Riders on the Storm*

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Abstract

Online food delivery platforms typically operate through a controversial business model that relies on subcontracting self-employed workers, known as *riders*. Using a search and matching model, we quantify the labor-market effects of the Spanish Riders' Law in 2021 where the presumption of dependent employment for riders was established. Riders with heterogeneous preferences for leisure trade off work flexibility and easier employability as self-employed against enjoying higher wages as employees. Our main finding is that the reform succeeded in increasing the share of employees but failed to fully absorb the large outflows from self-employment and decreased riders' wages, resulting in welfare losses. However, complementing the reform with a payroll tax cut for platforms hiring employees preserves employment levels and increases substantially riders' welfare.

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JEL: J21, J60

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1 Introduction

Like a dog without a bone, an actor out on loan, riders on the storm (**Riders on the Storm, The Doors**)

The digital platform economy is expanding quickly with the European Union (EU) being hot on the heels of the U.S. Next to taxi driving, one of its soaring industries is the online food delivery service which is the topic on which this work focuses. Although its growth dates back to the late 2000s, the COVID-19 pandemic boosted online food delivery usage world wide. Since then, the visibility of delivery couriers (commonly known as *riders*) pedaling through the streets of big cities with their striking backpacks have attracted a lot of media attention.[1]

Traditionally, most online food companies have relied on subcontracting self-employed riders to deliver orders. This practice has sparked intense debate on whether self-employed riders should instead become dependent workers. Those favoring this proposal argue that riders are incorrectly classified as independent contractors and should be granted the same level of social protection as employees in other non-platform industries, including a fixed work schedule and the right to collective bargaining. Against this view, opponents claim that riders should remain operating as independent contractors, not only because this labor status provides them with flexible working hours and compatibility with other activities (e.g. formal education or part-time jobs) but also because it facilitates lower barriers to market entry, as all it takes for riders to start working is to sign up to a digital platform. As reflected by the classic song of The Doors (a famous Californian rock group of the 1970s) heading this section and giving title to the paper, food delivery riders seem to be weathering a storm full of uncertainties about their future labor conditions.

In line with this debate, over the last few years, EU authorities have sought to ease the access of people working for digital platforms to their legal employment status. Consequently, in 2023 the EU Council made a proposal advocating

[1] Although rider means cyclist or motorcyclist, note that in many countries this term also refers generically to any worker performing food and grocery delivery tasks, regardless of the type of transport being used, including cars or vans.

procedures to ensure safer and fairer working conditions of platform workers by determining their correct employment status. Spain, the country we study, has gone substantially further by approving of the so-called "Riders' Law" (RL, hereafter) in September 2021 establishing: (i) the presumption of riders as employees, and (ii) the requirement of algorithmic transparency, paving the way for collective bargaining in that sector. Furthermore, a key feature of this reform for further analysis is that some platforms refused to comply with the new regulations and accumulated severe administrative fines.[2]

We quantify the effects of the RL reform in Spain through the lens of a search and matching model with heterogeneous workers and firms that captures the key policy trade-offs described above. Riders can always opt to work as independent contractors in the so-called casual sector (C sector, hereafter), where they have control over their work schedules and get paid a fraction of the delivered orders. However, the immediate availability of these jobs, where workers pay their own social security contributions, comes at a cost: when labor demand is slack, their hourly pay decreases as they have to wait for delivery orders. By contrast, riders working as employees in the regular sector (R sector, hereafter) are paid by the hour while their employers are the ones in charge of payroll taxes. Their pay rate is negotiated by a labor union through Nash bargaining with the employer, and workers have a fixed working day schedule determined by the platform. Furthermore, unlike the frictionless C sector, the R sector is subject to search and matching frictions.[3] Riders decide where to search for employment given heterogeneous preferences for leisure arising from differences in heterogeneous home, education, or caregiving commitments. Importantly, they have the option to use the C sector as an entry-level job and continue searching on-the-job for R jobs if that is in their interest.

[2]Note that, since (i) is only a presumption, employers could provide evidence to the contrary by proving that powers of organization, direction and control over their platform-based riders are not exercised. As discussed later in more detail, this explains why several platforms have challenged the RL in the hope of winning the court cases against the fines imposed on them.

[3]Since employers in the R sector behave just as any other employer in the economy, these frictions provide a realistic modeling setup. In particular, as firms have to pay each worker by the hour and cannot lay them off at will, they will screen workers to ensure that only profitable matches are formed.

The model parameters are calibrated to fit the empirical moments on employment, hours worked, wages, labor market flows, payroll taxation, and unemployment benefits in the Spanish online food delivery sector. The model yields two cut-off values in the distribution of preferences for hours worked/leisure that ensure the coexistence of both C and R jobs in equilibrium. Accordingly, riders who wish to work relatively long hours choose C jobs and, among those who prefer fixed work schedules, some search directly for R jobs while others opt first for C jobs to escape unemployment, and then have the option of transiting to their preferred jobs through on-the-job search.

We simulate the effects of the RL by allowing for the imposition of administrative sanctions on those C platforms that challenged the new regulations, in line with the big fines they have accumulated in Spain. These sanctions increase the marginal cost of producing orders, leading to lower labor demand for C jobs, which translates into longer waiting times for their riders when collecting food orders from restaurants. This, in turn, reduces riders' hourly pay since they get paid by each order served and not by their supplied hours of work. Facing this pay reduction, some C riders reallocate to the R sector. Overall, the employment share in the C sector drops by nearly 13 percentage points while hourly wages fall by 7 percent. In contrast, as more workers search for R jobs, R firms open more vacancies, increasing its employment share by 6 percentage points, only partially absorbing C job losses. In addition, as the worsening conditions in the C sector deteriorate riders' outside options, wages in the R sector do not rise.

All in all, we find that the RL alone reduces total employment in the riders sector by 7 percentage points, while average hourly wages and effective hours fall by 3 percent and 2.5 percent, respectively. Hence, we conclude that the reform decreases riders' welfare in terms of consumption equivalent units.[4]

In view of these findings, we study how the introduction of a tax bonus in employers' payroll taxes in the R sector could play a useful role in achieving a

[4]At any rate, given that the actual number of riders has increased by 40 percent since the RL (see Sections 2 and 6 below), these negative results should be interpreted as deviations from a growing trend in households' demand for online food delivery, which is taken as exogenously determined in our counterfactual simulations regarding steady-states comparisons.

further push in its labor demand. In particular, we study two potential tax-bonus reforms complementing the use of administrative sanctions: (i) a tax cut maintaining welfare levels, and (ii) a tax cut preserving employment. We find that the first tax cut (9 percentage points lower than the benchmark tax rate of 29 percent) is smaller than the second tax cut (21 percentage points), therefore having milder fiscal budgetary consequences. However, the employment-neutral tax bonus leads to large welfare gains via a stronger rise in labor demand, which further increases the probability of finding R jobs for on-the-job searchers and reduces the earnings losses for riders remaining in the C sector.

1.1 Related literature and outline

The literature on the characteristics of the online gig economy is still scant at this stage, due to the difficulties of studying these work arrangements through conventional administrative and survey data. In effect, very often these standard data sources do not provide sufficiently detailed information on this type of workers (see, e.g., Abraham et al., 2021; Katz and Krueger, 2019, for efforts to distill these data in the U.S.). To overcome these limitations, other studies use administrative data (Collins et al., 2019), design specific surveys (Boeri et al., 2020), or conduct field experiments and RCTs (Mas and Pallais, 2017; Angrist et al., 2021). In line with these approaches, our paper uses a mix of an own-elaborated survey and administrative data on riders' outcomes.

In addition, a small set of recent papers embed casual jobs in structural search and matching equilibrium models to analyze the general equilibrium employment, wage, and welfare effects of these flexible work arrangements. Our paper falls into this last strand of research where the closest forerunners are Scarfe (2019) and Dolado et al. (2023). Scarfe (2019) builds a frictional labor market model which is calibrated to Australia, where casual workers (not just riders) account for 10 percent of the labor force. In turn, Dolado et al. (2023) model zero-hour contracts, which represent about 16 percent of the low-paid segment of the UK labor market. In their paper, agents are ex-ante heterogeneous in their time availability to work and they always receive the minimum wage whereas Scarfe (2019) deals with ex-ante homogeneous workers whose wages are Nash bargained. Our approach extends these modeling strategies by allowing for both ex-ante heterogeneity and endogenous wages.

Our paper is also linked to the literature that uses structural search models to study labor market regulations in the presence of an informal economy which somewhat resembles the C sector. Similar to us, Zenou (2008) and Satchi and Temple (2009) model the informal sector as one without search and matching frictions. Different from us, workers are homogeneous and always prefer formal-economy jobs. In contrast, Albrecht et al. (2009) develop a model where some workers prefer the frictional formal sector (resulting from idiosyncratic productivity differences) but the informal sector also features search frictions. Apart from highlighting a different sorting mechanism across sectors based on preferences for leisure, our paper also differs in the focus of the policies: those papers deal with the effects of regulating formal-sector jobs on the number of informal jobs, whereas we show that regulating C sector jobs changes workers' outside options for the R sector and, thereby, has spillover effects on wages and employment in that sector.

Other strands of the literature that our paper speaks to are those dealing with the introduction of short-time work arrangements or furlough (Cahuc et al., 2021; Carrillo-Tudela et al., 2021; Díaz et al., 2025), the effects of changing legal work-time regulations (Carry, 2022), and the modeling of hours of work in search and matching models (Cooper et al., 2017; Frazier, 2018). We depart from these models in allowing for two-sided heterogeneity regarding labor- demand decisions by firms and labor supply decisions by workers. Finally, there is some recent work on the gig economy dealing with platforms where buyers post one-time projects and workers compete for these projects by posting wages. Stanton and Thomas (2025) show that regulating this type of labor market reduces overall and workers' surplus. Key to this finding is that: (i) workers already capture a large share of the surplus, and (ii) regulation decreases demand for their services. Ours is a very different market structure with longer employment relationships and wages not being set by workers. Nevertheless, the conclusion is similar: regulation of these types of jobs leads to lower labor demand and an overall loss in workers' welfare.

The rest of the paper is organized as follows. Section 2 provides some historical background about food delivery platforms in Spain, involving a detailed discussion of the 2021 Riders' Law. Section 3 describes an online survey we run to draw data on riders' characteristics and their main stylized facts. Section 4 lays out the quantitative model. Section 5 describes its calibration. Section 6 discusses the counterfactual results. Finally, Section 7 concludes.

2 Overview of Food Delivery Services in Spain

2.1 Historical Background

The first signs of activity in the online food delivery sector in Spain date back to the early 2000s, when a startup launched a website (ComerComer.com) following the operating procedures that would become widespread a decade later. Restaurants began to create online branches and provided fleets of delivery couriers. These early attempts to open a new market were followed by the entry of other smaller platform companies (Sin Delantal.com and La Nevera Roja) which relied on the use of improved technologies developed by bigger platforms, like Just Eat in the UK or GrubHub in the U.S. Although some of these small companies had to exit the market following the dot.com stock price fall, the stronger platforms survived and were subsequently absorbed by the international bigger players (e.g. Delivery Hero, Just Eat, and Rocket Internet).

These acquisitions gave a great boost to the sector around 2015, once the Spanish economy recovered from its long recession during the global financial crisis. By 2019, this expansion resulted in online food delivery platforms achieving: (i) 4.7 million customer profiles, (ii) 36.2 million managed annual orders, and (iii) an annual overall employment growth of 2.4 percentage points, leading to 12,500 riders in 2019, whose gross annual wages hovered around 1.2 and 1.4 times the national minimum wage (*Salario Mínimo Interprofesional*, SMI). All this led to a direct contribution to GDP of €250 m. which reached about €700 m. once indirect-induced effects are considered.

More recently, as in most countries, the business activity of these online platforms in Spain has grown considerably during the COVID-19 lockdown, having

Figure 1: Market shares in the Spanish food delivery sector

Source: Dashmote (Spain's Food Delivery Market: An Analytical Overview)
Note: The graph displays the revenue market share in the Spanish food delivery sector between 2020 and 2023.

become one of the essential channels for food and goods delivery to households. Regarding the size of the big players, Figure 1 shows that, by the end of 2019, Glovo was the leading platform for deliveries (with 40 percent of market share), followed by Just Eats (33 percent) and Uber Eats (17 percent), while Deliveroo and some other smaller companies accounted for the remaining 10 percent. By 2021, orders increased by 40 to 50 percent as teleworking became widespread during the pandemic. As a result, Glovo and Uber Eats expanded their market shares to 43 and 22 percent, respectively, at the expense of Just Eat and other smaller platforms. The number of riders increased substantially, from 12,500 in 2019 to about 25,000 in mid-2021 (just before the RL), out of which 5,500 were employees (73 percent of them under open-ended contracts) while the remaining 19,900 were self-employed. Finally, by 2023, the presumption of dependent employment for riders imposed in the RL has led to a decline of 11 percent in the market shares of the C platforms that ignored the new regulations (Glovo and Uber Eats), whereas Just Eat has surged to reach 39 percent of this market.

According to the results of a survey among 1850 riders carried out by the consulting firm Adigital (2020) in 2019, 81 percent positively value the flexible hours provided by platforms, while 65 percent appreciated the ability to combine platform collaboration with the development of other activities, both personal (studies, preparation of public sector competitions or others) and labor-related ones (part-time or temporary employment). Moreover, the following socio-economic characteristics stand out among respondents: (i) 66 percent are aged below 29 years while 21 percent exceed 50 years; (ii) the dominant nationalities are Latin Americans (64 percent) followed by Spaniards (28 percent); (iii) their educational attainments are similar to those of natives between 18 and 50 years of age, with 53 percent having achieved at most compulsory secondary education and 40 percent involved in college education; (iv) 12 percent are unemployed and 5 percent inactive, and (v) their gross annual labor earnings reach about €15,900 (the annual SMI in Spain was €14,700 in 2019)

2.2 The Riders' Law

In September 2021, Spain approved the RL establishing the presumption of riders as employees instead of independent contractors. The result was a market segmentation with some platforms signing their riders as employees while others challenged the new rules in the courts of justice and kept employing their riders as independent contractors (see below). Among the former, the most prominent compliant was Just Eat, together with some new smaller new platforms, like GoDelivery, Stuart, Getir, and Gorillas (the latter two left Spain in 2023 and 2022, respectively). As employees, riders receive a fixed weekly work schedule, a fixed hourly pay, dismissal protection, and social security contributions that are paid by the employer. Moreover, Just Eat signed a collective agreement with its employees in 2023 ensuring €15,200 a year with four weeks of holidays and a maximum of 9 working hours per day.

Turning to the employment trends around the adoption of the RL, just before the reform there were around 25,000 riders in total, while this figure reached 35,000 by 2024. Regarding the effectiveness of the new hiring rules, as illustrated in Figure 2, Esade (2022) reports that the number of riders with employee contracts has doubled after the RL, from 5,500 in mid-2021 to about 11,000 in mid-2022, out of which 98 percent (vs. 73 percent before the RL) hold open-ended contracts. This evidence seemingly points to an apparent success of the reform. However, as noted earlier, this substantial rise in the number of riders has to be seen in light of the secular trend in the demand of online food orders since the pandemic in most countries (many of which did not approve similar regulations to the RL), together with the subsequent rise in the number of new platforms entering this sector. Thus, this calls for a quantitative model to disentangle the role played by the RL in explaining these developments.

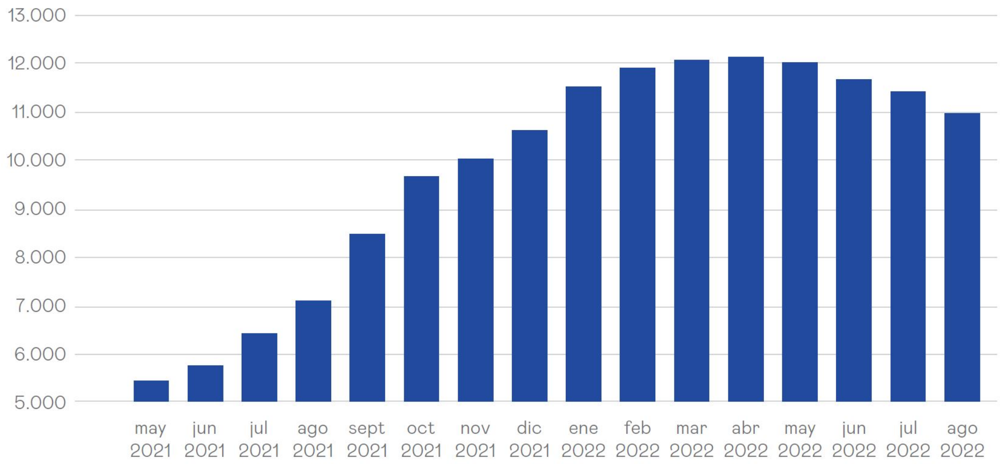
Interestingly, the two biggest C platforms persisted in using independent contractors, either completely (Glovo) or partially (Uber Eats), after the RL. Their resistance to the new hiring rules relies on claiming that their riders can decline orders in their apps, as well as freely choose their hours of work.[5] However, these claims have not been supported so far by several court rulings, including one by the Supreme Court that ultimately rejected their arguments. As a result, Glovo alone has accumulated to date more than €200 m. in administrative fines though it survives due to the above-mentioned global trend for online food delivery services.[6]

Finally, among those oppposing the RL, there have also been some organized labor groups. For example, according to one of the main workers' associations (Asociación Autónoma de Riders), about 65 percent of its members dislike the new regulations. They argue that the reform reduces monthly earnings mainly due to the lack of freedom in deciding the number of hours worked for those employed in the compliant platforms, as well as a weaker demand for their services among those who remained subcontracted.

[5]This legal strategy follows the European Court of Justice's decision in the Yodel case when it did find that a parcel delivery driver with the discretion to subcontract, decline deliveries, provide services to third parties or fix her/his own hours could be considered self-employed according to the Working Time Directive.

[6]However, at the end of 2024, Glovo has announced that it will comply with the RL in the near future, following the opening of an investigation by the European Commission for possible anti-competitive practices

Figure 2: Number of employees among riders in the food delivery sector



Source: Esade (2022).
Note: The figure displays the number of employees in the Spanish food delivery sector between May 2021 and August 2022.

3 Data and Empirical Analysis

This section summarizes the stylized facts of the Spanish food delivery sector that help us develop a quantitative model. Given the scarcity of official statistical information on riders' specific outcomes, we resort to an own-elaborated online survey to collect detailed data.[7] Two main findings stand out from this survey: (i) R jobs offer a wage premium conditional on hours worked, and (ii) C jobs offer greater flexibility in terms of work schedules.

More concretely, with the help of some personal contacts among riders, we distributed a small survey to their workmates in a completely anonymous format through the Google Forms platform in September and October of 2023. The questionnaire is organized around three blocks: (i) general information about the worker (age, gender, educational attainment, nationality, and availability of a work permit); (ii) information about the job (current platform, tenure, number of platforms where (s)he has worked during 2023); and (iii) wages and turnover (net

[7]In principle, part of this information should be available in the registry of economically dependent self-employed workers by the Public Employment Services (SEPE). Yet, the data is found to be incomplete and fairly outdated to be able to identify riders' main outcomes

Table 1: Descriptive statistics from online riders' survey

	Mean	**s.e.**
Worker		
Age	27.3	7.4
Gender (Male)	0.86	
Education (Upper)	0.46	
Nationality (Foreign)	0.77	
Work Permit (Yes)	0.82	
Platform		
Glovo	0.48	
Uber Eats	0.20	
Just Eat	0.24	
Others	0.08	
No. of platforms (2023)	1.3	0.3
Tenure (years)	1.5	1.2
Wages/Turnover		
Net hourly wage (Euros)	5.6	2.3
Daily hours	4.6	1.4
Employee	0.4	
Self-employed	0.6	
Quit/Dismissed (Yes)	0.4	
Unemployed (previous status)	0.2	

Note: Sample size: 162 riders. Responses were collected during Sept.-Oct. 2023 through Google.form and Facebook.

hourly wage, previous labor-market status– employed, unemployed and inactive– and dismissed/ quits over that year). Overall, 275 riders received the questionnaire, out of which we received 162 replies.

Table 1 summarizes the main descriptive statistics of this online-survey sample which are found to be in line with those reported in the much larger survey run by Adigital (2020) mentioned in subsection 2.1 above. The typical respondent works 4-5 hours a day with a net hourly wage of €5.6. A comparison of the self-reported wages with administrative data can be undertaken using the Quarterly Survey of Labor Costs (Encuesta Trimestral de Coste Laboral) which provides information on wages broken down by NACE sectors of activity at the 4-digit level. Riders are

Table 2: Wage regression (OLS)

Dep. Var	**ln(wage)**
Age	0.042 (0.037)
Gender (Male)	0.121* (0.063)
Nationality (Foreign)	0.069 (0.058)
Work Permit (Yes)	-0.057** (0.029)
Tenure	0.031** (0.015)
Glovo/Uber Eats	-0.176*** (0.033)
Education (Upper)	0.018 (0.026)
ln(hours)	0.052*** (0.020)
R-sq.	0.71
No. Obs.	162

Note: Reference categories are female, Spaniard, no work permit, Just Eat and other R platforms, and less than upper education. Robust standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

included in sector 532 H (”Other postal services and courier activities”), together with postmen and other types of couriers. Its raw hourly wage is close to €7 in 2019. Taking into account that the corresponding wage in the survey is net of social security contributions and maintenance costs and that the remaining postal officers and couriers in this NACE sector typically earn more, the self-reported net hourly wage of €5.6 in the survey seems like a plausible figure.

The survey also shows that mean hourly wages mask important heterogeneity across sectors. In particular, the mean hourly wage (net of payroll taxes and other maintenance costs borne by the rider) is higher in the R sector than in the C sector. To investigate whether this difference is driven by workers with different characteristics sorting into distinct jobs, we run the following *mincerian*

OLS regression with the online survey data:

$$\ln w_i = \beta_0 + \beta_1 \mathbb{I}_{C=1} + \beta_2 \boldsymbol{X_i} + \gamma \ln h_i + \varepsilon_i \tag{1}$$

where $\ln w_i$ is (logged) net hourly wage, $\mathbb{I}_{R=1}$ is a dummy variable capturing if a rider works in the C sector (Glovo or Uber Eats), $\boldsymbol{X_i}$ is a vector of socio-demographic covariates (age, gender, nationality, work permit, tenure and education), and $\ln h_i$ is (logged) hours worked.[8] Table 2 reports the corresponding results of this regression. We find that, on average, riders with similar observable characteristics and the same hours worked earn a wage premium of 18 log points in R jobs relative to C jobs, a result that is consistent with the fact that trade unions are effective in extracting rents. It also highlights that hourly wages are increasing in the number of hours worked, with an elasticity of 0.05, as plotted in Figure 3. This last result suggests that it is more profitable for platforms to have riders working long hours, possibly because it facilitates delivery planning.[9] These patterns will help discipline wage setting in the calibration of the model discussed below in Section 4.

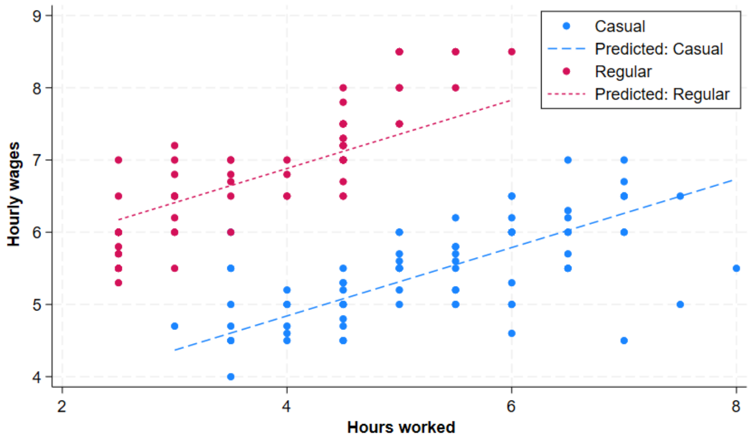
Note that, despite offering lower wages, a sizable share of workers opt for C jobs. To explain this fact, Figure 4 displays the densities of daily hours worked in both types of jobs, where four findings stand out. First, and consistent with the Adigital (2020) survey, there is large dispersion in daily hours across riders suggesting large heterogeneity in time availability across riders. Second, the distribution of hours worked in C jobs is more disperse than in R jobs; in particular, the density of hours worked in the former sector is smooth, while it is bimodal in the latter.[10] Third, C jobs mainly provide upward flexibility in hours worked: while R riders work less than 6 hours per day, a significant proportion of C riders exceed this threshold; this implies that the average daily hours worked is higher in the C

[8]Hours of work are assumed to be an exogenous regressor in (1) in line with our assumption in subsection 4.1 below that riders' hours supply schedules only depend on their preferences for leisure but not on wages, as income and substitution effects cancel each other

[9]In line with this reasoning, Chen et al. (2022) argue that delivery assignment algorithms reward drivers who work long hours with high-revenue deliveries.

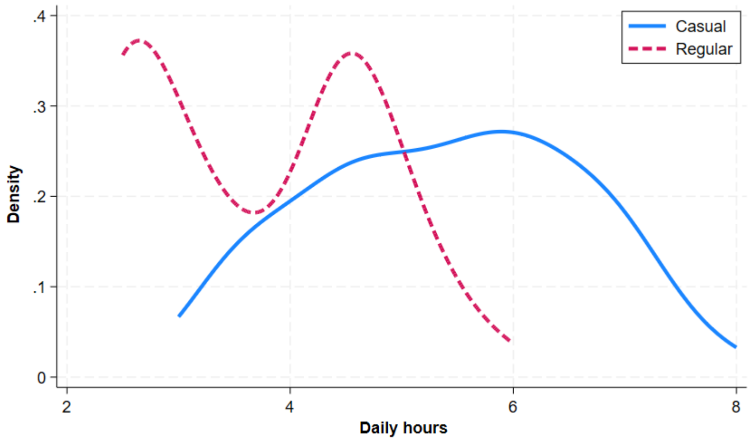
[10]This result is consistent with Just Eat offering two main job contracts: one of 12 weekly hours during weekends and another one ranging from 16 to 30 hours during the entire week.

Figure 3: Hourly wages and hours worked



Note: The figure displays hourly wages as a function of hours worked for riders in the casual and the regular sector. The prediction results from a linear OLS regression.

Figure 4: Distribution of hours worked



Note: The figure displays the density of hours worked for workers in the casual and regular sector using a Gaussian Kernel estimate.

sector than in the R sector (5.4 h. vs 3.7 h.), a result that also holds after after controlling for observable characteristics. Fourth, the distribution of hours worked has a significant mass in both sectors at low hours worked, e.g. below 4 hours. We interpret this fact as being consistent with the existence of search frictions in the R sector limiting the access of riders with higher preference for these jobs due to their wage premium.

4 Quantitative Model

4.1 Environment

Sectors. This section presents a two-sector model featuring heterogeneous jobs (platforms) and workers (riders) which enables us to evaluate the effects of the 2021 RL. The model distinguishes between: (i) a frictionless casual sector (C), where riders can instantly find jobs as self-employed, and (ii) a regular sector (R) which, in contrast to the C sector, is subject to search and matching frictions, and where workers can only be hired as employees. Moreover, payroll taxes in the C sector are paid by its self-employed riders (labeled τ_w) and by employers in the R sector (τ_f). The optimal choice of sector depends on the riders' preferences for hours worked. Note that we abstract from the rest of the economy by only modeling the behavior of those workers who operate as riders.

Production. Time is discrete and infinite and we assume a representative firm in each sector, $j = C, R$. Motivated by our empirical findings on wages (see Figure 3), it is also assumed that all firms operate a technology where the number of orders per hour increases with hours worked. Thus, the hourly productivity of riders, a, is given by:

$$a = Ah^{\gamma}, \quad \gamma > 0. \tag{2}$$

where A is a constant TFP parameter, and h is hours worked. Riders in the R sector always work a fixed amount of time $h = \bar{h}$ and are paid for these hours.[11] Conversely, C riders freely choose their total hours worked in a decentralized way, with the app ensuring that supply equals demand. Correspondingly, the effective number of hours worked for which riders get paid, $\tilde{h} = \varphi h$, may be lower than h. This feature is captured by an endogenous proportionality factor $0 < \varphi \leq 1$, which is strictly smaller than 1 whenever the demand for hours in the C sector falls short of the supply. As already highlighted, one way to think about this relationship is that, when demand is weak, C riders will experience longer waiting times to

[11] A single work-time schedule is assumed for tractability of the model. Allowing for two work schedules (e.g. full and part time) in the R sector (see Figure 4) is left for future research (see Section 7 below)

pick up new orders, with this idle time not being counted as leisure. Another interpretation could be that the verification process for a new rider in the app of a C platform is not instantaneous, with the waiting period being related to overall demand in that sector. The effect of the RL on the labor demand in the C sector through administrative sanctions against non-compliant platforms is a key mechanism that will be examined below. Given these considerations, the number of orders in each sector j can be expressed as follows:

$$o_C = E_C \int a(h_i)\tilde{h}_i dG^C(\epsilon) \tag{3}$$

$$o_R = a(\bar{h})\bar{h}E_R, \tag{4}$$

where E_j represents the total employment in sector j, and G^C is the cumulative distribution function of the preference parameter ϵ for the hours worked in the C sector, to be defined in the next subsection. Firms in both sectors face two types of costs: (i) labor costs, and (ii) a convex cost o_j^ϕ in the number of orders, where $\phi > 1$; this parameter captures the fact that, when demand for online food delivery is high, platforms often need to work with less efficient restaurants to satisfy the extra orders. In addition to these costs, firms in the R sector have to pay the flow costs of posting vacancies, given by κv_R, on top of payroll taxes, given by τ_f. Therefore, flow profits in each of the two sectors become:

$$\pi_C = o_C - o_C w_C(1+\Gamma) - o_C^\phi \tag{5}$$

$$\pi_R = o_R - o_R w_R(1+\tau_f) - \kappa v_R - o_R^\phi, \tag{6}$$

where Γ denotes the fine per order that firms in the C sector have to pay if they continue hiring riders as self-employed once the RL was approved. The absence of search frictions in the C sector implies that its platforms face a static problem to decide the total supply of orders, where it is assumed that they take their riders' labor supply decisions as given. Therefore, profit maximization in Equation (5) yields the optimal number of orders in the C sector, given by:

$$o_C = \left(\frac{1 - w_C(1+\Gamma)}{\phi} \right)^{\frac{1}{\phi - 1}}. \tag{7}$$

In equilibrium, we have that the demand for orders in (7) needs to be equal to the number of orders stemming from the labor supply of effective hours by riders in the C sector, that is:

$$o_C = E_C \int a(h)\tilde{h}\, dG^C(\epsilon) = \varphi E_C \int a(h)h\, dG^C(\epsilon), \tag{8}$$

where the endogenous factor φ is the variable adjusting the demand and supply of hours given by expressions (7) and (8) above, respectively.

Preferences and income. The economy is populated by a unit mass of workers i who are ex-ante heterogeneous in their disutility of work, reflecting differences in caregiving responsibilities, educational commitments, and other time constraints. The preference parameter for the number of hours worked, ϵ, is distributed as a left-truncated normal distribution, $\epsilon \sim N(\mu_\epsilon, \sigma_\epsilon^2) \in [0, \infty]$, across workers. Individuals are endowed with one unit of time every period and their preferences depend on current consumption c and leisure $1 - h$:

$$u(c, h) = \ln(c) + \epsilon \ln(1 - h). \quad h \in [0, 1] \tag{9}$$

In the absence of savings, consumption equals riders' labor income, which depends on their employment status (employees, self-employed) and hours worked. Employed workers in sector j earn a constant fraction w_j of each produced order, o_j, while job seekers receive unemployment benefits equal to a fraction b of the earnings in the R sector. Therefore, consumption is given by:

$$c = b w_R \bar{h} a(\bar{h}) \quad \text{if searcher} \tag{10}$$

$$c = w_R \bar{h} a(\bar{h}) \quad \text{if employed in } R \tag{11}$$

$$c = w_C \tilde{h} a(h)(1 - \tau_c) \quad \text{if employed in } C, \tag{12}$$

The fraction of an order that R riders earn, w_R, is determined through a bargaining process between the firm and workers that will be discussed shortly.

The period-by-period utility resulting from the optimal h choice in the C sector and working $\bar{h}$ hours in the R sector is:

$$u_C(\epsilon) = \max_h \ln(c) + \epsilon \ln(1-h) \tag{13}$$

$$u_R(\epsilon) = \ln(c) + \epsilon \ln(1-\bar{h}). \tag{14}$$

Labor Market. As mentioned above, riders always have the option to take up a C job by registering to an app as independent contractors. This explains how the business model in the C sector overcomes the search and matching frictions traditionally associated with labor markets. In effect, employers do not need to take into account product market demand conditions as they pay their riders exclusively for the delivered orders. Moreover, screening costs are greatly reduced as the endogenous evaluation scheme of the app, together with the absence of a dependent employment contract, allows the platform to sort out inefficient workers ex-post.

In contrast, the market for R jobs works like a more typical labor market. Firms hire workers as employees, they pay payroll taxes τ_r, and search and matching frictions hinder the formation of new jobs. Workers and the representative firm meet according to a Cobb-Douglas matching technology that determines the meeting probability of workers and vacant jobs. The contact probability for job seekers $p(\theta)$ and the contact probability for open vacancies $q(\theta)$ are therefore given by:

$$p(\theta) = \chi \theta^{1-\alpha},$$

$$q(\theta) = \chi \theta^{-\alpha},$$

where χ is a matching-efficiency parameter, α is the matching elasticity of searchers, and the labor market tightness $\theta = v/s$ is the ratio of vacancies to searchers. Two types of people search for jobs in the R sector. First, there is the mass of unemployed searchers, u, who are only willing to accept a direct job offer from the R sector. Second, there are on-the-job searchers, c, who are currently working in the C sector but would rather prefer transiting to the R sector. We introduce on-the-job search in this sector to mimic the evidence presented in Figure 4, which shows that the distributions of hours worked in the two sectors exhibit a substantial overlap at their lower end. We interpret this fact as reflecting that there are riders with a relatively high disutility of work who would still accept C jobs to avoid unemployment, despite preferring to work in the R sector where working hours are fixed. Given these considerations, the total mass of job searchers is given by:

$$s = u \cdot \int_0^\infty \mathbb{I}_{=1}^{R}(\epsilon)\mathbb{I}_{=1}^{RC,u}(\epsilon)\ dG^U(\epsilon) + c \cdot \int_0^\infty \mathbb{I}_{=1}^{RC}(\epsilon)\ dG^C(\epsilon), \tag{15}$$

where, as mentioned earlier, G^U and G^C are the cumulative distribution functions of the unemployed searchers' and the C riders' preference parameter ϵ, respectively. Moreover, the $\mathbb{I}$ symbols represent indicator variables capturing the policy functions that encapsulate the riders' decisions about accepting R jobs either from unemployment or from C jobs, to be defined momentarily.

4.2 Value functions

Worker values. Let $U(\epsilon)$ be the value of unemployed searchers which solves:

$$U(\epsilon) = \ln(b) + \beta\Omega^U(\epsilon) \tag{16}$$

$$\Omega^U(\epsilon) = \mathbb{I}_{=0}^{RC,u}\, W_C(\epsilon) + \mathbb{I}_{=1}^{RC,u}\left[(1-p(\theta))U(\epsilon) + p(\theta)\Omega^R(\epsilon)\right] \tag{17}$$

$$\Omega^R(\epsilon) = \mathbb{I}_{=1}^{R}\, W_R(\epsilon) + \mathbb{I}_{=0}^{R}\, U(\epsilon) \tag{18}$$

Unemployed searchers decide whether to take instantly a job in the C sector that yields a value $W_C(\epsilon)$ or search for a job in the R sector to achieve a value $W_R(\epsilon)$. In the latter case, due to frictions, they fail to receive a job with probability $1-p(\theta)$, in which case they remain unemployed. Alternatively, with probability $p(\theta)$, they can choose between remaining unemployed or accepting the job offer in R. The policy indicator $\mathbb{I}^{RC,u}$ captures the decisions to search for R jobs rather than taking a C job when unemployed, while $\mathbb{I}^{R}$ denotes the decision to accept an offer from the R sector. For simplicity, we omit the dependence of policy functions on the preference parameter ϵ throughout the sequel.

When self-employed in the C sector, a rider may search for a job in the R sector. Assuming that the job offer rate, $p(\theta)$, is the same as for the unemployed searchers, the resulting value becomes:

$$\begin{aligned} W_C(\epsilon) =& u_C(\epsilon) + \beta \Lambda^C(\epsilon) && (19) \\ \Lambda^C(\epsilon) =& (1 - p(\theta))\Lambda^{CC}(\epsilon) && (20) \\ & + p(\theta) \left[\mathbb{I}^{CR}_{=1} \left(\mathbb{I}^{R}_{=1} W_R(\epsilon) + \mathbb{I}^{R}_{=0}\, U(\epsilon) \right) + \mathbb{I}^{CR}_{=0}\, \Lambda^{CC}(\epsilon) \right] \\ \Lambda^{CC}(\epsilon) =& \mathbb{I}^{C}_{=1}\, W_C(\epsilon) + \mathbb{I}^{C}_{=0}\, U(\epsilon), && (21) \end{aligned}$$

where $\mathbb{I}^{C}_{=1}$ is an indicator of the worker preferring a C job over unemployment, and $\mathbb{I}^{CR}_{=1}$ denotes that the worker prefers a C job over a job offer from R. Likewise, $\Lambda^{CC}(\epsilon)$ captures the value of staying in the C-sector or move to unemployment. Without loss of generality, we assume that there is no on-the-job search in the R sector as the worker could always choose to get a job directly in the C sector. Hence, the value function for a rider in the R sector solves:

$$W_R(\epsilon) = u_R(\epsilon) + \beta \Lambda^R(\epsilon) \tag{22}$$

$$\Lambda^R(\epsilon) = \mathbb{I}^{R}_{=1} \left[(1 - \delta) W_R(\epsilon) + \delta U(\epsilon) \right] + \mathbb{I}^{R}_{=0}\, U(\epsilon), \tag{23}$$

where δ is an exogenous job destruction rate.

Firm value. The representative firm in the R sector chooses the number of vacancies and employees to maximize its value:

$$\begin{aligned} J_R(E_R, \bar{\epsilon}_R) = \max_{v_r, E'_R} \Big\{ & \bar{h} a(\bar{h}) E_R - \bar{h} a(\bar{h}) E_R w_R (1 + \tau_f) - \kappa v_R - \left(\bar{h} a(\bar{h}) E_R \right)^{\phi} \\ & + \beta J_R(E'_R, \bar{\epsilon}'_R) \Big\} && (24) \end{aligned}$$

subject to

$$E'_R = (1 - \delta_R)E_R + v_R q(\theta), \tag{25}$$

$$\bar{\epsilon}'_R = \frac{(1 - \delta_R)E_R \bar{\epsilon}_R + v_R q(\theta)\bar{\epsilon}_S}{(1 - \delta_R)E_R + v_R q(\theta)}, \tag{26}$$

The state variable for the R firm is its current employment, E_R, and, for reasons of wage bargaining, the average value of the utility parameter ϵ among its workers, $\bar{\epsilon}_R$. The next period's employment consists of those not losing their job and the newly hired workers. Note that the mass of searchers that the firm meets corresponds to the total number of hired workers, as all searchers accept the job offer by definition. In addition, the next period's average $\bar{\epsilon}'_R$ is a weighted average of the disutility parameter of those R riders who have not lost their jobs and the average preferences of the newly hired job searchers, $\bar{\epsilon}_S$, which is given by:

$$\bar{\epsilon}_S = u \cdot \int_0^\infty \mathbb{I}^R_{=1} \mathbb{I}^{RC,u}_{=1} \, \epsilon \, dG^U(\epsilon) + c \cdot \int_0^\infty \mathbb{I}^{RC}_{=1} \, \epsilon \, dG^C(\epsilon). \tag{27}$$

Therefore, the first-order condition for vacancy creation yields:[12]

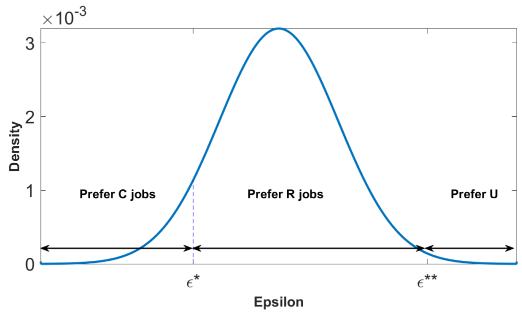
$$\frac{\kappa}{q(\theta)} = \beta \frac{\partial J_R(E'_R, \bar{\epsilon}'_R)}{\partial E'_R}. \tag{28}$$

Accordingly, the firm chooses the number of vacancies such that the marginal costs equals the discounted marginal benefit of hiring an extra worker.

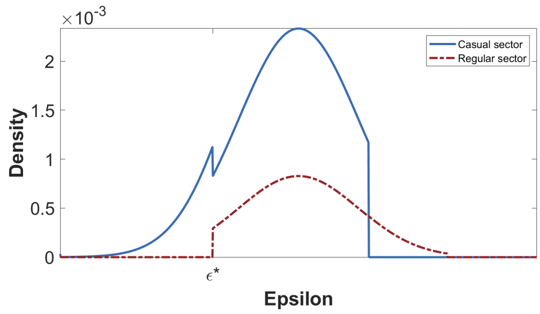
Wage determination. Wages in the R sector are determined by period-by-period Nash bargaining, where η is the bargaining weight of workers. As pointed out above, these wages are collectively bargained. We assume the union cares about the riders with the mean ϵ in R, $\bar{\epsilon}_R$. As a result, the bargained wage in this sector solves the following Nash maximand:

[12]Note that, for simplicity, this condition ignores that hiring more workers can also affect $\bar{\epsilon}$

Figure 5: Employment distribution and cutoff values



(a) Policy function



(b) Distribution over jobs

Source: Own elaboration from simulated data.
Note: The left panel displays workers' policies as a function of their time preferences. The right panel displays the employment distributions of the two sectors over workers' time preferences.

$$\max_{w_R} \left\{ \Big(W_R(\bar{\epsilon}_R) - U(\bar{\epsilon}_R)\Big)^{\eta} \left(\frac{\partial J_R(E'_R, \bar{\epsilon}'_R)}{\partial E'_R}\right)^{1-\eta} \right\}, \tag{29}$$

4.3 How the model works

Before examining in detail the model calibration strategy, we first discuss the riders' choices of their preferred job type and the resulting distribution of workers across jobs. Panel (a) of Figure 5 shows the distribution of ϵ under the benchmark calibration for the economy prior to the RL to be discussed in Section 5 below, along with two cutoff values (ϵ^* and ϵ^{**}) determining sectoral and unemployment choices. Riders prefer C jobs over R jobs whenever $\epsilon < \epsilon^*$, where ϵ^* solves $W_C(\epsilon^*) = W_R(\epsilon^*)$, because C jobs offer them the possibility of achieving higher earnings by working a greater number of hours. Conversely, riders prefer unemployment over any type of job whenever $\epsilon > \epsilon^{**}$, where ϵ^{**} solves $W_R(\epsilon^{**}) = U(\epsilon^{**})$. Finally, those in an intermediate position, i.e. with $\epsilon \in (\epsilon^*, \epsilon^{**})$, prefer R jobs due to their fixed-hours schedule and wage premium. However, note that, due to frictions, there are some riders within this last group who will accept C job offers because they give them the option of on-the-job search for their desired R jobs.

Panel (b) of Figure 5 displays the resulting employment distribution over C

and R jobs. As it can be seen, there is a substantial share of self-employed riders who would rather prefer to become employees. Thus, this group may benefit from policies that induce worker reallocation from the C sector to the R sector.

5 Calibration

Table 3 summarizes the calibration parameter choices in the baseline model. This model captures the main features of the food delivery labor market before the RL, that is, at a time when there were no administrative sanctions, $\Gamma = 0$, in the C sector. The model period is taken to be one month, and individuals are assumed to discount the future at a 4 percent annual rate. We set the hours worked in the R sector to 0.15, consistent with a mean daily hours of 3.7 in this sector. As for the parameters determining the distribution of work preferences, ϵ, we choose its mean and standard deviation to match an average of 5.4 and a 95^{th} percentile of 7 hours worked in the C sector, respectively.

Next, we turn to the choice of parameters related to the production technology and the wage schedules. Following the literature that ignores physical capital as an input, we set the wage share in the C sector, w_C, close to output, i.e., we target a flow profit share of 5 percent. We choose the firm's TFP to match the average hourly wage of €6.8 in the R sector. Regarding the parameters characterizing wages, we consider the estimates of the wage regression reported in Table 2 above, namely, a wage premium of 0.18 log points for R riders, and an elasticity of wages w.r.t. hours of 0.05. Given that wages are taken to be fixed in the C sector, this pay gap is driven by the match surplus in the R sector. Hence, the search efficiency parameter, χ, is chosen to replicate such a wage premium in the model. Finally, since the parameter capturing the degree of convexity in the cost function, ϕ, directly influences the production level in the C sector, which in turn impacts the distribution of employment between sectors, we set it to match an employment share of 76 percent in that sector (once unemployment is taken into account) before the approval of the RL.

Turning to the parameters that guide labor market flows, we follow Petrongolo and Pissarides (2001) in setting the elasticity of matches with respect to unem-

Table 3: Summary of calibration parameters

Parameter	Description	Value	Moment
A: Utility			
β	Discount factor	0.99	4% annual discount rate
B: Hours			
$\bar{h}$	Hours worked in R	0.15	Mean hours in $R/24$
μ_ϵ	Work disutility: Mean	4.0	Mean hours in $C/24 = 0.22$
σ_ϵ	Work disutility: Std. dev.	0.76	95^{th} percentile hours in $C = 7/24$
C: Production and Wages			
A	TFP	8.3	Mean wages in $R = 6.8$
γ	Returns to scale	0.05	Elasticity wages to hours
χ	Matching efficiency	0.01	Wage premium $R = 17\%$
ϕ	Convex costs	2.6	Employment share of C sector
w_C	Net wage share in C	0.80	Flow profits in C sector $= 5\%$
D: Labor Market			
α	Matching elasticity	0.50	Petrongolo and Pissarides (2001)
η	Workers' bargaining weight	0.50	$\eta = \alpha$
κ	Vacancy costs	17.6	Hagedorn and Manovskii (2008)
δ	Destruction rate in R	0.04	EU flow $R = 4\%$
E: Benefits and taxes			
b	Replacement rate	0.37	Mean replacement rate riders
τ_c	Payroll taxes in C	0.16	Payroll taxes self-employed
τ_f	Payroll taxes in R	0.29	Payroll taxes employers

Note: The table describes the calibrated parameters and their respective targets.

ployment, α, equal to 0.5, and equate it to the workers' bargaining weight in the R sector, so that $\eta = \alpha = 0.5$. As in Hagedorn and Manovskii (2008), we set the vacancy posting costs to 3.7 percent of wages and 4.5 percent of output in the R sector. Regarding the monthly job destruction rate, δ, we rely on administrative data from the Muestra Continua de Vidas Laborales (January 2019-July 2021) for salaried workers employed work for two consecutively months in NACE sector 532 H. Given that this sector includes other workers with more stable contracts than riders (see Section 3), tenure in the sample is restricted to be no longer than 18 months. This yields $\delta = 0.04$, and an unemployment rate close to 10 percent.

Lastly, we consider the level of benefits and taxes in the economy. The replacement rate of a typical unemployed worker in Spain is about 58 percent of average wages (Bentolila et al., 2012). Given that about one-third of the riders have not reached the contribution period of one year to be entitled to unemployment benefits, we set the replacement rate of unemployed searchers to 37 percent. Moreover, the payroll taxes in the C and R sectors are chosen to match the average social security taxes of the self-employed (16 percent) and employers' contributions (29 percent), respectively.

6 Policy experiments

This section quantifies the labor market effects of the RL on working hours and wages in both sectors. To do so, we incorporate in the model administrative sanctions, Γ, for non-compliant firms in the C sector (e.g. Glovo and Uber Eats) after the reform. Thus, while $\Gamma = 0$ in the baseline model (prior to the RL), our simulation relies on assuming that $\Gamma > 0$, while keeping the other calibrated parameters the same as before. Sanctions increase the marginal cost of delivering orders, thereby reducing the demand for these orders, o_C. Thus, we calibrate Γ to match the 11 percentage points decline in the share of total orders for this sector, $o_C/(o_C + o_R)$ (see Table 1), leading to $\Gamma = 0.02$.

Before turning to the main simulation results in the sequel, some clarifications about the correct interpretation of these findings are in order. First, we abstract from the fiscal implications of the reform as this mirrors the Spanish experience. With the resulting fines and changes in payroll-tax revenues being absorbed by the general treasury, the effects of the RL should be interpreted as exclusively affecting this specific (small) sector of the economy. Second and foremost, as discussed in Section 2, the number of riders grew from 25,000 just before the 2021 RL to 35,000 in 2024, possibly due to an upward shift in the demand for online food services since the pandemic. By focusing exclusively on the effects of the RL via administrative sanctions, we abstract from this shift by assuming that the overall population remains invariant across the simulations. Therefore, our results should be interpreted as a counterfactual of how the riders' sector would have behaved had the RL not been implemented, *conditional* on the the above-mentioned trends.

6.1 Labor-market effects of the Riders' Law

As fewer orders are available after the RL, C riders confront longer waiting times. In equilibrium, factor φ in Equation (12) drops from a value of 0.80 to 0.75.[13] Panel A in Table 4 shows that, as waiting times increase in the C sector, the hourly wage decreases by 6.8 percent, implying that some riders no longer find it optimal to work in that sector. This is illustrated by the reduction in the cutoff value ϵ^* (panel D). This leads to an employment decrease of 13 percentage points in the C sector (panel B), which represents about one-fifth of its share before the reform was passed, and a fall of 4.6 percent in hours worked (panel C). Regarding the effects of the RL on economy-wide average working hours, panel C shows that they fall by 2.4 percent for two different reasons. First, because C riders spend more unpaid waiting time, captured by a decrease in φ, and second, because a substantial proportion of workers reallocate from the long-hours to the short-hours sector (see Figure 4).

The negative effects of the RL on the C sector have non-trivial spillover effects on the R sector. As working in the C sector becomes less attractive, the outside option for R riders worsens, weakening their bargaining position and reducing wages in this sector. Taken together, the falling wage in the C sector and the slightly declining wage in the R sector translate into a decline in economy-wide average wages of 3.3 percent. Declining wages in R boosts additional vacancy creation and rises labor market tightness, θ, increasing its employment by 6 percentage points (panel B). Therefore, given that this sector is only able to absorb 46 percent of the employment decline in the C sector after the RL, the unemployment rate among riders goes up from 10 percent to 17 percent.

In sum, the reason for why the R sector does not fully offset the employment decline in the C sector has to do with both labor demand and labor supply effects. First, unlike the C sector, costly vacancy creation, plus employers in the R sector having to pay payroll taxes, prevent a stronger rise in labor demand, a feature to

[13] We are not aware of quantitative evidence that would allow us to test this model prediction. However, qualitatively, there is media evidence about riders reporting substantially longer waiting times for their account to be activated by Glovo after the RL: https://www.que.es/2024/05/07/glovo-cuentas-espera/

Table 4: Labor market effects of the Riders' Law

	Baseline	**After reform**
Panel A: Wages		
Mean hourly wages C	5.8	5.4
Mean hourly wages R	6.8	6.7
Mean hourly wages	6.1	5.9
Labor market tightness	2.0	3.3
Panel B: Employment		
Employment C	0.66	0.53
Employment R	0.24	0.30
Unemployment	0.10	0.17
Panel C: Hours		
Mean effective hours C	4.3	4.1
Mean effective hours	4.1	4.0
Panel D: Job preferences		
Indifference cutoff for jobs, ϵ^*	2.9	2.5

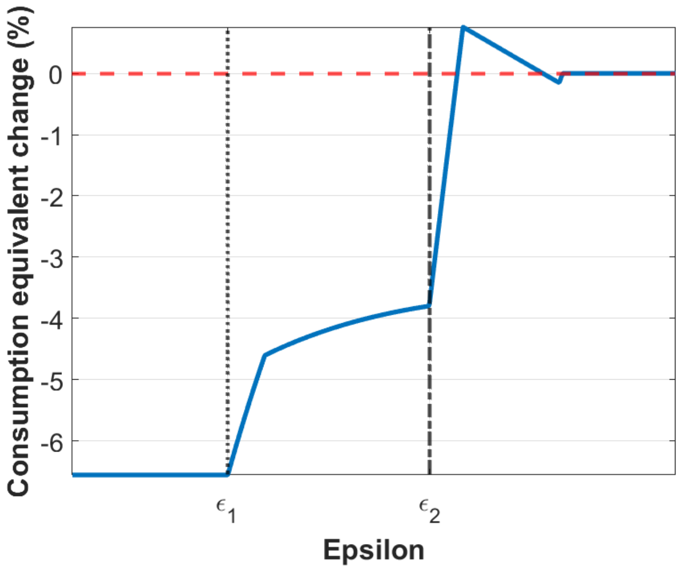
Note: The table displays the model results from the counterfactual simulation where firms in the C sector pay a fine: $\Gamma = 0.02$.

which the next subsection is devoted. Second, regarding the labor supply channel, now more riders prefer to remain unemployed to accept C job offers. Likewise, those riders with the highest disutility of work will find R jobs no longer attractive as their wages have not gone up. At any rate, it is important to remark that our model interprets an employment decline in the riders' sector necessarily as an increase in the unemployment rate when in reality it is likely that some of them may now find jobs outside the riders' sector instead of remaining unemployed.

6.2 Welfare effects of the Riders' Law

The RL affects individual welfare through changes in wages, hours worked, and the sectoral allocation of labor. Welfare is measured in terms of consumption-equivalent variation, i.e. the percentage of lifetime consumption that an average rider would be willing to forgo to remain indifferent between the benchmark economy and the one with the RL regulations. We find that the reform leads to a

Figure 6: Distributional welfare effects of the Riders' Law



The figure displays the welfare effect of the Riders' Law as a function of workers' time preferences.

welfare loss of 3.4 percent of lifetime consumption for the average rider.[14]

To examine the distributional effects of the reform, Figure 6 shows how welfare losses vary across riders' different leisure preferences. To do so, we define three main groups which are identified through the following two cutoff values: (i) ϵ_1 such that $W_R^{\text{RL}}(\epsilon_1) = W_C^{\text{RL}}(\epsilon_1)$, and (ii) ϵ_2 such that $W_C^{\text{RL}}(\epsilon_2) = U^{\text{RL}}(\epsilon_2)$, where the superscript "RL" in the riders' value functions corresponds to the economy where the RL rules are operative.

Our main findings are as follows. First, about 3 percent of riders always prefer the C sector due to their low disutility of work, $\epsilon < \epsilon_1$. These riders suffer large welfare losses because of the substantial pay decline in the C sector which is not offset by better more job opportunities for those riders moving to the R sector.

Second, nearly 75 percent of riders prefer the R sector and engage in on-the-job search when they do not have such opportunity, i.e. $\epsilon \in (\epsilon_1, \epsilon_2)$. Thus, these

[14]This and the subsequent welfare-change figures may look large but it should be recalled that they refer exclusively to a very small industry and not to the whole economy

riders are employed either in the R sector or the C sector. On the one hand, a small fraction of these riders benefit from the policy because the RL facilitates the transition from C to R jobs. On the other hand, the majority of these riders experience earnings/consumption losses because: (i) wages are now lower in the C sector where they are still partially stuck due to labor market frictions, and (ii) wages slightly decline in the R sector. Overall, the negative effects outweigh the positive effect, so the average welfare loss for this group is about 4 percent.

Finally, there is nearly 22 percent of riders who would like to work in the R sector but prefer unemployment over C jobs ($\epsilon > \epsilon_2$). A fraction of these riders do not benefit from the reform because they remain employed in the R sector and earnings in this sector hardly change. In contrast, the remaining riders in this group enjoy welfare gains due to increased labor-market tightness in the R sector. Specifically, some of them succeed in their transition from unemployment to R jobs, while those who remain unemployed face a higher probability of finding those. Overall, this group of riders achieves 1 percent welfare gain.

6.3 Complementing the Riders' Law with tax policies

As shown above, the RL turns out to be detrimental for workers as the R sector fails to expand sufficiently its employment share, and wages in that sector decline slightly. Here, we analyze the amount of social security subsidies in the R sector needed (while keeping the sanctions) to offset these results. Specifically, we simulate two policy reforms that pair the RL's government sanction ($\Gamma = 0.02$) with different firm-level taxes in the R sector through tax bonuses, namely: (i) a tax reduction that maintains welfare unchanged, and (ii) a tax reduction designed to preserve employment levels.

The middle column in Table 5 presents the simulated labor-market and welfare effects of complementing the ruling sanctions with welfare-neutral payroll taxes borne by R employers, which are found to be 8 percentage points lower than in the baseline simulation (i.e. $\tau_f = 0.21$ instead of $\tau_f = 0.29$). Not surprisingly, this tax cut increases labor demand in the R sector. We note that the resulting welfare gains spread throughout the economy. Riders now benefit from higher job-finding

Table 5: Results from complementary tax policies to the Riders' Law

	Baseline	**RL & tax reform**	
		Welfare-neutral tax	**Employment-neutral tax**
Policy changes			
Government fine C sector	0	0.02	0.02
Firm-level tax R sector	0.29	0.21	0.08
Panel A: Wages			
Mean hourly wages C	5.8	5.5	5.7
Mean hourly wages R	6.8	7.2	8.0
Mean hourly wages	6.1	6.2	6.7
Labor market tightness	2.0	4.5	6.6
Panel B: Employment			
Employment C	0.66	0.52	0.51
Employment R	0.24	0.34	0.39
Unemployment	0.10	0.14	0.10
Panel C: Hours			
Mean effective hours C	4.3	4.1	4.2
Mean effective hours	4.1	4.0	4.0
Panel D: Welfare			
Mean CEG	-3.4	0	7.0

Note: The table displays the model results from counterfactual simulations that implement the RL reform, $\Gamma = 0.02$, together with changes in employers' payroll taxes in the R sector.

rates and higher wages in the R sector. Moreover, as more riders reallocate to this sector, they benefit from lower waiting times in the C sector and, thus, enjoy higher hourly pay.

Lastly, the rightmost column in Table 5 reports the results from complementing the RL's fine with an employment-neutral payroll tax cut which is found to be 21 percentage points lower than in the benchmark simulation (i.e. $\tau_f = 0.08$ instead of $\tau_f = 0.29$). Note that this tax cut is much higher than the one required to maintain welfare. This is because most welfare losses from imposing sanctions alone affect workers who remain employed, reducing the need of additional tax cuts that preserve jobs. Overall, this policy leads to large welfare gains (7.0 percent) instead of big losses (-3.4 percent). In particular, it leads to very small earnings losses for those riders staying in C jobs relative to the benchmark while those remaining in R jobs experience large gains and those in transition to the R sector face a much higher probability of finding a job.

In sum, we conclude from this evidence that complementing the RL with payroll tax cuts for R employers would have improved substantially the negative outcomes of the reform. Admittedly, this policy could have fiscal budget consequences but, since the online food delivery sector is a small fraction of the aggregate labor market, changes in the overall budget are bound to be minimal. They could be interpreted as a subsidy from the overall economy to the riders' sector.

7 Conclusions

This paper quantifies the impact of policies mandating the use of dependent employees by online food delivery platforms on employment, hours worked, and wages. We focus on Spain which is a forerunner in implementing such policies through the so-called Riders' Law, approved in 2021. This Law establishes the presumption of dependent employment for workers, known as riders, in this sector and levied large fines on non-complying platforms. We find that almost half of the riders transition from self-employment to dependent employment after the reform. Yet, the new rules also lead to lower employment, working hours, and wages, especially among those riders who remained working as self-employed in platforms challenging the new reform. Instead, we claim that a bonus reducing employers' payroll taxes for the compliant platforms could offset these detrimental effects.

To reach these conclusions, we develop a two-sector search and matching model with heterogeneous workers and firms, which is calibrated using both a novel online survey collected by us and administrative data. The model rationalizes the coexistence of casual/C and regular/R jobs differing in terms of employability, work time flexibility, and wages. In particular, riders with low preferences for leisure choose C jobs because they offer higher earnings by working long hours and are instantaneously available. In contrast, those with high preferences for leisure prefer R jobs due to their wage premium and pay by the hour, though they often accept C jobs to avoid non-employment while seeking R jobs.

Our finding that fines imposed on platforms defying the reform will be partially passed through to workers in the form of lower employment and wages should not be surprising. Yet, our model allows for the possibility that this standard effect may not hold. Since wages are higher in the R sector due to collective bargaining, riders could benefit if all firms simply transform C jobs into R jobs. This rationale likely explains politicians' desire to promote the regulations studied in this paper. However, there are three reasons why this effect is not strong enough. First, since we calibrate a low profit per worker in the C sector, the possibilities for profit shifting to its riders are slim.[15] Second, the data suggests that workers do value the working-hours flexibility provided by the C sector. Third, from a search-model perspective, the C sector's sign-up-at-will technology is very powerful in overcoming search frictions.

Finally, given that our paper highlights differences in wages, hours flexibility, and search frictions between the two sectors, we see two promising avenues for future research. First, allowing for a larger variety of hours contracts (e.g. part-time and full-time) in the R sector could be an optimal policy by better adapting to riders' preferences. Second, the model could be extended to include employment and health protection differences between these sectors.

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[15] The share of profits out of flow output is difficult to pin down in the data. We note that Glovo lost 412 million euros in 2022 alone suggesting that wage mark-downs are small.

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