# The Coin of AI Has Two Sides: Matching Enhancement and Information Revelation Effects of AI on Gig-Economy Platforms

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**Abstract**

Artificial intelligence (AI) has been increasingly integrated into the process of matching between workers and employers requesting job tasks on a gig-economy platform. Unlike the conventional wisdom that adopting AI in the matching process always benefits the platform by assigning better-matched jobs (employers) to workers, we discover unintended but possible revenue-decreasing consequences for the AI-adopting platform. We build a stylized game-theoretical model that considers gig workers' strategic participation behavior. We find that while the matching enhancement effect of AI can increase the platform's revenue by improving matching quality, AI-assigned jobs can also reveal information about the uncertain labor demand to workers and thus unfavorably change workers' participation decisions, resulting in revenue loss for the platform. We extend our model to the cases where (1) the share of revenue between workers and platform is endogenous and (2) the workers compete for the job tasks, and find consistent results. Furthermore, we examine two approaches to mitigate the potential negative effect of AI-enabled matching for the platform and find that under certain conditions, the AI-adopting platform can be better off by revealing the labor demand or competition information directly to workers. Our results shed light on both the intended positive and unintended negative roles of utilizing AI to facilitate matching, and highlight the importance of thoughtful development, management, and application of AI in the gig economy.

**Keywords:** economics of artificial intelligence, gig worker, game theory, platform strategy

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# 1 Introduction

Gig-economy platforms (such as Uber, Instacart, Fiverr, etc.), defined as digital, service-based, on-demand platforms that enable flexible work arrangements (Greenwood et al., 2017), have attracted growing participation of workers and employers in recent years (Chen et al., 2019; Huang et al., 2020). Gig workers actively engage in short-term job tasks and temporary freelance projects requested by the employers on the platforms (Allon et al., 2018; Hall and Krueger, 2018). Given the significant number of workers and tasks requested in the rapidly growing gig economy, work assignments, i.e., the matching between workers and tasks, are generally coordinated by the platforms and facilitated by digital technologies (Burtch et al., 2018; Sundararajan, 2014). To efficiently manage job tasks for the gig workers, recent years have seen a rise in the integration of automated and algorithmic systems empowered by artificial intelligence (AI) on those gig-economy platforms (Moore, 2019). Driven by contemporary machine learning-based approaches, AI is now capable of taking on managerial roles to revolutionize the gig workspace by optimally evaluating, matching and assigning the job tasks to gig workers (Cameron, 2020; Lee et al., 2015).

An AI-enabled system can efficiently perform predictions and make recommendations to improve matching quality (Agrawal et al., 2018b; Faraj et al., 2018; WIPO, 2019). For example, with the goal of reducing wait time for riders and idle time for drivers (Uber, 2021a), Uber develops an AI-enabled dispatch system with ensemble machine learning models to match riders and drivers in a better way (Turakhia, 2017). The system is able to scrutinize a massive number of features including distance, time, traffic, and a diverse set of other real-world dynamics to produce 15,000 optimal match pair predictions just within a 100ms response time. AI-based matching is also pervasive beyond the ride-hailing platform. Deliveroo, an online food delivery platform, leverages machine learning algorithms trained on historical matching records in its dispatch engine, “Frank,” to predict the best possible match between gig riders and customer orders in real time (Sen, 2021). Instacart, a platform offering grocery delivery service, also designs machine learning-based matching algorithms to enhance the quality of service. The algorithm can optimally balance the number of shoppers with customer demand for groceries and minimize wait time for grocery orders (Mixson, 2021). As a freelance platform, Gigster develops machine learning-based matching models into which various characteristics of freelancers, such as their expertise level and availability, are factored to identify the best-match candidates for on-demand projects (Klimenko, 2019). According to these examples, AI can efficiently recognize the optimal mapping between the supply and demand of the labor market and, thus, significantly improve the quality of matching for many platforms. As the AI-enabled systems utilize a rich set of data inputs about labor supply and demand at a large scale to arrive at precise, real-time predictions of best matches, they could be significant drivers for increasing workers' productivity and platforms' operational efficiency (Cramer and Krueger, 2016; Faraj et al., 2018), ultimately generating higher revenues for both.

However, due to the flexible nature of the gig economy, workers can decide proactively whether to participate in a gig-economy platform strategically after observing the job tasks assigned on the platform by its AI-enabled matching system (Cameron, 2020; Lee et al., 2015). This strategic reaction of workers to the algorithmic job assignments may not always benefit the platform, since the benefit of an AI-enabled matching algorithm is contingent on the workers' participation and involvement in performing the matched tasks. Unlike traditional workers with a fixed schedule, gig workers are more independent, possessing greater autonomy and flexibility in setting their own work schedule. A gig worker can decide whether to continue participating in a platform based on the information revealed by a job assignment. For example, on gig platforms that offer delivery service, the couriers can choose not to work for the platform at certain times if the expected payoff does not offset the cost of working (Shapiro, 2018). In ride-hailing platforms, drivers can infer demand information from the AI-enabled matching outcome to plan their work schedule (Cameron, 2020). These strategic behaviors could lead to a reduced labor supply that may be insufficient to meet the demand, and consequently, a revenue loss of the platform. AI-enabled matching outcomes may induce workers' strategic participation because of the information potentially revealed by the matching outcomes. Specifically, because the employers are algorithmically and optimally chosen by AI to match the workers (couriers or drivers in the examples), the matching outcomes can reflect the realization of the demand of labor markets that was uncertain to the workers before seeing the matching outcomes. That is, along with the AI-recommended employers assigned to the workers, information about the uncertain labor demand could be unintentionally disclosed to the workers and drive a sense of autonomy by updating their beliefs about the demand. For example, if a poor-match job task is assigned by AI, the worker may speculate that the labor demand is likely low and spending time working may not be profitable, and then strategize and exercise her discretions to suspend work. In other words, gig workers can strategically choose when to stay on a platform and will continue working only when AI-assigned jobs indicate that it is profitable to do so.[1] As gig platforms are designed to support flexible work arrangements (Chen et al., 2019)

[1]Generally these strategic behaviors are neither rewarded nor penalized as long as the workers engage with the

and need consent from gig workers before assigning work, the workers' sense of autonomy being reinforced by demand signals from AI-enabled matching may be unavoidable, potentially leading to an unexpected loss of revenue for the platform.

Therefore, two effects brought by the adoption of AI in matching workers and employers jointly determine the overall revenue of a gig platform: the increased worker performance as a result of improved matching quality (named as the *"matching enhancement effect"*), and the demand information revealed by matching outcomes, which can lead to workers' strategic participation decisions (named as the *"information revelation effect"*). The platform can obviously benefit from a revenue boost by the "matching enhancement effect" of AI adoption. However, workers may strategically respond to AI-facilitated job assignments, taking advantage of the disclosed labor demand information to compare the expected payoff and the opportunity cost of continual participation (Agrawal et al., 2018a). This strategic participation could influence the platform's revenue positively or negatively, depending on the information revealed. Ultimately, how the platform's revenue is affected by the adoption of AI in matching is thus inconclusive and determined by the possible trade-off between the matching enhancement effect and the information revelation effect. Motivated by this trade-off, in this study, we seek to answer the following three research questions: 1) How does the AI-enabled matching motivate or demotivate the workers and affect their decisions of participating in a gig platform to perform job activities? 2) Given the presence of the two potentially countervailing effects, will a gig platform benefit from adopting AI-enabled matching in its job assignment? 3) How to mitigate the possible negative impact of adopting AI-enabled matching on the gig platform?

To address these research questions, we develop a stylized model to take into account the two effects driven by AI-enabled matching that shape worker participation behavior on a gig platform. We unpack under what circumstances AI-enabled matching deployed in the gig platform may have unintended negative consequences on the total revenue of the platform. We consider two different types of job tasks, good-match and poor-match job tasks. When adopted by the platform, the AI-enabled matching selects from what is available and assigns to a worker the better-matched job task that generates a higher payoff for the worker as well as a higher revenue for the platform. Given the demand situation, good-match job tasks may not be available at all times. It is possible that at times, only poor-match job tasks are available and thus assigned to the worker. When demand is uncertain, upon observing an AI-assigned job task, the worker can infer the labor demand information and update her belief about the uncertain demand on the platform in a

job task assigned by AI as intended or in a way that is not explicitly against the platform policy (Cameron, 2020).

Bayesian manner. For example, the worker may attribute a poor-match job assignment to low labor demand, knowing that AI would have assigned a better-match job if the demand condition were better. Our model analyzes the impact of adopting AI in job assignments on the worker's decision of continual participation on the platform and the resultant change in the platform's overall revenue by comparing the outcome to the result in the scenario when AI is not used, i.e., when a job task is randomly assigned to the worker.

We find that while the matching enhancement effect of AI can increase platform revenue by improving matching quality and worker performance, under some circumstances, the information revelation effect that undermines worker participation can dominate, resulting in lower overall revenue for the platform, compared to when AI is not adopted. This negative impact of AI adoption happens when the good-match and poor-match job tasks do not differ significantly in value and the opportunity cost for workers to participate is in the region where the demand signal from a poor-match job assignment provides sufficient incentive for a worker to continue participating only when AI is not used. This result highlights the importance for gig platforms to fully understand the consequences of adopting AI-enabled matching beyond the consideration of matching quality itself.

We further examine two model extensions to demonstrate the robustness of our main results. First, we endogenize the share of revenue between the workers and the platform. Conventional wisdom suggests that, with an AI-enabled matching algorithm, a platform may have a better control of labor demand allocation and thus have a greater bargaining power over the commission rate, giving rise to a smaller commission rate or more severe "labor exploitation" of workers. Instead, we find that applying AI in matching may continue to exacerbate the platform's revenue when the platform has enough market power to adjust its revenue split between the workers and itself, even without considering the cost of applying AI. Our insights pertaining to the two competing effects driven by AI-enabled matching still persist. Second, we consider the scenario where workers do not work independently but engage in labor competition for job assignments. Our main results that AI may hurt the platform's revenue still hold.

Lastly, we examine two possible remedies to mitigate the potential negative impact of AI-enabled matching on the gig platform. First, we find that when AI-enabled matching hurts platform revenue, the platform can be better off by revealing demand information directly to the workers to prevent them from mistakenly inferring demand from job assignments, which leads to a lower participation rate. In the meanwhile, even if revealing demand information can mitigate the negative impact on the platform brought by AI, the platform may, although not always, still be worse off than when no AI is used. Second, contrary to the conventional wisdom that revealing competition information to workers can discourage workers from continuing their participation, we find that, surprisingly, the platform adopting AI can be better off sometimes by revealing the competition information to workers. This is because although the presence of competition typically implies lower demand for competing workers, revealing competition information can also mitigate the negative information revelation effect of AI for a worker upon receiving a poor-match job task. That is, because competition can serve as another reason for not receiving a good match, workers may not attribute a poor matching outcome to low labor demand. Comparison between the two approaches suggests that when platform revenue is deteriorated by the adoption of AI, revealing demand information outperforms revealing competition information for the platform. This result is consistent with the fact that in practice, we often observe gig platforms reveal real-time demand information to their workers, instead of competition information.

This study bridges several strands of literature on AI, algorithmic management and the gig economy. First, our work adds to the studies in the information systems literature on the design of the gig platforms to incentivize worker participation and enhance market efficiencies (e.g., He et al., 2021; Hong et al., 2016; Huang et al., 2020). Gig platforms can adopt AI that helps in reducing transaction cost and matching frictions by processing a sheer volume of market information in an efficient way to identify the optimal match between workers and employers requesting job tasks (Einav et al., 2016). We show, however, that the AI-matched job tasks can motivate or demotivate the workers to participate in the gig platforms. Second, we advance the burgeoning literature on algorithmic management in the gig economy which provides initial anecdotal evidence of gig workers' strategic responses to algorithmic job assignments (e.g., Cameron, 2020; Tambe et al., 2019), by systematically examining the impact of matching empowered by AI, at its contemporary algorithmic status, on the gig platform's revenue, through a comprehensive analytical model. Third, we expand the growing body of studies on the economics of AI by pointing out the possible negative consequences of AI-enabled matching, one of the most important and increasingly adopted applications of AI in the operation of gig platforms. We also provide actionable solutions to alleviate such consequences not intended by the platforms. As AI is becoming a prominent tool for work arrangement in the gig economy, our study underscores the importance of understanding both the intended positive role of AI and its unintended outcomes.

The rest of the paper is structured as follows. In Section 2, we review the literature related to our paper. In Section 3, we develop our main theoretical model and discuss the conditions under which adopting AI to facilitate matching may backfire for the platform. Section 4 explores two model extensions. In Section 5, we examine two potential approaches to mitigate the potential negative impact of AI. Finally, we conclude in Section 6.

## 2 Related Literature

The prominence of the gig economy is attributable to the emergence of the peer-to-peer marketplace mediated by digital platforms (Einav et al., 2016). The gig-economy digital platforms create labor markets by facilitating transactions between workers (i.e., service providers) and employers requesting job tasks. They create employment forms that are service-based, on-demand, and, more importantly, enabling a flexible working environment for workers (Chen et al., 2019; Greenwood et al., 2017).

The development of gig platforms and their implications to business and society have received wide attention in the information systems literature. Existing work has mainly touched on three diverse topics, ranging from (1) workers' labor supply decisions related to worker characteristics and motivations to contribute to the gig economy (e.g., He et al., 2021; Huang et al., 2020) to (2) platform design for increasing market efficiencies (e.g., Deng et al., 2016; Hong et al., 2016; Horton, 2017; Mo et al., 2018) and (3) the socioeconomic impact of the platforms – for example, ride-sharing gig platforms can reduce traffic congestion (Li et al., 2016) and the rate of alcohol-related motor vehicle fatalities (Greenwood and Wattal, 2017), and food-delivery gig platforms can help small restaurants survive during the COVID-19 crisis (Raj et al., 2020). Our work is closely related to the studies on the design of gig platforms to incentivize workers' participation and enhance market efficiencies by reducing transaction costs and matching frictions. The platforms need to leverage the substantial market information efficiently to identify the optimal match between employers and workers (Einav et al., 2016). AI can properly increase the quality of matching on the platform. The matching process can be optimized by AI's capability of processing the sheer volume of information about the dynamics of supply and demand of workers and their activities.

AI plays an increasingly important role in transforming business practices and the platform economy (Brynjolfsson et al., 2019; Lou and Wu, 2021). AI represents a set of technologies and tools that can ingest, process and analyze external information in a complex environment and optimize its actions to achieve specific goals and perform tasks (Kaplan and Haenlein, 2019; Legg et al., 2007). As defined in Nilsson (2009), AI is the "activity [that is] devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment." Although it is not a new field, AI has received widespread renewed interests over the past few years. The current wave of AI, especially advances in machine learning (ML) and its subfield of deep learning, is principally fueled by the explosive growth in digitized data and the advancement of computational power for analytics (Brynjolfsson and McAfee, 2017). A powerful AI system possesses the capability of effectively dealing with contextual information in the environment. In particular, the ML-based AI, which is the dominant form of contemporary AI in practice, can directly learn from existing data about digital traces that capture the details and dynamics in the environment, quickly detect patterns from the data, and conduct prediction tasks typically performed by humans without human intervention (Jordan and Mitchell, 2015; WIPO, 2019). It can accurately make better and faster predictions than humans can in many tasks such as language translation, image classification and speech recognition (He et al., 2015; Hu et al., 2018; Ng, 2016).

This is particularly the case for the increasing adoption of AI-based matching technologies in a variety of gig platforms as shown in the aforementioned examples in this paper. AI can improve current matching technologies and algorithms by effectively consuming and processing a comprehensive set of environment information at a large scale pertaining to the supply and demand of labor in a platform. With the goal of improving operational efficiency and maximizing the platform's revenue, AI is designed to automatically predict and recommend the best match of workers and employers. Therefore, matching outcomes derived from AI can well reflect the market conditions of labor. A worker is supposed to receive the optimal employer by the AI-enabled matching that can help her raise earnings and the platform gain higher revenue (Cramer and Krueger, 2016).

Nevertheless, as discussed earlier, the improved predictions and recommendations enabled by AI can convey demand information and thus affect human workers' decisions such as whether to participate in the gig platform. AI applications can be developed to provide information in the form of automated predictions to a human decision-maker (Agrawal et al., 2018a; Boyaci et al., 2020). Specifically, the participation of AI in human decisions involves AI's prediction serving as an input for a human decision-maker to make decisions about choosing an action to maximize expected payoffs. In the case of AI-enabled matching in the gig platform, as AI has strong computational information-processing capability, AI-based matching can enable the matched outcomes to provide an accurate signal of labor market condition to workers, allowing them to compare expected cost and benefit for making optimal participation decision. It is indeed documented that humans generally adapt to AI predictions and recommendations, which can assist and augment the decision-making process (Jarrahi, 2018).

In spite of the recognition of AI applications interfering with human decision-making, there is a scarcity of research that systematically studies the impact of AI on the participation behavior of gig workers, the strategic implications, and possible unintended consequences that AI adoption may have on gig platforms. In terms of the labor market effect of AI, prior studies focus more on whether AI can be a substitute or complement for human workers to change the overall workforce structure and estimate the impact of AI on workers' employment and wages (Acemoglu et al., 2020; Autor, 2015; Felten et al., 2019; Hou et al., 2021). While the potential changes of the overall workforce structure by AI are still to be determined, in practice, the human-AI co-operation mode takes place more frequently on gig platforms: AI engages in managerial activities such as allocating job tasks to human workers to perform (Bai et al., 2020; Bundorf et al., 2019; Wang et al., 2019). Our study aims to fill the gap in this literature by explicitly examining the potential negative consequence of AI-enabled matching for the platform because of the induced workers' strategic participation behavior.

In line with the role of AI recommendations in the human decision-making process, there has been considerable progress in knowledge development in an emerging stream of research that examines algorithmic management in gig platforms, which refers to the practice of using algorithms to guide incentives and make recommendations to platform workers about actions they may take (Tambe et al., 2019). The studies in this stream of literature provide an increasing number of narrative anecdotes, investigating the influence that algorithmic management can have on workers' behavior on gig platforms (Kellogg et al., 2020; Möhlmann and Zalmanson, 2017; Rosenblat and Stark, 2016; Wood et al., 2019). As AI-enabled algorithmic technologies are increasingly used to enhance the competency of platform operations, especially the process of matching workers and employers, a systematic framework is needed to understand the impact of AI and its implication for the platform, which is what this study focuses on. With the shift of agency and management of job tasks in the platform from human to AI, it is important to advance the understanding of how AI interacts with workers, which is central to the platform moving forward in the gig economy.

# 3 Main Model

Consider a gig-economy platform with employers (he/him/his) requesting and workers (she/her/hers) taking job tasks. When an employer's job task has a good match with a worker, the generated revenue is $x_H$ if the worker takes the job. When an employer's job task is a poor match with a worker, the generated revenue is $x_L$ if the worker takes it, where $0 < x_L < x_H$. Taking Uber as an example, the objective of optimally matching a driver (worker) and a rider (employer) is to achieve lower wait time for the rider and more revenue for the driver. It should take a good-match driver less time to pick up a given rider and send him to the destination, thus generating higher revenue per unit time.

In the main model, we assume that workers are working independently. This assumption precludes the role of competition between workers and allows us first to introduce the key mechanism and driving forces clearly. We will further relax this assumption in the extended model where competition among workers is considered. Under this assumption, without loss of generality, we consider a representative worker and two representative potential employers, one with a good match and the other with a poor match.[2] Each employer appears with probability $p$, where a higher $p$ indicates a higher labor demand on the platform. This fluctuation of labor demand reflects the demand uncertainty in real life. In the above example of Uber, each rider (employer) may come to the platform with some probability. When there is a higher demand for Uber service, for instance, after a social event or when a gathering is over, such probability $p$ will be higher. The worker does not know the exact value of $p$.

The platform assigns the worker to an available employer who appears on the platform. We consider two scenarios in this job assignment procedure: (1) no AI-matching algorithm is used, and (2) AI-matching algorithm is applied. In the first case without AI, the worker is randomly assigned to an available employer. That is, the platform cannot take matching quality into consideration because it is technologically incapable or lacks enough historical data to identify the match between each employer and the worker. Specifically, if both employers appear on the platform, the worker is assigned to each employer ($x_H$, $x_L$) with equal probability $\frac{1}{2}$; if only one employer appears on the platform, the worker is automatically assigned to the employer; if no employer appears, no job is available and thus zero revenue is generated. In the second case with AI, the platform is able to identify the match between each employer and the worker and always assigns the worker to the

[2] The results are not qualitatively changed for a model with more than two employers.

better-match employer who appears on the platform to maximize its revenue. This is essentially how AI nowadays manages matching for platforms and helps firms make more informed decisions. Specifically, if both employers appear on the platform, the worker is assigned to the good-match employer ($x_H$) with probability 1; otherwise, the assignment result happens to be the same as the no-AI case since only one or no employer appears and thus matching is pre-determined.

We consider the context where there is demand stickiness over time. For example, in ride-sharing and food-delivering markets, demand is typically stable within a short period of time. To capture this stability, we consider a two-period model and assume that the labor demand probability $p$ stays the same in both periods.[3] We use $x_1$ and $x_2$ to denote the job assigned to the worker in the first and second periods, respectively, which also represent the revenue in the two periods. The platform and the worker split the revenue so that the worker takes a $\delta$ proportion of the revenue. That is, the $1-\delta$ proportion of the generated revenue is taken by the platform as a commission fee. In the first period, the worker participates in the platform and is assigned to an available employer by the platform.[4] The worker works on the assigned job, obtains the revenue from the job, and thus observes the match between herself and the assigned employer: high ($x_1 = x_H$), low ($x_1 = x_L$), or no job assigned ($x_1 = 0$).

The worker will then infer the labor demand based on what she obtains in the first period and her knowledge of the matching procedure used by the platform (i.e., whether AI-matching is utilized), and update her belief on $p$ in a Bayesian manner. We assume that the prior of $p$ follows a uniform distribution between 0 and 1. The likelihoods of a worker being assigned to a good-match employer ($x_1 = x_H$), a poor-match employer ($x_1 = x_L$), and no employer ($x_1 = 0$) are given below in equations (1) and (2) for the cases without and with AI, respectively. Since the technology remains the same across two periods, such likelihoods also apply to the second period ($x_2$). Throughout the paper, we use superscript "0" to indicate the case without AI-matching and superscript "$AI$" to indicate the case with AI-matching. When no AI-matching is adopted, the

[3]Even if the demand probability $p$ changes across periods, as long as there is a strong correlation between periods, our results hold qualitatively.

[4]We consider the first period as a "testing" period in which the worker always participates, i.e., the first period's opportunity cost is normalized to zero. We have also considered the case where the worker also incurs a cost $c$ (which will be later introduced in the main text of the paper) in the first period if she participates and can decide whether to participate in the first period based on the expected revenue and cost. Our main result continues to hold qualitatively.

likelihoods are

$$\begin{cases} Pr^0(x_1 = x_H|p) = Pr^0(x_2 = x_H|p) = p(1-p) + \frac{p^2}{2} = p(1-\frac{p}{2}), \\ Pr^0(x_1 = x_L|p) = Pr^0(x_2 = x_L|p) = p(1-p) + \frac{p^2}{2} = p(1-\frac{p}{2}), \\ Pr^0(x_1 = 0|p) = Pr^0(x_2 = 0|p) = (1-p)^2. \end{cases} \tag{1}$$

When AI-matching is applied, the likelihoods are

$$\begin{cases} Pr^{AI}(x_1 = x_H|p) = Pr^{AI}(x_2 = x_H|p) = p(1-p) + p^2 = p, \\ Pr^{AI}(x_1 = x_L|p) = Pr^{AI}(x_2 = x_L|p) = p(1-p), \\ Pr^{AI}(x_1 = 0|p) = Pr^{AI}(x_2 = 0|p) = (1-p)^2. \end{cases} \tag{2}$$

Based on the above likelihoods and the distribution of the prior ($U[0,1]$), the Bayesian posterior of the demand probability is calculated as follows. Without AI-matching, the probability density function (PDF) of the posterior, $f^0$, is given by

$$\begin{cases} f^0(p|x_1 = x_H) = \frac{p(1-\frac{p}{2})}{\int_0^1 p(1-\frac{p}{2})dp} = 3p(1-\frac{p}{2}), \\ f^0(p|x_1 = x_L) = \frac{p(1-\frac{p}{2})}{\int_0^1 p(1-\frac{p}{2})dp} = 3p(1-\frac{p}{2}), \\ f^0(p|x_1 = 0) = \frac{(1-p)^2}{\int_0^1 (1-p)^2 dp} = 3(1-p)^2. \end{cases} \tag{3}$$

The posterior PDF with AI-matching, $f^{AI}$, is given by

$$\begin{cases} f^{AI}(p|x_1 = x_H) = \frac{p}{\int_0^1 p dp} = 2p, \\ f^{AI}(p|x_1 = x_L) = \frac{p(1-p)}{\int_0^1 p(1-p)dp} = 6p(1-p), \\ f^{AI}(p|x_1 = 0) = \frac{(1-p)^2}{\int_0^1 (1-p)^2 dp} = 3(1-p)^2. \end{cases} \tag{4}$$

From equations (3) and (4), we make the following observations. First, when no AI is applied in job assignments, the worker will make the same inference on $p$ as long as there is non-zero demand. That is, receiving either $x_H$ or $x_L$ in the first period updates the worker's belief on $p$ in the same way, i.e., $f^0(p|x_1 = x_L) = f^0(p|x_1 = x_H)$. This differs from the case where AI-matching is used because an AI-assigned job carries additional information. For example, if the worker is assigned to a poor-match employer by an AI-matching algorithm, she will know that only one employer appears, because otherwise the AI-matching algorithm would have assigned a good-match employer to her. This implies a lower demand probability $p$ than when the worker is assigned to a good-match employer in the first period. Therefore, the posterior belief on the demand probability $p$ puts lower weights on larger values of $p$ when $x_1 = x_L$ than when $x_1 = x_H$, i.e., $f^{AI}(p|x_1 = x_L) < f^{AI}(p|x_1 = x_H)$ for $p > \frac{2}{3}$. Second, regardless whether AI-matching is used, the posterior of $p$ given $x_1 = 0$ is identical, i.e., $f^0(p|x_1 = 0) = f^{AI}(p|x_1 = 0)$. This is because the labor demand is independent of the platform's matching method, and AI plays no role in matching when there is no employer available on the platform.

Now that the worker updates her belief on the demand probability, in the second period, she will decide whether to continue participating in the gig platform based on this posterior belief on $p$. If the worker decides to stay on the platform, there will be some opportunity cost $c$, which reflects the revenue of other non-gig jobs or opportunities on other competing platforms. Let $\Pi_t^l, \pi_t^l, w_t^l$ where $t \in \{1, 2\}$ and $l \in \{0, AI\}$ be the expected total revenue, the expected revenue of the platform, and the expected payoff of the worker, respectively, in the $t$-th period for scenario $l$ (without or with the AI-matching algorithm). The worker will participate if and only if her expected payoff in the second period, which is a function of the job assigned in the first period $x_1$, $w_2^l(x_1) = \delta\Pi_2^l(x_1)$, is no less than the opportunity cost $c$, where

$$\Pi_2^l(x_1) = \mathbf{E}^l[x_2|x_1] = \int_0^1 \mathbf{E}^l[x_2|p]f^l(p|x_1)dp. \tag{5}$$

In the second period, the likelihoods of the worker being assigned to different types of employer are the same as those in the first period, which are given in equations (1) and (2). Without AI-matching, depending on $p$, the conditional expected revenue is calculated as

$$\mathbf{E}^0[x_2|p] = p(1 - \frac{p}{2})x_H + p(1 - \frac{p}{2})x_L = p(1 - \frac{p}{2})(x_H + x_L). \tag{6}$$

Plugging equations (3) and (6) to equation (5) for $x_1 = x_H$, $x_L$, and 0, we know that the expected total revenue in the second period given the worker's observation of the first period assignment,

$\Pi_2^0(x_1)$, is given by

$$\begin{cases} \Pi_2^0(x_1 = x_H) = \mathbf{E}^0[x_2|x_1 = x_H] = \int_0^1 p(1-\frac{p}{2})(x_H + x_L)3p(1-\frac{p}{2})dp = \frac{2}{5}(x_H + x_L), \\ \Pi_2^0(x_1 = x_L) = \mathbf{E}^0[x_2|x_1 = x_L] = \int_0^1 p(1-\frac{p}{2})(x_H + x_L)3p(1-\frac{p}{2})dp = \frac{2}{5}(x_H + x_L), \\ \Pi_2^0(x_1 = 0) = \mathbf{E}^0[x_2|x_1 = 0] = \int_0^1 p(1-\frac{p}{2})(x_H + x_L)3(1-p)^2dp = \frac{1}{5}(x_H + x_L). \end{cases} \tag{7}$$

In the case with AI-matching, depending on $p$, the conditional expected total revenue can be derived as

$$\mathbf{E}^{AI}[x_2|p] = px_H + p(1-p)x_L, \tag{8}$$

and thus the corresponding expected revenue in the second period, $\Pi_2^{AI}(x_1)$, is given by

$$\begin{cases} \Pi_2^{AI}(x_1 = x_H) = \mathbf{E}^{AI}[x_2|x_1 = x_H] = \int_0^1 (px_H + p(1-p)x_L)2pdp = \frac{2}{3}x_H + \frac{x_L}{6}, \\ \Pi_2^{AI}(x_1 = x_L) = \mathbf{E}^{AI}[x_2|x_1 = x_L] = \int_0^1 (px_H + p(1-p)x_L)6p(1-p)dp = \frac{x_H}{2} + \frac{x_L}{5}, \\ \Pi_2^{AI}(x_1 = 0) = \mathbf{E}^{AI}[x_2|x_1 = 0] = \int_0^1 (px_H + p(1-p)x_L)3(1-p)^2dp = \frac{x_H}{4} + \frac{3x_L}{20}. \end{cases} \tag{9}$$

Clearly, we have $\Pi_2^l(x_1 = x_H) > \Pi_2^l(x_1 = x_L) > \Pi_2^l(x_1 = 0)$ for $l \in \{0, AI\}$. Given any opportunity cost $c$, a worker's participation decision depends on the job assigned in the first period ($x_1$). For example, a worker may decide to continue participating in the second period if $x_1$ is $x_H$ or $x_L$ but choose not to continue if $x_1$ is 0. Denote the set of all the first-period assignments that make the worker willing to participate in the second period as $\mathcal{X}^{par}$. Then in the above example, $\mathcal{X}^{par} = \{x_H, x_L\}$. In the following discussion, we add superscripts "0" and "$AI$" to $\mathcal{X}^{par}$, i.e., use $\mathcal{X}^{0,par}$ and $\mathcal{X}^{AI,par}$, to denote this set for the case with and without the adoption of AI, respectively. By comparing $\mathcal{X}^{0,par}$ and $\mathcal{X}^{AI,par}$, we observe that the usage of AI-matching can completely change the expected revenue in the second period and thus the participation decision of the worker, based on which we obtain the following lemma.

**Lemma 1.** *In the second period,*

- *if $x_H < 2x_L$ and $\delta(\frac{x_H}{2} + \frac{x_L}{5}) < c \le \delta\frac{2}{5}(x_H + x_L)$, the worker participates when no AI is adopted as long as she would participate when AI is adopted, or mathematically, $\mathcal{X}^{AI,par} \subset \mathcal{X}^{0,par}$, and specifically, $\mathcal{X}^{AI,par} = \{x_H\}$ and $\mathcal{X}^{0,par} = \{x_H, x_L\}$;*
- *otherwise, the worker participates when AI is adopted as long as she would participate when no AI is adopted, or mathematically, $\mathcal{X}^{0,par} \subseteq \mathcal{X}^{AI,par}$.*

The proofs of all the lemmas and propositions are in the Appendix. Lemma 1 asserts that while the worker in general has a higher incentive to participate when AI-matching is adopted because of the improved matching quality, the opposite can be true when the outside opportunity cost $c$ is intermediate and the revenues of different types of matches (good/poor) are close to each other. In this case, $\mathcal{X}^{AI,par} \subset \mathcal{X}^{0,par}$, which implies that the use of an AI-matching algorithm may undermine worker participation, by revealing extra information in the AI-facilitated matching outcomes. Without AI-matching, the worker has limited information over the demand probability. She will choose to participate in the second period as long as an employer is matched, either good-match or poor-match. However, when AI-matching is used, the worker infers that the underline demand probability is low if she is assigned to a poor-match employer. In this case, she may leave the platform and take other opportunities in the second period, which will result in expected revenue loss for the platform. This phenomenon is more prominent when the good-match and poor-match job tasks do not differ significantly in value ($x_H < 2x_L$), so that the gain from a better match enabled by AI will not dominate the expected loss due to the information revelation by AI. In addition, to make this phenomenon happen, the opportunity cost for workers to participate needs to be in a range of some intermediate values such that a poor-match job in the first period is a good enough signal for a worker to participate without AI, but not so with AI.

We next examine how the platform's revenue, $\pi^l \equiv \pi_1^l + \pi_2^l$, is affected by the adoption of AI-matching. We first focus on the case when $\mathcal{X}^{AI,par} \subset \mathcal{X}^{0,par}$, which is equivalent to the assumption that $x_L < x_H < 2x_L$ and $\delta(\frac{x_H}{2} + \frac{x_L}{5}) < c \leq \delta\frac{2}{5}(x_H + x_L)$ based on Lemma 1. Under this assumption, the platform's realized revenue in each period is illustrated in Figures 1 and 2 for the two cases (with and without AI-matching), respectively. In the figures, the cases where $\pi_2^0$ always equals 0 regardless of $x_2$ happen when the worker chooses not to participate in the platform in the second period, based on Lemma 1.

Depending on the demand probability $p$, the platform's expected revenue is

$$
\begin{aligned}
\mathbf{E}[\pi^0|p] =& \mathbf{E}[\pi_1^0 + \pi_2^0|p] \\
=& (1-\delta)\Big[p(1-\frac{p}{2})(x_H + p(1-\frac{p}{2})x_H + p(1-\frac{p}{2})x_L) \\
& \quad + p(1-\frac{p}{2})(x_L + p(1-\frac{p}{2})x_H + p(1-\frac{p}{2})x_L)\Big] \\
=& (1-\delta)\frac{p}{2}((1-p)(3-p)p+2)(x_H + x_L) \qquad (10)
\end{aligned}
$$

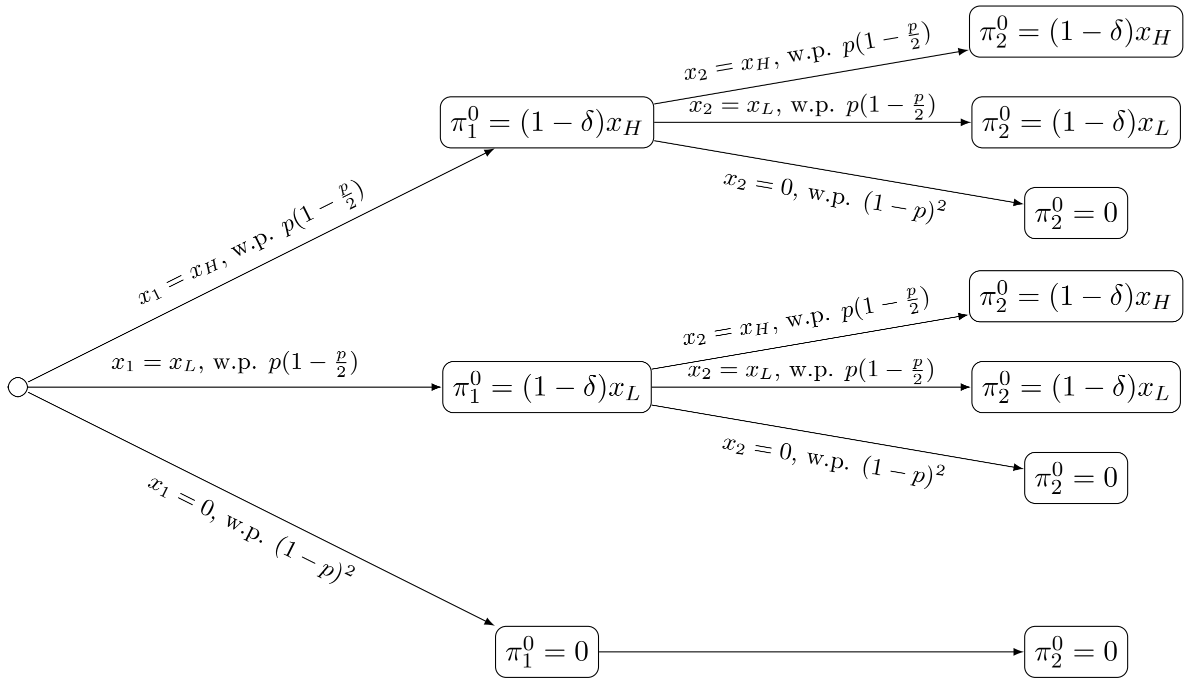



Figure 1: Platform revenue: when no AI-matching is used

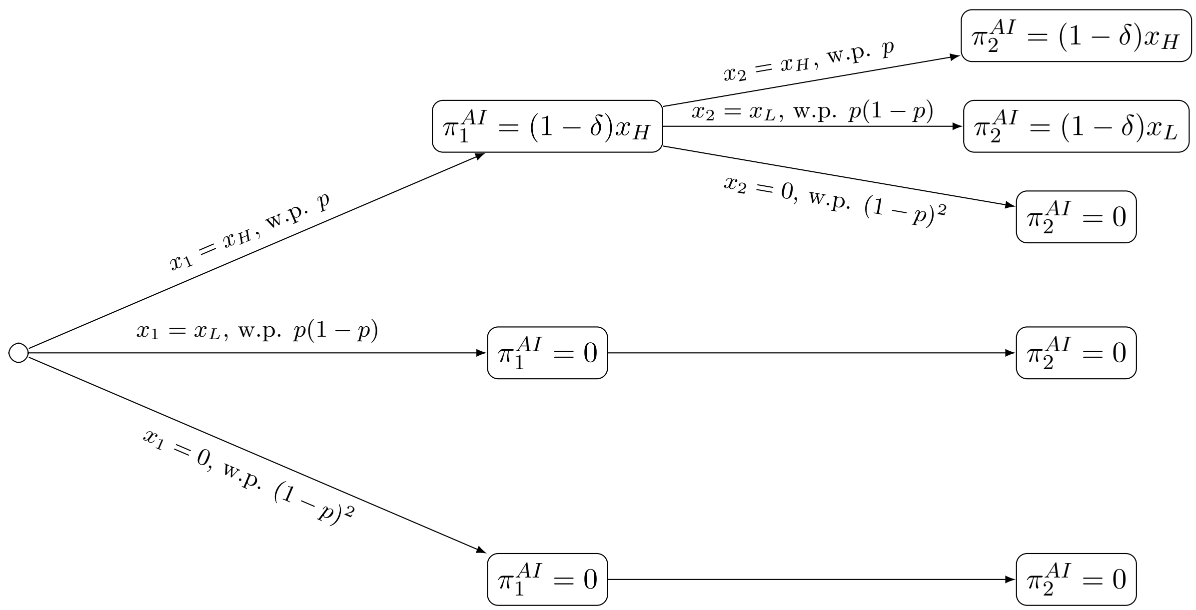



Figure 2: Platform revenue: when AI-matching is used

for the case without AI-matching, and

$$
\begin{aligned}
\mathbf{E}[\pi^{AI}|p] =& \mathbf{E}[\pi_1^{AI} + \pi_2^{AI}|p] \\
=& (1-\delta)\big[p\big(x_H + px_H + p(1-p)x_L\big) + p(1-p)x_L\big] \\
=& (1-\delta)(p(1+p)x_H + p(1-p^2)x_L)
\end{aligned} \tag{11}
$$

for the case with AI-matching. By integrating over $p$ in Equation (10) or (11), the ex ante expected revenue of the platform can be calculated as

$$\pi^{0*} \equiv \int_0^1 \mathbf{E}[\pi^0|p]dp = (1-\delta)\frac{3}{5}(x_H + x_L) \tag{12}$$

for the case with no AI-matching and

$$\pi^{AI*} \equiv \int_0^1 \mathbf{E}[\pi^{AI}|p]dp = (1-\delta)(\frac{5}{6}x_H + \frac{x_L}{4}) \tag{13}$$

for the case with AI-matching. The above calculations are under the assumption that $x_L < x_H < 2x_L$ and $\delta(\frac{x_H}{2} + \frac{x_L}{5}) < c \leq \delta\frac{2}{5}(x_H + x_L)$, or $\mathcal{X}^{AI,par} \subset \mathcal{X}^{0,par}$. Following the same procedure, we can calculate the platform's ex ante expected revenue under all conditions as

$$\pi^{l*} = (1-\delta)\int_0^1 \sum_{x\in\{x_H,x_L,0\}} Pr^l(x_1 = x|p)\Big(x + \mathbf{1}_{\{x\in\mathcal{X}^{l,par}\}} \sum_{x'\in\{x_H,x_L,0\}} Pr^l(x_2 = x'|p)x'\Big)dp, \tag{14}$$

where $l \in \{AI, 0\}$. We then compare the expected revenue of the gig platform between the cases with and without the use of AI-matching, and summarize the results in the following proposition.

**Proposition 1.** *If $x_H < \frac{3}{2}x_L$ and $\delta(\frac{x_H}{2} + \frac{x_L}{5}) < c \leq \delta\frac{2}{5}(x_H + x_L)$, the platform's (ex ante) expected revenue is lower when it adopts AI-matching than when it does not, i.e., $\pi^{AI*} < \pi^{0*}$. Otherwise, the platform's expected revenue with AI is higher or equal to that without AI, i.e., $\pi^{AI*} \geq \pi^{0*}$.*

Proposition 1 asserts when the platform's expected revenue can be negatively affected by the use of AI-matching, even if we do not consider any cost associated with applying AI. Specifically, when the outside opportunity cost for the worker is intermediate and the values of different types of match are sufficiently close, AI-matching will hurt the gig platform in terms of expected revenue, as illustrated in Figure 3.

The platform's expected revenue is affected by the use of AI-matching in two ways. On one hand, the use of AI can enhance the quality of matching when employers with different match quality are present, yielding a higher expected revenue. We call it the *"matching enhancement effect"* of AI. On the other hand, strategic gig workers can potentially make use of the demand information revealed by AI-assigned jobs in the first period, thereby changing their participation behavior. Specifically, as shown in Lemma 1, under certain conditions, the adoption of AI-matching may undermine the participation of the worker compared to when AI is not adopted, leading to

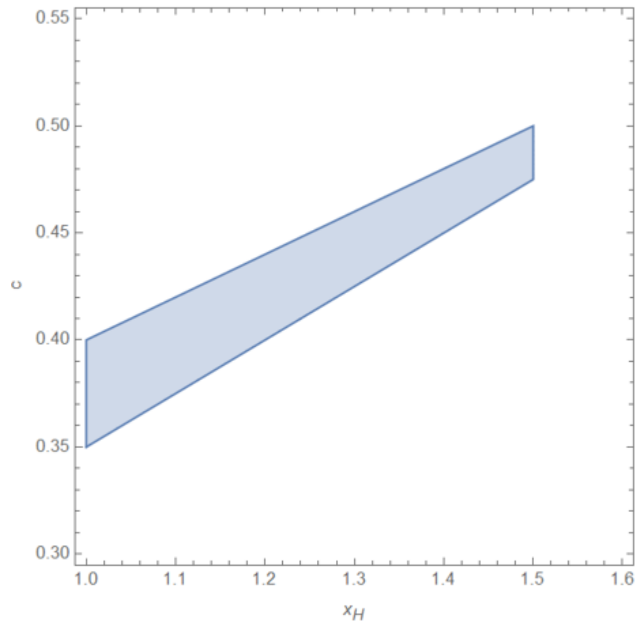



Figure 3: Parameter space for $\pi^{AI*} < \pi^{0*}$ (shaded area)
Note: $x_L = 1$, $\delta = 0.5$

potential expected revenue loss for the platform. We call it the *"information revelation effect"* of AI. The information revelation effect is, of course, not always detrimental, and sometimes can work to the platform's benefit, for example when a good-match employer is assigned indicating a strong demand condition. The overall impact of AI-enabled matching on the expected revenue of the platform is thus non-trivial and determined by the sign of the information revelation effect, and when it is negative, the relative strength of the two effects. When the information revelation effect is positive or otherwise when the matching enhancement effect dominates the information revelation effect, AI is instrumental to the gig platform to enable better matching which translates to higher revenue. When the opposite is true, however, the gig platform's revenue could be lessened by the adoption of AI in matching as a result of insufficient labor supply, even if we set aside the cost of developing and deploying AI.

Our model thus uncovers an important yet often-overlooked insight on how the revenue of a gig platform adopting AI to facilitate matching can be affected as a result of gig worker's strategic reaction to the demand information revealed by AI-assigned job tasks. Our findings suggest that although AI is effective in assigning best-match job tasks to gig-workers, a better matching between gig workers and job tasks may not necessarily lead to higher revenue for the gig platform, if it further takes into account the workers' strategic participation behavior. Specifically, the strategic participation behavior hurts the platform when a poor-match employer is assigned in the first period. In this case, the worker's participation incentive is lower when AI-matching is used than when AI-matching is not used. The "information revelation effect" here is more like an attribution effect from the worker's point of view: when a worker is assigned to a poor-match employer, she can attribute it to either a low demand or a poor matching system, until the adoption of AI effectively rules out the latter. That is, after receiving a poor-match employer, a worker will estimate the demand more positively in the case when AI is absent compared to the case when AI is used. Mathematically, this can be shown by comparing the cumulative distribution functions (CDFs) of the worker's posterior belief on $p$ without and with AI:

$$F^0(p|x_1 = x_L) = \int_0^p f^0(\tilde{p}|x_1 = x_L)d\tilde{p} = \frac{1}{2}p^2(3-p),$$
$$F^{AI}(p|x_1 = x_L) = \int_0^p f^{AI}(\tilde{p}|x_1 = x_L)d\tilde{p} = p^2(3-2p).$$

Note that for any $p \in (0,1)$, $\frac{1}{2}p^2(3-p) < p^2(3-2p)$, and thus $F^0(p|x_1 = x_L)$ first-order stochastically dominates $F^{AI}(p|x_1 = x_L)$, as shown in Figure 4.

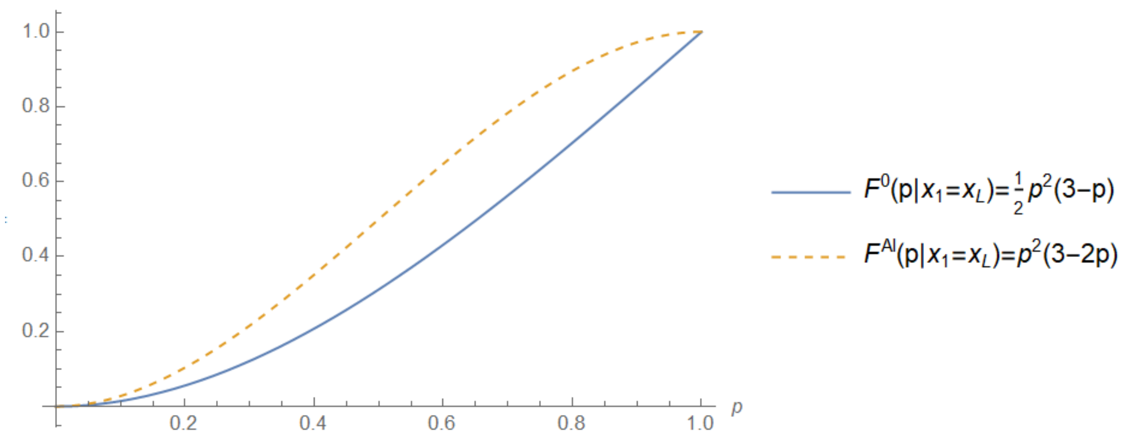



Figure 4: $F^0(p|x_1 = x_L)$ first-order stochastically dominates $F^{AI}(p|x_1 = x_L)$

Our analysis shows that AI is not silver bullet and the adoption of AI to facilitate matching may yield unintended consequences on participation decisions of gig workers, resulting in revenue loss for the gig platform. This result offers an important insight for gig platforms currently adopting or planning to adopt AI in their matching process. Ultimately, the performance of current state of AI is restricted to the contextual data or environment information it processes (Lum, 2017; Wang et al., 2019). For the worker-employer matching process, AI can only be adaptive to the provision of existing labor market information about supply and demand. With optimization as part of AI-enabled matching procedure, for each worker, the best recommendation of employer, conditional on the contextual labor demand information, is delivered. That is, *AI can only take what is given but cannot change demand condition.* In a market with low labor demand, even the best match may still be a poor match that cannot generate high revenue for the worker and the platform. The revealed demand information, however, unintentionally discourages workers from continual participation because of the notable flexibility offered for gig-platform employment (Chen et al., 2019). Workers may not respond in an adaptive manner, and can choose to strategize their future participation decisions based on received AI-assigned employers (Cameron, 2020; Lee et al., 2015). That is, workers can account for the labor demand information revealed by AI recommendations, adjust their beliefs about the labor market, estimate potential payoffs from continual participation, and strategically decide whether to continue working for the platform. While workers can also make strategic participation decisions when AI-matching is not used, the reassurance of the matching quality enabled by AI-matching makes it more likely for workers to associate a poor-match with low demand (rather than matching quality) and consequently stops participating.

# 4 Extended Models

In this section, we consider two model extensions to examine the robustness of our results to alternative model assumptions. In subsection 4.1, we investigate the case where the platform can strategically adjust its commission rate based on whether AI-matching is adopted. In subsection 4.2, we further consider competition among workers on the same platform.

## 4.1 Endogenous Revenue Sharing

In the main model, we consider a fixed commission rate (i.e., $1-\delta$) regardless of whether the AI is used for matching. In this subsection, we investigate whether our key insights are robust if the platform can strategically tailor its commission rate according to its AI strategy. That is, given the matching technology (AI or not) as well as the worker's opportunity cost $c$, the platform can choose a different commission rate. Consistent with the business reality that the commission rate is typically set once for all, we assume this commission rate $1-\delta$ (or equivalently, the revenue-sharing ratio with $\delta$ proportion for the worker) is decided at the very beginning before demand is realized and remains the same in both periods.

Let $\delta^{0*}$ and $\delta^{AI*}$ denote the optimal revenue-sharing ratio decided by the platform for the cases without and with AI, respectively. The platform's optimal revenue-sharing ratio and the corresponding expected revenue $\pi_{endo}^{0*}$ and $\pi_{endo}^{AI*}$ are given by the following lemma.

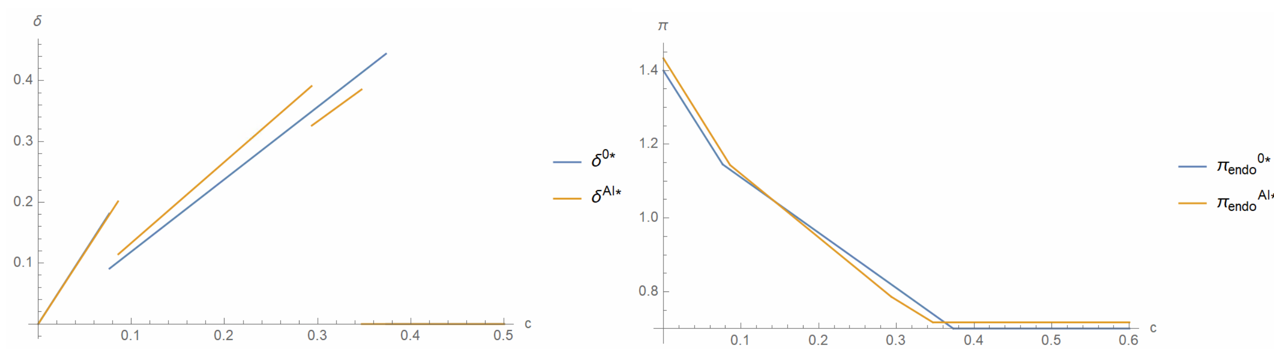
**Lemma 2.** *When there is no AI,*

- *if* $c \leq c_1^0$, $\delta^{0*} = \frac{5c}{x_H+x_L}$ *and* $\pi_{endo}^{0*} = \frac{2x_H}{3} + \frac{2x_L}{3} - \frac{10c}{3}$,
- *if* $c_1^0 < c \leq c_2^0$, $\delta^{0*} = \frac{5c}{2(x_H+x_L)}$ *and* $\pi_{endo}^{0*} = \frac{3x_H}{5} + \frac{3x_L}{5} - \frac{3c}{2}$,
- *if* $c > c_2^0$, $\delta^{0*} = 0$ *and* $\pi_{endo}^{0*} = \frac{x_H}{3} + \frac{x_L}{3}$.

*When AI is used,*

- *if* $c \leq c_1^{AI}$, $\delta^{AI*} = \frac{20c}{5x_H+3x_L}$ *and* $\pi_{endo}^{AI*} = \frac{(3x_H+x_L)(5x_H+3x_L-20c)}{15x_H+9x_L}$,
- *if* $c_1^{AI} < c \leq c_2^{AI}$, $\delta^{AI*} = \frac{10c}{5x_H+2x_L}$ *and* $\pi_{endo}^{AI*} = \frac{(55x_H+17x_L)(5x_H+2x_L-10c)}{60(5x_H+2x_L)}$,
- *if* $c_2^{AI} < c \leq c_3^{AI}$, $\delta^{AI*} = \frac{6c}{4x_H+x_L}$ *and* $\pi_{endo}^{AI*} = \frac{(10x_H+3x_L)(4x_H+x_L-6c)}{12(4x_H+x_L)}$,
- *if* $c > c_3^{AI}$, $\delta^{AI*} = 0$ *and* $\pi_{endo}^{AI*} = \frac{x_H}{2} + \frac{x_L}{6}$,

*where* $c_1^0 = \frac{2(x_H+x_L)}{55}$, $c_2^0 = \frac{8(x_H+x_L)}{45}$, $c_1^{AI} = \frac{(5x_H+2x_L)(5x_H+3x_L)^2}{10\left(325x_H^2+190x_Hx_L+29x_L^2\right)}$, $c_2^{AI} = \frac{(4x_H+x_L)(5x_H+2x_L)^2}{10\left(70x_H^2+18x_Hx_L-x_L^2\right)}$, *and* $c_3^{AI} = \frac{(4x_H+x_L)^2}{60x_H+18x_L}$. *By construction,* $c_1^0 < c_2^0$ *and* $c_1^{AI} < c_2^{AI} < c_3^{AI}$.




(a) Revenue Sharing Ratio ($\delta^{0*}$ and $\delta^{AI*}$)

(b) Platform Revenue ($\pi_{endo}^{0*}$ and $\pi_{endo}^{AI*}$)

Figure 5: Optimal Revenue Sharing Ratio and Expected Platform Revenue
Note: $x_H = 1.1$ and $x_L = 1$

Figure 5 illustrates the optimal revenue sharing ratio and the platform's expected revenue described in Lemma 2. This lemma implies that when the platform sets the commission rate based on whether AI is adopted, the worker might in fact get a larger proportion out of the total revenue when AI-matching is adopted compared to when it is not (see Figure 5a). Conventional wisdom may suggest that, with AI-matching, the platform has a better control over the demand allocation and thus should have more bargaining power when setting the commission rate, leading to a smaller $\delta$ or more severe "labor exploitation" from workers. In contrast, we find that because the information revelation effect of AI may undermine worker participation, in order to motivate the worker to participate, the platform may have to increase the worker's share of revenue instead (i.e., it is possible that $\delta^{0*} < \delta^{AI*}$). Accordingly, the application of AI in matching may not necessarily lead to the expected more severe exploitation.

Figure 5b also implies that under some circumstances, adopting AI-matching may still hurt the platform's revenue even when the ratio of revenue sharing is determined conditionally based on the use of AI. Proposition 2 gives a more comprehensive investigation on the conditions under which this phenomenon happens.

**Proposition 2.** *Even if the platform can choose the worker's share of revenue based on the use of AI-matching, when $x_H$ is not too large compared to $x_L$ and $c$ is in an intermediary range (as illustrated in Figure 6), the platform's expected revenue is lower when it adopts AI-matching than when there is no AI, i.e., $\pi^{AI*}_{endo} < \pi^{0*}_{endo}$.*

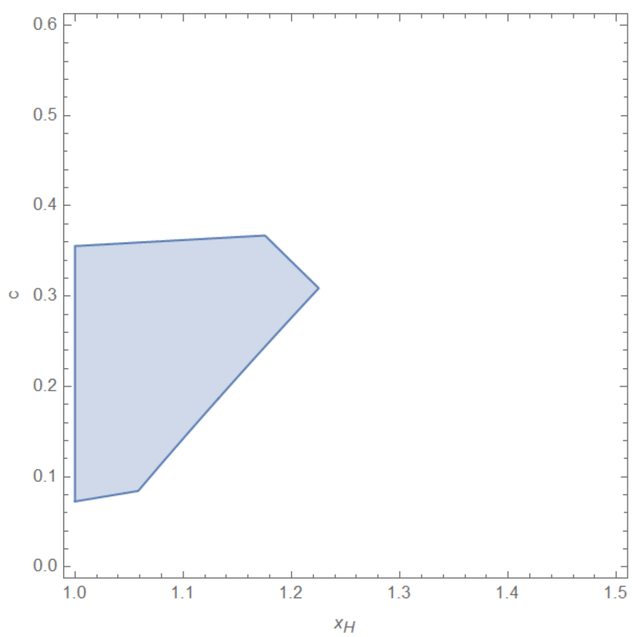



Figure 6: Parameter space for $\pi^{AI*}_{endo} < \pi^{0*}_{endo}$ (shaded area)
Note: $x_L = 1$

Comparing Propositions 1 and 2, we can see that even when the gig platform's revenue sharing is strategic, the structural property with respect to AI's influence on the platform's expected revenue remains intact. That is, the adoption of AI in matching might hurt the gig platform when the opportunity cost lies in some intermediate range and the difference in values of different types of match is sufficiently small. The two effects of AI adoption, matching enhancement effect and information revelation effect, remain to play a similar role. Even if the platform has enough market power to adjust its revenue split with the worker, applying AI to matching may still lead to lower expected revenue for the platform, even if we do not need to consider the cost of applying AI.

## 4.2 Interrelated Worker Demand

In the main model, we assume that workers' demands are independent, that is, workers' potential markets do not overlap such that each individual worker monopolizes her own market demand. In practice, workers' potential markets may overlap and thus the workers may engage in labor competition. In this case, while a worker may not be aware of the existence of other workers potentially serving the same demand, the platform considers all the workers who can potentially take these jobs when it matches employers and workers.

In the following, we take this demand interrelation into account and focus on a representative case of two workers and four potential employers on the platform.[5] We first examine the case where workers are not aware of the existence of other workers serving the same demand when this competition information is not revealed by the platform. Later in Section 5, we will examine how worker behavior and platform revenue are affected if the platform reveals this competition information to the workers.

Each potential employer appears with probability $p$, which again describes the demand condition. Among the four potential employers, two of them are good match for the workers and generate revenue $x_H$, while the other two with poor match generate revenue $x_L$. Below we show the results when the two workers have homogeneous preferences. In the Appendix on page A7, we also show the results for the case where the two workers' preferences are differentiated, i.e., one worker's good-match employer is the other worker's poor match. With the heterogeneous preferences, our results continue to hold qualitatively, although the region where AI-matching hurts the platform shrinks as a result of the stronger matching enhancement effect.

With interrelated worker demand, the gig platform without AI-matching still assigns jobs randomly, while the platform with AI-matching assigns good-match employers to both workers whenever possible to maximize the revenue. If the number of good-match employers appearing on the

[5] We consider four potential employers in this extension to ensure that our representative case covers all possible scenarios for job assignments, including assigning both good-match employers to workers, assigning both bad-match employers, assigning different types of employers and so on.

platform is lower than the number of workers, each worker has the same chance to be assigned to a good-match employer, and the rest will serve a poor-match employer or even have no job assigned depending on the total number of employers present. Whenever the total number of employers who actually appear is lower than the number of workers, e.g., if there are two workers but only one employer, then the two workers will be assigned to the employer with equal probability.

In the rest of this subsection, we will discuss the workers' participation decisions and the platform's expected revenue if (1) AI is adopted and (2) no AI is used, and show when a platform's adoption of AI can backfire, which demonstrates the robustness of our key insights to the consideration of worker competition. Let $\pi_{rela}^{0*}$ and $\pi_{rela}^{AI*}$ denote the platform's expected revenue without and with AI-matching when workers are interrelated, respectively. Following the same analysis in Section 3, we find the results that are in line with those of the main model, which are summarized in the following proposition.

**Proposition 3.** *When workers' demands are interrelated, if $x_H < \frac{215}{121}x_L$ and $\delta(\frac{4x_H}{7} + \frac{4x_L}{21}) < c \leq \delta(\frac{4x_H}{9} + \frac{4x_L}{9})$, the platform's (ex ante) expected revenue when it adopts AI-matching is lower than that without AI, i.e., $\pi_{rela}^{AI*} < \pi_{rela}^{0*}$. Otherwise, the platform's expected revenue with AI is higher or equal to that without AI, i.e., $\pi_{rela}^{AI*} \geq \pi_{rela}^{0*}$.*

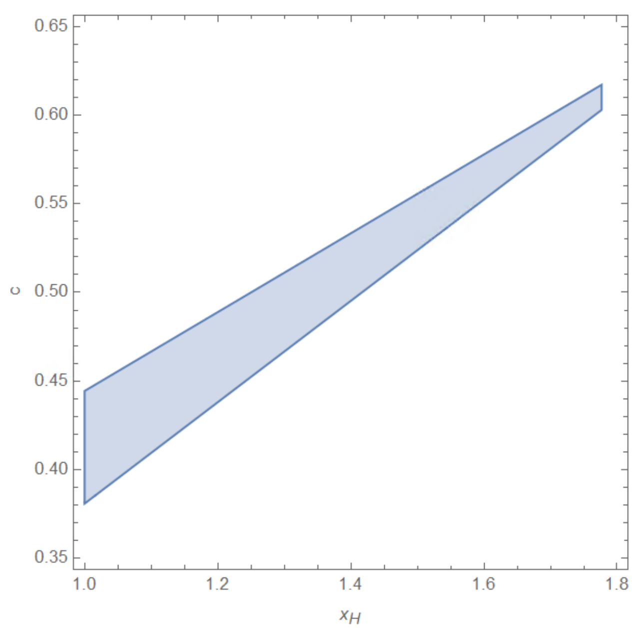



Figure 7: Parameter space for $\pi_{rela}^{AI*} < \pi_{rela}^{0*}$ (shaded area)
Note: $x_L = 1$, $\delta = 0.5$

Proposition 3 is illustrated in Figure 7 and continues to show that the adoption of AI-matching algorithm may hurt the revenue of the platform by undermining worker participation. Specifically, when the outside opportunity cost $c$ is intermediate and the value $x_H$ of a good-match job is not too high, the platform's ex ante expected revenue can be even lower when it adopts AI-matching than when it does not. This implies that the insights from our main model are robust to whether the workers have independent demand or not.

# 5 Approaches to Mitigate the Negative Effect of AI-Matching

Our discussion in the above two sections highlights that the use of AI-matching algorithm may at certain times hurt the platform's revenue. The anticipated benefit of AI-matching is tenable only when the matching enhancement effect dominates the information revelation effect if the revealed demand information discourages worker participation. In practice, gig platforms can reveal demand information to workers. For example, ride-hailing platforms, such as Uber and Lyft, provide a "heat map" to drivers which reveals the real-time demand in different areas of a city (Uber, 2021b). The usage of surge pricing can also be considered as a demand signal. Since competition from workers targeting the same demand can also affect job assignments, revealing competition information may also influence workers' interpretation of demand information carried by AI-assigned jobs and thus worker participation. In this section, we examine two approaches that could mitigate the negative effect of AI-matching for the gig platforms: revealing demand information directly and revealing competition information to the workers, and compare their relative effectiveness. Since competition information is involved, in this section, we use the model introduced in subsection 4.2 with interrelated worker demand as the benchmark.

## 5.1 Revealing Demand Information

In subsection 4.2, the worker cannot observe the market demand probability $p$ before participating, but she can infer this information through a Bayesian manner after observing her first period job assignment. Unlike concealing the demand information in our main model, the platform could instead reveal this demand information directly to the worker.

Suppose that the platform can commit to truthfully revealing the demand information, i.e., $p$, to the worker.[6] Then the worker's participation decision in the second period will simply depend

[6] Providing deceiving demand information to the workers will result in the loss of trust from the workers. Ultimately, the workers will overlook the revealed demand information, and go back to inferring demand information from job assignments.

on the revealed $p$, but not on the matching outcome in the first period because the inference for $p$ is no longer needed. Consider the case when the platform adopts AI to match the two workers with the four potential employers. The worker participates in the second period if and only if the demand information $p$ satisfies

$$\delta\left(Pr^{AI}_{worker}(x_2 = x_H|p)x_H + Pr^{AI}_{worker}(x_2 = x_L|p)x_L\right) \geq c, \tag{15}$$

where $Pr^{AI}_{worker}(x_2 = x_H|p)$ (or $Pr^{AI}_{worker}(x_2 = x_L|p)$) is the probability that the worker *thinks* a good-match (or poor-match) employer is assigned to her with AI-matching, whose expressions are in Equation (A2) on page A5 of the Appendix. In this case, the worker does not know the existence of the competitor so she assumes she faces all the four potential employers. Inequality (15) is equivalent to

$$p > \overline{p} \equiv \frac{1}{2}\left(2 - \sqrt{2}\sqrt{\frac{\sqrt{(x_H + x_L)^2 - 4cx_L/\delta}}{x_L} - \frac{x_H}{x_L} + 1}\right). \tag{16}$$

In this case, the platform's revenue, denoted as $\pi^{AI*}_{RD}$, is given by

$$\begin{aligned}\pi^{AI*}_{RD} = &\underbrace{(1-\delta)\int_0^1 \left[Pr^{AI}_{actual}(x_1 = x_H|p)2x_H + Pr^{AI}_{actual}(x_1 = x_L|p)2x_L\right]dp}_{\text{revenue from the first period}} \\ &+ \underbrace{(1-\delta)\int_{\overline{p}}^1 \left[Pr^{AI}_{actual}(x_2 = x_H|p)2x_H + Pr^{AI}_{actual}(x_2 = x_L|p)2x_L\right]dp,}_{\text{revenue from the second period}}\end{aligned} \tag{17}$$

where $Pr^{AI}_{actual}(x_t = x_H|p)$ (or $Pr^{AI}_{actual}(x_t = x_L|p)$), $t = 1, 2$, is the *actual* probability that a good-match (or poor-match) employer is assigned to a worker with AI-matching, whose expressions are in Equation (A4) on page A6 of the Appendix. The platform cares about whether the potential negative effect brought by the adoption of AI-matching, as we have shown in subsection 4.2, can be alleviated by truthfully revealing $p$, i.e., whether $\pi^{AI*}_{RD} > \pi^{AI*}_{rela}$. The following proposition answers this question.

**Proposition 4.** *If the platform's expected revenue is lower when it adopts AI-matching than when there is no AI, then the platform adopting AI is better off by truthfully revealing p to the worker, i.e.,* $\pi^{AI*}_{RD} > \pi^{AI*}_{rela}$*, but it may still be worse off compared to the case without the use of AI (*$\pi^{AI*}_{RD}$ *may be less than* $\pi^{0*}_{rela}$*).*

The above proposition shows that when information revelation effect works against the platform's benefit, the revealed demand information will mitigate the unfavorable information revelation effect of AI-matching, resulting in an increase in platform revenue, i.e., $\pi_{RD}^{AI*} > \pi^{AI*}$. However, in some cases where the demand condition is not good, revealing this information directly, even though it is better than letting the worker inferring from the AI-assigned matching outcome, still hurts platform revenue compared to when workers infer information from a randomly matched job assignment. This leads to the outcome that by truthfully revealing $p$, the platform may still be worse off compared to the case without the adoption of AI. Of course, sometimes, the information revelation effect enabled by AI-matching may work to the platform's benefit, e.g., when it leads to an over optimistic demand expectation. When this happens, revealing demand information directly may hurt the platform's revenue as well. Therefore, whether to commit to direct demand revelation is a strategy that the platform needs to consider thoughtfully, gauging the benefits and risks of different situations.

### 5.2 Revealing Competition Information

In subsection 4.2, we assume that the workers are not aware of other workers competing for the same labor demand when this information is not revealed by the platform. Here, we analyze what happens if the platform instead reveals the number of workers competing for the same demand to the workers. In this case, each worker knows the existence of the other worker on the platform competing for the same potential labor demand. When a worker infers demand information from first-period job assignment, she takes into account the effect of competition on the type of the assignment she receives. When she decides whether to continue participating in the second period, her expected payoff for the second period not only depends on the inferred demand information, but also depends on her expectation over the other worker's participation decision. We focus on the case where the platform adopts AI for matching, since our interest is to examine whether revealing competition information can alleviate the negative effect of AI adoption. We develop the symmetric Nash Equilibrium (mixed strategy allowed) in Lemma 3.

**Lemma 3.** *When the platform that adopts AI-matching reveals the competition information to workers who compete for the same potential demand, in the following cases, there exists a unique symmetric pure strategy equilibrium regarding worker participation:*

- *when $c \leq c_1$, workers always participate in the second period;*
- *when $c_{21} < c \leq c_{22}$, workers participate in the second period iff $x_1 = x_H$ or $x_1 = x_L$;*

- *when* $c_{31} < c \leq c_{32}$*, workers participate in the second period iff* $x_1 = x_H$*;*

- *when* $c > c_4$*, workers will not participate in the second period.*

*In other cases, there is a unique symmetric mixed strategy equilibrium:*

- *when* $c_1 < c \leq c_{21}$*, workers participate in the second period with probability 1 if* $x_1 = x_H$ *or* $x_1 = x_L$*, with probability* $\lambda_1 = \frac{3(\delta(38x_H+23x_L)-126c)}{5\delta(6x_H+x_L)} \in (0,1)$ *if* $x_1 = 0$*;*

- *when* $c_{22} < c \leq c_{31}$*, workers participate in the second period with probability 1 if* $x_1 = x_H$*, with probability* $\lambda_2 = \frac{7(\delta(21x_H+8x_L)-36c)}{\delta(9x_H-4x_L)} \in (0,1)$ *if* $x_1 = x_L$*, and with probability 0 if* $x_1 = 0$*;*

- *when* $c_{32} < c \leq c_4$*, workers participate in the second period with probability* $\lambda_3 = \frac{7(\delta(25x_H+3x_L)-30c)}{3\delta(7x_H-5x_L)} \in (0,1)$ *if* $x_1 = x_H$*, and with probability 0 if* $x_1 = x_L$ *or* $x_1 = 0$*,*

*where* $c_1 = \delta(\frac{2x_H}{9} + \frac{32x_L}{189})$*,* $c_{21} = \delta(\frac{19x_H}{63} + \frac{23x_L}{126})$*,* $c_{22} = \delta(\frac{23x_H}{42} + \frac{5x_L}{21})$*,* $c_{31} = \delta(\frac{7x_H}{12} + \frac{2x_L}{9})$*,* $c_{32} = \delta(\frac{11x_H}{15} + \frac{6x_L}{35})$*, and* $c_4 = \delta(\frac{5x_H}{6} + \frac{x_L}{10})$*. By construction,* $c_1 < c_{21} < c_{22} < c_{31} < c_{32} < c_4$*.*

Given the workers' responses when the competition information is revealed, we can calculate the expected revenue of the platform, denoted as $\pi_{RC}^{AI*}$, and compare that to the revenue when no competition information is revealed in subsection 4.2 ($\pi_{rela}^{AI*}$). The following proposition gives the result of this comparison.

**Proposition 5.** *If the platform's expected revenue is lower when it adopts AI-matching than when there is no AI, then the platform adopting AI is no worse off by revealing the competition information to the workers, i.e.,* $\pi_{RC}^{AI*} \geq \pi_{rela}^{AI*}$*, but it may still be worse off compared to the case without the use of AI (*$\pi_{RC}^{AI*}$ *may be less than* $\pi_{rela}^{0*}$*).*

Conventional wisdom may suggest that revealing competition information to workers will discourage workers from continuing their work, since their expected payoff is less in the presence of competition from the peers. However, our analysis suggests that this argument may not be universally true. This is because in our case, there are two factors that a worker needs to consider when she is making the participation decision: (1) the competition from other workers, and (2) the estimated labor demand in the market. Revealing competition information indeed makes the former more salient and thus discourages a worker from participating, but it also, on the other hand, induces a worker to think more positively about the labor demand after seeing the first-period assignment being poor-match. This is because competition serves as another source of not getting a good match in the first period, and thus a worker may not blame the demand after being assigned to a poor-match employer in the first period, mitigating the unfavorable information revelation effect discussed in the main model.

Now we have examined two possible approaches to mitigate the potential negative effect brought by AI adoption – revealing the information of labor demand or worker competition. The natural next question is which approach, revealing demand information, competition information, or both, is more effective in mitigating the negative effect. We answer this question in the following corollary.

**Corollary 1.** *Among the choices of revealing demand information, competition information, or both, the platform benefits the most from revealing demand information alone.*

Corollary 1 makes two interesting observations. First, it indicates that revealing both the demand and competition information is suboptimal for the platform. This is because when the demand information is truthfully revealed to gig workers, there is no need for them to infer demand information from assigned jobs. Therefore, the issue of unfavorable information revelation effect is resolved. In this case, further revealing the competition information only demotivates workers from participating in the platform. Second, the corollary also points out that when AI-matching induces unfavorable information revelation effect, revealing demand information is more effective than revealing competition information in mitigating this effect. The underlying intuition is that in the cases where AI-matching hurts the revenue of the platform, information revelation effect dominates the matching enhancement effect. While both approaches can mitigate this negative impact of AI, revealing competition information additionally discloses the presence of competition that workers might not have been aware of and thus become reluctant to participate as a result of competitive pressure. In fact, we observe in practice that Uber reveals the demand information to its drivers by facilitating a "heat map" in their Driver app, but it does not allow drivers to see how many competing drivers are near them in the app, consistent with the optimal strategy that our results suggest.

## 6 Concluding Remarks

In this study, we construct an analytical model to examine how the adoption of AI-enabled matching can affect workers' behavior on a gig platform, and uncover under what circumstances AI-enabled matching can have unintended negative consequences on the total revenue of the platform. Prior literature has focused on the platform-enabled market design to reduce transaction costs and use information efficiently for the matching between employers and workers (Einav et al., 2016). Recent development in the field of AI has substantially enhanced the algorithmic performance in worker-employer matching and overall operational efficiency of gig platforms. However, little attention is paid to whether the improvement in matching by AI can help the platform obtain higher revenue. To the best of our knowledge, our study is the first to provide a comprehensive model that can systematically examine the impact and implication of adopting AI on a gig platform when matching gig workers and employers requesting job tasks. As AI can learn from contextual information for the matching between workers and employers on the platform, information about the labor demand can be revealed to each worker through the AI-assigned employer. Our model considers the crucial factors in decision making about a worker's participation in the platform, such as beliefs updated by the information revealed in AI-assigned jobs through a Bayesian manner as well as expected payoffs associated with the participation (Boyaci et al., 2020).

We show that AI can induce strategic participation decisions of workers, which could lead to negative impacts on the platform's revenue. We contribute to the recent development of literature on economics of AI by revealing that AI, although enhancing the quality of matching between workers and employers, is a double-edged sword in the gig economy. While researchers are interested in studying how digital technologies can be used to motivate workers to contribute to the gig economy and enhance the market efficiency (Fradkin, 2017; He et al., 2021; Horton, 2017), our study highlights the unintended consequences of AI on worker behavior and platform revenue. This is because the outcomes of AI-enabled matching may disclose demand information unintentionally which leads the workers not to continue participating in the gig platform as anticipated, and thus result in a loss of platform revenue.

Our results are robust to alternative model assumptions regarding conditional revenue sharing and worker competition. We also examine two approaches that can remedy the unanticipated effect of AI on the gig platform. As the gig economy is rapidly expanding and AI is becoming more widely adopted for optimally evaluating, matching and assigning the job tasks to workers, our study provides valuable insights regarding the overall impacts that the choice of AI adoption and response to AI by human workers can have on the workplace enabled by gig platforms (Lee, 2018).

In addition, we extend the emerging literature on algorithmic management in the gig economy. The findings derived from our model can deepen the understandings of the "good bad job" coined to describe the nature of the contemporary gig work empowered by digital technologies. While the job tasks are bounded and the autonomy of gig workers can be squelched by algorithmic technologies, a sense of autonomy can also be further engendered by algorithmic controls, besides the flexible work arrangements offered in the gig workplace (Cameron, 2020; Manyika et al., 2016). Our model offers a more nuanced way of examining how gig workers can navigate the tension between AI-assigned job tasks and autonomy by strategically engaging with the job tasks and using them to make informed decisions of their gig platform participation, as well as the influence of their participation decisions on the revenue of the platform.

This study provides a broader and more complete understanding of the landscape of AI-human worker interactions in gig platforms. It yields significant managerial implications for AI practitioners and managers rolling out AI in the gig economy. First, we alert gig platforms to the unintended negative consequences of adopting AI to facilitate matching, even if we do not need to consider the cost of applying AI, mainly resulting from the possible negative information revelation effect as the human workers interact with the demand signal carried in AI-assigned jobs on the platform. This negative impact likely occurs when the "good-match" and "poor-match" job tasks do not differ significantly in value to workers. Even if the platform has enough market power to adjust its revenue split with its workers, applying AI to matching may still give rise to lower revenue for the platform. As AI is emerging as a revolutionary technology and continues to progress, with improvement in its capability in learning from contextual information of the labor market, the adverse effect in presence of AI-enabled matching in the gig platform unveiled from this study could be even amplified, and should not be overlooked. Developing such AI-enabled matching systems that can analyze all the information presented and exhibit superior matching performance is not always the best course of action to improve platform revenue. The platform should recognize the adoption of AI as a strategic choice, taking into account its potential information revelation effect. Second, we provide immediate actionable guidance and showcase that the gig platform adopting AI to match workers and their employers could directly disclose some information about labor supply and demand to the workers, in order to mitigate the negative consequence caused by AI adoption. The information disclosure strategy could help adjust the workers' belief towards the correct direction about the labor market when the workers receive the AI-enabled matching outcome and decide whether to continue working for the platform or not.

In summary, this study formulates a modeling framework as a foundation to study human-AI interactions in the context of gig platforms where human workers can update their beliefs about uncertain labor demand revealed through AI-matched outcomes in a Bayesian manner and decide whether to participate in the platforms. Contrary to the anticipation that gig platforms can always achieve substantial boosts in revenue by utilizing AI to enhance the quality of matching between gig workers and their employers, we demonstrate the conditions under which applying AI for managing human workers in the platforms does not realize economic gain. The gig platforms lacking an understanding of the advantages and disadvantages of AI could misallocate valuable AI resources to the conditions where AI provides minimal benefits and possible negative consequences for their revenue. The insights derived from this study can enrich collective understandings of managing both intended and unintended AI-related outcomes (Berente et al., 2019). Taken together, our findings shed light on the thoughtful development, management, and application of AI in the gig economy.

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## Appendix: Proofs

*Proof of Lemma 1.* First note that

$$\Pi_2^{AI}(x_1 = x_H) - \Pi_2^0(x_1 = x_H) = \frac{2}{3}x_H + \frac{x_L}{6} - \frac{2}{5}(x_H + x_L) = \frac{8x_H - 7x_L}{30} > 0,$$

and

$$\Pi_2^{AI}(x_1 = 0) - \Pi_2^0(x_1 = 0) = \frac{x_H}{4} + \frac{3x_L}{20} - \frac{1}{5}(x_H + x_L) = \frac{x_H - x_L}{20} > 0.$$

This means that upon receiving $x_H$ or 0 in the first period, the worker's expected payoff is higher when AI is adopted than that when no AI is adopted. Thus, the worker's participation in the second period when no AI is adopted implies his participation when AI is adopted. Or mathematically, $x_H \in \mathcal{X}^{0,par} \Rightarrow x_H \in \mathcal{X}^{AI,par}$ and $0 \in \mathcal{X}^{0,par} \Rightarrow 0 \in \mathcal{X}^{AI,par}$.

However, upon receiving $x_L$ in the first period, this may not be the case, since

$$\Pi_2^{AI}(x_1 = x_L) - \Pi_2^0(x_1 = x_L) = \frac{x_H}{2} + \frac{x_L}{5} - \frac{2}{5}(x_H + x_L) = \frac{x_H - 2x_L}{10},$$

which is non-negative if and only if $x_H \geq 2x_L$. That is, $\Pi_2^{AI}(x_1 = x_L) < \Pi_2^0(x_1 = x_L)$ iff $x_H < 2x_L$. This means that when $x_H < 2x_L$, upon receiving $x_1 = x_L$, the worker participates if no AI is adopted but does not participate if AI is adopted, as long as

$$\delta\Pi_2^{AI}(x_1 = x_L) < c \leq \delta\Pi_2^0(x_1 = x_L),$$

which is equivalent to

$$\delta(\frac{x_H}{2} + \frac{x_L}{5}) < c \leq \delta\frac{2}{5}(x_H + x_L).$$

If, on the other hand, $c \leq \delta(\frac{x_H}{2} + \frac{x_L}{5})$ or $c > \delta\frac{2}{5}(x_H + x_L)$, upon receiving $x_L$, the worker's participation decision for the second period is the same under the cases with and without AI.

Therefore, the only possible case for $\mathcal{X}_1^{AI,par} \subset \mathcal{X}_1^{0,par}$ is when $x_H < 2x_L$ and $\delta(\frac{x_H}{2} + \frac{x_L}{5}) < c \leq \delta\frac{2}{5}(x_H + x_L)$, where we have $\mathcal{X}^{0,par} = \{x_H, x_L\}$ and $\mathcal{X}^{AI,par} = \{x_H\}$.

In fact, based on Equations (7) and (9), we can list the optimal participation decisions of the worker without and with AI as below:

$$\mathcal{X}^{0,par} = \begin{cases} \{x_H, x_L, 0\} & \text{if } c \leq \delta\frac{1}{5}(x_H + x_L), \\ \{x_H, x_L\} & \text{if } \delta\frac{1}{5}(x_H + x_L) < c \leq \delta\frac{2}{5}(x_H + x_L), \\ \emptyset & \text{if } c > \delta\frac{2}{5}(x_H + x_L), \end{cases}$$

$$\mathcal{X}^{AI,par} = \begin{cases} \{x_H, x_L, 0\} & \text{if } c \leq \delta(\frac{x_H}{4} + \frac{3x_L}{20}), \\ \{x_H, x_L\} & \text{if } \delta(\frac{x_H}{4} + \frac{3x_L}{20}) < c \leq \delta(\frac{x_H}{2} + \frac{x_L}{5}), \\ \{x_H\} & \text{if } \delta(\frac{x_H}{2} + \frac{x_L}{5}) < c \leq \delta(\frac{2}{3}x_H + \frac{x_L}{6}), \\ \emptyset & \text{if } c > \delta(\frac{2}{3}x_H + \frac{x_L}{6}). \end{cases}$$

□

*Proof of Proposition 1.* In general, the platform's ex ante revenue can be calculated as

$$\pi^{l*} = (1-\delta)\int_0^1 \sum_{x\in\{x_H,x_L,0\}} Pr^l(x_1 = x)\Big(x + \mathbf{1}_{\{x\in\mathcal{X}^{l,par}\}} \sum_{x'\in\{x_H,x_L,0\}} Pr^l(x_2 = x')x'\Big)dp.$$

First, if the conditions that $x_H < 2x_L$ and $\delta(\frac{x_H}{2} + \frac{x_L}{5}) < c \leq \delta\frac{2}{5}(x_H + x_L)$ are not satisfied, it must be the case that $\pi^{AI*} \geq \pi^{0*}$. This is because if these conditions are not satisfied, we know that $\mathcal{X}^{0,par} \subseteq \mathcal{X}^{AI,par}$. In addition, when AI is adopted (compared to when AI is not adopted), the probability that $x_H$ is assigned to the worker is higher and the probability that $x_L$ is assigned to the worker is lower (see Equations (1) and (2)). Therefore,

$$\begin{aligned}
\pi^{AI*} &= (1-\delta)\int_0^1 \sum_{x\in\{x_H,x_L,0\}} Pr^{AI}(x_1 = x)\Big(x + \mathbf{1}_{\{x\in\mathcal{X}^{AI,par}\}} \sum_{x'\in\{x_H,x_L,0\}} Pr^{AI}(x_2 = x')x'\Big)dp \\
&\geq (1-\delta)\int_0^1 \sum_{x\in\{x_H,x_L,0\}} Pr^{AI}(x_1 = x)\Big(x + \mathbf{1}_{\{x\in\mathcal{X}^{0,par}\}} \sum_{x'\in\{x_H,x_L,0\}} Pr^{AI}(x_2 = x')x'\Big)dp \\
&\geq (1-\delta)\int_0^1 \sum_{x\in\{x_H,x_L,0\}} Pr^{0}(x_1 = x)\Big(x + \mathbf{1}_{\{x\in\mathcal{X}^{0,par}\}} \sum_{x'\in\{x_H,x_L,0\}} Pr^{0}(x_2 = x')x'\Big)dp \\
&= \pi^{0*}.
\end{aligned}$$

If the conditions that $x_H < 2x_L$ and $\delta(\frac{x_H}{2} + \frac{x_L}{5}) < c \leq \delta\frac{2}{5}(x_H + x_L)$ are satisfied, $\pi^{0*}$ and $\pi^{AI*}$ are given by Equations (12) and (13), respectively. Then,

$$\begin{aligned}
\pi^{AI*} - \pi^{0*} &= (1-\delta)(\frac{5}{6}x_H + \frac{x_L}{4}) - (1-\delta)\frac{3}{5}(x_H + x_L) \\
&= (1-\delta)(\frac{7x_H}{30} - \frac{7x_L}{20}),
\end{aligned}$$

which is negative if and only if $x_H < \frac{3}{2}x_L$. This implies $\pi^{AI*} < \pi^{0*}$ if and only if $x_H < \frac{3}{2}x_L$. Combining this condition with $x_H < 2x_L$ and $\delta(\frac{x_H}{2} + \frac{x_L}{5}) < c \leq \delta\frac{2}{5}(x_H + x_L)$, we know that $\pi^{AI*} < \pi^{0*}$ if and only if $x_H < \frac{3}{2}x_L$ and $\delta(\frac{x_H}{2} + \frac{x_L}{5}) < c \leq \delta\frac{2}{5}(x_H + x_L)$.

**More General Setting: $2n$ Employers** In fact, we can also show that our qualitative results do not change if we assume the potential number of employers is $2n$, with $n$ of $x_H$ and $n$ of $x_L$.

In this more general case, following the steps in the proof of Lemma 1 and Proposition 1, we can show that the worker's optimal participation decision is given by:

$$\mathcal{X}^{0,par} = \begin{cases} \{x_H, x_L, 0\} & \text{if } c \le \delta \frac{n(x_H+x_L)}{4n+1}, \\ \{x_H, x_L\} & \text{if } \delta \frac{n(x_H+x_L)}{4n+1} < c \le \delta \frac{2n(x_H+x_L)}{4n+1}, \\ \emptyset & \text{if } c > \delta \frac{2n(x_H+x_L)}{4n+1}, \end{cases}$$

and

$$\mathcal{X}^{AI,par} = \begin{cases} \{x_H, x_L, 0\} & \text{if } c \le \delta \frac{n((4n+1)x_H+(2n+1)x_L)}{(3n+1)(4n+1)}, \\ \{x_H, x_L\} & \text{if } \delta \frac{n((4n+1)x_H+(2n+1)x_L)}{(3n+1)(4n+1)} < c \le \delta \frac{2n((4n+1)x_H+(n+1)x_L)}{(3n+1)(4n+1)}, \\ \{x_H\} & \text{if } \delta \frac{2n((4n+1)x_H+(n+1)x_L)}{(3n+1)(4n+1)} < c \le \delta \frac{2n((3n+1)x_H+x_L)}{(2n+1)(3n+1)}, \\ \emptyset & \text{if } c > \delta \frac{2n((3n+1)x_H+x_L)}{(2n+1)(3n+1)}. \end{cases}$$

The only case such that $\mathcal{X}^{AI,par} \subset \mathcal{X}^{0,par}$ is when $\delta \frac{2n((4n+1)x_H+(n+1)x_L)}{(3n+1)(4n+1)} < c \le \delta \frac{2n(x_H+x_L)}{4n+1}$. A necessary condition for this to hold is $x_H < 2x_L$. With the worker's participation decision, we can also identify the condition such that the platform's revenue is lower with than without AI ($\pi^{AI*} < \pi^{0*}$):

$$x_H < \frac{3(n(8n+5)+1)x_L}{(3n+1)(8n-1)} \text{ and } \delta \frac{2n((4n+1)x_H+(n+1)x_L)}{(3n+1)(4n+1)} < c \le \delta \frac{2n(x_H+x_L)}{4n+1}.$$

□

*Proof of Lemma 2.* When the platform can strategically choose the revenue-sharing parameter $\delta$, it will either set $\delta = 0$ to extract all the surplus (so that workers only participate in the first period) or make the worker indifferent between participate or not in the second period upon receiving some $x_1$, i.e., $\delta^{l*}\Pi_2^l(x_1) = c$ or $\delta^{l*} = \frac{c}{\Pi_2^l(x_1)}$, where $x_1 \in \{x_H, x_L, 0\}$ and $l \in \{0, AI\}$. Therefore, candidates for the optimal revenue-sharing parameter are $\delta^{0*} \in \{\frac{5c}{x_H+x_L}, \frac{5c}{2(x_H+x_L)}, 0\}$ without AI, and $\delta^{AI*} \in \{\frac{20c}{5x_H+3x_L}, \frac{10c}{5x_H+2x_L}, \frac{6c}{4x_H+x_L}, 0\}$ with AI. Which $\delta$ to choose depends on which one generates the highest revenue for the platform. Note that here the platform makes the following tradeoff: a smaller $\delta$ implies a higher $1-\delta$ and thus directly increases the revenue share for the platform, but a smaller $\delta$ also decreases the worker's participation and thus may indirectly decrease the platform's revenue.

Without AI, if $\delta^{0*} = \frac{5c}{x_H+x_L} \equiv \delta_a^{0*}$, the worker always participates in the second period, and thus the platform's revenue is given by

$$\pi_{endo,a}^0 = \int_0^1 (1-\delta_a^{0*}) \left(2p\left(1-\frac{p}{2}\right)(x_H+x_L)\right) dp = \frac{2x_H}{3} + \frac{2x_L}{3} - \frac{10c}{3}.$$

If $\delta^{0*} = \frac{5c}{2(x_H+x_L)} \equiv \delta_b^{0*}$, the worker participates in the second period iff $x_1 = x_H$ or $x_1 = x_L$, and thus the platform's revenue is given by

$$\begin{aligned}\pi^0_{endo,b} = &\int_0^1 (1-\delta_b^{0*})\Big(\left(1-\frac{p}{2}\right)p\left(\left(1-\frac{p}{2}\right)p(x_H+x_L)+x_H\right) \\ &+\left(1-\frac{p}{2}\right)p\left(\left(1-\frac{p}{2}\right)p(x_H+x_L)+x_L\right)\Big)dp \\ = &\frac{3x_H}{5}+\frac{3x_L}{5}-\frac{3c}{2}.\end{aligned}$$

If $\delta^{0*} = 0 \equiv \delta_c^{0*}$, the worker does not participate in the second period, and thus the platform's revenue is given by

$$\pi^0_{endo,c} = \int_0^1 (1-\delta_c^{0*})\left(p\left(1-\frac{p}{2}\right)(x_H+x_L)\right)dp = \frac{x_H}{3}+\frac{x_L}{3}.$$

Then, $\pi^{0*}_{endo} = \max\{\pi^0_{endo,a}, \pi^0_{endo,b}, \pi^0_{endo,c}\}$. With some algebra, one can get

- if $c \le c_1^0$, $\delta^{0*} = \frac{5c}{x_H+x_L}$ and $\pi^{0*}_{endo} = \frac{2x_H}{3}+\frac{2x_L}{3}-\frac{10c}{3}$,
- if $c_1^0 < c \le c_2^0$, $\delta^{0*} = \frac{5c}{2(x_H+x_L)}$ and $\pi^{0*}_{endo} = \frac{3x_H}{5}+\frac{3x_L}{5}-\frac{3c}{2}$,
- if $c > c_2^0$, $\delta^{0*} = 0$ and $\pi^{0*}_{endo} = \frac{x_H}{3}+\frac{x_L}{3}$,

where $c_1^0 = \frac{2(x_H+x_L)}{55}$, $c_2^0 = \frac{8(x_H+x_L)}{45}$.

Similar analysis can be done for the case with AI. The result is

- if $c \le c_1^{AI}$, $\delta^{AI*} = \frac{20c}{5x_H+3x_L}$ and $\pi^{AI*}_{endo} = \frac{(3x_H+x_L)(5x_H+3x_L-20c)}{15x_H+9x_L}$,
- if $c_1^{AI} < c \le c_2^{AI}$, $\delta^{AI*} = \frac{10c}{5x_H+2x_L}$ and $\pi^{AI*}_{endo} = \frac{(55x_H+17x_L)(5x_H+2x_L-10c)}{60(5x_H+2x_L)}$,
- if $c_2^{AI} < c \le c_3^{AI}$, $\delta^{AI*} = \frac{6c}{4x_H+x_L}$ and $\pi^{AI*}_{endo} = \frac{(10x_H+3x_L)(4x_H+x_L-6c)}{12(4x_H+x_L)}$,
- if $c > c_3^{AI}$, $\delta^{AI*} = 0$ and $\pi^{AI*}_{endo} = \frac{x_H}{2}+\frac{x_L}{6}$,

where $c_1^{AI} = \frac{(5x_H+2x_L)(5x_H+3x_L)^2}{10\left(325x_H^2+190x_Hx_L+29x_L^2\right)}$, $c_2^{AI} = \frac{(4x_H+x_L)(5x_H+2x_L)^2}{10\left(70x_H^2+18x_Hx_L-x_L^2\right)}$, and $c_3^{AI} = \frac{(4x_H+x_L)^2}{60x_H+18x_L}$.

□

*Proof of Proposition 2.* Based on Lemma 2, when the profit sharing parameter $\delta$ is endogenously set by the platform, the platform's revenue without and with the adoption of AI is given below, respectively:

$$\pi^{0*}_{endo} = \begin{cases} \frac{2x_H}{3}+\frac{2x_L}{3}-\frac{10c}{3} & \text{if } c \le c_1^0 \\ \frac{3x_H}{5}+\frac{3x_L}{5}-\frac{3c}{2} & \text{if } c_1^0 < c \le c_2^0 \\ \frac{x_H}{3}+\frac{x_L}{3} & \text{if } c > c_2^0 \end{cases}$$

where $c_1^0 = \frac{2(x_H+x_L)}{55}$, $c_2^0 = \frac{8(x_H+x_L)}{45}$, and

$$\pi_{endo}^{AI*} = \begin{cases} \frac{(3x_H+x_L)(5x_H+3x_L-20c)}{15x_H+9x_L} & \text{if } c \leq c_1^{AI} \\ \frac{(55x_H+17x_L)(5x_H+2x_L-10c)}{60(5x_H+2x_L)} & \text{if } c_1^{AI} < c \leq c_2^{AI} \\ \frac{(10x_H+3x_L)(4x_H+x_L-6c)}{12(4x_H+x_L)} & \text{if } c_2^{AI} < c \leq c_3^{AI} \\ \frac{x_H}{2} + \frac{x_L}{6} & \text{if } c > c_3^{AI} \end{cases}$$

where $c_1^{AI} = \frac{(5x_H+2x_L)(5x_H+3x_L)^2}{10\left(325x_H^2+190x_Hx_L+29x_L^2\right)}$, $c_2^{AI} = \frac{(4x_H+x_L)(5x_H+2x_L)^2}{10\left(70x_H^2+18x_Hx_L-x_L^2\right)}$, and $c_3^{AI} = \frac{(4x_H+x_L)^2}{60x_H+18x_L}$.

Therefore, with some algebraic calculation, based on the fact that $x_L < x_H$, $\pi_{endo}^{AI*} < \pi_{endo}^{0*}$ is equivalent to the following condition:

$$\begin{cases} \frac{60x_H^2-4x_H-24}{375x_H+65} < c < \frac{1}{45}(3x_H+13) & \text{if } x_L < x_H < 1.05837x_L, \\ \frac{-95x_H^2+57x_H+38}{10-100x_H} < c < \frac{1}{45}(3x_H+13) & \text{if } 1.05837x_L \leq x_H < 1.17552x_L, \\ \frac{-95x_H^2+57x_H+38}{10-100x_H} < c < \frac{7}{60}\left(-8x_H+\frac{3}{x_H}+10\right) & \text{if } 1.17552x_L \leq x_H < 1.22512x_L, \end{cases}$$

as is illustrated in Figure 6.

□

*Proof of Proposition 3.* In this case, each worker does not know the existence of the other worker, so she will think as if she was the only worker in the market with four potential employers, among which two are $x_H$ and two are $x_L$. Therefore, we can follow a similar procedure as that in the proof of Lemma 1, except that we use the following likelihoods that a worker *thinks* she would be assigned to the good-match employer ($x_1 = x_H$), poor-match employer ($x_1 = x_L$), and no employer ($x_1 = 0$). These likelihoods are denoted as $Pr_{worker}^l$ where $l \in \{0, AI\}$. By definition, we have:

Without AI-matching,

$$\begin{cases} Pr_{worker}^0(x_1 = x_H|p) = Pr_{worker}^0(x_2 = x_H|p) = \frac{1}{2}\left(1-(1-p)^4\right), \\ Pr_{worker}^0(x_1 = x_L|p) = Pr_{worker}^0(x_2 = x_L|p) = \frac{1}{2}\left(1-(1-p)^4\right), \\ Pr_{worker}^0(x_1 = 0|p) = Pr_{worker}^0(x_2 = 0|p) = (1-p)^4, \end{cases} \tag{A1}$$

and with AI-matching,

$$\begin{cases} Pr_{worker}^{AI}(x_1 = x_H|p) = Pr_{worker}^{AI}(x_2 = x_H|p) = 1-(1-p)^2, \\ Pr_{worker}^{AI}(x_1 = x_L|p) = Pr_{worker}^{AI}(x_2 = x_L|p) = (1-p)^2\left(1-(1-p)^2\right), \\ Pr_{worker}^{AI}(x_1 = 0|p) = Pr_{worker}^{AI}(x_2 = 0|p) = (1-p)^4, \end{cases} \tag{A2}$$

Finally, we can derive that the worker's participation decision is given by

$$\mathcal{X}_{rela}^{0,par} = \begin{cases} \{x_H, x_L, 0\} & \text{if } c \leq \delta \frac{2(x_H+x_L)}{9}, \\ \{x_H, x_L\} & \text{if } \delta \frac{2(x_H+x_L)}{9} < c \leq \delta \frac{4(x_H+x_L)}{9}, \\ \emptyset & \text{if } c > \delta \frac{4(x_H+x_L)}{9}, \end{cases}$$

and

$$\mathcal{X}_{rela}^{AI,par} = \begin{cases} \{x_H, x_L, 0\} & \text{if } c \leq \delta \frac{2(9x_H+5x_L)}{63}, \\ \{x_H, x_L\} & \text{if } \delta \frac{2(9x_H+5x_L)}{63} < c \leq \delta \frac{4(3x_H+x_L)}{21}, \\ \{x_H\} & \text{if } \delta \frac{4(3x_H+x_L)}{21} < c \leq \delta \frac{4(7x_H+x_L)}{35}, \\ \emptyset & \text{if } c > \delta \frac{4(7x_H+x_L)}{35}. \end{cases}$$

The only case such that $\mathcal{X}_{rela}^{AI,par} \subset \mathcal{X}_{rela}^{0,par}$ is when $\delta \frac{4(3x_H+x_L)}{21} < c < \delta \frac{4(x_H+x_L)}{9}$. A necessary condition for this to hold is $x_H < 2x_L$.

However, when the platform matches workers with employers, it can assign the four potential employers to both of the workers. That is, given the worker's participation decision, the platform's profit will depend on the *actual* likelihoods that a worker can be matched with each type of employers. These likelihoods are denoted as $Pr_{actual}^{l}$ where $l \in \{0, AI\}$. By definition, we have:

When AI is not applied,

$$\begin{cases} Pr_{actual}^{0}(x_1 = 0|p) = Pr_{actual}^{0}(x_2 = 0|p) = \frac{1}{2}\binom{4}{1}p(1-p)^3 + (1-p)^4 = (1-p)^3(1+p), \\ Pr_{actual}^{0}(x_1 = x_H|p) = Pr_{actual}^{0}(x_2 = x_H|p) = \frac{1-Pr_{actual}^{0}(x_1=0|p)}{2} = \frac{p^4}{2} - p^3 + p, \\ Pr_{actual}^{0}(x_1 = x_L|p) = Pr_{actual}^{0}(x_2 = x_L|p) = \frac{1-Pr_{actual}^{0}(x_1=0|p)}{2} = \frac{p^4}{2} - p^3 + p, \end{cases} \tag{A3}$$

and when AI-matching is applied,

$$\begin{cases} Pr_{actual}^{AI}(x_1 = 0|p) = Pr_{actual}^{AI}(x_2 = 0|p) = \frac{1}{2}\binom{4}{1}p(1-p)^3 + (1-p)^4 = (1-p)^3(1+p), \\ Pr_{actual}^{AI}(x_1 = x_H|p) = Pr_{actual}^{AI}(x_2 = x_H|p) = p, \\ Pr_{actual}^{AI}(x_1 = x_L|p) = Pr_{actual}^{AI}(x_2 = x_L|p) = 1 - p - (1-p)^3(1+p) = p^4 - 2p^3 + p. \end{cases} \tag{A4}$$

The platform's revenue is given by

$$\pi_{rela}^{l*} = 2(1-\delta) \int_0^1 \sum_{x \in \{x_H, x_L, 0\}} Pr_{actual}^{l}(x_1 = x)\Big(x + \mathbf{1}_{\{x \in \mathcal{X}_{rela}^{l,par}\}} \sum_{x' \in \{x_H, x_L, 0\}} Pr_{actual}^{l}(x_2 = x')x'\Big)dp.$$

Similar to the case when there were no interrelated workers, a necessary condition for $\pi_{rela}^{AI*} < \pi_{rela}^{0*}$ is $\mathcal{X}_{rela}^{AI,par} \subset \mathcal{X}_{rela}^{0,par}$, or $\delta \frac{4(3x_H+x_L)}{21} < c < \delta \frac{4(x_H+x_L)}{9}$. Under this condition, $\mathcal{X}_{rela}^{AI,par} = \{x_H\}$

and $\mathcal{X}_{rela}^{0,par} = \{x_H, x_L\}$. Plugging in them into the platform's revenue, we can show under this condition,

$$\pi_{rela}^{0*} = (1-\delta)\frac{404}{315}(x_H + x_L) \text{ and } \pi_{rela}^{AI*} = (1-\delta)(\frac{5x_H}{3} + \frac{3x_L}{5}).$$

Simple algebra tells $\pi_{rela}^{0*} > \pi_{rela}^{AI*}$ if $x_H < \frac{215}{121}x_L$.

In fact, we can calculate $\pi_{rela}^{AI*}$ and $\pi_{rela}^{0*}$ under all conditions. The results are:

$$\pi_{rela}^{AI*} = \begin{cases} 2(1-\delta)\left(\frac{x_H}{2} + \frac{x_L}{5}\right) & \text{if } c > \delta\left(\frac{4x_H}{5} + \frac{4x_L}{35}\right) \\ 2(1-\delta)\left(\frac{5x_H}{6} + \frac{3x_L}{10}\right) & \text{if } \delta\left(\frac{4x_H}{5} + \frac{4x_L}{35}\right) \geq c > \delta\left(\frac{4x_H}{7} + \frac{4x_L}{21}\right) \\ 2(1-\delta)\left(\frac{14x_H}{15} + \frac{22x_L}{63}\right) & \text{if } \delta\left(\frac{4x_H}{7} + \frac{4x_L}{21}\right) \geq c > \delta\left(\frac{2x_H}{7} + \frac{10x_L}{63}\right) \\ 2(1-\delta)\left(x_H + \frac{2x_L}{5}\right) & \text{if } c \leq \delta\left(\frac{2x_H}{7} + \frac{10x_L}{63}\right), \end{cases}$$

and

$$\pi_{rela}^{0*} = \begin{cases} 2(1-\delta)\left(\frac{7x_H}{20} + \frac{7x_L}{20}\right) & \text{if } c > \delta\left(\frac{4x_H}{9} + \frac{4x_L}{9}\right) \\ 2(1-\delta)\left(\frac{202x_H}{315} + \frac{202x_L}{315}\right) & \text{if } \delta\left(\frac{4x_H}{9} + \frac{4x_L}{9}\right) \geq c > \delta\left(\frac{2x_H}{9} + \frac{2x_L}{9}\right) \\ 2(1-\delta)\left(\frac{7x_H}{10} + \frac{7x_L}{10}\right) & \text{if } c \leq \delta\left(\frac{2x_H}{9} + \frac{2x_L}{9}\right). \end{cases}$$

**Attachment: Heterogeneous Worker Preferences** We can also consider the case where the two workers have reverse preferences for the employers, or the same employer is of $x_H$ for one worker but of $x_L$ for the other. In this case, $\mathcal{X}_{rela}^{AI,par}$ and $\mathcal{X}_{rela}^{0,par}$ remain identical to the analysis above because this new setup does not change the worker's participation decision since she does not know the existence of the other worker anyway.

This setup also does not change the *actual* likelihoods that a worker can be matched with each type of employers when AI is not applied since the matching is randomly conducted. However, it does change the likelihoods when AI is applied. In this case, they are given by:

$$\begin{cases} Pr_{actual}^{AI}(x_1 = 0|p) = Pr_{actual}^{AI}(x_2 = 0|p) = \binom{2}{1}p(1-p)^3 + (1-p)^4 = (1-p)^3(1+p), \\ Pr_{actual}^{AI}(x_1 = x_H|p) = Pr_{actual}^{AI}(x_2 = x_H|p) = 1-(1-p)^2 = p(2-p), \\ Pr_{actual}^{AI}(x_1 = x_L|p) = Pr_{actual}^{AI}(x_2 = x_L|p) = 1-p(2-p)-(1-p)^3(1+p) = p^2(1-p)^2. \end{cases}$$

Again, a necessary condition for $\pi_{rela}^{AI*} < \pi_{rela}^{0*}$ is $\mathcal{X}_{rela}^{AI,par} \subset \mathcal{X}_{rela}^{0,par}$, or $\delta\frac{4(3x_H+x_L)}{21} < c < \delta\frac{4(x_H+x_L)}{9}$. Under this condition, $\mathcal{X}_{rela}^{AI,par} = \{x_H\}$ and $\mathcal{X}_{rela}^{0,par} = \{x_H, x_L\}$. Plugging in them into the platform's revenue, we can show under this condition,

$$\pi_{rela}^{0*} = (1-\delta)\frac{404}{315}(x_H + x_L) \text{ and } \pi_{rela}^{AI*} = (1-\delta)(\frac{12x_H}{5} + \frac{4x_L}{35}).$$

Simple algebra tells $\pi_{rela}^{0*} > \pi_{rela}^{AI*}$ if $x_H < \frac{23}{22}x_L$. $\square$

*Proof of Proposition 4.* As mentioned in Section 5.1, we can find the threshold $\overline{p}$ such that a worker participates by solving

$$\delta\left(\left(1-(1-\overline{p})^2\right)x_H+\left(1-(1-\overline{p})^2\right)(1-\overline{p})^2x_L\right)=c,$$

which gives

$$\overline{p}=\frac{1}{2}\left(2-\sqrt{2}\sqrt{\frac{\sqrt{(x_H+x_L)^2-4cx_L/\delta}}{x_L}-\frac{x_H}{x_L}+1}\right).$$

Then the platform's revenue is

$$\pi_{RD}^{AI*}=(1-\delta)\int_0^1[p2x_H+(p^4-2p^3+p)2x_L]dp+(1-\delta)\int_{\overline{p}}^1[p2x_H+(p^4-2p^3+p)2x_L]dp.$$

This expression is mathematically too involved, so we rely on a numerical exercise to show this proposition. First note that $\delta$ is just a scaling factor, since one can let $c'=\frac{c}{\delta}$ without loss of generality. The same argument applies for $x_L$ since one can let $x'_H=\frac{x_H}{x_L}$. Therefore, we only need to prove that the result is true for some $\delta$ and $x_L$. We take $\delta=0.5$ and $x_L=1$. Figure A1 below shows the region where $\pi_{RD}^{AI*}$ is larger than, smaller than, or equal to $\pi_{rela}^{AI*}$ and $\pi_{rela}^{0*}$, where the x-axis is $x_H$ and the y-axis is $c$. The whole region plotted out (non-white) is where the condition $\pi_{rela}^{AI*}<\pi_{rela}^{0*}$ is satisfied. If there is no region with a certain color plotted in the figure, it means that the condition indicated by the color never holds when $\pi_{rela}^{AI*}<\pi_{rela}^{0*}$.

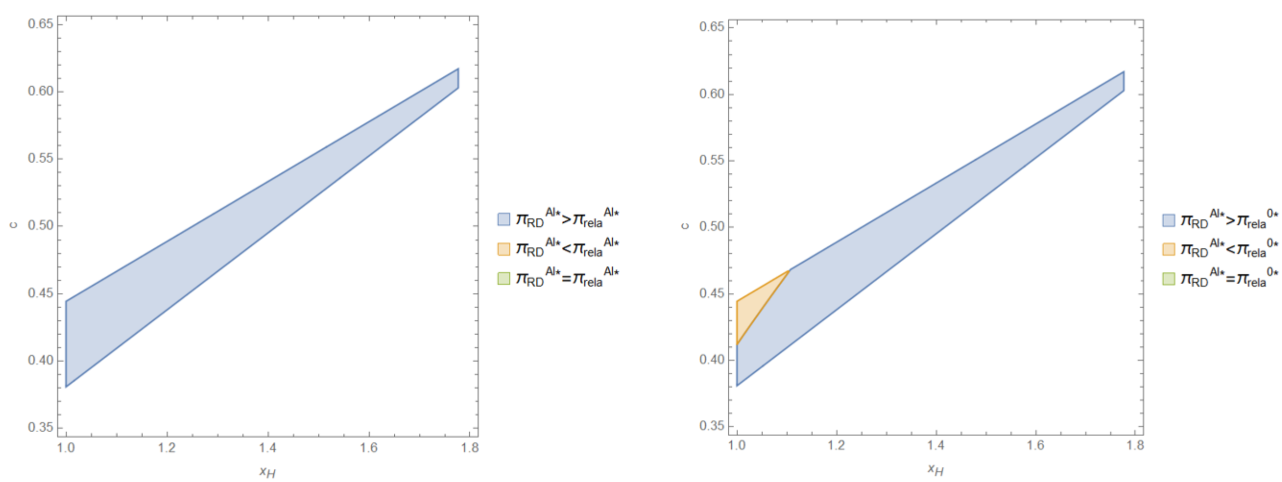


Figure A1: Revealing demand information when AI is facilitated
Note: $x_L=1$, $\delta=0.5$.

The numerical exercise shows that the platform adopting AI is better off by truthfully revealing $p$ to the worker, i.e., $\pi_{RD}^{AI*}>\pi^{AI*}$, but it may still be worse off compared to without the use of AI ($\pi_{RD}^{AI*}<\pi^{0*}$) for smaller $x_H$.

□

*Proof of Lemma 3.* In the case when competition information is revealed, a worker's participation decision depends on both the revenue generated from the first period and the other worker's decision. Our solution concept is symmetric Nash equilibrium. We first solve for a pure strategy Nash equilibrium when it exists.

Clearly, due to the monotonicity in the expected payoff for a worker in the second period for $x_1 = 0, x_L, x_H$, if a worker participates in the second period when $x_1 = 0$, then she will also participate when $x_1 = x_L$ or $x_1 = x_H$; if a worker participates when $x_1 = x_L$, then she will also participate when $x_1 = x_H$. Therefore, the possible pure strategy equilibria are

1. Each worker always participates in the second period;
2. Each worker participates in the second period iff $x_1 = x_H$ or $x_1 = x_L$;
3. Each worker participates in the second period iff $x_1 = x_H$;
4. Each worker never participates in the second period.

Next, we find conditions for each of these possible equilibria.

If only one worker participates in the second period, the likelihoods of a worker being assigned to an employer generating revenue $x_H$, $x_L$, and 0 are:

$$\begin{cases} P^{AI}_{x_H,single} = 1 - (1-p)^2, \\ P^{AI}_{x_L,single} = (1-p)^2 \left(1 - (1-p)^2\right), \\ P^{AI}_{0,single} = (1-p)^4, \end{cases} \tag{A5}$$

when AI is facilitated, and are:

$$\begin{cases} P^{0}_{x_H,single} = \frac{1}{2} \left(1 - (1-p)^4\right), \\ P^{0}_{x_L,single} = \frac{1}{2} \left(1 - (1-p)^4\right), \\ P^{0}_{0,single} = (1-p)^4, \end{cases} \tag{A6}$$

when AI is not facilitated.

In each period, when two workers both participate, denote the probability that worker 1 is assigned employer with revenue $x$ and worker 2 is assigned employer with revenue $x'$ where $x, x' \in \{x_H, x_L, 0\}$ as $p^l_{x,x'}$, where $l$ = "$AI$" or "0" indicating the cases when AI is facilitated or not, respectively. Then we have

| | | |
|---|---|---|
| $p^{AI}_{x_H,x_H} = p^2$ | $p^{AI}_{x_H,x_L} = p(1-p)\left(1-(1-p)^2\right)$ | $p^{AI}_{x_H,0} = p(1-p)^3$ |
| $p^{AI}_{x_L,x_H} = p(1-p)(1-(1-p)^2)$ | $p^{AI}_{x_L,x_L} = p^2(1-p)^2$ | $p^{AI}_{x_L,0} = p(1-p)^3$ |
| $p^{AI}_{0,x_H} = p(1-p)^3$ | $p^{AI}_{0,x_L} = p(1-p)^3$ | $p^{AI}_{0,0} = (1-p)^4$ |

and

| | | |
|---|---|---|
| $p^0_{x_H,x_H} = \frac{1}{4}p^2(6-p(8-3p))$ | $p^0_{x_H,x_L} = \frac{1}{4}p^2(6-p(8-3p))$ | $p^0_{x_H,0} = p(1-p)^3$ |
| $p^0_{x_L,x_H} = \frac{1}{4}p^2(6-p(8-3p))$ | $p^0_{x_L,x_L} = \frac{1}{4}p^2(6-p(8-3p))$ | $p^0_{x_L,0} = p(1-p)^3$ |
| $p^0_{0,x_H} = p(1-p)^3$ | $p^0_{0,x_L} = p(1-p)^3$ | $p^0_{0,0} = (1-p)^4$ |

If both workers participates, denote the likelihoods of a worker being assigned to an employer generating revenue $x$ as $P^l_{x,both}$, where $x \in \{x_H, x_L, 0\}$ and $l \in \{AI, 0\}$. Clearly, $P^l_{x,both} = \sum_{x' \in \{x_H,x_L,0\}} p^l_{x,x'}$. Then, when AI is facilitated, we have:

$$\begin{cases} P^{AI}_{x_H,both} = p^2 + p(1-p)\left(1-(1-p)^2\right) + p(1-p)^3 = p, \\ P^{AI}_{x_L,both} = p(1-p)(1-(1-p)^2) + p^2(1-p)^2 + p(1-p)^3 = p^4 - 2p^3 + p, \\ P^{AI}_{0,both} = p(1-p)^3 + p(1-p)^3 + (1-p)^4 = (1-p)^3(1+p), \end{cases} \tag{A7}$$

and when AI is not facilitated, we have:

$$\begin{cases} P^0_{x_H,both} = \frac{1}{4}p^2(6-p(8-3p)) + \frac{1}{4}p^2(6-p(8-3p)) + p(1-p)^3 = \frac{p^4}{2} - p^3 + p, \\ P^0_{x_L,both} = \frac{1}{4}p^2(6-p(8-3p)) + \frac{1}{4}p^2(6-p(8-3p)) + p(1-p)^3 = \frac{p^4}{2} - p^3 + p, \\ P^0_{0,both} = p(1-p)^3 + p(1-p)^3 + (1-p)^4 = (1-p)^3(1+p), \end{cases} \tag{A8}$$

For any given $p$, denote a worker's expected payoff by participating in the second period when the competing worker does not participate as $u^l_{single}$ and that when the competing worker also participates as $u^l_{both}$, where $l \in \{AI, 0\}$. Then by definition,

$$u^l_{both} = \delta(x_H P^l_{x_H,both} + x_L P^l_{x_L,both}), \tag{A9}$$

$$u^l_{single} = \delta(x_H P^l_{x_H,single} + x_L P^l_{x_L,single}). \tag{A10}$$

Upon observing the outcome in the first period $x_1 = x$, a worker will update her belief about $p$. Denote the posterior of $p$ given $x_1 = x$ in Period 1 as $f^l_{RC}(p|x_1 = x)$, where $l \in \{AI, 0\}$. Then

$$f^l_{RC}(p|x_1 = x) = \frac{P^l_{x,both}}{\int_0^1 P^l_{x,both}dp}. \tag{A11}$$

The worker will also update the belief about what her competitor has received in the first period (denoted as $x'$). Let $q^l_{x,x'}$ denote the posterior probability that the competing worker has received $x'$ in the first period given that a worker has received $x$ in the first period, where $l \in \{AI, 0\}$. Then

$$q^l_{x,x'} = \frac{p^l_{x,x'}}{P^l_{x,both}}. \tag{A12}$$

To make (1) "each worker always participating in the second period" an equilibrium, it requires the following condition: Given that the competing worker always participates in the second period, a worker gets a higher expected payoff from participating than not participating in the second period even when $x_1 = 0$, or

$$\int_0^1 (u^{AI}_{both} q^{AI}_{0,x_H} + u^{AI}_{both} q^{AI}_{0,x_L} + u^{AI}_{both} q^{AI}_{0,0}) f^{AI}_{RC}(p|x_1 = 0) dp \geq c.$$

Plugging in the values, this is equivalent to

$$c \leq c_1, \text{ where } c_1 = \delta(\frac{2x_H}{9} + \frac{32x_L}{189}). \tag{A13}$$

Similarly, make (2) "each worker participating in the second period iff $x_1 = x_H$ or $x_1 = x_L$" an equilibrium, it requires the following conditions: Given that the competing worker participates in the second period iff $x_1 = x_H$ or $x_1 = x_L$, a worker's expected payoff by participating is higher than not participating when $x_1 = x_L$ but lower when $x_1 = 0$, or

$$\int_0^1 (u^{AI}_{both} q^{AI}_{x_L,x_H} + u^{AI}_{both} q^{AI}_{x_L,x_L} + u^{AI}_{single} q^{AI}_{x_L,0}) f^{AI}_{RC}(p|x_1 = x_L) dp \geq c,$$

as well as

$$\int_0^1 (u^{AI}_{both} q^{AI}_{0,x_H} + u^{AI}_{both} q^{AI}_{0,x_L} + u^{AI}_{single} q^{AI}_{0,0}) f^{AI}_{RC}(p|x_1 = 0) dp < c.$$

Plugging in the values, this is equivalent to

$$c_{21} < c \leq c_{22}, \text{ where } c_{21} = \delta(\frac{19x_H}{63} + \frac{23x_L}{126}), c_{22} = \delta(\frac{23x_H}{42} + \frac{5x_L}{21}). \tag{A14}$$

The conditions for the other two possible pure strategy equilibria can be found through similar procedures:

When $c_{31} < c \leq c_{32}$ where $c_{31} = \delta(\frac{7x_H}{12} + \frac{2x_L}{9})$, $c_{32} = \delta(\frac{11x_H}{15} + \frac{6x_L}{35})$, (3) "each worker participating in the second period iff $x_1 = x_H$" is an equilibrium.

When $c > c_4$ where $c_4 = \delta(\frac{5x_H}{6} + \frac{x_L}{10})$, (4) "each worker always not participating in the second period" is an equilibrium.

It is not hard to verify $c_1 < c_{21} < c_{22} < c_{31} < c_{32} < c_4$.

Note that when $c_1 < c \leq c_{21}$, $c_{22} < c \leq c_{31}$, or $c_{32} < c \leq c_4$, there is no pure strategy equilibrium but a mixed strategy one. Due to the monotonicity in the expected payoff for a worker at $t = 2$ when $x_1 = 0, x_L, x_H$, the structure of the mixed strategy equilibrium should be:

- When $c_1 < c \leq c_{21}$, a worker participates in the second period with probability $\lambda_1 \in (0, 1)$ if $x_1 = x_H$, and with probability 0 if $x_1 = x_L$ or $x_1 = 0$;

- When $c_{22} < c \leq c_{31}$, a worker participates in the second period with probability 1 if $x_1 = x_H$, with probability $\lambda_2 \in (0,1)$ if $x_1 = x_L$, and with probability 0 if $x_1 = 0$;

- When $c_{32} < c \leq c_4$, a worker participates in the second period with probability 1 if $x_1 = x_H$ or $x_1 = x_L$, with probability $\lambda_3 \in (0,1)$ if $x_1 = 0$.

To get the values of $\lambda_1$, $\lambda_2$, and $\lambda_3$, we can leverage the revenue equivalence in a mixed strategy.

To find $\lambda_1$, we know that this mixed strategy makes each worker feel indifferent between participating and not when receiving $x_1 = x_H$ in the first period. That is

$$\int_0^1 ((\lambda_1 u_{both}^{AI} + (1-\lambda_1)u_{single}^{AI})q_{x_H,x_H}^{AI} + u_{single}^{AI} q_{x_H,x_L}^{AI} + u_{single}^{AI} q_{x_H,0}^{AI}) f_{RC}^{AI}(p|x_1 = x_H))dp = c,$$

which gives

$$\lambda_1 = \frac{3(\delta(38x_H + 23x_L) - 126c)}{5\delta(6x_H + x_L)}.$$

Similarly, we have the revenue equivalence conditions for solving $\lambda_2$ and $\lambda_3$:

$$\int_0^1 (u_{both}^{AI} q_{x_L,x_H}^{AI} + (\lambda_2 u_{both}^{AI} + (1-\lambda_2)u_{single}^{AI})q_{x_L,x_L}^{AI} + u_{single}^{AI} q_{x_L,0}^{AI}) f_{RC}^{AI}(p|x_1 = x_L)dp = c,$$

and

$$\int_0^1 (u_{both}^{AI} q_{0,x_H}^{AI} + u_{both}^{AI} q_{0,x_L}^{AI} + (\lambda_3 u_{both}^{AI} + (1-\lambda_3)u_{single}^{AI})q_{0,0}^{AI}) f_{RC}^{AI}(p|x_1 = 0)dp = c,$$

which respectively imply

$$\lambda_2 = \frac{7(\delta(21x_H + 8x_L) - 36c)}{\delta(9x_H - 4x_L)}$$

and

$$\lambda_3 = \frac{7(\delta(25x_H + 3x_L) - 30c)}{3\delta(7x_H - 5x_L)}.$$

□

*Proof of Proposition 5.* In this proposition, we focus on the situation where the platform's expected revenue when it facilitates perfect AI-matching is lower than that when there is no AI ($\pi^{AI*} < \pi^{0*}$). This happens when $x_H < \frac{215}{121}x_L$ and $\delta(\frac{4x_H}{7} + \frac{4x_L}{21}) < c \leq \delta(\frac{4x_H}{9} + \frac{4x_L}{9})$, which can be found through a similar procedure to the one through which we got Proposition 1.

Based on Lemma 3, when using AI, the profits with ($\pi_{RC}^{AI*}$) and without ($\pi^{AI*}$) revealing the competition information are respectively given by:

$$\pi_{RC}^{AI*} = \begin{cases} 2(1-\delta)(\frac{x_H}{2}+\frac{x_L}{5}) & \text{if } c > \delta\left(\frac{5x_H}{6}+\frac{x_L}{10}\right) \\ 2(1-\delta)(\frac{x_H}{2}+\frac{x_L}{5}-X) & \text{if } \delta\left(\frac{5x_H}{6}+\frac{x_L}{10}\right) \geq c > \delta\left(\frac{11x_H}{15}+\frac{6x_L}{35}\right) \\ 2(1-\delta)(\frac{5x_H}{6}+\frac{3x_L}{10}) & \text{if } \delta\left(\frac{11x_H}{15}+\frac{6x_L}{35}\right) \geq c > \delta\left(\frac{7x_H}{12}+\frac{2x_L}{9}\right) \\ 2(1-\delta)(\frac{5x_H}{6}+\frac{3x_L}{10}-Y) & \text{if } \delta\left(\frac{7x_H}{12}+\frac{2x_L}{9}\right) \geq c > \delta\left(\frac{23x_H}{42}+\frac{5x_L}{21}\right) \\ 2(1-\delta)(\frac{14x_H}{15}+\frac{22x_L}{63}) & \delta\left(\frac{23x_H}{42}+\frac{5x_L}{21}\right) \geq \text{if } c > \delta\left(\frac{19x_H}{63}+\frac{23x_L}{126}\right) \\ 2(1-\delta)(\frac{14x_H}{15}+\frac{22x_L}{63}-Z) & \delta\left(\frac{19x_H}{63}+\frac{23x_L}{126}\right) \geq \text{if } c > \delta\left(\frac{2x_H}{9}+\frac{32x_L}{189}\right) \\ 2(1-\delta)(x_H+\frac{2x_L}{5}) & \text{if } c \leq \delta\left(\frac{2x_H}{9}+\frac{32x_L}{189}\right) \end{cases}$$

where $X = \frac{7(30c-25\delta x_H-3\delta x_L)(105c(5x_H-3x_L)-\delta(7x_H-3x_L)(25x_H+3x_L))}{270\delta^2(7x_H-5x_L)^2}$,
$Y = \frac{(-36c+21\delta x_H+8\delta x_L)\left(126c(22x_L-51x_H)+\delta\left(2952x_H^2-15x_Hx_L-536x_L^2\right)\right)}{90\delta^2(9x_H-4x_L)^2}$,
$Z = \frac{(126c-38\delta x_H-23\delta x_L)\left(189c(54x_H+x_L)-8\delta\left(126x_H^2+75x_Hx_L-16x_L^2\right)\right)}{5250\delta^2(6x_H+x_L)^2}$,
and

$$\pi_{rela}^{AI*} = \begin{cases} 2(1-\delta)\left(\frac{x_H}{2}+\frac{x_L}{5}\right) & \text{if } c > \delta\left(\frac{4x_H}{5}+\frac{4x_L}{35}\right) \\ 2(1-\delta)\left(\frac{5x_H}{6}+\frac{3x_L}{10}\right) & \text{if } \delta\left(\frac{4x_H}{5}+\frac{4x_L}{35}\right) \geq c > \delta\left(\frac{4x_H}{7}+\frac{4x_L}{21}\right) \\ 2(1-\delta)\left(\frac{14x_H}{15}+\frac{22x_L}{63}\right) & \text{if } \delta\left(\frac{4x_H}{7}+\frac{4x_L}{21}\right) \geq c > \delta\left(\frac{2x_H}{7}+\frac{10x_L}{63}\right) \\ 2(1-\delta)\left(x_H+\frac{2x_L}{5}\right) & \text{if } c \leq \delta\left(\frac{2x_H}{7}+\frac{10x_L}{63}\right). \end{cases}$$

Under condition $\pi_{rela}^{AI*} < \pi_{rela}^{0*} \Leftrightarrow x_H < \frac{215}{121}x_L$ and $\delta(\frac{4x_H}{7}+\frac{4x_L}{21}) < c \leq \delta(\frac{4x_H}{9}+\frac{4x_L}{9})$, we can know that within this range,

$$\begin{cases} \pi_{RC}^{AI*} > \pi_{rela}^{AI*} & \text{if } c < \delta\left(\frac{7x_H}{12}+\frac{2x_L}{9}\right) \\ \pi_{RC}^{AI*} = \pi_{rela}^{AI*} & \text{otherwise.} \end{cases}$$

The profit when no AI is used is given by

$$\pi_{rela}^{0*} = \begin{cases} 2(1-\delta)\left(\frac{7x_H}{20}+\frac{7x_L}{20}\right) & \text{if } c > \delta\left(\frac{4x_H}{9}+\frac{4x_L}{9}\right) \\ 2(1-\delta)\left(\frac{202x_H}{315}+\frac{202x_L}{315}\right) & \text{if } \delta\left(\frac{4x_H}{9}+\frac{4x_L}{9}\right) \geq c > \delta\left(\frac{2x_H}{9}+\frac{2x_L}{9}\right) \\ 2(1-\delta)\left(\frac{7x_H}{10}+\frac{7x_L}{10}\right) & \text{if } c \leq \delta\left(\frac{2x_H}{9}+\frac{2x_L}{9}\right), \end{cases}$$

and we have under the condition that $\pi_{rela}^{AI*} < \pi_{rela}^{0*} \Leftrightarrow x_H < \frac{215}{121}x_L$ and $\delta(\frac{4x_H}{7}+\frac{4x_L}{21}) < c \leq$

$\delta(\frac{4x_H}{9} + \frac{4x_L}{9})$,

$$\begin{cases} \pi_{RC}^{AI*} > \pi_{rela}^{0*} & \text{if } c < \underline{c} \\ \pi_{RC}^{AI*} < \pi_{rela}^{0*} & \text{otherwise,} \end{cases}$$

where $\underline{c} = \frac{\delta\left(9x_H^2\left(9A+1489\right)-24x_Hx_L\left(3A+17\right)+16x_L^2\left(A-144\right)\right)}{504(51x_H-22x_L)}$ and $A = \frac{\sqrt{80697x_H^2-94856x_Hx_L+39440x_L^2}}{9x_H-4x_L}$.

The results are illustrated in Figure A2. The whole region plotted out (non-white) is where the condition $\pi_{rela}^{AI*} < \pi_{rela}^{0*}$ is satisfied. If there is no region with a certain color plotted in the figure, it means that the condition indicated by the color never holds when $\pi_{rela}^{AI*} < \pi_{rela}^{0*}$.

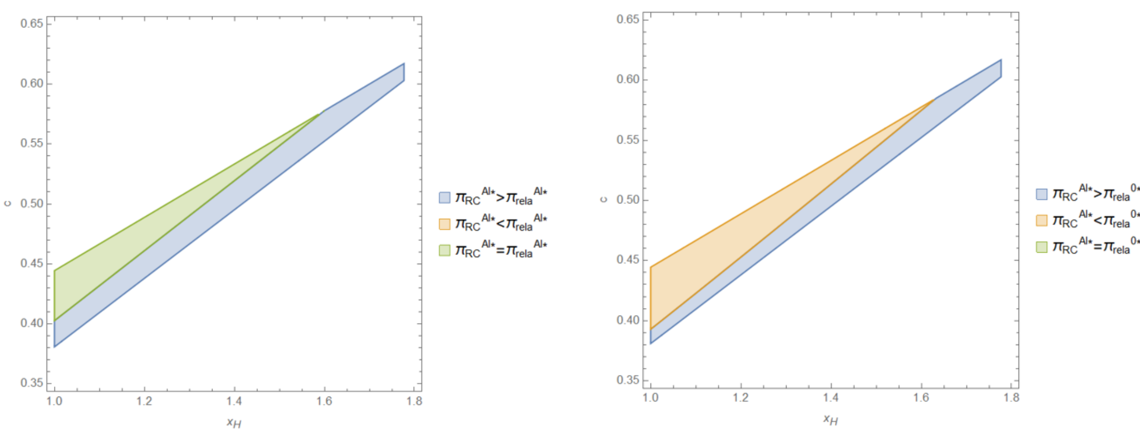


Figure A2: Revealing competition when AI is facilitated
Note: $x_L = 1$, $\delta = 0.5$

□

*Proof of Corollary 1.* First, we claim that upon revealing demand information, there is no need to further reveal competition information, because doing so will only hurt the incentive for workers to participate without doing anything good for the platform. Therefore, we only focus on the comparison of the two revealing strategies alone.

As mentioned in the proof of Proposition 4, the platform's revenue when demand information is revealed is $\pi_{RD}^{AI*} = (1-\delta)\int_0^1 \left[p2x_H + (p^4 - 2p^3 + p)2x_L\right]dp + (1-\delta)\int_{\overline{p}}^1 \left[p2x_H + (p^4 - 2p^3 + p)2x_L\right]dp$, where $\overline{p} = \frac{1}{2}\left(2 - \sqrt{2}\sqrt{\frac{\sqrt{(x_H+x_L)^2-4cx_L/\delta}}{x_L} - \frac{x_H}{x_L} + 1}\right)$.

This expression is mathematically too involved, so we again rely on a numerical exercise to compare $\pi_{RD}^{AI*}$ and $\pi_{RC}^{AI*}$, with $\delta = 0.5$ and $x_L = 1$ since $\delta$ and $x_L$ are again just scaling parameters. The result of the numerical exercise is summarized below in Figure A3, where the total region plotted out (non-white) represents the parameter space such that $\pi_{rela}^{AI*} < \pi_{rela}^{0*}$ is satisfied. If there is no region with a certain color plotted in the figure, it means that the condition indicated by the color never holds when $\pi_{rela}^{AI*} < \pi_{rela}^{0*}$. We can see that within all this region, $\pi_{RD}^{AI*} > \pi_{RC}^{AI*}$, which is what we have claimed in Corollary 1.

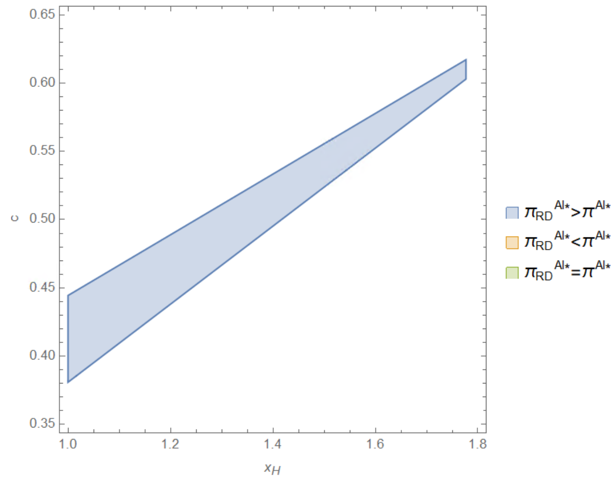


Figure A3: Revealing demand vs competition information
Note: $x_L = 1$, $\delta = 0.5$

$\square$