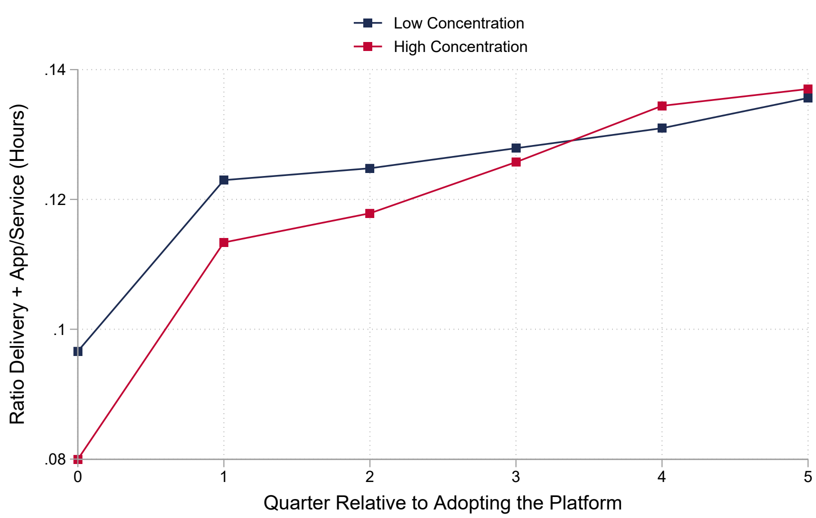

*Notes:* This figure displays a binscatter plot of the establishment level difference-in-difference estimates of the adoption of the platform on the number of waiters plotted against the log quarterly average hours of platform usage by restaurants (slope -0.0001441, SE 0.0000647). $\Delta_{dd}$ represents the establishment level treatment effect estimate and is equivalent to $\Delta_{dT} - \Delta_{dC}$ where $\Delta_{dT}$ and $\Delta_{dC}$ are the change before (-7 to -1 quarters) and after (0 to 5 quarters) the adoption of the platform for the treated and control establishment of the matched pair. Number of waiters is defined as the number of formal workers that have the waiter occupations as defined in Table B8. A formal worker is defined to be employed in a quarter if they have at least one day of work recorded in RAIS. The x-axis reflects the quarterly average hours that the restaurant used the platform for delivery services in the quarters $t^* + 1$ to $t^* + 5$. The figure conditions on restaurants that averaged at least 10 hours in a quarter of usage of the platform. Both average of quarterly usage of the platform and $\Delta_{dd}$ are winsorized at the 98 percentile and latter is also winsorized at the 2 percentile.

**Figure A20:** Ratio of Delivery Workers and Service Workers at Treated Establishments by Density

**(a)** Wage Bill



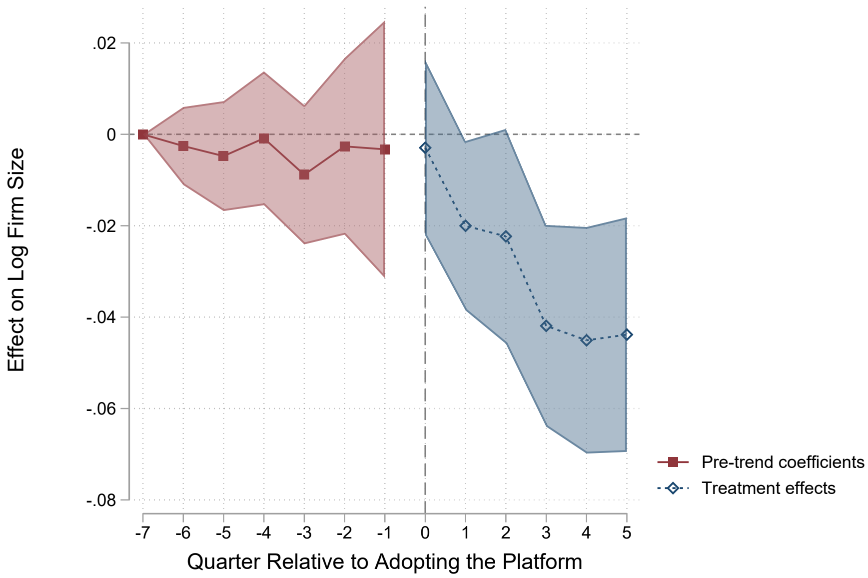

**(b)** Hours



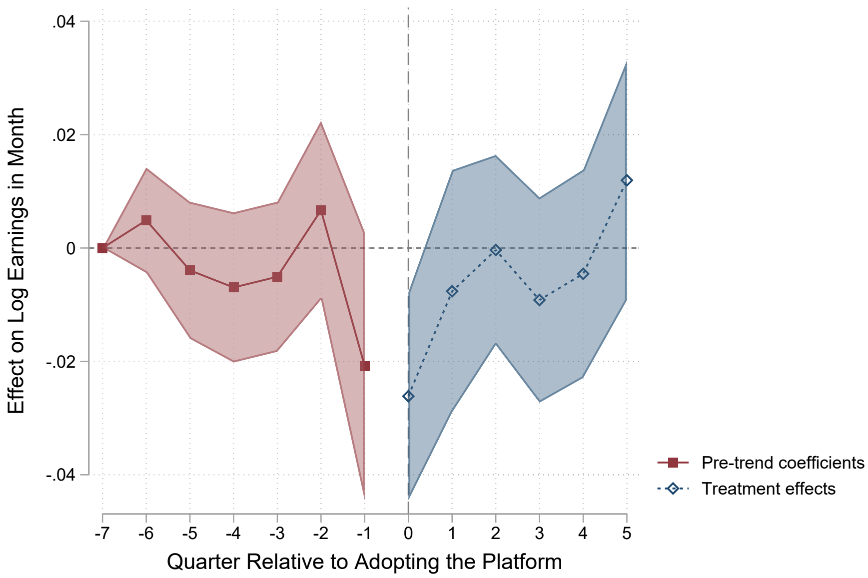

*Notes:* This figure reports the ratio of platform to service wage bill (panel a) and hours (panel b) at treated establishments after the restaurants starts offering services through the platform. The ratio in panel (a) is calculated by dividing the quarterly wage bill of platform workers by the quarterly wage bill of service workers. 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 ($\tau$). The median of restaurant density is calculate using the distribution of $\tau$ corresponding to the microregion of each restaurant in each quarter. The density assigned to each restaurant corresponds to the $\tau$ calculated using the quarter prior to the first quarter in which the treated restaurant of the pair started offering delivery services through the platform. The ratio in panel (b) is calculated by dividing the total hours hired of platform workers by the total number of hours hired of service 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. Quarter 0 is the quarter when the treated restaurant starts offering delivery services through the platform. Service workers are defined by all workers in a restaurant that are not cooks as defined by their 6 digit *Classificação brasileira de ocupações* (CBO). Appendix Table B8 presents how occupations were classified using the CBO reported in RAIS. Service workers also include platform workers, once the restaurant starts offering delivery services through the platform.

**Figure A21:** Effect of Adopting the Platform using Borusyak et al. (2024) estimator

**(a)** Log In-House Firm Size



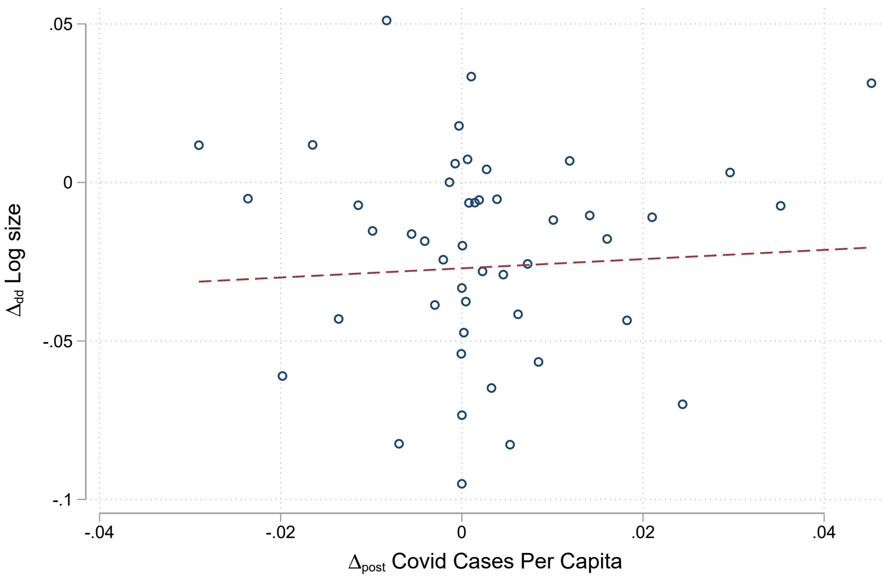

**(b)** Log Monthly Wages



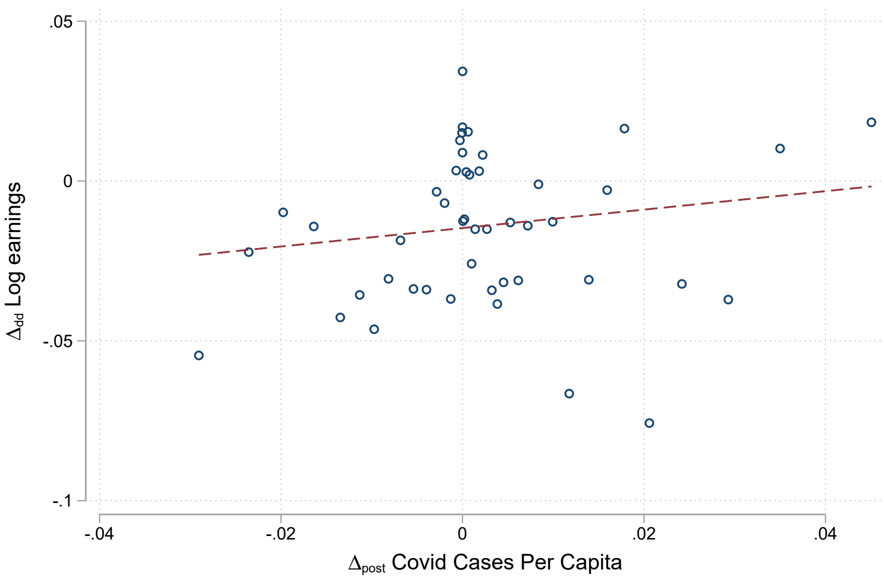

*Notes:* This figure reports the corresponding event-study estimates obtained after fitting equation (10) on the logarithm of firm size (panel a) and the logarithm of the average monthly wages paid by restaurants (panel b) using the estimator proposed by Borusyak et al. (2024). The x-axis reflects the 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 quarter 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 formally each month in the quarter by the establishment after applying the restrictions described in Section 3. Average monthly wages in a quarter are constructed by taking the quarterly average of all the monthly wages reported in RAIS by the establishment in the corresponding quarter. Wages are expressed in real terms (2018 CPI). Both panels report 95% confidence intervals based on standard errors clustered at the establishment level.

**Figure A22:** Establishment level treatment effect and COVID-19 Cases

**(a)** Log In-House Firm Size

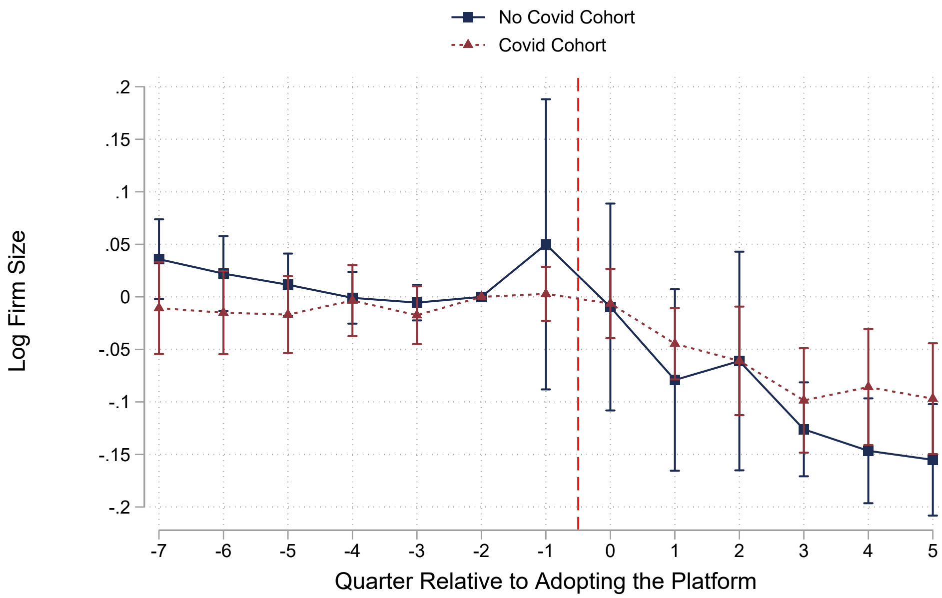



**(b)** Log Monthly Wages



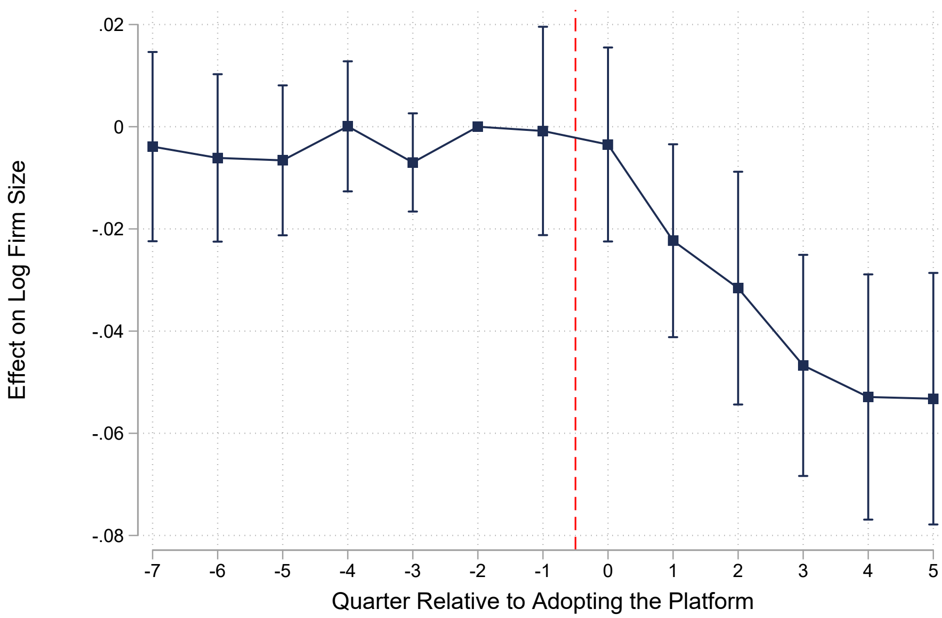

*Notes:* This figure displays a binscatter plot of the establishment level difference-in-difference estimates of the adoption of the platform on log in-house establishment size (panel a) and log average monthly wages paid by restaurants (panel b) plotted against the difference of average covid cases per capita in the municipality of the matched treated and control establishments between $t^* + 5$ and $^*0$. $\Delta_{dd}$ represents the establishment level treatment effect estimate and is equivalent to $\Delta_{dT} - \Delta_{dC}$ where $\Delta_{dT}$ and $\Delta_{dC}$ are the change before (-7 to -1 quarters) and after (0 to 5 quarters) the adoption of the platform for the treated and control establishment of the matched pair. Covid cases per capita are calculated as the total covid cases reported in a quarter divided by the population of the municipality. Panel (a) has a linear slope of 0.145 (SE 0.357). Panel (b) has a linear slope of 0.289 (SE 0.246). A formal worker is defined to be employed in a quarter 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 formally each month in the quarter by the establishment after applying the restrictions described in Section 3. Average monthly wages in a quarter are constructed by taking the quarterly average of all the monthly wages reported in RAIS by the establishment in the corresponding quarter. Wages are expressed in real terms (2018 CPI).

**Figure A23:** Effect of Platform Adoption on Log Firm In-House Size by COVID-19 period



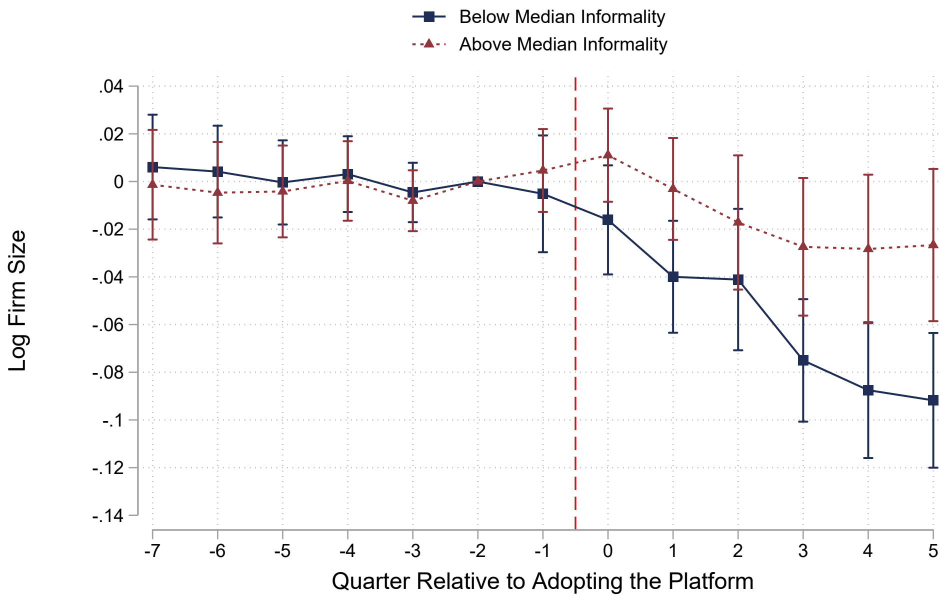

*Notes:* This figure reports the corresponding event-study estimates obtained after fitting equation (10) on the logarithm of in-house restaurant size. The blue line represents cohort of restaurants that started offering delivery services through the platform before the first quarter of 2019. That is, this quarter had five full quarters after offering services through the platform before the Covid-19 pandemic started. The red dashed line represents the cohort of restaurants that started offering delivery services through the platform between the second quarter of 2920 and the last quarter of 2020. This cohort started offering delivery services through the platform during the pandemic and I can observe at least four quarters after they adopted 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. A formal worker is defined to be employed in a quarter 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 formally each month in the quarter by the establishment after applying the restrictions described in Section 3. The panel reports 95% confidence intervals based on standard errors clustered at the establishment level.

**Figure A24:** Effect of Platform Adoption on Log Firm In-House Size with State *times* Year Fixed Effects




*Notes:* This figure reports the corresponding event-study estimates obtained after fitting equation (10) on the logarithm of in-house restaurant size when including state by year fixed effects. 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 quarter 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 formally each month in the quarter by the establishment after applying the restrictions described in Section 3. The panel reports 95% confidence intervals based on standard errors clustered at the establishment level.

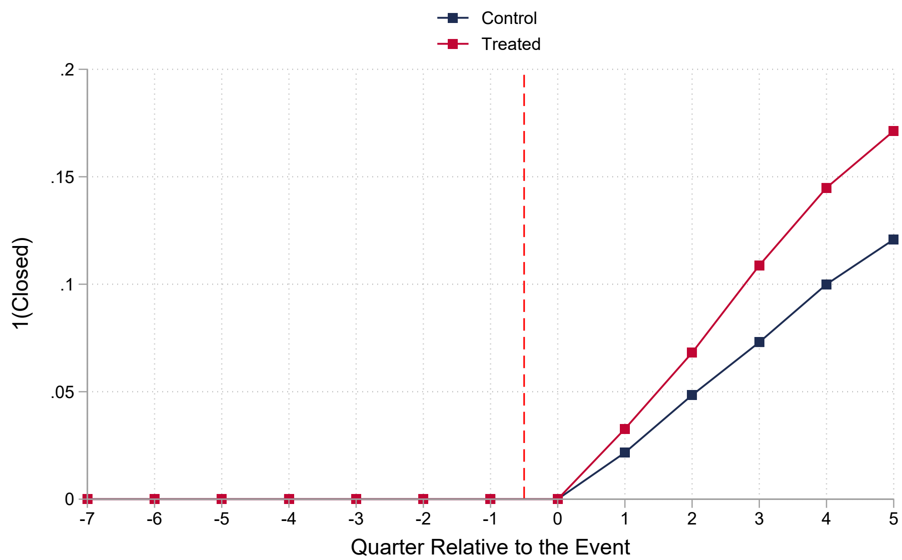
**Figure A25:** Effect of Platform Adoption on Log Firm Size By Informality of the Municipality of the Establishment



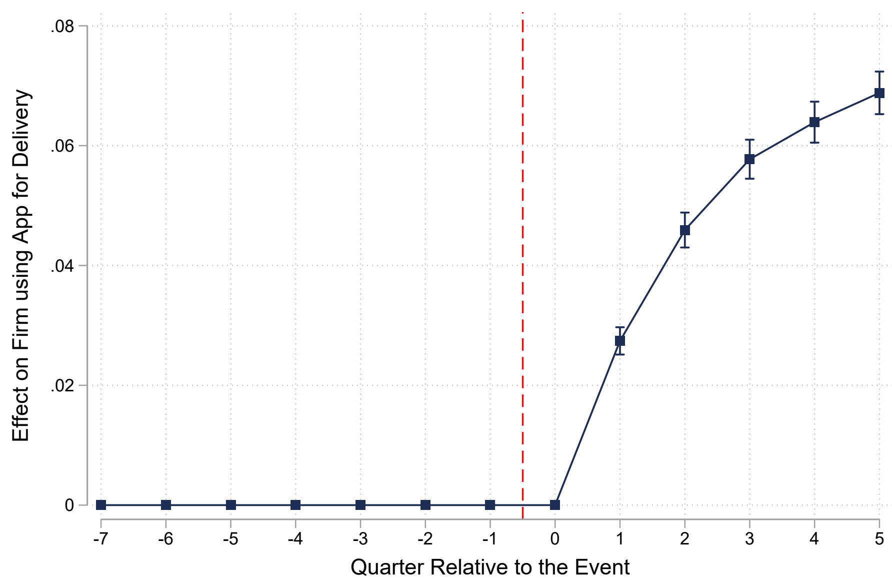

*Notes:* This figure reports the corresponding event-study estimates obtained after fitting equation (10) on the logarithm of in-house restaurant size. The plot presents the estimated coefficients by the levels of informality in the restaurant sector at the municipality of each restaurant as estimated using the 2010 Brazilian Census. Informality is calculated as the share of informal workers in the restaurant sector in each municipality. The median of informality is calculated using the distribution of informality of restaurants that adopt the platform and match to a control group. Control restaurants are assigned the level of informality of their matched treated restaurant. The blue line presents the estimated coefficients for treated restaurants located in municipalities that have above the median levels of informality. The red dashed line presents the estimated coefficients for treated restaurants located in municipalities that have below the median levels of informality. 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 quarter 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 formally each month in the quarter by the establishment after applying the restrictions described in Section 3. The panel reports 95% confidence intervals based on standard errors clustered at the establishment level.

**Figure A26:** Spillover Effects of Platform Adoption on Non-Adopting Restaurants Closure and Platform Adoption

**(a)** Closure



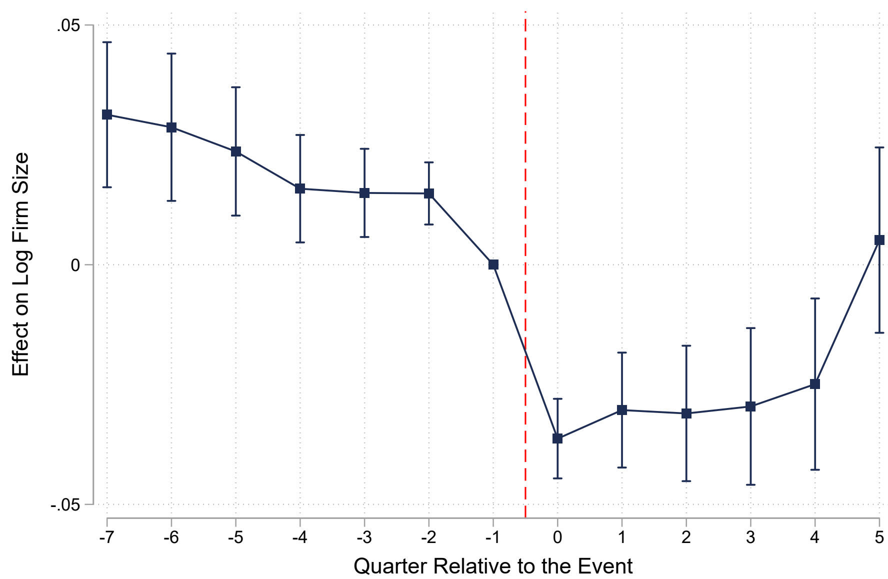

**(b)** Likelihood of Platform Adoption



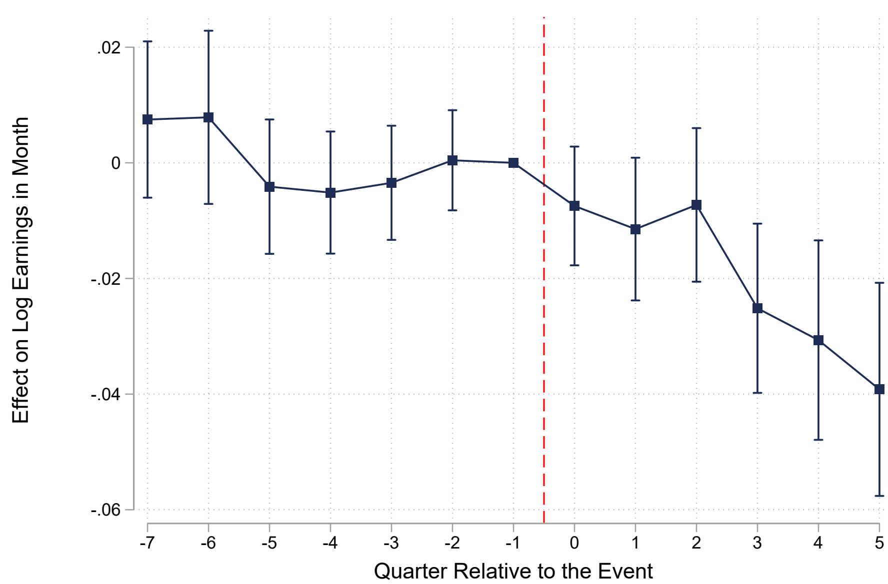

*Notes:* Panel (a) reports the trajectories of establishment closure for matched restaurants that are exposed to a spillover event and matched control restaurants. A spillover event is defined as a restaurant that is exposed to a large increase in the share of restaurants within a 1 kilometer radius that start offering services through the platform. As described in Section 5.2, a large increase is defined as the top 5 percentile of the distribution of quarterly changes in the share of nearby restaurants that adopt the platform. The date of closure is defined as the last quarter in which the establishment reported having workers to RAIS (previous to the last quarter available in my sample). Panel (b) reports the corresponding event-study estimates obtained after fitting equation (10) for restaurants that are exposed to a spillover event on the likelihood of offering delivery services through the platform. Both panels report 95% confidence intervals based on standard errors clustered at the establishment level.

**Figure A27:** Spillover Effects of Platform Adoption on Non-Adopting Restaurants (2KM)

**(a)** Log Firm Size

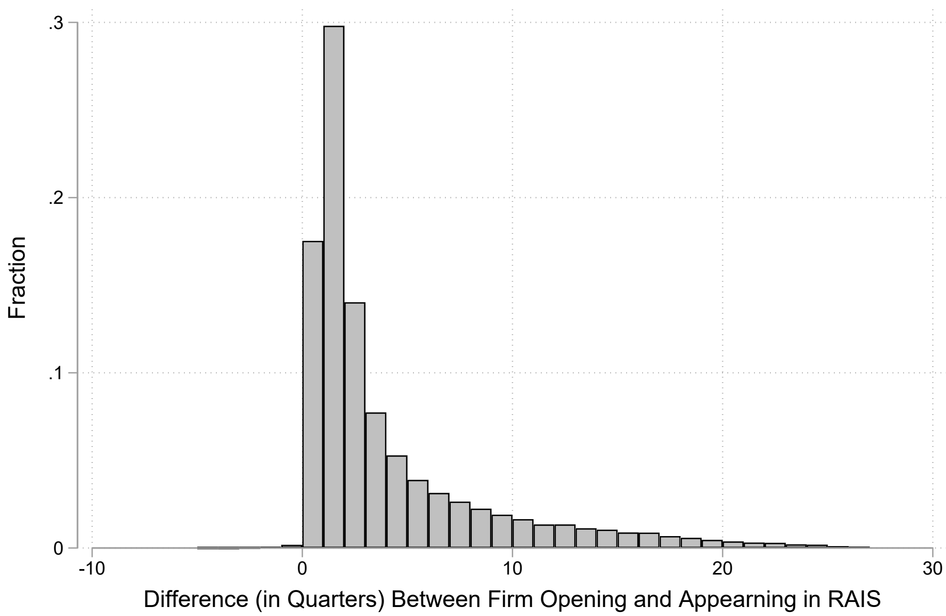



**(b)** Log Avg. Monthly Wages




*Notes:* This figure reports event study estimates for restaurants that are exposed to a spillover event. In this figure, a spillover event is defined as a restaurant that is exposed to a large increase in the share of restaurants within a 2 kilometer donut that start offering services through the platform. As described in Section 5.2, a large increase is defined as the top 5 percentile of the distribution of quarterly changes in the share of nearby restaurants that adopt the platform. Panel (a) reports the corresponding event-study estimates obtained after fitting equation (10) 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 quarter 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 formally each month in the quarter by the establishment after applying the restrictions described in Section 3. Panel (b) presents the estimates for the log average monthly wages paid at restaurants. The x-axis reflects the quarter relative to the quarter in which the spillover event occurs. Average monthly wages in a quarter are constructed by taking the quarterly average of all the monthly wages reported in RAIS by the establishment in the corresponding quarter. Wages are expressed in real terms (2018 CPI). Both panels report 95% confidence intervals based on standard errors clustered at the establishment level.

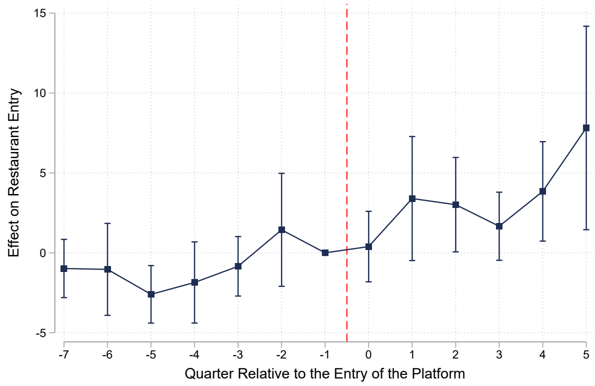
**Figure A28:** Histogram of the Difference Between Restaurant Opening Date and First Appearance in RAIS



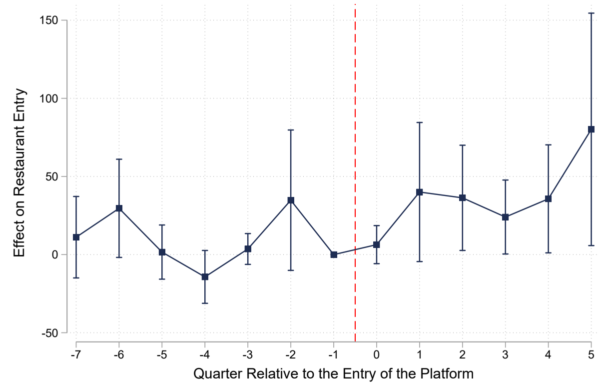

*Notes:* This figure reports the histogram of the difference between the opening date of restaurants as reported in Cadastro Federal and the date of the first appearance in RAIS. Restaurants appear in RAIS when they report that they are hiring formally an employee. The figure reports the histogram for the years in te sample previous to the entry of the platform to any microregion, that is, for the years 2015-2017. The average of the difference between both sources of reporting for new restaurants is 3.6 quarters.

**Figure A29:** Effect of Delivery Platform Availability on Restaurant Entry

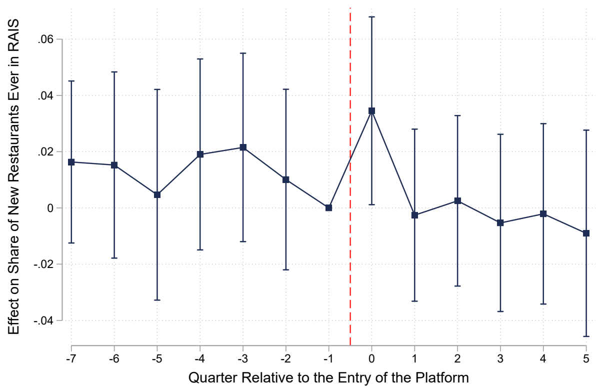
**(a)** Effect on Restaurant Entry



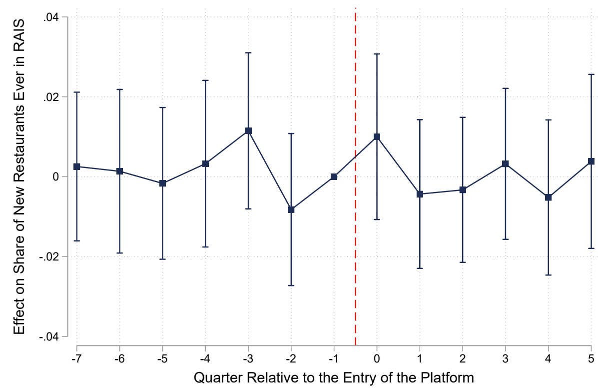

**(b)** Effect on Restaurant Entry (Weighted)



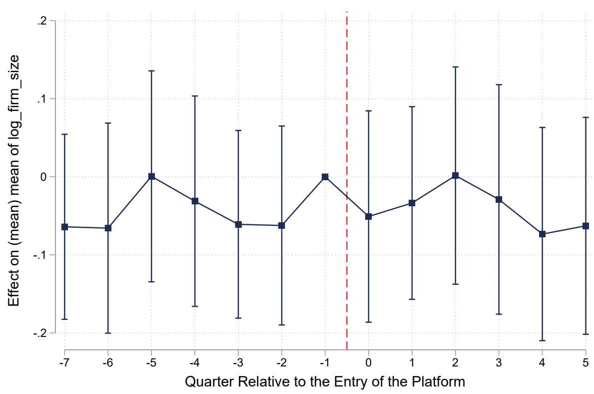

**(c)** Effect on New Restaurants in RAIS



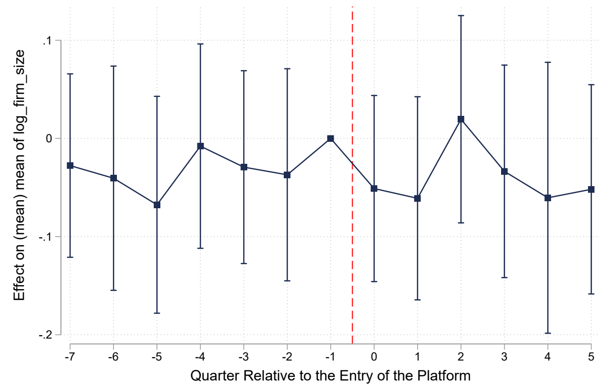

**(d)** Effect on Share of New Restaurants in RAIS (Weighted)




**(e)** Effect on New Restaurants' Log Size



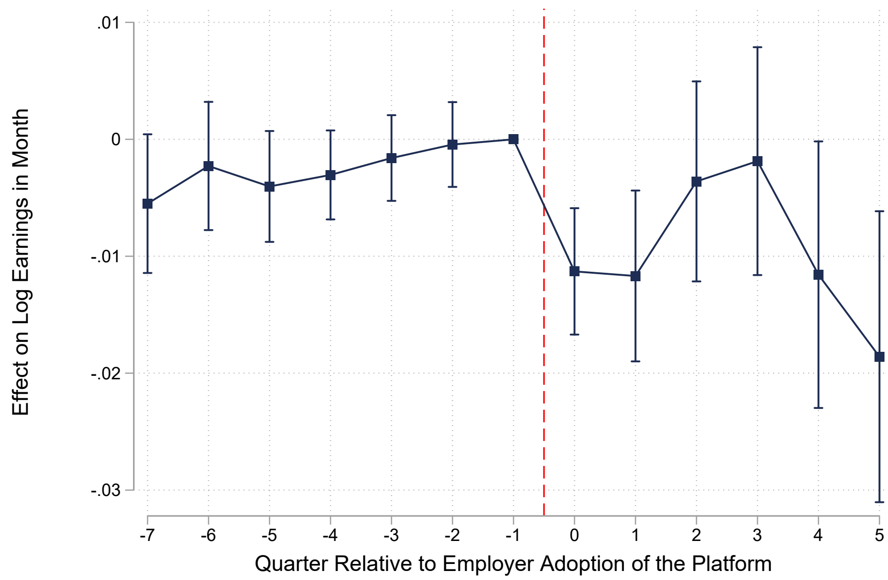

**(f)** Effect on New Restaurants' Log Size (Weighted)



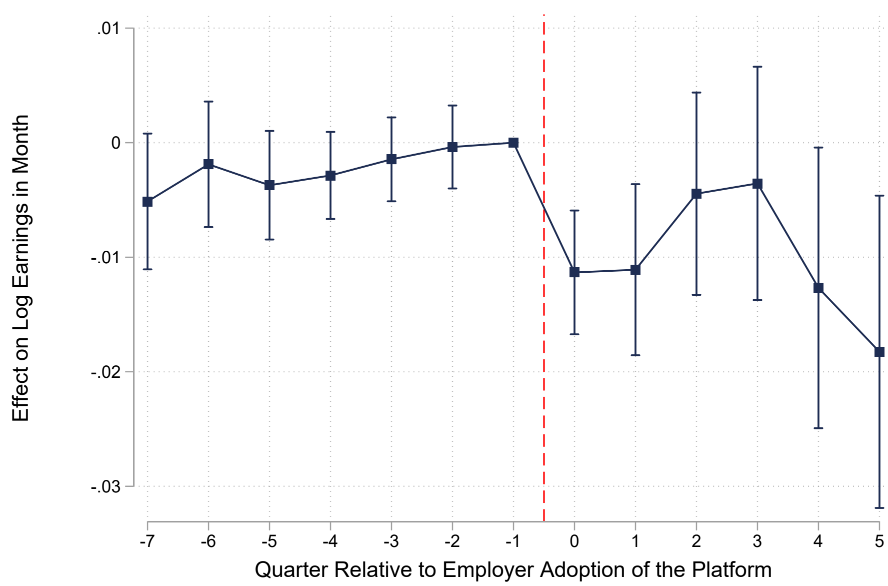

*Notes:* This figure reports reports the corresponding event-study estimates obtained after fitting equation (D50) on the number of new restaurants in microregion $m$ in quarter $t$ (panel a and b),on the share of new restaurants that appear in RAIS at some point (panel c and d) and the size of new restaurants—conditional on reporting in RAIS (panel e and f). Panel (a),(c) and (e) report the unweighted estimates. The mean restaurant entry in $t^* - 1$ is 52, the share of new restaurants that at some point in time appear in RAIS is 0.48. Panel (b), (d) and (f) report estimates when weighting the regression by the average number of workers in 2017. The mean restaurant entry in $t^* - 1$ when weighting the sample is 410 while the share of new restaurants that at some point in time appear in RAIS is 0.53. The log size of new restaurants is calculated as an average of the reported employees across the first five quarters after the opening. Restaurant opening is defined using the reports of Cadastro Federal based on *CNPJ*. The x-axis reflects the quarter relative to the quarter in which the delivery platform entered the microregion. Both panels report 95% confidence intervals based on standard errors clustered at the microregion level.

**Figure A30:** Effect of Employer Platform Adoption on Restaurant Workers Log Earnings

**(a)** Log Avg. Monthly Earnings



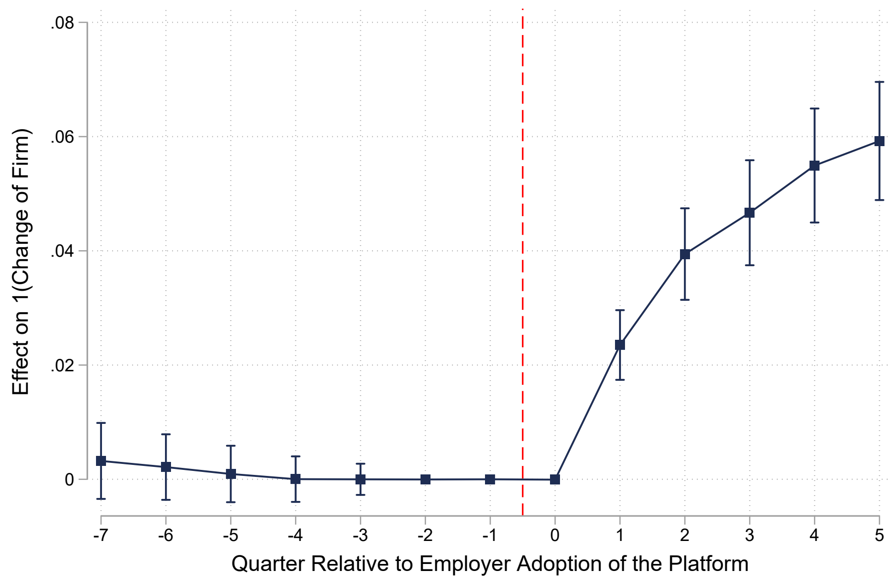

**(b)** Log Avg. Monthly Earnings: Dropping Compliers



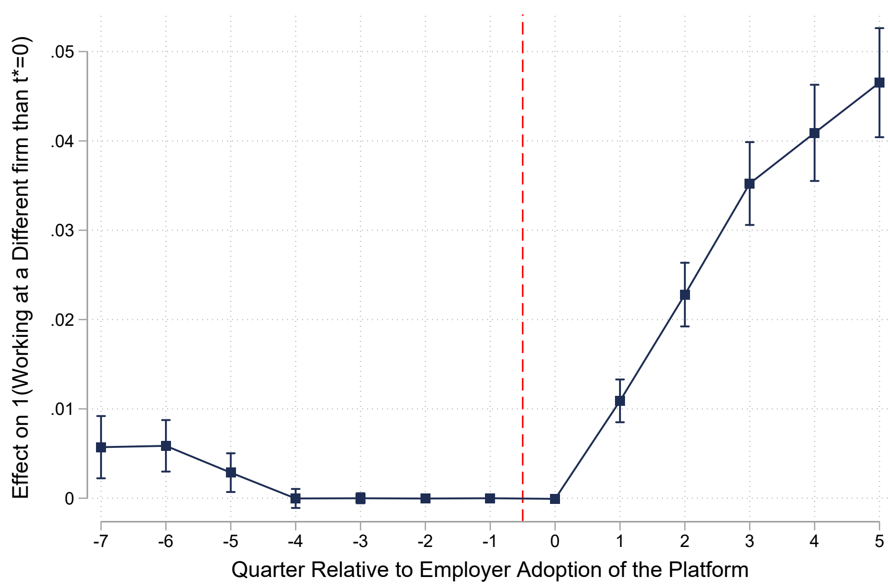

*Notes:* This figure reports event-study results on log daily wages (panel a) obtained after fitting equation (10) on the log daily wage of individual $i$ in period $t$. Panel (b) estimates this equation after dropping from the sample pairs where the treated worker is not employed but the control worker is. I label this control worker as a "complier", one who would not be employed if exposed to outsourcing. Average monthly earnings reflects the quarterly average of the monthly formal wages that a worker earns in the corresponding quarter. The x-axis reflects the quarter relative to the first quarter in which the employer of the treated worker offered delivery services through the platform for the first time. Quarter 0 is the quarter when the restaurant that employs the treated worker starts offering delivery services through the platform. Both panels report 95% confidence intervals based on standard errors clustered at the worker level. Wages are expressed in real terms (2018 CPI).

**Figure A31:** Effect of Employer Platform Adoption on Worker Probability of Changing Firm

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

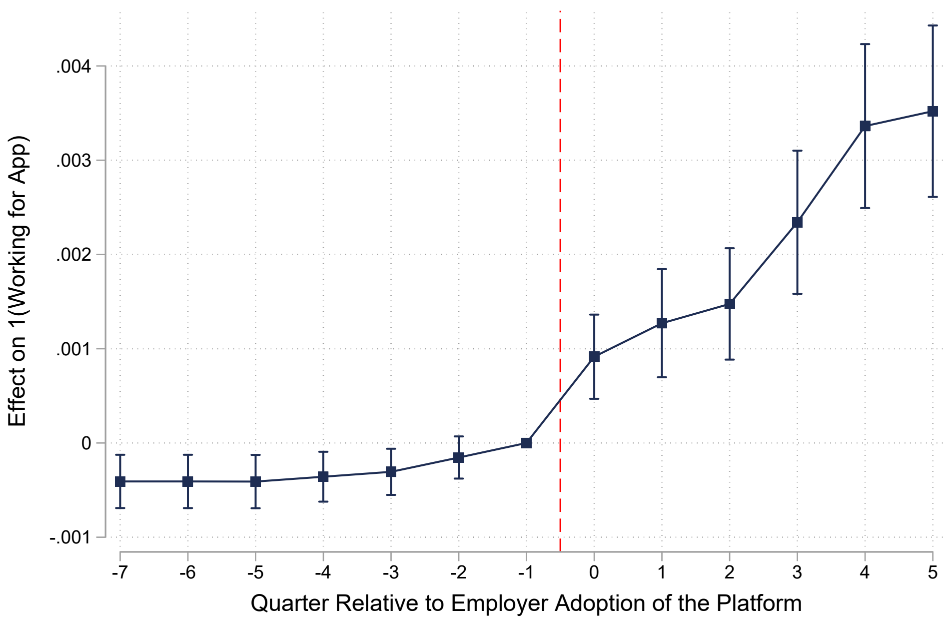



**(b)** Likelihood of Working for a different Employer than t*=0




*Notes:* Panel (a) reports the corresponding event-study estimates obtained after fitting equation (10) on a dummy equal to one if individual $i$ in time $t$ no longer works for the employer they had in $t^* - 1$ (either because of non-employment or they are employed at another establishment). Panel (b) reports the corresponding event-study estimates obtained after fitting equation (10) on a dummy equal to one if individual $i$ is employed by a different employer than the one they had in $t^* - 1$. The employer in a quarter is defined as the employer that pays the highest total wages in a quarter (the dominant employer of the quarter). The x-axis reflects the quarter relative to the first quarter in which the employer of the treated worker offered delivery services through the platform for the first time. Quarter 0 is the quarter when the restaurant that employs the treated worker starts offering delivery services through the platform. Both panels report 95% confidence intervals based on standard errors clustered at the worker level.

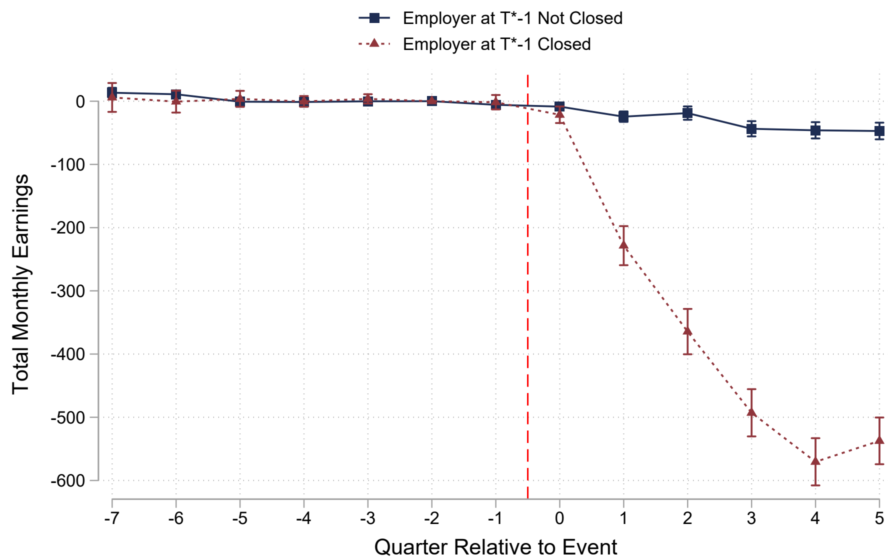
**Figure A32:** Effect of Employer Platform Adoption on Worker Probability of Working at Delivery Platform



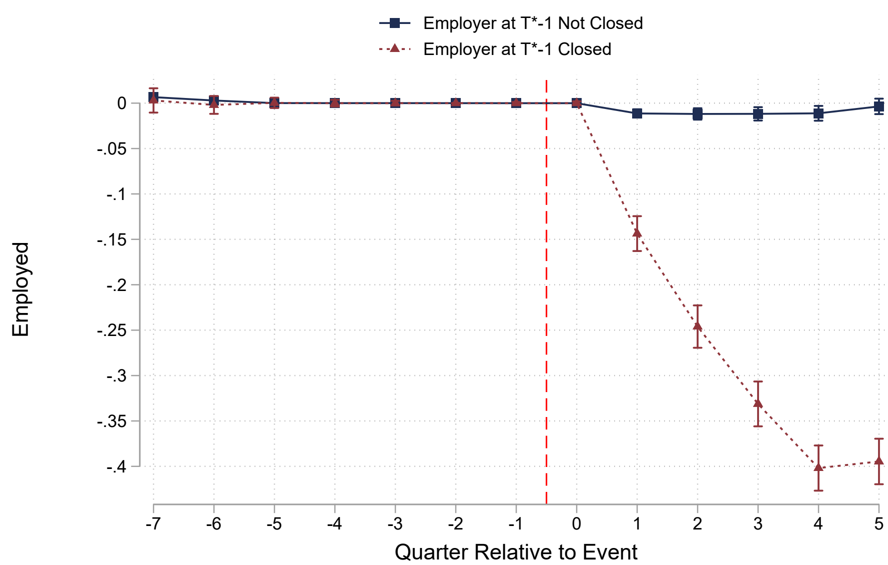

*Notes:* This figure reports the corresponding event-study estimates obtained after fitting equation (10) on a dummy equal to one if individual $i$ in time $t$ works in the platform. Employment at time $t$ in the platform is defined as doing at least one delivery in quarter $t$. The x-axis reflects the quarter relative to the first quarter in which the employer of the treated worker offered delivery services through the platform for the first time. Quarter 0 is the quarter when the restaurant that employs the treated worker starts offering delivery services through the platform. The panel reports 95% confidence intervals based on standard errors clustered at the worker level.

**Figure A33:** Spillover Effects of Platform Adoption on Restaurant Workers by Employer Closure

**(a)** Total Earnings



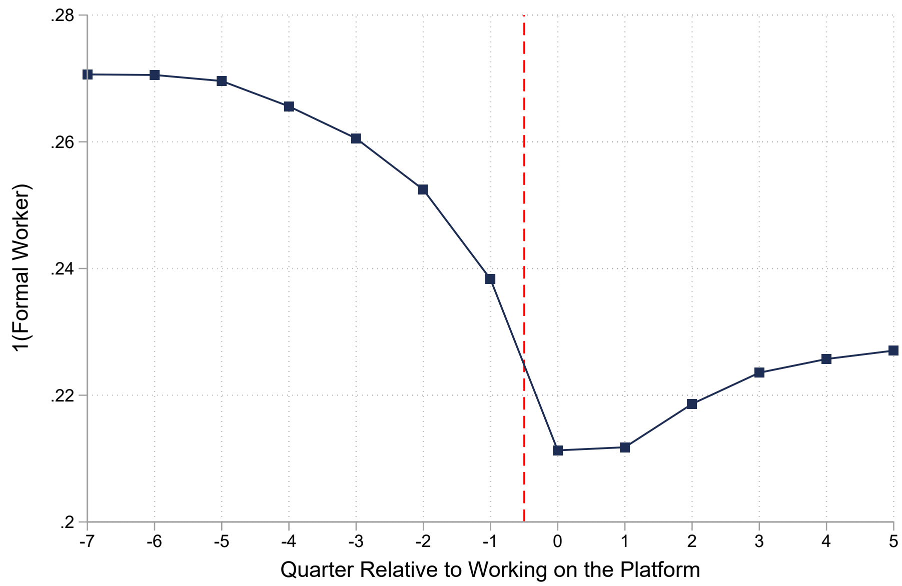

**(b)** Employment



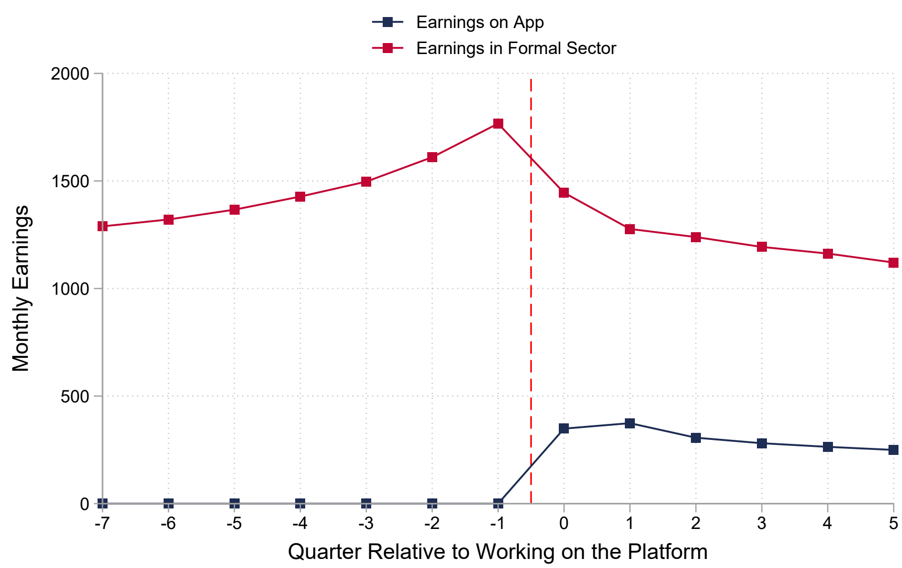

*Notes:* This figure reports event study estimates for workers who are employed at restaurants that are exposed to a spillover event. A spillover event is defined as a restaurant that is exposed to a large increase in the share of restaurants within a 1 kilometer radius that start offering services through the platform. As described in Section 5.2, a large increase is defined as the top 5 percentile of the distribution of quarterly changes in the share of nearby restaurants that adopt the platform. Panel (a) reports the corresponding event-study estimates obtained after fitting equation (10) on on the quarterly average of monthly earnings. Average monthly earnings reflects the quarterly average of the monthly formal wages that a worker earns in the corresponding quarter. If the worker did not hold a formal job during the period, the earnings are equal to 0. The red dashed line shows the estimates for workers whose employer at $t^* - 1$ closes within the period $t^*0$ and $t^* + 5$. The black line represents the estimates for workers whose employer at $t^* - 1$ does not close the following five quarters after the event. Panel (b) presents the estimates for employment. A formal worker is defined to be employed in a quarter if they have at least one day of work recorded in RAIS. The x-axis reflects the quarter relative to the quarter in which the spillover event occurs. Wages are expressed in real terms (2018 CPI). Both panels report 95% confidence intervals based on standard errors clustered at the worker level.

**Figure A34:** Trends of Formal Employment and Earnings for Platform Workers

**(a)** Formal Employment

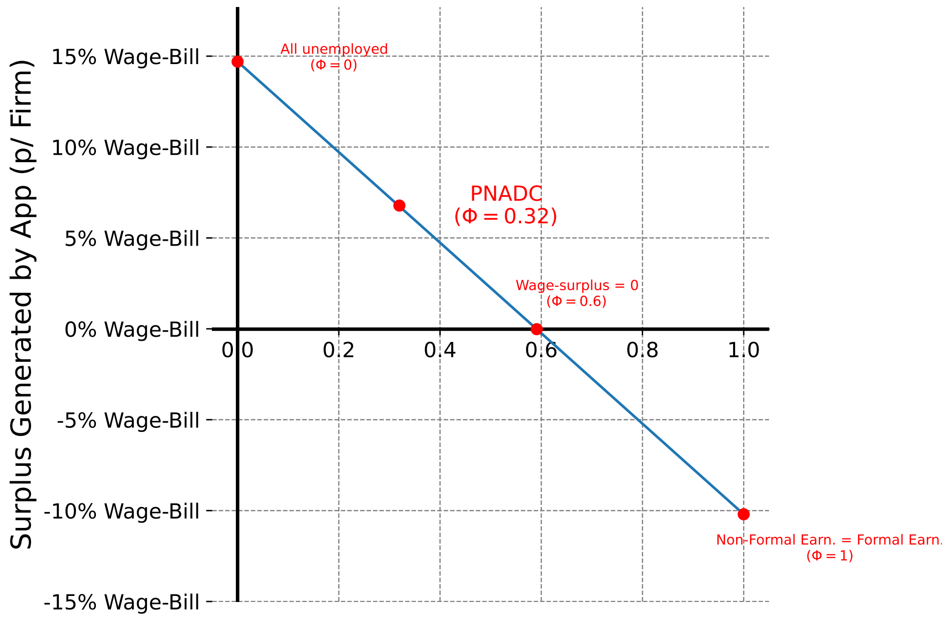



**(b)** Total Earnings Conditional on Worker Employed in $t^* - 1$




*Notes:* Panel (a) presents the trajectories of formal employment for workers who at some point in time work as delivery workers in the platform. A worker is defined as a platform worker if they did at least one delivery through the platform. The worker is considered to be formally employed in quarter $t$ if they are employed in the quarter for at least one day and they're employment is recorded in RAIS. The x-axis reflects the quarter relative to the first quarter in which the individual $i$ worked for the first time on the platform. Panel (b) reports the monthly earnings made in formal employment (red line) and on the platform (blue line) for workers that held a formal employment the quarter prior to working on the platform (and were not laid-off either in $t^* - 1$ or in $t^*0$). Wages are expressed in real terms (2018 CPI).

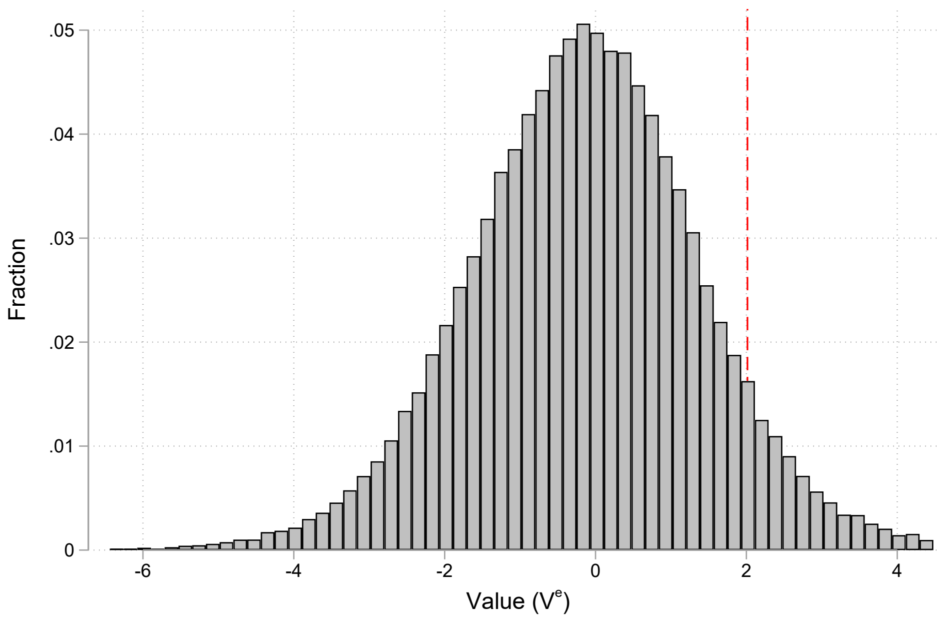
**Figure A35:** Total Wage Bill Effect from Platform Adoption as a Function of Non-Formal Platform Workers Outside Option




$$\Phi = \frac{Non - Formal\ Earnings}{Formal\ Earnings}$$

*Notes:* This figure reports the estimated total wage bill surplus generated by the platform as estimated using equation (12). The figure plots the wage bill surplus as a function of different outside options for app workers that did not hold a formal employment prior to working on the platform. Workers are considered to not have a formal employment prior to working on the platform if they did not have 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. The x-axis expresses the outside option for these workers as a share of the average hourly wage that platform workers that did have a formal employment prior to working on platform earned prior to working on the platform (Φ). The y-axis represents the surplus generated by each restaurant that adopts the platform as a percentage of the average quarterly wage bill of adopting restaurants the 4 quarters prior to offering delivery services through the platform (t*-7 to t*-2). The figure highlights four different points. All unemployed means that the outside option of platforms workers that did not hold a formal employment prior to working on the platform is 0. PNADC is the estimated outside option using the Brazilian household survey (PNAD-C). Wage-surplus equal 0 is the outside option for non-formal workers that makes the total wage bill surplus of the platform equal to 0. Non-Formal earnings equal to formal earnings means that the outside option of non-formal workers is the same as the outside option of formal workers.

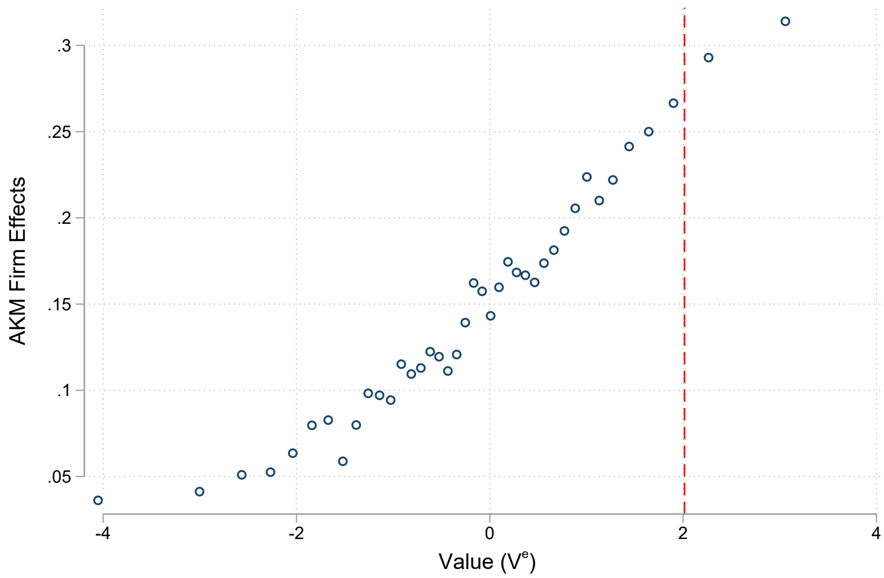
**Figure A36:** Histogram of Values ($V_j^e$) for all Restaurants



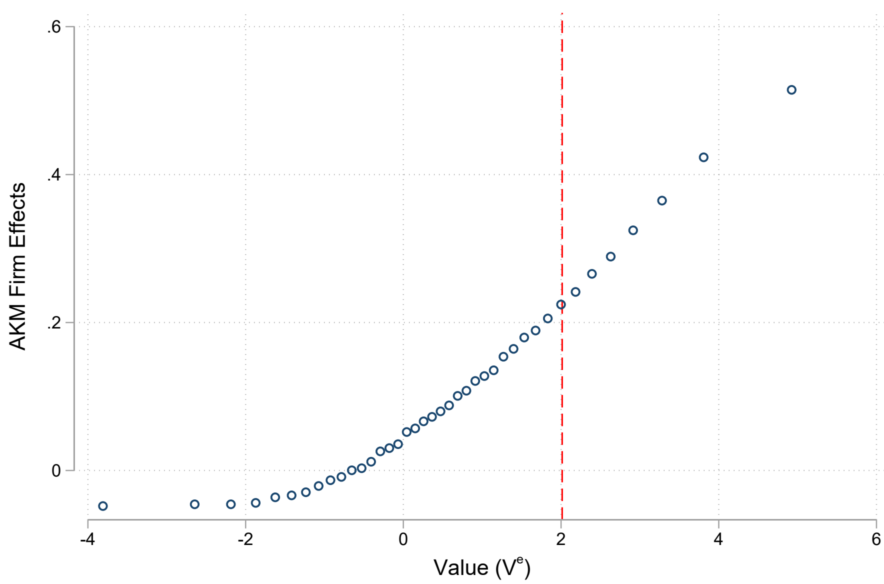

*Notes:* This histogram reports the distribution of $V_j^e$ for all restaurants in the sample for whom it was possible to estimate the value (30%). $V_j^e$ was estimated using the algorithm developed by Sorkin (2018) and represents the value of a firm. The average $V_j^e$ in the sample is -0.158. The red dashed line represents the $V_j^e$ of the delivery platform (2.014). This places the delivery platform in the percentile 93 of the distribution. Values $V_j^e$ are winsorized at the 0.05 and 99.5 level.

**Figure A37:** Relationship Between Values ($V_j^e$) and Earnings

**(a)** Restaurants




**(b)** All Establishments




*Notes:* This figure presents a binscatter plot of the relationship between the value of the AKM firm effects and firm $V_j^e$. Panel (a) presents the relationship for restaurants. Panel (b) presents the relationship for all establishments in the sample. The value of the firm $V_j^e$ was estimated using the algorithm developed by Sorkin (2018) and represents the value of a firm. The red dashed line represents the $V_j^e$ of the delivery platform (2.014). Both AKM firm effects and Values $V_j^e$ are winsorized at the 0.05 and 99.5 level. The Binscatter plots 40 bins.

## B Appendix: Tables

**Table B6:** Summary Stats Restaurant Workers (RAIS & Census)

| | (1) | (2) | (3) |
|---|---|---|---|
| | RAIS | Census (2010) | |
| | | Formal Workers | Informal Workers |
| Monthly Wage (2018 - R$) | 1,574 | 1,353 | 842 |
| | (686) | (2,831) | (860) |
| Age | 34.84 | 33.20 | 31.37 |
| | (11.50) | (11.29) | (13.35) |
| Share of Brazilians | 0.99 | 0.74 | 0.75 |
| Female | 0.56 | 0.56 | 0.60 |
| Hours | 42.84 | | |
| | (4.35) | | |
| Share of Black Workers | 0.06 | 0.09 | 0.09 |
| Delivery | 0.02 | 0.01 | 0.02 |
| Kitchen | 0.24 | 0.43 | 0.34 |
| Waiters | 0.53 | 0.29 | 0.43 |
| Other | 0.21 | 0.27 | 0.21 |
| Number of Workers | 1,795,250 | 94,559 | 59,115 |

*Notes*: Column 1 presents the summary statistics of restaurant workers in 2017 using data from RAIS. These statistics are weighted at the individual level. Column (2) and Column (3) present statistics for restaurant workers using the 2010 Brazilian Census (the latest census available). A worker is considered to be formal if they respond that they have a *Carteira de trabalho assinada* in their job. An individual is considered to work in a restaurant if they are working for an establishment that has a two digit CNAE industry code equal to 56. Definitions of occupations are presented in Table B8.

**Table B7:** Summary Stats for Platform 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*: Column 1 presents the summary statistics of individuals that at some point in time work as delivery workers in the platform. Statistics reflect the demographics at the first quarter in which the individual worked for the platform. Demographic information is only available for individuals who at some point in their career hold a formal employment. Unconditional formal earnings represents earnings that include zeros for individuals that are not employed in the formal sector. Workers in RAIS at some point, are workers that at some point in my sample hold a formal employment as reported in RAIS. Column 2 reports the performance on the platform for workers that the quarter prior to joining the platform held a formal employment (and were not laid-off either the quarter prior to joining the platform or the quarter in which they joined the platform). Column 3 reports the performance for workers that the quarter prior to joining the platform did not hold a formal employment. Hours online are hours in which the individual had the platform open (either in the background or actively using it). Hours worked are hours in which the individual was actively doing a delivery. Standard deviations are reported in parentheses.

**Table B8:** Crosswalk of Occupations from CBO to Waiters, Cooks and Delivery Workers

| CBO Code | CBO Definition | Occupation Crosswalk |
|---|---|---|
| 513405 | Waiter | Waiter |
| 513435 | Snack Bar Attendant | Waiter |
| 513505 | Food Service Assistant | Waiter |
| 513425 | Pantry Worker | Waiter |
| 521110 | Retail Salesperson | Waiter |
| 421125 | Cashier | Waiter |
| 513420 | Bartender | Waiter |
| 422105 | Receptionist | Waiter |
| 513415 | Busser (Assistant Waiter) | Waiter |
| 141510 | Restaurant Manager | Waiter |
| 271105 | Head Chef | Cook |
| 513205 | General Cook | Cook |
| 513215 | Industrial Cook | Cook |
| 513605 | Barbecue Cook | Cook |
| 513610 | Pizza Maker | Cook |
| 513615 | Sushi Chef | Cook |
| 841408 | Food Preserver (Conservation of Food) | Cook |
| 841416 | Meat Cooker | Cook |
| 841420 | Fruit and Vegetable Cooker | Cook |
| 848315 | Pasta Maker | Cook |
| 848310 | Confectioner | Cook |
| 848305 | Baker | Cook |
| 519110 | Motorcyclist for Document and Small Parcel Delivery | Delivery |
| 782310 | Van or Similar Vehicle Driver | Delivery |
| 782305 | Passenger Car Driver | Delivery |
| 782510 | Truck Driver (Regional and International Routes) | Delivery |
| 783225 | Driver's Assistant | Delivery |
| 782820 | Pedal Vehicle Driver | Delivery |

## C Appendix: Model

### *C1 Main Model: Derivations*

This section presents the derivations of the model discussed in Section 2. The model is a job posting model that builds on Card et al. (2018). I start by providing a microfoundation to the labor supply of each type of worker. I then derive the profit maximization problem for restaurants, and finally derive the comparative statics for waiters and cooks.

There are $J$ firms in the economy and two types of workers: cooks ($C$) and waiters ($W$). Each firm $j$ posts wages for both groups of workers. These wages are observed with no cost by the workers, and restaurants will hire any worker willing to work at the posted wage. Each firm offers a unique workplace environment for each type of worker, and workers have heterogeneous preferences of these environments. Specifically, the indirect utility of worker $i$ from working at firm $j$ is given by:

$$u_{i\aleph j} = \beta \ln\left(w_{\aleph j}\right) + a_{\aleph j} + \varepsilon_{i\aleph j} \tag{C13}$$

Where $\aleph = \{C, W\}$, $a_{\aleph j}$ is a restaurant specific amenity comon to each type of worker $\aleph j$, and $\varepsilon_{i\aleph j}$ is an idisosyncratic worker specific taste shock. As in Card et al. (2018), I assume that $\varepsilon_{i\aleph j}$ is distributed as a standard type-I extreme value distribution. Following McFadden (1972) the probability of a worker $\aleph$ working at firm $j$ is given by:

$$p_{\aleph j} = \frac{\exp(\beta \ln\left(w_{\aleph j}\right) + a_{\aleph j})}{\sum_{k=1}^{J} \exp(\beta \ln\left(w_{\aleph k}\right) + a_{\aleph k})} \tag{C14}$$

When assuming that the number of firms $J$ is sufficiently large—that is, abstracting from strategic interactions—, the probability of a worker $\aleph$ working at firm $j$ can be approximated by:

$$p_{\aleph j} \approx \tilde{\lambda_{\aleph}} \exp(\beta \ln\left(w_{\aleph j}\right) + a_{\aleph j}) \tag{C15}$$

Where $\tilde{\lambda_{\aleph}}$ is constant across all firms. Taking logs gives the labor supply presented in Section 2:

$$ln(\aleph) = \lambda_{j\aleph} + \beta\, ln(w_{j\aleph}) \tag{C16}$$

Where $\lambda_{j\aleph} = ln(\tilde{\lambda_{\aleph}}) + a_{\aleph j}$. In contrast to Card et al. (2018), I subtract from heterogeneity in labor supply and assume that the labor supply elasticity of cooks and waiters is constant and equal to $\beta$. The production function of each restaurant is given by:

$$Y_j = T_j\, C_j^{\alpha}\, S_j^{1-\alpha} \tag{C17}$$

$$S_j = [\theta W^{\rho} + (1-\theta) D^{\rho}]^{\frac{1}{\rho}} \tag{C18}$$

Where cooks and service workers are complements in production, where the output elasitcity is defined by $\alpha$. Within the service sector, waiters and delivery drivers operate through a CES function with elasticity of substitution equal to $\sigma = (1-\rho)^{-1}$ and relative productivity equal to $\theta$. The profit maximization problem for restaurant $j$ is given by:

$$\max_{w_W, w_C, D} P_{jl} Y_j - w_W W - w_C C - w_D D \tag{C19}$$

subject to the following constraints:

$$ln(W) = \lambda_{jW} + \beta\, ln(w_{jW}) \tag{C20}$$

$$ln(C) = \lambda_{jC} + \beta\, ln(w_{jC}) \tag{C21}$$

$$P_{jl} = P_{0jl} Y_j^{-\frac{1}{\epsilon}} \tag{C22}$$

Where $w_W$ and $w_C$ are the wages of waiters and cooks respectively and $P_{0jl}$ is the firm specific demand shifter for the good produced by firm $j$. Motivated by marignal number of delivery drivers in the data previous to online-delivery platforms, I start by assuming that pre-delivery platforms the $\theta \approx 1$. That is, that the productivity delivery drivers was essentially 0 previous to delivery platforms, and so restaurants would not hire them (neither through platforms or formally). Dropping the $j$ suscripts for simplicity, the first order conditions of the profit maximization problem for waiters can be expressed as:

$$(\xi_{p,y} + 1)\, P(Y)\, \frac{1}{\xi_{w_W} + 1}\, \frac{\partial Y}{\partial W} \tag{C23}$$

Where

$$\frac{\partial Y}{\partial W} = C^{\alpha}\, (1-\alpha)\, S^{-\alpha}\, [\theta W^{\rho} + (1-\theta)^{\rho}]^{\frac{1-\rho}{\rho}}\, \theta\, W^{\rho-1} \tag{C24}$$

Define $R$ as $P\ Y = P_{0l}\ Y^{\frac{\epsilon-1}{\epsilon}}$. Then pluggining equation C24 into equation C23 gives equation 6 of Section 2:

$$w_W = \underbrace{\frac{\beta}{1+\beta}}_{\text{Markdown}}\ \underbrace{\frac{\epsilon-1}{\epsilon}\, \frac{R}{S}\, \theta\, (1-\alpha) \left(\frac{W}{S}\right)^{\rho-1}}_{\text{MRPL}} \tag{C25}$$

Similarly, using the fact that that:

$$\frac{\partial Y}{\partial C} = \alpha C^{\alpha-1} S^{1-\alpha} = \frac{Y\,\alpha}{C} \tag{C26}$$

We get equation 7 of Section 2:

$$w_C = \frac{\beta}{1+\beta}\,\frac{\epsilon-1}{\epsilon}\,\frac{R}{C}\,\alpha \tag{C27}$$

To derive the comparative statics for waiters and cooks, define the difference between pre and post platform of $X$ as $\Delta X$. Taking logs, plugging in the labor supply of waiters and writing the post platform minus the pre platform FOC for waiters, we get the following:

$$\Delta \ln P_{0j} \; + \; \frac{\epsilon-1}{\epsilon}\,\Delta \ln Y + \frac{1-\sigma}{\sigma}\Delta \ln S + \Delta \ln \theta = \left(\frac{1}{\beta} + \frac{1}{\sigma}\right) \Delta \ln W \tag{C28}$$

Where I am using the fact that the amenities at the firm level $\lambda_j$ do not vary with the platform, and the labor supply elasticity is also fixed. This equation can be re-writte as equation 8 of Section 2:

$$\Delta\, ln(W) = \frac{\beta\sigma}{\beta+\sigma}\left[\underbrace{\underbrace{\Delta\, ln(V_S)}_{\substack{\Delta \text{ Revenue p/} \\ \text{Service Worker}}} + \frac{1}{\sigma}\underbrace{\Delta\, ln(S)}_{\substack{\Delta \text{ Service Sector} \\ \text{Size}}}}_{\textit{Product demand effect}} + \underbrace{\underbrace{\Delta\, ln(\theta)}_{\substack{\Delta \text{ relative productivity} \\ \text{waiters}}}}_{\textit{Outsourcing Effect}}\right] \tag{C29}$$

Where $V_s$ is the revenue per service worker $\left(\frac{R}{S}\right)$. The comparative statics for cooks can be derived in a similar way.

## *C2 Model Extension: Selection into Delivery Platform*

The setup of the model follows a similar structure to the model proposed in Section 2. The main difference respect to the baseline model is that the service sector now is not separated in delivery and waiters but instead in a continium of service workers that are indexed by their tasks index by $a$. Under this setup, the firms problem prior to adopting the platform is as follows:

$$\max_{w_{Sa}, w_C} P_{jl} Y_j - w_C\, C - \int_a w_{sa}\, s_a\, da$$

subject to

$$Y_j = T_j C_j^{\alpha} S_j^{1-\alpha}$$
$$S = \left[\int_a \theta_a \, s_a^{\rho} \, da\right]^{\frac{1}{\rho}}$$
$$ln(\aleph_j) = \lambda_{j\aleph} + \beta \, ln(w_{j\aleph})$$
$$P_{jl} = P_{0jl} Y^{-\frac{1}{\epsilon}}$$
$$\int_a \theta_a = 1$$

Where $\aleph = \{C, s_a\}$. That is, each task of service workers has their own labor supply to firm $j$ and has a relative productivity of $\theta_a$. Tasks in the service sector are assumed to have a certain degree of complementarity, such that the revenue function is supermodular.[70] The first order conditions for each task are analogous to the baseline case:

$$w_{sa} = \underbrace{\frac{\beta}{1+\beta}}_{\text{Markdown}} \underbrace{\frac{\epsilon-1}{\epsilon} \frac{R}{S} \, \theta_a \, (1-\alpha) \, \left(\frac{s_a}{S}\right)^{\rho-1}}_{\text{MRPL}} \tag{C30}$$

Similar to the baseline model, the adoption of delivery platforms shifts $P_0$—the product demand effect. However, under this setup the outsourcing effect has a different structure. Similar to Bilal and Lhuillier (2022), once adopting the platform, a restaurant can decide to outsource a task or hire it in-house. When outsourcing the task, the firm pays a fixed price of $w_O$ per outsourced worker and an idisyncratic cost of $1 \leq \varepsilon_a \leq \bar{\varepsilon_a}$, which may be correlated with firm productivity. That is, the profit maximization problem of the firm after adopting the platform is as follows:

$$\max_{w_{Sa}, S_a, O=\{0,1\}, w_C} P_{jl} Y_j - w_C \, C - \int_a \left[(1-O) \, w_{sa} + O \, P_O \, \varepsilon_a\right] \, s_a \, da$$

subject to

$$Y_j = T_j C_j^{\alpha} S_j^{1-\alpha}$$
$$S = \left[\int_a \theta_a \, s_a^{\rho} \, da\right]^{\frac{1}{\rho}}$$
$$ln(\aleph_j) = \lambda_{j\aleph} + \beta \, ln(w_{j\aleph})$$

[70] Supermodularity in the revenue function imposes strictly positive cross derivatives of the revenue function between $T$ and all types of service tasks, as well as between any two types of tasks. That is, it implies a form of complementarity between the firm level productivity and every type of task, as well as between any two types of tasks.

$$P_{jl} = P_{0jl} Y^{-\frac{1}{\epsilon}}$$
$$\int_a \theta_a = 1$$

As discussed in Bilal and Lhuillier (2022), under a supermodular profit function there is a firm productivity threshold for each task $T_a(\varepsilon_s)$ such that the minimum of the cost function is attained in-house for $T \leq T_a(\varepsilon_s)$ and attained outsourced for $T > T_a(\varepsilon_s)$. This is because the number of of workers hired in each task is increasing $T$. Given that firms face a positive labor supply curve for their in-house labor, $w_{Sa}$ increases in $S_a$, which implies that more productive firms pay higher wages to workers in $a$ and therefore have higher incentives to outsource and face a vertical labor supply curve instead. This threshold, however, is increasing in $\varepsilon_a$ as it is less profitable to outsource as the idiosyncratic cost of outsourcing increases.

For simplicity assume the tasks can be ordered such that all in-house tasks are $a_{\text{In-house}} = \{\underline{a}, \tilde{a}\}$ and all outsourced tasks are $a_O = \{\tilde{a}, \bar{a}\}$. Then the difference in in-house service workers before and after the adoption of the platform is given by:

$$\Delta s^{\text{in-house}} = \int_{\underline{a}}^{\tilde{a}} s_a^{\text{app}} \, da - \int_a s_a^{\text{no-app}} \, da \tag{C31}$$

Where $s_a^{\text{app}} = s_a^{\text{no-app}} + \Delta s_a$ and $\Delta s_a$ is the difference in the labor hired in-house in task $a$ before and after the adoption of the platform. This allows to decompose the difference in in-house labor in the following way:

$$\Delta s^{\text{in-house}} = \underbrace{\int_{\underline{a}}^{\tilde{a}} \Delta s_a \, da}_{\text{Product Demand Effect}} - \underbrace{\int_{\tilde{a}}^{\bar{a}} s_a^{\text{no-app}} \, da}_{\text{Outsourcing Effect}} \tag{C32}$$

Where the first term reflects the change in labor for the tasks that are still hired in-house and the second term reflects that certain tasks are now outsourced. The percentage change in labor demand for the tasks that are still hired in-house has the same structure as the product demand effect under the baseline model:

$$\Delta\, ln(S_a) = \frac{\beta\sigma}{\beta+\sigma} \left[ \underbrace{\Delta\, ln(V_S)}_{\substack{\Delta \text{ Revenue p/} \\ \text{Service Worker}}} + \frac{1}{\sigma} \underbrace{\Delta\, ln(S)}_{\substack{\Delta \text{ Service Sector} \\ \text{Size}}} \right] \tag{C33}$$

Under this model restaurants outsource not because the relative productivity of delivery workers increases with the platform, but because highly productive firms find it cheaper to outsource labor to the platform given their target size. The outsourcing effect reflects that the technology allows to switch from a positive labor supply curve to a competitive market for the tasks that are outsourced. The overall impact on in-house labor, however, will also depend on the product demand effect that depends additionally on the change in the revenue per worker and the size of the service sector as in the baseline model.

### *C3 Extension: Product Demand*

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).

The economy consist of a set of locations $l = \{1, 2..., N\}$, and a finite number of firms and consumers indexed by $j$ and $i$, respectively. Firms produce a differentiated good and consumers can purchase only one good. Consumers are assumed to all be located in some reference location $l'$. The model is static, but chain of events is as follows:

1. Consumers pick in which location to Search
2. Within each location, consumer pick which good to buy

The utility of consumer $i$ from consuming good $j$ in location $l$ is given by:

$$U_{ijl} = \left[\ln(\zeta_j) + \frac{1}{\epsilon}\varepsilon_{ij} - C_l - \ln(P_{jl}) + \mathbf{1}\{\text{App}_j > 0\}\ln(\eta_{jl})\right]\alpha \tag{C34}$$

Where $\zeta_{jl}$ is a measure of the quality of good $j$, $C_l$ is a variable that encapsulates the cost that all consumers face when searching in location $l$ for good $j$, $P_{jl}$ is the price of good $j$ in location $l$, and $\alpha$ is a taste shifter. $\eta_{jl}$ is a measure of the utility that ordering through the delivery platform provides to the consumer. This measure depends on the product that the restaurant sells and the location of the restaurant. Specifically, $\eta_{jl}$ increases as the distance between the average consumer and the restaurant increases. However, $\eta$ also will depend on the good produced by restaurant $j$. Consumers will gain more utility from some goods as they are available on the platform while they will gain less utility—or even potentially negative utility— from others.

For the rest of this section, I will assume the scenario in which restaurants have adopted the platform and so $\mathbf{1}\{\text{App}_j > 0\} = 1$. This is the direct effect of delivery platforms for restaurants that adopt. Lastly, similar to Vitali (2022), I assume that $\varepsilon_{ij}$ is an idiosyncratic taste shock that is distributed as a standard type-I extreme value, with $\epsilon$ governing its variability.

The cost term can be divided into two components:

$$C_l = ln\left(\underbrace{\tau_1\ g_1(\|z - z_l\|)}_{\text{Avg. Distance}}\right) + ln\left(\underbrace{\tau_2\ g_2\left(App_l, \frac{N_l}{ar_l}\right)}_{\text{Spillovers}}\right) \tag{C35}$$

The first component refers to the distance between the average consumer and the location of firm $j$. The second term reflects the fact that as the density of firms in location $l$ increases, the likelihood of buying from $j$ decreases due to larger competition. The function $g_2$ governing the relation between density and search costs also depends positively on the number of firms in the location that adopt delivery platform. Intuitively, as more firms in location $l$ offer services through delivery platforms, this crowds the market for the remaining firms in the location. This is the indirect effect of platform adoption. Finally $\iota_{jl}$ reflects an idiosyncratic individual specific search cost that is distributed according to a standard type-I extreme value distribution.

Prior to searching, consumers observe all product and location characteristics, but do not observe the match-specific values $\varepsilon_{ij}$. Given this information, they choose which location to visit. Upon visiting a location, consumers observe the match value and buy the product that gives them the highest utility. Conditional on being in a location, consumers must buy a product.

The decision to search in location $l$ is given by:

$$V_{il} = \mathrm{E}_{\varepsilon}\left[\max_{j\in l}\left\{U_{ijl}\right\}\right] = \alpha\frac{1}{\epsilon}\ \ln\ \left[\sum_{j=1}^{N_l} \exp\left(\delta_{lj}\ \epsilon\right)\right]\ -\ C_l +\ \gamma\ \alpha\ \frac{1}{\epsilon} \tag{C36}$$

With $\delta_{lj}\ =\ \ln\ (\zeta_{jl})\ +\ \ln\ (\eta_{jl}) -\ \ln(P_{jl})$ reflecting the mean utility of good $j$ for consumer $i$ in location $l$ and $\gamma$ being the Euler constant. The share of consumers that search for a good in location $l$ is given by:

$$S_l = \Pr(V_{il} > V_{il}^{'}, \forall l^{'} \neq l) \tag{C37}$$

$$= \frac{\left[\sum_{j=1}^{N_l}\ \exp\left(\delta_{jl}\ \epsilon\right)\right]^{\frac{1}{\epsilon}\alpha}\ \ \exp(-C_l)}{\exp(u_0) + \sum_{k=1}^{N}\left[\left(\sum_{h=1}^{N_h}\ \exp\left(\delta_{hk}\ \epsilon\right)\right)^{\frac{1}{\epsilon}\alpha}\ \ \exp(-C_k)\right]} \tag{C38}$$

Conditional on searching in $l$, the share of consumers buying good $j$ is given by:

$$S_{j|l} = \frac{\exp\left(\delta_{jl}\ \epsilon\right)}{\sum_{h=1}^{N_l} \exp\left(\delta_{hl}\ \epsilon\right)} \tag{C39}$$

Which gives the following unconditional share of consumers buying good $j$:

$$S_{jl} = S_l \times S_{j|l} \tag{C40}$$

$$= \frac{\exp\left(\delta_{jl}\ \epsilon\right)\ \left[\sum_{j=1}^{N_l}\ \exp\left(\delta_{jl}\ \epsilon\right)\right]^{\frac{1}{\epsilon}\ \alpha\ -\ 1}\ \exp(-C_l)}{\exp(u_0) + \sum_{k=1}^{N}\left[\left(\sum_{h=1}^{N_h}\ \exp\left(\delta_{hk}\ \epsilon\right)\right)^{\frac{1}{\epsilon}\alpha}\ \exp(-C_k)\right]} \tag{C41}$$

Re-arranging terms we then end up with a formulation that gives a foundation to the product demand presented in Section 2:

$$P_{jl} = \underbrace{\underbrace{(\mathrm{S}\Lambda)^{\frac{1}{\epsilon}}}_{\text{Macro Context}}\ \underbrace{\eta_{jl}}_{\text{Direct Effect of App}}\ \zeta_{jl}\underbrace{\left[\sum_{j'=1}^{N_l}\exp\left(\epsilon\ \psi_{l\,j'}\right)\right]^{\frac{1}{\epsilon}(\alpha\frac{1}{\epsilon}-1)}}_{\text{Quality in } l}\left[\underbrace{\frac{1}{C_{jl}}}_{\text{Search costs}}\right]^{\frac{1}{\epsilon}}}_{\mathrm{P}_{0jl}} Y_j^{-\frac{1}{\epsilon}} \tag{C42}$$

$$= P_{0jl}\ Y_j^{-\frac{1}{\epsilon}} \tag{C43}$$

Where I renamed $S_j$ as $Y_j$ to reflect that in equilibrium the demand equals production, and S$\Lambda$ is the denominator of equation (C40). This parametrization of the demand curve decomposes the demand for a restaurants good in four elements: (i) an overall macro-context that affects all restaurants in the economy, (ii) the direct effect of the adoption of the delivery platform, (iii) 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 (iv) 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 ($\iota_{jl}$), and the spillovers due to competing restaurants adopting the platform. In summary, under this framework, the introduction of online-delivery platforms can potentially mitigate search costs for adopting restaurants (if $\eta_{jl} > 0$), and increases search costs for non-adopting restaurants.

Finally, equation (C42) 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.

## D Appendix: Empirics

### *D1 Imputation of informality: restaurants*

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 then input to each restaurant in my sample the share of informal workers in the restaurant sector at the municipality level. This yields a per-restaurant share of informal workers. I estimate that the average restaurant in my sample has 25 percent of informal workers.

To recover the pre-treatment earnings of informal workers per restaurant I use the Brazilian household survey PNAD-C, which is representative at the state level. For each state and quarter I calculate the ratio informal wages to formal wages in the restaurant sector. I estimate that informal restaurant workers in my sample earn on average 70 percent of the wages of formal workers. Finally, I assume that the earnings effect (in percentage of their pre-event earnings) on informal workers is the same as for formal workers. This inputed effect, in combination with the number of informal workers calculated with the census and the earnings for informal workers calculated with PNAD-C, yields a per-restaurant earnings effect for informal workers.

### *D2 Estimation of Informal/Unemployed to Employed Wage Ratio*

To compute the wage ratio between informal/unemployed and employed platform workers, I use the Brazilian household survey PNAD-C. Given the large share of men among delivery drivers, I restrict the sample to men that are between 18 and 65. For employed workers, I keep individuals in PNAD-C with only 1 non-agricultural job. I define unemployed individuals as those that did not hold a job in the week of reference of the survey but answered that they were actively searching for a job. Within employed workers, I define a formal worker if they answer having a *Carteira de trabalho assinada* in their job, and informal if they don't.

I re-weight the sample of formal and non-formal workers in PNAD-C to match the distribution of age, education, race and gender of my sample of delivery drivers using the procedure developed by DiNardo et al. (1996). I then estimate the wage ratio between informal/unemployed and employed workers in the restaurant sector at the state-quarter level. The average adjusted wage ratio of informal/unemployed to formal workers in my sample is 0.32.

*D3 Imputation of Wage on Delivery Platform per Restaurant*

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 platform workers at 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 platform at each month/municipality. I overcome this limitation by calculating the average per hour earnings on the platform of workers in each month and municipality (weighted by the number of hours each platform worker worked in that month and municipality). I define the per hour wage on the platform for each worker as the total earnings they made in a month divided by 1.15 times the total hours they worked on the platform 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). To recover a per-restaurant wage-bill, I then multiply the average per hour wage in the corresponding municipality-month by the number of hours each restaurant utilizes delivery platforms in that period.

*D4 Procedure to Rescale Spillover Effects*

This sections provides the details of how I rescale the worker level effects of spillovers presented in Section 7.2 to reach the results presented in Column 4-6 of Table 5. I start by defining a spillover event as:

$$\mathbf{1}\left[\text{Spillover}\right] = \mathbf{1}\left[\Omega_{jt} > 95 \text{ percentile of } \Omega\right] \tag{D44}$$

Where $\Omega_{jt} = \chi_{jt} - \chi_{jt-1}$ and $\chi_{jt}$ is the share of restaurants within 1km that are enrolled in the platform in each quarter. I then estimate the effect of spillovers on workers earnings, as discussed in Section 7.2. The effect of spillovers on workers earnings is estimated using the following regression:

$$Y_{it} = \beta_0 + \alpha_i + \delta_t + \sum_{k=-7}^{k=5} \theta_k \mathbf{1}\{t = t^*(i) + k\} + \sum_{k=-7}^{k=5} \beta_k \mathbf{1}\{t = t^*(i) + k\} \times \mathbf{1}\left[\text{Spillover}_i\right] + \epsilon_{it} \tag{D45}$$

I then convert the spillover effects into units of $\chi_{jt}$ by applying a two-step procedure. First, I estimate the following regression:

$$\chi_{jt} = \beta_0 + \alpha_j + \delta_t + \sum_{k=-7}^{k=5} \gamma_k \mathbf{1}\{t = t^*(j) + k\} \times \mathbf{1}\left[\text{Spillover}_j\right] + \epsilon_{jt} \tag{D46}$$

where $\gamma_k$ provides the effect spillover events on the share of restaurants within 1km that are enrolled in the platform. The second step is to re-scale the estimated the effect of spillover events on workers earnings into units of $\chi_{jt}$:

$$\beta_{\text{rescaled\{k\}}} = \frac{\beta_k}{\gamma_k}$$

I then multiply each $\beta_{\text{rescaled\{k\}}}$ by the average $\chi_{jt}$ in my sample to get the average effect of spillovers on workers earnings. Finally, I multiply the average effect of spillovers on workers earnings by the average size of restaurants in my sample to get a per restaurant effect of spillovers which are the effects presented in Columns 4-6 of Table 5.

### *D5 AKM Estimation Details*

The AKM model builds on Abowd et al. (1999) to estimate the worker effects and firm effects in the data. To estimate the AKM model, I start by constructing an yearly panel of workers where log earnings reflect the average monthly earnings at the dominant employer in the year. That is, each worker is assigned to one employer in a year that reflects the employer that paid the largest total wages in the year to the worker. The model assumes that the log monthly wage paid to worker $i$, at firm $j$ in year $t$ is given by:

$$\ln y_{ijt} = \alpha_i + \psi_{j(i,t)} + \beta X'_{it} + \epsilon_{it} \tag{D47}$$

Where $\alpha_i$ is the worker fixed effect that is fully portable to every job the worker has, $\psi_{j(i,t)}$ is the firm wage premium which is specific to each firm (where $J(i,t)$ is an index indicating the workplace for worker $i$ at year $t$), $X_{it}$ is a vector of time-varying controls including a polynomial of age and year fixed effects, and $\epsilon_{it}$ is the error term.

If we assume that the conditional expectation of the error term $\epsilon_{it}$ in equation (1) is independent of the worker's job history (the "exogenous mobility" assumption), then estimating equation (1) using ordinary least squares (OLS) will provide unbiased estimates of establishment wage premiums. Several specification tests introduced by Card et al. (2013) and later applied in studies such as Card et al. (2016); Macis and Schivardi (2016); Song et al. (2019), indicate that wage changes among job movers in countries like Germany, Italy, Portugal, and the United States generally align with the exogenous mobility assumption. Furthermore, Gerard et al. (2021) test these specifications in Brazil using RAIS and find that the exogenous mobility assumption is also likely to hold in this setting.

To estimate the AKM model, I follow the leave-out procedure outlined by Kline et al. (2020). As AKM highlights, in a two-way fixed effects model, establishment effects are only identifiable across "connected sets" of workplaces that are tied together by the movement of workers between them. Therefore, I restrict my analysis to the largest connected set in my sample to ensure the identification of these effects.

Finally, if a worker did not work in the formal sector during my estimation, I impute their worker effects when possible. To input the worker effects, I leverage equation D47 and compute the worker effects at each year as:

$$\alpha_{it} = \ln y_{ijt} - \psi_{j(i,t)} - \beta X'_{it}$$

And then I average the worker effects across all the years in which the worker was employed in the formal sector such that:

$$\hat{\alpha}_i = \frac{\sum_{t=2012,2021} \alpha_{it}}{T}$$

### *D6 Estimation of Firm Values $V_j^e$ using PageRank*

In this section I present a summary of the algorithm utilized to estimate the firm valuation $V_j^e$ developed by Sorkin (2018). The starting point is to define the utility that a worker $i$ receives from working at firm $j$ as $u_{ij} = V_j^e + \varepsilon_{ij}$ where $V_j^e$ is a firm specific value that is common to all workers and $\varepsilon_{ij}$ is a worker specific idiosyncratic shock. I further assume that $\varepsilon_{ij}$ is distributed as a standard type-I extreme value. In a market with 2 firms, the likelihood that a worker favors firm $j$ over firm $k$ is given by: $\frac{\exp(V_j^e)}{\exp(V_j^e)+\exp(V_k^e)}$. When allowing for $N$ workers and defining $M_{jk}$ as the number of workers selecting firm $j$ over firm $k$, the following relation holds between employment choices and firm specific employment valuations: $\frac{M_{kj}}{M_{jk}} = \frac{\exp(V_k^e)}{\exp(V_j^e)}$.

When accounting for multiple firms $j \in J$, the condition described above imposes the following condition for each pair of firms:

$$M_{kj}\exp(V_j^e) = M_{jk}\exp(V_k^e), \ \forall\ j \in\ J \tag{D48}$$

Summing (D48) over all firms in the market, one arrives to the following expression:

$$\frac{\overbrace{\sum_{j\in J} M_{kj}\exp(V_j^e)}^{\text{value-weighted entry}}}{\underbrace{\sum_{j\in J} M_{jk}}_{\text{exits}}} = \underbrace{\exp(V_k^e)}_{value} \tag{D49}$$

which imposes a linear restriction for each firm $j$. As explained by Sorkin (2018), it is possible to solve for $V_j^e$ as a fixed point of a linear system and a unique solution exists for the set of strongly connected firms. Intuitively, equation (D49) follows the same logic as Google's PageRank algorithm in website searches. While in Google's case a good website is linked to other good webpages, in the labor market a good employer is defined as one that receives workers from other good employers while loses few employees to other firms. To estimate the value of working on the delivery platform (and the rest of the establishments in Brazil), I restrict to employer-to-employer transitions in the formal sector (or delivery platform) between quarters.[71]. This implies that I only measure the valuation of the delivery platform for workers who transitioned to (from) gig work from (to) the formal sector and earn their main income through the platform. The tradeoff is that while this is a restrictive group of transitions, it represents a group of workers for whom the gig job is somewhat comparable to a formal job.

To keep the analysis consistent, I consider the delivery platform in each microregion as a different establishment. Furthermore, similar to Sorkin (2018), I adjust $\exp(V_j^e)$ by the hours hired and by the share of unemployment-to-employment transitions that the establishment has. The adjustment is done to account for the fact that larger establishments will have more separations, while the share of unemployment-to-employment transitions adjusts for the job offer rates. [72]

### *D7 Estimation of the Effect of Delivery Platforms on Firm Entry*

This section describes the empirical design used to estimate the impact of delivery platforms on firm entry and provides some additional results. To measure firm entry, I use data collected from Cadastro Nacional de Pessoas Jurídicas (CNPJ), which is a database that contains information on the start of operations of all formal firms in Brazil. [73] Importantly, this dataset allows to

[71]A worker is considered to work for establishment $j$ in quarter $t$ if the main source of income during $t$ was from $j$.

[72]In contrast to Sorkin (2018), I use hours instead of firm size to make it comparable between the delivery platform and the rest of the establishments.

[73]This data is the same as used in Feinmann et al. (2022) and was kindly shared by the authors.

uncover firm entry even in the cases where the firm does not have any employees or all employees are hired informally. Figure A28 shows the histogram of the difference in quarters between firm opening and reporting employees in RAIS for the first time. Between 2015 and 2017, restaurants opened on average 3.6 quarters before reporting employees in RAIS for the first time. [74]

To study the impact of delivery platforms on firm entry, I leverage the staggered entry of the platform across microregions. Specifically, I estimate the following regression at the microregion:

$$Y_{m,t} = \alpha_m + \delta_t + \sum_{k=-7}^{k=5} \beta_k \mathbf{1}\{t = t^*(j) + k\} \times \text{Platform}_m + \gamma X_{m,t} + \varepsilon_{m,t} \tag{D50}$$

Where $Y_{m,t}$ is the number of restaurants (as estimated using CNPJ) that opened in the microregion $m$ in quarter $t$ and $\text{Platform}_m$ is a dummy variable that takes the value of one if the delivery platform ever entered microregion $m$ in my sample. The vector $X_{m,t}$ includes the covid cases per capita that each micoregion had in each quarter to control for the potential impact of covid. The coefficient of interest, $\beta_k$, captures the impact of the delivery platform on firm entry in each quarter $t^*(j) + k$ respect to the quarter prior to the entry of the platform. Similar to the baseline regression presented in Section 5, the identification assumption relies on the parallel trends assumption of firm entry across regions.

In addition to the results presented in Section 8 that suggest that platform availability affected positively the entry of new restaurants, it is possible that the composition of these restaurants may have changed as well. Figure A29 panel (c) and panel (d) show the (unweighted and weighted) estimates of equation (D50) when considering as an outcome the share of new restaurants that ever show up in RAIS. Both panels present similar results: there is no significant change in the likelihood of new entrants reporting in RAIS after the platform enters a microregion. Panel (e) and (f) investigate whether the average size of the new entrants that report employees in RAIS is different across treated and control microregions. Both panels show that there is no significant change in the average size of new entrants up to five quarters after the platform enters the microregion. In summary, the evidence suggests that the composition of these new restaurants in terms of their size (conditional on having at least one formal worker) and their likelihood of ever reporting a formal worker is unaffected by the availability of the delivery platform.

[74] 43 percent of all restaurants that opened between 2015 and 2017 never show up in RAIS, suggesting that a significant set of restaurants either never have employees or only hire employees informally.

### *D8 Geolocation details*

To geolocate restaurants in the data, I leverage the address of the restaurants and the name of the establishments available in RAIS. Importantly, the address is only available until 2020, and so I assume that restaurants do not change addresses when open in 2021. Specifically, the steps I take to geolocate the restaurants are the following:

1. I use the Google Maps API to obtain the latitude and longitude of the address of each restaurant.

2. For restaurants that met any of the following criteria:

    - More than one observation in the same latitude and longitude, with only a partial match for the address found in Google Maps,
    - Latitude and longitude were missing after the first geolocation attempt,
    - The geolocation type in Google Maps was approximate or corresponded to a geometric center.

3. For these cases, I attempted a second round of geolocation. This second attempt involved:

    - Geocoding the postal code and municipality
    - Running the places autocomplete API from Google Maps, using the original addresses but restricting the search to being within a radius of 20 kilometers of the geometric center of the postal code.
    - Using the predicted address to geolocate the restaurant again with the Google Maps API.

4. For those that have non-missing address after step 2 (90% of the observations), I compare the postal codes found in step 2 with the original postal code from RAIS. I drop the cases when these two postal codes do not match.

5. I finally combine the restaurants that geo-coded in step 1 with the restaurants that I was able to geocode in step 3, and that forms my final sample of geocoded restaurants.

Table D9 shows the share of restaurants in RAIS that I am able to find geocoded in each year using the procedure described above.

**Table D9:** Share of Restaurants that Geocode in Each Year

| | Share of Restaurants that are Geocoded |
|---|---|
| **2016** | 90% |
| **2017** | 91% |
| **2018** | 88% |
| **2019** | 88% |
| **2020** | 88% |

*Notes*: Restaurants are defined as those that have a CNAE code equal to 56.