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ABSTRACT

Piecework and Job Search in the Platform Economy

The massive growth of jobs in the platform economy has reignited a long-standing debate on the wage elasticity of labour supply for the self-employed. Overwhelming empirical evidence seems to suggest that workers in the platform economy will work more hours than they wish to, for a lower wage, suggesting a backward-bending labour supply curve. Is this puzzling outcome explained by target earning behaviour or rather by the uncertainty arising from task search? In this paper, we test these hypotheses making use of new data on on-location and online platform workers earning on a piece-rate basis in the EU, exploiting search shocks in a difference-in-differences strategy to reassess the wage elasticity of labour supply. We find that uncertainty in search plays a central role in inflating hours of work, revealing a positive and inelastic wage elasticity for all platform workers. On average, a percentage increase in job search leads to a net loss in income, suggesting that piecework might be an endemic source of demand surplus for monopsonistic markets.

JEL Classification: J22, J32, J33, J42

Keywords: platform economy, piecework, self-employment, job search, labour supply

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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 taxi 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 number 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 workers 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 rather are 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 usually set by the platform or are left to clients to decide. As these workers 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 matchmakers between clients and a pool of potential workers.

For this reason, labour demand-supply mismatches are directly converted into search frictions

[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 under-utilised 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.

emerging from this match-making process alone. Empirical evidence about 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 more hours on the platform than what expected, as they face difficulties in finding available tasks (Cantarella and Strozzi, 2021; Barcevičius et al., 2021; Bogliacino et al., 2020; Berg et al., 2018).

Workers usually cannot interrupt search or dedicate search times to leisure: for example, riders cannot return home when searching for the next task, and online workers should be ready to be the first to accept a task when it is made available. Search inflates the hours of work but leaves the pay-out 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. This behaviour would suggest that these workers either value leisure differently than workers in traditional occupations, or they are located in a different section of the supply curve. A popular interpretation is that these workers might be target earners, and work towards pre-defined earning targets (Horton and Chilton, 2010; Kukavica et al., 2022). However, on the workers' side, evidence on wage[3] elasticities remains mixed, and is not supported by platform-side estimates of supply elasticities (Dube et al., 2020; Duch-Brown et al., 2022), which are estimated as being positive and inelastic (around 0.14), at least for what concerns online micro-task workers.

This ambiguity on the labour supply of piece-rate workers goes beyond platform work. Negative supply estimates which usually are observed for the self-employed are rationalised either as target-earning behaviour (Camerer et al., 1997; Wales, 1973) or as the result of uncertainty (Parker et al., 2005). In the former case, workers are working 'one day at a time', and the backwards supply is endogenous. In the latter case, backwards supply is structural and is the result of wage uncertainty. A stream of literature has also claimed that evidence in favour of target earning result from endogeneity issues such as division bias (Farber, 2005; Stafford, 2015), but nonetheless experimental studies have shown that backward-bending estimates are still plausible for loss-averse individuals (as in Fehr and Goette, 2007), and the intellectual debate is still ongoing.

Inevitably, the online platform economy has offered many new case studies. However, supply-side estimates on the platform economy notably disregard uncertainty. Most studies on the labour supply of

[3] While for autonomous workers, earnings (or pay rate) elasticity would be a more appropriate term, in this paper we use the terms "wage", "earnings" and "pay rate" interchangeably so not to depart from the literature on self-employed labour supply in terms of nomenclature.

platform workers usually make the implicit or explicit (as is the case for Chen et al., 2019) assumption that workers can forecast wage shocks at the beginning of each hour of work. This assumption alone does not consider the presence of task search itself and how workers react to it.

The question arises as to whether the uncertainty in the hourly wage arising from search alone can inflate the total number of hours supplied so much so that workers end up working more than they would if they had perfect information on the search shock. Under a perfect information scenario, a backward-bending labour supply curve is plausible, and utility is maximised for all workers. However, with imperfect information, 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 take advantage of a new survey on platform workers from the EU which captures precise information on paid hours of work, desired supply, earnings, and task search times (net of on-the-job leisure). Exploiting search shocks in a difference in differences setting, we find that search plays a central role in shaping the labour supply of platform workers, revealing an inelastic labour supply rather than a backwards-bending one. Our approach is robust to all sources of variation in earnings unrelated to the search shock, ensuring that workers' ability to predict surge pricing, heterogeneity in platform types and pricing schemes, or more generally endogeneity in earnings levels, are not an issue. By showing that uncertainty in task search affects labour supply by making workers behave as target-earners, these findings reconcile the target-earners hypothesis with platform-side evidence on inelastic labour supply.

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 and, as discussed, evidence on labour supply elasticities remain mixed. 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 into the nature of the platform economy, but could easily be extended to other contexts with little effort.

From this point of view, our work contributes to the aforementioned debate on the labour supply of the self-employed sparked by the work of Camerer et al. (1997). We also contribute to the literature on 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 is affected by the presence of unpaid work in general. This goes beyond the self-employed. While employed workers should be insured against fluctuations in demand, there is evidence of them being exposed to shocks of a similar nature through bonuses, commissions, and overtime (Anger, 2011; Devereux, 2001; Swanson, 2007).

Secondly, we develop a simple yet novel method for estimating labour supply elasticities for all types of platform workers which exploits the variation in actual and desired hours of work conditional on the presence of search. The methods belongs to the family of difference-in-differences, and aims at separating search into its effort and shock components and rendering these exogenous to the outcome. This methodological innovation is important because it allows for the retrieval of elasticity parameters which are very close to experimental ones, and because it can also be extended to other contexts with relatively little effort. This methodology can free up the degrees of freedom of labour supply models significantly, and can be particularly useful in contexts in which longitudinal data is not available, or with small samples. A set of rigorous tests suggests that our results are robust to all sources of observable heterogeneity in salary and search.

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; Stewart and Swaffield, 1997). However, in traditional employment, these demand restrictions do not enter supply as search shocks but rather will affect the employment status and the type of contract. With piecework, instead, there is no limit to the number of workers on platforms and to the hours they can potentially 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 the only difference between the desired and actual status. Rarely have researchers 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 of regulations on minimum working hours completely removes adjustment costs (Dube et al., 2020) and allows 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.

The effect of waiting times under imperfect information has been studied in several contexts, but rarely from the perspective of labour supply. Waiting times have been used to study demand surplus in on-demand ridesharing apps such as Uber (Cohen et al., 2016; Lam et al., 2021). More generally, the effect of delay information in queues has long been studied from both a consumer and service provider perspective (see, for example, Yu et al., 2017; Guo and Zipkin, 2007), and this research seems to converge with the idea that lack of information about waiting times can in many cases hurt some economic agents (consumers, in these cases).

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 initiated this process in 2016 with the adoption of an European Agenda for the Collaborative Economy[4] 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.[5] 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

[4] 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.

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

more specific assumptions that could better fit the behaviour of online platform labour markets. It is also valuable to follow these approaches to show how the uncertainty in search problem reduces to a multiplicative wage shock with the same implications for supply optimisation studied in Parker et al. (2005).

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 to the best of their abilities and that the reward will not change once the task is approved by the platform. In the reference period t, define as $\bar{w}$ average pay-out for the tasks that to worker i can potentially perform.[6] This pay-out is determined by the demand-side characteristics of a task, including its on-demand or online nature, its difficulty, and any other requirement attached to it.

Platform workers devote time to search for available tasks. This "search effort" is conducted at the expense of leisure (l) only, as paid work hours (h) can only result from search: with zero search, workers find zero hours of paid work.

As in Arellano and Meghir (1992), search takes place by devoting leisure time to this activity and as such it would only be a source of disutility for the worker if it job opportunities were not revealed through search.[7] However, while in their model job seekers will face *ceteris paribus* a higher wage profile in the future, in our framework search generates additional hours of paid work in the same reference period. The time workers spend in searching for a job (i.e., waiting for new job offers by the platform) is S, which is the number of hours workers spend looking for available tasks on the platform. Effectively, if paid work is revealed through search, search is the only choice variable available to workers.

Paid work hours are then no longer a choice variable, but a function of the pay-out, idiosyncratic ability, the number of workers available to platforms and the search effort, $H(\bar{w}, a, L, S) = h$. This function can be treated as separable, so that $h = H_a(\bar{w}, a)H_s(\bar{w}, L, S)$. The first term refers to a wage/efficiency specific demand shock, revealing the average amount of time it would take the worker to perform a task of value $\bar{w}$. We can visualise this term as any function of ability, location factors, and pay-out.

[6] We henceforth omit the individual and time indices.

[7] 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. On-the-job leisure is not an issue for our empirical model because, in the survey, workers were asked specifically how much time they spend on the platform *searching* for tasks.

The second term is the search function, revealing how many tasks of average pay-out $\bar{w}$ are found conditional on search. We further separate the function and model it as $H_s(\bar{w}, L, S) = \rho S$. The term ρ is the idiosyncratic search shock $\rho = H_w(\bar{w}, L)$ capturing labour demand by revealing how many potential tasks of value $\bar{w}$, on average, are realised into actual jobs for an extra unit of search. Note that, as there is no substitution between labour and capital, capital already is omitted from the labour demand function, and since L is also fixed in the reference period, the demand function reduces to $\rho = H_w(\bar{w})$. The *actual* number of hours spent on the platform adjusts the paid hours supply for search, and is defined as $h^A = h+S$, so that the total time endowment is $T = l+h+S = l+h^A$, where l is leisure. This means that the search effort is subjected to the following constraints: $S \leq T(1 + \rho H_a(\bar{w}, a))^{-1}$ and $S \geq 0$.

The separation of search into an effort and shock component is an important feature of our model. Note the true entity of the idiosyncratic shock ρ is unknown to workers, as the demand parameters, along with concurrent aggregate supply, are unknown to each worker. Workers can form expectations on the shock (for example, depending on peak demand and surge pricing expectations), but ultimately its true value remains unknown, so that the realised shock will equal its expectation plus a random stochastic term $\rho = E[\rho] + \theta$. These features make our model flexible enough to allow for individual-varying time endowments and changes in the aggregate supply as long as these are exogenous to workers. Most importantly, these considerations come with the implication that the shock is not revealed to workers until they search for tasks.

The function $h_t = H_a(\bar{w}, a)H_s(\bar{w}, S)$ has the advantage of separating the number of tasks found to the time it took the worker to perform them, and allows us to see how efficiency and search can affect the realised pay rate in two separate ways. To see how, begin with the hourly *nominal* rate of pay w. This is obtained by dividing platform income in the reference period by the total amount of paid hours, so that $w = \bar{w}H_s(\bar{w}, S)(H_a(\bar{w}, a)H_s(\bar{w}, S))^{-1} = \bar{w}H_a(\bar{w}, a)^{-1}$. The rate of pay corrected for unpaid hours is the hourly *actual* rate of compensation, and equals $w^A = \bar{w}H_s(\bar{w}, S)(H_a(\bar{w}, a)H_s(\bar{w}, S)+S)^{-1}$. Unless the worker decides not to work, the search effort is always non-zero, so the hourly actual compensation will always be lower than the hourly nominal compensation.

An important caveat is that if search is separable into an idiosyncratic shock and an effort component, then the rate of change between actual and nominal salary is independent to the search effort, and only depends on the search shock. The proof is trivial but is detailed in Appendix A, and has important implications for our empirical strategy, as it justifies our approach of separating search unto its two fundamental demand shock and effort components.

Following from Parker et al. (2005), we assume, for simplicity, concave and separable utility. We assume that the leisure disutility from the hours of actual work equals the disutility from the hours paid work and search, so that $U_h(h^A) = U_h(h) + U_s(S)$. The optimisation problem for an individual at period t then follows $\max_{C,S}\{U(C, h^A)\}$. The expected utility is expressed as:

$$
\begin{aligned}
U(C, h^A) = \int_{-\infty}^{+\infty} U_c(C)\, dF(\theta) + U_h(T - l) \\
= \int_{-\infty}^{+\infty} U_c(\bar{w}(E[\rho] + \theta)S + \mu)\, dF(\theta) + U_h(T - l) \quad (1)
\end{aligned}
$$

where C is consumption, which equals

$$
C \equiv wh + \mu = \bar{w}(E[\rho] + \theta)S + \mu \quad (2)
$$

where μ is a measure of other income which reflects net dissaving at the end of the period t.

An important feature of this model is that workers are always in control of how much leisure they are sacrificing. Uncertainty in search enters utility expectations in the left term of the equation, in the form of a multiplicative shock on wages. The implication of this source of uncertainty in the budget constraint are immediately evident in equation (2) with reference to the work of Parker et al. (2005), as the authors have shown that, under multiplicative shocks such as the one our model reduces to, there is no solution for labour supply for an increase in uncertainty, even under separable utility. This can be shown from the first order condition for labour supply:

$$
\bar{w}(E[\rho] + \theta)U_c^{'}(\cdot) + U_h^{'}(\cdot) = 0 \quad (3)
$$

This means that, holding leisure constant, while workers can optimise labour supply through search, so that $S^* = S^*(\bar{w}E[\rho], \mu)$, there is no effective solution to the optimisation problem for an increase in ρ through θ. In other words, we cannot determine how platform workers respond to an increase in the search shock. Also, without holding leisure constant, idiosyncratic efficiency and, in turn, nominal wages, will enter the optimal search function.

For platform workers with control over the pay-out, and for workers for which the pay-out is controlled by the platform but has little time variation, the pay-out might be known. However, for some other workers, uncertainty in pay-out could also be a factor. Further extensions of the model can either treat uncertainty in pay separately – so that $\bar{w} = (E[\bar{w}] + \psi)$ – or integrate this uncertainty term within θ. The implications of an increase in uncertainty remain, generally, the same.[8]

An alternative approach would require modelling the expectation formation process task-by-task in a manner that is not dissimilar to the one that Stenborg Petterson (2022) follows when modelling taxi drivers' reference points with a Markov process. However, solving the model for a change in the search shock before the worker experiences it remains effectively impossible. 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. This is a matter than can only be settled empirically.

An important implication of the utility maximisation problem is that optimal search will depend on nominal hourly earnings (and, by extension, efficiency) and unearned income. Similarly, both the nominal and actual pay rates will depend on efficiency, as efficient workers will complete tasks quicker. This means that the rate of change between the actual and nominal states of the compensation rate will depend on efficiency through the nominal compensation rate, so that $dw^A/dw^2 = \rho/(\rho w + 1)^2$. Our empirical model then needs to keep the nominal pay as fixed, so that both the search effort S and the shock ρ can be studied independently of it.

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). [9] 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.[10] 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,

[8]The implications of wage uncertainty for our empirical model are discussed later in Subsection 3.2.

[9]The data used in this analysis was collected by PPMI for the report "Study to support the impact assessment of an EU Initiative on improving the working conditions of platform workers" issued by DG EMPL - European Commission (No VC/2021/0093) (Barcevičius et al., 2021). The authors of this paper collaborated on the report in the context of a service request. The views expressed in the paper are the authors' own and do not necessarily reflect those of DG EMPL or PPMI.

[10]Ibid. 5.

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 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 effort 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 to state, without a change in compensation, *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 these supply 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. Figure 2 further investigates the relationship between search effort and the rate of change in supplied hours of work, suggesting that a positive association can be found between search and (i) the rate of change in actual/paid and (ii) actual/desired hours, and (iii) that the rate of change between desired and paid hours seems to be independent from search.

The first finding does not contradict our earlier discussion about the nature of the search shock. While changes in search should not affect the actual/paid hours rate, the positive correlation between the two variables emerges precisely because of the conflict between target-earning behaviour and uncertainty. This correlation might be explained by the rate of pay: workers could tolerate higher frictions longer if these are also accompanied by a higher nominal rate of compensation. At the same time, it is also possible that it might take longer for workers to generate expectations about, or simply accept, the demand-side search shock in the reference week.

It is difficult to draw conclusions about these two apparently contradictory findings. At once, the

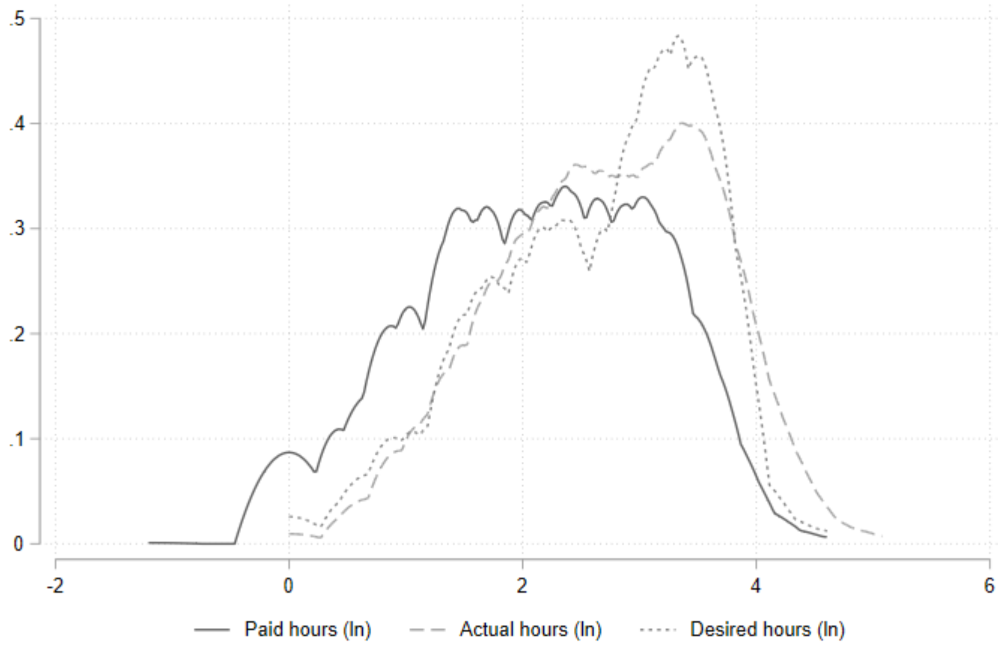

Figure 1: Potential labour supply in online labour platforms

second figure shows that workers who search longer also seem to be the most far off from desired supply level, giving credence to the uncertainty hypothesis. Yet, the non-significant relationship between search and the rate of change in desired and paid supply suggests the presence of target-earning behaviour. The figure is then indicative of the fact that demand-side frictions can have a multi-faceted effect on the behaviour of workers in labour platforms. It is then fundamental to study this relationship holding the salary, and other controls, fixed. In other words, we need abstracting search away from its endogenous components, by studying aspects of labour supply which no longer depend on the nominal rate of pay. The next section of this paper focuses precisely on this task.

3.2 Econometric specification

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

Our estimation strategy exploits the piecework modality of work to estimate the elasticity of labour supply among workers from various types of platforms. 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

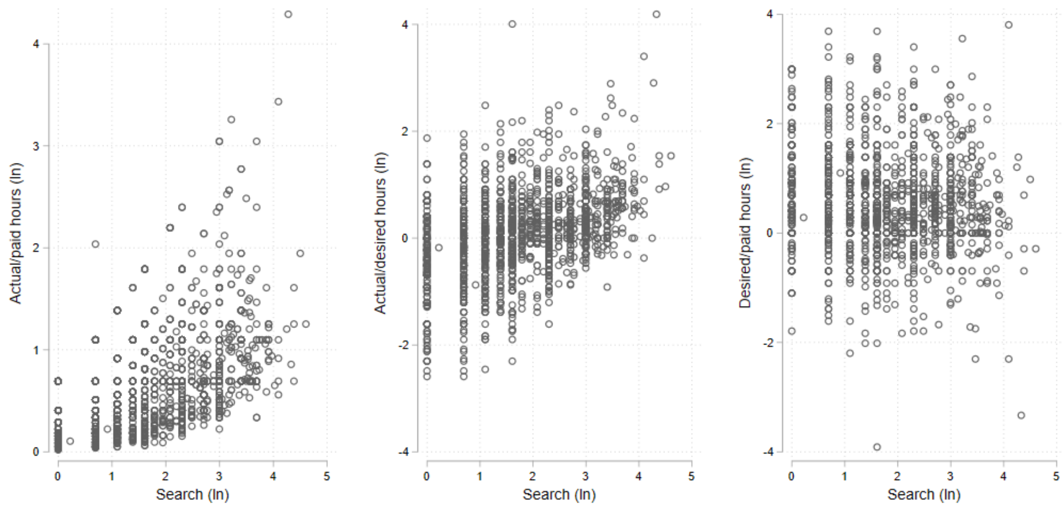

Figure 2: Search and search shocks in online labour platforms

desired and actual labour supply is given by the presence 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). Search frictions in online labour markets have been similarly exploited to retrieve elasticity parameters in 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. 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. Cohen et al. (2016) and Lam et al. (2021) also introduced waiting times in a similar way in their labour demand equations for on-demand services. Outside the literature on online labour platforms, unpaid overtimes has been used to correct the desired supply equation in Stewart and Swaffield (1997).

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

$$ln(h^D) = \alpha_1 ln(w) + U\beta + X^{'}\delta + \eta_1 \tag{4}$$

where α_1 is the elasticity of (desired) labour supply to the wage. As in traditional labour supply functions, U is a vector of controls for any other source of income, including unearned income and income from other non-platform occupations, if available. X is a vector of observed and unobserved individual characteristics affecting labour supply participation. These can include both observed and unobserved preferences and all factors affecting efficiency in task completion, including ability but also location characteristics.

In the presence of search, workers devote $h^A = h + S$ actual hours of work on the platform. The increase in working hours caused by (unpaid) search lowers the nominal rate of pay w to the actual rate $w^A = (wh)/h^A$.[11] The labour supply equation with search is:

$$ln(h^A) = \alpha_1 ln(w^A) + \alpha_2 ln(S) + U\beta + X^{'}\delta + P^{'}\zeta + \eta_2 \tag{5}$$

The parameter α_2 denotes the effect of search on hours of work. It is easy to show how this model relates to the theoretical model discussed in section 2, as actual labour supply remains a function of the expected nominal wage and unearned income, but here uncertainty is incorporated in the search adjusted wage term w^A, plus the search effort term. Demand-side platform factors 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 also by the intuition 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 5 alone because of the endogeneity between search and actual hours of work.

Indeed, equations (5) and (4) are both difficult to estimate because of the endogeneity of wages and search caused by the unobserved part of the X vector. In other words, in equation (4) the nominal

[11] 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.

salary will still depend on unobserved efficiency and be endogenous to the desired hours; in equation (5) search and the actual rate of pay will be endogenous to the actual hours worked as they simultaneously depend on the nominal rate of pay. 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:

$$\begin{cases} ln(h^D) = \alpha_1 ln(w) + U\beta + X^{'}\delta + \eta_1 \\ ln(h^A) = \alpha_1 ln(w^A) + \alpha_2 ln(S) + U\beta + X^{'}\delta + P^{'}\zeta + \eta_2 \end{cases} \tag{6}$$

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 condition 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 the piecework modality of work allows workers to supply as much work as they wish with the only major demand-side restriction being search, unlike in traditional employment.

Later in this section we discuss how this condition can be satisfied. For now, it will suffice to say that it is, 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 (6) and simplifying, we reach:

$$ln(h^A/h^D) = \alpha_1 ln(w^A/w) + \alpha_2 ln(S) + P^{'}\zeta + \eta_3 \tag{7}$$

This setting allows us to study how the wage deviation in relative terms affects the relative deviation from desired hours, depending on how much they have searched. For simplicity, we henceforth refer to this model as the *differenced* specification. Interpretation of the terms in the equation remains straightforward, as the parameters can be interpreted as they appear in the system (6). The most important parameters are α_1 and α_2, respectively wage and search effort elasticity. If the search shock were to be captured by the change in salary alone, then search effort should not affect the estimated wage elasticity α_1, and the equation would reduce to a standard labour supply equation.

Taking differences between the two equations implies that the outcome no longer depends on *levels* of wage but only the *change* in it, keeping all idiosyncratic workers' characteristics fixed, as the $X^{'}\delta$ term is now null. From this perspective, conditional independence of the search term is achieved by the disappearance of the vector of individual characteristic X in equation (7). The intuition can be understood with reference to our theoretical model in section 2: if desired hours are a function of the nominal salary and unearned income, and actual hours result from the optimisation of search under the same expected nominal salary, search effort and shock are the only differences between the two states.

Furthermore, note that this specification addresses division bias in the wage elasticity term, which is a common problem in labour supply models computing wages from income and hours of work when there is measurement error in the latter (Farber, 2005; Stafford, 2015). As there is no reason to assume that measurement error should differ for search and paid hours, then w/w^A will no longer depend on misspecification of the hours worked. This is an important feature of the model because, after omitting the search term S, our differenced specification will be comparable to the model from Camerer et al. (1997).

Effectively, specification (7) offers difference in differences estimates for labour supply by comparing outcomes across two different states depending on the intensity of the search shock. In our case, treatment is continuously defined so that deviations from desired supply for "controls" experiencing low frictions are compared with outcomes for "treatments" experiencing high frictions. In the difference in differences jargon, the "common trends" assumption is satisfied if, under the same search shock (or in the absence of it), the change in actual and desired supplied hours of work would be identical for all workers. From another perspective, equation (7) 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 pre-treatment equilibrium against the piecework outcome.

What this means in terms of our model is that, for common trends to hold, the terms associated with wage and search elasticity have to be exogenous from the outcome, i.e., the change from desired to actual supply. We have discussed already that, from the optimisation of supply, search effort will be higher for workers facing a higher nominal pay level, which can then induce these workers to tolerate higher levels of friction in their nominal to actual rate. It is then imperative that the nominal rate is successfully made independent with the outcome via differencing. In that case, there is no issue of simultaneity as long as nominal wage term upon which the search effort and search shock both depend is now exogenous to the outcome, no more than a random disturbance term.

The point is that both actual and desired supply equations depend already on the nominal rate, so differencing the two equations should cancel out this term. *Ex ante* workers do not know the entity of the search shock and might not know the nominal rate, *ex post* they express desired supply keeping this same nominal rate fixed. Therefore, we can focus only on variations in the stochastic component of search between the actual and desired state. If valid, this methodology allows consideration of idiosyncrasies of platforms in task allocation and schemes, including uncertainty or efficiency factors contributing to the nominal rate of pay. While the above-stated independence condition might generally be a strong one, these considerations suggest that violations of this condition would boil down to measurement error in the desired hours equation, so this assumption fundamentally reduces to two simple conditions which are not only reasonable but also empirically testable in several ways.

The first is a condition of *"Self-consciousness"*. Accordingly, workers should consider how efficiently they can perform a task when expressing desired labour supply. The intuition is that, if they were offered unlimited tasks at a fixed pay-out, workers will never assume they can complete them the moment they accept them, but will take into account idiosyncratic factors affecting how efficiently they can perform it.

The second one is the *"No devil's advocate"* condition. When expressing desired hours of work in ideal conditions, sources of disutility arising from the demand-side should not be considered. In other words, workers should not express their preference for hours of work based on the search shock they experienced in the reference period, because in ideal conditions search should be zero as it comes at a net loss of leisure.

As mentioned, in Section 4 we test these conditions in several ways. First, we can perform a simple Z test for comparing the coefficients of interests (α_1 and α_2) in the differenced model before and after all other controls have been removed. If the terms connected to the two coefficients are now exogenous from the other observable controls, then the coefficients should be statistically identical.

Furthermore, we test whether the nominal wage term specifically has been absorbed out, by adding it as a predictor in differenced specification, and testing the significance and magnitude of its coefficient. A similar robustness check is also performed to test if income per hour of search, which is independent from efficiency, also has a non-significant effect in the differenced supply equation. This test complements the previous one by testing the "Self-consciousness" condition more explicitly using a proxy for nominal wage which is independent of efficiency. A significant positive effect of this term would indicate that workers are overestimating how efficiently they can perform a task.

Finally, the "No devil's advocate" condition can be tested in two ways, first by checking how demand-side restrictions affect the parameters estimated in the desired hours equation, and then by checking how the removal of all controls bar the elasticity estimates affect the search elasticity parameter. If the condition is satisfied, we expect demand side restrictions to have no effect on the estimated wage elasticities in the desired equation, and the search elasticity parameter to be unaffected by the presence of other predictors.

Some final considerations apply. We discussed earlier in section 2 that the rate of change in salary depends on the nominal rate of pay and the search shock only. What if search effort affected the search shock? We exclude this possibility *a priori*, as intuitively workers cannot control whether or not a task will be made available at a given time, or whether other workers will decide to search at the same moment, as abundantly discussed in section 2. Stenborg Petterson (2022) makes a similar assumption when modelling taxi drivers' reference points, and similarly we argue that individual search effort cannot affect the search shock, which is instead revealed after searching.

However, workers can search in atypical hours for better pay. This behaviour is perfectly consistent with our model, as being able to keep the nominal salary fixed also ensures changes in the pay rate, because high demand or low supply, or uncertainty, are taken care of. This means that the model will be equally valid in context in which the platform requires workers to be available in certain hours, or the platform allows workers to choose their own pay rate, or more generally workers working with atypical schedules. It is trivial to prove (see Appendix A) that the amount of search is exogenous to the rate of change between actual/paid wage even if the number of hours of work (and the wage) depends on efficiency, and that, after the nominal rate is held fixed, the only factor affecting the change from paid to actual salary is the search shock. In short, uncertainty in nominal salary is absorbed by the wage elasticity term only. This reasoning also applies the subset of platform workers who are able to set their wage, as the change between w and w^A occurs after the nominal salary has been set.

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 and labour market experience. Specifically, we are interested in seeing how these elasticity parameters can change depending on whether services are offered online, whether workers have control over their pay, or whether workers have access to a second "traditional" job.

Note that platform characteristics can still play a significant role determining the rate of change between desired and actual hours in equation (7), but the supply-side components determining access onto these platforms are absorbed by differencing the two equations with the disappearance of the $X^{'}\beta_S$ term. However, if our strategy is correct, 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-specific elasticities (*heterogeneous* model, henceforth) 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), partner's income, 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 (i.e., the "ever-unemployed") 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 outcomes that often predate access into platforms. As such, they can actually be

Table 1: Labour supply elasticity estimates

	Desired hours (ln)		Actual hours (ln)		Delta hours (ln)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Wage (ln)	-0.086***	-0.076***	-0.128***	-0.037***	-0.205***	0.201***	0.193***	0.206***	0.200***	0.185**	0.262***
	(0.014)	(0.013)	(0.016)	(0.011)	(0.043)	(0.055)	(0.054)	(0.055)	(0.059)	(0.056)	(0.055)
Search (ln)		0.385***		0.694***		0.372***	0.379***	0.372***	0.371***	0.415***	0.375***
		(0.021)		(0.021)		(0.024)	(0.024)	(0.024)	(0.025)	(0.025)	(0.024)
On-location worker	-0.030	-0.016	0.160*	0.158***	0.173***	0.166**	0.199***		0.167**	0.160**	0.167**
	(0.084)	(0.071)	(0.073)	(0.046)	(0.050)	(0.052)	(0.052)		(0.052)	(0.053)	(0.052)
Price-setting power	0.110	0.070	0.228***	0.119**	0.089	0.030	0.069		0.030	0.029	0.025
	(0.057)	(0.050)	(0.054)	(0.039)	(0.046)	(0.043)	(0.042)		(0.043)	(0.043)	(0.043)
On-location × Price-setting	-0.056	-0.047	-0.296**	-0.242***	-0.213*	-0.161	-0.201*		-0.161	-0.164	-0.159
	(0.120)	(0.109)	(0.108)	(0.066)	(0.100)	(0.093)	(0.091)		(0.093)	(0.092)	(0.093)
Experience in platforms	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000		-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Wage (nominal, ln)									-0.001		
									(0.012)		
Income per hour of search (ln)										0.012	
										(0.012)	
Employed in traditional job											-0.010
											(0.073)
Employed in trad. job × Wage (ln)											-0.130
											(0.100)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Last occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.127	0.275	0.120	0.575	0.111	0.242	0.222	0.237	0.242	0.256	0.245
Observations	1590	1580	1592	1592	1580	1580	1581	1580	1580	1513	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	-0.060**	-0.060**	-0.097***	-0.010	-0.245***	0.164*	0.152*
	(0.022)	(0.021)	(0.023)	(0.016)	(0.064)	(0.078)	(0.075)
Wage (ln) × Online, Price-setting	-0.097***	-0.084***	-0.133***	-0.049**	-0.180*	0.236**	0.221**
	(0.026)	(0.022)	(0.026)	(0.017)	(0.088)	(0.073)	(0.069)
Wage (ln) × On-location, No price-setting	-0.091**	-0.064*	-0.182***	-0.063**	-0.111	0.323***	0.311**
	(0.033)	(0.028)	(0.030)	(0.020)	(0.099)	(0.092)	(0.096)
Wage (ln) × On-location, No price-setting	-0.162**	-0.144**	-0.168***	-0.084***	-0.168	0.153	0.180
	(0.050)	(0.044)	(0.039)	(0.024)	(0.123)	(0.121)	(0.119)
Search (ln)		0.384***		0.694***		0.373***	0.379***
		(0.021)		(0.020)		(0.024)	(0.024)
On-location worker	0.017	-0.018	0.259**	0.215***	0.254**	0.263**	0.296**
	(0.117)	(0.097)	(0.091)	(0.058)	(0.090)	(0.087)	(0.089)
Price-setting power	0.168	0.110	0.260***	0.157***	0.130	0.074	0.112
	(0.085)	(0.072)	(0.064)	(0.042)	(0.074)	(0.068)	(0.064)
On-location × Price-setting	0.029	0.076	-0.347*	-0.251**	-0.287	-0.311*	-0.324*
	(0.182)	(0.166)	(0.134)	(0.079)	(0.154)	(0.142)	(0.143)
Experience in platforms	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
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-Rquared	0.131	0.277	0.124	0.578	0.112	0.243	0.223
Observations	1590	1580	1592	1592	1580	1580	1581

SE clustered by occupation/sector clusters in parentheses. Other controls: Experience in platforms, Active in how many platforms (1, 2, 3, 4 or more), 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

proxies for unobserved ability. 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 a number of 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 workers' characteristics which might affect search. We account for the possibility that more experienced workers are better informed about peak demand hours by controlling for years of experience in platforms, and the regularity of the worker's activity over the last six months. Our empirical approach should be robust to all sources of heterogeneity in search, even when driven by individual characteristics. Intuitively workers will learn to optimise their search activity over time, so the removal of this set of controls in the context of our robustness checks can provide a useful indication of the validity of our approach. Furthermore, while we can control for the number of platforms the worker was active in at the time of the interview to account for the fact that some workers might be able to search from multiple platforms simultaneously, we have preferred to exclude such control because it is clearly endogenous to the search effort.[12]

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 (4). 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, and the largest difference in magnitude is of 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 ~ 0.01 points in the average estimated elasticity. Even more negligible changes are also to be noted for the heterogenous elasticities model, as estimated elasticities show minimal changes after adding search to the specification. Platform types also appear to have no significant effect on desired hours. These findings provide further evidence in support of our fundamental assumption that workers do not generally take current search into account when expressing their desired labour supply and that task search is independent from ability.

[12]Nonetheless, we have tested all our specifications with this control included, and found no difference in our results.

In other words, the "ideal conditions" do imply zero search. This is an important result, suggesting that desired hours are revealed net of demand-side effects, to which we will come back later in this section.

Actual hours are studied in columns (3) and (4) of both tables, corresponding to the specification from equation (5). Estimated elasticities are, 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 (column 3) into a nearly perfectly elastic one (column 4).

However, the results so far 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 (7) in columns (5) to (11) in Table 1 and (5) to (7) in Table 2. 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. However, these estimates 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 number 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. Columns (7) from both tables show that the removal of all regressors has a very small effect on our elasticity estimates, with a very minor influence over the overall predictive power of the model. Further tests[13] reveal that we cannot reject the null hypothesis that both coefficients α_1 (Z-test: $.44244795 < 1.96$) and α_2 (Z-test: $-.06118602 < 1.96$) remain the same even after removing all other

[13]Not shown in the table.

controls in the model, including country and last occupation effects. These results suggest that the endogenous components of search have been absorbed out in the difference equation. Furthering our evidence in support of the validity of our approach, we also find that none of the platform experience controls are statistically significant in any of the differenced specifications once search is introduced.

Interestingly, search has already been found to be exogenous to all individual characteristics, even before looking at the differenced equations. In Appendix B, Table 3, we test whether is the search effort correlated with individual characteristics in any way, and find that search is already independent from most observable variables bar the platform's control over working hours (as expected). A joint test of significance reveals that we cannot reject the hypothesis that these coefficients are jointly zero at the 5% significance level (F(17, 179) = 1.56, Prob > F = 0.0802). After removing the variables for the platform's control over working hours, the null hypothesis cannot be rejected at the 10% level (F(15, 179) = 1.02, Prob > F = 0.4392). Removing all other fixed effects, including country fixed effects, in columns (2) and (3), we still find no individual-level control to be related to search.

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.

Probably the most important robustness test for the validity of our approach is offered in column (9), Table 1. Here we take the specification from column (6) and reintroduce the nominal pay rate term within the differenced equation, finding (i) that the magnitude of the term is approximately zero, (ii) that its significance is also zero, and (iii) that the other coefficients are nearly completely unaffected by the introduction of this term. This finding suggests that the differencing strategy successfully holds the nominal rate fixed and that the rate of change in desired hours is indifferent from the rate of pay, properly cancelling out all unobserved confounders which might have posed as a source of endogeneity. Column (10) reinforces these findings by replacing the nominal wage term with the pay-out for hour of search, a proxy which is indifferent from idiosyncratic efficiency. The magnitude of its coefficient is slightly larger than one of the nominal wage but is still close to zero (0.012). The non-significant effect of the term, along with the non-significant influence on the wage elasticity term suggest that the bias originating from workers overestimating their efficiency is negligible at best.

It could be valuable to check whether heterogeneous effects conditional on access to other sources of income might make target-earning behaviour reappear after search is accounted for. Individuals with no access to other jobs other than platform work may indeed act as target-earners. We test this in column (11) of Table 1, by introducing interactions between wage and employment status in non-platform jobs, so that heterogeneous elasticities could be studied. This specification studies the heterogeneous effect of not working, net of ever-unemployed status, which we recall is already included in the control vector. However, the estimated interactions coefficient are statistically not significant, ruling out the hypothesis that workers without access to other occupations might act as target earners net of search.

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, turning elasticity estimates from backwards-bending to inelastic.[14] Most notably, our estimates are remarkably close to the estimates of Dube et al. (2020). 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 the authors' work, whose mean experimental elasticities average at 0.14. 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.

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, notwithstanding the limitations of self-reported data.

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. On average, a percentage increase in search leads to a net loss of 13.4% in income. These results reconcile supply-side backwards-bending

[14] In our case, some elasticities turn slightly positive rather than perfectly inelastic, but it should be noted that platform workers can be qualitatively different from the self employed in general.

estimates for the wage elasticity of micro-task platform workers with the demand-side evidence on weakly elastic supply and broaden these results 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 entity 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 because they have a limited amount of time to dedicate to work and search.

Note that these interpretations and our results are perfectly consistent with the self-insurance hypothesis from Parker et al. (2005) and do not necessarily contradict the target-earning hypothesis from Camerer et al. (1997) as they both imply increasing disutility of search effort. We believe that the conflicting results emerging from the literature on the labour supply of platform workers and the self-employed in general can be easily reconciled once the search effort is considered. There are two sides to the same coin: backwards-bending elasticity estimates emerge when search is omitted but, net of search, these same estimates would be positive and inelastic. In other words, we show that piecework itself makes workers behave as target-earners, even if normally they would not be.

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 up 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.

How does piecework relate with monopsony? While the labour supply elasticity we estimate is positive, it is still lower than one, supporting existing evidence on monopsony in labour platforms. What is even more interesting is that the effect of uncertainty is sufficiently large to completely distort this inelastic supply. These results reveal that piecework offers the perfect opportunity for platforms to exercise this monopsony power by making workers work longer than intended due to uncertainty. This is all to the benefit of platforms and clients, with workers experiencing a net loss in utility. The combination of piecework and monopsony might then offer avenues for social dumping, in terms of competition policy. If in competition with 'traditional' or regulated markets, platforms might be exploiting piecework to pursue predatory pricing strategies transferring net losses to labour.

Ultimately, our findings suggest that piecework itself could be at the centre of regulatory efforts. 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. Regulation could address the fundamental information imbalances between workers and platforms, ensuring at least that estimated search times are transparently advertised to workers, or insuring workers against uncertainty by re-classifying them as dependent workers. The Commission's proposal for regulation of platform work (COM/2021/762 final) goes in the latter direction but would also require platforms to inform workers about all algorithmic management systems that can significantly affect work conditions, which might include search.

As a final note, 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 overtime, bonuses, or commissions. With the expansion of the platform economy, these issues gain more relevance than ever.

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Appendices

A Note on independence of wage frictions over search

Showing that the rate of change in salary from its *nominal* to *actual* state is trivial. Omitting the individual subscripts, begin with the fundamental identity:

$$\frac{w^A}{w} = \frac{h}{h^A} = \frac{H_a(\bar{w}, a)\rho S}{H_a(\bar{w}, a)\rho S + S} \tag{8}$$

Taking the derivative of both sides of this equation with respect to S, it is easy to show that the rate of change in w^A/w is zero:

$$\frac{dw^A}{dwS} = \frac{d}{dS}\left(\frac{H_a(\bar{w}, a)\rho S}{H_a(\bar{w}, a)\rho S + S}\right) = 0 \tag{9}$$

This shows that the rate of change between actual and nominal salary cannot be determined by the search effort, but only by the search shock. This is, after all, already an obvious implication of the nature of w and w^A. Being the product of the total pay-out weighted by the number of hours of work, w obviously depends only on efficiency α and the average task pay-out $\bar{w}$. w^A instead clearly depends on these same factors, plus the search shock, but both can be considered independent from the search effort.

The only consideration that applies is that the choice variable search has to be independent from efficiency for the function $H(W(a), S)$ to be separable. This assumption is not only reasonable but is also similar to assumptions which have been treated as standard in the related literature, such as Stenborg Petterson (2022). The decision to keep searching is independent from efficiency factors, after holding the pay rate fixed.

As the search effort results from a utility optimisation process on the part of the worker, observational studies will certainly find S to correlate with w^A/w, 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. Changes in the search effort have to be studied net conditional on the nominal salary.

B Supporting regressions

Table 3: Search, predictors

	Search (ln)		
	(1)	(2)	(3)
Non-platform income (ln)	-0.004	-0.004	-0.002
	(0.012)	(0.011)	(0.011)
Non-platform income (zero)	-0.111	-0.114	-0.100
	(0.138)	(0.136)	(0.133)
Education: Medium (ISCED 3-4)	-0.074	-0.073	-0.064
	(0.120)	(0.116)	(0.118)
Education: High (ISCED 5-8)	0.019	-0.011	0.004
	(0.128)	(0.119)	(0.121)
Gender: female	-0.001	-0.001	-0.008
	(0.080)	(0.077)	(0.078)
Married or living with a partner	-0.017	0.031	0.033
	(0.070)	(0.068)	(0.070)
Female × Partner	0.019	-0.011	-0.001
	(0.111)	(0.108)	(0.108)
Partner's income, similar	-0.035	-0.037	-0.034
	(0.071)	(0.070)	(0.068)
Partner's income, lower	-0.123	-0.133	-0.126
	(0.075)	(0.075)	(0.074)
Age	0.004	0.008	0.009
	(0.013)	(0.013)	(0.012)
Regular platform worker	-0.068	-0.083	-0.071
	(0.055)	(0.055)	(0.055)
Platform's control over work hours, None	-0.160**	-0.184***	-0.174***
	(0.048)	(0.046)	(0.046)
Platform's control over work hours, N/A	-0.084	-0.096	-0.085
	(0.125)	(0.122)	(0.122)
Experience in platforms	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Foreign nationality	-0.041	-0.068	-0.063
	(0.100)	(0.096)	(0.096)
Household size	0.007	0.004	0.008
	(0.028)	(0.027)	(0.027)
Number of children	0.025	0.027	0.023
	(0.031)	(0.030)	(0.030)
Constant	2.083***	2.119***	2.028***
	(0.380)	(0.357)	(0.353)
Country FE	Yes	Yes	No
Last occupation FE	Yes	No	No
Adjusted R-squared	0.042	0.022	0.015
Observations	1580.000	1580.000	1580.000

SE clustered by occupation/sector clusters in parentheses. Specification (1): joint test of significance (all controls): $F(17, 179) = 1.56$, Prob > F = 0.0802; joint test of significance (all controls minus platform work hours controls): $F(15, 179) = 1.02$, Prob > F = 0.4392.

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