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Task search and labor supply in the platform economy☆

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ABSTRACT

In this paper, we study how platform workers adjust their labor supply in response to fluctuations in the task offer rate. Using extensive survey data from platform workers throughout Europe, we develop a novel method to estimate workers' labor supply elasticity to the wage fluctuations that result from the unpaid time spent searching for or waiting for available tasks. Our findings reveal that variations in hourly earnings, when attributable to task search, are inversely related to labor supply. Conversely, labor supply appears to be largely inelastic in response to absolute changes in the pay rate. The estimated elasticities are applicable across diverse categories of platform workers and are robust to a wide array of misspecification and endogeneity tests.

1. Introduction

The proliferation of digital platforms has led to an unprecedented increase in workers earning income on a task-by-task basis rather than under traditional employment relationships. Platforms, in fact, usually do not employ their workers under stable arrangements, acting instead as intermediaries that match clients and service providers. As a result, workers engaged through them face a disproportionate level of exposure to search frictions due to the absence of stable employment arrangements that typically protect earnings from demand volatility, and therefore experience significantly higher levels of economic insecurity compared to traditional workers (International Labour Office, 2021; Berg et al., 2018; Cirillo et al., 2023).

These search frictions are structural and stem not only from variations and mismatches in the demand and supply of work, but also from the organizational dynamics of platforms themselves. Their extensive use of algorithmic management tools can, on the one hand, enhance the quality and efficiency of the matching process by identifying the right worker for the task (Kokkodis and Ipeirotis, 2023; Horton, 2017) but, on the other hand, allows platforms to influence the workers' supply by, for example, controlling ratings and rankings, generating price surges, and so on (Piasna, 2024). Whatever their source, these frictions manifest themselves as variation in the task offer rate, leading workers to actively search or passively wait for assignments without compensation (Dube et al., 2020; Bogliacino et al., 2020; Fernández Massi and Longo, 2023), directly affecting their effective hourly earnings, as search time is rarely remunerated (Hara et al., 2018).

Research across multiple platform types confirms that unpaid search and waiting periods remain a systemic feature of platform work, with workers consistently reporting that the prevalence of unpaid labor makes it difficult to rely on platform work as a primary source of income (Pulignano et al., 2021).[1] This persistent volatility in earnings

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[1] Recent regulatory developments at the European level have formally recognized these challenges, with the EU Platform Work Directive 2024/2831 acknowledging the systemic nature of unpaid waiting time and establishing regulatory frameworks to limit stand-by time requirements, thereby addressing situations where workers must remain available for work without compensation. Source: Proposal for a Directive of the European Parliament and of the Council on improving working conditions in platform work; COM/2021/762 final.

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creates fundamental tension in platform work arrangements. While platforms provide workers with enhanced autonomy and flexibility in work scheduling, they simultaneously generate new forms of employment uncertainty where income depends entirely on the ability to secure and complete individual assignments.

On the labor supply side, this tension materializes into a trade-off between allocating time to leisure activities and continuing to search for lower hourly pay. The theoretical implications of this search-induced variability remain contested in the literature. Standard economic models predict that workers should reduce their labor supply when search frictions increase, yet behavioral models suggest the opposite response due to target-earning behaviors and loss aversion. These theoretical contradictions are further complicated by persistent methodological challenges in empirical research, as the literature has rarely adopted a consistent approach to measuring the time spent on productive work and unpaid activities. This ambiguity may explain some of the contradictory findings across studies of the labor supply of autonomous workers, often yielding contrasting estimates of wage elasticity (Camerer et al., 1997; Farber, 2005; Parker et al., 2005). Search activities might then play a crucial role in determining the elasticity of labor supply, potentially bridging these inconsistencies, as recent evidence suggests that equivalent wage elasticities can reverse sign when framed as changes in unit completion rather than in unit compensation (Shen and Hirshman, 2023).

To address these issues, this paper focuses specifically on the effect of unpaid time spent awaiting task assignments on labor supply, separating it from paid hours of productive work. We define this unpaid waiting time as *task search*, whereas we denote its marginal impact on the hours of paid work as the *task offer rate*, consisting of the variation in paid work hours resulting from additional time spent searching for tasks. Our key research question is the following: How do autonomous workers adjust their labor supply in response to task search shocks? And, more in general, is it possible to distinguish this elasticity of labor supply to search shocks from the more general notions of wage elasticity?

Our research question is closely linked to two potential empirical challenges regarding the nature of task search and counterfactual supply preferences. The first concerns the extent to which search shocks can be considered exogenous, an issue that is particularly relevant given the subjective nature of search and the platforms' ability to adjust matching efficiency based on workers' performance, since pay variations arising from search frictions may themselves be endogenous. The literature, so far, has not tackled this challenge directly.

The subjectivity of search also revolves around how the search effort is integrated into workers' preferences and expectations, leading to our second empirical challenge: how much work would be supplied in the absence of task search? Since the search effort is nearly unavoidable, counterfactual information about labor supply in the absence of task search can only be derived from stated labor supply preferences rather than revealed ones. Our interpretation of the effects of task search on supply needs to be balanced by an assessment of the comparability of these preferences and the associated error term. It is unclear from the literature if these stated preferences are reliable.

To tackle these empirical challenges, we develop an integrated analytical framework leveraging a purpose-built online survey of European platform workers that elicits dimensions often impossible to observe in other data sources, including inherently subjective variables such as time devoted to search and desired labor supply preferences, along with paid hours of work, earnings, and a rich set of background variables. Our analytical strategy estimates two wage elasticity parameters: a *search-induced wage elasticity*, which reveals how workers react to wage variations caused by changes in the task offer rate, and a *frictionless wage elasticity*, which reveals how hourly earnings affect workers' supply before accounting for the task offer rate.

To estimate these labor supply elasticities, we propose a dual-model estimation strategy that combines two complementary specifications — in levels and in differences — each relying on distinct assumptions regarding the exogeneity of the task offer rate and the accuracy of stated labor supply preferences. Both models exploit the wage variation induced by the exogenous component of the task search as the main source of identifying variation. The first model assumes that the task offer rate is uncorrelated with unobservable individual characteristics affecting supply, while the second assumes that these unobservables exist but can be eliminated by absorbing individual fixed effects between stated and revealed supply preferences. This approach enables the analysis of actual supply decisions while addressing limitations associated with self-reported subjective data and accommodating potential endogeneity in the task offer rate.

Our findings indicate that wage elasticity parameters are negative but less than proportional in response to search-induced changes, and nearly inelastic in a frictionless context. These search elasticities are uniform across types of platform work, implying that these behavioral responses are not driven by how actively a worker must search or by the immediate opportunity cost of staying on-call. These results are further supported by evidence that search shocks are exogenous and that variation in stated and revealed preferences, at least with respect to search, aligns well with workers' behavior.

The paper is structured as follows. Section 2 provides an overview of the related literature and underlines the policy relevance of the issues at hand. Section 3 describes our data sources, Section 4 presents our empirical approach, Section 5 discusses the conditions under which our results are valid and consistent; Section 6 outlines our results, and Section 7 concludes. The Appendix offers some theoretical insights, along with additional statistics, robustness checks, and Monte Carlo simulations.

2. Literature review

This paper contributes to several interconnected strands of literature examining worker behavior and labor supply responses, spanning neoclassical and behavioral perspectives on how workers adjust their labor supply in the presence of wage uncertainty and search frictions.

From a neoclassical perspective, task search in labor supply can be conceptualized with a model of labor supply under wage uncertainty, drawing on theoretical contributions on self-employment uncertainty (Parker et al., 2005) and job search (Arellano and Bond, 1991). However, such a theoretical approach indicates that fully analytical solutions are elusive without considering reference points under some behavioral framework (Stenborg Petterson, 2022).[2]

On the empirical side, labor supply responses to changes in wage seem to vary significantly once we factor task search in. Positive labor supply elasticities have been observed among platform workers in response to surge pricing (Chen et al., 2019; Angrist et al., 2021) and increases in demand for services (Cullen and Farronato, 2021). However, descriptive evidence suggests that after taking into account the time invested in searching for tasks, workers often end up working longer than initially intended, at lower effective pay rates (Cantarella and Strozzi, 2021; Berg et al., 2018), indicating a negative relationship between pay and the amount of time workers allocate to both work and task search. Such behavior, also observed among YouTube content creators (Barbos and Kaisen, 2022), may indicate target-earning behavior and reference-dependent preferences (Kukavica et al., 2022; Horton and Chilton, 2010). Estimates of the wage elasticity of supply to clients (determining how long clients, and not workers, wait) tend instead to show positive but inelastic values (Dube et al., 2020; Duch-Brown et al., 2022; Caldwell and Oehlsen, 2024).

The ambiguity concerning the slope of the labor supply curve goes beyond platform work. Negative wage elasticity estimates have also

[2] The analytical derivation is shown in our theoretical Appendix A.

been observed among self-employed workers more broadly. In a seminal paper from Camerer et al. (1997), taxi drivers were first observed to display negative elasticity estimates after accounting for the effect of idle time, breaks, and trips on the salary. Similar results have emerged from other studies (Wales, 1973; Martin, 2017) and, more recently, in Duong et al. (2023), who studied variation in booking cancellations and no-shows for on-demand workers. These estimates have been attributed to reference points and target-earning behavior, sparking a heated debate in the literature. Some of these backward-bending estimates have been criticized based on endogeneity issues such as division bias (Stafford, 2015; Farber, 2005), while alternative interpretations suggest that negative estimates could result from wage uncertainty typical of self-employment (Parker et al., 2005). Nonetheless, experimental studies, although occasionally producing ambiguous results (Cosaert et al., 2022), have demonstrated that backward-bending estimates are plausible and can arise among loss-averse individuals (Fehr and Goette, 2007).

Behavioral research suggest that the sign and nature of the wage deviation from a subjective reference point might help reconcile these estimates. Experimental research on platform workers indicates that responses to wage increases and decreases at the extensive margin of each task, while positive, are highly dependent on the sign of the wage change (Doerrenberg et al., 2023). Similarly, recent studies have argued that heterogeneity in elasticity estimates might result from diverse responses to absolute and relative changes in the wage rate (Zubrickas, 2023). Most importantly, Shen and Hirshman (2023) show that wage decreases, which would otherwise trigger a decrease in labor supply, can have the opposite effect when framed through changes in total hours. In the context of task search, these framing effects could suggest that workers prefer to keep searching for uncertain tasks when the alternative is framed as giving up potential income (Tversky and Kahneman, 1981). Workers who have already invested time searching for tasks might also be more inclined to continue searching before deciding to quit, reflecting a sunk cost fallacy (Dertwinkel-Kalt and Köhler, 2016). If the unavoidability of task search makes it the default state of platform work, deviations from this default might generate expectations of regret, thereby discouraging workers from interrupting their search (Miller and Taylor, 2014). Negative labor supply elasticity estimates may thus arise in contexts where search frictions are unavoidable and not directly perceived as wage changes. Consequently, the elasticities before and after such losses may differ significantly.

Other research has touched on responses to search frictions more directly. Search frictions from the employers' side have been studied extensively by the "modern monopsony" literature (see Manning, 2020; Sokolova and Sorensen, 2020, for a review), a body of research which has also interested digital labor platforms (Dube et al., 2020). This literature is also related to the literature reassessing labor market returns after accounting for unpaid activities, such as piecework (Hart, 2008) and unpaid overtime (Bell and Hart, 1999). This body of research emphasizes search frictions as a primary marker of monopsony power in labor markets. When workers cannot seamlessly transition from one job to another, or when, in platforms, task requests are filled in the same amount of time regardless of the wage, then employers, platforms and clients have more power to keep wages low.

In decision theory and operations research, studies on queuing (Hassin and Haviv, 2002) have also dealt with similar problems, as uncertainty on the task offer rate can be understood as a queuing problem. The impact of delay information in queues has been examined from both consumer and service provider perspectives (see, for example, Yu et al., 2017; Guo and Zipkin, 2007), indicating that uncertainty in waiting times often comes with net utility losses for those who wait. On the demand side of platforms, search and wait times for clients have also been exploited to study demand-side utility surpluses in on-demand labor platforms such as Uber (Yu et al., 2022; Cohen et al., 2016; Lam et al., 2021).

All these works suggest that responses to changes in the task offer rate remain rather elusive. However, additional considerations on the nature of the task offer rate remain in order and further complicate the problem.

Firstly, the discussion so far implicitly assumes that search frictions are exogenous to worker's characteristics. However, in the literature on job offer rates, these frictions have instead been treated as endogenous, being affected by individual characteristics that determine the distribution of available opportunities (see, for example, Bloemen, 2005). However, in the context of online platforms, individual characteristics might exert considerably less influence on the availability of tasks. While some studies have addressed compensation uncertainty within platforms (Butschek et al., 2022), much of the literature on platform workers tends to treat the task offer rate as exogenous (as is the case for Stenborg Petterson, 2022) or assumes that workers can anticipate wage shocks at the beginning of each work hour (Chen et al., 2019), thereby categorizing these shocks as endogenous. Furthermore, research suggests that workers not only have little control over the amount of paid work they can perform, but are also encouraged to search and make themselves available as much as possible, suggesting that the intensity of search may be determined more by the platform than by the workers. Recent studies have shown that, by structurally manipulating earnings, ratings, and penalties, platforms can affect the workers' supply (Xu et al., 2023), and that workers' flexibility to search at any time might also be limited by cognitive, behavioral and social constraints (Lehdonvirta, 2018), suggesting that the algorithmic management practices of platforms might push workers towards being always available and always searching for work, rather than being free to schedule their working lives as they please (Glavin et al., 2024).

Secondly, we have also implicitly assumed that search does not affect workers' taste for work. The economics literature has often considered stated preferences regarding working hours as credible and reliable under hypothetical conditions (Altonji and Paxson, 1988; Kahn and Lang, 1991; Euwals and van Soest, 1999; Stewart and Swaffield, 1997). In contrast, behavioral evidence suggests that these preferences may be malleable, especially in the context of risky decisions (Vosgerau and Peer, 2018), and could be influenced by endowment effects (Miller and Taylor, 2014), especially if task search is perceived as the default state of platform work. However, other studies indicate that, with experience, individuals can learn to establish appropriate expectations and goals through experience (Camerer, 2004). Therefore, it remains unclear whether stated supply preferences can be affected by search frictions and, if not, if they can then serve as reliable counterfactuals for estimating the effect of task search. These considerations are also relevant in the context of measurement error in self-reported measures of labor supply. Evidence on measurement error and biased recall in self-reported measures of supply is abundant in the literature (Borjas, 1980; Barrett and Hamermesh, 2019), and extends to platform workers (Pires, 2025), providing a rationale for dismissing many estimates based on self-reports on the basis of division and recall bias. Our work contributes to this literature by studying whether variation in potentially unreliable statements, by absorbing a shared error term, can instead be considered reliable.

Overall, all these considerations also have relevance from a policy perspective, where we contribute to the debate on the regulation of the platform economy and autonomous work. While some have welcomed the flexibility that comes with these arrangements (Hall and Krueger, 2017), other scholars and commentators have been less enthusiastic (Berg and Johnston, 2018), and have underlined their disruptive effect on labor markets (Berger et al., 2018). Our results underline that flexibility might not necessarily benefit workers if responses to search frictions have a different sign than responses to broader variations in pay rates, potentially turning into a source of market power for platforms.

3. Data

3.1. The platform work survey

The data used for our empirical analysis originates from an online survey on platform work conducted by the PPMI research group[3] in June 2021 (Barcevičius et al., 2021). The survey comprises a total of 10,938 respondents, sampled from a population of working-age (16–74 years old) internet users in nine EU countries (Denmark, France, Germany, Italy, Lithuania, the Netherlands, Poland, Romania, and Spain).[4] The sampling frame, therefore, corresponds to internet users reachable through existing online panels rather than the general resident population. The survey transcript is available as supplementary material.

The survey follows the procedures detailed in the methodological report of Barcevičius et al. (2021) (Annex 4F). PPMI applied extensive pre-testing before fieldwork, testing the questionnaire by applying several different pre-testing methods, including expert reviews, cognitive interviewing, technical testing, and piloting. Respondents were recruited from online access panels using quotas on age and gender to approximate the composition of each country's internet-using population. As acknowledged in the methodological report, this sampling approach systematically oversamples individuals who interact frequently with digital tools, who are consequently more likely to have experience with platform-mediated labor. Moreover, participants in online access panels are often themselves compensated for completing surveys, an activity that technically qualifies as online platform work. This explains the higher share of online relative to on-location workers in the sample, and implies that the raw prevalence rate is, if anything, conservative: it captures only those panel respondents who were also active on platforms other than online access panels at the time of the survey. This procedure yields a sufficiently large analytical sample, but the raw share of respondents reporting that they have ever earned income via platforms should not be interpreted as an estimate of the prevalence of platform work in the general population, which is not the purpose of this paper.

A well-known challenge in survey-based research on platform work is the risk of false positives, particularly for respondents who confuse the receipt of services with the provision of paid labor. The PPMI survey addresses this issue by adding a multi-step screening and verification strategy on top of the checks already adopted in the JRC COLLEEM surveys (Pesole et al., 2018, 2019; Urzí Brancati et al., 2019, 2020), and additional ex-post checks have been implemented by the authors.

The initial screener asks respondents whether they have gained income from a series of online activities. Importantly, the screener differentiates labor-platform work from non-labor platform activities. Respondents are asked separately about income earned from selling goods online, renting out property, leasing goods, or engaging in crowd-funding and peer-to-peer lending. Only those who indicate that they have gained income from providing labor via web-based platforms (for instance, platforms such as Upwork, Freelancer, Clickworker, or PeoplePerHour) or from providing labor via on-location platforms (for instance, Uber, Deliveroo, TaskRabbit, Handy, or similar services) are routed into the platform-work module that forms the basis of our analysis. Individuals engaged exclusively in capital-platform or e-commerce activities do not enter the analytical sample. Respondents who answer negatively to both labor platform categories, who subsequently select "I have not worked via online platforms" for all task types, who report using zero platforms, whose last activity predates the six-month reference window, or who indicate having worked only once or a handful of times before stopping, are similarly routed out at each respective step. Numeric validation on the hours questions additionally prevents implausible or non-numeric entries from reaching the estimation sample.

After this initial screener, respondents are required to describe the precise types of tasks performed, both for web-based and on-location work. These questions refer explicitly to recognized forms of platform-mediated labor and are based on an extensive review of platform activities conducted by PPMI.[5] Respondents may also provide an open-ended description, which was manually coded by PPMI. If a respondent left the text blank or did not select any of the task categories, that respondent is not classified as a platform worker and is dropped from the sample.

In a subsequent verification step, respondents are also asked to identify the platforms they used most frequently for the activities previously reported from a list of platforms active in the EU, which expands upon the mapping effort from de Groen et al. (2021). Social media platforms such as Facebook were also included as a "honeypot" for misclassified responses. Cases where respondents could not find any of their main platforms of choice, or who reported social media platforms as their platform of use, were excluded from the analysis (128 observations). This step serves as an additional safeguard against misclassification.

Cross-item validation checks were also performed by the authors to check for inconsistencies in responses. More specifically, we cross-validated reported platform income against the reported income share, which we applied to total platform and non-platform income. A small number of responses with implausible figures were flagged and corrected where possible. PPMI also performed basic checks for poor quality responses, specifically straight lining, such as selecting the same answer for all options in a grid-type question or selecting none at all, and other suspicious speeding behaviors, assessed by examining both overall and page-by-page completion times. Respondents who failed these checks or showed implausible patterns were removed from the dataset.[6]

Once all these validity checks are applied, 2440 respondents remain who have at some point earned income from labor platforms, and 2055 have been active within the last six months. Because our empirical specifications rely on logarithmic transformations of hours and earnings, observations reporting zero hours of paid work or zero income are mechanically excluded from all estimations. This provides an additional built-in robustness check, ensuring that individuals who might have mistakenly answered affirmatively to the initial screeners, but did not actually provide paid labor via platforms, do not enter the estimation sample. Full and internally consistent information on working hours, search time, and earnings is then available for 1722 respondents. This is the analytical sample used in our study.

While the multi-stage validation process yields a comparatively large analytical sample of platform workers relative to conventional labor-force surveys (Bracha et al., 2015), we cannot claim to meet the same quality standard. Conventional labor-force surveys benefit from more representative sampling designs and more rigid screening strategies, and are likely more reliable at correctly classifying platform workers, even if they capture fewer of them. As underlined in prior work based on similar surveys (Pesole et al., 2018, Urzí Brancati et al., 2020), the validation procedures implemented in the PPMI survey reduce but cannot eliminate the risk of false positives: respondents who pass the screening may still not qualify as platform workers in the

[3] https://ppmi.lt/who-we-are

[4] For the purposes of this study, we refer to this survey as the platform work survey. The survey was conducted in the context of a background report for the impact assessment of the proposed EU Directive on improving working conditions in platform work.

[5] See Section 1.2 of the final report (Barcevičius et al., 2021) for further details.

[6] See the methodological report of Barcevičius et al. (2021), Annex 4F, for a detailed description of screening, coding, recoding, and data-quality checks, which mirror those implemented in the COLLEEM surveys.

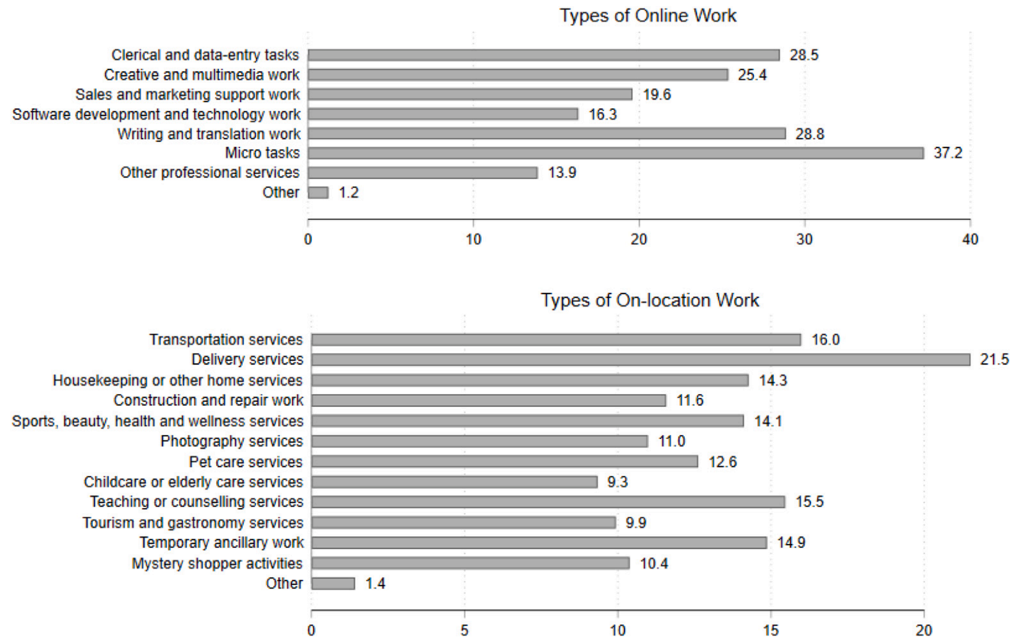

Fig. 1. Task content in online labor platforms.

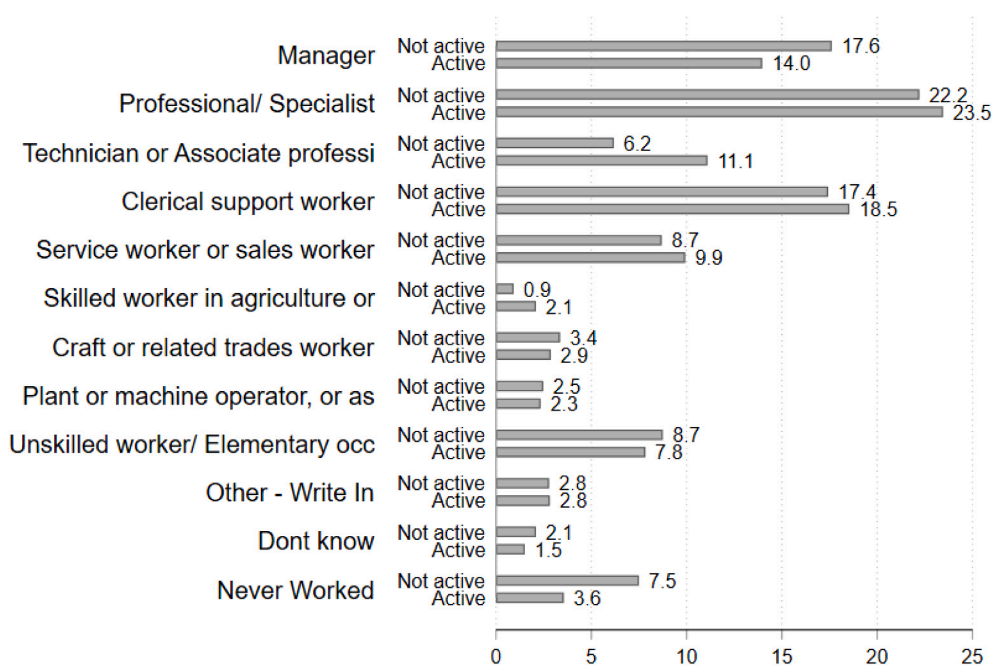

Fig. 2. Last non-platform occupation of all respondents.

strictest sense, and the prevalence rate observed in our sample exceeds consensus estimates from institutional sources, likely reflecting the over-representation of digitally engaged individuals in online panels. Some uncertainty about sample composition therefore persists, and our estimates of task search behavior should be interpreted as applying to the population of individuals who self-identify as platform workers within this sampling frame.

The resulting dataset offers rich information on demographic characteristics, employment history, and use of online platforms for all respondents, and includes an ad-hoc module for platform workers, containing information on remuneration, experience, hours of work, and working conditions, allowing us to study labor-supply behavior in platform work with a level of detail that standard surveys cannot provide.

In terms of platform experience, workers are asked to report which platform they work on, how many years they have worked on the platform, how regularly they have worked on the platform over the last 6 months, and whether the platform has any control over remuneration and/or working hours. The sampled platform workers perform several different types of tasks. In Fig. 1, we present all the types of tasks that workers reported performing. The categories are non-exclusive, meaning the same worker may have engaged in multiple types of work. Micro-tasks are the most common type of online work, but higher-skilled tasks are also fairly prevalent. For on-location work, transportation and delivery services together account for the majority of services offered on the platform, although other in-person services are also quite popular.

Platform workers come from diverse backgrounds, and a few differences with the sample of internet users are to be noted. Since the sampling frame captures online users rather than the full resident population, general statistics are not necessarily representative, and the relevant comparison is between platform and non-platform respondents within the same web-based sample, where certain demographic profiles, such as younger and more educated individuals, are naturally more prevalent.[7]

Full summary statistics are reported in Table 1. Platform workers in our sample tend to be younger, more educated, and more frequently male than non-platform respondents. This pattern is well documented in previous European surveys on platform work, such as Huws et al. (2017), Piasna and Drahokoupil (2019), Pesole et al. (2018), and a 2018 Eurobarometer survey,[8] and is not unexpected in samples drawn from online access panels. Summary statistics by platform type[9] are reported in Appendix E, Table E.2.

Fig. 2 shows the last or current non-platform occupation of all respondents using one-digit ISCO (*International Standard Classification of Occupations*) codes. NACE (*Statistical Classification of Economic Activities in the European Community*) classifications are also collected but omitted from the figure for clarity. As the target population is representative of online users, non-manual occupations are more prevalent overall. Compared to the target population, differences are rather modest: platform workers are found across a broad range of occupations, with most coming from professional, clerical, technical, or service roles. Only a small share report no previous work experience. Platform workers are slightly less likely to have no work history and less likely to report managerial experience, which reflects the younger age profile of platform workers.

3.2. Labor supply variables

Task search is an inherently subjective measure. Task search may be active (e.g., refreshing a task feed, negotiating with potential clients, or physically repositioning near areas of higher demand) or passive (e.g., waiting for app notifications while remaining idle). The way search is experienced varies widely across the gig-economy: an online translator working from home may be able to call it a day at any moment, whereas a ride-share driver might be confronted with a higher opportunity and switching cost of quitting mid-shift. What all these situations share is that workers make themselves available for work during this time and perceive it as time committed to work, because an offer can arrive at any moment and usually must be accepted promptly. This internally felt obligation distinguishes task search from leisure, even when no productive labor occurs and the worker is engaged in other activities or otherwise "kills time". Because this state of readiness can be known only to the worker, the boundary between search and leisure is inherently subjective.

To account for these considerations, survey respondents are first asked how many hours they spend *searching or waiting for tasks/ work assignments* in a usual week. The answer to this question provides our measure for the job search effort, which we define as S. The question is framed to avoid any conceptual overlapping with leisure but is agnostic to the subjective level of effort that search requires. This allows us to capture the time that workers use to make themselves available to work, regardless of how active this search effort is.

This approach is consistent with established statistical standards on the measurement of working time, particularly those set by the International Labor Organization (International Labour Organization, 2008). Specifically, our definition of task search directly aligns with the activities not included among the core tasks of a job (the "direct hours"). These include activities that facilitate work, such as waiting or being on call (the "related hours"), but also downtime and resting time. All these activities are treated as working time and contribute to the measurement of the statistical standard of "hours actually worked".

To measure direct hours, workers are asked, in the same usual week, how many hours they spend *implementing paid tasks/ work assignments*, yielding our paid hours variable h. Summing the search and hours of work terms yields our main *revealed preference* term, *actual hours of work* $h^A = h + S$, which is aligned to the ILO definition of "hours actually worked". The reference timeframe for all working time variables is the usual week. Focusing on a usual week rather than the last working week allows us to absorb uncertainty in the hours it takes to complete a task while also capturing the systematic component of task search.

Next, workers are asked to report how much they earned from platforms in the reference month. The wage terms are similarly obtained by dividing the weekly income $I = wh$ by the paid hours of work for the *frictionless* wage w, and by the actual hours of work for the *actual* wage term w^A. Naturally, the self-reported nature of our hours of work term exposes our measures to measurement error, which could lead to division bias if the wage terms are obtained by dividing income by the hours of work. We discuss in Sections 4 and 5 how our econometric model appeases these concerns.

Finally, workers are asked to report, *in an ideal situation*, how many hours per week they would prefer to work implementing paid tasks/ work assignments via online platforms, which is our *desired hours of work* variable h^D, our main *stated preference* term. Appendix C reports all these survey questions in their original formulation.

The relationship between the search effort and paid work variables is central to our analysis and contributes to the definition of the task offer rate. We define the task offer rate as the additional hours of paid work that are generated by an additional hour of search, hence the ratio between hours of paid work and search $\rho = h/S$. This "shock" is not necessarily exogenous. While we assume it to be so in our theoretical Appendix A, our main specifications do not always make this assumption.

The task offer rate defines the relationships between all revealed labor supply variables. In fact, while the actual wage might be mechanically measured by dividing the income by the actual hours of work $w^A = wh(h + S)^{-1}$, the relationship simplifies to:

$$w^A = w\rho(\rho + 1)^{-1} \tag{1}$$

reminding us that the task offer rate is the only source of variation between the frictionless and the actual wage. Rearranging, we define the wage shock as

$$w^S = w^A/w = \rho(\rho + 1)^{-1}. \tag{2}$$

Similarly, the relationship between hours of work simplifies to $h^A = S(\rho + 1)$. This discussion underlines that understanding the nature of the task offer rate and ensuring it is effectively exogenous is key to the estimation of the search-induced elasticity.

Summary statistics for the hours of work and wage variables are reported in Table 1, suggesting significant variability in the hours of work and salary: the lowest decile of workers can work as little as 2 h per week against the 30 h of the highest decile, with the lowest decile of earners earning as little as €0.68 per hour in opposition with the

[7] In the empirical analysis, these differences are absorbed through controls for education, age, occupation, and other observables. Our estimation approach also ensures that our elasticity estimates are net of these individual characteristics. In fact, as highlighted by our results, removing these controls does not alter the estimated parameters.

[8] Directorate-General for Communication (2018). *Flash Eurobarometer 467: The use of the collaborative economy*. Available at https://data.europa.eu/data/datasets/s2184_467_eng?locale=en, last access: 18/11/2025.

[9] Depending on the platform and the degree of control over remuneration, workers are classified into four categories: online workers with control over pay, online workers with no control over pay, on-location workers with control over pay, and on-location workers with no control over pay.

Table 1
Summary statistics.

	(1) Platform workers				(2) Non-platform workers			
	Mean	sd	p10	p90	Mean	sd	p10	p90
Paid hours of work	12.926	12.606	2.000	30.000	–	–	–	–
Actual hours of work	22.086	19.749	4.000	45.000	–	–	–	–
Desired hours of work	19.692	15.080	4.000	40.000	–	–	–	–
Frictionless hourly wage	31.170	173.613	0.346	43.446	–	–	–	–
Actual hourly wage	13.594	59.949	0.176	21.978	–	–	–	–
Experience in platforms	4.731	4.455	2.000	11.000	–	–	–	–
Regular platform worker	0.734	0.442	0.000	1.000	–	–	–	–
Employed in trad. job	0.486	0.500	0.000	1.000	0.516	0.500	0.000	1.000
Non-platform hours of work	30.243	13.512	9.000	40.000	35.977	10.659	20.000	42.000
Non-platform income	1177.123	1341.861	0.000	2800.000	1537.476	1440.293	1.108	3300.000
Gender: Female	0.412	0.492	0.000	1.000	0.536	0.499	0.000	1.000
Married or living with a partner	0.621	0.485	0.000	1.000	0.597	0.491	0.000	1.000
Age	34.752	12.312	20.000	53.000	45.228	15.035	23.000	65.000
Born outside the survey country	1.911	0.284	2.000	2.000	1.946	0.226	2.000	2.000
Household size	3.040	1.226	1.000	5.000	2.655	1.247	1.000	4.000
Number of children	0.656	0.889	0.000	2.000	0.461	0.827	0.000	2.000
Education: Low (ISCED 1–2)	0.054	0.225	0.000	0.000	0.119	0.324	0.000	1.000
Education: Medium (ISCED 3–4)	0.315	0.465	0.000	1.000	0.394	0.489	0.000	1.000
Education: High (ISCED 5–)	0.631	0.483	0.000	1.000	0.487	0.500	0.000	1.000
Observations	2055				8883			

Notes: Mean, Standard Deviation and bottom/top deciles for individual-level descriptors. Sample of all workers having supplied at least 1 h of paid platform work in the reference week.

€46.15 per hour of the highest decile.[10] Most importantly, the hours of desired work appear to be smaller than the hours of actual work, suggesting already that, in ideal conditions, our respondents would rather devote much of the extra time to leisure rather than to additional work.

4. Empirical specification

In this section, we develop an empirical strategy for estimating the wage elasticity of labor supply in response to variations in task search, which we define as the *search-induced* wage elasticity of labor supply and which we treat as distinct from the *frictionless* wage elasticity, denoting responses to absolute changes in wage levels instead.

To address this, addressing the potential endogeneity issues in the task offer rate is central to our identification strategy. In fact, not only the frictionless wage w might be endogenous to unobserved individual characteristics X, but the task offer rate could also depend on X and/or w. The following diagram (Fig. 3) illustrates the relationships between the frictionless wage w, (unobserved) characteristics X, the task offer rate ρ, and the actual hours of work h^A. Each line represents a potential channel of influence on another variable.

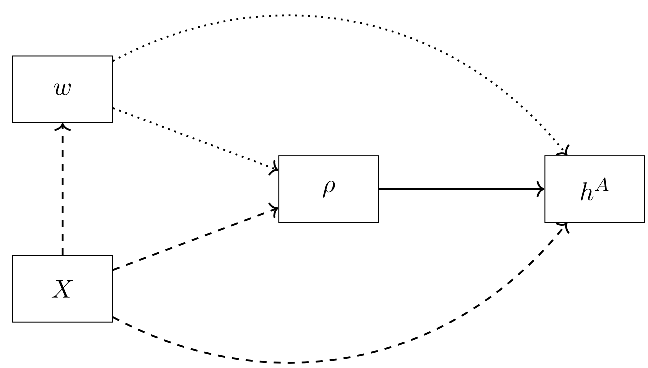

Fig. 3. Graphical representation of relationships between variables X, w, ρ, and h^A.

The task offer rate could, first, be endogenous to the frictionless wage. We define this channel as "weak" endogeneity. These instances occur when, for example, high-ability (or high profit-margin) workers are given priority when new tasks become available or when search times are affected by surge pricing or any other demand factors affecting the payout of a task. Other sources of variation in the wage, including targets and expectations, may similarly affect expectations of the task offer rate.

Secondly, even after controlling for the variation in the frictionless wage, other unobserved characteristics might still affect the task offer rate. We define this channel as "strong" endogeneity. Unobserved skill factors such as the ability to predict peak demand hours might allow workers to search more efficiently and can all be a source of endogeneity if they also affect the workers' supply. These characteristics can affect the task offer rate directly and/or through the frictionless wage term.

Finally, forms of measurement error in the hours worked could lead to division bias (Borjas, 1980) and recall error (Barrett and Hamermesh, 2019) in the wage elasticity, and this error term could affect the wage elasticity estimates. This is a common problem in labor supply models computing wages from income and hours of work when there is measurement error in the latter (Farber, 2005; Stafford, 2015).

To address these issues, we develop two parallel models. While both models aim to exploit residual exogenous variations in task search as a source of identifying variation, each model makes different and empirically testable assumptions on how to identify this variation. The first model assumes that the task offer rate is, net of the *frictionless* salary, an exogenous source of variation in *actual* earnings. In contrast, the second model assumes that the task offer rate is correlated with unobservable characteristics and aims to make it conditionally exogenous by absorbing individual fixed effects shared between *desired* and *actual* labor supply, assuming that stated supply choices are accurate. In our dual-model approach, these assumptions are likely to be satisfied if both models converge to the same estimates, mitigating the limitations inherent to self-reported measures, as explained later in Section 5.

[10] These extreme tails in the hourly earnings distribution are also attributable to the variation in hours of work: some workers work very little for very low, others work very little for very much.

For simplicity, we begin by detailing a pair of baseline models of labor supply for the estimation of generic wage elasticities, which we then develop into our final pair of models.

4.1. Baseline models of labor supply

Exogenous task offer rate and frictionless wage

The baseline models assume that both the task offer rate and the frictionless wage are exogenous. The first of these is the *baseline desired* specification. We assume that workers express their desired hours of work conditional on their usual pay rate w. Omitting the individual subscript i, the desired labor supply function is expressed as:

$$ln(h^D) = \alpha ln(w) + M'\beta + X'\delta + \eta_1 \tag{3}$$

where α is the elasticity of (desired) labor supply to the rate of pay w. As in textbook labor supply functions (Cahuc, 2014), M 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 labor supply participation. These can include both observed and unobserved preferences and all factors affecting efficiency in task completion, including ability and location characteristics.

This model assumes that no task search takes place in the desired equation because search is only a source of disutility so that w is simultaneously the actual and frictionless rate. Also, it assumes that the usual frictionless wage w coincides with the expected hourly rate of pay, and that is inclusive of idiosyncratic efficiency factors.[11] Under these assumptions, the desired supply equation might be treated as a hypothetical reference point under no search conditions.

The conditions characterizing the desired supply are never satisfied in reality. De facto, unpaid search adds up to the supply of h^A actual hours of work and lowers the actual (and final) rate of pay from w to w^A. The *baseline actual* labor supply equation is expressed as:

$$ln(h^A) = \alpha ln(w^A) + M'\beta + X'\delta + P'\zeta + \eta_2, \tag{4}$$

which is identical to the previous model with the exception of the outcome term and the wage term w^A, which is now discounted by the task offer rate (where $w^A = w\rho(\rho+1)^{-1}$). Furthermore, demand-side platform factors outside the worker's control can also intervene to affect the amount of work available, so the P term is included to represent different types of platforms.[12] As a matter of fact, we expect the search effort to be perceived differently depending on the nature of the platform: while *on-location* work will require a more active search effort, *online* work can allow for a more passive form of search. Similarly, workers who are able to set their own wage independently can substitute between higher search and lower payouts. These platform controls are omitted from the desired supply equation because, as mentioned, we assume that search and other demand-side constraints are not accounted for in desired ideal conditions.

Eqs. (3) and (4) can be difficult to estimate because of the endogeneity of the wage term caused by the unobserved part of the X vector. In other words, in both equations, the salary attached to α_1 still depends on unobserved characteristics, which could be endogenous to the hours of work. Furthermore, wage elasticity estimates from both equations would also be exposed to division bias and recall error, as these models offer no correction for the error term.

Furthermore, the two equations estimate a single elasticity term that compounds all sources of variation in salary into a generic one. Surge pricing, task search and many other factors can all be a source of said variation. Compounding these factors goes against our main goal of studying the effect variations in pay caused by task search net of variations in the pay rate. In the next subsection, we will discuss how separating the elasticity terms can help us with an unbiased identification of the wage elasticity of task search.

4.2. Final models of labor supply with endogenous task offer rate

Both baseline models rely on the same assumption of exogeneity of a single wage term. Our final pair of models improves upon our baseline models by (i) separating search-induced variations in wage from the frictionless component and (ii) making more distinct and specific assumptions on the endogeneity of the task offer rate.

The benefits of this approach are evident. By separating the wage variation into its two components, we can now study how workers, on average, value the time spent on search, regardless of other sources of variation in wage and individual characteristics.

4.2.1. Actual labor supply model

Task offer rate endogenous to the frictionless wage

The first model assumes that the task offer rate is uncorrelated with unobservable characteristics, but allows it to be endogenous to the frictionless wage.

The baseline actual labor supply Eq. (4) analyzed earlier ignores the presence of the *ex-ante* frictionless pay rate. However, the frictionless wage can be included to absorb the endogenous components affecting the actual rate as, by definition, the task offer rate ρ and the frictionless salary w are the only sources of variation in the actual wage (recall that $w^A = wh(h^A+S)^{-1} = w\rho(\rho+1)^{-1}$). We update the *actual* supply model as follows:

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

Should the task offer rate also depend on w, revealing itself as a function of the frictionless wage and the true task offer rate, controlling for the fully observed frictionless term will sufficiently control for variation in the task offer rate dependent on the frictionless salary.

If we assume, after controlling for w, the residual component of the task offer rate ρ to be uncorrelated with the potentially unobserved X term, Eq. (5) can consistently estimate the α_1 parameter by controlling for unobserved factors affecting w^A through w. This means that endogenous components of w^A, along with the possible sources of measurement error leading to division bias or recall error, will be absorbed by w so that w^A will only reflect the change in wage caused by the task offer rate, so that $w^A = w^S$. We can then treat α_1 as the wage elasticity of supply to the task offer rate experienced during a usual week. Henceforth, we refer to this parameter as *search-induced wage elasticity of supply*. We define this elasticity as the average response in terms of work and search effort to the variation in wage caused by the task offer rate.

Furthermore, the inclusion of the frictionless rate yields an additional elasticity parameter of interest in the form of α_2. The parameter captures the wage elasticity of supply under pre-search salary conditions, which include an idiosyncratic component, along with random shocks that might be caused by surge pricing, traffic, or any other factor affecting the pre-search wage. We refer to this parameter as the *frictionless wage elasticity of supply*. The interpretation of α_2 is not straightforward, as the expectation channel is also mediated by this parameter since the pay experienced during a week might not necessarily

[11] We will return to these assumptions later in Sections 5 and 4.2.

[12] As mentioned earlier in Section 3, we classify these platforms 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 that the services sold offline and online will also vary significantly in nature and feature different demand elasticities. Platforms can also exploit their monopsony power when they can exercise control over pay, ultimately affecting the total amount of work available. We then 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 platform type are shared between the equations and are to be included in the X vector instead.

correspond to its expectation. Since, as discussed, w^A only differs from w by the task offer rate ρ, it follows that expectations are also entirely captured by the parameter α_2. In short, the parameter will capture the effect of variation in the pay rate, along with its reference point.[13] Since X remains unobserved, α_2 might still suffer from endogeneity, but the next model will address this issue.

The final actual supply model relies on the single assumption of exogeneity of the task offer rate, net of variations in w. However, this assumption might be difficult to accept at face value. The task offer rate might still be endogenous if workers with higher skills also have better chances of finding tasks or better knowledge of the task offer rate. Higher skilled workers might also be able to influence the task offer rate (for example, by searching during specific hours or from multiple platforms), enabling them to raise their actual salary. The task offer rate might also be endogenous if measurement error that is not already absorbed by w is also correlated with the task offer rate, leading again to division (or recall) bias.[14]

4.2.2. First-difference labor supply

Task offer rate endogenous to unobserved characteristics

The second model addresses the possibility that the task offer rate might depend on unobservable characteristics and leverages the relationship between actual and desired supply to cancel out the unobserved term.

To introduce the next model, we begin by making the assumption that the baseline models of desired (3) and actual (4) supply share the same subset of parameters, leading to the system of equations:

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

As discussed earlier, this assumption implies that desired and actual hours of work are the product of the same supply function or, in other words, that stated and revealed supply preferences are comparable. In this scenario, both equations in system (6) model two optimal combinations of work and leisure under different work conditions and levels of salary. Later in Section 5, we discuss the conditions under which this assumption is satisfied and their implications for our estimates.

If this assumption holds, then 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:

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

obtaining first-difference estimators of the wage elasticity of labor supply. By taking differences, we now concentrate on how *changes* in wage affect *changes* in labor supply, while holding all idiosyncratic worker characteristics constant: in fact, the time-invariant $X'\delta$ term, including its unobserved components, is now canceled out.[15] Similarly, division bias and recall error are unlikely to pose an issue as long as the measurement error term in the hours of work also cancels out.[16]

In summary, by first differencing the two equations, all wage variations unrelated to the task offer rate are eliminated, allowing the generic wage elasticity parameter to be equated to its search-induced counterpart so that $\alpha = \alpha_1$.

Task offer rate endogenous to frictionless wage and unobserved characteristics

The previous model can be updated to fully lift the assumptions of exogeneity of the task offer rate. The last specification assumes that the wage is endogenous to X, but exogenous to w. We lift this assumption and reintroduce the frictionless wage, resulting in the following equation:

$$ln(h^A/h^D) = \alpha_1 ln(w^A/w) + \alpha_2 ln(w) + P'\zeta + \eta_3 \tag{8}$$

By canceling out X and controlling for w, the task offer rate is now fully rendered exogenous as long as stated and revealed supply choices are comparable. We henceforth refer to this model as the *first-difference* specification, and will refer to the previous model (Eq. (7)) as the *baseline first-difference* specification.

Furthermore, first-differencing allows us to obtain conditional independence for the *level* of frictionless salary (w), which is no longer endogenous to the outcome, meaning that α_2 will also be consistently estimated. As an additional benefit, removing the X term will free up several degrees of freedom and then allow for the estimation of wage elasticities in smaller samples.

Interpretation of the terms in the equation remains straightforward, as the parameters α_1 (search-induced wage elasticity) and α_2 (frictionless wage elasticity) can be interpreted as they appear in the actual supply model (5).[17] A variation in elasticity estimates indicates that changes in wage and the task offer rate are perceived as separate alternatives, each influencing workers' labor supply decisions in different ways.

Just as in the actual supply model, the first-difference supply model relies on strong assumptions, which can fail under specific conditions. However, as we detail in the next section, the strength of our approach resides in the fact that each model can support the other's results.

5. Validity assessment

5.1. General assumptions

The actual (5) and first-difference (8) supply models rely on different and independent assumptions. While the former assumes that the task offer rate is uncorrelated with unobservable characteristics, the latter assumes that the task offer rate is rendered conditionally exogenous after canceling individual fixed effects shared by the actual and desired supply equations.

In the next subsections, we analyze the robustness of our approach to measurement and recall error which would lead to division bias in our estimates.

While the assumptions underlying both models can be strong, both models will converge to statistically identical estimates for α_1. A simple z-test of coefficients between the two models will provide such a test. If this single test succeeds, we can safely argue that both models are

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[13] For an in-depth analysis of the effect of this disturbance on our estimates, see the discussion in Section 5 and the Monte Carlo simulations in Appendix G.

[14] We discuss all these scenarios in Section 5.

[15] The frictionless wage term w cancels out from w^A/w, so that the wage term now directly captures the task offer rate in the form of $w^A/w = \rho(\rho+1)^{-1} = w^S$.

[16] Compared to a "classic" division bias setting, the error is now time-invariant. Then, it is easy to prove that when the true hours terms equal $S^* = S\xi$, $h^* = h\xi$ (a case of proportional classical measurement error), then the error ξ clearly cancels out from the w^A/w term. This condition is sufficient for removing the error tem. If the desired hours are also affected by the same error, so that $h^{D*} = h^D\xi$, then the error also cancels from h^A/h^D but, if unaffected by this term or affected by a different error, the residual disturbance will not affect our estimates as long as it remains uncorrelated w^A/w. Other issues can arise if the error term is different between the search effort and the hours of paid work. We will see the implications of all these special cases of division bias in Section 5.

[17] An interesting caveat of this first-difference approach is that knowing that w^A/w equals h/h^A, the equation can be rewritten as $ln(h^A/h^D) = \alpha_1 ln(h/h^A) + \alpha_2 ln(w) + P'\zeta + \eta_3$. This equivalence is entirely expected and can help us understand how the α_1 term is not only related to the task offer rate as $w^A/w = h/h^A = \rho(\rho+1)^{-1}$. As long as the assumptions of the difference equation are met, α_1 remains consistently estimated.

correctly specified and both assumptions are satisfied, as, for higher levels of bias, it is increasingly improbable for both assumptions to fail and both models to produce the same results. All these properties can be shown via Monte Carlo simulation, as presented in Appendix G, where we show that, should any of the two assumptions fail, the estimates of either model will begin to diverge significantly.

Furthermore, comparing the results of these two models along with the *baseline first-difference* model can provide an additional indication of the exogeneity of the search to both X and w. Since model (5) assumes that the task offer rate is exogenous after controlling for w, model (7) after controlling for X, and model (8) after controlling for w and X, it follows that convergence between the three models will indicate that the task offer rate is also fully exogenous. Similarly, convergence will also indicate that stated preferences can be considered reliable and unrelated to the search effort.

Furthermore, we can follow the Altonji et al. (2005) and Oster (2017) test for selection on unobservables to further test for endogeneity in both ρ and w in the first-difference model. Variations in the elasticity estimates before and after conditioning on observable confounders will suggest that ρ and w might not have been rendered conditionally exogenous.

While the z-test remains a sufficient robustness check, in Appendix F we analyze a number of additional (but not necessary) checks that can further corroborate our approach and test for exogeneity of the task offer rate, comparability of the labor supply measures, and measurement error more directly. All these tests are included in the text of Section 6, where our main results are discussed.

5.2. Division bias

Our approach is robust to standard forms of division bias. This bias occurs when the wage is obtained by dividing the income by the observed hours of work when this term suffers from measurement error. This error can severely impact the estimates when this term is used as the outcome supply variable. Our actual hours of work variable might introduce this bias when used in both the actual and first-difference supply equation.[18]

In the standard case of proportional classical measurement error, it is a well-known fact that division bias disappears when the error is time-invariant (Angrist, 1991). Since our observations take place at the same time, the error is time-invariant and then completely absorbed in both models if this error is shared by all hours of work terms. This quirk allows us to overcome the limitations of self-reported data, which would otherwise lead to division bias and affect the estimated parameters.

In this standard setting, the observed search and paid hours of work terms equal $S^* = S\xi$ and $h^* = h\xi$, where ξ is the error term. Since the observed task offer rate is measured as $\rho^* = h\xi/S\xi$, it follows that the measured shock equals the real one $\rho^* = \rho$. As, in the actual (5) and in the first-difference supply Eq. (8), the α_1 term captures only the variation in the task offer rate after controlling for w in the former and dividing w^A/w in the latter, this form of division bias cannot affect our main estimates. The α_2 term from the first-difference model (8) might still be affected, so it is important to treat the frictionless wage elasticities with some caution.

In Fig. 4, using Monte Carlo simulation, we show the impact of classical division bias on our estimates, where the observed values used for the estimation of our models replace the error-free, true values.[19] We let the error term ξ vary between −0.25 and 0.25. The results underline how the α_1 parameter is completely unaffected by division bias in both models and that α_2, while affected by the bias, is subjected to a negligible, less-than-proportional effect.

5.3. Differential division bias

There is, however, a special case of measurement error that occurs when the recorded search effort is affected by a different source of error that is not shared by the observed hours of paid work term. While this might seem like a very specific edge case, it is plausible that individuals might give different salience to their hours of work and search, leading to this scenario, which we define as differential division bias.

Under this non-standard form of division bias, both models will produce the same results for the search-induced elasticity parameter, potentially invalidating our estimates. We show this in Fig. 5 where, using Monte Carlo simulation, we subject our estimates to increasing differential division bias. The econometrician, in this case, observes h^{A*}, inclusive of error, with observed wage term w^{A*}, while the observed h and w remain (for simplicity) error-free. Again, we let the error term vary between −0.25 and 0.25. The results immediately suggest that no matter the degree of bias, both models will still produce similar and biased estimates for α_1.

It is possible to detect the bias by looking at how the coefficients change after introducing the interaction between the wage terms.[20] In fact, this interaction will introduce spurious correlation into the model, increasing the variability of the estimates before and after the introduction of the term, as shown via Monte Carlo simulation in Fig. 6. Estimates which feature large variations after introducing the interaction term can be affected by differential division bias.

However, this test cannot sufficiently detect all instances of error. This discussion suggests that we might want to offer an additional robustness check to validate our estimates for both α_1 and α_2, the latter of which can, as discussed, already suffer from standard division bias.

We then propose an instrumental variable approach based on the “proxy instrument” approach from Borjas (1980) and the “grouping estimator” approach from Blundell et al. (1998). More specifically, we find instruments for w^A/w and w by creating wage measures that are unrelated to the observed hours of search and paid work. To do so, we group individuals by last non-platform occupation, country, and their interactions (all factors that can strongly influence the task offer rate), and, via OLS, we estimate their effect on search and the hours of paid work. After taking out occupation and country means from the fitted values, we are left with the occupation-country cells effect, with the assumption that any residual variation in wages across these cells is exogenous. Using these fitted values, we create instruments for w^A/w and w by dividing the individual platform work incomes by the fitted hours of actual and paid work and deriving the fitted shock and frictionless wage terms.

By doing so, we can remove the correlated error term from the wage terms and produce consistent estimates for our search-induced and frictionless elasticity. Compared to typical instruments, proxy instruments do not necessarily need to be exogenous. In any case, by using fitted hours obtained through the grouping approach, we can ensure that the wage variables produced are, at least in the denominator, exogenous. Our instrumental variable results are reported in Section 6.

6. Results

6.1. Labor supply estimates

Our labor supply estimates are shown in Tables 2 and 3. In Table 2, we offer average elasticities for all platforms. Platform-specific elasticities, obtained by interacting the elasticity terms with platform type P, (*heterogeneous* elasticities, henceforth) are shown in Table 3. Platform types are captured by the online or on-location nature of the services offered (*On-location worker*), the degree of control over pay that the worker enjoys (*Control over pay*), and the interactions

[18] The desired supply model, instead, is completely unaffected by division bias.

[19] The parametric set-up of the Monte Carlo simulation is described in detail in Appendix G.

[20] $\alpha_3 log(w^A) \times log(w)$ for the actual supply model and $\alpha_3 log(w^A/w) \times log(w)$ in the first-difference model.

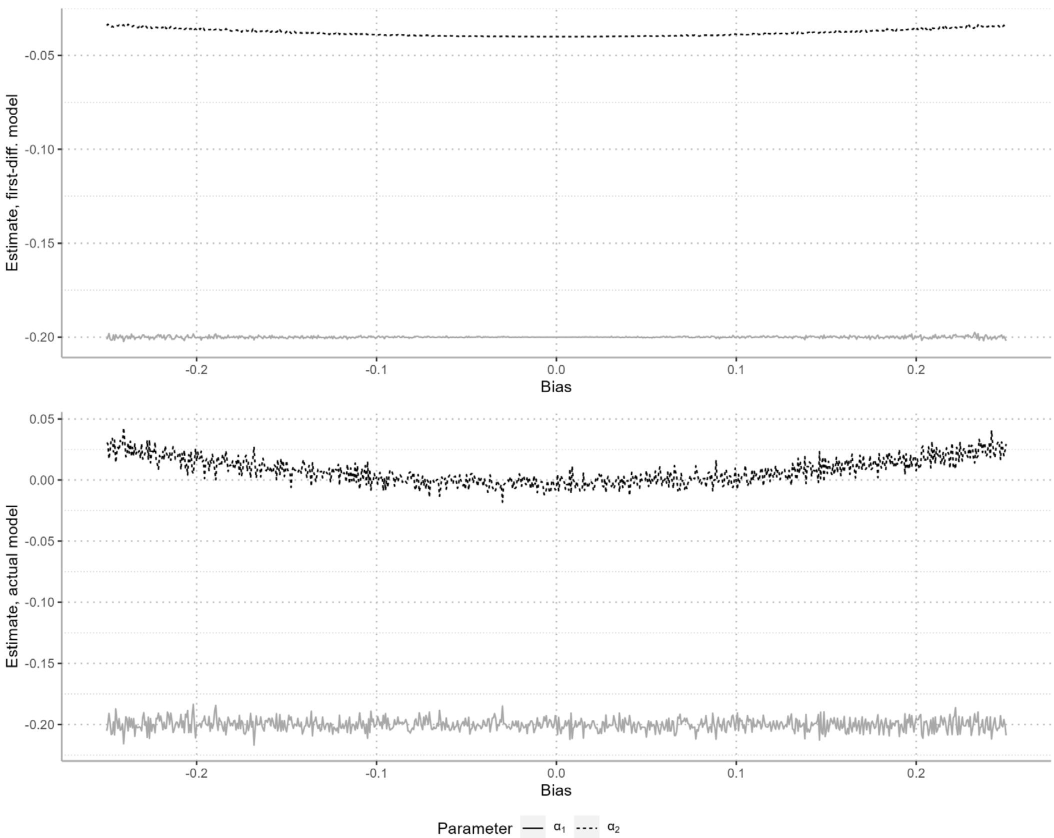

Fig. 4. Monte Carlo Simulation - Elasticity Estimates with classical division bias.
Notes: Monte Carlo results for the first-difference and actual supply models under varying levels of classical division bias.

Table 2
Labor supply elasticity estimates.

	Hours, desired (ln)		Hours, actual (ln)			Hours, first-difference (ln)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(11)
$w^{A,S}$		0.013	−0.153***	−0.224***	−0.219***	−0.202***	−0.236***	−0.234***	−0.223***	−0.238***	−0.239***	−0.196
		(0.054)	(0.017)	(0.044)	(0.044)	(0.045)	(0.045)	(0.045)	(0.044)	(0.042)	(0.056)	(0.132)
w	−0.090***	−0.116*		0.073	0.113**		−0.048***	−0.037**	−0.034*	−0.020	−0.047*	0.090***
	(0.016)	(0.052)		(0.042)	(0.042)		(0.014)	(0.012)	(0.014)	(0.012)	(0.018)	(0.020)
On-location worker		−0.070	0.125	0.118	0.134	0.162**	0.188***	0.206***			0.188***	0.129*
		(0.080)	(0.069)	(0.073)	(0.076)	(0.052)	(0.053)	(0.053)			(0.053)	(0.052)
Control over pay		0.006	0.099	0.080	0.098	0.053	0.059	0.055			0.060	0.089
		(0.133)	(0.111)	(0.111)	(0.112)	(0.106)	(0.105)	(0.101)			(0.105)	(0.047)
On-location worker × Control over pay		−0.006	−0.261*	−0.249*	−0.271*	−0.215*	−0.237*	−0.266*			−0.237*	−0.161
		(0.123)	(0.108)	(0.109)	(0.109)	(0.105)	(0.104)	(0.104)			(0.104)	(0.105)
Experience in platforms (yrs.)	−0.021**	−0.017*	−0.012	−0.013	−0.013	0.002	0.003		0.005		0.003	0.002
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)		(0.006)		(0.006)	(0.006)
Regular platform worker	0.157**	0.140*	0.134*	0.114*	0.099	−0.033	−0.030		−0.064		−0.030	−0.032
	(0.057)	(0.057)	(0.053)	(0.054)	(0.053)	(0.050)	(0.050)		(0.044)		(0.050)	(0.047)
$w^{A,S} \times w$					−0.027***						0.002	
					(0.004)						(0.019)	
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Last occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes
Platform controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes
Adjusted R-Squared	0.130	0.178	0.183	0.184	0.205	0.147	0.155	0.112	0.101	0.040	0.155	0.006
N	1590	1580	1592	1584	1584	1580	1580	1581	1580	1581	1580	1580
F-Test - wage shock IV												52.76
F-Test - frictionless wage IV												855.95

Notes: SE clustered by occupation/sector clusters in parentheses. All wage and labor supply variables are expressed in natural logarithms.
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

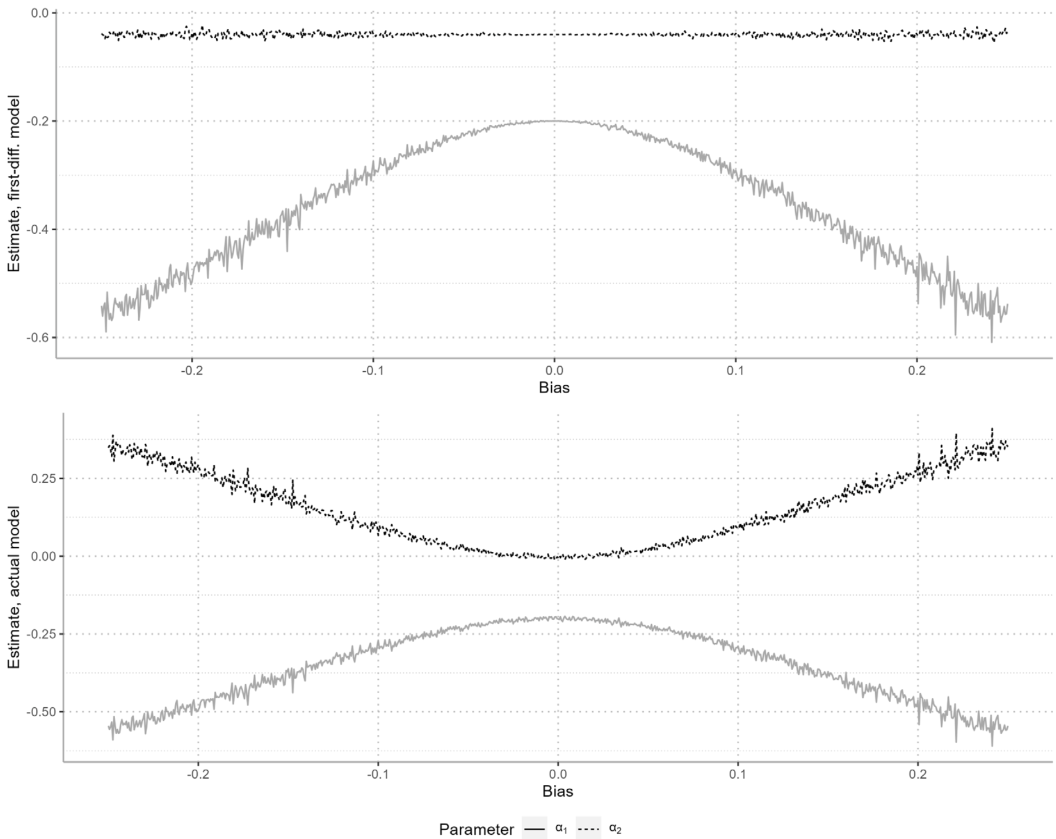

Fig. 5. Monte Carlo Simulation - Elasticity Estimates with differential division bias.
Notes: Monte Carlo results for the first-difference and actual supply models under varying levels of differential division bias.

between the two. All hours of work and wage variables are expressed as natural logarithms. Appendix D offers additional robustness checks, including specifications with heterogeneous elasticities interacting the wage terms with gender and access to traditional employment.

Our control variables are detailed below. These are split into sets of *individual controls*, *occupation fixed effects*, *platform controls* and *country fixed effects*.

Our set of *individual controls* (X) includes three subsets of variables. The first subset includes variables that are traditionally included in most labor supply models: age and its squared term, education (ISCED), foreign nationality, marital status, gender, the interaction between marital status and gender, partner's income (equal, higher or lower than respondent), household size, and the number of dependent children.

The second subset of individual characteristics includes controls for workers' idiosyncratic experiences on platforms, which can potentially generate non-linearities in search. Specifically, we account for the possibility that more experienced workers are better informed about optimal search schedules by controlling for years of experience in platforms and the regularity of the worker's activity in platforms over the last six months.[21]

The third and final subset controls for characteristics related to the respondents' access to "traditional" labor markets, which will inevitably affect the amount of time that can be allocated to platform work. Namely, we control for their employment status (that is, whether they have another non-platform job), hours of work in non-platform employment (in logarithm), and total income from other sources (in logarithm). The latter includes income from another job but also social security transfers.

Furthermore, we add intercepts for the interaction of the ISCO-08 occupation and NACE-Rev2 industry codes of the last non-platform occupation held by the respondent, treating the absence of prior labor market experience (that is, the "ever-unemployed") as the baseline level (*Last occupation FE*). 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 to platforms and, as such, they can proxy for unobserved ability. We also cluster standard errors by each occupation-sector cell (for a total of 180 clusters). In this way, we implicitly account for the possibility that the error residual follows a similar structure for people of similar skill.

Demand-side platform characteristics are instead included in the vector of *Platform controls*, that is, the P vector discussed earlier in Section 4. These include the generic platform types discussed above (*Online vs on-location; Control over pay*) but also a rich set of other minute characteristics of platform jobs that can capture demand-side variations in the task offer rate. These include the presence of the following benefits provided by the platforms: guaranteed minimum monthly or weekly salary, private health insurance, paid holidays, paid sick leave, insurance against accidents at work, work-related training, pension contributions, and paid parental leave.[22]

Organizational aspects of work in the platform are also included, specifically whether the platform: pays workers periodically rather

[21] 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 prefer to exclude such control because it is clearly endogenous to the search effort. Nonetheless, we have tested all our specifications with this control included and found no difference in our results.

[22] All responses are categorical: Not applicable/ Do not know; No; Yes; I have it, but not because of the platform.

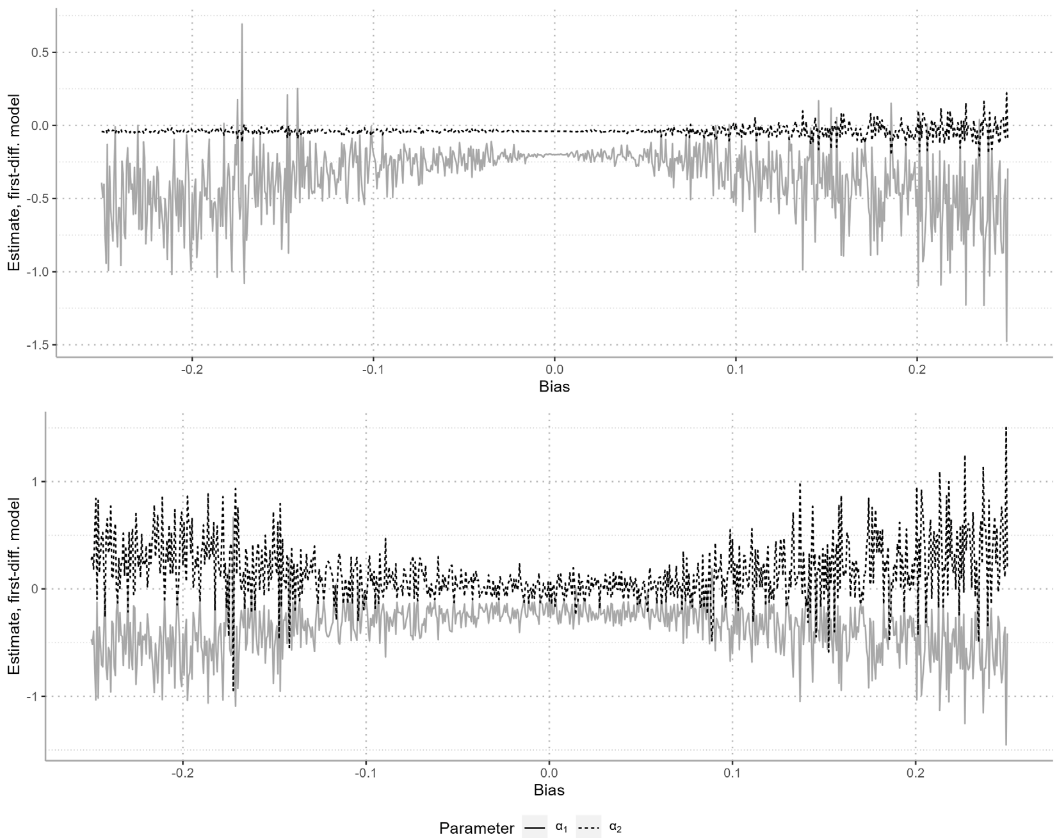

Fig. 6. Monte Carlo Simulation - Elasticity Estimates with differential division bias.
Notes: Monte Carlo results for the first-difference and actual supply models with wage term interactions under varying levels of differential division bias.

than on task completion, sets working schedules and/or minimum work periods, guarantees at least a minimum amount of work every week or month, allocates clients and/ or work assignments, disciplines workers when they refuse clients or work assignments (for example, account terminations, fewer assignments, etc.), provides tools, materials and/ or protective equipment, monitors the implementation of work assignments, and prevents workers from working via other similar platforms.[23]

Finally, intercepts for each country in the survey are added too (*Country FE*), to account for differences in platforms and contracts across the countries surveyed.

Looking at the main results, column 1 from both Tables displays generic wage elasticities for the desired labor supply, corresponding to Eq. (3), compounding both the base pay and the task search effects together. In all instances, the results seem to suggest a backward-bending labor supply curve, with a percentage increase in the (frictionless) wage leading, on average, to a statistically significant ~ 0.09 percentage point reduction in desired hours. There are no differences in sign between types of platforms, and the largest difference in magnitude is 0.041 log points.

While the elasticity estimates are not reliable because the frictionless wage may be endogenous to the desired supply, the inclusion of platform-side controls in column 2 allows us to perform a first test for the veracity of stated preferences. More specifically, we explicitly test whether the task offer rate affects desired supply outcomes by introducing the actual wage term in the equation. Further details on this test are discussed in Appendix F. Our results indicate that this effect is statistically zero. Platform types also appear to have little effect on desired hours, as all platform type coefficients are statistically insignificant. Furthermore, the inclusion of these controls does not seem to affect the frictionless elasticity, as a Z-test between the frictionless coefficients suggests that we cannot reject the null hypothesis that they are the same (Z-test: $0.479 < 1.96$). Table D.1 from Appendix D provides further checks in columns 1 and 2, first by removing all individual controls and then controlling for search. Similarly, negligible changes are also to be noted for the heterogeneous elasticities model (column 2, Table 3), as estimated elasticities show minimal changes after adding platform-side controls to the specification. These findings provide preliminary evidence in support of the idea that workers do not generally consider platform-side constraints when expressing their desired labor supply. In other words, the "ideal conditions" do imply zero search, suggesting that desired hours are revealed net of demand-side effects.

Actual hours are studied in columns 3 of both tables, corresponding to the baseline specification from Eq. (4). Estimates for α_1 from column 3 are negative and inelastic, and the magnitude of the effect is stronger than the one estimated for the desired hours specifications, suggesting that search-induced wage shocks contribute to a reduction of 0.153 log points in the actual hours of work. This holds true for the heterogeneous effects model from Table 3 as well.

The models presented so far prevent us from understanding how much negative estimates can be attributed to task search: in fact, the task offer rate is not a determinant of desired hours, while the baseline actual hours model still compounds all sources of wage variation together. Furthermore, column 3 results might still suffer from the same endogeneity issues affecting the desired hours equation. If the frictionless wage is not controlled for, the actual wage might be endogenous to the actual hours of work. We are now ready to move to our final models by separating the wage elasticity into its *search-induced* and *frictionless* components.

[23] All responses are categorical: Not applicable/ Do not know; No; Yes.

Table 3
Labor supply elasticity estimates, by platform type.

	Hours, desired (ln)		Hours, actual (ln)		Hours, first-difference (ln)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$w^{A,S}$ (Online worker, No control over pay)		−0.020	−0.120***	−0.277***	−0.235***	−0.256***	−0.256***	−0.179**	−0.173**
		(0.064)	(0.024)	(0.055)	(0.064)	(0.065)	(0.064)	(0.055)	(0.053)
$w^{A,S}$ (Online worker, Control over pay)		0.071	−0.166***	−0.140	−0.172*	−0.207*	−0.216**	−0.268***	−0.311***
		(0.115)	(0.027)	(0.081)	(0.081)	(0.082)	(0.077)	(0.077)	(0.074)
$w^{A,S}$ (On-location worker, No control over pay)		−0.068	−0.205***	−0.295*	−0.139	−0.225*	−0.210	−0.363***	−0.389***
		(0.132)	(0.031)	(0.114)	(0.111)	(0.108)	(0.106)	(0.091)	(0.092)
$w^{A,S}$ (On-location worker, Control over pay)		0.182	−0.187***	−0.003	−0.164	−0.186	−0.191	−0.218	−0.271*
		(0.156)	(0.040)	(0.146)	(0.137)	(0.155)	(0.146)	(0.131)	(0.120)
w (Online worker, No control over pay)	−0.082***	−0.060		0.165**		−0.031	−0.017	−0.038*	−0.020
	(0.021)	(0.065)		(0.055)		(0.018)	(0.016)	(0.018)	(0.016)
w (Online worker, Control over pay)	−0.076***	−0.186		−0.024		−0.049**	−0.036*	−0.032	−0.021
	(0.021)	(0.109)		(0.075)		(0.018)	(0.018)	(0.018)	(0.017)
w (On-location worker, No control over pay)	−0.110***	−0.038		0.089		−0.099***	−0.082**	−0.053*	−0.032
	(0.027)	(0.138)		(0.112)		(0.025)	(0.026)	(0.025)	(0.023)
w (On-location worker, Control over pay)	−0.123***	−0.341*		−0.191		−0.033	−0.045	−0.028	−0.031
	(0.031)	(0.146)		(0.137)		(0.043)	(0.037)	(0.038)	(0.034)
On-location worker		−0.057	0.225*	0.278*	0.221*	0.334**	0.355***		
		(0.146)	(0.093)	(0.121)	(0.098)	(0.101)	(0.101)		
Control over pay		0.114	0.149	0.250	0.092	0.124	0.113		
		(0.162)	(0.118)	(0.134)	(0.112)	(0.117)	(0.113)		
On-location worker × Control over pay		0.148	−0.333*	−0.253	−0.268	−0.401*	−0.379*		
		(0.223)	(0.139)	(0.189)	(0.167)	(0.182)	(0.179)		
Experience in platforms (yrs.)	−0.021**	−0.018*	−0.012	−0.013	0.003	0.003		0.005	
	(0.007)	(0.007)	(0.008)	(0.007)	(0.006)	(0.006)		(0.006)	
Regular platform worker	0.145*	0.137*	0.134*	0.109*	−0.035	−0.033		−0.053	
	(0.057)	(0.057)	(0.052)	(0.054)	(0.050)	(0.051)		(0.045)	
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Last occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No
Platform controls	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Adjusted R-Squared	0.132	0.182	0.186	0.192	0.148	0.158	0.115	0.105	0.046
N	1590	1580	1592	1584	1580	1580	1581	1580	1581

Notes: SE clustered by occupation/sector clusters in parentheses. All wage and labor supply variables are expressed in natural logarithms.
*p < 0.05, **p < 0.01, ***p < 0.001

We introduce the frictionless wage term in column 4, reaching our final actual supply specification from Eq. (5). The search-induced wage elasticity α_1, while negative and inelastic, appears to be larger in magnitude than the generic elasticity parameter estimated earlier, suggesting that a point percentage decrease in (actual) wage caused by task search leads, on average, to a 0.22 percent increase in the hours worked. Furthermore, experience and regularity of activity in the platform (a subset of individual characteristics X) retain the same sign and magnitude as in the desired supply model, but only regularity remains statistically significant.

The estimates for the frictionless wage elasticity α_2 are not statistically different from zero, pointing to the absence of a frictionless wage effect. However, these estimates for α_2 are far from final because the frictionless wage term might still be endogenous. Estimates for α_1 are more reliable but, as discussed earlier in Section 4, are only valid if the task offer rate is uncorrelated with unobserved characteristics in X, which is the fundamental assumption of the actual supply model. These same patterns can be observed in Table 3 (columns 3 and 4) when looking at platform-specific elasticities, this time with some elasticities turning fully inelastic after introducing the frictionless wage term.

In column 5, Table 2, we conduct a first test for differential division bias by interacting the two wage terms in the actual hours equation. The fact that the actual wage term is virtually unchanged (Z-test: $0.080 < 1.96$) does not suggest the presence of division bias. However, this single test is far from conclusive, as it is only a necessary but not sufficient test for division bias. Looking at the interaction term, its negative and statistically significant effect suggests some non-linearities with the frictionless wage. However, since the frictionless wage might be endogenous, this evidence is again inconclusive.

While we have ascertained that the task offer rate does not affect stated preferences for ideal working hours, we have not yet tested for its independence. We can conduct a first non-exhaustive test for the exogeneity of the task offer rate, testing whether it is correlated with unobservable characteristics. In Table 4, column 1, we test whether the search effort is correlated with individual characteristics after controlling for the frictionless wage. Our results suggest that this is not the case: none of the individual-level coefficients are statistically significant, and a joint test of significance suggests that we cannot reject the hypothesis that these coefficients are jointly zero at the 5% significance level. Furthermore, we test for joint significance of the individual controls vector again after removing the wage (column 2), occupation fixed effects 3, and platform controls (column 4) to find that these individual-level predictors have no effect on the search effort.[24]

[24] Furthermore, these results suggest that these ability factors do not even indirectly affect search through the frictionless salary, reinforcing the results from Cantarella and Strozzi (2021) which suggested that the frictionless rate of pay in online platforms is independent of idiosyncratic ability.

In any case, we cannot rule out that other unobserved characteristics might intervene in the task offer rate.

We then study the baseline first-difference Eqs. (7) and (8) in columns 6 to 11 in Table 2 and columns 5 to 9 in Table 3. As we discussed in Section 4, the first-difference model relaxes the assumption that the task offer rate is exogenous and relies instead on the central assumption that the vector of observed and unobserved characteristics X is canceled out via first-differencing. The baseline specification from column 6 suggests that a point percentage search-induced decrease in wage corresponds to a 0.20 percent increase in the hours of work, significant at the 0.001 level. Reintroducing the frictionless wage term in column 7, we obtain the final first-difference model, and the wage elasticity coefficient turns to −0.22 percent. Our tests suggest that the two actual wage coefficients are not statistically different from each other (Z-test: $0.534 < 1.96$), supporting the assumption that the task offer rate is fully exogenous. Furthermore, the coefficients for years of experience in the platform and for regularity of activity in the platform turn statistically zero once we move to the first-difference model, suggesting that platform experience does not affect the variation between actual and desired hours of work and that these idiosyncratic supply-side factors have indeed been absorbed via differencing.[25]

The canceling of the X vector suggests that estimates for the frictionless wage elasticity α_2 from columns 6 and 7 of Table 2 and column 6 of Table 3 are net of unobserved individual characteristics affecting the salary. In column 7, Table 2, we estimate that a point percentage increase in the frictionless wage leads to a 0.048% reduction in the final supply. These estimates suggest that most of the negative elasticity estimates associated with the generic wage are due to variations in the task offer rate and that wage changes not framed as task offer rates are associated with a much more inelastic response, in line with the estimates from the literature on platform work.

Platform-specific elasticities from Table 3 also point to negative search-induced elasticities for all workers (columns 6 and 7), albeit statistically significant at the 0.001 level for the subset of online workers with no control over pay, which is also our sample's largest group of workers. The standard errors are larger due to the smaller size of each subsample of platforms, but, in general, there are no differences in a statistical sense between the coefficients from columns 6 and 7 after the introduction of frictionless wage interactions. Frictionless wage elasticities, while negative, are again revealed to be much more inelastic than search-induced elasticities.

As discussed in Section 4, the fact that wage elasticity coefficients from the first-difference model are statistically unchanged from those estimated in the labor supply model with actual hours worked provides a fundamental double-robustness test for our models, suggesting that our estimates are not affected by endogeneity in unobservable characteristics affecting the task offer rate.

Comparing the α_1 coefficients between the final actual (column 4) and first-difference (column 7) supply models, Table 2, our tests reveal that the coefficients are not statistically different from each other (Z-test: $0.191 < 1.96$), providing the additional finding that the task offer rate is exogenous to individual characteristics contained in X, and that the desired supply equation is parametrically identical to the actual supply equation. Similarly, the difference in coefficients between columns 5 and 6 remains statistically not significant (Z-test: $0.349 < 1.96$), which would not otherwise be if the task offer rate were endogenous. As discussed in Section 5, the double robustness test is exhaustive, being sufficient and necessary for establishing the validity of the assumptions of either model. Similar estimates emerge between the actual and first-difference model when looking at platform-specific elasticities in Table 3, columns 4 and 6, although the lower statistical power introduces more variability.

Nonetheless, other tests can be offered to further support our arguments. Columns 8 to 10, Table 2, test the robustness of the estimates from column 7 by removing sets of variables in a stepwise fashion, further testing for endogeneity.

We begin in column 8 with the strong endogeneity tests by removing all individual-level controls and last-occupation fixed effects corresponding to the first-difference supply model from Eq. (8) in which X was canceled out. These include platform-specific experience terms, which, as can be seen from the Table, are already turned statistically zero in the first-difference specification. The removal of all regressors has a very small effect on our elasticity estimates ($\alpha_1 = -0.234$, $\alpha_2 = -0.037$) with a minor influence over the overall predictive power of the model. Further tests reveal that we cannot reject the null hypothesis that both coefficients α_1 (Z-test: $0.032 < 1.96$) and α_2 (Z-test: $0.596 < 1.96$) remain the same even after removing all other individual controls in the model. Similar conclusions can be drawn from the heterogeneous elasticity models from Table 3, as the differences between columns 6 and 7 remain minimal and statistically not significant. These results suggest that the task offer rate is independent of unobserved individual characteristics affecting only one of the two supply equations.

We repeat these tests in columns 9 and 10, Table 2, first by removing all platform-side controls and then all platform and individual controls. While we do not expect our estimates to be robust to the removal of platform-side controls,[26] we still note that our wage elasticity estimates are relatively unaffected by the removal of these controls. The fact that the α_1 coefficient remains statistically unchanged even after nearly all controls have been removed (column 9, Table 2) suggests that labor supply elasticities might even be estimated semi-parametrically.

The α_2 coefficient loses some of its magnitude (but the magnitude of the standard error is unchanged) after the removal of these controls, suggesting that the platform characteristics might play an important role in shaping workers' expectations or introduce further variability in the frictionless salary. Similar findings can be drawn from the heterogeneous elasticity estimates from Table 3, columns 8 and 9. Here, the standard error is not low enough to warrant significance for many of the estimated elasticities. The smaller size of each platform-specific cell probably prevents us from absorbing the variability in w, explaining the larger variation across each platform-specific estimate relative to the results from Table 2. The estimates remain, nonetheless, far from inconclusive, as the actual and frictionless wage elasticities remain negative and higher than -1.

We conduct a final test for the presence of measurement error in column 11 of Table 2 by introducing an interaction between the two wage terms, yielding the α_3 parameter. As discussed in Appendix F, the introduction of the interaction term should leave our elasticity estimates unchanged from our main specification. Our statistical tests suggest that there is no difference in a statistical sense between the elasticity estimates from columns 6 and 10 (α_1, Z-test: $0.041 < 1.96$; α_2, Z-test: $0.044 < 1.96$). Furthermore, a non-zero interaction effect would suggest that there is residual variation in supply driven by the wage that is not explained by our two wage terms. However, the estimated interaction coefficient α_3 is statistically not significant and close to zero in magnitude (0.001), while the estimates of α_1 and α_2 are fundamentally unaffected, further reinforcing the validity of our estimates. This test suggests that measurement error is negligible and that, in this scenario, it does not affect the validity and consistency of the estimates for both elasticities.

[25] To test for sample selection, we also tested the same model on a subsample of 614 workers who, other than being active in the last six months, have started working in a one-year window (six-month windows could not be obtained from the survey). Although the full results are not presented in the Table to maintain a clear focus on the main findings, the α_1 and α_2 coefficients remain virtually unchanged, shifting to −0.248 (0.063) and −0.044 (0.025), respectively.

[26] Recall that, in the model (8), the P vector is not canceled out.

Table 4
Search effort, individual determinants.

	Search effort (ln)			
	(1)	(2)	(3)	(4)
w (ln)	−0.041**			
	(0.016)			
Non-platform income (ln)	−0.011	−0.028	−0.022	−0.031*
	(0.018)	(0.016)	(0.016)	(0.014)
Non-platform income (zero)	−0.106	−0.270	−0.237	−0.230
	(0.157)	(0.145)	(0.140)	(0.126)
Education: Medium (ISCED 3-4)	−0.081	−0.076	−0.068	−0.074
	(0.123)	(0.123)	(0.119)	(0.117)
Education: High (ISCED 5-8)	0.026	0.026	0.009	−0.010
	(0.130)	(0.130)	(0.124)	(0.122)
Gender: female	−0.012	0.005	0.005	−0.016
	(0.082)	(0.082)	(0.079)	(0.074)
Married or living with a partner	−0.038	−0.025	0.016	0.046
	(0.069)	(0.069)	(0.067)	(0.067)
Female × partner	0.038	0.021	−0.002	−0.010
	(0.108)	(0.108)	(0.104)	(0.106)
Partner's income: similar	−0.061	−0.060	−0.062	−0.042
	(0.074)	(0.073)	(0.071)	(0.070)
Partner's income: lower	−0.066	−0.071	−0.078	−0.148
	(0.075)	(0.076)	(0.076)	(0.075)
Age	0.007	0.009	0.012	0.006
	(0.014)	(0.014)	(0.013)	(0.013)
Foreign born	−0.017	−0.029	−0.049	−0.060
	(0.102)	(0.102)	(0.099)	(0.095)
Household size	0.002	0.002	0.000	0.005
	(0.027)	(0.027)	(0.027)	(0.027)
Number of children	0.024	0.018	0.019	0.035
	(0.032)	(0.032)	(0.031)	(0.031)
Regular platform worker	−0.042	−0.041	−0.047	−0.077
	(0.055)	(0.055)	(0.055)	(0.055)
Experience in platforms (yrs.)	−0.005	−0.005	−0.004	−0.000
	(0.007)	(0.007)	(0.007)	(0.006)
Country FE	Yes	Yes	Yes	Yes
Last occupation FE	Yes	Yes	No	No
Platform controls	Yes	Yes	Yes	No
Adjusted R-Squared	0.090	0.086	0.068	0.015
N	1580	1580	1580	1580

Notes: SE clustered by occupation/sector clusters in parentheses. Joint test of significance (individual controls): Specification (1) $F(17, 179) = 0.64$, Prob > F = 0.851; Specification (2) $F(16, 179) = 0.85$, Prob > F = 0.623; Specification (3) $F(16, 179) = 0.76$, Prob > F = 0.732; Specification (4) $F(16, 179) = 1.49$, Prob > F = 0.107. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

The models presented so far cannot fully dispel the possibility that our estimates of α_2 and α_1 are affected by measurement error in the hours of work and search, leading to division bias and differential division bias, respectively. We conduct a final test for division bias in column (11), which offers instrumental variable estimates for the first difference model, where the wage shock and the frictionless wage are instrumented by wage proxies obtained by dividing the individual income by the de-meaned predicted hours of work in our occupational and country cohorts, combining the methods from Borjas (1980) and Blundell et al. (1998), as we discussed in Section 5. Both instruments pass conventional first-stage tests, with F-tests of 53.76 and 855.95, respectively. The instrumental variable approach urges us to reassess our estimates for the frictionless wage elasticity of supply. In fact, while the estimate remains nearly inelastic, the sign of the coefficient is flipped, suggesting that a 1 percent increase in the frictionless wage leads to a less than proportional 0.09 percent increase in supply. The instrumental variable estimates for the search-induced elasticity of supply are, instead, nearly unchanged in their sign and magnitude, albeit statistically not significant.[27] These results suggest that, while division bias can plausibly affect our frictionless estimates, its non-standard differential form is most likely not affecting our search-induced wage elasticity estimates.

Appendix D offers some more minor checks. Among these, we test for other minor measurement error issues and heterogeneity in labor supply conditional on gender and access to "traditional" labor markets, which we both find not to be statistically significant.

6.2. Discussion and interpretation

Our results show that platform workers react to variation in task offer rate by increasing their labor supply, regardless of platform type. In particular, we find that workers adjust to pay rate variations caused by task search by increasing their supply by about 0.20 percent for each percentage decrease in wage. These results emerge even taking into account the potential endogeneity of the shock, suggesting that our results are not affected by division bias. Overall, these results suggest a systematic pattern in which individuals increase their work effort in response to greater shocks. These results align with the target-earning literature and recent research on the framing of wage changes, suggesting loss aversion and the presence of endowment effects in task search. Especially if task search is perceived as the default state of work, workers might prefer to keep looking for jobs rather than quitting because deviations from default norms generate greater expectations of regret. While other explanations might entail that workers are slow to update their beliefs about the actual wage, the fact that these estimates are obtained using usual measures of search and hours of work means that these are systematic responses to anticipated variations in the task offer rate and not the result of transitory changes.

As both of our selected labor supply models converge on the same estimate, the underlying assumptions of each model are also met, resulting in two additional findings. First, the validity of the first-difference model indicates that the stated preferences of platform workers, which we use as hypothetical earnings targets, are quite reliable and parametrically comparable to their revealed preferences. It follows that variations in stated and revealed preference statements, even when these statements are individually unreliable, can reliably be used for inference. Second, the validity of the actual model suggests that variations in the task offer rate are exogenous to the workers, implying that workers have little influence over the effectiveness of their search efforts.

Our findings also indicate that the supply effect of earnings net of task search is significantly different than the effect of task search. For each percentage point increase in the rate of pay net of search — that is the *frictionless* wage — the supply is reduced by around 0.04 percentage points only. Instrumental variable estimates suggest that the real effect, corrected for division bias, might be positive, but still inelastic (0.09 percentage points). These results are fairly aligned with the inelastic wage elasticities found in the literature on platform work and suggest that search-induced elasticities are *qualitatively* different from other measures of wage elasticity.

7. Conclusions

This paper examines how platform workers adjust their labor supply in response to variations in task search time, defined as the unpaid hours spent waiting for or seeking assignments. Using a comprehensive survey of European platform workers, we employ two complementary estimation methods to ensure reliable results while addressing potential biases in self-reported data. The first method assumes search time variations are exogenous, while the second controls for endogeneity by comparing workers' actual behavior with their stated work preferences.

Our findings demonstrate that workers consistently increase their working hours when task search becomes more time-consuming, regardless of platform type. This behavioral response reflects workers'

[27] This is, however, an understandably common occurrence when using instrumental variables. The relatively weaker first stage for the wage shock might explain the larger standard errors compared to the error of the frictionless elasticity term.

attempts to maintain their income targets despite reduced efficiency from prolonged search periods. The results provide strong evidence for target-earning behavior, where workers compensate for effective wage reductions by extending their labor supply. Importantly, the analysis reveals two distinct labor supply elasticity patterns: workers exhibit negative labor supply elasticity when wages decline due to longer search times, but show near-zero (inelastic) responses to direct wage changes. These divergent responses reveal that search frictions trigger fundamentally different worker behaviors compared to pure compensation adjustments in platform labor markets. These findings have crucial implications for understanding platform market power. The combination of negative elasticity for search-induced wage reductions and inelastic responses to direct wage changes indicates that platforms possess substantially greater monopsony power than previously estimated. Unlike studies documenting positive but inelastic labor supply, this evidence shows that platforms benefit doubly: workers increase hours when search becomes less efficient (i.e., more time-consuming) while remaining unresponsive to direct pay cuts. These negative search-induced elasticities appear universally across all platform types, whether online or in-person, regardless of workers' control over pay. This consistency suggests that loss-averse responses to search-induced wage reductions represent a structural feature of platform work rather than platform-specific characteristics. Whether this behavior stems from worker self-selection into platform work or from the inherent nature of freelance employment arrangements remains an open question for future research.

These findings have significant implications for the proposed EU Platform Work Directive,[28] which aims to reclassify many autonomous platform workers as employees entitled to hourly wages and protections under the Working Time Directive. This directive would require compensation for idle "stand-by" time, directly addressing the unpaid search periods documented in this paper. By demonstrating how unpaid search time systematically reduces worker welfare while enhancing platform market power, this research provides empirical support for the directive's regulatory approach and reinforces the need for intervention that recognizes the full scope of time workers dedicate to platform work.

However, effective regulation must extend beyond employment reclassification to address the systemic nature of unpaid labor in platform work. This requires establishing minimum working time and wage standards, recognizing workers' subordinate employment status, and guaranteeing contractual minimum hours. While hourly-paid employment models reduce unpaid work compared to piece-rate arrangements, they remain insufficient without predictable scheduling guarantees. Comprehensive reform should also mandate data transparency and portability rights for worker ratings and portfolios to support career development, while granting platform workers access to collective bargaining mechanisms and representation structures. Finally, revising EU competition law would enable collective agreements across different platform labor categories, addressing current regulatory gaps that limit worker protection and perpetuate the market inefficiencies documented in this research.

We conclude with a short discussion of the limitations of our approach. From a methodological standpoint, task search remains a self-reported measure, and our identification strategy can only partially alleviate the measurement error connected with such subjective dimensions. Similarly, a more ontological issue concerns the nature of platform workers sampled in this study, as the distinction between platform workers and misclassified respondents becomes subtle, especially when responses are sampled from online panels. The quality and robustness checks implemented can mitigate these issues, but some uncertainty might persist, as we cannot know what qualifies as task search for misclassified respondents. Future research on these frictions should therefore leverage data from platform registries or field experiments, where the boundary between work and search is directly observable rather than self-reported.

[28] Ibid .

CRediT authorship contribution statement

Michele Cantarella: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Chiara Strozzi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Theoretical framework

We present a model of labor supply in the presence of job search and uncertainty. This is a simple framework that does not take into account the behavioral mechanisms that might give rise to loss aversion and other non-rational behaviors. The model's main purpose is to introduce our main concepts and show how uncertainty in task search leads to difficulties in reaching an analytical solution to supply optimization, motivating our empirical approach in Section 4. 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 labor supply in the presence of task search and refer to the latter to model uncertainty in task search. While we borrow from both sources, we also depart from each one by using more specific assumptions that could better fit the functioning of online platform labor markets. Following these approaches to show how the task offer rate reduces to a multiplicative wage shock with the same implications for supply optimization studied in Parker et al. (2005) is also valuable.

In our theoretical model, we assume that job offers (that is, available tasks) appear directly in the platform (or are sent to the worker) as soon as they are available. Each task (job) is compensated by an advertised reward, which is known to the worker. In the reference period t, define as $\bar{w}$ expected pay-out for the tasks that worker i can potentially perform.[29] 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 searching for available tasks. The *search effort* is conducted at the expense of leisure (l) only, as paid work hours (h) can only result from search: with no search, workers find no 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 job opportunities were not revealed through search.[30] In our framework, search generates additional hours of paid work in the same reference period. The time workers spend searching for a job is S, which is the number of hours workers spend looking for

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

[30] Similarly, our model ties with the on-the-job leisure labor 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.

available tasks or job offers on the platform. As paid work is revealed through search, search is the only choice variable available to workers.

Paid work hours are then 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 is separable so that, at the end of the reference period[31]:

$$h = H_a(\bar{w}, a) H_s(\bar{w}, L, S). \tag{9}$$

The first term refers to a wage/efficiency-specific shock, revealing the average amount of time it would take the worker to perform a task of value $\bar{w}$. It is a function of the expected pay-out and the factor a, which can include ability, location, and any other factors contributing to how quickly a worker can complete a task. The second term is the search function, revealing how many tasks of expected pay-out $\bar{w}$ are found conditional on search. Note that, as there is no substitution between labor and capital, capital is omitted from the labor demand function, and since L is also fixed in the reference period, the search function reduces to $H_s(\bar{w}, S)$.

We assume the search function takes a simple linear form, assuming no increasing or decreasing returns to the search or intercept terms. We further separate the function and model it as $H_s(\bar{w}, S) = H_w(\bar{w})S$. The term $H_w(\bar{w})$ can be treated as an idiosyncratic *task offer rate* $\rho = H_w(\bar{w})$ capturing labor demand by revealing how many potential tasks of value $\bar{w}$, on average, are turned into actual jobs for an extra unit of search.

The worker does not know the true functional form of $H_s(\bar{w}, S)$, so the idiosyncratic functional form that each worker experiences after searching can be approximated with a single parameter. The true entity of the final idiosyncratic shock ρ is unknown to workers, as the demand parameters and concurrent aggregate supply are also unknown. Workers can form expectations on the shock so that the realized shock will then equal its expectation plus a random stochastic term $\rho = E[\rho] + \theta$.

This specification comes with two important simplifications. First, we have assumed that the task offer rate is linear in search. Secondly, expectations on the shock are assumed, for now, to be uncorrelated with individual characteristics or the wage. These are naive simplifications which are only made to make our theoretical model concise and tractable. As discussed in Appendix B, a non-linear form implies that the task offer rate is also endogenous to the wage. Similar arguments are made when the expectations (and the ability to manipulate the shock) are endogenous to unobserved individual characteristics, as discussed in Section 5. Our empirical model (Section 4) lifts all these assumptions.

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:

$$S \le T(1 + \rho H_a(\bar{w}, a))^{-1}; \qquad S \ge 0. \tag{10}$$

The function $h = H_a(\bar{w}, a)\rho S$ 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 pay rate in two separate ways. To see how begin with the hourly *frictionless* rate of pay w. This is obtained by dividing platform income in the reference period by the total amount of paid hours, so that

$$w = \bar{w}\rho S(H_a(\bar{w}, a)\rho S)^{-1} = \bar{w} H_a(\bar{w}, a)^{-1}. \tag{11}$$

The rate of pay corrected for unpaid hours is the hourly *actual* rate of compensation and, being equal to $w^A = wh(h + S)^{-1}$, simplifies to:

$$w^A = w\rho(\rho + 1)^{-1} \tag{12}$$

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 frictionless compensation.

[31] We define as reference period the time that occurs between the start and the end of a working session. In our empirical setting, this lasts a week.

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 task offer rate. The simple proof is detailed in Appendix B, and has important implications for our empirical strategy, as it justifies our approach of separating search into 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 optimization problem for an individual at period t then follows $\max_{C,S}\{U(C, h^A)\}$. The expected utility is expressed as:

$$U(C, h^A) = \int_{-\infty}^{+\infty} U_c(C)\, dF(\theta) + U_h(T - l)$$
$$= \int_{-\infty}^{+\infty} U_c(\bar{w}(E[\rho] + \theta)S + \mu)\, dF(\theta) + U_h(T - l) \tag{13}$$

where C is consumption, which equals

$$C \equiv wh + \mu = \bar{w}(E[\rho] + \theta)S + \mu \tag{14}$$

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 is immediately evident in Eq. (14) 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 labor supply for an increase in uncertainty, even under separable utility. This can be shown from the first order condition for labor supply:

$$\bar{w}(E[\rho] + \theta)U_c'(\cdot) + U_h'(\cdot) = 0 \tag{15}$$

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

The pay-out might be known for platform workers with control over the pay-out and for those for whom the platform controls the pay-out but has little time variation. 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.[32] What matters for our purposes is that, even in a highly stylized scenario in which the payout is certain, the model still reduces to a labor supply model with uncertainty in pay.

An alternative approach would require modeling the expectation formation process task-by-task in a manner that is not dissimilar to the one that Stenborg Petterson (2022) follows when modeling taxi drivers' reference points with a Markov process. However, solving the model for a change in the task offer rate before the worker experiences it remains effectively impossible.

An important implication of the utility maximization problem is that optimal search will depend, *ceteris paribus*, on the frictionless hourly

[32] The implications of wage uncertainty for our empirical model are discussed later in Section 4.

earnings (and, by extension, efficiency) and the expectations on the task offer rate. Ultimately, these expectations remain unobserved, and their effect on supply remains ambiguous. This is a matter that can only be settled empirically.

Appendix B. Non-linear task offer rate

Assuming a linear form for the search function, it is easy to show that the rate of change from the *frictionless* to *actual* wage is independent of search. Omitting the individual subscripts, we obtain this equation:

$$\frac{w^A}{w} = \frac{h}{h^A} = \frac{H_a(\bar{w}, a)\rho S}{H_a(\bar{w}, a)\rho S + S} \tag{16}$$

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

$$\frac{dw^A}{dwS} = \frac{d}{dS}\left(\frac{H_a(\bar{w}, a)\rho S}{H_a(\bar{w}, a)\rho S + S}\right) = 0 \tag{17}$$

This shows that, under the assumption of a linear task offer rate, the search effort cannot determine the rate of change between actual and frictionless salary, but only by the task offer rate. This is, after all, already an implication of the nature of w and w^A.

The only consideration that applies is that the choice variable (the search effort) has to be independent of efficiency a for the function $H(W(a), S)$ to be separable. This assumption is reasonable and, at the same time, similar to assumptions which have been treated as standard in the related literature, such as Stenborg Petterson (2022). In other words, the decision to keep searching is independent of efficiency factors after holding the pay rate fixed.

We then turn to the non-linear specification. The claim that w^A is not related to S relies on the specific functional form assumption of ρS. Different specifications might change this result.

For example, assume that the search function has a positive intercept term, which indicates that workers acquire a minimum number of tasks without searching. When the search function is specified as $\rho S + K$, the ratio of w^A/w becomes:

$$\frac{w^A}{w} = \frac{H_a(\bar{w}, a)(\rho S + K)}{H_a(\bar{w}, a)\rho(\rho S + K) + S} \tag{18}$$

In this case, S will not be easily canceled out, and w^A/w will become a function of S, and therefore violate the exogeneity condition by depending on w. Similarly, if the search function takes any non-linear form to capture increasing/decreasing returns to the search effort, w^A/w will also become a function of S. The implications are clear: for a lower or higher level of effort, the rate of change in salary will also change.

These considerations delimit the application of our simplified theoretical model to a supply-only equilibrium, which, demand-side, takes into account only the final task offer rate experienced by each worker once the working week has ended. At the end of the working week, workers have already experienced the salary change w^A/w, and have already adjusted their labor supply for w^A, the hourly rate they settled with. What matters for each worker, *given* w^A/w and their utility function, is whether a different level of supply h^A and then S would have been more optimal, no matter if w^A/w would have been different under a different level of search.

This suggests that a non-linear task offer rate might be endogenous to the frictionless wage w, which is the main determinant of the search effort. Our empirical models explicitly address this problem by controlling for w. Further issues are related to the situation in which the shock is endogenous to X, that is when workers' skills correlate with the ability to predict the shock or to manipulate it and enter the search function. We discuss these issues in Section 4.

Appendix C. Survey questions: original text

The questions below are in the original English-version text of the survey.

Usual paid work and search hours:

> (11) Think about a usual week that you have worked via online platforms. How many hours per week did you spend searching or waiting for tasks/ work assignments, and how many implementing them?
>
> (11a) Hours per week searching or waiting for tasks/ work assignments or implementing other unpaid tasks: ...
>
> (11b) Hours per week implementing paid tasks/ work assignments: ...

Desired work hours:

> (12) In an ideal situation, how many hours per week would you prefer to work implementing paid tasks/ work assignments via online platforms? ...

Last month earnings:

> (52) In the most recent month when you worked via online platforms, how much did you earn from this work, after taxes and platform fees?
>
> Please enter the approximate amount in [national currency]. ...

Appendix D. Additional robustness checks

Table D.1 offers further robustness checks for our results from Table 2, and studies heterogeneous effects with gender and access to employment.

Column 1 tests for the possibility that workers overestimate their ability to complete tasks in time. This can be tested by removing all individual controls and checking for a change in the wage term in the desired equation. While this is far from an exhaustive test, a lack of change would indicate that individuals already take ability into account when expressing their desired labor supply. According to our results, this seems to be the case, as the elasticity coefficient is not particularly affected by the removal of individual controls (moving from −0.083 to −0.076, Z-test: $0.35 < 1.96$).

Column 2 instead tests for the possibility that workers take task search into account when expressing their desired supply. This can be tested by adding task search as a regressor in the desired hours equation in column 2. Recall that search is a platform-side constraint that is not supposed to enter the desired hours equation. In case task search is correlated with the desired labor supply, a significant change in the wage term would indicate that desired supply schedules are endogenous to the wage. This is not the case, as the change in coefficient from the original estimate is not statistically different from zero (Z-test: $0.11 < 1.96$).

Turning to the actual and first-difference equations, we study differential gender-based elasticity responses in columns 3 and 5. For both models, we find no statistical evidence of gender-specific heterogeneities in supply responses, while the main elasticity coefficients remain virtually unchanged from our main results.

We then conduct one final check to study whether workers with access to other sources of income display different behaviors in the labor market. Individuals with no access to jobs other than platform work may be less risk-averse and display different elasticities. We test this in columns 4 and 6 by introducing interactions between wage and employment status in non-platform jobs so that heterogeneous elasticities can be studied. However, the estimated interaction coefficients

Table D.1
Labor supply elasticity estimates.

	Hours, desired (ln)		Hours, actual (ln)		Hours, first-diff. (ln)	
	(1)	(2)	(3)	(4)	(5)	(6)
w^S			−0.255***	−0.191***	−0.231***	−0.191***
			(0.052)	(0.055)	(0.066)	(0.052)
w	−0.076***	−0.088***	0.122*	0.046	−0.038*	−0.044**
	(0.014)	(0.014)	(0.050)	(0.052)	(0.017)	(0.016)
On-location worker	−0.100	−0.041	0.121	0.121	0.189***	0.188***
	(0.079)	(0.071)	(0.073)	(0.073)	(0.053)	(0.053)
Control over pay	0.091	−0.027	0.080	0.076	0.062	0.063
	(0.059)	(0.117)	(0.110)	(0.112)	(0.106)	(0.105)
On-location worker × Control over pay	0.002	−0.005	−0.250*	−0.265*	−0.238*	−0.237*
	(0.118)	(0.115)	(0.108)	(0.108)	(0.104)	(0.104)
Search (ln)		0.378***				
		(0.021)				
Experience in platforms (yrs.)		−0.015*	−0.013	−0.012	0.003	0.003
		(0.006)	(0.008)	(0.007)	(0.006)	(0.006)
Regular platform worker		0.161**	0.116*	0.121*	−0.029	−0.030
		(0.052)	(0.054)	(0.054)	(0.050)	(0.050)
Employed in trad. job				−0.250**		−0.027
				(0.088)		(0.077)
w^S (Employed in trad. job)				−0.087		−0.099
				(0.078)		(0.102)
w (Employed in trad. job)				0.053		−0.009
				(0.079)		(0.022)
w^S (Female)			0.084		−0.010	
			(0.095)		(0.091)	
w (Female)			−0.131		−0.025	
			(0.089)		(0.022)	
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Last occupation FE	No	Yes	Yes	Yes	Yes	Yes
Individual controls	No	Yes	Yes	Yes	Yes	Yes
Platform controls	No	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.080	0.311	0.187	0.199	0.156	0.156
N	1591	1580	1584	1584	1580	1580

Notes: SE clustered by occupation/sector clusters in parentheses. All wage and labor supply variables are expressed in natural logarithms.
*p < 0.05, **p < 0.01, ***p < 0.001

for α_1 and α_2 are statistically not significant, ruling out the hypothesis that workers without access to other occupations might act differently, while the estimated elasticity coefficients are not significantly different from our main estimates.[33]

Appendix E. Additional statistics

Table E.2 reports additional summary statistics complementing the statistics from Table 1 in the main text. More specifically, mean statistics are now broken down by type of platform, depending on the type of work performed (on-location or online) and the degree of control that the platform exercises over pay.

Appendix F. Additional validity checks

F.1. Endogenous task offer rate

Error in the task offer rate is a source of concern only if this error is also correlated with other factors correlated with the task offer rate ρ.

This error can have many sources. Firstly, workers might endogenously influence the task offer rate ρ. Some workers might search during peak demand hours or, in some instances, be allowed to search over multiple platforms, and this behavior might correlate with unobserved individual ability. Furthermore, due to the self-reported nature of our data, the task offer rate might still be correlated with measurement error that would otherwise give rise to division bias or recall error. For example, individuals with a lower task offer rate might also give higher salience to their search effort, thus making the observed rate endogenous. These considerations suggest that the task offer rate can also be endogenous to individual characteristics X, which could, in turn, influence w already.

The issue is also related to the functional form of the search function. We assumed earlier in Appendix A that the task offer rate is linear. This might not necessarily be the case in the empirical context. If the task offer rate is non-linear, then the value of w^A will also change under different levels of search effort.[34] As the search effort is endogenous, under a non-linear task offer rate, workers with higher w will adjust their search effort and experience a different shock.

This discussion suggests that both (i) w and (ii) w^A/w terms can be endogenous due to the task offer rate. The first is a case of "weak" endogeneity and, as discussed, affects only the assumption of the actual supply model (5). In this case, the same unobserved factors from X that affect w also affect the shock ρ. In the presence of endogeneity in the task offer rate, α_1 will be incorrectly estimated in the actual supply model. These factors, however, are absorbed through first-differencing: in such a scenario, estimates from the first-difference model can still be deemed reliable if X is canceled out.[35]

The second is a case of "strong" endogeneity, which would also affect the first-difference model (8). In this case, the threat to identification would come from the possibility that unobserved ability factors affected h^A and h^D differently so that X is not canceled out while also affecting the shock. Should this be the case, then α_1 and α_2 will also

[33] In any case, this is far from a definitive check because access to other occupations might be endogenous to the salary, even if the ever-unemployed status is controlled for within the last occupation FE vector.

[34] See Appendix B for a discussion.

[35] The stability of the first-difference model can also be appreciated in our simulation. See Appendix G for further reference.

Table E.2
Summary statistics by type of platform.

Control over pay:	(1) On-location		(2) Online	
	No	Yes	No	Yes
Paid hours of work	13.360	12.398	12.178	15.159
	(13.367)	(11.524)	(11.501)	(14.138)
Actual hours of work	22.027	21.643	21.161	25.245
	(19.501)	(18.653)	(18.083)	(21.840)
Desired hours of work	17.521	18.760	20.338	21.192
	(13.766)	(14.164)	(15.355)	(15.702)
Frictionless hourly wage	41.530	39.680	20.290	44.656
	(121.350)	(185.425)	(88.932)	(275.838)
Actual hourly wage	20.518	17.181	10.231	16.196
	(68.078)	(80.985)	(36.682)	(77.789)
Gender: Female	0.338	0.404	0.447	0.383
	(0.474)	(0.492)	(0.498)	(0.487)
Married or living with a partner	0.592	0.667	0.630	0.649
	(0.493)	(0.473)	(0.483)	(0.478)
Age	33.983	33.690	36.945	33.129
	(12.344)	(12.192)	(12.730)	(11.489)
Foreign born	1.900	1.942	1.937	1.900
	(0.301)	(0.235)	(0.244)	(0.301)
Household size	3.087	3.152	2.960	3.168
	(1.260)	(1.222)	(1.211)	(1.186)
Number of children	0.754	0.724	0.621	0.715
	(0.999)	(0.857)	(0.856)	(0.915)
Education: Low (ISCED 1–2)	0.071	0.047	0.037	0.035
	(0.257)	(0.212)	(0.189)	(0.184)
Education: Medium (ISCED 3–4)	0.358	0.310	0.309	0.275
	(0.481)	(0.464)	(0.462)	(0.447)
Education: High (ISCED 5–8)	0.571	0.643	0.654	0.691
	(0.496)	(0.480)	(0.476)	(0.463)
Non-platform hours of work	30.093	30.401	31.164	28.713
	(13.874)	(12.237)	(13.319)	(13.611)
Non-platform income	1065.227	1321.413	1050.572	1048.876
	(1150.047)	(1426.95)	(1140.568)	(1170.945)
Employed in trad. job	0.454	0.485	0.458	0.512
	(0.499)	(0.501)	(0.499)	(0.500)
Partner's income: higher	0.627	0.500	0.571	0.520
	(0.485)	(0.502)	(0.495)	(0.500)
Partner's income: similar	0.254	0.281	0.199	0.302
	(0.437)	(0.451)	(0.400)	(0.460)
Partner's income: lower	0.120	0.219	0.230	0.178
	(0.326)	(0.416)	(0.421)	(0.383)
Experience in platforms (yrs.)	4.604	4.287	4.684	4.795
	(4.401)	(3.665)	(4.342)	(4.206)
Regular platform worker	0.654	0.602	0.821	0.769
	(0.477)	(0.491)	(0.384)	(0.422)
Platform's control over work hours, None	0.487	0.427	0.655	0.503
	(0.501)	(0.496)	(0.476)	(0.501)
Observations	240	471	459	725

Notes: Mean coefficients; Standard Deviation in parentheses. Breakdown by platform type (On-location vs. Online) and remuneration schemes (workers having control over pay vs. workers having no control over pay). Partner's income statistics only estimated for the subsample of workers who are married/ living with a partner.

be incorrectly estimated in the first-difference model. Under "strong" endogeneity, the first-difference equation updates to:

$$ln(h^A/h^D) = \alpha_1 ln(w^A/w) + \alpha_2 ln(w) + (X^A - X)'\delta + P'\zeta + \eta_3 \tag{19}$$

Where $(X^A - X)'$ is the residual subset of individual characteristics whose effect on the difference outcome is non-zero, meaning that they only affect only one of the two supply equations. Alone, this residual term is a source of differential measurement error that clearly affects the assumption underlying the first-difference model (that is, failure to absorb the X term), as we discuss in the next subsection. This measurement error can be correlated with the task offer rate, giving rise to strong endogeneity.[36]

Testing for differences in estimates across the two models will sufficiently dispel both endogeneity concerns, as both forms of endogeneity will generate large variations in the estimates across both models. This is also shown via Monte Carlo simulation in Appendix G.

The results from this test can be supported by other checks. Firstly, an explorative regression of the search effort on the full set of observable controls can provide hints on the presence of weak endogeneity in the task offer rate. Since workers optimize the search effort conditional on their level of expected pay and unearned income, regressing search effort on the full set of observable controls, we expect the search effort to depend on no other individual characteristics. While this is far from an exhaustive test, if factors other than the frictionless wage also affect the search effort, then we cannot rule out that these factors also affect the actual wage and the shock.

[36] This strong endogeneity scenario is, in general, unlikely. There is very little workers can do to influence the task search process. The strategies workers can use to improve search times are not particularly hard to master, and it is unlikely that any individual ability that does not already affect the frictionless wage would help workers reduce the task offer rate they will experience. It is, however, not unlikely that measurement error might affect the search effort and paid hours of work in a different way, and that this error might be correlated with search.

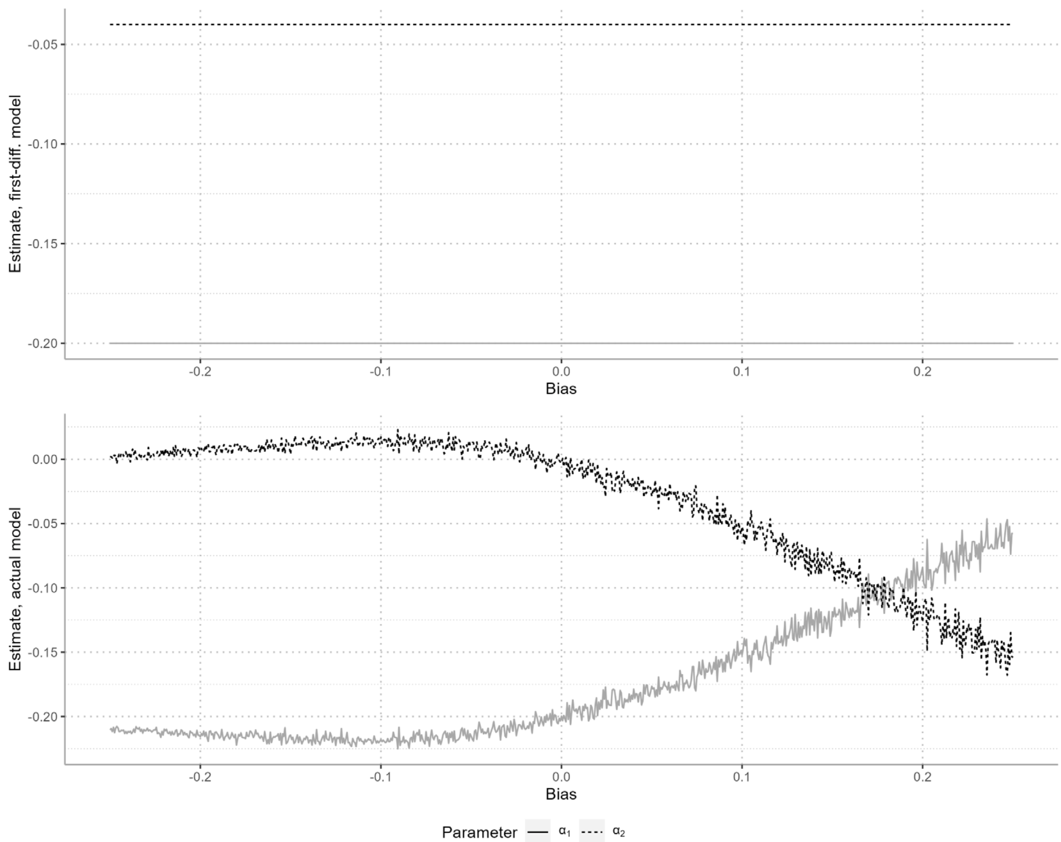

Fig. G.1. Monte Carlo Simulation - Elasticity Estimates with unobserved bias in the task offer rate.
Notes: Monte Carlo results for the first-difference and actual supply models under varying levels of bias in the task offer rate.

A direct test for weak independence can also be achieved by removing the frictionless wage term from the first-difference supply model and then measuring the change in coefficients from the first-difference model (8). Statistically significant differences in the coefficients will suggest the presence of an endogenous shock. Similarly, variations in the point estimates of α_2 will indicate the presence of weak endogeneity.

We can also test for strong independence directly. As a first test, we can check for changes in the coefficients of interest (α_1 and α_2) in the first-difference model before and after all other controls have been removed. After removing the observable set of controls, a change in the coefficients could suggest that components of the X term, which might also simultaneously affect the task offer rate and the outcome, have not been absorbed correctly. We want the elasticity coefficients to remain statistically unchanged for the test to succeed.

Finally, since strong endogeneity can be considered a special case of differential measurement error, dispelling measurement error through the X term will also dispel this form of endogeneity. These considerations suggest that tests for the measurement error discussed in the next subsection, if passed, will also dispel "strong" endogeneity concerns.

F.2. Differential measurement error

The second condition relates to differential measurement error, which occurs when the stated (desired hours) preference term suffers from sources of measurement errors that do not already affect the revealed (actual hours) preference term. This error affects the first-difference equation only. If this form of error is also correlated with the task offer rate,[37] then a "strong" endogeneity scenario will also arise, as discussed above.

Differential measurement error can affect the *first-difference* supply equation in two ways. The first involves the X term. Differential measurement error implies that individual characteristics might contribute differently to desired supply schedules as they do to actual supply schedules. The idea that some characteristics that do not affect the actual supply might affect the desired supply (and vice-versa) is not unreasonable: desired hours might, for example, include some form of search effort, or some other unobserved preference might affect "ideal" supply conditions. Recall errors could also feature a differential aspect, becoming another source of error between the reported usual and desired hours.

The second form concerns variation in the frictionless wage term w. This can arise from a number of factors, which are all related to variation in w during the estimation window. In our design, the frictionless rate w is assumed to be the same *before* and *after* the working week. However, the frictionless salary in the desired equation might not correspond with the frictionless salary in the actual equation: workers might incorporate some form of search in their rate of pay, overestimate (or underestimate) their capabilities, or simply be uncertain about the time it takes them to complete a task.[38] Allowing w to change,

[37] For example, by helping reduce the search effort.

[38] So far, we have implicitly assumed that workers take into account how efficiently they can perform a task when expressing desired labor supply. The intuition is that, if offered unlimited tasks at a fixed payout, workers will never assume they can complete them immediately but will take into account idiosyncratic factors affecting how efficiently they can perform them. Additionally, when expressing desired hours of work in ideal conditions, we assumed that 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 task offer rate they experienced in the reference period because, in ideal conditions, the search effort should be zero as it comes at a net loss of leisure.

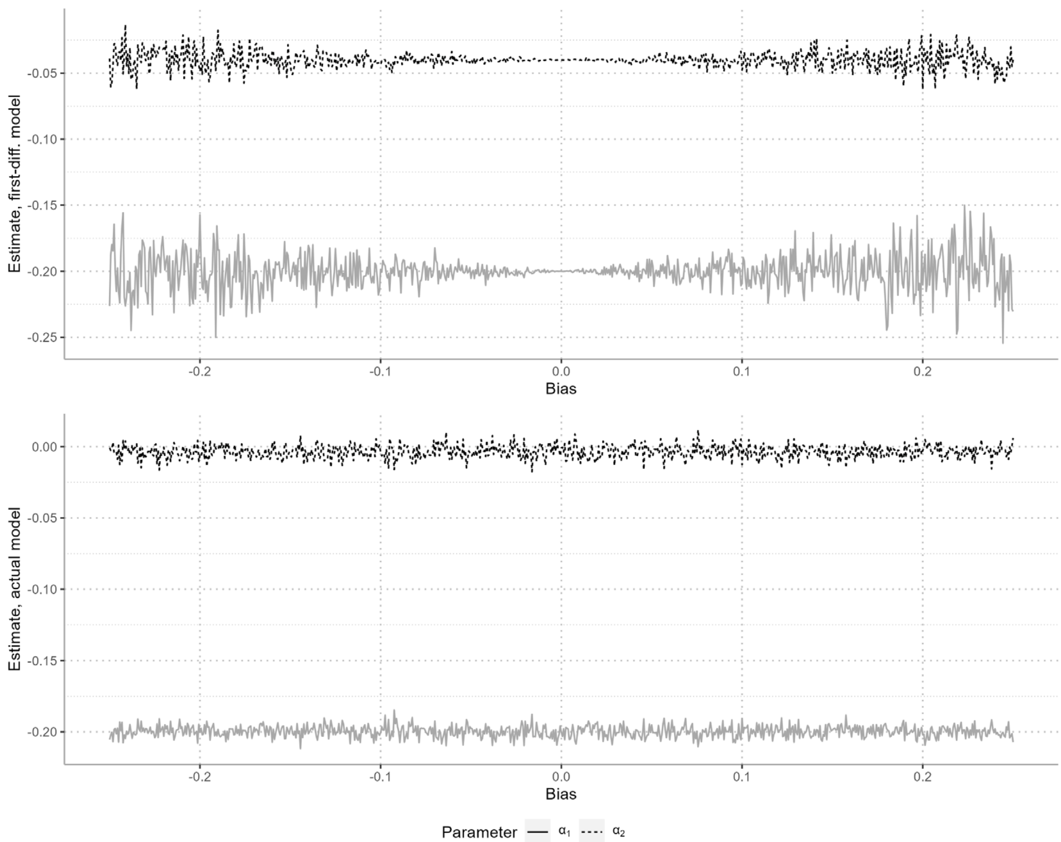

Fig. G.2. Monte Carlo Simulation - Elasticity Estimates with unobserved differential measurement error.
Notes: Monte Carlo results for the first-difference and actual supply models under varying levels of bias in measurement error.

the desired hours equation will be based on the ex-post frictionless wage w_1, while the actual hours equation will be based on the ex-ante frictionless wage w_0. Both w_0 and w_1 could be unobserved and be affected by several sources of variation.

Including all forms of differential measurement error, the first-difference equation updates to:

$$ln(h^A/h^D) = \alpha_1 ln(w^A/w_1) + \alpha_2 ln(w_0) + (X^A - X)'\delta + P'\zeta + \eta_3 \tag{20}$$

Measurement error has different implications for estimation depending on its nature. The error can feature both a fixed intercept and a random term. For example, workers, on average, might overestimate their desired hours or frictionless salary by a fixed amount, with random variation between workers.

The idiosyncratic random term (be it on X or w) will introduce noise in the estimates of the first-difference model only, with the estimates growing increasingly inconsistent as the variance of the idiosyncratic component grows. The effects of these idiosyncratic disturbances are illustrated in detail through Monte Carlo simulation in Appendix G.

The fixed part of the error can affect our estimates depending on whether the error affects w or X directly. If it affects X only, it will have no effect on the model, as the term is clearly uncorrelated with other variables of interest. If it instead affects w, then the error will simply be absorbed by α_2 in the first-difference model. In this case, differences between $w_{0,1}$ and w are to be considered systematic. This is not at odds with our interpretation of α_2, as the frictionless wage elasticity is already assumed to incorporate average variation in salary expectations, which might as well account for systematic variations in the frictionless wage before and after the working week.

Therefore, while the error intercept will not affect the interpretation of our results, the random term can be problematic, as this term should also be negligible for the model to be unaffected.

Since differential measurement error affects the first-difference model only, the most exhaustive test for this idiosyncratic error involves checking for differences in estimates across the actual and first-difference supply model, as we discussed earlier.

Additionally, there is a way to test for this error even when the assumptions of the actual supply model fail, and it is not possible to cross-check for estimates across models. This test involves the introduction of an interaction term between w^A/w and w (so w^A, after simplifying) in the first-difference equation. The intuition comes from the fact that w^A/w should capture variation in wage net of w. If either of the two terms is affected by measurement error, spurious correlation between the two will be introduced in the model.

It follows that this residual variation can be assessed by adding the interaction term, whose parameter we define as α_3. If the "true" unobserved w differs significantly between the two wage terms, the term will have a non-zero coefficient, and estimates for α_1 and α_2 will change even drastically after the introduction of the interaction term. If this variation is, instead, negligible, then the parameter α_3 should be approximately zero, and estimates for α_1 and α_2 will remain statistically unchanged. An interesting caveat of this relationship is that the interaction term can, by chance, be zero even if idiosyncratic variation in measurement error is high: as long as this term is zero, α_1 and α_2 remain identified. This is demonstrated by our Monte Carlo simulations Appendix G, Fig. G.3: note how when α_3 is approximately zero, then α_1 and α_2 are close to their "real" predetermined values.

F.3. Differential measurement error correlated with search

As we discussed, the measurement error in the desired hours of work might be correlated with the task offer rate, giving rise to a scenario of "strong" endogeneity. A simple modification of the desired supply model can offer important insight into the presence of this error.

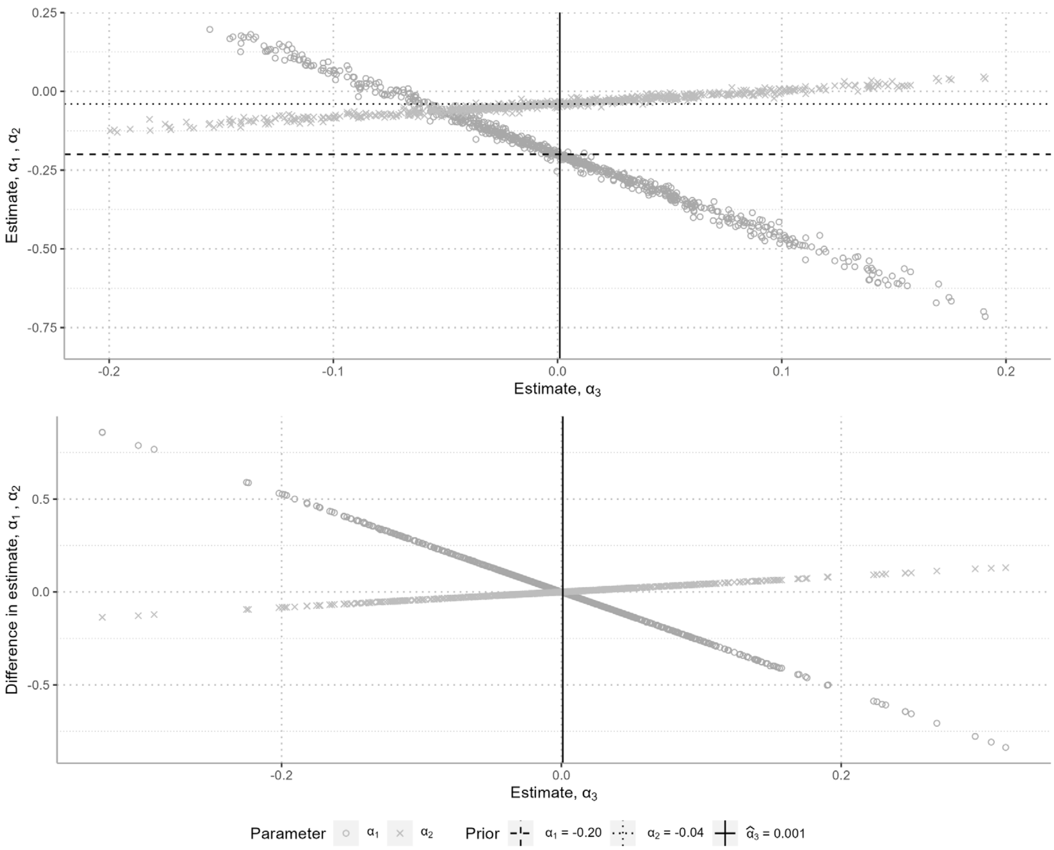

Fig. G.3. Monte Carlo Simulation - Elasticity Estimates with unobserved differential measurement error.
Notes: Monte Carlo results for elasticity estimates and the difference in estimate before and after introducing the interaction term for the first-difference supply model, including interactions between the wage terms.

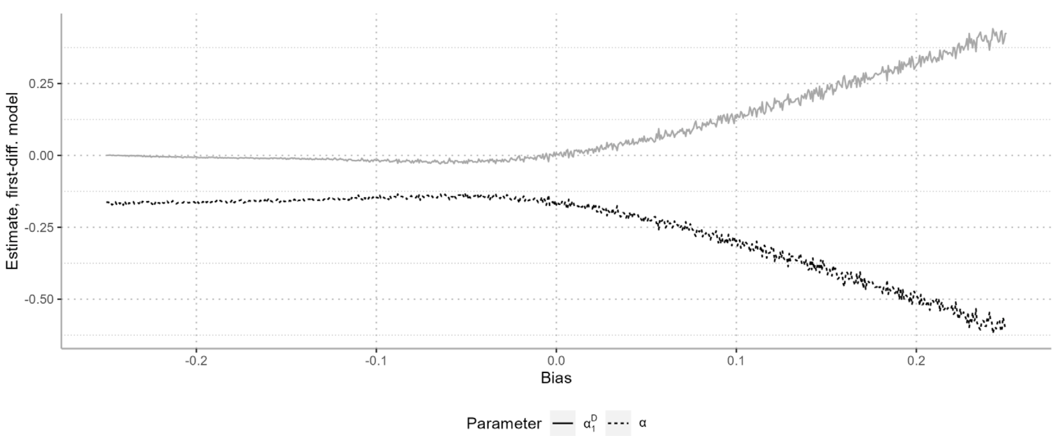

Fig. G.4. Monte Carlo Simulation - Elasticity Estimates with unobserved differential measurement error.
Notes: Monte Carlo results for the updated desired supply model under varying levels of measurement error correlated with the task offer rate.

The desired supply model can also be updated as follows

$$ln(h^D) = \alpha_1^D ln(w^A) + \alpha ln(w) + M'\beta + X'\delta + P'\zeta + \eta_1 \tag{21}$$

where the actual wage term, along with platform controls, is introduced.

It should be noted that the parameters estimated here are expected to be very different from the ones of our final models, which also contain the wage shock (either w^A or w^S) and the frictionless wage term. However, here the effect of the search-adjusted term should not, in theory, affect supply preferences under ideal conditions. The actual wage elasticity parameter is then expected to be zero, while it can be very different in our other models, hence $\alpha_1^D \neq \alpha_1$.

Nonetheless, our considerations from earlier are still valid: the actual wage differs from the frictionless only by search, so that w^A equals w^S after controlling for w. It follows that, under the assumption of exogeneity of search, the α_1^D parameter should be consistently estimated. This property allows us to directly test whether the task offer rate affects stated labor supply preference. If the search effort comes as a source of disutility and is not considered under ideal supply conditions, then the effect of α_1^D should not be statistically different from zero. It

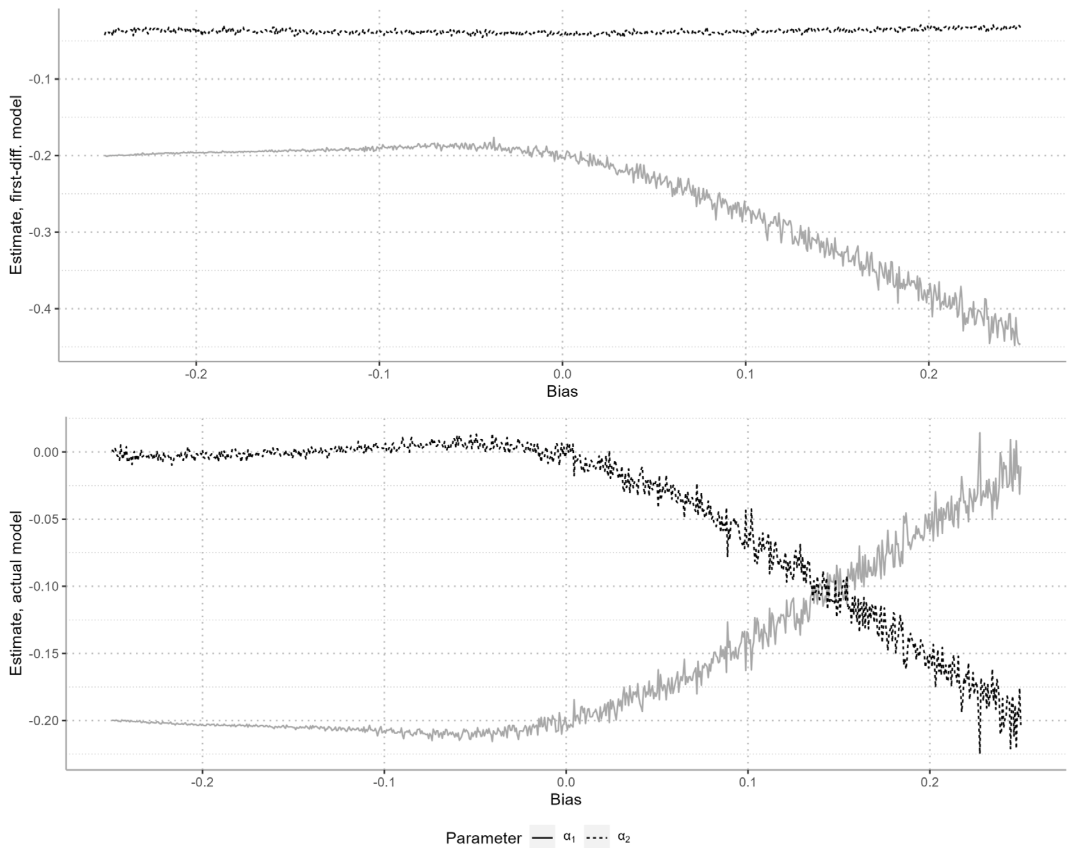

Fig. G.5. Monte Carlo Simulation - Elasticity Estimates with unobserved differential measurement error.
Notes: Monte Carlo results for the first-difference and actual supply models under varying levels of measurement error correlated with the task offer rate.

follows that in the presence of "strong" exogeneity, variations in search should be proportional to variations in the desired supply.

The α term should, instead, be conceptually comparable to the concept of frictionless wage elasticity α_2 estimated in our other models. However, its interpretation might be ambiguous. While division bias cannot affect this equation, as the desired hours term is not used to construct the wage terms, the estimates might still be affected by endogeneity in w.

Appendix G. Monte Carlo results

In this section, we study how violations of our assumptions on the exogeneity of search and the nature of measurement error affect our estimates through the use of Monte Carlo simulations.

In our Monte Carlo simulations, the desired equation is specified as follows:

$$ln(h^D) = C + \alpha_1 ln(w) + \delta ln(X). \tag{22}$$

The actual supply equation, instead, is specified as:

$$ln(h^A) = C + \alpha_1 ln(w^A) + \alpha_2 ln(w) + \delta ln(X). \tag{23}$$

Monte Carlo replicates are produced using priors $\alpha_1 = -0.20$ and $\alpha_2 = -0.04$ (mirroring our results). We fix the constant C at $ln(10)$, and model the unobserved experience term X as $X = \mathcal{N}(4,1)$. A one-point increase in X affects the supply by $\delta = -0.045$. The frictionless salary w is endogenous to experience, and we model it as $w = \mathcal{N}(10,2) + \delta_w X$. We fix δ_w at 1. The task offer rate is modeled as $\rho = \mathcal{N}(2,0.4)$ and it follows that the actual wage equals $w^A = w\rho(\rho+1)^{-1}$. All priors are arbitrary and have been tuned to reproduce our main results. They are instrumental in allowing us to examine the impact of unobserved bias on our estimates within a controlled setting.

For each of the assumptions our two models are based upon, we produce series of Monte Carlo replicates under different levels of bias. For each series, we produce 800 replicates, holding the sample size fixed at 1580, replicating our empirical setting. For each replicate, the actual and first-difference supply models are estimated with OLS. In all cases, we omit the unobserved experience term X when estimating the parameters.

G.1. Endogenous task offer rate

We begin by studying how estimates of the actual and first-difference supply models change under varying levels of unobserved bias in the task offer rate, replicating the "weak" endogeneity scenario discussed in Section 5 and Appendix F.

We do so in Fig. G.1 in which we show, through Monte Carlo simulations, how the elasticity parameters react to variation in unobserved endogeneity in the task offer rate across the first-difference (top) and actual (bottom) supply models. We add an additional source of bias to the task offer rate so that $\rho = \mathcal{N}(2,0.4) + \delta_s X$. In the simulation, the bias δ_s is allowed to take values between -0.25 and 0.25.

The results immediately show that increasing levels of bias do not affect the validity of the estimates for both elasticity parameters in the first-difference model, where the X term is fully absorbed, so much in fact that there is no noticeable variation in the estimates. In contrast, for the actual model, as bias increases, the estimates of α_1 get closer to zero, while the magnitude of the estimates of α_2 increases. This inversion of results between the two models highlights the sensitivity of our estimates to unobserved biases in the task offer rate.

Most importantly, when the bias is zero, estimates for α_1 (but not α_2) are instead perfectly valid in the actual supply model, as the task offer rate is completely exogenous and all residual endogeneity is captured by w.

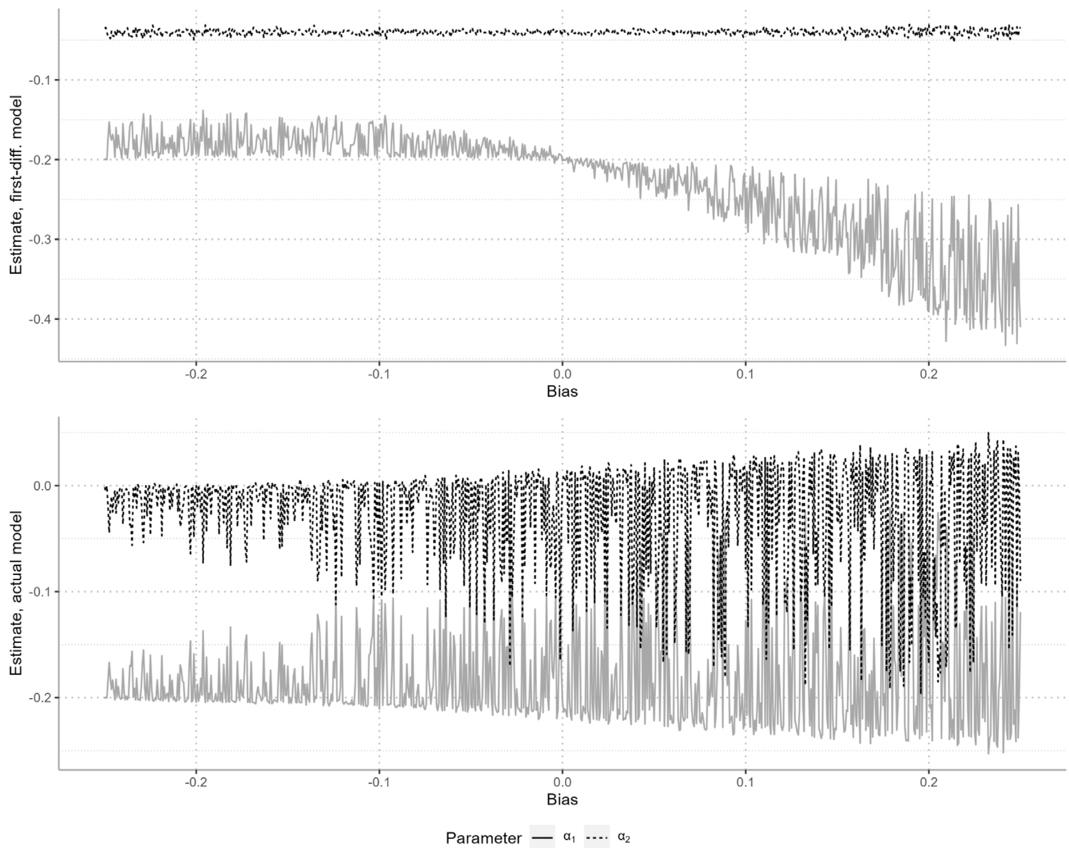

Fig. G.6. Monte Carlo Simulation - Elasticity Estimates with unobserved differential measurement error.
Notes: Monte Carlo results for the first-difference and actual supply models under varying levels of measurement error correlated with the task offer rate.

This discussion suggests that it might be very unlikely, if not impossible, for both models to converge to the same result if the task offer rate happened to be endogenous.

G.2. Differential measurement error

We now move to the assumption of the absence of differential measurement error on the desired hours of work, upon which the first difference model relies.

We introduce differential measurement error in our replicates by introducing a random disturbance term in the desired hours equation as $\delta_H ln(X_2)$, where δ_H is allowed to take values between −0.25 and 0.25 and $X_2 = \mathcal{N}(4, 1)$. As we mention in the main text, this disturbance can equivalently be treated as a disturbance in the frictionless wage term in one of the two equations.

Our results are reported in Fig. G.2. The top figure clearly shows that the first-difference model is affected by measurement error with increasing variability in the estimates of both elasticity parameters. The average estimates, however, point to the correct priors, suggesting that only the idiosyncratic random term connected to the error is a source of concern, while fixed intercepts are fully absorbed. The actual hours model, as expected, is instead unaffected by measurement error, and estimates of α_1 (but not α_2, because of the endogeneity of w) are correctly estimated. With larger values of bias, it becomes increasingly difficult for both first-difference and actual supply models to converge to the same estimate.

Checks for measurement error can be conducted on the first-difference model estimates themselves. Increases in the variability of w will, in fact, affect the elasticity of the interaction term between the actual and frictionless wage elasticity α_3, once introduced, as discussed in Appendix F.

This is shown in Fig. G.3, which uses the same Monte Carlo simulation set-up from Fig. G.2 but includes an interaction between the observed wage terms w^A/w and w, marked by α_3, providing key evidence of the relationship between the estimated elasticity of α_3 and the estimated elasticity of the other elasticity parameters α_1 and α_2 in the first-difference model. The top figure shows that whenever the estimated α_3 is close enough to zero, both α_1 and α_2 are close enough to their true elasticities, regardless of measurement error. The vertical line sits at the estimated elasticity of α_3 from Table 2, Column 10. As the estimated elasticity is basically zero (0.001), we can conclude that the elasticity estimates we produced are unaffected by measurement error, regardless of its level. This is exemplified by the bottom figure, which also shows that the variation in first-difference estimates before and after the introduction of the interaction term is statistically zero if the interaction is also zero.

G.3. Differential measurement error correlated with search

So far, we have assumed that the error is not correlated with the wage terms.

We update the Monte Carlo simulation so that the task offer rate is correlated with both unobserved experience terms X and X, so that $\rho = \mathcal{N}(2, 0.4) + \delta_s(X + X_2)$, introducing a source of endogeneity in the task offer rate which is only correlated with the error in the desired supply equation. We let δ_s vary between −0.25 and 0.25. We now fix δ_H at 0.25. This setting replicates the "strong" endogeneity scenario discussed in Section 5 and Appendix F.

In Fig. G.4, we look at the effects of this source of bias on the updated version of the desired supply model, which we discussed earlier in Appendix F. The model includes the actual wage term, which should be zero under the assumption of exogeneity. The figure shows that, for increasing levels of bias, the actual wage term turns different than zero.

In Fig. G.5 we look at the effects of this bias on the first-difference and actual supply models. As it is evident from the figure, increases in bias correlated with the shock lead to a reduction in the estimates of α_1 in the first-difference model. This is mirrored by the equivalent increase in the estimates of α_1 in the actual hours model, which we already observed earlier.[39] In short, differential measurement error will affect the estimates in opposite directions unless the effects of the unobserved experience on the task offer rate have opposite signs.

Of course, it is entirely possible that δ_s affects X and X_2 differently. In Fig. G.6 we update the task offer rate so that $\rho = \mathcal{N}(2, 0.4) + \delta_{s0}X + \delta_s X_2$, where $\delta_{s0} = \mathcal{U}(-0.25, 0.25)$. Under these priors, the estimates become increasingly unstable under higher levels of bias. In other words, elasticity estimates could vary depending on the value of δ_{s0}, and it becomes very difficult for both models to yield the same estimate. In conclusion, as both assumptions are lifted and the bias in either search or the error term increases, the actual and first-difference supply models can produce the same results only under extremely specific circumstances that are unlikely to occur.

Appendix H. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.strueco.2026.06.007.

Data availability

The authors do not have permission to share data.

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[39] If we remove the correlation between X and the task offer rate, then the actual hours model is unaffected.

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