Piecework and job search in the platform economy*

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Abstract

Unpaid work in the form of task search is a defining feature of jobs in the platform economy. Workers in these markets spend hours waiting for tasks to become available within the platform. Overwhelming empirical evidence seems to suggest that, once search activity is accounted for, these workers would end up working more than they wish. Is this a puzzling outcome explained by a backward-bending labour supply curve, or is it due to the uncertainty arising from job search? In this paper, we test these hypotheses making use of a new dataset on on-location and online platform workers from the EU, employing a difference-in-differences strategy to estimate a search-adjusted labour supply elasticity. We find that search and uncertainty play a central role in inflating hours of work, revealing a positive inelastic wage elasticity for all types of platforms. These results suggest that unpaid work might be an endemic source of employer surplus even within traditionally regulated markets.

Keywords: *Platform economy, Piecework, Job search, Labour supply*

JEL codes: J22, J32, J33, J42

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1 Introduction

Workers earning on a piece-rate basis have traditionally been the most exposed to uncertainty in income. This group of workers comprises the self-employed (Parker et al., 2005), but also any worker whose pay is related to current output, from high skilled professionals (Hart, 2008; Hart and Roberts, 2012) to cab drivers (Camerer et al., 1997). These studies suggest that piecework can adapt faster to demand-side shocks precisely because the hours of paid work can fluctuate depending on demand.

The recent expansion of the platform economy extends this uncertainty to a vast new pool of workers. An increasing amount of people generate income by selling goods and services through online platforms, a process sped up by the labour market shock generated by the Covid-19 pandemic, which has affected the supply and demand for platform-mediated services (Barcevičius et al., 2021; International Labour Office, 2021).

Platform workers are a large subset of people generating income through platforms,[1] and can provide their services either online or in person. The former are more generally defined as online platform workers, including people working in low-skill micro-task platforms (i.e. Amazon Mechanical Turks, Crowdflower, etc.) and medium/high-skill freelancers (i.e. Upwork, Fiverr, etc.). The latter are better known as on-location (or on-demand) platform workers, and usually provide services in person: these can include e.g. Foodora riders, Uber drivers, and Taskrabbit handymen.

Most of the people selling services through platforms are not employed by their platforms, but are rather contracted as autonomous workers, even if platforms, either directly or indirectly, often exercise a significant degree of control over the activities of people finding work through them. Pay levels are indeed usually set by platforms, or are left for clients to decide. As workers in these platforms are usually paid on task completion with a fixed reward, platforms characterise as a typical piecework labour market, with no demand-side restrictions to entry. As a matter of fact, entry costs are especially low, and entering these platforms is usually as simple as creating a new account. Even when some barriers to entry are in place, there is often no limit to the number of workers who can entry a platform once some minimal requirements are met.[2] As a result, the hiring process is performed on a task-by-task basis, with platforms acting as match-makers between clients and a pool of potential workers.

[1] This group of people can also include people selling goods on Ebay, or renting apartments through Airbnb. The distinction can be subtle, but platform workers are defined as such because they sell their own services though platforms, instead of selling goods or accruing rents from underutilised capital too.

[2] For example, Uber drivers might need to obtain a licence or show that they have access to a vehicle before entering a platform. See De Stefano and Aloisi (2018) for an overview of the contractual framework of platforms and their entry requirements.

For this reason, labour demand-supply mismatches are directly converted into search frictions emerging from this match-making process alone. Empirical evidence on the platform economy suggests that these markets might be subject to high level of unpaid work in the form of job search, as workers end up working in the platform more than what they expect, while at the same time facing difficulties in finding available tasks (Cantarella and Strozzi, 2021; Barcevičius et al., 2021; Bogliacino et al., 2020; Berg et al., 2018). Search inflates the hours of work leaving income unchanged, resulting in a discounting of the hourly pay rate. These unpaid hours take up so much time that workers often end up working more than desired for a lower actual salary per hour.

This stylised fact alone would suggest a backwards-bending labour supply curve, with workers working more to reach a desired income level. However, this consideration alone does not take into account the presence of search itself and how workers react to it. The question arises as to whether the uncertainty in actual wage arising from search alone can inflate the number of hours supplied in a way that would exceed the hours supplied if workers had perfect information on the amount of search required. Under a perfect information scenario, a backward-bending labour supply curve is plausible, and utility is maximised for all workers. With imperfect information, however, uncertainty alone leads to a sub-optimal outcome for all workers involved.

In this paper, we argue that the imperfect information scenario can better explain supply outcomes in online labour platforms. We argue that the piecework modality of work not only allows platforms to offload the costs of demand shocks to workers (as search time remains unpaid), but also allows for the extraction of further value due to the uncertainty in search itself, all to the benefit of the platform. Platforms then act as the perfect environment to study labour supply under piecework: by looking at how much leisure workers are forsaking to reach a sufficient level of income conditional on the uncertainty of search, we can estimate labour supply elasticities and study how search interacts with salaries for workers in non-salaried employment.

Exploiting this search shock in a difference in differences setting, we find that search plays a central role in shaping the labour supply of platform workers, revealing a inelastic labour supply rather than a backwards-bending one. This contrasts with the target-earners hypothesis (implying a backwards-bending supply curve) from Horton and Chilton (2010), and supports evidence on the elasticity of labour supply in online-micro task markets (Dube et al., 2020) and on the effects of wage uncertainty affects on labour supply of the self-employed (Parker et al., 2005).

The contribution of our paper is threefold. First, we re-evaluate the monopsonistic premium of online labour platforms in the context of piecework. The literature has mostly focused the monopsony power of these labour markets (Dube et al., 2020; Cantarella and Strozzi, 2021; Kingsley et al., 2015), but the role of piecework and search is less explored. While some contributions have delineated platforms' piecework power in general terms (Lehdonvirta, 2018; Alkhatib et al., 2017; Davis and Hoyt, 2020), no explicit attempts to analyse the economic implications of piecework have been made.

We believe that the key to understanding these markets lies precisely in focusing on the relationship between search and piecework. This focus offers novel insight on the nature of the platform economy, but could easily be extended to other contexts with little effort. From this point of view, we contribute to the literature of the economics of piecework in general (Hart, 2008), but also on the literature on unpaid overtime (Bell and Hart, 1999) and uncertainty in self-employment (Parker et al., 2005) by providing a novel outlook on these topics, as our results cast many interrogatives on how supply really is affected by the presence of unpaid work in general. For example, while employed workers should be insured against fluctuations in demand, there is evidence for them to be exposed to shocks of similar nature through bonuses, commissions, and overtimes (Anger, 2011; Devereux, 2001; Swanson, 2007).

Secondly, we develop a novel method for estimating labour supply elasticities for all types of platform workers by the exploiting the variation in actual and desired hours of work conditional on the presence of search. This is a novel contribution, first because evidence on these elasticities has been limited on online micro-task platforms only (see Dube et al., 2020, who also offer a review of the literature), and second because of the methodological innovation alone.

Comparing actual and desired hours of work to identify hours restriction in labour supply is not new to the literature (see, for example, Euwals and van Soest, 1999). In traditional employment, however, these demand factors however do not enter supply as a search shock but rather will affect the employment status and the type of contract. With piecework, there is no limit to the number of workers in platforms and to the hours they can supply, and these demand factors are incorporated directly into labour supply by affecting the amount of time needed to find the next available task; with no restrictions to supply, the presence of job search is by all means the only difference between the desired and actual status. Rarely also researchers have had access to such detailed information on pieceworkers, specifically including search and desired hours.

Platforms are also the ideal candidate for this kind of exercise because the absence of hiring/dismissal costs and regulation on minimum working hours completely remove adjustment costs (Dube et al., 2020) and allow for a continuous definition of labour supply. This, together with the perfect complementarity between labour and capital (platforms only need to remunerate workers, who provide both their work and capital) makes online labour platforms the ideal candidate for studying the effect of search-mediated demand shocks on labour supply. Variations in search can then only be attributed to mismatches between supply and demand of labour alone, holding capital as fixed.

Finally, our paper contributes to the ongoing policy discussion on online labour platforms. Due to their disruptive nature, these platforms have garnered the attention of policy-makers across the world, with national courts and legislators working towards reassessing the employment status of some of these workers (for an overview, see De Stefano et al., 2021). In Europe, EU institutions have initiated this process in 2016 with the adoption of an European Agenda for the Collaborative Economy[3] as a part of an ongoing initiative to improve the working conditions of platform economy workers, recently culminating into the proposal of a EU Directive pushing towards reclassification of many autonomous platform workers into paid employees.[4] Advancing the theoretical framework and empirical evidence on the economics of the online labour markets is then paramount to better inform policy-makers and understand how these regulations can affect work in these platforms.

The paper is structured as follows. Section 2 discusses the economic implications of piecework from a theory perspective. Section 3 discusses our empirical approach, and results are discussed in Section 4. Section 5 concludes.

2 Modelling piecework labour supply with search frictions

In this section we present a model of labour supply in the presence of job search and uncertainty which is used as the basis for our empirical specification in Section 3. The model we adopt draws from two main theoretical contributions: Arellano and Meghir (1992) and Parker et al. (2005). We rely on the former to specify labour supply in the presence of job search and uncertainty and we refer to the latter to model uncertainty. While we borrow from both sources, we also depart from each one by using more specific assumptions that could better fit the behaviour of online platform labour markets.

In our theoretical model we assume that job offers (i.e. available tasks) appear directly within the platform as soon as they are available. Each task (job) is compensated by an advertised reward, which is known to the worker. It is assumed that workers are encouraged to work as efficiently as possible

[3]Communication From the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions; A European agenda for the collaborative economy; COM/2016/0356 final.

[4] Proposal for a Directive of the European Parliament and of the Council on improving working conditions in platform work; COM/2021/762 final.

to the best of their abilities and that the reward will not change, once the task is approved by the platform. Platform workers should devote time to search for available tasks.[5] This "search effort" is conducted at the expenses of leisure (l_t) only, as paid work hours (h_t) can only result from search: with zero search, workers find zero hours of work. Paid work hours are then a function of idiosyncratic workers' ability (α) and of their search effort. As in (Arellano and Meghir, 1992), search takes place by devoting time to this activity and does not yield utility as an individual activity.[6] However, while in their model job seekers will face *ceteris paribus* a higher wage profile, in our framework search produces utility by generating additional hours of paid work. The time workers spend in searching for a job (i.e. waiting for new job offers by the platform) is S_t, which is the amount of hours workers spend looking for available tasks in the platform. The actual amount of hours spent within the platform is $h_t^A = h_t + S_t$ (which incudes search), while total time endowment is $T = l_t + h_t + S_t = l_t + h_t^A$.

As in Parker et al. (2005), uncertainty is modelled as a multiplicative shock on wages, but in our case the wage effect has non-zero mean. In particular, uncertainty is modelled as a shock which affects wages by operating both on search effort and on the availability of paid work. This shock is properly defined as a "search shock" (ρ_t) and denotes how many hours of search are required to produce an additional hour of paid work, holding ability fixed ($\alpha\rho_t = S_t/h_t$). By such, it is time variant and unknown to workers until they experience it. Workers can form expectations on its true value over time (depending e.g. on peak demand hours), but ultimately the true value of the shock remains unknown.[7]It is important that remind that the search shock and the search effort are two distinct concepts, and higher search effort will not necessarily correspond to higher search shock. See Appendix A for a further discussion.

In such a framework, hourly nominal compensation (w_t) can be calculated as the ratio between total rewards (i.e. the number of tasks multiplied by the average reward per task) and (paid) work hours. Hourly nominal compensation is then not the advertised reward per task, but the average hourly rate of pay for each (paid) work hour in the platform: as such, it is inclusive of idiosyncratic ability shocks. Due to the repetitive nature of tasks within the platform, workers are generally aware of the true value of w_t. However, given the presence of uncertainty, they cannot know their actual

[5]The model is also consistent with the possibility that platforms send different job offers to different workers.

[6]Similarly, our model ties with on-the-job leisure labour supply model of Dickinson (1999) inasmuch as we separate productive hours from total work hours. In our model, however, search effort is not considered as on-the-job leisure, but rather as a source of additional hours of work.

[7]We will discuss in section 3 how to account for this empirically. We also assume that workers will not be searching during unusual working hours where the search shock is particularly unfavourable (e.g. food delivery riders will not search late in the night after most restaurants have closed), unless they were already planning to search during these hours.

hourly compensation (w_t^A). Since uncertainty affects the searching time required to get a task and taking into account that search is not paid, it is however possible to conclude that the (unknown) actual compensation that workers can retrieve for each hour spent in the platform will be lower than their (known) hourly compensation ($w_t^A = w_t h_t / h_t^A < w_t$). The rate of change between the nominal and the actual hourly compensation is related to the search shock: $w_t^A / w_t = h_t / h_t^A = (1+\rho_t)^{-1}$.

The optimization problem for an individual at period t follows:

$$\max_{C_t, l_t}\{E[U_t(C_t, l_t | S_t)]\} \tag{1}$$

where C_t is consumption, l_t is leisure time and S_t is time spent searching. Define the within-period budget constraint as

$$C_t \equiv w_t h_t + \mu_t \tag{2}$$

where μ_t is a measure of other income which reflects net dissaving at the end of the period t. The budget constraint can be riformulated as

$$w_t l_t + C_t \equiv w_t(T - S_t) + \mu_t = w_t^A(T) + \mu_t \tag{3}$$

Note that since the search shock is unknown to the worker, $w_t^A = w_t(1+\rho_t)^{-1}$ is stochastic and is always $< w_t$. This has immediate implications on the marginal rate of substitution between consumption and leisure, which depends on the nominal hourly wage w_t and the search shock ρ_t itself, bringing uncertainty into the equation:

$$\frac{\partial U_t / \partial l_t}{\partial U_t / \partial C_t} = w_t(1+\rho_t)^{-1} \tag{4}$$

Hence solving eq. (1) subject to eq. (3) will not be possible as ρ_t will still appear in the first order condition. Utility expectations will never coincide with the realised wage equation, and this uncertainty can explain why workers might end up working more than they wish.

The implications are made clear once we look at the actual hours of work equation in terms of leisure:

$$h_t^A = T - l_t(w_t, C - w_t(h_t + S_t)) \tag{5}$$

As in Arellano and Meghir (1992), the $w_t S_t$ term points at the lost income of search. Integrating this lost income effect into salary, the hours of work equation reduces to:

$$h_t^A = T - l_t(E[w_t^A], C - w_t h_t) \tag{6}$$

which is equivalent to a standard labour supply function with w_t^A salary and no search. But here in the leisure function lies the real issue at hand: would workers supply the same amount of working hours if the entity of the search shock were to be known? Since w_t^A is never known to workers, the actual hours supplied will never reflect the true wage-elasticity of labour supply.

The hypothesis we intend to test in this paper is whether any equivalence between these last two equations exists. If the estimated wage-elasticity of labour supply is indifferent to search, then the equivalence is satisfied and workers' expectations on the actual wage are realistic enough. If the wage-elasticity is instead affected by search, then volatility in these markets makes expectations unreliable and workers suffer a net loss in utility. Settling how much search plays a role in inflating the hours of work is then an issue that can only be solved empirically.

3 Estimation

3.1 Data

Our main source of information on labour supply comes from an online survey on platform work conducted by PPMI in June 2021 (for more information, see Barcevičius et al., 2021, and its online annex). We will refer to this survey as the PPMI survey from now on.

This survey was conducted in the context of a background report for the impact assessment of the aforementioned EU directive proposal for improving the conditions of platform workers.[8]

The survey comprises a total of 10,938 respondents, sampled from a population of working age (16-74 y.o.) internet users from 9 EU countries (Denmark, France, Germany, Italy, Lithuania, the Netherlands, Poland, Romania and Spain).

The sampling frame implies that survey respondents are not necessarily active in online platforms, producing income by selling their services via them: people in "traditional" employment, along with the unemployed, are also sampled. Out of all respondents, 2,440 have produced income from online or on-location platforms at least once, while 1,722 have been active on platforms in the last 6 months.

The survey captures information on demographics, employment history and use of online platforms for all respondents, and adds specific modules for platform workers, including information on

[8] Ibid. 4.

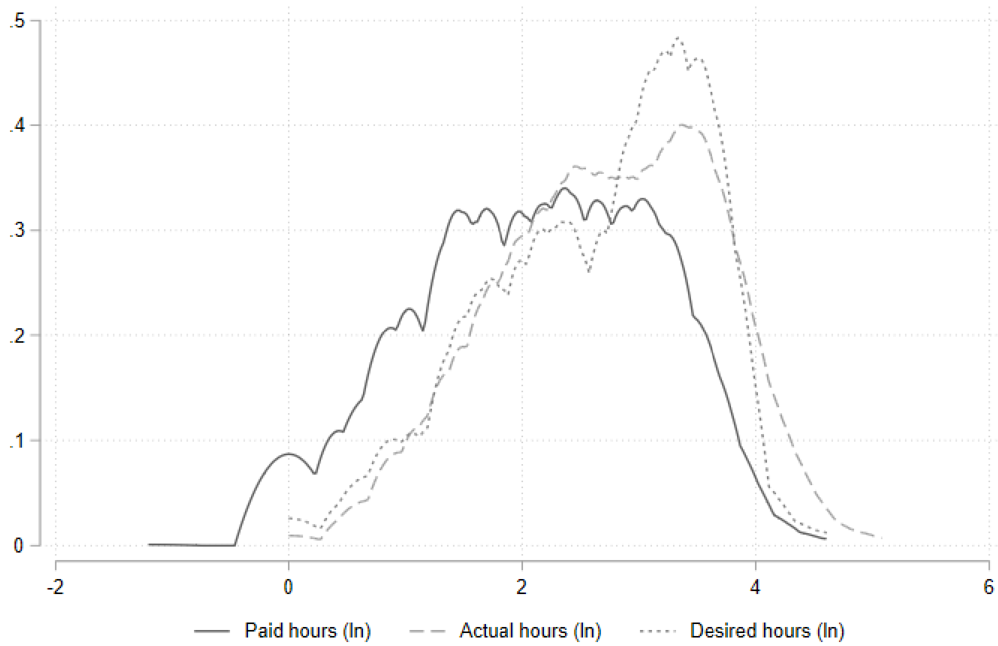

FIGURE 1: POTENTIAL LABOUR SUPPLY IN ONLINE LABOUR PLATFORMS

remuneration, hours of work (both desired, paid, and effective), and working conditions in general.

In the survey, workers are first asked, in a *usual week*, how many hours do they spend *searching or waiting for tasks/ work assignments*. The answer to this question will be our search variable.

Then workers are asked, again in a *usual week*, how many hours do they spend *implementing paid tasks/ work assignments*, yielding our paid hours variable, which returns actual hours after summing it with search. Immediately after this question, workers are asked: *in an ideal situation, how many hours per week would you prefer to work implementing paid tasks/ work assignments via online platforms?*. This is our desired hours variable.

The relationship between the three hours of work variables in our sample is illustrated in Figure 1. We notice immediately that the difference between paid and actual hours can be be really large. Notably the tail of actual hours is thicker than the one of desired hours, reminding us of the fact that many of these workers spend more time on the platform than they wish.

3.2 Econometric specification

In this section we develop an empirical specification to estimate the elasticity of labour supply for workers participating in the platform economy.

Our estimation strategy exploits the piecework modality of work to estimate the elasticity of labour supply among platform workers of various kind. As can observe the nominal rate of pay w and the actual rate w^A, along with the paid hours of work h, the actual hours of work h^A and the desired hours of work h^D, our strategy is based on the intuition that, in piecework, the only difference between desired and actual labour supply is given by the need of a search effort.

Our empirical model draws from several sources, including the approaches from the aforementioned works of Arellano and Meghir (1992) and Parker et al. (2005). The intuition to exploit search frictions in the online labour market to retrieve elasticity parameters is instead shared with Dube et al. (2020): here, the authors focus on the Amazon Mechanical Turks (AMT, henceforth) online micro-task platform, exploiting variation in the duration of a job posting conditional on the advertised reward to retrieve labour supply elasticity parameters. The authors estimate low elasticity supply for online AMT workers, suggesting the presence of strong monopsony power in the hands of platforms. Our work diverts from Dube et al. (2020) inasmuch as we study and exploit these search frictions from the workers' perspective, and not from the platform's.

Starting with labour supply in the absence of search, workers are offered a nominal salary, inclusive of idiosyncratic ability factors, and adjust their desired hours of work accordingly. Omitting the individual subscript i, the labour supply function with no uncertainty is expressed as:

$$ln(h^D) = \alpha_1 ln(w) + U\beta + X^{'}\delta + \eta_1 \tag{7}$$

where α_1 is the elasticity of (desired) labour supply to the wage. As in traditional labour supply functions, U controls for any other source of income, and X is a vector of observed and unobserved individual characteristics affecting labour supply participation. These include both observed and unobserved preferences and ability factors, but also regional characteristics affecting local labour markets.

In the presence of search, workers devote $h^A = h + S$ actual hours of work in the platform. The increase in working hours caused by (unpaid) search lowers the nominal rate of pay w to the actual rate $w^A = (wh)/h^A$.[9] The labour supply equation with search is:

$$ln(h^A) = \alpha_1 ln(w^A) + \alpha_2 ln(S) + U\beta + X^{'}\delta + P^{'}\zeta + \eta_2 \tag{8}$$

The parameter α_2 denotes the effect of search on hours of work. Demand-side platform factors

[9] Recall that if the search shock is exogenous, then w^A also does not depend on the search effort S. see Appendix A for further details.

outside of the control of the worker can also intervene to affect the amount of work available, so the P term is included to represent different types of platforms. We identify these based on the on-location or online nature of the work performed, the level of control the platform exercises over pay, and the interaction between these two variables. This is not only motivated by our review of the literature, but intuitively the services sold offline and online will also vary significantly in nature and feature different demand elasticities. Platforms can also exploit their monopsony powers when they can exercise control over pay, ultimately affecting the total amount of work available. It is then important to control for these characteristics in the P vector as these can affect the equilibrium levels of supply. Unobserved supply-side factors determining access into each of these types of platforms are to be included in the X vector instead.

Note that this empirical labour supply function with search is comparable to the one proposed in Arellano and Meghir (1992). In contrast with Arellano and Meghir (1992), however, search time generates utility for platform workers as it allows them to find work, and has a negative direct effect on leisure only. However, this search effect cannot be retrieved from equation 8 alone because of the endogeneity between search and actual hours of work.

Indeed, equations (8) and (7) are both difficult to estimate because of the endogeneity of wages and search caused by the unobserved part of the X vector. A solution is to find a way to instrument w (see Blundell and Macurdy, 1999, for an overview), but this is not always possible. We can however exploit information on desired and actual labour supply to retrieve these parameters.

In this context, the main argument here is that the two equations reveal how many hours workers would wish to supply as only the idiosyncratic search shock changes. This leads to the system of equations:

$$\begin{cases} ln(h^D) = \alpha_1 ln(w) + U\beta + X^{'}\delta + \eta_1 \\ ln(h^A) = \alpha_1 ln(w^A) + \alpha_2 ln(S) + U\beta + X^{'}\delta + P^{'}\zeta + \eta_2 \end{cases} \tag{9}$$

The two equations share a subset of parameters by definition, as they both model two optimal combinations of work and leisure under different levels of utility for the worker deriving from different combinations of leisure, work and search. These differences in utility arise from the changes in salary and search between the two states: in the absence of search, they both reduce to textbook labour supply functions.

The fundamental assumption needed for this system of equations to be correct is that demand-side restrictions, including search, are the only differences between the two equations. This is motivated by the fact that, unlike in traditional employment, the piecework modality of work allows workers to supply as much work as they wish with the only major demand-side restriction being search. Most importantly, the amount of search experienced should not affect the desired hours of work. In other words, we do not want workers to "play the devil's advocate" and express their preference for hours of work based on the experienced amount of search. For our strategy to work, desired hours should not include search because in ideal conditions search should be zero as it comes at a net loss of leisure. We will later test this fundamental assumption in Section 4.

If this assumption is satisfied, then the parameters of both equations are effectively the same, and the two equations can be differenced to study the change in wage across the two states and cancel out the unobserved term. Taking differences from the equations in system (9) and simplifying, we reach:

$$ln(h^A/h^D) = \alpha_1 ln(w^A/w) + \alpha_2 ln(S) + P^{'}\zeta + \eta_3 \tag{10}$$

Effectively, this specification offers difference in differences estimates for labour supply by comparing outcomes across two different statuses (the desired non-piecework outcome and the effective piecework outcome) depending on the intensity of search. From another perspective, equation (10) estimates quasi-Frischian elasticities of supply by differencing between the piecework and non-piecework status, as the desired outcome in terms of hours of work provides us with a counterfactual equilibrium against the piecework outcome.

In the difference in differences jargon, treatment is continuously defined by search so that controls, experiencing low frictions, will be able to work as much as they like, while workers experiencing high search frictions will adjust their supply accordingly. What we are explicitly testing is whether these search frictions create any non-linearities in the labour supply function that add up to the effect that search already has on the actual salary. In this framework, the change in wage captured by the term w^A/w, together with search S, introduce uncertainty into the model, in a way that is not too dissimilar to Parker et al. (2005).[10]

This is a potent identification strategy, as it allows to keep all idiosyncratic workers' characteristics as fixed: note that the act of differencing renders the $X^{'}\beta_S$ term null, as long as there are no other non-linearities between the two states. Note also that multiplicative ability components factoring into salary would also disappear by studying the rate of change between the actual and nominal rate of pay.

[10] Who control for uncertainty through the time variation in earnings.

Empirically, we can test the robustness of our estimate by checking for residual significance of the $X^{'}\delta$ term in the differenced equation. Interpretation of the difference equation remains straightforward, as the parameters can be interpreted as they appear in the system (9).

The most important parameter is, f the search shock were to be captured by the change in salary alone, the coefficient α_2 should not affect the estimated elasticity, and the equation would reduce to a standard labour supply equation. The attentive reader will notice that the search term in the differenced equation (10) appears twice, first as a percentage change in salary and then as the entity of search itself. The fact that w^A/w already appears in the equation, with its effect captured by α_1, is not a cause of concern, as the focus of this study resides precisely in quantifying the non-linearities of search in a piecework setting.

In any case the search shock becomes independent from the outcome after differencing the desired and actual labour supply equations. Taken alone, search is endogenous to hours of work as higher levels of search will correspond to higher levels of supply due to a growth in salary. However, as we have discussed in Appendix A, search does not affect the relationship between actual and paid salary meaning that, with this approach, we eliminate the issue of simultaneity between salary and search. From another perspective, conditional independence of the search term is achieved by the disappearance of the vector of individual characteristic X in equation (10).

This specification also offers the advantage of offering labour supply elasticities for the minority of platform workers who are able to set their wage, as the change between w and w^A occurs even after the worker has changed their salary. We can then further study the interactions of the elasticity term α_1 with the aforementioned platform type characteristics included in vector P to study heterogeneity in supply elasticity across platform types. Specifically, we are interested in seeing how these elasticity parameters can change depending on whether services are offered online, and whether workers have control over their pay.

Note that platform characteristics can still play a significant role determining the rate of change between desired and actual hours in equation (10), but the supply-side components determining access into these platforms are absorbed by differencing the two equations with the disappearance of the $X^{'}\beta_S$ term. If our strategy is correct, however, the resulting term on platform type coefficient ζ will yield platform specific demand effects, and as such should also prove to be independent of labour supply elasticity. This consideration is related to the fundamental assumption discussed earlier, as search is the only demand-side restriction assumed to be introducing uncertainty. In the next section, we show that this is indeed the case.

4 Results

Our labour supply estimates are shown in Table 1 and 2. In Table 1, we offer average elasticities for all platforms, controlling for type of platform. Heterogeneous platform elasticities are shown in Table 2. Platform types are defined by the online or on-location nature of the services offered, the degree of price-setting power that the worker enjoys, and the interactions between the two.

Other controls include variables traditionally included in most labour supply models: gender, marital status (and their interactions), age and its squared term, education, household size and number of children, and immigration status.

We also control for characteristics related to the respondents' access to "traditional" labour markets. Namely we control for their employment status (i.e. whether platform work is their only source of income) and for total income from other sources (in logarithm). This can include income from another job, but also social security transfers. Furthermore, we add intercepts for the ISCO-08 occupation and NACE-Rev2 industry characteristics of the last non-platform occupation held by the respondent, treating the absence of prior labour market experience as the baseline level.

Access to traditional markets will inevitably affect the amount of time that can be allocated to platform work, so it is important to control for these factors. As discussed in Cantarella and Strozzi (2021), the inclusion of these occupation controls does not constitute a "bad control" situation, as these conditions relate to to outcomes that often predate access into platforms. As such, they can actually proxy for unobserved ability better than many other controls. We also cluster standard errors by each occupation-sector cell. In this way, we implicitly account for the possibility that error residual followed a similar structure for people of similar skill.

We also include two other controls that, together with access to traditional employment, can affect our estimates by generating non-linearities in search. These involve the degree of platform's control over working hours, and a worker's experience in the platform, which we capture by the regularity of the worker's activity over the last six months. The level of experience can affect knowledge of the platform such as hours of peak demand: intuitively workers will learn to optimise their search activity over time, so it vital to control for experience factors.[11]

[11] We also tested specifications in which we include a term for years of experience in the platform. Our final results are unchanged and are available upon request.

Table 1: Labour supply elasticity estimates

	Desired hours (ln)		Actual hours (ln)		Delta hours (ln)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wage (ln)	-0.0865***	-0.0766***	-0.128***	-0.0370***	-0.205***	0.201***	0.193***	0.206***
	(-6.01)	(-5.92)	(-8.17)	(-3.39)	(-4.70)	(3.62)	(3.54)	(3.75)
Search (ln)		0.385***		0.694***		0.372***	0.379***	0.372***
		(18.02)		(33.41)		(15.63)	(15.69)	(15.65)
On-location worker	-0.0276	-0.0142	0.162*	0.160***	0.174***	0.167**	0.199***	
	(-0.32)	(-0.20)	(2.22)	(3.44)	(3.47)	(3.18)	(3.83)	
Price-setting power	0.110	0.0703	0.228***	0.119**	0.0893	0.0301	0.0695	
	(1.91)	(1.42)	(4.18)	(3.03)	(1.92)	(0.71)	(1.66)	
On-location $\times$ Price-setting	-0.0557	-0.0468	-0.295**	-0.242***	-0.213*	-0.161	-0.201*	
	(-0.46)	(-0.43)	(-2.74)	(-3.66)	(-2.13)	(-1.72)	(-2.21)	
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Last occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Adjusted R-squared	0.127	0.275	0.120	0.575	0.111	0.242	0.222	0.237
Observations	1590	1580	1592	1592	1580	1580	1581	1580

SE clustered by occupation/sector clusters in parentheses. Other controls: Non-platform income, age, age squared, education (ISCED), foreign nationality, marital status, gender, marital status × gender, partner's income (equal, higher or lower than respondent), household size, number of dependent children, regular platform worker (active last month), degree of platform's control over working hours.

*p<.05, **p<.01, ***p<.001

Table 2: Labour supply elasticity estimates, by platform type

	Desired hours (ln)		Actual hours (ln)		Delta hours (ln)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Wage (ln) × Online, No price-setting	-0.0607**	-0.0605**	-0.0978***	-0.0106	-0.246***	0.164*	0.152*
	(-2.73)	(-2.96)	(-4.25)	(-0.65)	(-3.82)	(2.09)	(2.02)
Wage (ln) × Online, Price-setting	-0.0966***	-0.0844***	-0.133***	-0.0488**	-0.180*	0.236**	0.221**
	(-3.66)	(-3.83)	(-5.11)	(-2.94)	(-2.05)	(3.22)	(3.20)
Wage (ln) × On-location, No price-setting	-0.0914**	-0.0640*	-0.182***	-0.0632**	-0.111	0.323***	0.311**
	(-2.73)	(-2.27)	(-6.08)	(-3.11)	(-1.12)	(3.53)	(3.23)
Wage (ln) × On-location, Price-setting	-0.161**	-0.144**	-0.168***	-0.0842***	-0.169	0.153	0.180
	(-3.24)	(-3.30)	(-4.28)	(-3.57)	(-1.37)	(1.26)	(1.52)
Search (ln)		0.384***		0.694***		0.373***	0.379***
		(18.31)		(34.15)		(15.65)	(15.73)
On-location worker	0.0179	-0.0167	0.260**	0.216***	0.256**	0.263**	0.296**
	(0.15)	(-0.17)	(2.84)	(3.73)	(2.81)	(2.99)	(3.32)
Price-setting power	0.167	0.109	0.259***	0.156***	0.130	0.0739	0.112
	(1.95)	(1.51)	(4.03)	(3.70)	(1.76)	(1.09)	(1.73)
On-location × Price-setting	0.0310	0.0772	-0.346*	-0.250**	-0.287	-0.311*	-0.324*
	(0.17)	(0.46)	(-2.58)	(-3.15)	(-1.86)	(-2.19)	(-2.26)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Last occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	No
Adjusted R-squared	0.130	0.277	0.124	0.577	0.112	0.243	0.223
Observations	1590	1580	1592	1592	1580	1580	1581

SE clustered by occupation/sector clusters in parentheses. Other controls: Non-platform income, age, age squared, education (ISCED), foreign nationality, marital status, gender, marital status × gender, partner's income (equal, higher or lower than respondent), household size, number of dependent children, regular platform worker (active last month), degree of platform's control over working hours.

*p<.05, **p<.01, ***p<.001

Intercepts for each country in the survey are added too, to account for differences in platforms and contracts across the countries surveyed.

Looking at the main results, columns (1) and (2) from both tables display wage elasticities for desired labour supply. These correspond to equation (7). In all instances, the results seem to suggest a backwards-bending labour supply curve, with a percentage increase in the (nominal) wage leading, on average, to a ~ 0.09 percent reduction in desired hours, supporting the target earning hypothesis from Horton and Chilton (2010). There are no differences in sign between types of platforms, with the differences magnitude maxing out at 0.1 log points.

The inclusion of search, while statistically significant, does not seem to particularly affect the magnitude of our elasticity estimates, pointing at a mere change of $\sim$ 0.01 points in the average estimated elasticity. Similar negligible changes are also to be noted for the heterogenous elasticities model. This confirms our fundamental assumption that workers do not generally take current search into account when expressing their desired labour supply or, in other words, that the "ideal conditions" do imply zero search. Platform types also appear to have no significant effect on desired hours. This is an important result, suggesting that desired hours are revealed net of demand-side effects.

Actual hours are studied in columns (3) and (4) of both tables, corresponding to the specification from equation (8). Estimated elasticities are backwards-bending and, as expected, strongly influenced by the magnitude of search. A point percentage increase in search leads on average to a ~ 0.7 increase in the hours worked and renders an initially backwards-bending labour supply (columns 4) into a nearly perfectly elastic one (columns 5).

The results so far, however, tell little about the real elasticities. The nominal wage will be endogenous to the hours desired, and both actual wage and search will be endogenous to the actual hours of work.

We then study the differenced equation (10) in columns (5) to (8) in Table 2 and (5) to (7) in Table 1. The initial specifications from columns (5) point at backwards-bending supply for all workers, albeit statistically significant for the subset of online workers only. Looking at average elasticities, a point percentage increase in wage would correspond to a 0.2 percent reduction in the hours of work, significant at the 0.001 level. These estimates, however, do not account for uncertainty.

The inclusion of search in columns (6) completely overturns the labour elasticity estimate, much more than it did for any previous specification. After its inclusion, a percentage increase in hours of search increases the amount of hours worked by 0.37 percent. Elasticities are now positive and average at 0.2, with some degree of heterogeneity across types of workers. Online workers display an elasticity of 0.16 when they have no control over their nominal salary, and 0.23 when they do. Elasticities for on-location workers are statistically significant only when there is no price setting power, with an elasticity of 0.32. Recall that that with perfect information search would not have been significant and its effect would have been captured by the change in salary entirely, with the labour supply model reducing to a textbook supply function as well. These results suggests that any extra hour of search has an effect on labour supply beyond the effect of the salary degradation generated by search.

As discussed earlier, differencing should render the term X null as long as it does not influence search. While not shown in the table, we find that after differencing the only significant predictors remain non-platform income, age, foreign origin and the degree of control of platforms. Taking non-platform income out,[12] a joint test of significance for all supply-side controls reveals that we cannot reject the hypothesis that these coefficients are jointly zero. Most importantly, columns (7) show the removal of all these regressors has a very small effect on our elasticity estimates, with a very minor influence over the overall predictive power of the model.

Column (8) from Table 1 further tests for robustness by removing all platform-side controls bar search. Recall that, if our fundamental differencing assumption is satisfied, demand-side components such as the ones contained in the P term should be independent of the idiosyncratic rate of change in wage and search. We find this to be the case, as the removal of these controls leaves the search and elasticity coefficients nearly unchanged.

We can compare our results against the relevant literature. Similarly to (Parker et al., 2005), who similarly studied the role of wage uncertainty on labour supply for the self-employed, we find uncertainty (which in our case is related to search) to play a significant role in inflating the hours of work of workers relying on piece rates.[13] Most notably, our estimates are remarkably close to the estimates of (Dube et al., 2020), whose mean experimental elasticities average at 0.14. While the average elasticity of our platform workers is estimated at ~ 0.20, we can compare elasticity estimates for workers similar to the micro-task workers studied in (Dube et al., 2020). Our elasticity for this subset of workers (online workers with no price-setting power) is estimated between 0.16 and 0.15. It is surprising that a model as simple as ours can approximate experimental estimates so closely.

[12] Which clearly affects search, as discussed.

[13] In our case, some elasticities turn slightly positive rather than perfectly inelastic, but it should be noted that platform workers cannot really be compared with the self employed in general.

5 Conclusions

In this paper, we have studied the wage elasticity of labour supply of workers in the online platform economy, differentiating between types of platform workers. We have offered a novel approach that relies on information on labour supply outcomes under ideal and actual conditions, and exploited this variation in a difference in differences setting to retrieve labour market elasticities that are comparable to experimental estimates.

We find that the backwards-bending labour supply curve that emerges from naive estimates is the by-product of task search instead. When accounting for search activity, we find wage elasticity to be positive and statistically different from zero, averaging at 0.2. These results reject the target earning hypothesis and broaden the evidence on the weakly elastic supply of online micro-task markets to the entirety of the platform economy.

Why does search play such a significant role in labour supply, so much that the income effect seems to prevail over the substitution effect when omitted? We argue that this is caused by the uncertainty in search itself. If platform workers do not know the exact amount of demand-side frictions they will encounter, search will inflate the hours of work either because workers want to self-insure against future losses or, better, because they "gamble" in an attempt to find more work and approach their desired level of income.

These results have important policy implications. If search did not play any role, the conditions in online labour markets could have been entirely attributed to workers' backwards-bending preferences. Instead, labour supply elasticities of platform workers are entirely consistent with a neoclassical specification, with workers ending working more than they wish only because the actual hourly rate of pay is never known. Imperfect information leads instead to a suboptimal outcome for workers that sacrifice more leisure than they wished.

From an economic perspective, these results suggests that piecework alone contributes to the monopsony power of platforms in a non-negligible way, so much that wage degradation increases the overall supply as long as the true degree of degradation is unknown to workers. This is all to the benefit of platforms and clients, with workers experiencing a net loss in utility.

If clients (and platform, in our case) can still exercise a significant amount of control over workers, workers lose the insurance against demand-side shocks that traditionally is attached to the employee status when piece rate becomes the default payment scheme. It is worth wondering whether search and other uncertainties related to demand-side factors might already possess a comparable inflating power in other markets as well, in the form of unpaid overtimes, bonuses, or commissions. With the expansion of the platform economy, these issues gain more relevance than ever.

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Appendix

A Note on independence of w^A over search

Recall that paid hours result from a stochastic shock on search. Adding idiosyncratic ability we have: $h_t = \alpha\rho_t^{-1}S_t$. Workers then decide how to adjust search to maximise their utility depending on the salary.

For this to hold we need both $w = \bar{w}\alpha^{-1}$ and w^A to be independent of search S, where $\bar{w}$ is the marginal cost of labour. This means that the actual salary w^A should not change with the amount of search and its relationship with the nominal salary (w^A/w) is fixed, depending only on the search shock. The proof is trivial: the nominal salary w is exogenous to S by definition, and w^A can be shown to be independent of S. Beginning with the definition of actual salary:

$$w^A = \frac{hw}{h^A} = \frac{\alpha^{1-1}\rho_t^{-1}S\bar{w}}{\alpha\rho_t^{-1}S + S} \tag{11}$$

Knowing by definition that the nominal salary and ability are independent of search: $(w, \alpha_i) \perp S$, we can take the derivative of both sides of this equation with respect to S to show that the rate of change in w^A zero.

$$\frac{dw^A}{dS} = \frac{\rho_t^{-1}\bar{w}}{\alpha\rho_t^{-1}S + S} - \frac{\rho_t^{-1}\left(\alpha\rho_t^{-1} + 1\right)\bar{w}S}{\left(\alpha\rho_t^{-1}S + S\right)^2} = 0 \tag{12}$$

It should be noted that independence of S on w^A cannot be tested in the data, because the endogeneity in the search effort S with respect to w: as the nominal salary increases, workers will supply more hours into the search as they maximise their utility. The resulting w^A parameter will reflect changes in the search effort conditional on the nominal salary. This is illustrated in Figure 2, in which we can appreciate how search, while strongly correlating with the ratio of actual to paid (and desired) hours due to labour supply factors, still retains a large degree of independence from these shocks.

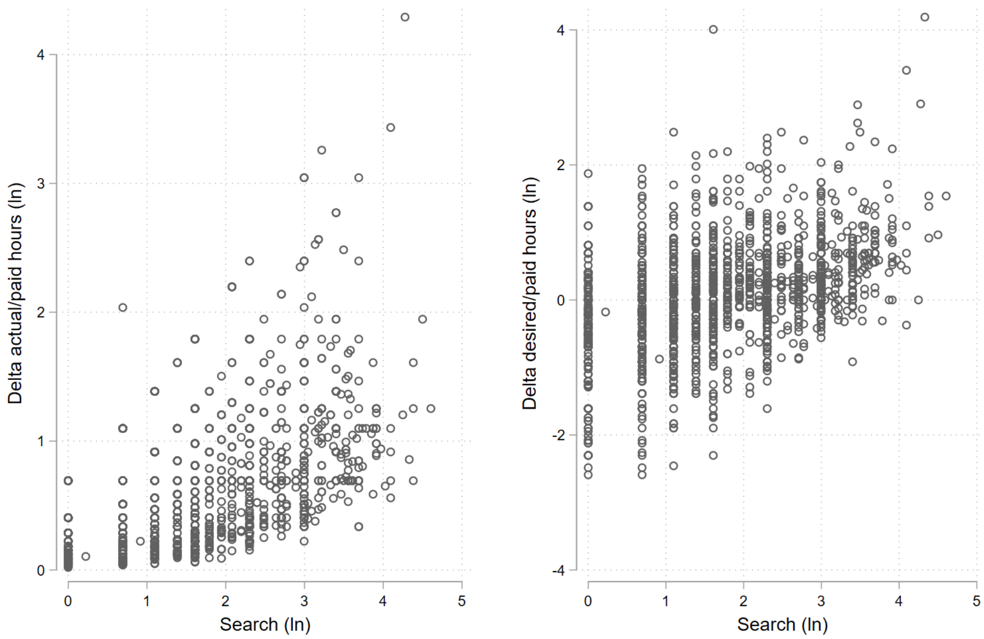

Figure 2: Search and search shock in online labour platforms