

# 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:** Alternative Work Arrangements, 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 affects the fortunes of firms and workers (Bakos, 1997; Dolfen et al., 2023).<sup>1</sup> 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 allow 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 creating opportunities for low-income workers with limited outside options. Critics argue that these platform replace higher-wage, less insecure jobs with lower-wage, more insecure jobs.<sup>2</sup> Understanding how delivery platforms affect 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 regulators.

Measuring the effects of delivery platforms is empirically challenging because it requires information on both gig workers and the restaurants that adopt the technology, which is often not available in standard datasets. Moreover, adopting a new technology is a strategic decision that may correlate with productivity or demand shocks at the firm level. This self-selection makes it difficult to identify the causal effect of online-delivery platforms in settings in which 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 data set linking adopting restaurants and platform-workers to administrative employer-employee data I am able to uncover technological adoption by restaurants, the incumbent restaurant workers impacted by this adoption and the degree of substitution with gig workers. I exploit the staggered rollout of a large online-delivery platform 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 it. 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 incumbent restaurant workers are only modestly negative, as many workers that separate reallocate to new formal sector jobs. Addi-

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<sup>1</sup>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., 2025).

<sup>2</sup>For arguments in favor of the gig economy, see, for example, this article in *The Economist*, October 2018. For arguments against the gig economy, see, for example, this article in *The New York Times*, January 2024.

tionally, delivery platforms have spillover effects: They increase the likelihood that non-adopting restaurants will shrink or close. However, the net earnings gains for gig workers more than offset the losses for in-house restaurant workers. These effects not only affect total earnings but potentially shift the income distribution, as most gig workers were previously employed informally or unemployed.

Brazil is a particularly suitable setting to study who wins and loses from 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 significant portion of the labor market. Additionally, the country has a sizable gig economy, with 1.5 million people working through digital platforms and more than 600,000 of them working on online-delivery platforms (IBGE, 2022). Brazil's high levels of informality and unemployment create conditions in which delivery platforms may offer opportunities to workers with limited alternatives ([Ulyssea, 2020](#)).

I start by building 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 adoption of the technology influences demand for in-house workers. First, there is a *substitution effect*, in which the platform increases the productivity of delivery workers relative to substitutable in-house workers, such as servers, similarly to a skill-biased technological change. Beyond the impact on the marginal rate of technical substitution between servers and delivery drivers, the platform creates a *product-demand effect* by expanding the market reach of the adopting restaurant, which can increase overall demand for restaurant meals and, in turn, boost restaurant employment. The overall impact of the platform on in-house employment and wages is thus ambiguous, depending on the relative strength of these two forces.

Next, I empirically examine the effects of adopting online-delivery platforms on in-house employment, wages, and workforce composition. I begin at the market level, studying the impact of platform entry on the restaurant sector. Following entry, the formal restaurant sector contracts: the number of formal restaurant workers falls by 6 percent, and the number of establishments declines by 4 percent. By contrast, wages and new restaurant entry are largely unchanged. These market-level effects aggregate the responses of both adopting and non-adopting restaurants.

Exploiting the granularity of the data, I then focus on adopting and non-adopting restaurants separately to decompose the market level effects. I first document that restaurants that adopt 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-differences design that compares restaurants that adopt the platform to observationally similar restaurants located in regions where no platform is available at the time, thus mitigating concerns about self-selection into adoption. The identifying assumption is that matched treated and control restaurants would have exhibited similar trends in labor demand in the absence of platform adoption. Adopting

restaurants reduce the number of in-house workers by 6 percent a 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 substitution effect dominates the product-demand effect for the average adopting restaurant. These results are robust to using an early adopting sample not exposed to the Covid-19 pandemic and to using an alternative instrumental variable specification that instruments platform adoption with platform availability at the microregion level.

Does this mean the product-demand effect is irrelevant for all restaurants? I answer this question by studying heterogeneous effects of adoption on restaurants located in areas with high and low restaurant density. Establishments in low-density areas typically experience less walk-in traffic ([Leonardi and Moretti, 2023](#)) and therefore face limited reductions 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 percentage points 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 importance of the product-demand effect for restaurants in less central locations ([Overby and Forman, 2015](#); [Kitchens et al., 2018](#); [Couture et al., 2021](#)).

Online-delivery platforms might affect not only 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 one-kilometer radius of non-adopters. In line with the idea that adopting establishments crowd out non-adopting restaurants' demand ([Chava et al., 2024](#)), I find evidence that these platforms also affect restaurants that do not 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 restaurants are not on a stronger downward trend than adopters, indicating that preexisting conditions are unlikely to explain the effects.

I then leverage the granularity of my data to study the effect these platforms have on employment and earnings of 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 adopts 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. This low impact on earnings is explained by treated workers finding a new job at a quick pace: 75 percent of treated workers that separate find a new job by the fifth quarter after their former employer adopts a delivery platform.

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. The impact is larger because the risk of displacement is higher, as many non-adopting restaurants close. As a result, these workers' likelihood of remaining employed drops more sharply: One year after the shock, they are 3.8 percentage points less likely to be employed than control-group workers.

The reduced-form estimates indicate that online-delivery platforms have a persistent negative impact on the earnings of in-house workers at adopting restaurants and negative spillovers on workers at non-adopting restaurants. However, the earnings losses might not tell the full story. It is possible that the earnings gained by 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 all incumbent 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 a sum of earnings equivalent to 7.2 and 19.5 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 who voluntarily transition to 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 2.2 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 29.1 percent of the pre-platform wage bill. Summing the gains and losses across all groups, the total (worker) earnings effect per adopting restaurant is positive and represents 5.7 percent of the pre-platform average wage bill.

The average effects mask substantial heterogeneity arising from differences in the gender composition of workers. While more than 90 percent of delivery drivers in Brazil are men, approximately 60 percent of workers hired in the restaurant sector are women. This compositional difference translates into a pronounced divergence in overall impacts: as a share of the pre-platform restaurant wage bill, men gain approximately 28.4 percentage points more earnings than women

after platform adoption.

Though 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 because of these platforms' flexibility.

This paper contributes to several strands of the literature. First, it integrates research on online-delivery platforms into the broader literature on technology adoption. Part of this strand 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).<sup>3</sup> Firms play a crucial role in the diffusion of technologies, making the analysis of firm-level adoption particularly relevant (Griliches and Corn, 1961; Mokyr, 2003; Bloom et al., 2016).<sup>4</sup> 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).<sup>5</sup> Typically, these two dimensions of technological impact—labor and product demand—are studied independently. This paper bridges the gap by proposing a simple framework that decomposes the effects of technology 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, affects workers.

This paper also relates to the growing literature on the rapid growth of alternative work arrangements (Katz and Krueger, 2019) and, more specifically, the gig economy (Harris and Krueger, 2015; Fisher, 2022; Garin et al., 2023, 2025).<sup>6</sup> Previous research has examined the impact of ride-

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<sup>3</sup>Acemoglu et al. (2024) synthesize the literature and presents a framework showing how technological change can affect labor through changes in productivity, automation, or the creation of new tasks.

<sup>4</sup>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.

<sup>5</sup>Studying eBay, Dinerstein et al. (2018) show that search-ranking algorithms play a significant role in reducing consumer search frictions. Fang et al. (2024) find that search tools in e-commerce increase customer orders. More closely related to the setting in this paper, Zheng et al. (2023) show that a query recommender system on online-delivery platforms increases the probability that customers place a food order.

<sup>6</sup>In the US, the gig economy has been found to smooth consumption (Koustas, 2018) and alleviate the negative effects of job displacement (Jackson, 2022). Degenhardt and Nimczik (2025) show that in delivery platforms are associated with lower human capital investment for refugees.

sharing 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 (employee) jobs and gig roles. Unlike ride-sharing 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.<sup>7</sup> 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., 2025). 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 because high levels of informality and unemployment are high (Ulyssea, 2018). Notably, I find that the main benefits of online-delivery platforms accrue to workers who did not hold formal jobs when 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, 2025; 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 focus 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 to platforms while potentially shifting the demand for their products.<sup>8</sup>

### 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

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<sup>7</sup>Delivery platforms represent a form of domestic outsourcing that has not been studied extensively. Most micro-level evidence has focused on outsourcing events in which 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, 2025). Because of data limitations, there is limited evidence on 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.

<sup>8</sup>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.

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:

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

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

where  $\lambda_{\{C,W\}}$  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.<sup>9</sup> 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 interact through a cobb-douglas production function that has constant returns to scale. Waiters and 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 (see 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:

$$Y_j = T_j C_j^\alpha S_j^{1-\alpha} \quad (3)$$

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

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:

$$P_{jl} = P_{0jl} Y^{-\frac{1}{\epsilon}} \quad (5)$$

**Firms Profit Maximization Problem** Restaurants must choose between the three types of labor. Within a market  $l$  restaurants post wages for waiters and cooks and choose the

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<sup>9</sup>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.

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):

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

$$w_C = \frac{\beta}{1+\beta} \frac{\epsilon-1}{\epsilon} V_C \alpha \quad (7)$$

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

**Substitution 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 technical substitution (MRTS) 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.<sup>10</sup> I call this the *substitution 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

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<sup>10</sup>A microfoundation of the comparative advantages of firms that provide outsourcing services can be found in Bilal and Lhuillier (2021).

may face limited losses in in-house demand but can stand to gain significantly from the platform's expanded customer base. I call this potential shift in demand the *product demand effect*.<sup>11</sup>

### 2.3 Comparative Statics

The changes in labor demand for in-house waiters after a restaurant adopts an online-delivery platform depend on the relative magnitude of the product demand effect and the substitution 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:

$$\Delta \ln(W) = \frac{\beta\sigma}{\beta + \sigma} \left[ \underbrace{\Delta \ln(V_S)}_{\Delta \text{Revenue p/ Service Worker}} + \frac{1}{\sigma} \underbrace{\Delta \ln(S)}_{\Delta \text{Service Sector Size}} + \underbrace{\Delta \ln(\theta)}_{\Delta \text{relative productivity waiters}} \right] \quad (8)$$

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.<sup>12</sup> 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. Finally, the third term, the substitution effect, reflects the changes in the relative productivity between waiters and delivery workers. 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 substitution 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.<sup>13</sup>

The impact of the adoption of delivery platforms on the number of in-house cooks hired is

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<sup>11</sup>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 7.2, I provide suggestive evidence that this model is unlikely to hold.

<sup>12</sup>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.

<sup>13</sup>The product demand effect can be microfounded through the lens of a consumer search model, where platforms reduce search costs and these effects are different depending on the agglomeration forces (Vitali, 2022).

expressed as follows:

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

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.<sup>14</sup>

### 3 Setting

Online-delivery platforms operate as intermediaries in a contractual relationship between restaurants, consumers, and workers. Figure I 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 platform 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 at the time.

To work for an online-delivery service in Brazil, individuals must pass a background check and own a smartphone. Deliveries can be made by bicycle, motorbike, or car.<sup>15</sup> 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.<sup>16</sup>

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

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<sup>14</sup>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.

<sup>15</sup>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.

<sup>16</sup>This is in contrast with ridesharing workers, 60 percent of whose earnings are taxable. For more details, see: [this article](#).

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.<sup>17</sup> Restaurants must provide a tax identifier and, therefore, must be formally registered with the government to offer services through the platform.

The flipside of the delivery service industry is the restaurant sector. The restaurant sector represents approximately 4% of the private sector employment in Brazil. As most industries in Brazil, restaurants are exposed to meaningful levels of informality. In 2010—the latest available Census—, informal workers represented 38% of the total employment in the sector. As in most settings, information regarding informal workers is limited which constraints the main analysis of this paper to focus on formal employment and wages. However, in Section 7.5 I discuss how the results differ in low and high informality areas, while in Section 9 I use an imputation method based on information available in the census and household surveys to study the impacts of delivery platforms once considering non-formal workers in the restaurant sector.

The time covered by this paper includes the Covid-19 Pandemic. The pandemic had severe public health consequences in the country, such that by July 2021, Brazil had reported more than 19 million cases and 550,000 deaths (leaving it only behind India and the US). In contrast to other countries in the region, the Brazilian federal government expressed itself actively against a national lockdown and the closure of non-essential services generating disagreement between local authorities and the federal administration. Ultimately, public policy decisions related to social distancing and closure of non-essential businesses were taken at the state and municipal level, such that they varied in speed, intensity and duration.<sup>18</sup> These policies started in March 2020 and were short-lived: by September 2020, essentially no municipalities had active policies regarding the closure of non-essential services (Norden et al., 2021). In section 7.5 I discuss the robustness of my results using a subset of early adopters for which I can estimate the impact of the delivery platform prior to the pandemic.

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<sup>17</sup>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.

<sup>18</sup>A remarkable exception was the Provisional Measure N.1,045 (Emergency Program to Mantain Employment and Income) which was a short-time work policy that allowed companies to reduce working hours and wages if agreed with the worker or the collective bargaining unit.

## 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 B2 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.<sup>19</sup> platform-workers are on average 29 years old and predominantly 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 and for workers who did not hold a formal job prior to working on the platform, 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). Employers are required to submit yearly reports to the federal government detailing all formal job contracts established in the previous year. This information is used to calculate various benefits for both workers and firms. Com-

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<sup>19</sup>Demographic characteristics are only available for workers who at some point in their career held a formal job.

pliance 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 earnings, contracted hours, occupation, age, gender, education, and race. Importantly for the restaurant sector, monthly 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 earnings 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).<sup>20</sup>

**Descriptive Statistics: RAIS** Column (1) of Table B1 reports summary statistics for restaurant workers in RAIS during 2018.<sup>21</sup> The average formal restaurant worker in RAIS earned 1,574 BRL in 2018, significantly above the minimum wage of 954 BRL-2018.<sup>22</sup> 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 B1 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).

## 5 Impact of Delivery Platforms on Labor Markets

A natural starting point for understanding the implications of delivery platforms for workers and firms is to examine how the restaurant sector evolves as platforms become available. Figure A2 shows that as the delivery platform becomes available in a microregion, the mass of restaurants adopting the platform for delivery purposes increases every quarter, reaching 15 percent of

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<sup>20</sup>Formal employment represented 62 percent of all employment in Brazil in 2023. The vast majority of workers earn above the minimum wage (see Figure A6). However, it is possible that some may earn less due to low hours, suspensions, or leaves.

<sup>21</sup>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."

<sup>22</sup>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.

all formal restaurants in the region three years after entry.<sup>23</sup> To study the impact of the availability of delivery platforms formally, I exploit the staggered roll-out of the platform and estimate the following event-study specification:

$$Y_{mt} = \beta_0 + \gamma_m + \delta_t + \sum_{k=-7}^{k=5} \beta_k \mathbf{1}\{t = t^*(m) + k\} \times Platform_m + \epsilon_{mt} \quad (10)$$

Here,  $\gamma_m$  are microregion fixed effects,  $\delta_t$  are time fixed effects, and  $Platform_m$  is a dummy equal to 1 if the platform ever entered market  $m$ . The coefficients  $\beta_k$  are the parameters of interest, capturing the dynamic effects of platform availability. I exclude microregions where the platform was available before 2018 (because I can not define an exact entry date) and those where entry occurred between December 2020 and December 2021 (the end of my sample period) to maintain a balanced sample. Identification relies on the assumption that, absent platform entry, treated and control markets would have followed parallel trends.

As a first check, I estimate a logit model of the probability that a platform ever enters a microregion on baseline characteristics (in 2018) of the restaurant sector and the pre-entry trends:

$$Pr(\text{Platform Ever Available} = 1 | X_i) = \Lambda(X'_i \beta) \quad (11)$$

Appendix Table B3 reports the results. Unsurprisingly, larger restaurant sectors (and higher levels of education) predict entry, while average tenure is negatively correlated. By contrast, pre-trends in sector outcomes do not predict entry, suggesting that platform decisions are driven by levels rather than trends.

Figure II presents the event-study estimates from equation (10) for total workers (panel a), average monthly wages (panel b), number of establishments (panel c), and new firm entry (panel d) in the restaurant sector.<sup>24</sup> Consistent with the logit results, there are no visible pre-trends prior to platform entry. After entry, however, both the number of formal workers and establishments decline, suggesting that the formal restaurant sector contracts when delivery platforms become available. Five quarters after entry, the number of workers falls by about 400 (6% of the pre-treatment average) and the number of establishments falls by about 40 (4% of the pre-treatment average). By contrast, average monthly wages and new restaurant entry remain unaffected.<sup>25</sup>

The contraction of the formal restaurant sector reflects the combined effects of platform adoption on both adopting and non-adopting restaurants. In the next sections, I use the granularity of

<sup>23</sup>This share essentially doubles when I don't restrict that at least 50 percent of the revenues that the restaurant generates on the platform must be through delivery services.

<sup>24</sup>Appendix A3 shows that the results are robust to the difference-in-differences estimator of Borusyak et al. (2024).

<sup>25</sup>Firms included in RAIS must have a tax identifier and at least one formal employee. Anecdotal evidence suggests that delivery platforms have facilitated the rise of “dark kitchens”—establishments that operate exclusively through delivery without in-house dining (Globo, 2022). If these establishments are informal or never hire formal workers, they will not appear in RAIS.

the data to disentangle these forces.

## 6 Impact of Delivery Platforms on Workers and Firms: Research Design

This section discusses the research design to estimate the causal effect of online-delivery platforms on restaurants' labor demand and incumbent workers' labor market outcomes.

### 6.1 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.<sup>26</sup> 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, in my baseline specification 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. In Section 7.5 I discuss an alternative research design that instruments adoption with the availability of 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 platform revenues using delivery services.<sup>27</sup> 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 minimize multihoming. 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 enrolled at least five quarters before the end of my sample period.

To build an appropriate comparison group, I use a matching procedure.<sup>28</sup> The potential control

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<sup>26</sup>Figure A1 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.

<sup>27</sup>The restaurants that meet this criterion represent 36 percent of all establishments that enrolled on the app between 2018 and 2021.

<sup>28</sup>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.

group of establishments includes restaurants located in labor markets where no online-delivery platform technology was available up to the time of treatment (neither the platform studied or competitors), and where the platform did not enter for at least five quarters after treatment.<sup>29</sup> 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 monthly wages among restaurants in the year. Additionally, to ensure that treated and control restaurants face similar competition, I calculate the number of competing restaurants that each restaurant faces within a 1 kilometer radius and assure that both treated and control are within the same median of number of competitors.<sup>30</sup> 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 monthly wages 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 wages 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 wages 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:

$$Y_{\{j,i\}t} = \beta_0 + \alpha_{\{j,i\}} + \delta_t + \sum_{k=-7}^{k=5} \theta_k \mathbf{1}\{t = t^*(j) + k\} + \sum_{k=-7}^{k=5} \beta_k \mathbf{1}\{t = t^*(j) + k\} \times Treated_{\{j,i\}} + \epsilon_{\{j,i\}t} \quad (12)$$

Here,  $Y_{jt}$  represents the outcome of interest (e.g., average monthly 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.<sup>31</sup>  $\mathbf{1}\{t = t^*(j) + k\}$  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 effect of establishment enrollment on the platform on the outcome of interest.

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<sup>29</sup>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).

<sup>30</sup>I normalize the number of competing restaurants by the total number of restaurants in the micro region to take into account differences in market size.

<sup>31</sup>In the matched sample, control restaurants are assigned the treatment date of their matched treated pair.

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.<sup>32</sup> 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 monthly 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 IV. Both average wages 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 monthly 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 A4 shows no discrete increase in the likelihood of nearby restaurants (within 1 km) adopting the platform after a treated firm adopts the platform. Relatedly, an additional 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 adopted the platform before January 2019 and therefore I can observe their post-adoption outcomes up to five quarters prior to 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 municipality of the treated establishment

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<sup>32</sup>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.

(Chauvin, 2021).

## 6.2 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.<sup>33</sup> 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 that are exposed to a large sudden increase in the adoption of their competitors, such that they belong to 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 A5 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 (12).

## 6.3 Research Design: Workers

This section provides an empirical strategy to estimate the causal effect of online-delivery platforms on restaurant workers' labor market outcomes. 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 was available at the time of treatment (and up to five quarters after treatment).

**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. As with the restaurant analysis, I restrict the sample to workers who are treated up to five quarters prior to December 2021. Additionally, I impose a requirement that these workers must have at least two quarters of tenure at the time

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<sup>33</sup>No restriction is imposed on the posterior probability of adopting the platform to avoid conditioning on an outcome.

that their employer adopts the platform.<sup>34</sup> For each cohort (quarter  $\times$  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, quartile of firm size and average firm monthly wage. Following the firm design, both treated and control workers must also be within the same median number of restaurants within a 1km radius in the workers micro-region.<sup>35</sup> I use one-to-one matching without replacement within each cohort using a caliper algorithm (Stepner and Garland, 2017). Matching variables include monthly earnings in  $t^* - 4$  to  $t^* - 1$  (with a bandwidth of  $\pm 200$  BRL), age (with a bandwidth of  $\pm 2$  years), and tenure (with a bandwidth of  $\pm 1$  quarter).

**Econometric Framework** I estimate the effect of employer platform adoption on incumbent restaurant workers' labor market outcomes by estimating equation (12) 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.  $1\{t = t^*(i) + k\}$  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  $\beta_{-2}$  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. Figure VIII provides evidence that both targeted and non-targeted moments in the matching display parallel trends prior to treatment.

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

This section discusses the impact that online-delivery platforms have on restaurants' labor demand.

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<sup>34</sup>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.

<sup>35</sup>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.

## 7.1 Effects of Adoption of the Platform

**Descriptive Evidence** Columns (1) and (2) of Table I 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 higher monthly wages.<sup>36</sup>

Figure III 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 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 IV panel (b) shows the trajectories for log average monthly wages paid to employees at treated and control restaurants. Both groups exhibit similar trends in wages 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 20 log points for treated and control establishments. This pattern suggests that treated establishments may start making adjustments the quarter prior to enrollment in the

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<sup>36</sup>Figure A7 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). 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 monthly wages for all their workers. AKM firm fixed effects also have predictive power for the intensive margin. Figure A7 panel (b) shows a positive correlation between the AKM firm fixed effects and the number of hours platform drivers work for each restaurant. Appendix D6 presents details on the AKM estimation.

platform, which motivates using  $t^* - 2$  as the baseline in the event study analysis.<sup>37</sup>

Panel (a) 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 18 log points for treated establishments and 12 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.

The decline in size for both treated and control is likely a reflection of the lifecycle of restaurants (which are imposed to be open the two years prior to treatment). Panel (c) illustrates the trends for the extensive margin of restaurants. Five quarters after the event, approximately 12 percent of the restaurants in the sample have closed, highlighting the high turnover in the sector. To investigate these patterns formally, I present the estimated results for the regression model in the next section.

**Effects of Platform Adoption on Size, Hours and Wages** Figure IV panel (d) presents the estimated  $\beta_k$  from equation (12) 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 V shows the estimated effect of platform adoption on the log number of hours worked by in-house workers (red line) and the log number of hours including platform-workers (blue line).<sup>38</sup> 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 gig workers. The total number of hours worked at the establishment, when including platform workers, is essentially unchanged five quarters after enrollment.

Figure IV panel (e) plots the effects of platform adoption on average monthly wages paid by 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. Although the estimates are

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<sup>37</sup>It is important to note that the reduction is in real average monthly wages of workers working at the establishments. RAIS reports hours contracted and monthly wages. The reduction in average worker wages across both treated and control is likely associated with the short-time work policy that allowed for hours reduction during Covid. Appendix Figure A8 splits the monthly wage trajectories for firms adopting prior to January 2019 and after, and finds that only treated and control exposed to Covid present this dip in wages paid.

<sup>38</sup>App worker hours are measured as the time a platform driver dedicates to delivering food from a specific establishment.

somewhat imprecise, the decrease seems to persists during the post-enrollment period such that average wages are approximately 2 percent lower between  $t^* + 1$  and  $t^* + 4$  for treated establishments and only seem to recover in  $t^* + 5$ . Although the impact on the extensive margin is marginal (1.5% as shown in panel f), these estimates let alone are hard to interpret as they may reflect a combination of compositional changes in occupations and a highly elastic labor supply, which I analyze in the next section.<sup>39</sup>

## 7.2 Effects by Occupation

This section presents the effects of platform adoption on labor demand for each occupation. I start by examining the change in the overall service sector (that is, all workers who are not cooks, including platform workers). Figure A11 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 II presents difference-in-difference estimates on hours hired and monthly wages by occupation 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 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 point estimates in Column (3) indicate that restaurants that did have delivery workers prior to adopting the app decrease the number of in-house delivery drivers by 8.8 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, through the lens of model presented in Section 2, 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 changes in the relative productivity between waiters and delivery workers—the substitution effect. Taken together, columns (1) and (3) suggest that the adoption of online-delivery platforms allows the average restaurant to shift its business

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<sup>39</sup>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 A10 panel (a) plots the effect of platform enrollment on the average worker fixed effects at the establishment and finds a null effect. Figure A10 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.

from in-house dining to delivery services without a clear effect on the product demand for the goods produced by adopting restaurants.<sup>40</sup>

Column (4) reports the effect of platform adoption on the monthly wages of waiters. On average, the wages of waiters decrease by 2.25 percent after platform adoption. 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 substitution 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 substitution effect from the product demand effect.<sup>41</sup>

### 7.3 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 substitution effect across local areas, the difference in the effect of platform adoption on in-house labor between areas with high and low density of restaurants 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). 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.<sup>42</sup>

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

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<sup>40</sup>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 substitution 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 A12, 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 an average negative correlation, but a positive correlation for a set of establishments.

<sup>41</sup>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.

<sup>42</sup>Intuitively, restaurants with lower baseline demand stand to gain the most from platforms, as they can reach new customers in previously inaccessible markets. By contrast, restaurants with higher initial demand are less likely to benefit as much, since platform adoption may simply shift consumption from in-house dining to delivery, resulting in little net change in overall demand.

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.<sup>43</sup>

The next step is to study whether there are heterogeneities in the substitution effect across locations. Although there are no strong ex-ante reasons to presume that the number of surrounding restaurants would impact the substitution effect, I compare the share of the wage bill and hours that delivery workers represent relative to in-house waiters in high- and low-density areas.<sup>44</sup> Figure A13 shows that the ratio of delivery over in-house waiters for both wage bill and hours is essentially the same across restaurants located in high- and low-density areas, suggesting that location is independent of the substitution effect.

I proceed to plot the effects of adoption on firm size and total hours (including platform workers) by restaurant density. Figure VI 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 that the large differences persist when considering the hours of 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 III presents the results for waiters and cooks separately. Column (1) shows that the hours hired of waiters at restaurants in high-density areas decrease by 7.2 percent after platform adoption. In contrast, column (3) reports that the effect on the hours of waiters at restaurants in less dense areas are not significantly different from zero. Consistent with the overall effect on hours, the hours of cooks are not significantly different from zero for restaurants in high-density areas (column 2), while the hours hired of cooks increase by 7.6 percent for restaurants in less dense areas (column 4), suggesting an overall increase in the product demand for the latter group after platform adoption.

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<sup>43</sup> Appendix D8 describes the steps taken to geolocate the restaurants in Brazil and the share of restaurants I was able to geolocate per year.

<sup>44</sup>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 waiters should identify the differential change in the ratio of productivities between the two types of workers:

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

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 similar 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).

#### 7.4 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 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). 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 6.2, 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 VII panel (a) shows the trends in firm size for firms exposed to a spillover event and their matched pairs. Panel (b) shows the equivalent trajectories for the average monthly wages paid by non-adopting restaurants. Prior to the event, non-adopting firms do not appear to experience a larger negative shock than adopting restaurants (as reported in Figure IV), suggesting that restaurants are not selecting into earlier adoption based on their ex-ante trends.<sup>45</sup>

Figure VII panel (d) 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. This negative effect on firm size is not persistent over time; five quarters after the event, the effect on firm size is essentially null. Panel (e) shows a slight decrease in average monthly wages of approximately 2% after 5 quarters. However, these patterns in firm size and wages are potentially influenced by changes in composition due to firm closures. Panel (c) and (f) show that restaurants exposed to a large share of neighbors adopting the technology are 5 percent more likely to close within five quarters of the event compared to control establishments. Taken together, these results suggest that restaurants adopting online-delivery platforms may crowd out demand for non-adopters, leading to a decrease in their size and a higher likelihood of closing.

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<sup>45</sup>Recall that I do not condition on post-event adoption of the platform. Approximately 7 percent of the ex-ante non-adopting restaurants adopt the delivery platform within 5 quarters following the spillover event. Table B5 presents the summary statistics for restaurants exposed to spillover events and matched control restaurants.

## 7.5 Robustness

**Alternative Estimators** First, following the recent difference-in-difference literature with staggered treatment, Figure A14 shows that the estimated effects of platform adoption on monthly wages and firm size are robust to the estimator proposed by [Borusyak et al. \(2024\)](#). This consistency is expected, since the control establishments are drawn from regions where the platform is not available and therefore are never exposed to treatment ([Roth et al., 2023](#)).

**Availability of the Platform as an Instrument for Adoption** Platform adoption is a strategic decision, so unobserved shocks among adopters may bias the estimates even when the control group is observationally similar and never exposed to the technology. To address this concern, Appendix D1 presents an instrumental variable strategy that uses platform availability at the microregion level as an instrument for firm-level adoption.<sup>46</sup> This approach involves a trade-off: while platform availability is exogenous to individual firms, the exclusion restriction may be violated due to market-level spillovers. Building on the results in Section 7.4, these spillovers are expected to bias the IV estimates of firm size downward. Consistent with this, the 2SLS estimates in Table B4 indicate a 21% decline in in-house firm size among compliers (i.e. restaurants whose adoption is moved by availability timing), with no detectable effect on average monthly wages.

**Covid** The period of consideration overlaps with the COVID-19 pandemic, raising external validity concerns. 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 A15 the establishment-level treatment effects on size (and wages) and the change in the number of COVID-19 cases per capita in the post-period. The figure shows that treatment effects 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 A16 shows that, if anything, establishments that adopt prior to the pandemic decrease even more their in-house size. 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 A17 shows that the results are not sensitive to the inclusion of these fixed effects.

**Informality** An additional feature of the Brazilian setting is related to the relatively high levels of informality 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

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<sup>46</sup>This research design is similar to what has been used to study the impact of broadband internet on productivity ([Akerman et al., 2015](#)).

changes in labor demand are not observed in RAIS (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 the matched sample into groups above and below the median of informality. Figure A18 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.<sup>47</sup> When considering the overall effect of the platform on workers in Section 9, I will account for the possibility that adoption of the delivery platform also affects informal workers.

## 8 Restaurant Workers

The results presented in Section 7 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 incumbent 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 9, where I assess the overall effects of delivery platforms by examining both incumbent restaurant workers affected by adoption and spillovers, as well as the impact on gig workers, providing a comprehensive view of the winners and losers.

### 8.1 Main Results: Effect of Employer Adoption on the Platform

**Summary Statistics** Table IV presents summary statistics for matched control workers (Column 1), matched treated 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 59 percent female workers. In terms of occupations, 67 percent of the matched workers are waiters, 18 percent are cooks, and the remaining 15 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.

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<sup>47</sup>This evidence is suggestive as treatment effects may also systematically differ across regions due to differences in the product demand effect, for example.

**Trajectories of Treated and Control Workers** Figure VIII 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. 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 VIII Panel (b) presents the estimated  $\beta_k$  from equation (12) for 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.<sup>48</sup> Panel (d) 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.

Figure A19 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 adopts the platform. These estimates reflect the worker-side dynamics of what is shown in Figure IV panel (d), 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 VIII panel (d), these results suggest that a significant share of

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<sup>48</sup>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).

restaurant workers leave their job as their employer adopts the platform but manage to find a new formal job relatively quickly afterward. Figure A19 panel (b) supports this hypothesis: approximately 75 percent of the workers whose separation is caused by the platform adoption 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 A20 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 workers 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 9.

## 8.2 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 7.4 discussed the spillover effects of platform adoption by nearby restaurants on non-adopting establishments, showing that non-adopting restaurants are more likely to downsize in the short-run and close. Figure IX panel (b) presents the estimated results of equation (12) 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 6.2.<sup>49</sup> The results show that workers at non-adopting restaurants experience on average 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 percentage points less likely to be employed in the formal sector in the quarter following the event, with the negative impact persisting and increasing to

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<sup>49</sup>Panels (a) and (c) display the raw means for matched treated and control restaurants. Table B6 presents the summary statistics for incumbent restaurant workers whose employer is exposed to a spillover event and matched control workers.

3.8 percentage points after five quarters.

The stronger impact on earnings and employment is driven by the larger fraction of non-adopting restaurants that close. Figure A21 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 (92 percent of the matched sample) see their earnings decrease by approximately 2.6 percent five quarters after the event. 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 in magnitude than the direct effects of employer adoption due to restaurant closures. The next section examines the trade-offs of online-delivery platforms, factoring in platform workers.

## 9 Winners & Losers

In this section, I decompose the total effect of online-delivery services on workers' earnings by considering incumbent restaurant workers and incoming gig workers. Following the discussion in Section 8, 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.<sup>50</sup>

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. Specifically, for each adopting

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<sup>50</sup>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.

restaurant  $j$ , I conduct the following accounting exercise:

$$\underbrace{\pi_{\text{app}}^j}_{\substack{\text{Total Wage-Bill Effect} \\ \text{App}}} = \underbrace{\pi_{\text{in-house}}^j}_{\substack{\text{Wage-Bill Effect} \\ \text{In-House Workers}}} + \underbrace{\pi_{\text{spillovers}}^{k \neq j}}_{\substack{\text{Wage-Bill Effect} \\ \text{Spillovers}}} + \underbrace{\pi_{\text{app-workers}}^j}_{\substack{\text{Wage-Bill Effect} \\ \text{App-Workers}}} \quad (13)$$

The wage bill effect is calculated as the sum of total earnings effects for each group of workers, multiplied within each group 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 V 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 2,878 BRL (in 2018 Reais). This amount represents 5.3 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 5.0 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 8.2 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 adopting restaurant. I then multiply this adjusted coefficient by the average restaurant size in my sample and scale it by the probability of a restaurant being exposed to a spillover event.<sup>51</sup> The cumulative discounted present value of spillovers per adopting restaurant, calculated over five quarters after starting delivery services, is -9,281 BRL (2018 Reais), which is equivalent to 17.0 percent of the pre-platform wage bill of these restaurants. When netting out contributions, the effect reduces to 15.6 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. Figure A22 panel (a) presents trends in formal employment for workers before and after they start on the platform. Seven quarters before their first delivery, 27 percent of drivers held formal jobs. This

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<sup>51</sup>For full details on this re-scaling procedure, see Appendix D2.

drops to 21 percent at the time of their first delivery, then slightly recovers to 23 percent after five quarters.<sup>52</sup> 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 information collected from surveys and previous studies reported in Callil and Picanço (2023) for the maintenance and transportation cost of delivery drivers, who estimate a cost of 3.7 BRL-2018 per hour worked.

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 earnings, implying that their formal sector hourly earnings would be available to them had they not worked for the delivery platform.<sup>53</sup> For the second group, I re-weight the workers in PNAD-C such that the distribution of their demographics match those of platform workers (DiNardo et al., 1996), and use the corresponding re-weighted wage of non-formal workers in each state and quarter to input the outside option of platform workers. Details of the construction of the outside option are provided in Appendix D3.

Specifically, I define  $\pi_{\text{app-workers}}^j$  the following way:

$$\pi_{\text{app-workers}}^j = H_{\text{app-workers}}^j \times W_{\text{app-workers}} - \zeta_{\{F,NF\}} - \kappa \quad (14)$$

Where  $H_{\text{app-workers}}^j$  are the hours restaurant  $j$  uses platform delivery workers,  $W_{\text{app-workers}}$  is the hourly earnings of delivery workers,  $\zeta_{\{F,NF\}}$  is the outside option of platform workers who transition from the formal sector ( $F$ ) and non-formal sector ( $NF$ ), and  $\kappa$  are their maintenance costs.

Table V Column (7) reports the average wage bill—per adopting restaurant—of platform-workers who held a formal job prior to working on the platform.<sup>54</sup> These workers made, on average, a cumulative present discounted value of 5,087 BRL (2018), equivalent to 9.3 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 earnings as the opportunity cost for these workers, the cumulative present discounted value decreases to 1,197 BRL (2018), equivalent to 2.2 percent of the pre-adoption wage

<sup>52</sup>Figure A22 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).

<sup>53</sup>I consider this to be conservative as it implies that workers who are transitioning voluntarily from the formal sector and are increasing their total hours are not hours constrained. If indeed workers were hours constrained, the benefits from the delivery platform for this set of workers should be considered as a lower bound.

<sup>54</sup>A limitation of my data is that I do not observe which worker delivered for each restaurant at a specific time. Instead, I observe the earnings per hour of each worker and the total number of hours that each restaurant used the app's delivery services at each month/municipality. I impute the hourly earnings of app workers for each restaurant by using the averages at the municipality/month level. Appendix D4 discusses the details of this imputation.

bill.

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 25,204 BRL (2018 Reais), equivalent to 46.1 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 15,892 BRL (2018), equivalent to 29.1 percent of the pre-adoption wage bill of restaurants.

Taken together, when considering the total effect of the delivery service on workers' earnings, I find that the platform generates a surplus equivalent to 10.6 percent of the average pre-adoption wage bill of restaurants. Put differently, the gains for delivery workers (net of their costs) are 52 percent larger than the combined direct and indirect impact on formal restaurant workers.

### 9.1 *Discussion & Limitations*

**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 PNAD-C to impute the number of informal workers per restaurant (see Appendix D5 for details on the imputation procedure). I estimate that approximately 25 percent of the workforce in each restaurant is informal. Column (3) shows that the negative effects on informal workers at adopting restaurants represent 1.2 percent of the pre-adoption wage bill. 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 negative effect on informal workers represents 3.9 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 5.7 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, who are likely smaller than formal firms ([Ulyssea, 2018](#)). Although informal firms can not adopt the platform, they may also be impacted by spillover effects which would imply that the magnitude of the effect of platform adoption on spillovers would be underestimated. If this were the case, the spillover effects on non-formal firms would need to account for 36.5 percent of the impact of spillovers on formal

workers at registered firms for the total effect of the platform on worker earnings to break even.<sup>55</sup>

**Effects by Gender** As reported in Table B2, the vast majority of delivery drivers are men, whereas about 60% of workers in Brazil's restaurant sector are women. This compositional difference implies that the overall earnings effects of delivery platforms are heterogeneous by gender. Table B7 reports impacts on in-house workers, spillovers, and platform workers separately for men and women. A clear contrast emerges: men experience gains equivalent to 14.7% of the pre-platform restaurant wage bill, while women experience losses of 13.7%.<sup>56</sup> Although explaining the low participation of women among platform drivers lies beyond the scope of this paper, future work should examine the sources of this participation gap on platforms, which could potentially be related to differences in supply elasticity across genders (Caldwell and Oehlsen, 2023).

**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 A23 shows the total earnings effect of the delivery service as a function of the outside option for non-formal app workers—expressed as the ratio of their earnings to the earnings of platform workers that transition from the formal sector ( $\Phi$ ). 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 13.75 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 12.77 percent. The break-even point occurs when non-formal workers have an outside option equal to 52 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

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<sup>55</sup>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 0.36 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.

<sup>56</sup>The sum of the effects of both genders can differ from the total effect as both the worker earnings effects and the outside options are estimated separately for each gender.

preference measure leverages employer-to-employer transitions to quantify the value of working at an establishment ( $V_j^e$ ). Appendix D7 provides details on the estimation.<sup>57</sup>

Importantly, this valuation includes both pecuniary and non-pecuniary characteristics of the firm. Figure A25 shows that firm value correlates with pay policies, as measured by AKM firm effects, both for restaurants (panel a) and for all establishments (panel b). Figure A24 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). 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.

**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 Roshholm, 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 gig 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 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.

## 10 Conclusion

Over the past 10 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.

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<sup>57</sup>As discussed in Appendix D7, a caveat to this design is that it only relies on workers who move between the platform and the formal sector (and use the platform as their main source of income while working on the platform). If these movers have above-average utility for the platform, these estimates could be upward biased.

Using a unique data set that combines detailed administrative employer-employee records with platform-worker data, I show that platform adoption profoundly affects labor demand. Specifically, adopting a platform leads to a substantial reduction in the number of servers employed, who are replaced by gig delivery drivers. However, these workers do not experience persistent earnings losses, as they are able to get 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 5.7 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 when joining the platform.

The results presented in this paper carry significant implications for policy makers considering regulating these platforms. The findings demonstrate that online-delivery platforms substantially affect both traditionally employed workers and gig workers. Regulatory efforts should carefully balance the benefit of protecting traditional workers against displacement with the potential benefits for gig workers. Policy makers 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 nonpecuniary 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 on delivery platforms, future research could explore how these platforms affect the job ladder for individuals. Specifically, it would be worthwhile to determine whether these platforms serve as stepping stones for workers to enter the formal sector or whether they, in fact, limit these workers' opportunities to find higher-quality jobs in the future.

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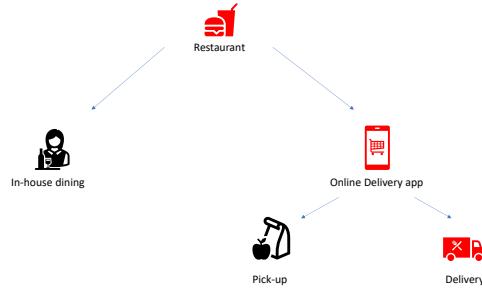
## Figures

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

(a) Restaurant Structure Previous to online-delivery Platforms      (b) Restaurant Structure After online-delivery Platforms

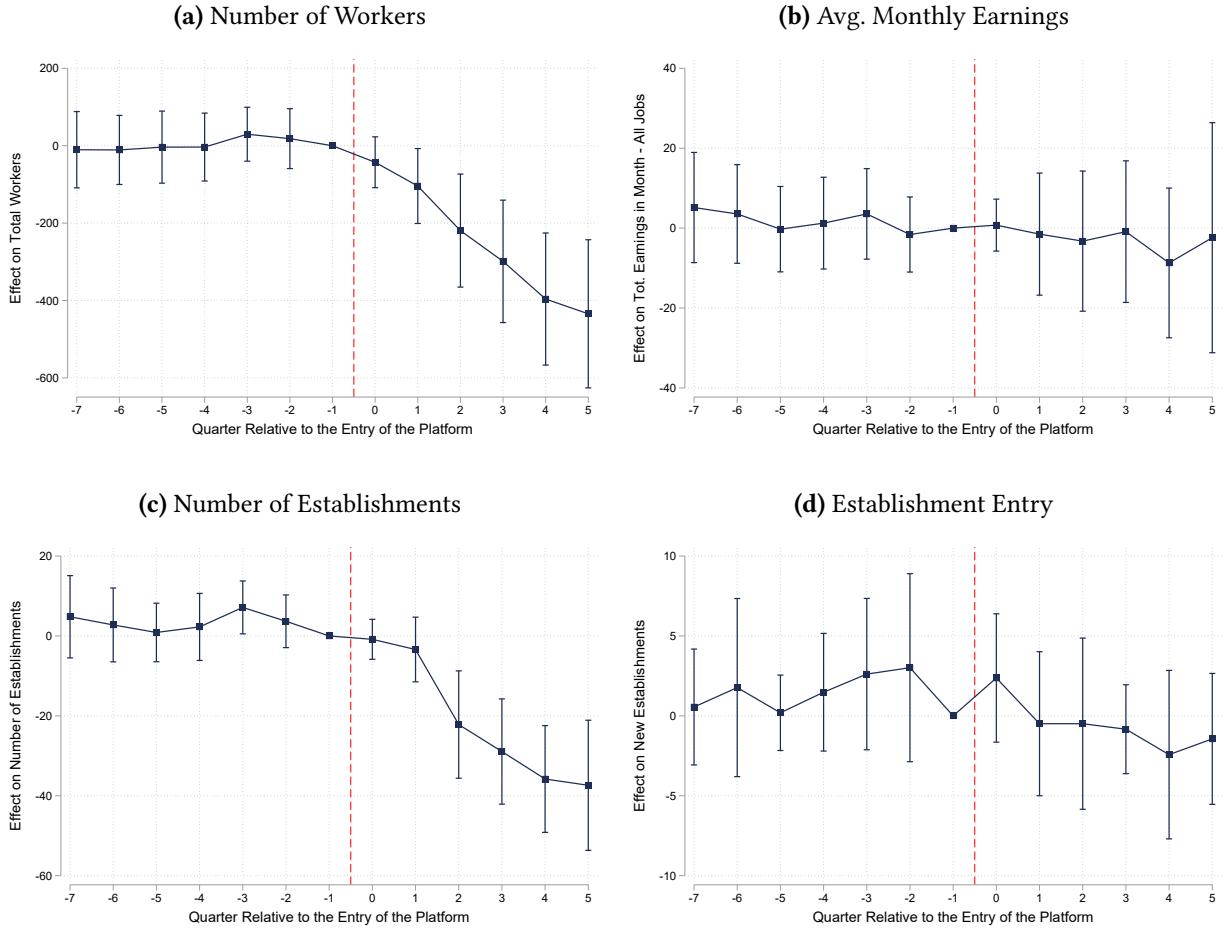


(c) Main Relationship Studied in the Paper



*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).

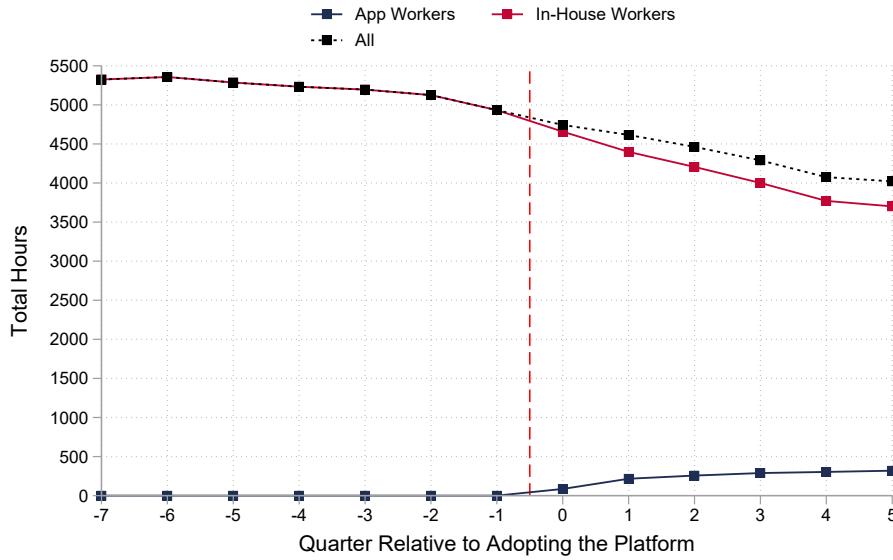
**Figure II: Effects of Delivery Platform Entry on Restaurant Sector**



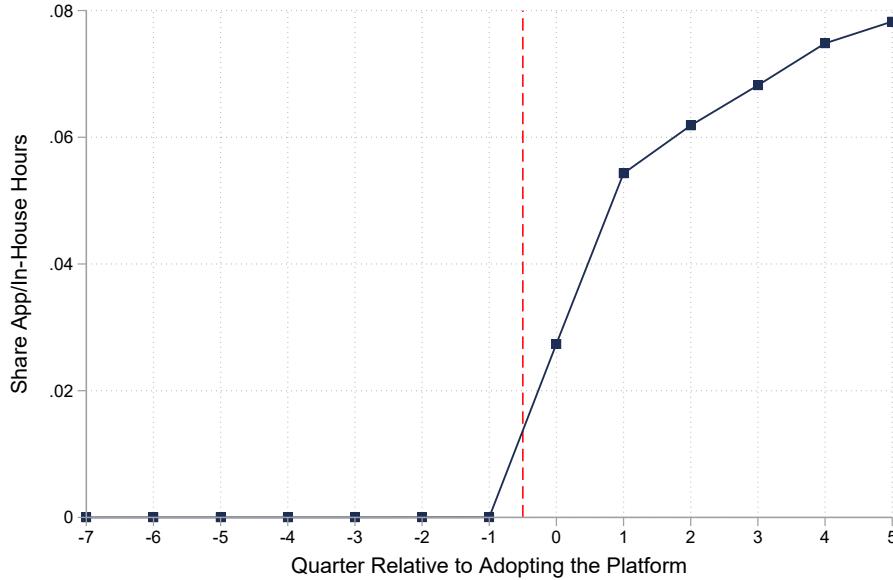
*Notes:* This figure presents estimates obtained after fitting equation (10) on total number of workers in the restaurant sector (panel a), average monthly earnings of restaurant workers (panel b), total number of establishments in restaurant sector (panel c) and establishment entry (panel d). The regressions are weighted by the number of restaurant workers in each microregion 2017 and controls for covid cases per capita at each date in each microregion. Establishment entry is defined as the first time that the establishment appears in RAIS. The mean number of restaurant workers prior to platform entry is 6,398 (SD 4,480), the mean earnings are 1,585 (SD 234), the mean number of establishments is 868 (SD 501), and the mean quarterly new establishments prior to treatment is 39 (SD 26). The regression excludes microregions where the platform had already entered prior to 2018. Standard errors are clustered at the microregion level.

**Figure III:** Trends in hours Hired for In-House and Platform Workers

(a) Total Hours by Type of Labor



(b) Share of Outsourced Labor



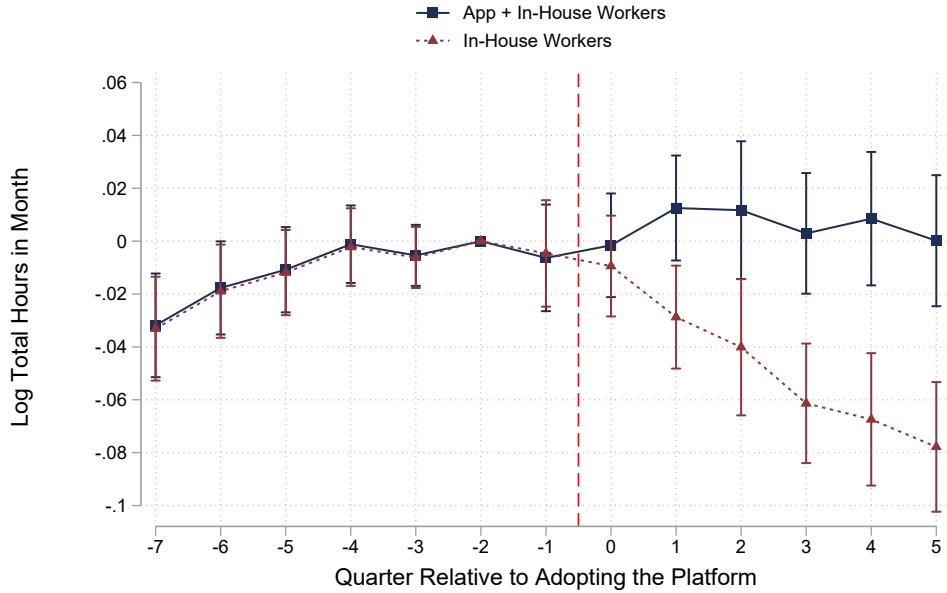
*Notes:* Panel (a) reports the total hours per quarter hired by restaurants that offer delivery services through the platform and match to a control restaurant. The red line reports the average quarterly hours for workers hired formally by these restaurants (in-house workers). The blue line reports the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



Notes: Panels (a)-(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), average paid wages (Panel b), and closure of restaurants that offer delivery services through the online platform and their matched-controls. Panels (d)-(f) report the corresponding event-study estimates obtained after fitting equation (12). 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 employed 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.

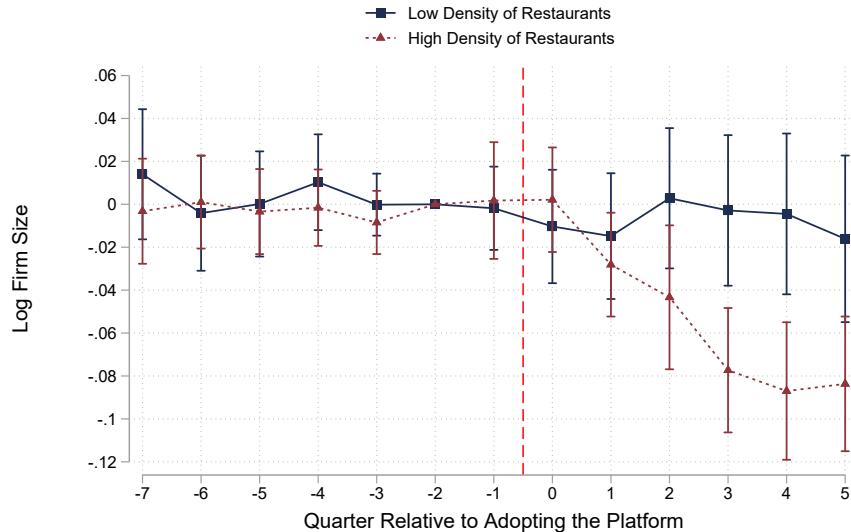
**Figure V:** Effects of Online-Delivery Platform Adoption on Total Hours Hired



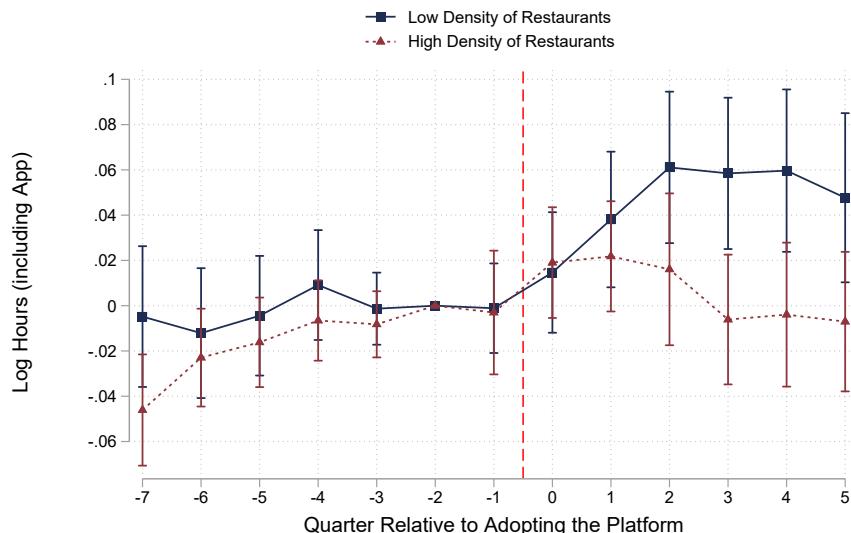
*Notes:* This figure reports the corresponding event-study estimates obtained after fitting equation (12) on log total hours hired quarterly for workers hired formally (the red dashed line) and log total hours hired quarterly when accounting for formal workers and platform-workers (the solid blue line). 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 VI:** Effects of Online-Delivery Platform Adoption on Total Hours Hired and In-House Size by Restaurant Density

(a) Log In-House Size of Restaurants



(b) Log Total Hours Hired



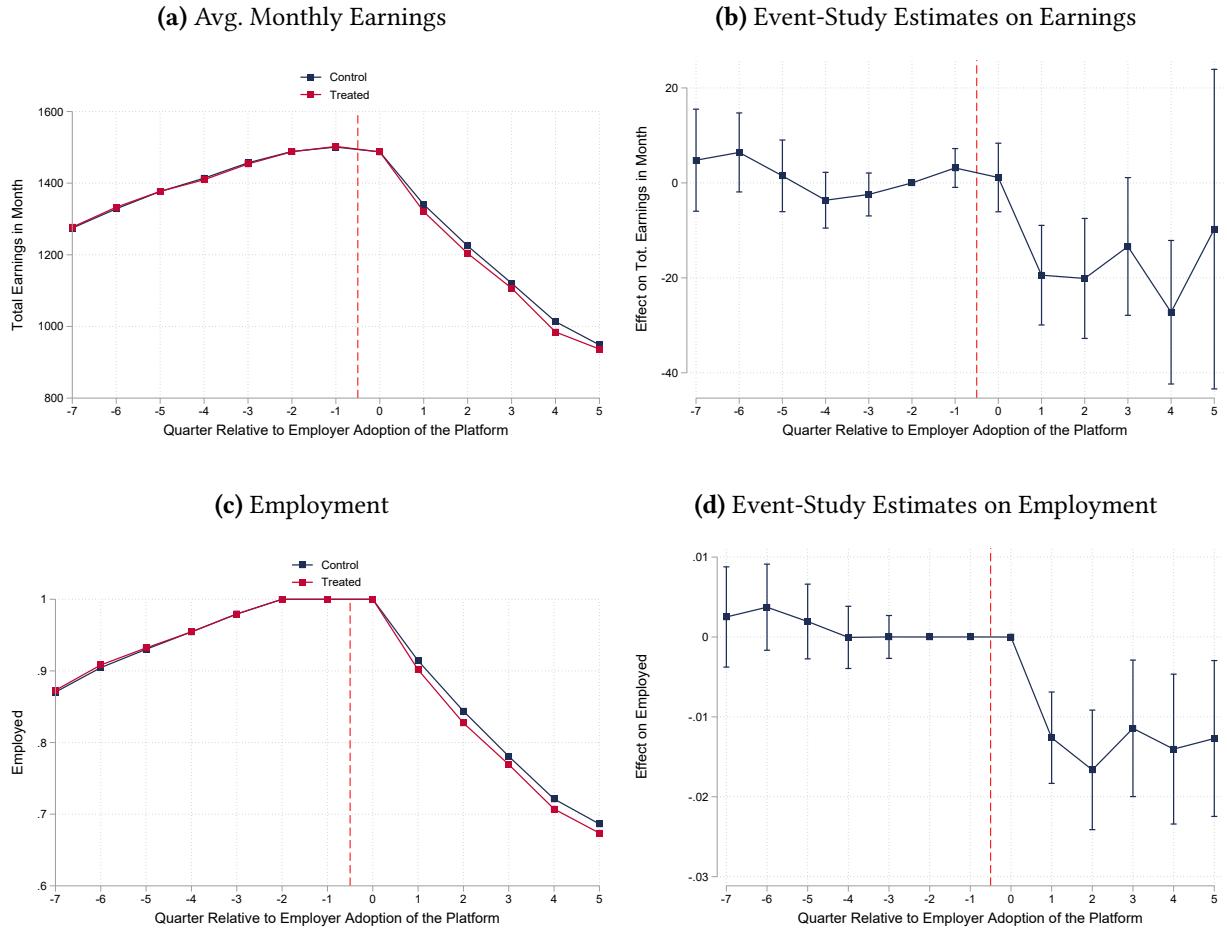
*Notes:* Panel (a) reports the corresponding event-study estimates obtained after fitting equation (12) on log restaurant size as defined by the average number of formal workers hired by the establishment. A formal worker is defined to be employed in a quarter if they have at least one day of work recorded in RAIS. Quarterly size is constructed by taking the average of the number of workers employed 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 (12) 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 VII: Spillover Effects of Platform Adoption on Non-Adopting 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 6.2, 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. Panels (a)-(c) report the trajectories of the logarithm of the size—as measured by the number of workers hired in a quarter—(Panel a), average paid wages (Panel b), and closure (Panel c) of restaurants exposed to a spillover event and their matched-controls. Panels (d)-(f) report the corresponding event-study estimates obtained after fitting equation (12). 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 employed formally each month in the quarter by the establishment after applying the restrictions described in Section 3. The x-axis reflects the quarter relative to the quarter in which the spillover event occurs. 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). All event-study panels report 95% confidence intervals based on standard errors clustered at the establishment level.

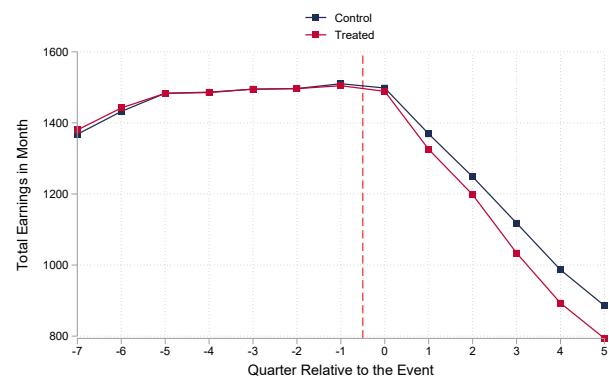
**Figure VIII:** Effects of Employer Adoption of Online-Delivery Platform on Worker Earnings and Employment



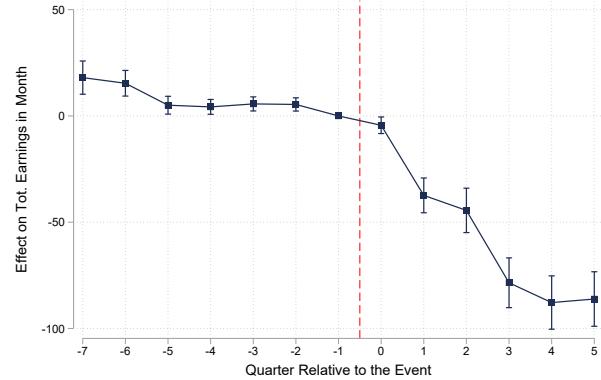
Notes: Panel (a) and Panel (c) reports the trajectories of total earnings and employment of restaurant workers whose employer starts offering delivery through the platform and their matched control workers. Panel (b) and Panel (d) report the corresponding event-study estimates obtained after fitting equation (12) 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 IX: Spillover Effects of Platform Adoption on Restaurant Workers**

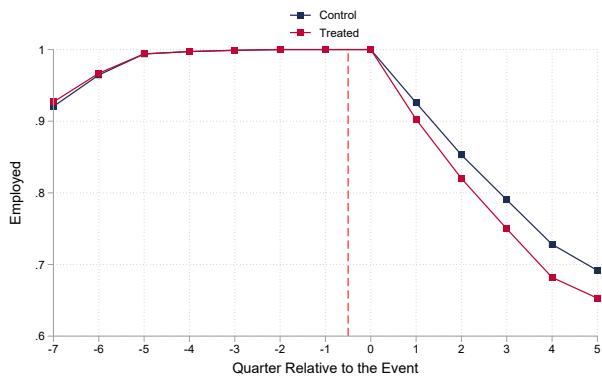
(a) Avg. Monthly Earnings



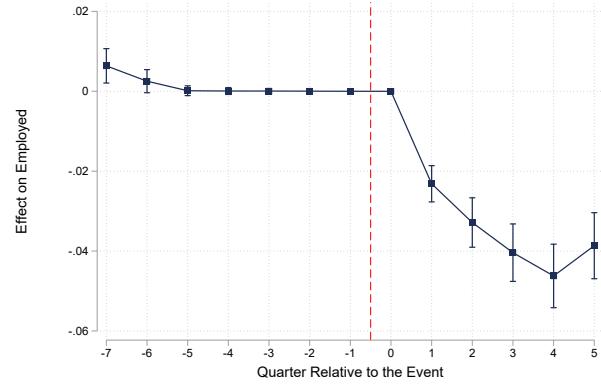
(b) Event-Study Estimates on Earnings



(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 6.2, 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) 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 (12) 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 I:** Summary Statistics for Adopting and Control Restaurants

	(1) Matched Control	(2) Matched Treated	(3) Potential Treated	(4) All Restaurants
Years of Education	11.02 (1.38)	11.29 (1.27)	11.28 (1.31)	11.01 (1.62)
Tenure (in years)	2.58 (1.78)	1.43 (1.92)	1.46 (1.99)	2.04 (2.43)
Monthly Wage (2018 - R\$)	1,484 (413)	1,530 (571)	1,522 (552)	1,438 (508)
Age	33.38 (7.02)	32.48 (6.94)	32.68 (7.10)	34.95 (8.42)
Share of Brazilians	1.00	0.99	0.99	0.99
Female	0.59	0.59	0.59	0.60
Full-Time	0.97	0.97	0.97	0.97
Establishment Size	11.34 (24.75)	11.50 (22.83)	11.86 (53.59)	7.36 (34.84)
Share of Waiters	0.48 (0.32)	0.50 (0.31)	0.52 (0.33)	0.49 (0.36)
Number of Establishments	7,836	14,862	15,933	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 within each cohort of treatment. 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 II:** Effect of Platform Adoption on Labor Demand per Occupation

	(1) Hours: Waiters	(2) Hours: Cooks	(3) Hours: Delivery	(4) Log Wage Waiters	(5) Log Wage Cooks	(6) Log Wage Delivery
$\beta(\text{Diff-in-Diff})$	-45.7*** (10.2)	3.6 (5.0)	-2.2 (1.5)	-0.025*** (0.007)	-0.011 (0.008)	-0.003 (0.024)
Mean prior to Adoption	913.2	351.1	24.9	7.1	7.2	7.2
Observations	379,254	379,254	379,254	292,984	207,408	29,466

Notes: The table reports the corresponding difference-in-difference estimates obtained after fitting equation (12) on the hours hired of waiters (column 1), cooks (column 2), 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. \(2024\)](#). Hours are defined as the average monthly hours hired of workers for each occupation 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 III:** Heterogeneous Effects of Platform Adoption on Labor Demand per Occupation

	Panel A: Restaurants at High Density Areas		Panel B: Restaurants at Low Density Areas	
	(1) Hours Hired: Waiters	(2) Hours Hired: Cooks	(3) Hours Hired: Waiters	(4) Hours Hired: Cooks
$\beta(\text{Dif-in-Diff})$	-68.77*** (12.11)	-5.19 (5.60)	0.20 (19.95)	25.45** (10.36)
Mean prior to App Adoption	947.85	359.89	820.34	333.17
Observations	242,794	242,794	110,676	110,676

*Notes:* The table reports the corresponding difference-in-difference estimates obtained after fitting equation (12) on the hours hired of waiters and cooks at each establishment  $j$  using the estimator from [Borusyak et al. \(2024\)](#). The table reports the heterogeneity by restaurant density. Columns (1) and (2) present the results for above the median restaurant density, while columns (3) and (4) present the results for below the median of density. 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. Hours are defined as the average monthly hours hired of workers for each occupation after applying the restrictions described in Section 3. 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 IV:** Summary Statistics for Workers whose Employer Adopts the Delivery Platform and Control Workers

	(1) Matched Control Workers	(2) Matched Treated Workers	(3) Potential Treated Workers
Years of Education	10.92 (2.18)	11.07 (1.87)	11.42 (2.05)
Avg Tenure (in years)	3.68 (1.35)	3.68 (1.35)	2.91 (1.58)
Avg Monthly Earnings (in 2018-R\$)	1,501 (377)	1,503 (389)	1,789 (1,475)
Age	32.51 (9.96)	32.45 (9.99)	33.14 (11.10)
Share of Brazilians	1.00	0.99	0.99
Female	0.59	0.59	0.51
Hours	43.13 (3.22)	41.29 (6.95)	41.69 (6.66)
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 V: 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 Formal Sector)	App Workers (From Non-Formal Sector)	App Workers (From Non-Formal Sector)	Wage Bill Net	Wage Bill Net
	Gross Wage	Net Wage	Gross Wage	Net Wage	Wage Bill App	Wage Bill App	Wage Bill Net	Wage Bill Net	Wage Bill Net	Wage Bill Net
<b>Quarter 0</b>	38 (121)	19 (108)	4 (25)	-46 (20)	-43 (18)	-11 (4)	330 (11)	88 (4)	1,494 (45)	973 (31)
<b>Quarter 1</b>	-652 (167)	-616 (152)	-143 (35)	-354 (41)	-327 (37)	-81 (9)	771 (25)	190 (7)	3,661 (96)	2,351 (64)
<b>Quarter 2</b>	-675 (213)	-633 (194)	-147 (45)	-509 (62)	-471 (56)	-117 (14)	869 (29)	199 (8)	4,317 (114)	2,717 (74)
<b>Quarter 3</b>	-449 (237)	-429 (216)	-100 (50)	-1,409 (107)	-1,293 (98)	-320 (24)	1,076 (35)	269 (9)	5,290 (128)	3,381 (85)
<b>Quarter 4</b>	-914 (237)	-845 (216)	-196 (50)	-2,856 (249)	-2,620 (219)	-649 (54)	1,111 (31)	260 (9)	5,548 (120)	3,478 (78)
<b>Quarter 5</b>	-327 (568)	-322 (508)	-75 (118)	-4,571 (502)	-4,184 (459)	-1,037 (114)	1,115 (30)	233 (7)	5,820 (123)	3,572 (77)
<b>Cumulative PDV</b>	-2,878 (974)	-2,731 (882)	-634 (205)	-9,281 (788)	-8,513 (719)	-2,109 (178)	5,087 (135)	1,197 (33)	25,204 (519)	15,892 (333)
<b>Percentage of Pre-Platform Wage Bill</b>	-5.3% -5.0%	-5.0% -1.2%	-1.2% -17.0%	-15.6% -3.9%	-9.3% 2.2%	-	-	46.1% 29.1%	-	-

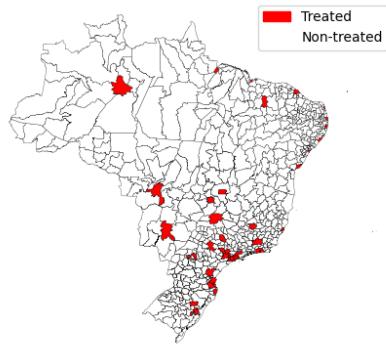
Notes: This table reports the estimated wage bill surplus generated by the platform for each component of equation (13). Column 1 presents the effects on in-house restaurant workers whose employer starts offering delivery services through the platform. Each quarter report the corresponding event-study estimates obtained after fitting equation (12) 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 2 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 6.2, 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 and then scaled by the average restaurant size in my sample and by the probability of a restaurant being exposed to a spillover event as described in Appendix D2. 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 Picanco \(2023\)](#). 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 workers who transition from non-formal status is imputed using a regression-adjusted earnings for non-formal workers within the same state-quarter 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 in  $t^* - 2$ . For all columns in the table, the pre-adoption wage bill is calculated including the inputed informal workers. Wages are expressed in real terms (2018 CPI). Standard errors were bootstrapped.

## **Appendix**

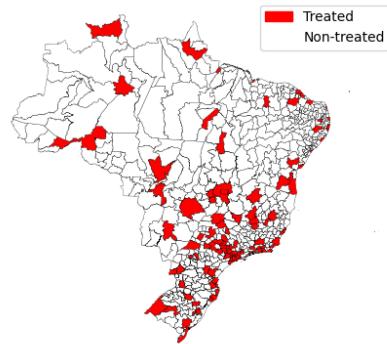
## A Appendix: Figures

**Figure A1:** Rollout of the Platform

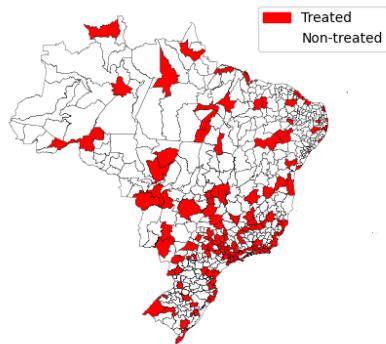
(a) 2018



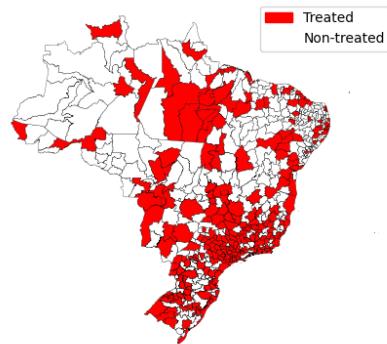
(b) 2019



(c) 2020

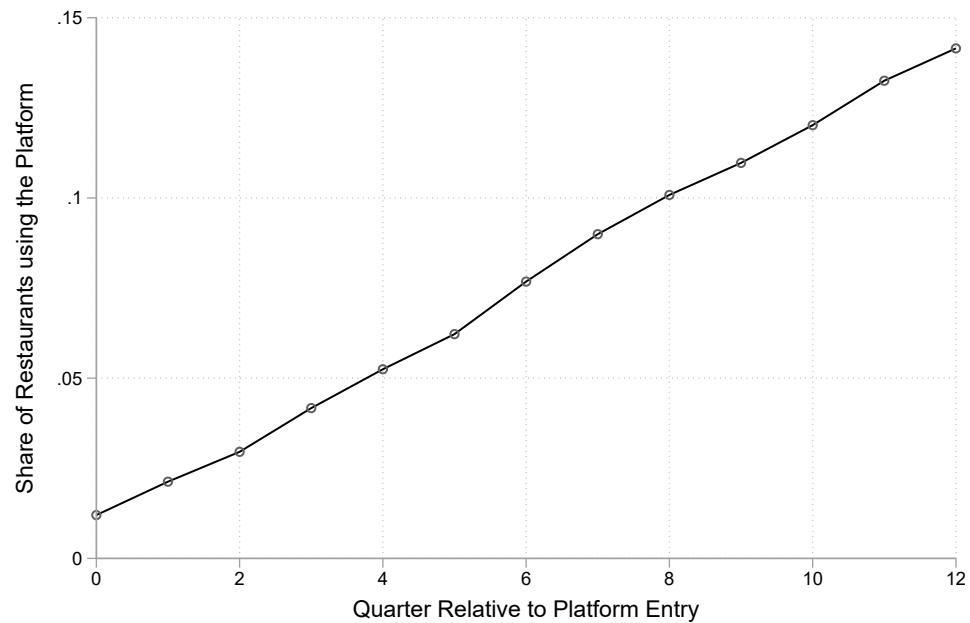


(d) 2021



*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 A2:** Share of Restaurants on the Platform

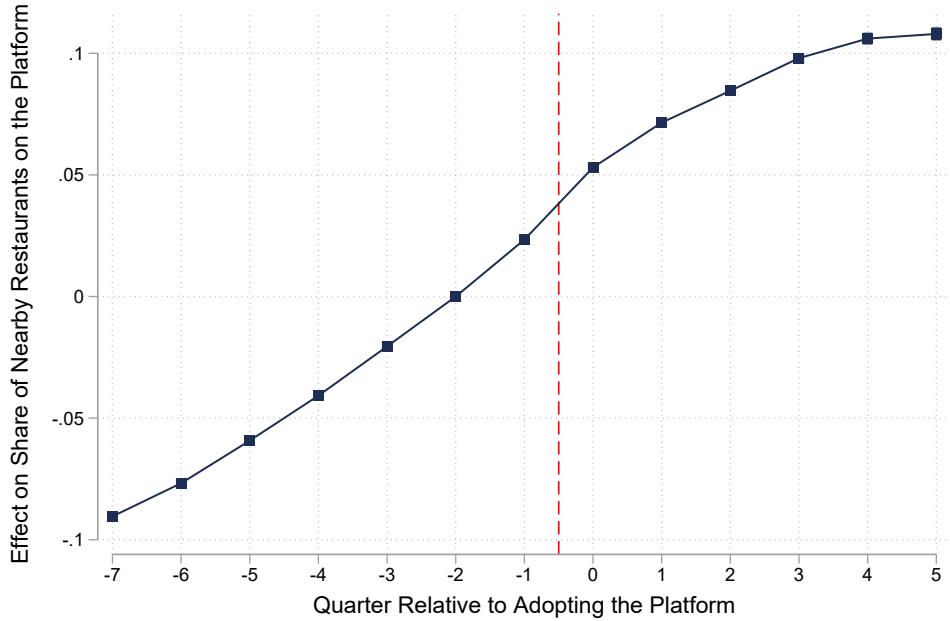


*Notes:* This figure reports the share of restaurants that adopt the platform (y-axis) respect to the the moment in which the platform becomes available in the microregion (x-axis). A restaurant is considered to adopt the platform if more than 50 percent of their revenues in the platform come through delivery services the first month in which they enroll. Observations are not weighted.  $T^*0$  represents the first month in which a restaurant in the microregion starts offering delivery services through the platform.

**Figure A3:** Effects of Delivery Platform Entry on Restaurant Sector using Borusyak et al. (2024) estimator

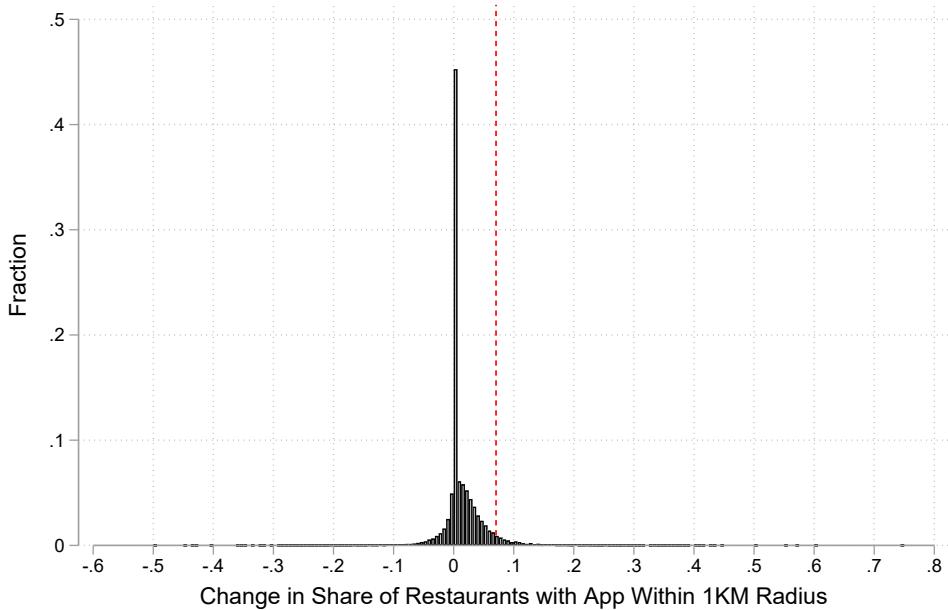


**Figure A4:** Restaurants within 1 Kilometer Adopting the Platform



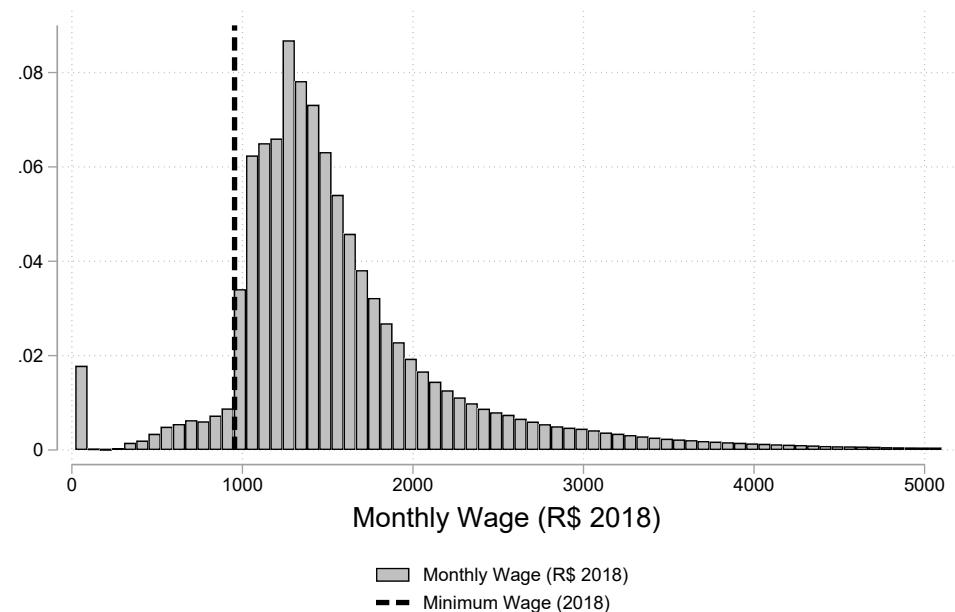
*Notes:* This figure reports the corresponding event-study estimates obtained after fitting equation (12) on the share of restaurants within a 1 kilometer radius that offer delivery services through the platform. The mean share of restaurant within 1 kilometer using the platform the quarter prior to 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 A5:** Distribution of  $\Omega$



*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 ( $\Omega$ ). 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.

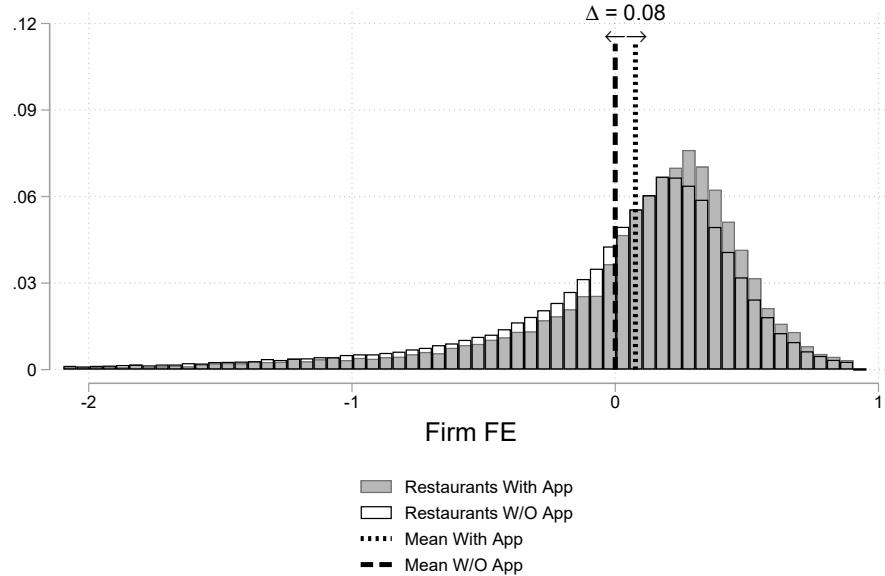
**Figure A6:** Distribution of Wages of Restaurant Workers (2018)



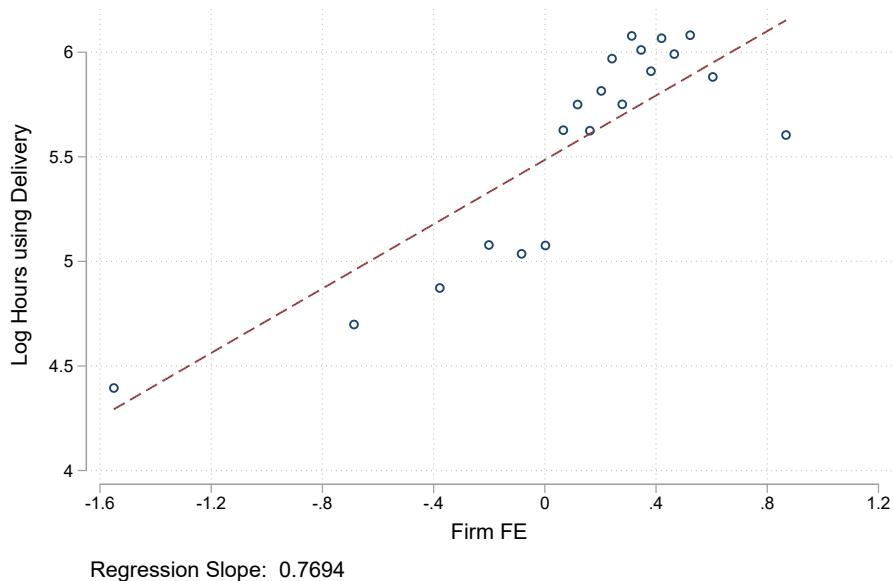
*Notes:* This figure reports the histogram of wages for restaurant workers in 2018. Restaurants are defined as establishments that have a CNAE two digit code equal to 56. The vertical black dashed line shows the minimum wage in 2018 (954 BRL). Wages are winsorized at the 99 percentile and are expressed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

**Figure A7: AKM Firm FE and usage of the Platform**

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



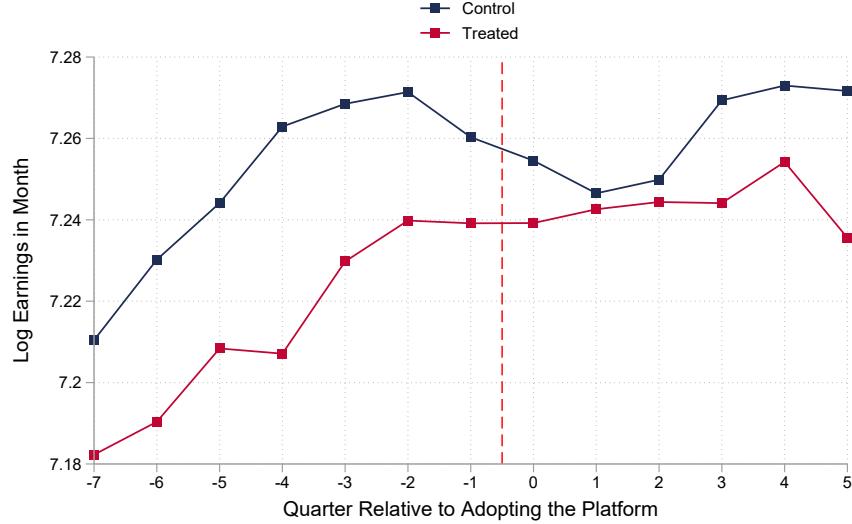
(b) Intensive Margin of Platform and AKM Firm FE



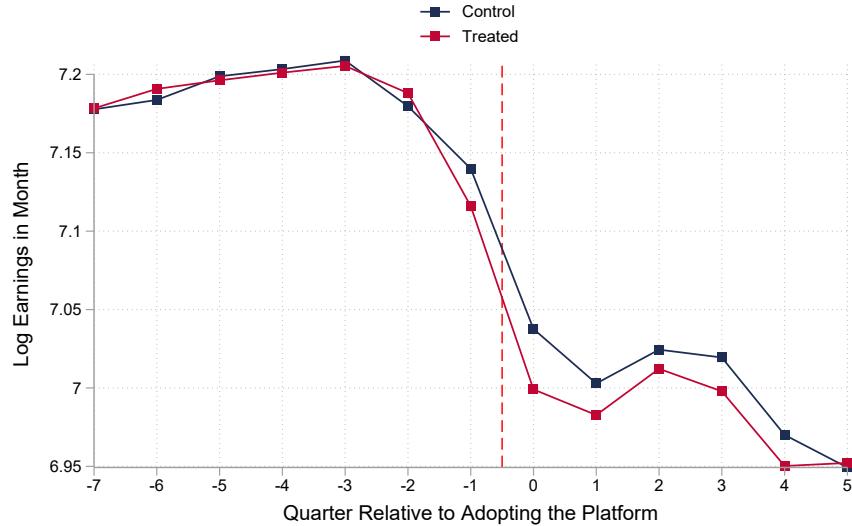
*Notes:* Panel (a) reports the histogram of AKM workplace effects for restaurants in Brazil. It plots the selection into offering deliveries through an online platforms. The figure plots the histogram of AKM firm effects for restaurants that at some point in time offered deliveries through the delivery 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 0.03). 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 A8:** Trends in Monthly Wages paid by Treated and Control Restaurants Before and After COVID-19

(a) Avg. Monthly Wages for Restaurants Adopting Prior to January 2019

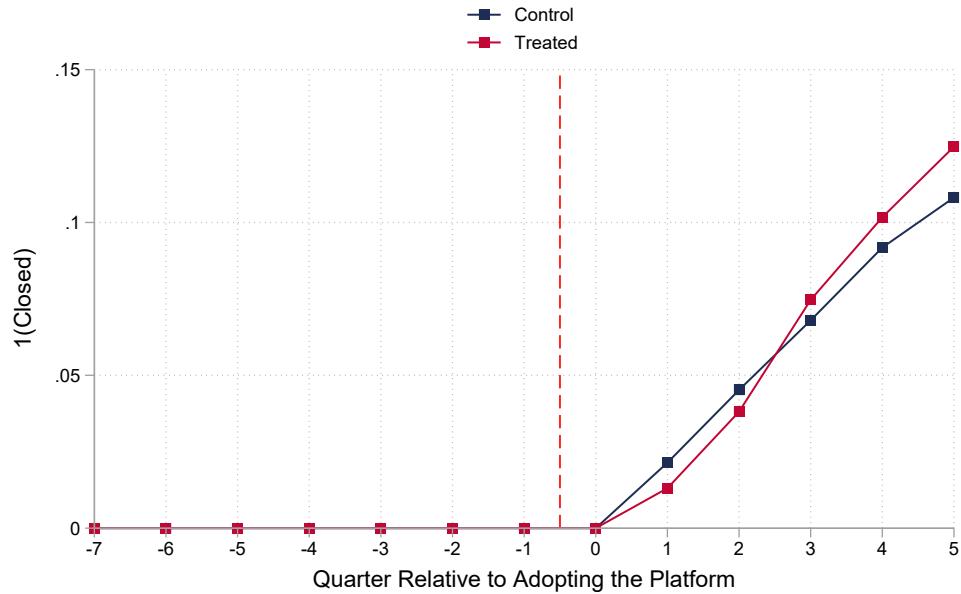


(b) Avg. Monthly Wages for Restaurants Adopting After January 2019



*Notes:* This figure reports the trajectories of establishment average of the monthly wages paid for matched restaurants that offered delivery services through the platform and matched control restaurants. Panel (a) presents the trajectories for those that adopt the platform prior to January 2019 and therefore are not exposed to COVID-19 up to 5 quarters after their adoption. Panel (b) presents the trajectories for those adopting after January 2019. 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 within each cohort of treatment. Restaurants are defined as establishments that have a CNAE two digit code equal to 56.

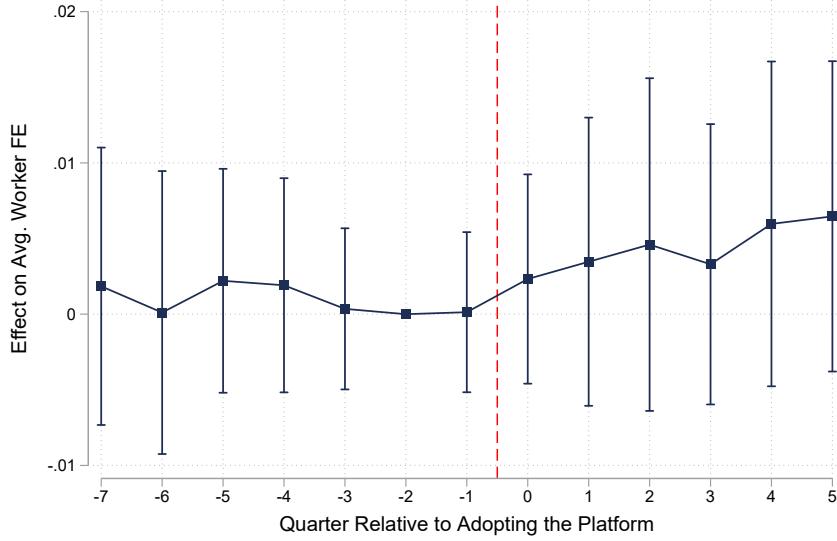
**Figure A9:** Trends in Closure for Adopting and Control Restaurants



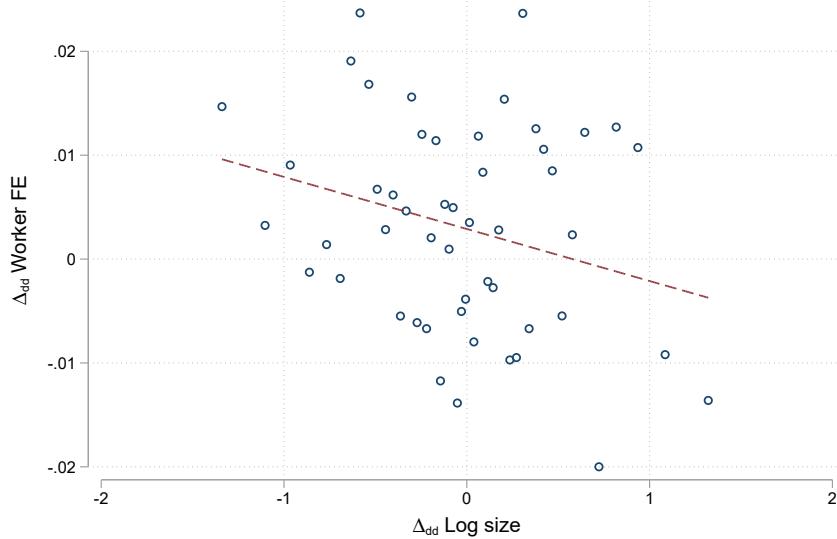
*Notes:* This figure reports the trajectories of establishment closure for matched restaurants that offered delivery services through the platform and matched control restaurants. The date of closure is defined as the last quarter in which the establishment reported having workers to RAIS (previous to 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 within each cohort of treatment. Restaurants are defined as establishments that have a CNAE two digit code equal to 56.

**Figure A10:** Effect of Platform Adoption on Avg. Worker Fixed Effects at Restaurants

(a) Avg. AKM Worker Fixed Effects

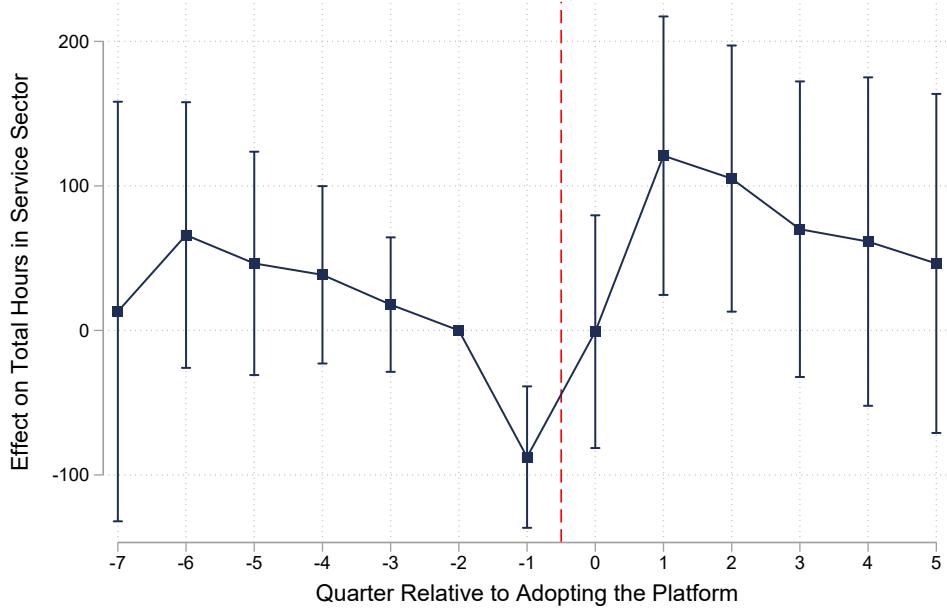


(b) Relation Between Log In-House Size Treatment Effects and Avg. AKM Worker Fixed Effects



*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 (12) 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 employed formally each month in the quarter by the establishment after applying the restrictions described in Section 3.

**Figure A11:** Effect of Platform Adoption on Total Hours for Service Workers



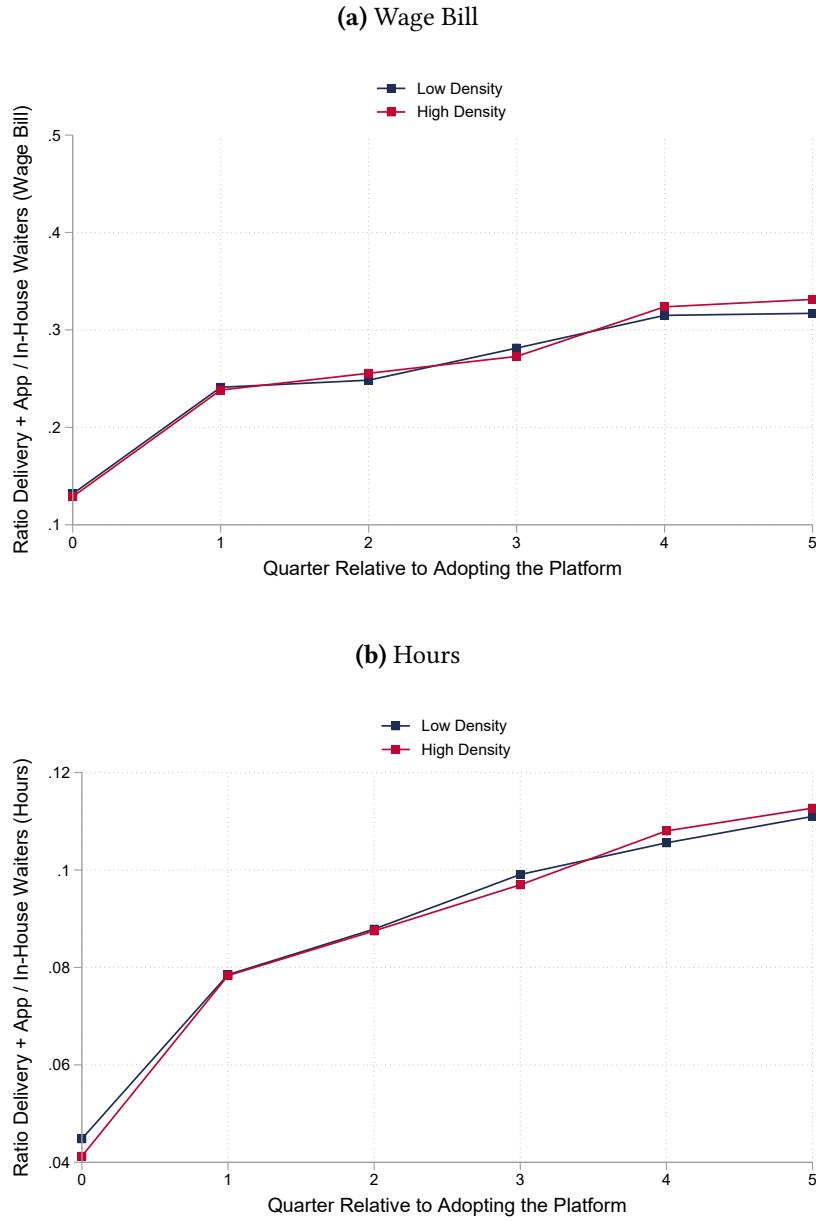
*Notes:* This figure reports the corresponding event-study estimates obtained after fitting equation (12) on the total quarterly hours hired of service workers. The average hours hired of service sector workers prior to the adoption of the platform for treated restaurants is 4,160. Service workers are 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 A12:** 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.

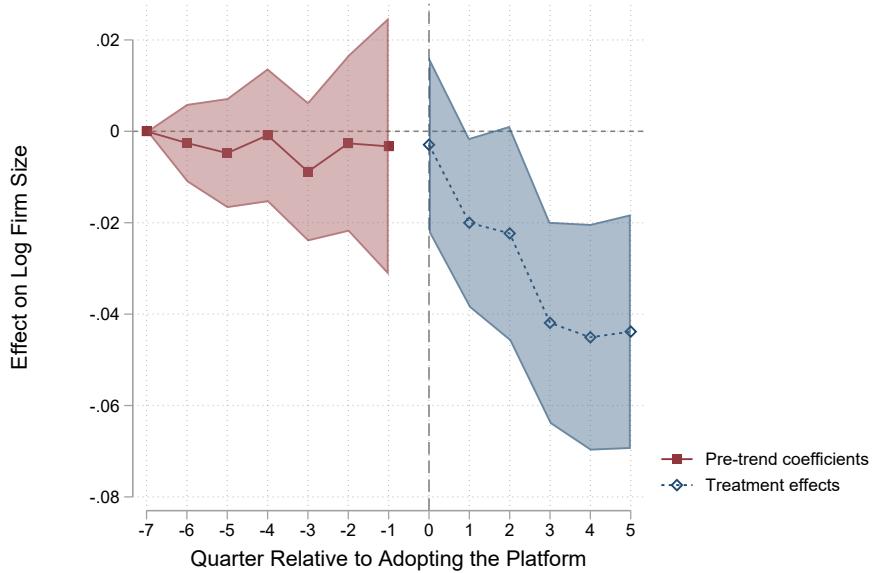
**Figure A13:** Ratio of Delivery Workers and Service Workers at Treated Establishments by Density



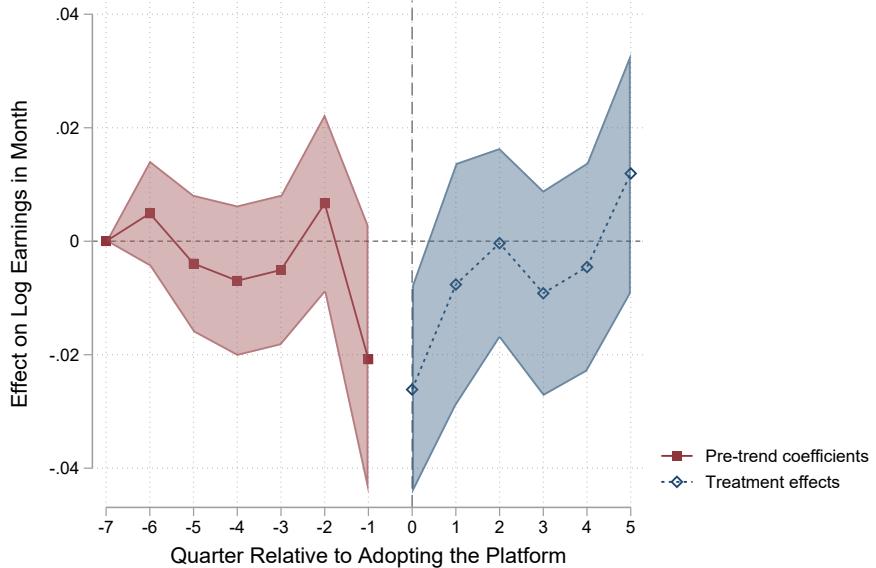
*Notes:* This figure reports the ratio of delivery drivers (both in-house and platform drivers) to in-house waiters wage bill (panel a) and hours (panel b) at treated establishments after the restaurants starts offering services through the platform. The ratio in panel (a) is calculated by dividing the quarterly wage bill of delivery drivers by the quarterly wage bill of in-house waiters. 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 delivery drivers by the total number of hours hired of in-house waiters. 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. Workers ocupcations are defined using the 6 digit *Classificação brasileira de ocupações* (CBO). Appendix Table B8 presents how occupations were classified using the CBO reported in RAIS.

**Figure A14:** Effect of Adopting the Platform using Borusyak et al. (2024) estimator

(a) Log In-House Firm Size



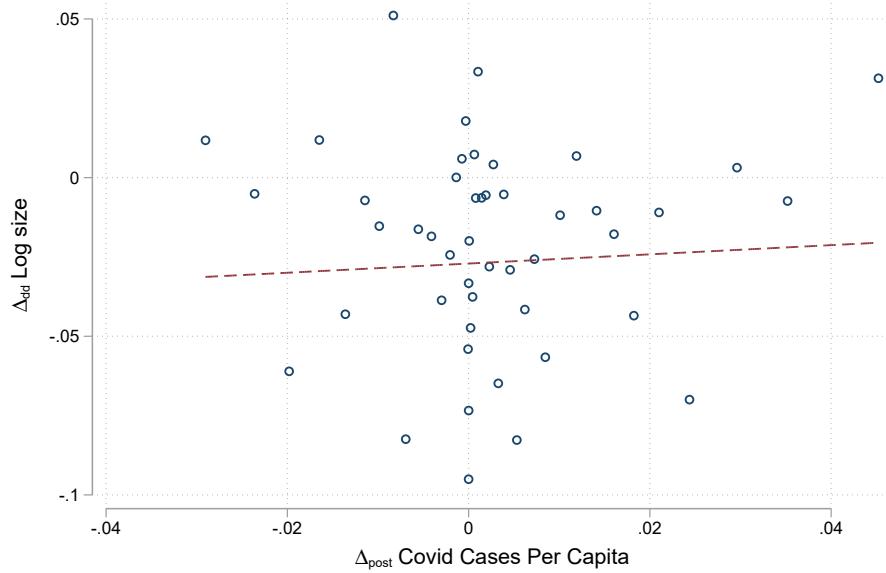
(b) Log Monthly Wages



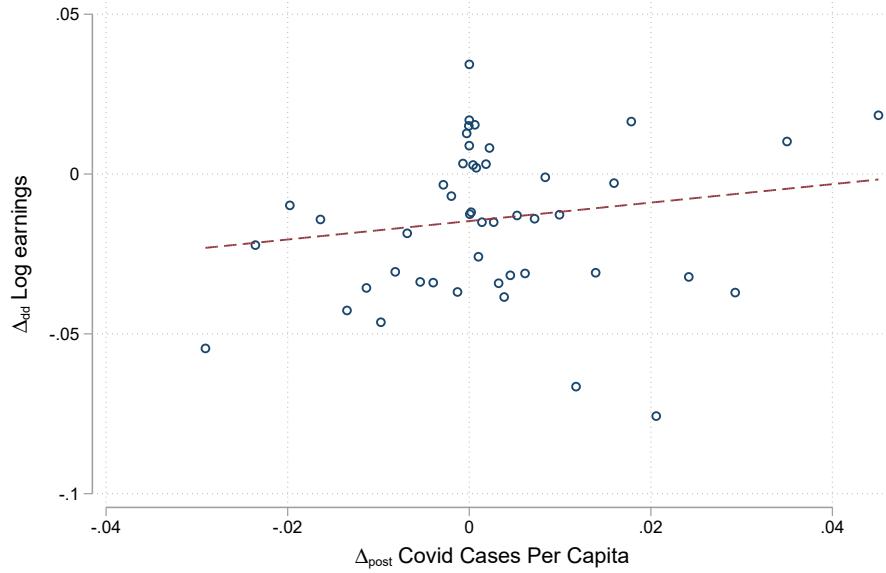
*Notes:* This figure reports the corresponding event-study estimates obtained after fitting equation (12) on the logarithm of firm size (panel a) and the logarithm of the average monthly wages paid by restaurants (panel b) using the estimator proposed by Borusyak et al. (2024). The x-axis reflects the 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 employed 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 A15:** Establishment level treatment effect and COVID-19 Cases

(a) Log In-House Firm Size

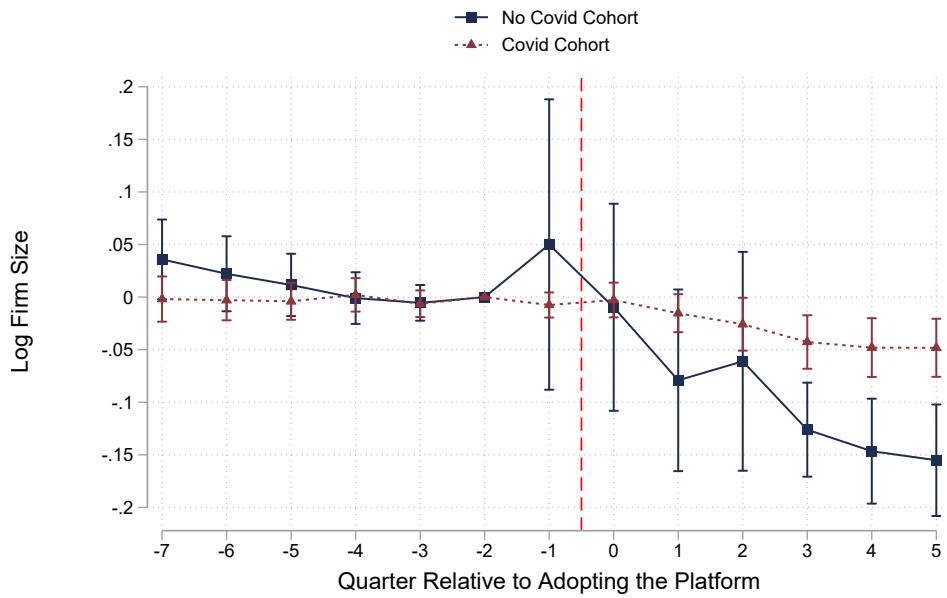


(b) Log Monthly Wages



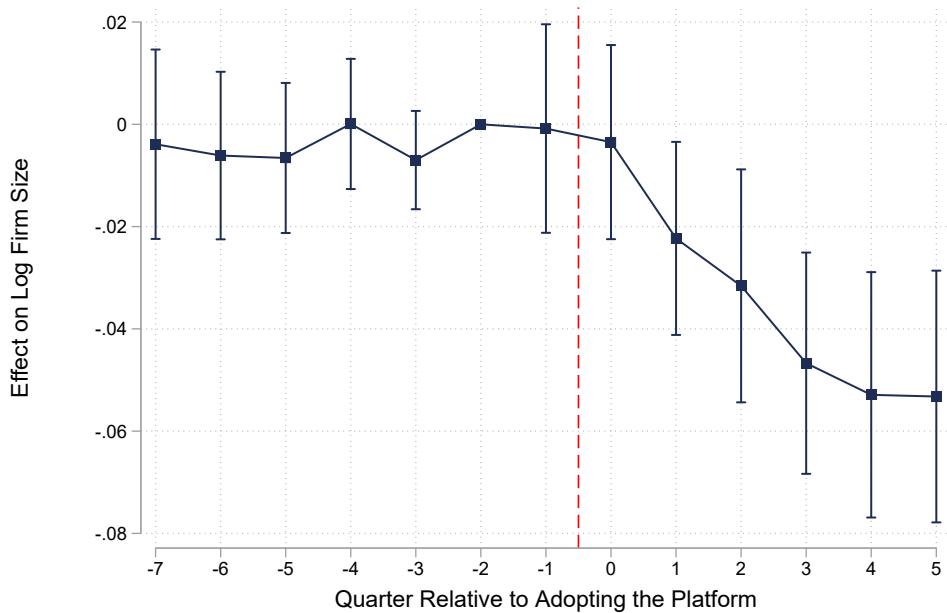
*Notes:* This figure displays a binscatter plot of the establishment level difference-in-difference estimates of the adoption of the platform on log in-house establishment size (panel a) and log average monthly wages paid by restaurants (panel b) plotted against the difference of average covid cases per capita in the municipality of the matched treated and control establishments between  $t^* + 5$  and  $t^* 0$  (post-period levels only).  $\Delta_{dd}$  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 employed 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 A16:** Effect of Platform Adoption on Log Firm In-House Size by COVID-19 period



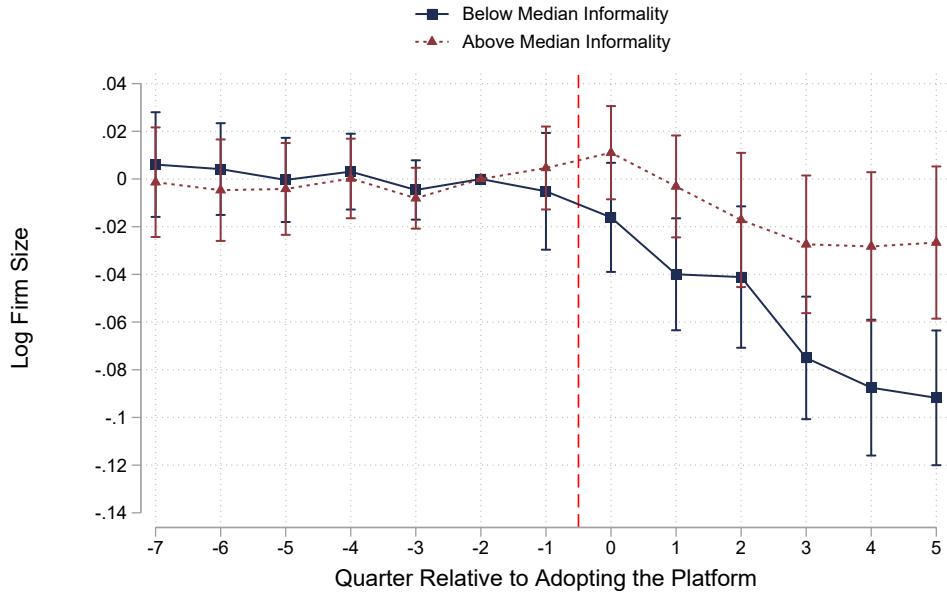
*Notes:* This figure reports the corresponding event-study estimates obtained after fitting equation (12) on the logarithm of in-house restaurant size. The blue line represents cohort of restaurants that started offering delivery services through the platform before the first quarter of 2019. That is, 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 2020 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 employed 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 A17:** 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 (12) 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 employed 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.

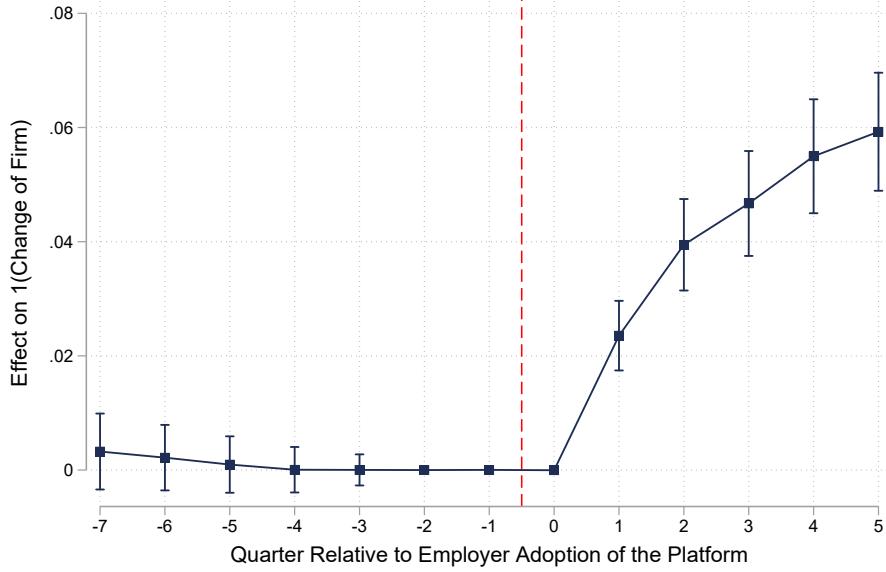
**Figure A18:** Effect of Platform Adoption on Log Firm Size By Informality of the Municipality of the Establishment



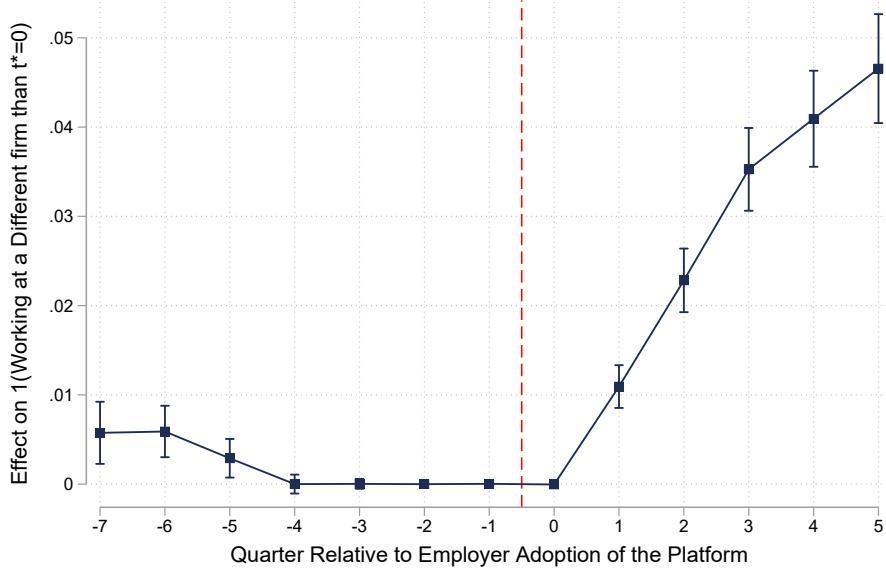
*Notes:* This figure reports the corresponding event-study estimates obtained after fitting equation (12) on the logarithm of in-house restaurant size. The plot presents the estimated coefficients by the levels of informality in the restaurant sector at the municipality of each restaurant as estimated 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 employed 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 A19:** Effect of Employer Platform Adoption on Worker Probability of Changing Firm

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

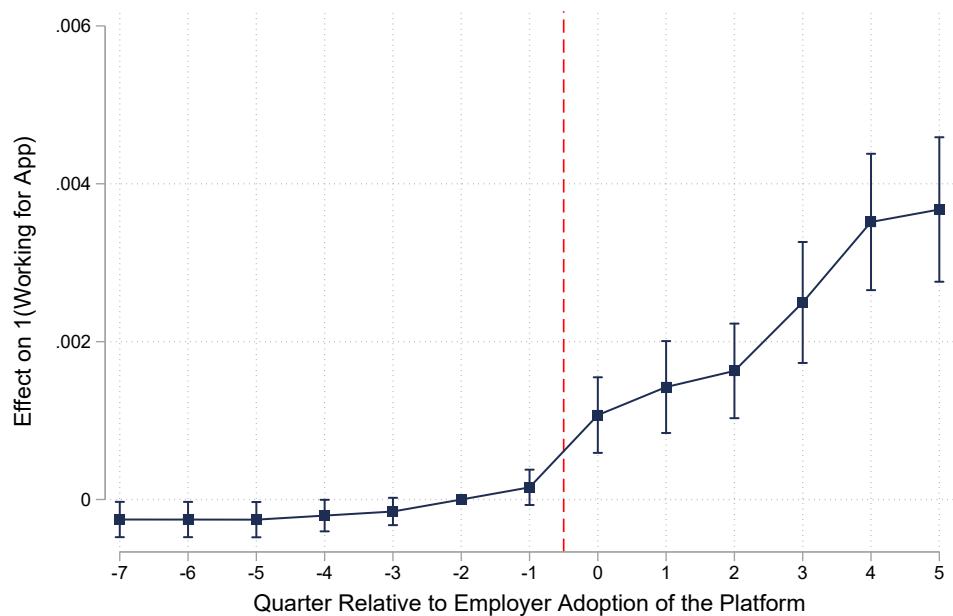


(b) Likelihood of Working for a different Employer than  $t^*=0$



*Notes:* Panel (a) reports the corresponding event-study estimates obtained after fitting equation (12) 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 (12) 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.

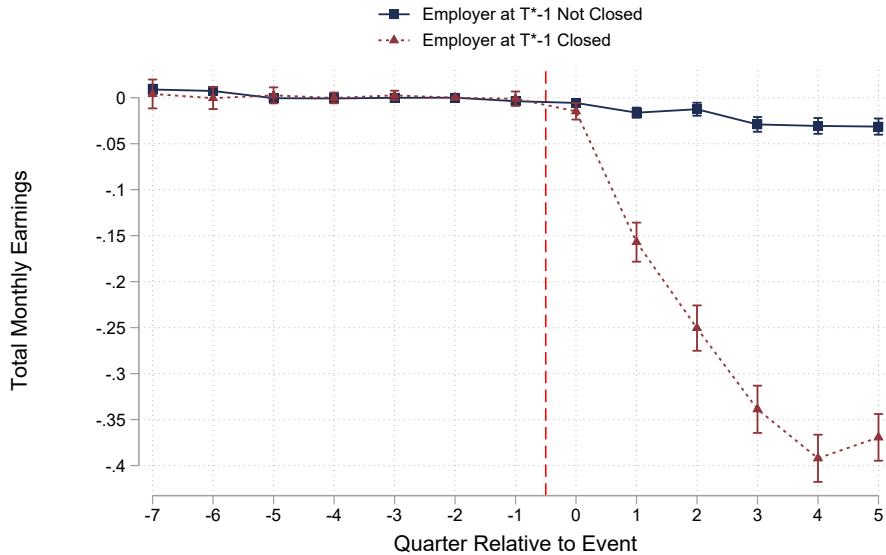
**Figure A20:** Effect of Employer Platform Adoption on Worker Probability of Working at Delivery Platform



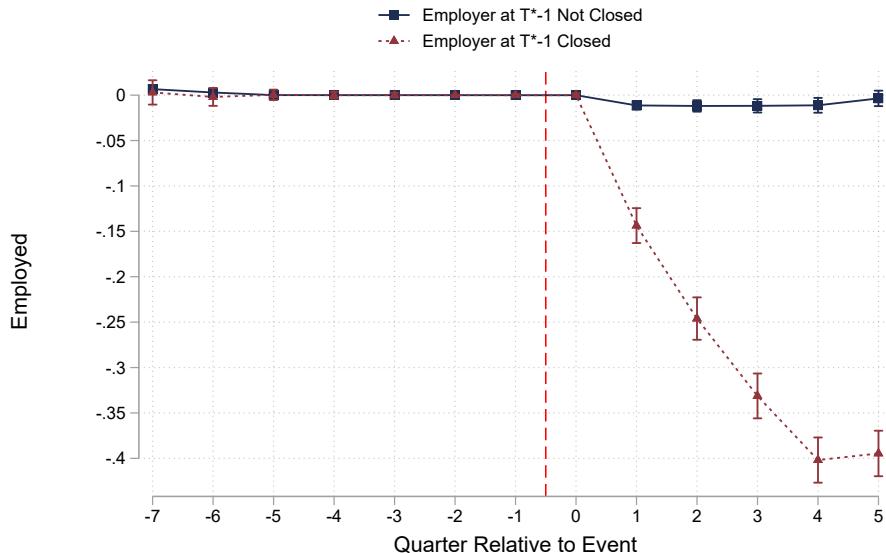
*Notes:* This figure reports the corresponding event-study estimates obtained after fitting equation (12) on a dummy equal to one if individual  $i$  in time  $t$  works in the platform. Employment at time  $t$  in the platform is defined as doing at least one delivery in quarter  $t$ . The x-axis reflects 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 A21:** Spillover Effects of Platform Adoption on Restaurant Workers by Employer Closure

(a) Total Earnings



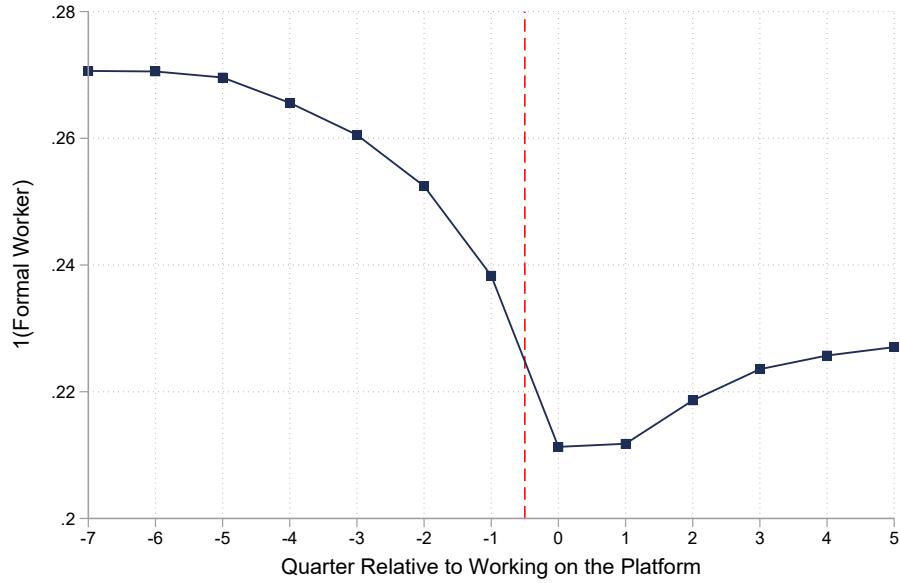
(b) Employment



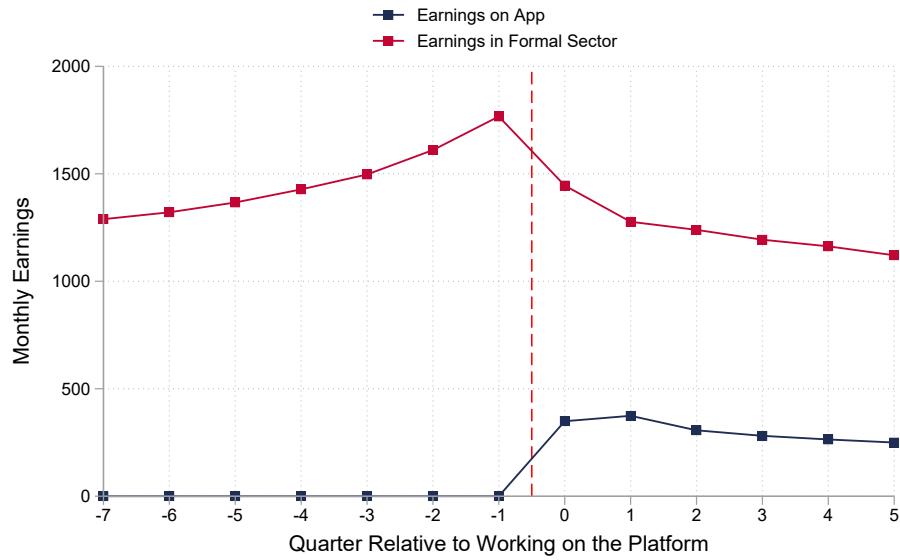
*Notes:* This figure reports event study estimates for workers who are employed at restaurants that are exposed to a spillover event. A spillover event is defined as a restaurant that is exposed to a large increase in the share of restaurants within a 1 kilometer radius that start offering services through the platform. As described in Section 6.2, 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 (12) 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 A22:** Trends of Formal Employment and Earnings for Platform Workers

(a) Formal Employment

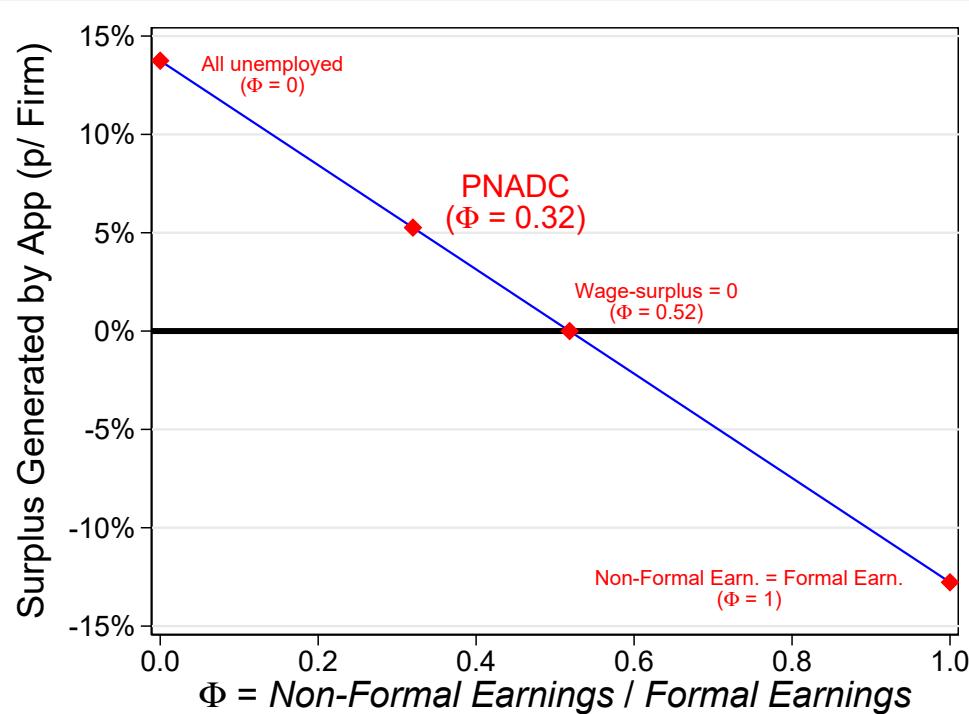


(b) Total Earnings Conditional on Worker Employed in  $t^* - 1$



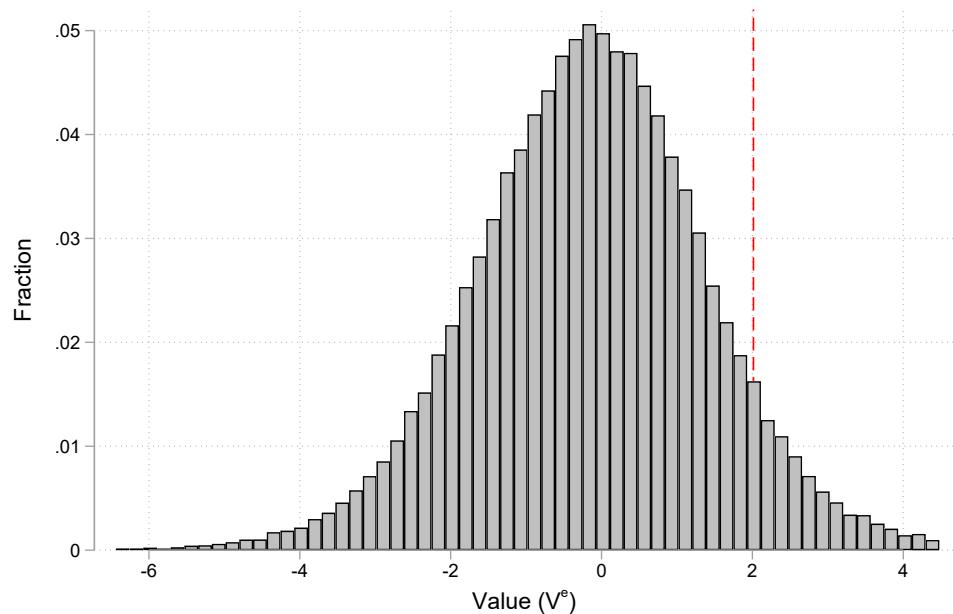
Notes: Panel (a) presents the trajectories of formal employment for workers who at some point in time work as delivery workers in the platform. A worker is defined as a platform-worker if they did at least one delivery through the platform. The worker is considered to be formally employed in quarter  $t$  if they are employed in the quarter for at least one day and their 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 A23:** Total Wage Bill Effect from Platform Adoption as a Function of Non-Formal platform-workers Outside Option



Notes: This figure reports the estimated total wage bill surplus generated by the platform as estimated using equation (13). 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 platform, 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 ( $\Phi$ ). 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 in  $t^*-2$ . 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.

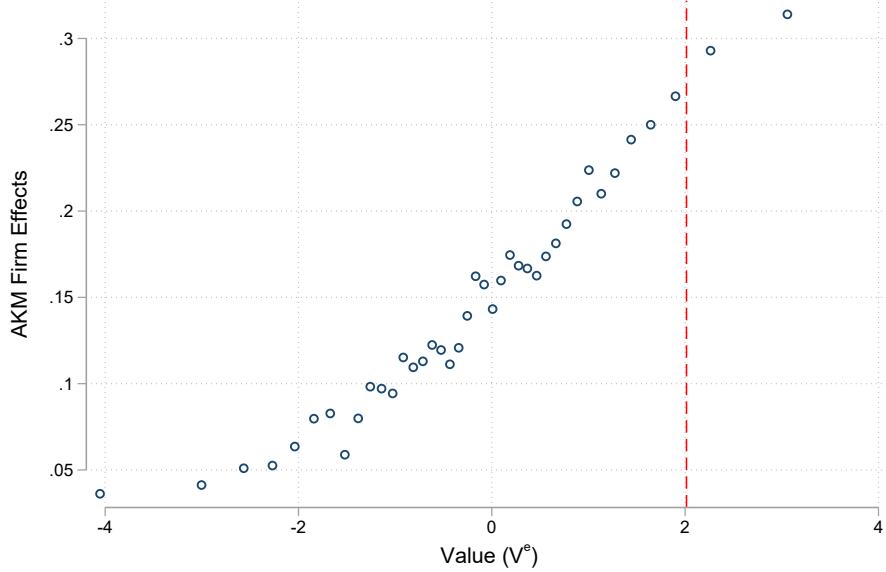
**Figure A24:** Histogram of Values ( $V_j^e$ ) for all Restaurants



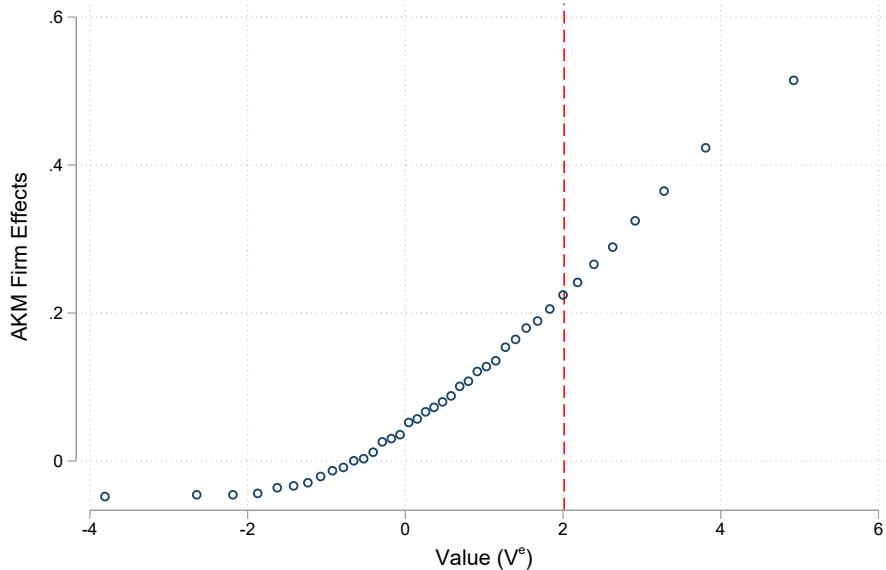
*Notes:* This histogram reports the distribution of  $V_j^e$  for all restaurants in the sample for whom it was possible to estimate the value (30%).  $V_j^e$  was estimated using the algorithm developed by Sorkin (2018) and represents the value of a firm. The average  $V_j^e$  in the sample is -0.158. The red dashed line represents the  $V^e$  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 A25:** 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 B1:** Summary Stats Restaurant Workers (RAIS & Census)

	(1) RAIS	(2) Census (2010)	(3) Formal Workers Informal Workers
Monthly Wage (2018 - R\$)	1,574 (686)	1,353 (2,831)	842 (860)
Age	34.84 (11.50)	33.20 (11.29)	31.37 (13.35)
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 2018 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 B2:** Summary Stats for Platform Workers

	Summary Stats App Workers (1)	Performance on the App	
		Worker Formal Before App (2)	Worker Non-Formal Before App (3)
<b>Demographics:</b>			
Age	29.5 (8.0)		
Female	0.08		
Monthly Earnings in Formal Job (Unconditional)	358 (867)		
Monthly Earnings in Formal Job (Conditional on Employment)	1,583 (1,177)		
Weekly Hours in Formal Job	41.7 (6.5)		
Tenure in Formal Job (in Years)	2.16 (2.9)		
Education (Years)	11.6 (1.7)		
Full Time	0.94		
Brazilian	1.0		
Workers in RAIS at some point	0.57		
<b>Performance on App:</b>			
Monthly Earnings (Tips)		10.2 (19.0)	11.2 (20.8)
Monthly Earnings (Trip)		571.2 (727.3)	646.6 (810.5)
Monthly Earnings (Promotions)		51.7 (92.2)	47.8 (88.7)
Monthly Hours Online		62.0 (62.9)	75.9 (73.0)
Monthly Hours Worked		30.1 (36.8)	34.9 (41.6)
Monthly Total Deliveries		79.5 (104.4)	91.8 (117.3)
Monthly Total Distance (KMs)		425.9 (593.5)	480.0 (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 B3:** Predictors of Platform Entry

	1 (Platform Entered Microregion)
Total Workers	0.0000954*** (0.0000216)
Total Firms	-0.000251 (0.000266)
Share of Female	2.91300 (4.50000)
Share of Black	7.87900 (5.99600)
Avg. Wages	-0.0000661 (0.000575)
Avg. Years of Education	1.95300*** (0.64800)
Avg. Tenure	-0.04170** (0.01680)
Avg. Age	0.15900 (0.17200)
Avg. Hours Hired	0.00306 (0.13400)
Growth of Total Workers	-2.49600 (3.00200)
Growth Total Firms	3.43200 (6.13900)
Growth Female Share	-1.77900 (5.65300)
Growth Black Share	0.32900 (0.84300)
Growth Avg. Wages	1.24200 (5.10300)
Observations	539

*Notes:* This table presents the estimates for a logit regression of platform availability in a microregion on covariates. Platform availability is defined as the platform ever entering a micro region in th period covered by the sample (2018-2021). Covariates are based on 2018 averages. Standard errors are reported in parentheses.

**Table B4:** Effects of Online-Delivery Platform Adoption: Instrumental Variable

	(1) $\Delta \text{Log Firm Size}$	(2) $\Delta \text{Log Avg. Wages}$
<i>OLS:</i>		
<b>Platform Adoption</b>	0.0158** (0.00684)	0.00183 (0.00264)
<i>Reduced Form:</i>		
<b>Platform Availability</b>	-0.00316*** (0.000921)	0.000240 (0.000437)
<i>2SLS:</i>		
<b>Platform Adoption</b>	-0.218*** (0.0629)	0.0161 (0.0292)
<b>Fstat</b>	1060.4	1001.5
<b>Observations</b>	73,708	73,672

*Notes:* This table presents the OLS, reduced form and instrumental variable estimates for the effects of platform adoption on changes in establishment log firm size (column 1) and changes in establishment log average wages (column 2). Details on the estimation procedure are described in Appendix D1. Changes in outcomes are differences between 2021 averages and 2017. Platform adoption is a binary variable equal to 1 if the platform was ever adopted by the restaurant. Platform availability is the amount of months the platform was available in the microregion between January 2018 and December 2021. Fstat refers to the Kleibergen-Paap rk Wald F statistic. Outcomes are winsorized at the 10-90 percentiles. Standard errors are clustered at the microregion level and reported in parenthesis.

**Table B5:** Summary Statistics for Restaurants Exposed to Spillovers and Control Restaurants

	(1) Matched Control Restaurant	(2) Matched Spillover Restaurants	(3) Potential Spillover Restaurants
Years of Education	10.88 (1.53)	11.05 (1.40)	11.03 (1.50)
Tenure (in years)	3.02 (2.10)	3.01 (2.22)	2.92 (2.29)
Monthly Earnings (in 2018-R\$)	1,501 (410)	1,521 (425)	1,488 (475)
Age	35.56 (7.19)	35.03 (7.51)	35.28 (8.10)
Share of Brazilians	1.00	0.99	0.99
Female	0.60	0.60	0.61
Hours	43.14 (2.69)	43.18 (2.46)	43.22 (2.54)
Full-Time	0.97	0.98	0.98
Establishment Size	10.86 (21.84)	10.96 (56.57)	9.32 (50.18)
Share of Waiters	0.46 (0.32)	0.48 (0.32)	0.48 (0.34)
Number of Establishments	9,998	19,885	34,082

Notes: Column 2 presents the summary statistics for restaurants who are exposed to a spillover event and for whom I can find a matched control restaurant. 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 6.2, 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. 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 spillover restaurant. Column 1 reports the characteristics of matched control restaurants, and Column 3 reports the summary statistics for the entire set of restaurants that are exposed to spillover events and are identified in RAIS. 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 B6:** Summary Statistics for Workers Exposed to Spillover Events and Control Workers

	(1) Matched Control Workers	(2) Matched Treated Workers	(3) Potential Treated Workers
Years of Education	10.73 (2.33)	10.83 (2.14)	11.09 (2.29)
Avg Tenure (in years)	4.04 1.26	4.04 (1.26)	3.11 (1.62)
Avg Monthly Earnings (in 2018-R\$)	1,510 (364)	1,504 (372)	1,641 (909)
Age	36.04 (10.26)	36.03 (10.26)	36.43 (11.66)
Share of Brazilians	1.00	0.99	0.99
Female	0.66	0.66	0.58
Hours	43.21 (3.01)	43.21 (3.04)	42.80 (4.43)
Delivery	0.01	0.01	0.02
Kitchen	0.25	0.25	0.25
Waiters	0.60	0.60	0.47
Other	0.14	0.14	0.26
Number of Workers	21,371	29,154	160,648

Notes: Column 2 presents the summary statistics for workers who are employed at restaurants that are exposed to a spillover event and for whom I can find a matched control worker. 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 6.2, 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. These summary statistics are calculated the quarter prior to the spillover event, 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 exposed to a spillover event. 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 B7: Total Wage Bill Effect of Platform Adoption by Gender**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	In-House Restaurant Workers	Net Earnings (Formal)	In-House Restaurant Workers Net Earnings (Informal)	Spillovers	Spillovers	Spillovers	App Workers Net Earnings (Informal)	App Workers Net Earnings (From Formal)	App Workers Net Earnings (From Non-Formal)	App Workers Net Earnings	App Workers Net Earnings	
	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men
<b>Quarter 0</b>	-208	214	-49	51	-39	-3	-10	-1	5.9	166	40	733
	(44)	(40)	(10)	(10)	(13)	(12)	(3)	(3)	(0.6)	(1)	(0)	(2)
<b>Quarter 1</b>	-664	15	-158	4	-203	-122	-50	-30	14.0	369	103	1,761
	(10)	(80)	(2)	(19)	(27)	(25)	(7)	(6)	(0.6)	(21)	(7)	(87)
<b>Quarter 2</b>	-539	-126	-128	-30	-246	-239	-61	-59	15.6	396	129	2,016
	(236)	(5)	(56)	(1)	(41)	(37)	(10)	(9)	(0.8)	(6)	(4)	(42)
<b>Quarter 3</b>	-361	-84	-86	-20	-678	-652	-168	-162	23.6	525	160	2,515
	(146)	(74)	(35)	(17)	(67)	(68)	(17)	(17)	(1.0)	(4)	(4)	(40)
<b>Quarter 4</b>	-475	-397	-113	-95	-1,419	-1,267	-352	-314	20.8	505	172	2,577
	(15)	(228)	(3)	(54)	(43)	(48)	(35)	(37)	(0.1)	(14)	(3)	(36)
<b>Quarter 5</b>	42	-385	10	-92	-2,230	-2,116	-553	-524	18.8	474	180	2,641
	(108)	(305)	(26)	(72)	(281)	(279)	(70)	(69)	(0.4)	(8)	(2)	(20)
<b>Cumulative PDV</b>	-2,151	-716	513	-171	-4,588	-4,188	-1,137	-1,038	95.3	2,351	756	11,814
	(406)	(610)	(96)	(145)	(459)	(452)	(114)	(112)	(0.1)	(50)	(19)	(221)
<b>Percentage of Pre-Platform Wage-Bill</b>	-3.9%	-1.3%	-0.9%	-0.3%	-8.4%	-7.7%	-2.1%	-1.9%	0.2%	4.3%	1.4%	21.6%

Notes: This table reports the estimated wage bill surplus generated by the platform for each component of equation (13) by gender. Columns 1-4 present the effects on the net earnings of in-house restaurant workers whose employer starts offering delivery services through the platform (for formal and imputed informal workers, respectively). Each quarter report the corresponding event-study estimates obtained after fitting equation (12) on monthly earnings, converting the coefficient to quarterly and multiplying it by the average firm size of restaurants that adopt the platform in  $t^* - 2$ . 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. Columns 5-8 present the estimated coefficients for formal and informal 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 6.2, 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 average restaurant size in my sample and by the probability of a restaurant being exposed to a spillover event as described in Appendix D2. Columns 9-12 report the total earnings gained for workers who work on the platform net of their outside option and their transportation costs. The outside option for workers who transition from the formal sector is equivalent to the average per hour wage that workers held prior to working on the platform. The outside option for workers who transition from non-formal status is imputed using a regression-adjusted earnings for non-formal workers within the same state-quarter using the PNAD-C. Transportation costs are based on estimates from Callil and Picanço (2023). 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 wage bill of restaurants that adopt the platform in  $t^* - 2$ . For all columns in the table, the pre-adoption wage bill is calculated including the imputed informal workers. Wages are expressed in real terms (2018 CPI). Standard errors are in parenthesis.

**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 three types of workers: cooks ( $C$ ), waiters ( $W$ ) and delivery drivers ( $D$ ). Each firm  $j$  posts wages for cooks and waiters, while delivery drivers are price takers in a competitive market. 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:

$$u_{iNj} = \beta \ln (w_{Nj}) + a_{Nj} + \varepsilon_{iNj} \quad (C15)$$

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

$$p_{Nj} = \frac{\exp(\beta \ln (w_{Nj}) + a_{Nj})}{\sum_{k=1}^J \exp(\beta \ln (w_{Nk}) + a_{Nk})} \quad (C16)$$

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

$$p_{Nj} \approx \tilde{\lambda}_N \exp(\beta \ln (w_{Nj}) + a_{Nj}) \quad (C17)$$

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

$$\ln(N) = \lambda_{jN} + \beta \ln(w_{jN}) \quad (C18)$$

Where  $\lambda_{jN} = \ln(\tilde{\lambda}_N) + a_{Nj}$ . 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:

$$Y_j = T_j C_j^\alpha S_j^{1-\alpha} \quad (C19)$$

$$S_j = [\theta W^\rho + (1 - \theta) D^\rho]^{\frac{1}{\rho}} \quad (C20)$$

Where cooks and service workers are complements in production and the output elasticity 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:

$$\max_{w_W, w_C, D} P_{jl} Y_j - w_W W - w_C C - w_D D \quad (C21)$$

subject to the following constraints:

$$\ln(W) = \lambda_{jW} + \beta \ln(w_{jW}) \quad (C22)$$

$$\ln(C) = \lambda_{jC} + \beta \ln(w_{jC}) \quad (C23)$$

$$P_{jl} = P_{0jl} Y_j^{-\frac{1}{\epsilon}} \quad (C24)$$

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 marginal 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:

$$(\xi_{p,y} + 1) P(Y) \frac{1}{\xi_{w_W} + 1} \frac{\partial Y}{\partial W} \quad (C25)$$

Where

$$\frac{\partial Y}{\partial W} = C^\alpha (1 - \alpha) S^{-\alpha} [\theta W^\rho + (1 - \theta) D^\rho]^{\frac{1-\rho}{\rho}} \theta W^{\rho-1} \quad (C26)$$

Define  $R$  as  $P(Y) = P_{0l} Y^{\frac{\epsilon-1}{\epsilon}}$ . Then plugging equation C26 into equation C25 gives equation 6 of Section 2:

$$w_W = \underbrace{\frac{\beta}{1+\beta}}_{\text{Markdown}} \underbrace{\frac{\epsilon-1}{\epsilon} \frac{R}{S} \theta (1-\alpha) \left(\frac{W}{S}\right)^{\rho-1}}_{\text{MRPL}} \quad (C27)$$

Similarly, using the fact that that:

$$\frac{\partial Y}{\partial C} = \alpha C^{\alpha-1} S^{1-\alpha} = \frac{Y \alpha}{C} \quad (\text{C28})$$

We get equation 7 of Section 2:

$$w_C = \frac{\beta}{1+\beta} \frac{\epsilon-1}{\epsilon} \frac{R}{C} \alpha \quad (\text{C29})$$

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:

$$\Delta \ln P_{0j} + \frac{\epsilon-1}{\epsilon} \Delta \ln Y + \frac{1-\sigma}{\sigma} \Delta \ln S + \Delta \ln \theta = \left( \frac{1}{\beta} + \frac{1}{\sigma} \right) \Delta \ln W \quad (\text{C30})$$

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:

$$\Delta \ln(W) = \frac{\beta\sigma}{\beta+\sigma} \left[ \underbrace{\Delta \ln(V_S) + \frac{1}{\sigma} \Delta \ln(S)}_{\substack{\Delta \text{ Revenue p/} \\ \Delta \text{ Service Sector} \\ \text{Worker} \\ \text{Size}}} + \underbrace{\Delta \ln(\theta)}_{\Delta \text{ relative productivity} \\ \text{waiters}} \right] \quad (\text{C31})$$

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

## D Appendix: Empirics

### D1 Robustness: Availability of the Platform as an Instrument for Adoption

As discussed in Section 6, the adoption of delivery platforms is based on a strategic decision of restaurants. If these decisions are based on unobservable firm level shocks, then it could be that the baseline matched difference-in-difference design could be biased. In this section, I present an alternative research design to estimate the impact of delivery platforms on restaurants based on an instrumental variable approach where I instrument platform adoption with the availability of the platform. The starting point is to define the outcome of interest which is defined as:  $Y_j =$

$\Delta (\ln Y_{j_{21}} - \ln Y_{j_{17}})$ , that is, the difference between log firm size (wages) in 2021 and log firm size (wages) in 2017. With this outcome at hand, I then estimate the following two stage least square model:

$$Y_j = \beta D_j + \delta X_j + u_j \quad (D32)$$

$$D_j = \pi_1 Z_j + \pi_2 X_j + v_j \quad (D33)$$

Where  $D_j$  is an endogenous binary variable equal to 1 when firm  $j$  adopted the technology, while  $Z_j$  is an exogenous variable equal to the amount of months in which the platform was available in  $j$ 's microregion between January 2018 and December 2021. Under this specification, the vector  $X$  includes firm level average of tenure, age, hours, firm age, share of service workers, share of female workers, share of restaurants within a 1 kilometer radius, quartile of firm wage, and quartile of firm size, all in 2017. Standard errors are clustered at the microregion level.

Within this framework, the panel data regression (10) presented in Section 5 can be interpreted as the intention-to-treat effects of the availability of delivery platforms in a labor market, where date and microregion indicators absorb common time shocks and unobservable restaurant productivity determinants that are fixed at the microregion level. As in the classical IV design, under regular assumptions (relevance, exogeneity and exclusion) the IV will identify the local average treatment effect for compliers (i.e. restaurants whose adoption is moved by availability timing), similar to Akerman et al. (2015). However, given the discussion in Section 7.4 regarding the spillover effects of delivery platforms on non-adopting restaurants, the exclusion restriction is likely to be violated. Specifically, to see this suppose platform availability has the following impact on firm level outcomes (beyond its effect on  $Y$  through  $D$ ):

$$u_i = \lambda Z_i + \epsilon \quad \text{with } \lambda \neq 0 \quad (D34)$$

$$E[u|Z] \neq 0 \quad (D35)$$

Given the results discussed in section 7.4, it is safe to assume that  $\lambda < 0$  for firm size while it will be closer to 0 for average wages. Then with one endogenous regressor and one instrument, the IV/Wald estimand becomes:

$$\hat{\beta}^{IV} = \frac{\text{COV}(Z, Y)}{\text{COV}(Z, D)} = \beta + \frac{\lambda}{\pi}, \quad (D36)$$

Where  $\pi$  is the first-stage effect of availability on adoption. From here, it is straightforward to see that under the assumption that the average treatment effect on compliers is similar to the effect on the average treated firm, the negative spillover effects on firm size will imply that  $\hat{\beta}^{IV} < \hat{\beta}^{DiD}$ . This is precisely what is found in Table B4.

## D2 Procedure to Rescale Spillover Effects

This sections provides the details of how I rescale the worker level effects of spillovers presented in Section 8.2 to reach the results presented in Column 4-6 of Table V. I start by defining a spillover event as:

$$\mathbf{1}[\text{Spillover}] = \mathbf{1}[\Omega_{jt} > 95 \text{ percentile of } \Omega] \quad (\text{D37})$$

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 8.2. The effect of spillovers on workers earnings is estimated using the following regression:

$$Y_{it} = \beta_0 + \alpha_i + \delta_t + \sum_{k=-7}^{k=5} \theta_k \mathbf{1}\{t = t^*(i) + k\} + \sum_{k=-7}^{k=5} \beta_k \mathbf{1}\{t = t^*(i) + k\} \times \mathbf{1}[\text{Spillover}_i] + \epsilon_{it} \quad (\text{D38})$$

I then convert the spillover effects into units of adopting restaurants within a 1 kilometer radius ( $Z_{jt}$ ) by applying a two-step procedure. First, I estimate the following regression:

$$Z_{jt} = \beta_0 + \alpha_j + \delta_t + \sum_{k=-7}^{k=5} \gamma_k \mathbf{1}\{t = t^*(j) + k\} \times \mathbf{1}[\text{Spillover}_j] + \epsilon_{jt} \quad (\text{D39})$$

where  $\gamma_k$  provides the effect of a spillover event on the number of restaurants within 1km that adopt the platform. The second step is to re-scale the estimated effect of spillover events on workers earnings into units of  $Z_{jt}$ :

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

I then multiply each  $\beta_{\text{rescaled}\{k\}}$  by the median number of non-adopters in my sample and the unconditional probability of a firm to be exposed to a spillover event (5 percent, as defined by spillover definition in Section 6.2) to get the average effect of platform adoption on workers earnings at non-adopting restaurants. 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 ( $\pi_{\text{spillover}\{k\}}$ ):

$$\pi_{\text{spillover}\{k\}} = (\beta_{\text{rescaled}\{k\}}) \times N_{\text{Restaurants non-adopt}} \times \text{Pr}(\text{event}) \times \bar{L} \quad (\text{D40})$$

which are the effects presented in Columns 4-6 of Table V.

### D3 Estimation of Outside Option for Delivery Drivers Transitioning from Non-Formality

To estimate the outside option of delivery drivers who transition from either unemployment or informality, I use the Brazilian household survey PNAD-C. Given potential inconsistencies across administrative earnings (reported in RAIS) and self-reported earnings from PNAD-C, I use PNAD-C to estimate the earnings ratio between non-formal and formal workers that follow the same distribution of demographics as platform workers. Then I multiply the corresponding ratio of each quarter and state to the average outside option of platform workers that are transitioning from the formal sector.

To compute the earnings ratio between non-formal and formally employed workers in PNAD-C, I start by restricting the sample of PNAD-C workers that are between 18 and 65. For employed workers, I keep individuals in PNAD-C who are employed in the non-agricultural sector and have one job. Within employed workers, I define a formal worker if they answered having a *Carteira de trabalho assinada* in their job, and informal if they don't. 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.

I re-weight the sample of PNAD-C workers 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). Specifically, the reweighting factor  $\hat{\Psi}(X)$  is constructed as follows:

$$\hat{\Psi}(X) = \frac{\hat{Pr}(D_{App} = 1|X)/\hat{Pr}(D_{App} = 1)}{\hat{Pr}(D_{App} = 0|X)/\hat{Pr}(D_{App} = 0)}$$

where  $Pr(D_{App} = 0|X) = 1 - Pr(D_{App} = 1|X)$  and  $\hat{Pr}(D_{App} = 1|X)$  is the estimated probability of being a platform worker estimated through a logit model. Once the PNAD-C sample is reweighted to match the distribution of demographics of platform workers, I calculate the earnings ratio between non-formal (informal and unemployed) and formal employed workers at the state-quarter level and multiply the ratio by the outside option of delivery drivers transitioning from the formal sector. The average re-weighted wage ratio of non-formal to formal workers in my sample is 0.32.

#### *D4 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. 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—the mid point of what has been used in other studies in Brazil following the same type of workers (Callil and Picanço, 2023). To recover a per adopting restaurant impact on platform worker earnings, I then multiply the average per hour wage in each restaurants corresponding municipality-month by the number of hours the restaurant utilized delivery platforms in that period. I finally take an average across all the adopting restaurant estimates.

#### *D5 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 impute 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 adopting 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 of 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 imputed 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.

## D6 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:

$$\ln y_{ijt} = \alpha_i + \psi_{j(i,t)} + \beta X'_{it} + \epsilon_{it} \quad (\text{D41})$$

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. I estimate the AKM model for the period 2012-2018.

Finally, if a worker did not work in the formal sector during my estimation period, I impute their worker effects when possible. To input the worker effects, I leverage equation D41 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:

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

where  $T$  is the number of calendar years in which worker  $i$  is observed with a formal job.

#### D7 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:

$$M_{kj}\exp(V_j^e) = M_{jk}\exp(V_k^e), \forall j \in J \quad (\text{D42})$$

Summing (D42) over all firms in the market, one arrives to the following expression:

$$\frac{\overbrace{\sum_{j \in J} M_{kj}\exp(V_j^e)}^{\text{value-weighted entry}}}{\underbrace{\sum_{j \in J} M_{jk}}_{\text{exits}}} = \underbrace{\exp(V_k^e)}_{\text{value}} \quad (\text{D43})$$

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 (D43) 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.<sup>58</sup> 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.<sup>59</sup>

## 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.

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<sup>58</sup>A worker is considered to work for establishment  $j$  in quarter  $t$  if the main source of income during  $t$  was from  $j$ .

<sup>59</sup>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.

- 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	
<b>2016</b>	90%
<b>2017</b>	91%
<b>2018</b>	88%
<b>2019</b>	88%
<b>2020</b>	88%

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