

Riders on the Storm^{*}

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Abstract

Digital platforms typically operate through a controversial business model that relies on subcontracting self-employed workers. We develop an equilibrium model of the labor market to quantify the effects of the Spanish Riders' Law in 2021, which establishes the presumption of dependent employment for food delivery couriers, known as riders. Heterogeneous riders trade off work flexibility and easier employability as self-employed against higher hourly wages as employees. We find that the reform failed in fully absorbing the large outflows from self-employment or in increasing wages. However, complementing the reform with a payroll tax cut for compliant platforms preserves riders' welfare levels.

Keywords: Riders, Food delivery platforms, Self-employed, Employees

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 rapidly worldwide, currently representing between 1 and 4 percent of total employment (ILO, 2024). This global expansion has been associated with many platform companies classifying their workers as independent contractors rather than dependent employees. This practice has sparked intense debate over whether self-employed platform workers should instead be reclassified as employees, thereby ensuring access to essential social protections, such as fixed work schedules and collectively bargained wages. However, critics of this view claim that self-employment not only offers workers greater flexibility in terms of working hours but also facilitates their employability, as all it takes to start working is to sign up to a digital platform app.

We contribute to this debate by analyzing the effects of a labor law reform in Spain affecting the online food delivery sector through the lens of a novel labor market model that accounts for the above-mentioned key policy trade-offs. This sector has become the second-largest platform industry after taxi services, especially since the Covid-19 pandemic which boosted the widespread use of these services globally. The so-called Riders' Law (RL, hereafter), approved in 2021, targeted labor conditions in this sector and became one of the first pieces of legislation enacted by a country that explicitly establishes the presumption of employment for food delivery couriers, commonly known as *riders*. A key feature of this reform is that some platforms resisted the new regulations and continued to hire their riders as self-employed contractor.¹ As a result of their actions, these companies have been accumulating substantial administrative fines that increased their relative operating expenses. Thus, as reflected by the lyrics of the classic song by The Doors that heads this section, our riders also seem to be weathering a storm full of uncertainties, this time related to their labor conditions.

¹Note that, since the RL only introduces a presumption, employers could provide evidence to the contrary by proving that their riders are not subordinated to the platform's guidelines. As discussed below, this explains why several platforms have challenged the new hiring regulations.

Specifically, we build an equilibrium model of the labor market with heterogeneous riders and jobs to quantify the effects of the RL reform. The economy features three types of jobs. First, there are *regular* (R) jobs, where riders are hired as employees, which are subject to standard search and matching frictions. These jobs offer fixed working hours, require employers to pay social security contributions, and pay hourly wages determined through Nash bargaining between a trade union and the employer. Second, there are frictionless *casual* (C) jobs performed by self-employed riders, in which they freely choose their hours worked, pay their own payroll taxes, and get paid per delivered order. Compensation per delivered order, rather than hours worked, is the rationale behind the immediate availability of these jobs. However, it comes at the cost of facing unpaid working hours in terms of waiting time between orders. Third, there is an exogenous outside option, which represents available job opportunities for riders in the rest of the labor market. Given idiosyncratic tastes for hours worked, riders choose where to search for employment and their number of hours worked when self-employed. Importantly, they always have the option to join a C platform and then search on-the-job for R jobs if those are their preferred option. Finally, imperfect substitutability of rider services from different platforms ensures that both C and R platforms operate in equilibrium and demand labor.

The model parameters are estimated to fit moments related to hours worked, wages, and market shares. To that end, we use microdata from a representative convenience survey and available aggregate statistics for the Spanish food delivery sector. Three key empirical facts guide the estimation approach: (i) riders with similar characteristics earn an hourly wage premium in R jobs relative to C jobs, (ii) a substantial fraction of C and R riders overlap in their hours worked, and (iii) some C riders work a relatively high number of hours. To reproduce these facts, the model implies that the riders whose distaste for hours worked is low enough choose C jobs to earn higher earnings by working many hours. The remaining riders search for R jobs due to their wage premium. However, since R platforms only hire a fraction of these workers due to the presence of imperfect competition and search frictions, some of them opt for C or outside jobs to then try to transit to the R jobs when given the opportunity.

We evaluate the RL by focusing on the effects of the administrative sanctions imposed on those C platforms that ignored the new regulations. These fines increase the marginal cost of producing orders by those firms, raising their relative prices and shifting consumer demand to R platforms. Specifically, we infer how these sanctions affect the marginal costs of non-complying C platforms from the evolution of their market shares after the RL. Our main results from the calibrated sanctions are as follows: lower labor demand for C riders translates into longer unpaid working time, which reduces their hourly wages and induces some of them to reallocate away from C platforms. Overall, their employment share falls by 16.2 percentage points, while hourly wages drop by 2.0 log points. Conversely, the higher consumer demand faced by R sector leads to an increase in their employment share of 1.8 percentage points, thereby only absorbing about one-tenth of C job losses. The insight for this result is that the creation of R jobs faces substantially higher marginal costs due to wage bargaining, vacancy posting costs, and payroll taxes. Hence, a large fraction of the shift in consumer spending is absorbed by higher prices rather than by increased production in the R sector. In addition, despite growing demand, wages in this expanding sector hardly change, as the worsening conditions in the C sector deteriorate R riders' bargaining position. All in all, we find that the RL reduces total employment in the food delivery sector by 14.4 percent and its average net hourly wage by 0.5 percent, leading to a reduction of both riders' and consumers' welfare.²

Finally, in view of the previous findings, we study how the introduction of a tax bonus in employers' payroll taxes in the R platform could play a useful role in achieving a further push in its labor demand. In particular, we study a potential tax-bonus scheme complementing the use of administrative sanctions. We find that a tax-rate cut of 22 percentage points, from 29 to 7 percent, preserves the average riders' pre-reform welfare level though it does not substantially reduce the welfare loss experienced by the representative consumer, as the imposition of sanctions still reduces the overall size of the online food delivery market.

²Given that the actual number of riders has increased by 40 percent since the pandemic (see Sections 2 and 6 below), these negative effects of the RL 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.

1.1 Related literature and outline

Our paper contributes to a growing literature on the characteristics of the online gig economy. A large body of empirical research deals with the difficulty of measuring platform work arrangements through either conventional administrative data, specific surveys, or field experiments (Mas and Pallais, 2017; Collins et al., 2019; Katz and Krueger, 2019; Boeri et al., 2020; Abraham et al., 2021). To reduce measurement problems, our paper uses an own-elaborated convenience survey that aligns with representative aggregate information from the food delivery sector.

Similar to us, there is a recent literature which also highlights the high value that digital platforms provide to workers through flexible working arrangements. Chen et al. (2019) study the case of Uber drivers and show that their reservation wages vary substantially over time, i.e. they value flexibility in their working hours. As a result, their surplus is higher than in alternative work arrangements which offer less flexibility. Stanton and Thomas (2025) analyze a platform environment where buyers post one-time projects and workers compete for these projects by posting wages. They find that imposing traditional employment regulations on short-term platform work reduces overall welfare and workers' surplus. Key to this finding is that: (i) workers already capture a large share of the surplus, and (ii) the regulation decreases demand for their services. We add to this literature by studying an environment where flexible platform jobs coexist with workers being hired as employees, therefore highlighting the importance of platforms using independent contractors to overcome labor market search frictions. Moreover, we show that regulating firms with independent contractors has negative spillover effects on employees' wages when these are bargained. Nevertheless, our conclusions are similar: some workers value the flexibility that the independent contractor status provides, and attempts to regulate these types of jobs often lead to lower labor demand and an overall loss in workers' welfare.³

Scarfe (2019) and Dolado et al. (2025) study casual and zero-hour contracts in Australia and the UK, respectively, which are other work arrangements that

³Angrist et al. (2021) study a yet different setup where drivers choose between permanent lease contracts (taxi driver) and revenue fees (Uber driver). In that case, the worker retains his work flexibility in both work arrangements.

are akin to those used for subcontracted riders. Under those work arrangements, firms only call-up workers when they need their services leading to workers being operative in some periods but not in others. Just like us, these papers employ structural search and matching models to analyze the general equilibrium effects of regulating flexible contracts. However, we differ from their approach in that we combine two labor markets, one with search and matching frictions and another where independent contractors can instantaneously work. Moreover, our model endogenously determines the amount of wasted waiting time in the latter sector through which platforms ensure that the demand and supply of riders match, as well as allows 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 platforms hiring independent contractors. Similar to us, [Zenou \(2008\)](#) and [Satchi and Temple \(2009\)](#) model the informal sector as being frictionless. 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) to the informal sector which also features search frictions. Apart from highlighting a different sorting mechanism across sectors based on leisure preference, we also differ in the focus of the policies: whereas this literature deal with the effects of regulating formal-sector jobs on the number of informal jobs, we show that regulating jobs in the C sector changes workers' outside options for the R sector, leading to spillover effects on wages and employment in those platforms.

Finally, our paper also speaks to other strands of the literature that deal with 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 works in allowing for two-sided heterogeneity regarding labor- demand and labor supply decisions made by firms and workers, respectively.

The rest of the paper is organized as follows. Section 2 provides some institutional background about food delivery platforms in Spain, as well as a detailed discussion of the 2021 Riders' Law. Section 3 describes the data sources and draws

stylized facts about the riders' labor market. Section 4 lays out the quantitative model. Section 5 describes its calibration. Section 6 discusses the counterfactual results from policy experiments. Finally, Section 7 concludes. An Appendix gathers further evidence discussed in the main text.

2 Institutional Background

As in many other developed countries, the Spanish online food delivery sector has expanded rapidly over the past decade. According to [Statista \(2025\)](#), this industry grew at an average annual rate of approximately 9.5 percent in meal delivery and 13.4 percent in grocery delivery prior to the COVID-19 pandemic. This expansion accelerated further during the lockdown periods of 2020–2021, when these growth rates surged to 26 percent and 57 percent, respectively. This large expansion took place in a context where there was hardly any explicit labor legislation on the employment status of riders. As a result, a widespread practice among platforms was to classify their workers as independent contractors rather than as dependent employees, with the former accounting for 81.2 percent of all riders. Hiring workers as independent contractors has several possible advantages for platforms. For one, they do not need to comply with labor law on overtime schedules and dismissal protection. Moreover, employers do not pay social security contributions. Finally, by compensating workers for actual completed orders, rather than by a fixed hourly wage, employers shift all risk of insufficient demand to the worker.

The widespread practice of hiring workers as independent contractors has led to an intense debate about the appropriate regulation of work arrangements in the food delivery sector. To deal with these policy concerns, the Spanish parliament approved the RL (*Real Decreto-Ley 9/2021*) in September 2021. Regarding the motivations of policy-makers, the preamble of the RL states that the advantages from the information and communication technologies "are perfectly compatible with the objective of labor law to re-balance the interests of the different agents in this sector", and that these regulations should "guarantee that technological change provides positive effects equitably". To achieve these goals, the RL introduces: (i) the presumption that riders are employees rather than independent

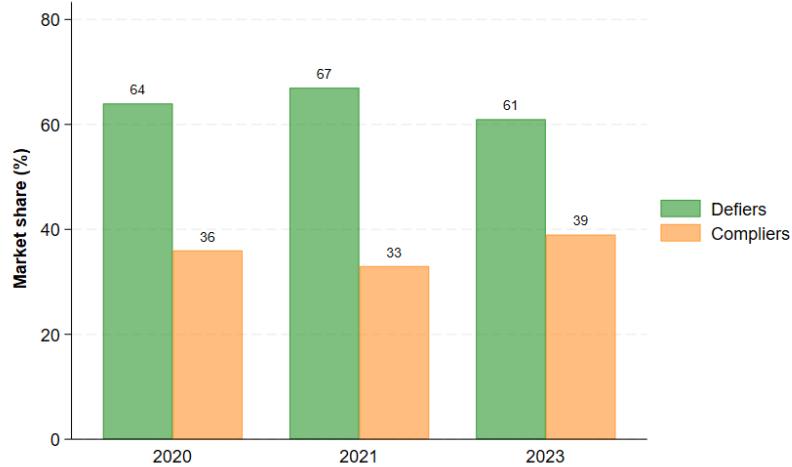
contractors, and (ii) the requirement that platforms disclose the rules underlying algorithmic decisions that affect workers' labor market conditions. Thus, in essence, the RL explicitly extends standard labor regulations for employees to food delivery riders, including more rigid work schedules and collectively bargained wages, supported by greater transparency in information.

Our analysis exploits a key feature of the RL, namely, the fact that the status of the rider is only a presumption that could be rebutted if the platform shows that it did not exert the powers of organization over the rider. Resulting from this remaining legal uncertainty, some platforms defied the new regulation on the obligation to hire riders as employees, while others complied with it. Consequently, we observe riders with different employment status both before and after the reform.

In particular, three of the four dominant players (Glovo, Uber Eats, and Deliveroo), with a joint market share of two-thirds, continued hiring most of their riders as independent contractors, so we call them "defiers". In contrast, the remaining major platform (Just Eat), with one-third of the market and which had already hired riders as employees before the RL, decided to move a step forward by signing a collective agreement with the main trade unions in the sector, so we label it as "complier". Importantly, the defiers' legal arguments fared poorly in several courts of appeal, as a result of which they have accumulated to date administrative sanctions of more than €800 m. Therefore, they have experienced a significant increase in their operating costs.

Indeed, market share data after the enactment of the reform is consistent with a deteriorating relative advantage of the defier platforms. Figure 1 shows that their market share declined by 6 percentage points within two years of the reform, despite having expanded previously. Partly, the decline results from the exit of Deliveroo from the Spanish market after conducting a mass-layoff of nearly 4,000 riders. Though shifting employment to platforms hiring employees is most likely consistent with the goal of the law's drafters, some organized labor groups have opposed the reform. For example, according to one of the main workers' associations (*Asociación Autónoma de Riders*), about 65 percent of its members dislike the new regulations, mainly due to the rigidity of hours of work in the *R* platforms.

Figure 1: Market shares in the Spanish food delivery sector



Source: We use information from Measurable AI (Spain Food Delivery Market Overview) for 2020 and 2021. For 2023, we use data from 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.

Moreover, the overall growth of the sector in the two years following the reform has notably slowed down, with an average annual growth of -2.6 percent in meal delivery and 24.6 percent in grocery delivery, which, in both instances, are about 20 percentage points lower than during the pandemic ([Statista, 2025](#)).

3 Data and Stylized Facts

This section summarizes the data sources and the stylized facts of the Spanish food delivery sector that help us develop a quantitative model to evaluate the effects of the RL. Given the scarcity of statistical information on this sector, we resort to an own-elaborated online convenience survey to obtain microdata on riders' labor market outcomes. Interestingly, a comparison of this dataset with aggregate data from alternative sources, shows that our survey respondents closely resemble the broader riders' population in terms of key sociodemographic attributes. Next, we document three main findings: (i) higher net hourly wages are earned by R riders, controlling for sociodemographics, (ii) relatively long hours worked are only common among C riders, and (iii) short hours are common for both types of riders.

Table 1: Descriptive statistics

	Convenience survey (2023)	Adigital (2020)
<i>Workers' characteristics</i>	Mean	Mean
Age	27.3	29.3
Gender (Male)	0.86	0.89
Education (Upper)	0.46	0.37
Nationality (Foreign)	0.77	0.72
Work Permit (Yes)	0.82	0.75
No. of platforms (2023)	1.3	
Tenure (years)	1.5	
<i>Wages and hours</i>		
Net hourly wage (Euros)	5.6	
Daily hours	4.6	
<i>Platform employment shares</i>		
Defiers	0.76	
Compliers	0.24	

Note: Convenience survey data contains information about 162 riders via Google.form corresponding to the period September-October 2023. The Adigital (2020) contains information about 1,852 riders during the period January-February 2020.

Data. With the help of some personal contacts among riders from complier and defier platforms, we distributed a small convenience survey to their workmates in a completely anonymous format via the Google- Forms platform between September and October of 2023. The questionnaire was organized around three blocks: (i) general information about the worker (age, gender, educational attainment, nationality, and availability of a work permit, number of platforms, and tenure); (ii) information about their net hourly wages and daily hours worked; and (iii) platform shares (defiers and compliers). In total, 320 riders received the questionnaire, out of which 162 responded. In addition, we complement this convenience survey with aggregate data from a larger survey conducted by the Spanish Association of Digital Economics (Adigital, 2020), which collects information on similar sociodemographic characteristics for a representative sample of 1,852 riders at the beginning of 2020. Yet, unlike ours, this survey lacks information on wages and hours worked, as well as on the type of platforms riders work for.

Table 1 summarizes the main descriptive statistics of the Adigital (2020) sur-

vey (pre-reform) and the convenience survey (post-reform). Respondents in the convenience survey closely resemble the broader population of riders captured in the larger survey across key sociodemographic dimensions, including age, gender, education, nationality, and work permits. This similarity supports the representativeness of our convenience survey, as there are few reasons to expect that the RL has altered the composition of riders, particularly given the strong segmentation of their labor market. Riders are predominantly young, male, foreign, and their tenure is 18 months. Moreover, the average rider typically works for a single platform despite the possibility of sharing several platforms. Interestingly, about 18-25 percent of riders are migrants without a work permit who work for C platforms since it would be illegal for R platforms to hire them as employees. This may partly explain the resistance of the C sector to comply with the RL.

Stylized facts about hours and wages. As described above, an advantage of being hired as an employee is being paid by the hour, with their wage is set by collective bargaining. Moreover, R platforms pay payroll taxes. To understand the effect of the employee status on net wages, our survey explicitly asks respondents to report their net hourly wage after deducting maintenance costs and payroll taxes. Using this information, we run the following *mincerian* OLS regression:

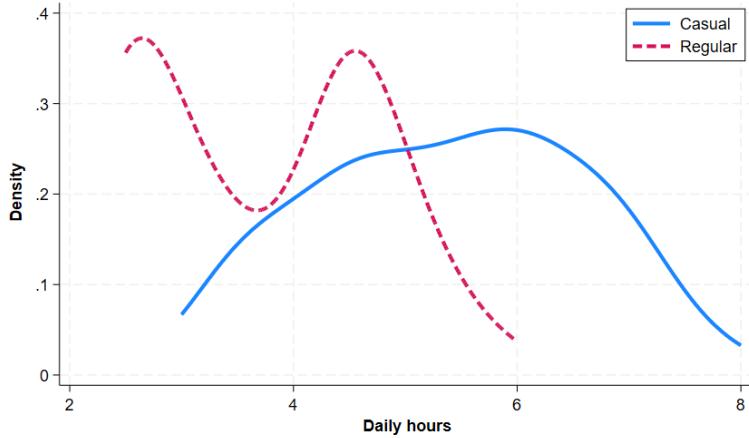
$$\ln w_i = \beta_0 + \beta \mathbb{I}_{C=1} + \gamma \mathbf{X}_i + \varepsilon_i$$

where $\ln w_i$ is (logged) net hourly wage, $\mathbb{I}_{R=1}$ is a dummy variable capturing if a rider works in platforms offering C jobs (Glovo or Uber Eats), and \mathbf{X}_i is a vector of socio-demographic covariates.⁴ We find that, on average, the hourly wage among C riders is about 17.2 log points lower than that of R riders with similar observable characteristics ($\beta = -0.172^{***}(0.033)$), a result which is consistent with trade unions being effective in extracting rents.

Note that a sizable share of riders (76 percent) opt for C jobs despite their lower wages. To understand this fact, Figure 2 displays the densities of daily hours worked in both types of jobs, where four findings stand out. First, and

⁴We include age, gender, nationality, work permit, tenure, and education.

Figure 2: 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.

consistent with the [Adigital \(2020\)](#) survey, there is a large dispersion in daily hours across riders, suggesting large heterogeneity in their time availability. Second, the distribution of hours worked in C jobs is more dispersed than in R jobs; in particular, the density of hours worked in the former sector is smooth, while it is bimodal in the latter.⁵ 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, implying that the average daily hours worked in C is higher than in R (5.4 h. vs 3.7 h.), a result that also holds after controlling for observables. Fourth, the distribution of hours worked has a significant mass in both sectors at low hours worked, typically below 4 hours. We interpret this fact as consistent with the existence of search frictions in the R platform rationing the access of riders with strong preferences for these jobs due to their wage premium.

4 Quantitative Model

Environment. To evaluate the effects of the 2021 RL, this section presents a quantitative equilibrium model in discrete time. The model incorporates the main

⁵This 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.

trade-offs described above between letting heterogeneous platforms hire workers either as self-employed or as employees. We distinguish between: (i) platforms offering frictionless casual (C) jobs, which can be instantly found by self-employed workers who choose their optimal working hours freely; (ii) platforms offering frictional regular (R) jobs, where workers can only be hired as employees and are paid a collectively-bargained hourly wage; and (iii) an outside option, which represents job opportunities amenable for riders in the rest of the labor market. Furthermore, riders are ex-ante heterogeneous in their tastes for hours worked, determined by parameter ϵ (to be defined below). Finally, platforms sell their output to a representative consumer who views their respective services as imperfect substitutes. Thus, the model features both types of platforms operating in equilibrium with their market shares being endogenously determined.

Production technology. We consider two representative groups of platforms with identical production technologies, which are characterized by the type of job they offer, $j = C, R$. The production of orders, o_j , is assumed to be linear in labor:

$$o_j = \int_0^{n_j} A h_j^e dj, \quad (1)$$

where n_j denotes employment, h_j^e are the effective hours worked (defined below), and A captures productivity per hour.

Labor market for regular jobs. The labor market for R jobs operates as in a standard Diamond-Mortensen-Pissarides setup, in which search and matching frictions hinder the formation of new matches. Riders are only hired as dependent employees, which implies that they earn collectively-bargained wages *per hour* worked, while employers pay payroll taxes τ_f . Hours worked in this sector are assumed to be fixed \bar{h}_R .⁶ Searchers and R platforms meet according to a matching technology that determines the contact probabilities of riders and vacant jobs. To ensure that these probabilities are bounded between 0 and 1, we adopt the CRS matching function proposed by Den Haan et al. (2000), namely, $m(s, v) =$

⁶As shown below, riders preferring short-hours jobs always choose work in R jobs due to its wage premium (see Figure 3). Thus, allowing for a part-time work schedule in the R sector does not affect worker sorting across jobs and, therefore, would not alter the main results of the paper.

$sv/(s^\iota + v^\iota)^{1/\iota}$, where ι is a matching parameter. Hence, the contact probabilities for job seekers and for vacancies are $p(\theta) = m(s, v)/s$ and $q(\theta) = m(s, v)/v = p(\theta)/\theta$, respectively, where $\theta = v/s$ is labor market tightness, given by the ratio of vacancies, v , to searchers, s .

Labor market for casual jobs. Riders always have the option to take up employment instantaneously by registering as self-employed in the app of a C platform, where they get paid *per order* produced. Thus, their labor market is fundamentally different from the one in the R sector, where riders are paid by the hour and face search frictions. Note that paying riders by the order, instead of by the hour, implies that C platforms do not experience an increase in their costs when the riders' labor supply exceeds the market demand for their orders.

In fact, C platforms let riders freely choose their hours worked in a decentralized fashion which determines the total labor supply in the C platform. The app, in turn, automatically aligns any labor supply with their demand for orders. When there is excess supply of hours, the effective productive hours that a C rider gets paid is only a fraction of the supply of total hours: $h_C^e = \varphi h_C$, where $0 < \varphi \leq 1$ is an endogenous proportionality factor strictly lower than one when demand for hours falls short of supply. The intuition is that when demand is weak, C riders experience longer waiting times between orders, with this idle time being wasted for the rider. Hence, the market-clearing condition for the C platform is

$$o_C = \int_0^{n_C} A h_j^e dj = n_C \varphi A \int h_C(\epsilon) dG^C(\epsilon), \quad (2)$$

where G^C is the cumulative distribution function of the riders' taste parameter ϵ for the hours worked in these jobs, so that $\int h_C(\epsilon) dG^C(\epsilon)$ are the average hours worked per rider.

Demand for food delivery orders. We model the demand for food delivery orders through a representative consumer with exogenous income m who chooses the number of orders o_j from each platform by maximizing the following CES

utility function subject to a linear budget constraint:

$$\mathcal{U}_c = \max_{o_C, o_R} \left(\sum_{j \in \{C, R\}} (s_j o_j)^{\frac{\mu-1}{\mu}} \right)^{\frac{\mu}{\mu-1}}, \quad (3)$$

$$\text{s.t. } p_C o_C + p_R o_R = m. \quad (4)$$

where $\mu > 1$ is the elasticity of substitution between orders provided by C and R platforms, and s_j are utility shifters capturing the importance of non-price characteristics of food delivery services in platform j . The first-order conditions (FOC) of the consumer problem yields the relative inverse demand of orders:

$$\frac{p_C}{p_R} = \left(\frac{s_C}{s_R} \right)^{\frac{\mu-1}{\mu}} \left(\frac{o_R}{o_C} \right)^{\frac{1}{\mu}}, \quad (5)$$

where we normalize $s_C = 1$ since consumption choices only depend on the relative utility shifter.

Firm's problem. Firms choose the number of orders to maximize flow profits, having internalized their downward-sloping demand functions and taking as given both the riders' labor supply decisions and their competitors' decisions:

$$\begin{aligned} & \max_{o_j} (p_j(o_j) - mc_j)o_j, \\ & \text{s.t. } p_j(o_j) = \left(\frac{s_j}{s_{-j}} \right)^{\frac{\mu-1}{\mu}} \left(\frac{o_{-j}}{o_j} \right)^{\frac{1}{\mu}} p_{-j}, \end{aligned}$$

with mc_j denoting the marginal cost of each platform j . The FOC yields the standard Lerner condition for the price as a markup over the marginal cost:

$$p_C^* = \frac{\mu}{\mu-1} \cdot mc_C, \quad \text{and} \quad p_R^* = \frac{\mu}{\mu-1} \cdot mc_R, \quad (6)$$

where the markup is determined by the elasticity of substitution between orders μ . Hence, (5) and (6) highlight that, besides the demand shifters s_j , relative market sizes are determined by the marginal costs of platforms to which we turn next.

Determinants of marginal costs. The specific structure of the riders' labor market implies that marginal costs are different for platforms according to whether they hire workers as independent contractors or employees. Platforms offering C jobs pay w_C to their riders *per order* produced, which is chosen to be the numeraire of the economy and normalized to $w_C = 1$. In addition, C platforms may have to pay administrative sanctions, $1 + \Gamma$, for each order whenever they defy the RL rules. Thus, given that these employers do not pay social security contributions, marginal costs for C platforms are given by:

$$mc_C = w_C(1 + \Gamma) = (1 + \Gamma). \quad (7)$$

Equation (7) implies that imposing administrative sanctions will increase marginal costs and, hence, raise prices of the C platform, thereby redirecting food delivery orders towards the R platform.

Turning to the marginal costs in the R sector, its platforms pay an hourly wage $w_R(\bar{\epsilon}_R)$ plus payroll taxes τ_f . Different from C riders, R riders enjoy bargaining power and have a union bargaining on their behalf that takes into account the average taste parameter of its members, denoted as $\bar{\epsilon}_R$. To avoid the complication of modeling multi-worker bargaining arising from the incentives of firms to over-hire (Stole and Zwiebel, 1996; Elsby and Michaels, 2013), which is not relevant to the main point of our analysis, we assume that there is a HR division within each R platform that is disconnected from the production side and treats the contribution of each rider to the firm individually.⁷ In particular, to cover labor costs, the production side of the platform transfers a fee c^{HR} to the HR division for each hour worked by a rider, which is then used to pay the corresponding gross hourly wage $(1 + \tau_f)w_R(\bar{\epsilon}_R)$. Thus, the value for this HR division of providing an additional rider to the platform becomes:

$$J_R(\bar{\epsilon}_R) = c^{HR}\bar{h}_R - (1 + \tau_f)w_R(\bar{\epsilon}_R)\bar{h}_R + \beta(1 - \delta)J_R(\bar{\epsilon}_R), \quad (8)$$

⁷An equivalent micro-foundation for abstracting from multi-worker bargaining is to assume that the firm hires labor from intermediate firms, each one with one worker, which play the role of the indirect provider of labor services to the platforms, as in Marimon and Zilibotti (2000).

where β is the time discount factor, and δ is an (exogenous) job destruction rate. Importantly, due to the presence of search and matching frictions, the HR division incurs a flow vacancy posting cost κ when searching for a rider. Thus, the value of a vacancy is given by:

$$J_R^v(\bar{\epsilon}_R) = -\kappa + \beta \left[q(\theta) J_R(\bar{\epsilon}_R) + (1 - q(\theta)) J_R^v(\bar{\epsilon}_R) \right].$$

In equilibrium, the R platform posts vacancies until the value of the vacancy becomes zero, implying that:

$$\kappa = \beta q(\theta) J_R(\bar{\epsilon}_R). \quad (9)$$

Plugging (9) into the value of a filled job given in (8) yields:

$$c^{HR} = (1 + \tau_f) w_R(\bar{\epsilon}_R) + (1 - \beta(1 - \delta)) \frac{\kappa}{\beta q(\theta) \bar{h}_R}. \quad (10)$$

As mentioned above, the labor costs of an R platform consist of paying a fee of $c^{HR} \bar{h}_R n_R$ to its HR division. Moreover, the production technology in (1) yields that the total number of hours worked by R riders is given by $\bar{h}_R n_R = o_R / A$. Consequently, its marginal cost of orders is given by:

$$mc_R = \frac{c^{HR}}{A}, \quad (11)$$

which highlights that, resulting from the search and matching friction, R platforms' marginal costs are driven not only by hourly wages and payroll taxes, but also by the expected discounted cost of posting vacancies.⁸

Finally, wages for R riders solve the standard Nash-bargaining problem:

$$w_R(\bar{\epsilon}_R) = \arg \max \left\{ [W_R(\bar{\epsilon}_R) - U(\bar{\epsilon}_R)]^\eta [J_R(\bar{\epsilon}_R)]^{1-\eta} \right\}, \quad (12)$$

where η is the riders' bargaining weight, and $U(\bar{\epsilon}_R)$ is the outside option value of

⁸Note that, unlike the marginal cost of the C platform, productivity per hour (A) enters the marginal cost of the R platform as it pays riders *per hour* worked, while the C platform pays riders *per order* produced.

not working in the R sector (for a rider with the average taste parameter, $\bar{\epsilon}_R$).

Summing up, differences in marginal costs and, hence, in demand for orders between the two types of platforms arise from: (i) C platforms having to pay fines after challenging the RL, and (ii) R platforms having to pay bargained wages with a union plus social security contributions, as well as internalizing the costly labor market search process. As discussed earlier in Section 3, the resulting bargained wage is higher in R platform than the labor compensation in C platforms. Hence, in the absence of administrative fines, C platforms set lower prices, which would allow them to capture a larger share of the online food delivery market.⁹

Riders' preferences There is a unit mass of workers who are ex-ante heterogeneous in their dis-utility of work, reflecting differences in caregiving responsibilities, educational commitments, and other time constraints. The taste parameter leisure, 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 \tilde{h} units of time per period, and their utility depends on both labor income, y , and the share of time allocated to leisure, $1 - h/\tilde{h}$. Specifically, the flow utility of riders is given by:

$$u(y, h) = \ln(y) + \epsilon \ln(1 - h/\tilde{h}), \quad h \in [0, \tilde{h}].$$

Modeling riders' utility as dependent on labor income captures that they are hand-to-mouth and hence do not save. Recall that riders earn labor income that depends on hours worked in R and on orders produced in C , and that the latter are not fully compensated for their supplied hours of work since they earn a fraction (φAw_C) of each hour effectively worked due to waiting time not being remunerated in this sector. Lastly, non-rider job seekers receive a flow value b_U from working \bar{h}_U hours in an outside option representing alternative job opportunities. Therefore,

⁹In our setup, note that these lower prices directly affect consumers. In practice, however, platforms may also compete in the fee they charge to restaurants. As a result, C platforms were able to sign more restaurants to their delivery services. We do not model this intermediate step. Yet, assuming that restaurants operate under perfect competition, they will pass any reduced fees to consumers in the form of lower meal prices.

consumption/income in each employment status is given by:

$$\begin{aligned} y_U &= b_U \bar{h}_U && \text{if searcher,} \\ y_R &= w_R(\bar{\epsilon}_R) \bar{h}_R && \text{if employed in } R, \\ y_C &= (1 - \tau_c) w_C \varphi A h_C && \text{if employed in } C, \end{aligned}$$

Accordingly, the period-by-period utility functions become:

$$u_C(\epsilon) = \max_{h_C} \ln(y_C) + \epsilon \ln(1 - h_C/\tilde{h}) \quad (13)$$

$$u_R(\epsilon) = \ln(y_R) + \epsilon \ln(1 - \bar{h}_R/\tilde{h}), \quad (14)$$

$$u_U = \ln(b_U) + \epsilon \ln(1 - \bar{h}_U/\tilde{h}). \quad (15)$$

A key simplification of our model is that the flow value of the outside option, u_U , is exogenous due to the relatively small size of the platform sector, which we assume does not influence equilibrium outcomes in the rest of the economy.

Labor supply choices by riders. Let $U(\epsilon)$ denote the value of potential riders currently not employed as a rider (non-rider searchers, hereafter). These potential riders may be either non-employed or they may work outside of the platform sector and wish to become a rider. Hence, their value solves:

$$U(\epsilon) = u_U + \beta \Omega^U(\epsilon) \quad (16)$$

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

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

The non-rider searchers decide whether to take instantly a job in the C platform that yields a value $W_C(\epsilon)$ or search for a job in the R platform 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 with their external option. Alternatively, with probability $p(\theta)$, they can choose between remaining with the external option or accepting the job offer in R . The policy indicator $\mathbb{I}^{RC,u}$ captures their decision to search for R jobs rather than taking a C job, while \mathbb{I}^R denotes their decision to

accept an offer from the R platform. To reduce notation, we omit the dependence of policy functions on the taste parameter ϵ here and throughout the sequel.

When self-employed in the C platform, a rider may search for a job in the R platform. We introduce on-the-job search to capture the evidence in Figure 2 showing substantial overlap in the distributions of hours worked for R and C jobs at relatively low hours. We interpret this fact as reflecting that riders with relatively high work dis-utility would still accept C jobs while keep on searching for better-paid shorter-hours R jobs. Then, assuming that the job offer rate, $p(\theta)$, is the same as for non-rider searchers, the resulting value becomes:

$$W_C(\epsilon) = u_C(\epsilon) + \beta \Lambda^C(\epsilon) \quad (19)$$

$$\Lambda^C(\epsilon) = (1 - p(\theta)) \Lambda^{CC}(\epsilon) \quad (20)$$

$$+ p(\theta) \left[\mathbb{I}_{=1}^{CR} \left(\mathbb{I}_{=1}^R W_R(\epsilon) + \mathbb{I}_{=0}^R U(\epsilon) \right) + \mathbb{I}_{=0}^{CR} \Lambda^{CC}(\epsilon) \right]$$

$$\Lambda^{CC}(\epsilon) = \mathbb{I}_{=1}^C W_C(\epsilon) + \mathbb{I}_{=0}^C U(\epsilon), \quad (21)$$

where $\mathbb{I}_{=1}^{CR}$ is an indicator of the rider preferring a C job over a job offer from the R sector, while $\mathbb{I}_{=1}^C$ denotes that the rider prefers a C job over non-employment. Likewise, $\Lambda^{CC}(\epsilon)$ captures the value of staying in the C sector or moving to the non-rider option. Note that on-the-job search in R platforms are omitted as riders could always choose to get a job directly in the C platform. Hence, with $\Lambda^R(\epsilon)$ capturing the value of staying in the R sector or becoming a non-rider, the value for a rider in the R platform solves:

$$W_R(\epsilon) = u_R(\epsilon) + \beta \Lambda^R(\epsilon) \quad (22)$$

$$\Lambda^R(\epsilon) = (1 - \delta) W_R(\epsilon) + \delta U(\epsilon), \quad (23)$$

Having characterized labor supply choices from the value of each job, we now define the two types of individuals who search for jobs in the R platform. First, there is a mass of searchers who are currently non-riders, u , and are only willing to accept a direct job offer as rider from the R platform. Second, there is a mass of on-the-job searchers who are currently working in the C platform, c , but would

prefer transiting to the R platform. Thus, the total mass of job searchers, s , is:

$$s = u \cdot \int_0^\infty \mathbb{I}_{=1}^R(\epsilon) \mathbb{I}_{=1}^{RC,u}(\epsilon) dG^{UR}(\epsilon) + c \cdot \int_0^\infty \mathbb{I}_{=1}^C(\epsilon) dG^{CR}(\epsilon), \quad (24)$$

where, G^{UR} and G^{CR} are the cumulative distribution functions of the taste parameter ϵ of the u and c searchers, respectively.

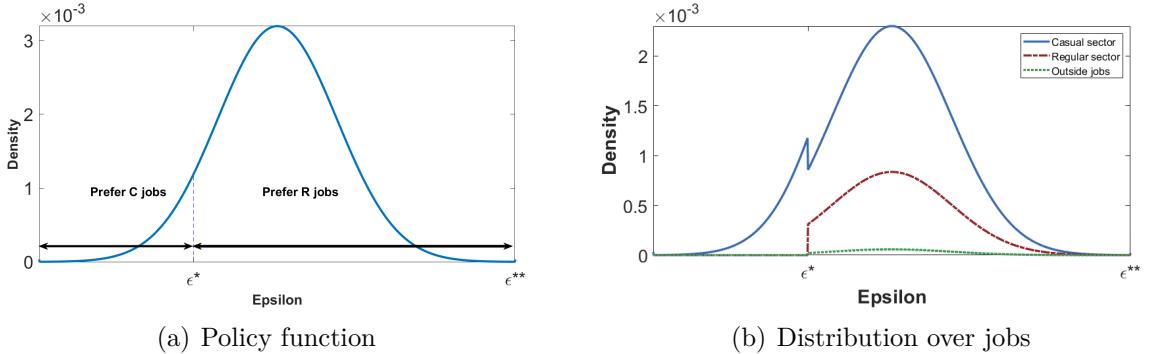
Equilibrium. The equilibrium consists of prices and quantities for food delivery services (p_R, p_C, o_R, o_C) , employment levels (n_R, n_C) , labor supply (h_C) , adjustment factor (φ) , labor market tightness (θ) , mean leisure taste $(\bar{\epsilon}_R)$, wage in the R platform (w_R) , value functions $(J_R, J_R^v, U, \Omega^U, \Omega^R, W_C, \Lambda^C, \Lambda^{CC}, W_R, \Lambda^R)$, and distributions $(G^C, G^R, G^{UR}, G^{CR})$ such that:

- **Food delivery market:** Consumer demand (o_j, o_{-j}) maximizes utility as given by equation (5) for $j \in \{C, R\}$, while satisfying the budget constraint in (4). Moreover, platforms maximize profits and set prices according to (6).
- **Labor market:** Riders optimize labor supply h_C in C jobs as in (13). Workers' value functions satisfy (16)-(23); the value of a vacant job J_R^v satisfies the free-entry condition (9); the value of a filled vacancy J_R satisfies (8); the hourly wage w_R is set by Nash bargaining as in (12), and the factor φ adjusts the demand for and supply of hours in C jobs following (2).
- **Distributions are consistent:** $(G^C, G^R, G^{UR}, G^{CR})$ arise from optimal policies and equilibrium outcomes, with G^R determining $\bar{\epsilon}_R$.

4.1 How the model works

Before examining in detail the strategy to quantify the model parameters, we first discuss riders' choices of their preferred job type and their resulting distribution across jobs. Panel (a) in Figure 3 shows the distribution of ϵ under the benchmark calibration for the economy to be discussed in Section 5 below, along with the key cutoff value, ϵ^* , determining employment choices. Riders prefer C jobs over R jobs whenever their idiosyncratic distaste for work is low enough, namely, $\epsilon < \epsilon^*$, where

Figure 3: Riders' preferences for jobs and employment distribution



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.

ϵ^* solves $W_C(\epsilon^*) = W_R(\epsilon^*)$. The insight is that C jobs offer them the possibility of achieving high earnings by working many hours.

Conversely, riders prefer R jobs over any other option whenever $\epsilon > \epsilon^*$, this time because they offer them a wage premium relative to both C and outside jobs. Yet, due to search frictions, some of these riders (those without a too high taste for leisure) are willing to accept C jobs and then search on-the-job for their preferred R jobs. This happens whenever $\epsilon \in (\epsilon^*, \epsilon^{**})$, where the cutoff value ϵ^{**} solves $W_C(\epsilon^{**}) = U(\epsilon^{**})$. Finally, those riders with very high taste for leisure, $\epsilon > \epsilon^{**}$, will search for R jobs from outside jobs, given our calibrated value of the latter.

Panel (b) of Figure 3 displays the resulting employment distribution over C and R jobs. It shows that there is a substantial proportion of self-employed riders who would rather prefer to become employees. Thus, this group may benefit from policies that induce worker reallocation from C platforms to R platforms.

5 Model Calibration

Table 2 presents the choice of the model parameters. Besides matching moments regarding the structure of the rider's labor market, the calibration aims to capture the riders' trade-off (see Section 3), between higher wages in R platforms and more

flexible hours in C platforms. We first calibrate parameters governing taxation, bargaining power and some of the features of the labor market and consumers' preferences. These choices shape labor income, riders' sorting incentives into the different platforms, and the incentives of R firms to post vacancies. Next, we jointly estimate the remaining set of parameters, related to preferences and technology, using the Simulated Method of Moments (SMM) which matches hours, wages and the relative size of the two sectors with their associated targets.

Table 2: Summary of model quantification

Parameter	Description	Value	Moment
Panel I: Calibration			
<i>A: Preferences</i>			
$(1 - \beta)^*100$	1 – Discount factor	0.34	4% annual discount rate
μ	Elasticity of substitution	6	García-Perea et al. (2021)
<i>B: Labor market</i>			
\bar{h}_R	Hours worked in R	0.15	Mean hours in $R/24$
$\log(\kappa)$	Vacancy costs	6.75	Hagedorn and Manovskii (2008)
η	Workers' bargaining weight	0.50	Petrongolo and Pissarides (2001)
δ	Destruction rate in R	0.04	EU flow $R = 7\%$
<i>C: Outside option</i>			
\bar{h}_U	Hours outside option	0.16	Predicted hours worked/24
$\log(b_U)$	Flow value outside option	1.66	Marginal C rider is indifferent
<i>D: Taxes</i>			
τ_c	Payroll taxes in C	0.16	Payroll taxes self-employed
τ_f	Payroll taxes in R	0.29	Payroll taxes employers
Panel II: SMM			
<i>A: Preferences</i>			
s_R/s_C	Utility shifter goods	1.79	Employment share of R platform
μ_ϵ	Work disutility: Mean	3.69	Mean hours in $C/24 = 0.22$
σ_ϵ	Work disutility: Std. dev.	0.71	95 th percentile hours in $C = 7/24$
<i>B: Technology</i>			
$\log(A)$	Hourly productivity	2.52	Mean log wages in $R = 2.07$
ι	Matching parameter	0.23	Wage premium in $R = 0.17$

Note: This Table describes the quantification of the parameters and their respective targets.

5.1 Calibrated parameters

The benchmark model captures the main features of the pre-reform labor market when no administrative sanctions in the C platform had been imposed, i.e. $\Gamma = 0$. The model period is monthly and the (annual) discount rate is 4 percent.

The elasticity of substitution between orders, μ , determines the size of markups. Empirical studies quantifying market power in Spain estimate that average markups have ranged between 20 and 50 percent over the past decades (García-Perea et al., 2021). We take the lower bound of these numbers and set $\mu = 6$ in our benchmark calibration, as accounting profits are likely to be small in the food delivery sector.

Turning to the parameters governing hours worked, we set the number of hours worked in the R platform to the mean observed in the convenience survey. Regarding the hours in the outside option, we interpret them as representing alternative opportunities to those found in the food delivery sector, including non-employment. Accordingly, we first calibrate the number of hours worked by outside job seekers as the predicted hours of workers in the Spanish economy with the same characteristics as the average rider. In particular, we regress the annual hours worked by an individual i , h_i , on a vector of characteristics, X_i , including sex, age, nationality, skills, occupation and sector. To estimate this regression, we use annual microdata from the 2018 wave of the Wage Structure Survey (EES), which is the last wave available with information for a representative sample of employees in Spain before the RL was enacted. To determine the average sociodemographic characteristics of riders, \bar{X}_i , we draw data from the Adigital survey (2020). Using the OLS estimated parameters, $\hat{\beta}$, from that regression yields a prediction of $\hat{\beta}\bar{X}_i = 5.0$ hours worked for workers with the average characteristics of riders in similar occupations. We then adjust this number for the unemployment rate among such workers using quarterly data from the Spanish Labor Force Survey (LFS) for 2009-2019. Our main finding is that the predicted unemployment probability for this specific type of workers is 24 percent. Assigning zero hours when unemployed, we obtain $\bar{h}_U = 0.76 \cdot 5.0/24 = 0.16$. Since we set the fraction of hours worked in the R platform equal to 0.15, consistent with a mean daily

hours of 3.7 in this sector, our calibration strategy implies that riders expect to work similar hours in outside jobs and R platforms.

Next, we discuss the choice of those parameters guiding labor market flows in the R platform. Following Hagedorn and Manovskii (2008), the flow vacancy costs κ is set to match an expenditure made by firms equivalent to forgoing 58 percent of average labor productivity per worker. As is common in search and matching models (Petronegolo and Pissarides, 2001), the bargaining power of riders, η , is set equal to 0.50. Regarding employment separations, we choose the monthly job destruction rate, δ , to match a 7 percent transition rate from employment to non-employment in the Postal Services and Courier Activities sector (NACE 532H) of the largest Spanish administrative dataset (Muestra Continua de Vidas Laborales-MCVL) for the pre-reform period January 2019-July 2021.¹⁰

As for payroll taxation, we choose tax rates in the C and R platforms to match the average payroll taxes of the self-employed, $\tau_c = 16$ percent, and the employers, $\tau_f = 29$ percent, respectively.

5.2 Jointly estimated parameters

The remaining six parameters $\mathbf{o} = (s_R, \mu_\epsilon, \sigma_\epsilon, \iota, A, b_u)$ are related to consumers' preferences, riders' tastes for hours worked, the matching and production technologies, and the flow value of riders' outside option. These parameters, which jointly determine the distributions of market shares of two types of platforms, hours worked, wages, and employment rates, are estimated by the above-mentioned SMM approach. Below, we describe each parameter and its closest associated moment. Moreover, Table A.1 in Appendix A reports the fit of the targeted moments, which turns out to be very satisfactory.

The utility shifter s_R is informative about the relative size of the R platform by affecting the relative demand for food delivery services, as shown in Equation (5).

¹⁰This NACE sector includes riders together with postal staff and other types of couriers. Since these workers have more stable labor contracts than riders, we restrict the sample to employees who work for two consecutive months and whose tenure is no longer than 18 months, to be consistent with the tenure reported in Table 1.

Therefore, following the results from the convenience survey in Table 1, we include 24 percent as the target for the employment share of riders in these platforms.

The distribution of work hours in the C platform is informative about riders' work tastes, ϵ , since self-employed riders choose their own working hours. Note that the model controls for the self-selection of workers with a strong taste for flexible hours into the C platform. In the data, we observe an average of 5.4 and a 95th percentile of 7.0 hours worked in the C platform. We use these moments to estimate the mean, μ_ϵ , and standard deviation, σ_ϵ , of idiosyncratic preferences.

Next, consider the parameters related to production and matching technologies. Given the exogenous consumer's spending, the productivity per hour, A , determines the marginal revenue productivity of riders and thereby affects hourly wages in both sectors. By influencing the matching probabilities, the parameter ι determines the size of the match surplus for R jobs, which influences the wage premium in the R relative to the C platform. To discipline these parameters, we target an average hourly wage net of social security contributions of 7.9 euros in the R platform, based on the sector's collective bargaining agreement.¹¹ In addition, using the evidence from the survey, we also target a wage premium of 17.2 log points for R jobs.

Lastly, we turn to the flow value of outside jobs, b_U . This parameter reflects the expected flow value of riders outside the delivery sector (including non-employment). As we are interested in workers who wish to work as riders, i.e. prefer working in the C platform over the outside option *before* the RL, we target that the marginal worker is indifferent between both alternatives, $W_C(\epsilon^{**}) = U(\epsilon^{**})$. As a result, the only non-employment in our calibration arises from frictional non-employment, i.e. those riders who lose their R jobs.

¹¹We use the [collective agreement](#) (M/441/2021/N), signed between Just Eat and trade unions in 2021 as a representative source of information for remuneration of R riders. We compute our estimate of hourly wages by dividing the annual base wage (15,232 euros), net of employees' social security and income taxes, by the annual number of hours for full-time riders (1,792). We find net hourly wages to be 7.8€. This result is reassuring, as we find that net hourly wages of R riders in the convenience survey are around 7.0€.

6 Policy experiments

This section quantifies the effects of the RL on the online food delivery sector. Given that the reform imposes heavy administrative sanctions on defier platforms, our focus is on the underlying influence of these sanctions on C platforms' decision-making, which is captured through parameter Γ . Hence, while we set $\Gamma = 0$ in the baseline (pre-reform) model, when hiring C riders was legal, we allow for positive sanctions in the counterfactual, $\Gamma > 0$. The mechanism of how sanctions affect the structure of the food delivery market is explicit in our model: sanctions increase the post-reform marginal cost of using C riders, which raises the relative prices of C orders, p_C/p_R , shifting consumer demand to R platforms. Specifically, we set $\Gamma = 0.12$ to match the 6 percentage-points rise in the market share of the R sector, $o_R/(o_C + o_R)$ (see Figure 1).

Before turning to the main counterfactual results, a few 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, as already pointed, we also abstract from sector-wide demand trends as the overall mass of available riders 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 those trends.

6.1 Labor-market effects of the Rider's Law

Panel A in Table 3 shows that administrative sanctions directly translate into a convergence of relative prices of orders, as C platforms raise prices to offset the increase in marginal costs and maintain profitability at the margin. Consequently, a higher relative price of C orders shifts consumer demand to R platforms. To be consistent with a calibrated increase of 6 percentage points in the market share of orders of R platforms, we find that the relative price of C orders increases by nearly 5.5 percent.

Table 3: The effects of the RL on the food delivery sector

	Baseline	Reform		Baseline	Reform
<i>A: Orders</i>			<i>D: Employment</i>		
Relative price (p_C/p_R)	0.52	0.55	Employment C	0.74	0.58
Adjustment factor (φ)	0.66	0.64	Employment R	0.24	0.26
			Outside jobs	0.02	0.16
<i>B: Wages</i>			<i>E: Hours</i>		
Mean log hourly wages C	1.94	1.92	Mean effective hours C	3.55	3.64
Mean log hourly wages R	2.10	2.10	Mean effective hours	3.60	3.67
Labor market tightness	0.34	0.38			
<i>C: Job preferences</i>			<i>F: Welfare change (%)</i>		
Cutoff C and R jobs, ϵ^*	2.70	2.57	Consumers		-8.81
Cutoff C and U jobs, ϵ^{**}	6.51	4.32	Riders		-1.23

Note: This Table displays the model results from the counterfactual simulation where defier firms in the C sector have to pay a fine: $\Gamma = 0.12$.

As consumers demand fewer orders from the C platform after the RL, C riders face longer waiting times, as reflected by the drop in their share of productive hours, φ .¹² Panel B in Table 3 shows that, as waiting times increase in the C platforms, their net hourly wage decreases by nearly 2.0 log points. The reduction in C wages implies that there are two groups of riders who no longer find it optimal to work in the C sector. First, a fraction of long-hours C riders now prefer R jobs, as illustrated by the reduction in the cutoff value ϵ^* (panel C). Second, a fraction of short-hours C riders move to outside jobs, namely, ϵ^{**} also goes down. Overall, this leads to a fall of 16.2 percentage points in the employment share of the C sector (panel D), which represents about one-fifth of its pre-reform share. Moreover, as the mass of riders from the second group is larger, average hours go up in C platforms (panel E) reflecting a selection effect: those riders who remain in C platforms have higher preference for long hours than those who leave this sector.

¹²We are not aware of quantitative evidence that would allow us to test this model prediction. However, qualitatively, there is media evidence about riders reporting longer waiting times for their account to be activated by Glovo after the RL: <https://www.que.es/2024/05/07/glovo-cuentas-espera/>

The negative effects of the RL on the C sector have meaningful spillover effects on R platforms. On the one hand, since working in a C platform becomes less attractive and the conditions of non-rider jobs are not affected by the RL, R riders' outside option worsens, weakening their bargaining position and pushing wages down in this sector. On the other hand, the rise in the demand for R orders leads to a higher price, p_R , which is partially passed-through to higher wages as their marginal revenue product of labor increases. Taken together, we find that both effects offset each other, leaving the R wage almost unchanged. Higher demand for R orders boosts additional vacancy creation and raises labor market tightness, θ , increasing its employment share by 2.0 percentage points (panel B). Therefore, there is a significant decline in the size of the food delivery sector, as this platform only absorbs about one-tenth of the employment decline in the C platform after the approval of the RL.

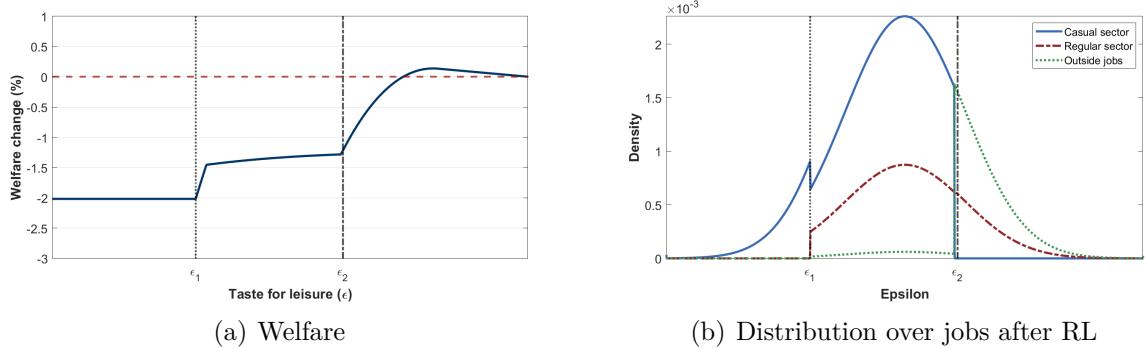
In sum, the reason why the R platform does not fully offset the employment decline in the C platform has to do with both labor demand and labor supply forces. On the demand side, the higher marginal costs in the R platform relative to the C platform implies that the shift in consumer spending across platforms mostly translates into higher prices rather than increased production of orders using R riders. On the supply side, outside jobs become more attractive than C jobs after the RL, which incentivizes riders to leave the online food delivery sector.

6.2 Welfare effects of the Riders' Law

The RL affects welfare through changes in household consumption and riders' labor income. We measure welfare in terms of consumption-equivalent variation, i.e. the percentage of lifetime consumption that an individual would be willing to forgo to remain indifferent between the benchmark economy and the one with the RL regulations. Following the reform, consumers demand fewer orders due to an increase in the price level. Consequently, we find that their welfare from food delivery consumption decreases by 8.8 percent.

Regarding riders' welfare, we find that the RL leads to an average welfare loss of 1.2 percent, mainly due to the employment and wage losses. However, the

Figure 4: Welfare effects of the Riders' Law



Note: The left panel of this Figure displays the welfare effect of the Riders' Law as a function of workers' time preferences. The right panel shows the distribution of riders over the different types of jobs after the RL.

reform has unequal effects on riders' welfare depending on their idiosyncratic tastes for working hours. To examine this distributional effect, the left panel of Figure 4 shows how welfare losses vary across riders' different tastes for working hours, while the right panel displays the employment distribution after the RL. Specifically, we define three groups of riders based on 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 indicates that the economy is operating under the new regulations.

Our main findings are as follows. First, nearly 5.7 percent of riders always prefer the C platform due to their low distaste for hours worked, $\epsilon < \epsilon_1$. These riders suffer large welfare losses due to the pay reduction in the C platform, which is not offset by better job opportunities from moving to the R platform.

Second, 75.8 percent of the riders with $\epsilon \in (\epsilon_1, \epsilon_2)$ would prefer to work in the R sector. Among them, those in the C platform engage in on-the-job search. Two contrasting effects operate. On the one hand, these riders benefit from the RL since it facilitates the transition from C to R jobs. On the other hand, they experience earnings/consumption losses because: (i) wages are now lower in C platforms, where they are still partially stuck due to labor market frictions, and (ii) wages barely change in the R platform. Overall, the negative effects outweigh the positive effects, so the overall riders' welfare change is again negative.

Third, given the improved job opportunities in R platforms, there is 18.5 percent of non-rider workers (i.e., those with $\epsilon > \epsilon_2$) who find it attractive to search for R jobs from their current outside jobs. However, these job seekers may fail to achieve their goals due to the shrinking of the food delivery sector. The overall effect on this group of riders depends on their attachment to work. The higher their taste for leisure, the lower are their welfare losses from losing the R job. As a result, while a fraction of these riders experience some welfare losses, the remaining ones slightly benefit from the RL.

Lastly, recall from Table 1 that about 18 percent of riders do not have a work permit. One may argue that politicians are less concerned about deteriorating employment prospects of this group of undocumented riders. As these workers work particularly long hours, i.e. they are those endowed with low ϵ , they have a relatively high weight in our welfare calculations. However, even when the 18 percent of workers with the lowest ϵ is ignored from our welfare calculations, the RL still leads to a 1.1 percent welfare loss among riders.

6.3 Complementing the Riders' Law with tax policies

As shown above, the RL proves detrimental for workers as the R platform fails to expand employment sufficiently to compensate for the job losses in the C platform. The reason is that higher prices, rather than increased production, absorb most of the consumer spending shift from the C to the R platforms induced by the RL, since producing orders using R jobs is costlier than with C jobs (see Panel A in Table 3). Our model captures this feature through job-specific marginal costs, arising from differences in payroll taxation, bargaining power, and vacancy creation costs. As a potential policy tool, we analyze the level of employer payroll tax exemptions in the R platform that would be required to offset the adverse effects of the reform, while keeping the same sanctions penalizing the defiers.

We find that a tax bonus close to a full exemption of payroll taxes in R jobs preserves riders' average welfare unchanged. Specifically, a reduction of 22 percentage points in the tax rate, from $\tau_f = 0.29$ to $\tau_f = 0.07$, would be required to achieve such a goal. Not surprisingly, this tax cut increases labor demand in the

Table 4: Results from complementary tax policy to the Rider’s Law

	Baseline	RL & tax reform
	Welfare-neutral tax	
<i>Policy changes</i>		
Government fine C platform	0	0.12
Firm-level tax R platform	0.29	0.07
<i>Panel A: Wages</i>		
Mean log hourly wages C	1.94	1.91
Mean log hourly wages R	2.11	2.14
Labor market tightness	0.34	0.45
<i>Panel B: Employment</i>		
Employment C	0.74	0.54
Employment R	0.24	0.29
Outside jobs	0.02	0.17
<i>Panel C: Hours</i>		
Mean effective hours C	3.55	3.65
Mean effective hours	3.60	3.67
<i>Panel D: Welfare change</i>		
Mean CEG: Riders	0	
Mean CEG: Consumers	-7.6	

Note: The table displays the model results from counterfactual simulations that implement the RL reform, $\Gamma = 0.12$, together with changes in employers’ payroll taxes in the R platform.

R platform, and the resulting effects spread throughout the economy. Riders now benefit from higher job-finding rates and wages in R platforms.

Nevertheless, two additional issues are worth noting. First, even nearly abolishing payroll taxes for R jobs turns out to be insufficient to prevent the food delivery sector from shrinking, so consumer welfare still falls, but by slightly less than before. Second, this reform does not avoid that riders remaining in the C sector are worse off due to lower wages (see Figure A.1 in Appendix A).

In sum, we conclude from this evidence that complementing the RL with payroll tax cuts for R employers would have improved the negative outcomes of the reform. Admittedly, this policy could have fiscal budget consequences, but since the online food delivery sector is a very 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, enacted in 2021. This reform established the presumption of dependent employment for workers, known as riders, in this sector and levies large fines on platforms not complying with this legislation. We find that only one-tenth of displaced self-employed riders transition into dependent employment after the reform. Thus, the food delivery sector shrinks. Moreover, the new rules also lead to lower wages, especially among those riders who remained working as self-employed in the defier platforms. We claim instead that a bonus reducing employers' payroll taxes for the RL-compliant platforms could offset some of these detrimental effects.

To reach these conclusions, we develop a quantitative equilibrium model with heterogeneous workers who sort into casual (C) and regular (R) jobs, each offered by a platform that provides services to a representative consumer. We allow these platform jobs to be heterogeneous in terms of employability, work time flexibility, and wages, capturing the main trade offs in the policy debate. We calibrate the model using both a representative convenience online survey collected by us and aggregate statistics. We find that riders with relatively low tastes for leisure choose C jobs because they offer greater flexibility in working long hours and are instantaneously available. In contrast, the remaining riders prefer to work in the R sector, due to their wage premium, though they often accept C jobs to avoid non-employment or less preferable outside jobs 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, wages, and ultimately welfare should not be surprising. Yet, our model allows for two equilibrium mechanisms to soften the blow to riders' wages and employment which, in principle,

could increase riders' welfare. First, resulting from higher wages in the R sector, a smaller relative size of the C sector may shift profits from firms to riders insofar as they are able to access the R sector. Second, as fines affect the marginal costs of platforms, firms shift part of the burden to consumers through higher prices which could also help riders depending on the price elasticity of the demand for orders. The insight for why these effects are not strong enough is that riders' jobs have a low surplus. Hence, any reduction in hourly wages in the C sector leads to large employment outflows, i.e. labor supply elasticities of riders are high and they transit to outside jobs. Moreover, the small surplus does not leave much room for R platforms to expand and, hence, their employment does not increase nearly as much to offset the employment loss in the C sector.

Finally, given that our paper highlights differences in wages, hours flexibility, and search frictions between the two types of jobs, 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 platform could be an optimal policy by better adapting to riders' preferences. Second, the model could be extended to include other regulatory differences between the sectors such as overtime pay, maximum hours regulations, vacation days, and health protection benefits.

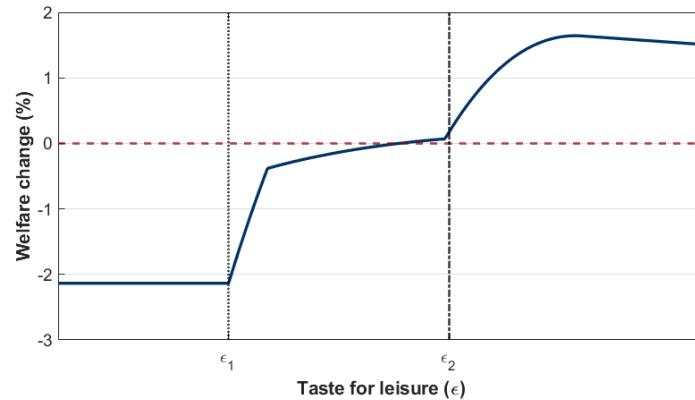
A Appendix

Table A.1: Model fit of estimated parameters

Parameter	Moment	Model	Data
<i>A: Preferences</i>			
s_R/s_C	Employment share of R platform	0.24	0.24
μ_ϵ	Mean hours in $C/24 = 0.22$	5.36	5.39
σ_ϵ	95 th percentile hours in $C = 7/24$	7.07	7.00
<i>B: Technology</i>			
A	Mean log wages in R	2.10	2.07
ι	Wage premium in R	0.17	0.17

Note: The table reports the values of the SMM approach targeted moments in the model and the data.

Figure A.1: Welfare effects of the RL with a welfare-neutral tax reform



Source: Own elaboration from simulated data.

Note: This Figure displays the welfare effect of the RL ($\Gamma = 0.22$) and the welfare-neutral tax ($\tau_f = 0.01$) as a function of workers' time preferences.

References

- Abraham, K. G., Haltiwanger, J. C., Hou, C., Sandusky, K., and Spletzer, J. R. (2021). Reconciling survey and administrative measures of self-employment. *Journal of Labor Economics*, 39(4):825–860.
- Adigital (2020). Importancia económica de las plataformas digitales de delivery y perfil de los repartidores en España. Technical report, Asociación Española de la Economía Digital (Adigital).
- Albrecht, J., Navarro, L., and Vroman, S. (2009). The effects of labour market policies in an economy with an informal sector. *The Economic Journal*, 119(539):1105–1129.
- Angrist, J. D., Caldwell, S., and Hall, J. V. (2021). Uber versus taxi: A driver’s eye view. *American Economic Journal: Applied Economics*, 13(3):272–308.
- Boeri, T., Giupponi, G., Krueger, A. B., and Machin, S. (2020). Solo self-employment and alternative work arrangements: A cross-country perspective on the changing composition of jobs. *Journal of Economic Perspectives*, 34(1):170–195.
- Carry, P. (2022). The effects of the legal minimum working time on workers, firms and the labor market. *Manuscript, Princeton University*.
- Chen, M. K., Rossi, P. E., Chevalier, J. A., and Oehlsen, E. (2019). The value of flexible work: Evidence from Uber drivers. *Journal of Political Economy*, 127(6):2735–2794.
- Collins, B., Garin, A., Jackson, E., Koustas, D., and Payne, M. (2019). Is gig work replacing traditional employment? Evidence from two decades of tax returns. *Manuscript, IRS SOI Joint Statistical Research Program*.
- Cooper, R., Meyer, M., and Schott, I. (2017). The employment and output effects of short-time work in Germany. Technical report, National Bureau of Economic Research.

- Den Haan, W. J., Ramey, G., and Watson, J. (2000). Job destruction and propagation of shocks. *American Economic Review*, 90(3):482–498.
- Dolado, J. J., Lalé, E., and Turon, H. (2025). Zero-hours contracts in a frictional labor market. *SSRN 3988202, The Economic Journal (forthcoming)*.
- Elsby, M. W. L. and Michaels, R. (2013). Marginal jobs, heterogeneous firms, and unemployment flows. *American Economic Journal: Macroeconomics*, 5(1):1–48.
- Frazier, N. (2018). *An equilibrium model of wage and hours determination: Labor market regulation in the retail sector*. PhD thesis, Rice University.
- García-Perea, P., Lacuesta, A., and Roldan-Blanco, P. (2021). Markups and cost structure: Small spanish firms during the great recession. *Journal of Economic Behavior & Organization*, 192:137–158.
- Hagedorn, M. and Manovskii, I. (2008). The cyclical behavior of equilibrium unemployment and vacancies revisited. *American Economic Review*, 98(4):1692–1706.
- International Labour Organization (2024). Realizing decent work in the platform economy. © ILO.
- Katz, L. F. and Krueger, A. B. (2019). The rise and nature of alternative work arrangements in the United States, 1995–2015. *ILR review*, 72(2):382–416.
- Marimon, R. and Zilibotti, F. (2000). Employment and distributional effects of restricting working time. *European Economic Review*, 44(7):1291–1326.
- Mas, A. and Pallais, A. (2017). Valuing alternative work arrangements. *American Economic Review*, 107(12):3722–3759.
- Petrongolo, B. and Pissarides, C. A. (2001). Looking into the black box: A survey of the matching function. *Journal of Economic Literature*, 39(2):390–431.
- Satchi, M. and Temple, J. (2009). Labor markets and productivity in developing countries. *Review of Economic Dynamics*, 12(1):183–204.

- Scarfe, R. (2019). Flexibility or certainty? The aggregate effects of casual jobs on labour markets. *Edinburgh School of Economics Discussion Paper*, 294.
- Stanton, C. T. and Thomas, C. (2025). Who benefits from online gig economy platforms? *American Economic Review*, 115(6):1857–1895.
- Statista (2025). Online food delivery - Spain. Technical report, (accessed December 28th, 2025).
- Stole, L. A. and Zwiebel, J. (1996). Intra-firm bargaining under non-binding contracts. *The Review of Economic Studies*, 63(3):375–410.
- Zenou, Y. (2008). Job search and mobility in developing countries. theory and policy implications. *Journal of Development Economics*, 86(2):336–355.