Unintended Consequences of Advances in Matching Technologies: Information Revelation and Strategic Participation on Gig-Economy Platforms

Yi Liu, Bowen Lou, Xinyi Zhao, Xinxin Li*

Abstract

Recent years have witnessed significant advancements in matching technologies used to improve the matching between workers and employers requesting job tasks on a gig-economy platform. While conventional wisdom suggests that technologies with higher matching quality benefit the platform by assigning better-matched jobs to workers, we discover a possible unintended revenue-decreasing effect. Our stylized game-theoretic model suggests that while a technology's matching enhancement effect can increase a platform's revenue, the jobs assigned by the better matching technology can also unintentionally reveal more information about uncertain labor demand to workers, especially when demand is low, and thus unfavorably change workers' participation decisions, resulting in a revenue loss for the platform. We extend our model to cases in which (1) the share of revenue between workers and platform is endogenous, (2) the matching quality can be improved continuously, (3) the opportunity cost of workers is affected by competition between platforms, and (4) workers compete for job tasks. We find consistent results with additional insights, including the optimal matching quality that a platform should pursue. Furthermore, we examine two approaches to mitigate the potential negative effect of employing an advanced matching technology for the platform, and find that under certain conditions, the platform can benefit from revealing labor demand or competition information directly to workers. Our results shed light on both the intended positive and unintended negative effects of improvements in matching quality, and also highlight the importance of thoughtful development, management, and application of matching technologies in the gig economy.

Keywords: matching technologies, gig worker, game theory, platform strategy

*Liu is at the University of Wisconsin-Madison, Email: yliu2396@wisc.edu. Zhao is at Amazon, Email: xinyixz@amazon.com. Lou and Li are at the University of Connecticut, Email: {bowen.lou,xinxin.li}@uconn.edu. We are grateful for comments from conference participants at the Platform Strategy Research Symposium, Seventh Marketplace Innovation Workshop, Production and Operations Management Society Annual Conference, Workshop on Information Systems and Economics, and Conference on Information Systems and Technology. All correspondence can be sent to bowen.lou@uconn.edu.

1 Introduction

Gig-economy platforms (e.g., Uber, Lyft, and Instacart), 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 employers on such 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., matching workers and tasks) are often coordinated by platforms and facilitated by advances in matching technologies (Burtch et al., 2018; Sundararajan, 2014).

To better manage job tasks for gig workers, managers of gig-economy platforms have been investing aggressively in developing and integrating automated and algorithmic matching systems (Moore, 2019). Recent years have seen a rise in the application of data mining and machine learning algorithms (with artificial intelligence (AI) at its contemporary status) in matching technologies. These new technologies can automatically discern patterns from large amounts of data, recognize the optimal mapping between the supply and demand of the labor market, and significantly improve the quality of matching for platforms. As matching technologies continue to improve, they start to take on managerial roles to revolutionize the gig workspace by autonomously evaluating job tasks to deliver better matches between workers and employers (Cameron, 2020; Lee et al., 2015). They are expected to become significant drivers for increasing workers' productivity and platforms' operational performance, ultimately generating higher revenues for both (Cramer and Krueger, 2016; Faraj et al., 2018).

While the industry sees significant promise from advancements in matching technologies, limited attention has been given to how worker behaviors may be influenced by the employment of such technologies, aside from their apparent benefit in improving matching quality. Unlike traditional workers with fixed schedules, gig workers are more independent, possessing greater autonomy and flexibility in setting their own work schedules. Specifically, gig workers can decide strategically whether to participate on a gig-economy platform based on information revealed by job tasks assigned on the platform by its matching technology (Cameron, 2020; Lee et al., 2015). For example, on gig-economy platforms that offer delivery service, 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). On ride-hailing platforms, drivers can perceive the matching technology and infer demand information from the matching outcome to plan their work schedules (Cameron, 2020; Zhang et al., 2022). The adoption of a well-performed matching technology may induce workers' strategic participation because of the additional information potentially revealed by better-matched outcomes. This strategic reaction of workers to job assignments can sometimes lead to a reduced labor supply that is insufficient to meet demand and consequently, a revenue loss for the platform.

Specifically, when matching quality is high, matching outcomes can, under certain conditions, reflect the realization of the demand of labor markets that was uncertain to workers before seeing any matching outcomes. That is, along with the employers assigned to the workers by a better matching, information about uncertain labor demand can sometimes be unintentionally disclosed to workers and promote their autonomy by updating their beliefs about the true demand. For example, if a poor-match job task is assigned by a technology with good matching quality, then the workers may speculate that labor demand is likely low (because otherwise a better-match job task would have been assigned to them) and continuing to spend time working may not be profitable; as a result, such workers may strategize and exercise their discretions to suspend work.[1] Such an unfavorable strategic reaction might not be triggered if the matching quality was low, because the worker would not rule out the possibility that the poor-match job task was caused by the poor matching technology rather than caused by the low demand. As gig-economy platforms are designed to support flexible work arrangements (Chen et al., 2019) and need consent from gig workers before assigning work, workers' sense of autonomy being reinforced by demand signals from a better matching technology may be unavoidable, potentially leading to an unexpected loss of revenue for a platform.

Therefore, two effects brought by the adoption of a better technology to match workers and employers jointly determine the overall revenue of a gig-economy platform: increased worker performance that results from improved matching quality (named as the *"matching enhancement effect"*) and the demand information revealed by matching outcomes, which can sometimes lead to workers' strategic participation decisions (named as the *"information revelation effect"*). The platform can obviously benefit from a revenue boost because of this "matching enhancement effect" that results from technologies with stronger matching capabilities. However, workers may strategically respond to job assignments facilitated by a better matching technology, taking advantage of disclosed labor demand information to compare expected payoffs and opportunity costs of continuing their participation (Agrawal et al., 2018). This strategic participation can 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 a better matching technology 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 research questions: 1) How does the matching outcome from a matching technology with greater matching quality motivate or demotivate workers and, in turn, affect their decisions to participate on a gig-economy platform and perform job activities? 2) Given the presence of the two potentially countervailing effects, to what extent will

[1] Generally, these strategic behaviors are neither rewarded nor penalized as long as workers engage with the job task assigned by a matching technology as intended or in a way that is not explicitly against platform policy (Cameron, 2020).

a gig-economy platform benefit from adopting a better matching technology with greater matching quality in its job assignment? In addition, how will the total welfare of workers and the platform be affected? 3) When a gig-economy platform does not benefit from adopting a matching technology with greater matching quality, how can the negative impact on the platform be mitigated?

To address these research questions, we develop a stylized model to take into account two effects – the matching enhancement effect and the information revelation effect – driven by advances in matching technologies that could alter worker participation behavior on a gig-economy platform. We explore the circumstances under which a better matching technology deployed on a gig-economy platform may have unintended negative consequences on the platform's total revenue. We consider two different types of job tasks: good-match and poor-match job tasks. When adopted by the platform, the matching technology with greater matching quality selects from available tasks and assigns to a worker a better-matched job task that generates not only a higher payoff for the worker but also higher revenue for the platform as well. For a given demand situation, good-match job tasks may not always be available; at times, only poor-match job tasks may be available and thus assigned to the worker. When demand is uncertain, the worker, upon observing a job task assigned by the matching technology, can infer the labor demand information and update her belief about the uncertain demand on the platform in a Bayesian manner. For example, the worker may attribute a poor-match job assignment to low labor demand, knowing that the matching technology with greater matching quality would have assigned a better-match job if the demand condition were better. Our model analyzes the impact of adopting a better matching technology to determine job assignments on workers' decision to continue participating on the platform and the resultant change in the platform's overall revenue.

We first compare the outcome of adopting a perfectly accurate matching technology to the result from our baseline scenario: when a job task is randomly assigned to a worker. We find that while the matching enhancement effect from a better matching technology can increase platform revenue by improving matching quality and worker performance, the information revelation effect that undermines worker participation can dominate under some circumstances, resulting in lower overall revenue for the platform. This negative impact linked to a better matching technology happens when good-match and poor-match job tasks do not differ significantly in value and the opportunity cost for workers to participate is in the intermediate region. This result highlights the importance for gig-economy platforms to fully understand the consequences of adopting a better matching technology beyond the consideration of matching quality itself.

We then consider the range of improvement in matching accuracy to investigate the optimal level of matching accuracy that gig-economy platforms should pursue. We find that as the matching quality of the technology improves, the platform is not necessarily better off. Specifically, there is a non-monotonic relationship between the level of matching accuracy and a platform's revenue. Thus, for a gig-economy platform that is designed to support flexible work arrangements, a perfectly accurate matching technology is not necessarily optimal, even if improving matching quality is costless.

We then extend our model to the case in which we endogenize the share of revenue between the workers and the platform and the case in which we consider the opportunity cost for workers to begin participating on the platform. We also extend our model to the case in which the opportunity cost of workers is endogenous and affected by the competition between platforms, as well as the case in which workers do not work independently but engage in labor competition for job assignments. Our insights with respect to the two competing effects driven by a better matching technology persist in our model extensions. In addition, we find that in the presence of a competing platform, a platform may still prefer not to adopt a more advanced matching technology due to the possible negative information revelation effect, which happens when the platform has some advantage, albeit slight, in other dimensions (e.g., reputation, service quality) compared to its competitor. The extension on interdependent workers shows that a platform is less likely to be hurt by adopting an advanced matching technology if worker preferences are more diversified; this finding leads to our discussion of possible solutions that encourage revealing information in order to mitigate the potential negative impact of a better matching technology on a gig-economy platform.

Specifically, we examine two approaches to mitigate the potential negative effect of a better matching for a platform. We find that a platform can be better off by revealing the labor demand or competition information directly to workers under certain conditions. When we compare two approaches, we find that when platform revenue decreases because a better matching technology is adopted, revealing demand information outperforms revealing competition information. This result is consistent with the fact that, in practice, we often observe gig-economy platforms reveal real-time demand information to their workers, rather than competition information.

Lastly, we provide policy implications of our model by studying the impact of a better matching technology on worker surplus and the total welfare of workers and the platform. We find that a matching technology with greater matching quality generally increases worker surplus, as it provides additional information about the labor market for workers to evaluate, unless the platform intervenes by means such as altering commission rates based on technology levels. That said, total welfare is not always improved by a better matching technology. It is also affected by both the matching enhancement and information revelation effects. Consequently, the possible decrease in the platform's revenue is not merely a redistribution of welfare across different parties.

Our study bridges several strands of literature on the design of digital platforms, algorithmic management, and the gig economy. Our work adds to the studies in the information systems literature with respect to the design of gig-economy platforms to incentivize worker participation and enhance market efficiencies (e.g., He et al., 2021; Hong et al., 2016; Huang et al., 2020). Gig-economy platforms can adopt an advanced matching technology that helps reduce transaction costs and matching frictions by processing a sheer volume of market information to identify the optimal match between workers and employers requesting job tasks (Einav et al., 2016). We show, however, that the job tasks assigned by a better matching technology can motivate or demotivate workers to participate on gig-economy platforms. Furthermore, we advance the growing literature on algorithmic management in the gig economy, which provides initial anecdotal evidence of gig workers' responses to algorithmic job assignments (e.g., Cameron, 2020; Tambe et al., 2019; Zhang et al., 2022). To the best of our knowledge, our study is one of the first to develop a comprehensive analytical model to systematically examine the interaction between human workers and matching technologies, which are improved by advances in algorithms, and analyze their impact on gig-economy platforms' revenue. While we point out the possible negative consequences of technologies with greater matching quality, we also provide actionable solutions to alleviate such consequences that are not intended by platforms. As matching technologies are essential for determining work arrangements in the gig economy, our study underscores the importance of understanding both their intended positive role and their 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 model and discuss the conditions under which adopting a better matching technology may backfire for a gig-economy platform. In Section 4, we explore several model extensions that offer additional insights. In Section 5, we examine two possible approaches to mitigate the potential negative impact of advances in matching technologies. In Section 6, we discuss the impact of a better matching technology on worker surplus and total welfare. We then conclude our paper with Section 7.

2 Related Literature

The gig economy's prominence can be traced to the emergence of the peer-to-peer marketplace mediated by digital platforms (Einav et al., 2016). These 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-economy platforms and their implications for business and society have received wide attention in the information systems (IS) literature. Existing work has mainly touched on three diverse topics: (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), (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 these platforms (e.g., ride-sharing platforms can reduce traffic congestion (Li et al., 2016) and the rate of alcohol-related motor vehicle fatalities (Greenwood and Wattal, 2017), food-delivering platforms can help small restaurants survive during the COVID-19 crisis (Raj et al., 2020)). Our work is closely related to studies on the design of gig-economy platforms to incentivize workers' participation and enhance market efficiencies by reducing transaction costs and matching frictions. Such platforms develop and adopt matching technologies to leverage substantial market information and identify best matches between employers and workers (Einav et al., 2016; Daniels and Turcic, 2021).[2] In particular, for app work-based gig-economy platforms (e.g., on-demand ride-hailing and delivery platforms), it is important to ensure a sufficient supply of gig workers to meet the demand of employers and centralize the time-sensitive matching process (Yan et al., 2020).[3]

Advances in matching technology improve the quality of matching in the gig economy by developing algorithms for automated matching (Azevedo and Weyl, 2016). Algorithms, as computer-programmed procedures for transforming input data into desired outputs (Gillespie, 2014), are central to advances in matching technology and time-sensitive processes on gig-economy platforms (Cameron, 2020). The algorithms can be used to automatically identify and assign a job task to a worker at a given time. For example, in the ride-hailing industry, Uber's algorithm can track and analyze location data from GPS or other sensors in riders' and drivers' smartphones (Duggan et al., 2020), and initially performed matching based on the shortest distance between riders and drivers. But closest does not always mean quickest (Uber, 2022). The matching algorithm was then improved to a time-based approach in which a rider is matched to the driver with the fastest estimated time of arrival (ETA) (Lekach, 2019). As the platform scaled with more workers and job tasks over the years, Uber developed a batching algorithm to advance its matching technology (Uber, 2022). For each rider, instead of matching the individual

[2]Prior studies classify gig work into three major categories: app work (e.g., Uber, Lyft, Deliveroo), crowd work (e.g., Amazon Mechanical Turk, Fiverr), and capital platform work (e.g., Airbnb, Etsy) (Duggan et al., 2020; Zhang et al., 2022). We primarily focus on app work-based platforms for which technologies for automatic matching are required. The matching technologies need to automatically identify and assign a job task to a worker at a time, while in crowd work and capital platform work, employers requesting job tasks need to select from a list of potentially matched gig workers, and then make a final matching decision.

[3]For example, in the process of matching drivers (gig workers) to riders (employers) on ride-hailing platforms such as Uber and Lyft, riders are generally happy to delegate the matching to the platforms, provided that they arrive at their destinations quickly and safely (Einav et al., 2016). Riders pay less attention to car features or driver characteristics. Instead of letting riders choose from a list of drivers, the platforms adopting centralized matching strategy can lower transaction costs by reducing unnecessary delays and prescreening unqualified drivers. Food and grocery delivery platforms, such as Deliveroo and Instacart, adopt similar centralized matching processes, although they may be less constrained in response time due to a lower level of urgency for the service (Yan et al., 2020). However, during the COVID-19 pandemic, the demand for food delivery rose dramatically and placed significantly higher pressure on providing service in a timely manner (Forman, 2021; DiSalvo, 2021). In comparison, other types of platforms that face less time constraints and have users with stronger preferences for making selection decisions perform matching in a decentralized manner (such as TaskRabbit for household tasks and Airbnb for hospitality service) (Einav et al., 2016). The decentralized matching process begins with employers who request service specifying what they need. The platforms then offer matching suggestions of gig workers to their employers; the final decisions, however, are made by these participants (Yan et al., 2020).

rider to that rider's closest driver, the algorithm would find the best match for a "batch" of riders and drivers - that is, a group of nearby drivers and people requesting rides in an area at the same time (Lekach, 2019). Thus, Uber optimizes its matching algorithm by reducing wait time for riders and idle time for drivers across the entire "batch" or group.

Furthermore, recent years have seen a rise in the application of data mining and machine learning algorithms in matching technologies. These new technologies can automatically discern patterns from large amounts of data, recognize the optimal mapping between the supply and demand of labor markets, and significantly improve the quality of matching for platforms (Cameron, 2020; Kitchin, 2017). For example, Uber's machine learning-driven matching technology takes into account a massive number of features from data, including distance, time, traffic, and a diverse set of other real-world dynamics, and produce millions of best-match pair predictions per minute (Turakhia, 2017). Matching enhancement driven by advanced algorithms is also pervasive beyond the ride-hailing platform. Deliveroo, an online food delivery platform, adopts machine learning algorithms trained on historical matching records in its dispatch engine. It is able to predict the best possible match between gig riders and customer orders in real time (Sen, 2021). Instacart, a platform offering grocery delivery service, designs machine learning-based matching algorithms to enhance the quality of service, and its algorithm can optimally balance the number of shoppers with customer demand for groceries (Mixson, 2021). Overall, matching quality can be improved by leveraging technologies' capability to process the sheer volume of information about the dynamics of supply and demand of workers and their activities. Accordingly, the matching outcomes from a better matching technology can well reflect the market conditions of labor.

In practice, the human-technology co-operation mode in which human workers are downstream of the technology's output takes place frequently on gig-economy platforms: advances in matching technologies engage in managerial activities such as allocating job tasks for human workers to perform (Lee et al., 2015; Bai et al., 2020; Bundorf et al., 2019). A worker in theory should receive the best employer through technologies with high quality matching, which can help that worker raise earnings and platform gain a higher revenue (Cramer and Krueger, 2016). Nevertheless, the improved matching outcome can convey demand information and thus affect human workers' decisions, such as whether to participate on the gig-economy platform. Specifically, the participation of a matching technology in human decisions involves the matching outcome serving as an input for a human decision-maker to make decisions about choosing an action to maximize expected payoffs (Agrawal et al., 2018; Boyaci et al., 2020). Advances in matching technologies can enable matched outcomes to provide a more accurate signal of labor market conditions to workers, allowing them to compare the expected costs and benefits for making optimal participation decisions more precisely. However, there is a scarcity of research that systematically studies the impact of advances in matching technologies on the participation behavior of gig workers, its strategic implications, and possible unintended consequences that a better matching technology may have on gig-economy platforms.[4] Our study aims to fill the gap in the literature by explicitly examining the potential negative consequences of a better matching for a platform because of the induced workers' strategic participation behavior.

In line with the role that technologies play in the human decision-making process, a growing stream of research examines algorithmic management on gig-economy platforms, which refers to the practice of using algorithms to guide incentives and make recommendations to platform workers about the actions they may take (Tambe et al., 2019). The studies in this literature provide an increasing number of narrative anecdotes, investigating the influence that algorithmic management can have on workers' behavior on gig-economy platforms (Kellogg et al., 2020; Möhlmann and Zalmanson, 2017; Rosenblat and Stark, 2016; Wood et al., 2019). As algorithmic technologies are increasingly improved and 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 such matching technologies and implications for these platforms, hence the focus of our study. Furthermore, a growing body of studies on algorithmic management discuss the notion of "algorithmic imaginary" of gig workers in practice (Zhang et al., 2022). Algorithmic imaginary is defined as "ways of thinking about what algorithms are, what they should be, and how they function" (Bucher, 2017). As the quality of matching can be improved through advances in algorithms, we use algorithmic imaginary as a lens to understand how gig workers perceive matching technologies enabled by algorithms, make sense of information from the matches, and make strategic decisions, all of which are central to platforms moving forward in the gig economy.

3 Main Model

3.1 Model Setup

We 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 a ride-hailing or a food-delivering platform (e.g., Uber and Deliveroo) as an example, the objective of optimally matching

[4] From the IS literature, Zhang et al. (2020) provide empirical evidence that drivers update their beliefs and infer demand based on the information observed on the platform to make driving decisions. The beliefs of platform users can also be updated based on information signals driven by AI or algorithms more broadly. For example, Fu et al. (2022) empirically examine the Zillow platform and find that Zillow's Zestimate, as an AI-driven estimate of the property's market value, offers a signal of the true property value and influences the beliefs of both buyers and sellers. Our model is built on a combination of the conditions in which 1) workers infer demand based on the information on a platform, and 2) the information can be provided by technologies that are enabled by AI or algorithms more broadly.

a driver (worker) and a rider or customer (employer) is to achieve lower wait time for the rider or customer 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, or to pick up food and deliver it to a given customer, thus generating a higher revenue per unit time.

In our main model, we assume that workers work 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 an extended model in which we consider competition among workers. Under this assumption, without loss of generality, we consider a representative worker and two potential representative employers, one with a good match and the other with a poor match.[5] Each employer appears with a probability p, where a higher p indicates a higher labor demand on the platform.[6] This fluctuation of labor demand reflects demand uncertainty in real life. In our Uber example, each rider (employer) may come to the platform with some probability. When there is a higher demand for Uber service (e.g., after a social event or a gathering), 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 advanced matching technology is used, and (2) an advanced matching technology is applied. In the first case without an advanced matching technology, 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 a given worker. Specifically, if both employers appear on the platform, then 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, then the worker is automatically assigned to the employer; if no employer appears, then no job is available, and thus zero revenue is generated. In the second case with an advanced matching technology, the platform is able to identify the match between each employer and the worker and always assigns the worker to the better-match employer who appears on the platform to maximize its revenue. This is essentially how advanced matching technologies such as AI-driven algorithms nowadays manage matching for platforms and help firms make more informed decisions. Specifically, if both employers appear on the platform, then the worker is assigned to the good-match employer (x_H) with probability 1; otherwise, the assignment happens to be the same as that in the no advanced technology case since only one or no employer appears, and thus matching is pre-determined. Here, we focus on the two extreme cases in which the platform

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

[6]The parameter p essentially represents the relative demand to supply. Because we consider the simple case in the main model for which demand conditions for workers are independent, p effectively captures the demand condition for a specific worker. When we consider the situation in which worker demand conditions are interrelated in the model extension in Section 4.5, a small (large) p suggests that the relative demand to supply is low (high). In that model extension, a match is determined by both demand and supply conditions.

either cannot identify or can perfectly identify the match for the easy exposition of the mechanisms at play. We will then examine the case in which the platform can identify the match with only a certain probability in the model extension in Section 4.3.

We consider the context in which 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.[7] 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 revenue in the two periods. The platform and the worker split the revenue so that the worker takes a δ proportion of the revenue. That is, the platform takes $1-\delta$ proportion of the generated revenue as a commission fee. In the first period, the worker participates on the platform and is assigned to an available employer by the platform. 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 an advanced matching technology is utilized), and then 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 an advanced matching technology, respectively. Since the technology remains the same across two periods, such likelihoods also apply to the second period (x_2). Throughout our paper, we use superscript "0" to indicate the case without an advanced matching technology and use superscript "T" to indicate the case with an advanced matching technology. When no advanced matching technology is adopted, the 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 the advanced matching technology is applied, the likelihoods are:

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

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

Based on these likelihoods and the distribution of the prior ($U[0,1]$), we calculate the Bayesian posterior of the demand probability as follows. Without the advanced matching technology, 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 in the case with the advanced matching technology, f^T, is given by:

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

From equations (3) and (4), we make the following observations. First, when no advanced matching technology 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 in which the advanced matching technology is used because with the advanced technology, an assigned job carries additional information. For example, if the worker is assigned to a poor-match employer by an advanced matching algorithm, then she will know that only one employer appears, because otherwise the 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 places lower weights on larger values of p when $x_1 = x_L$ than when $x_1 = x_H$ (i.e., $f^T(p|x_1 = x_L) < f^T(p|x_1 = x_H)$ for $p > \frac{2}{3}$). Second, regardless of whether the advanced matching technology is used, the posterior of p given $x_1 = 0$ is identical (i.e., $f^0(p|x_1 = 0) = f^T(p|x_1 = 0)$). This is because the labor demand is independent of the platform's matching method, and the technology 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, she will decide in the second period whether to continue participating on the gig-economy platform based on this posterior belief on p. If the worker decides to stay on the platform in the second period, there will be some opportunity cost c, which reflects the revenue of other non-gig jobs or opportunities on other competing platforms.[8] Let Π_t^l, π_t^l, w_t^l where $t \in \{1, 2\}$ and $l \in \{0, T\}$ 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 advanced matching technology). 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 the advanced matching technology, 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 the advanced matching technology, depending on p, the conditional expected total revenue can be derived as:

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

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

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

[8] We normalize the opportunity cost in the first period to zero to reflect that the opportunity cost typically increases over time for gig workers. Job tasks on gig-economy platforms are generally short-term work and temporary projects (Allon et al., 2018). Most gig workers do them on the side, rather than pursue them as their primary way of earning a living (Anderson et al., 2021; Mccabe, 2015). They typically have other full-time or part-time jobs, thus facing a more significant time commitment and opportunity cost as their work hours on gig-economy platforms increase. We have also considered the case in which a worker also faces an opportunity cost in the first period in Section 4.2, and our main results hold qualitatively.

Clearly, we have $\Pi_2^l(x_1 = x_H) \geq \Pi_2^l(x_1 = x_L) > \Pi_2^l(x_1 = 0)$ for $l \in \{0, T\}$. 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. We denote the set of all first-period assignments that make the worker willing to participate in the second period as $\mathcal{X}^{par}$. Then, in this example, $\mathcal{X}^{par} = \{x_H, x_L\}$. In the following discussion, we add superscripts "0" and "T" to $\mathcal{X}^{par}$ (i.e., use $\mathcal{X}^{0,par}$ and $\mathcal{X}^{T,par}$), to denote this set for the case without and with the adoption of an advanced matching technology, respectively. By comparing $\mathcal{X}^{0,par}$ and $\mathcal{X}^{T,par}$, we observe that using the advanced matching technology can completely change the expected revenue in the second period; thus, the participation decision of the worker changes as well. Table 1 summarizes the key notation in our model.

Table 1: Key Notation in the Model

Notation	Definition
x_L, x_H	Revenue generated with a poor- and good-match employer
p	Probability of each employer appearing on the platform
x_t ($t \in \{1, 2\}$)	Revenue in the t-th period
δ	Commission rate (worker's proportion of revenue)
c	Opportunity cost for a worker to continue participating in the second period
Π_t^0, Π_t^T	Expected total revenue in the t-th period without and with the advanced matching technology
π_t^0, π_t^T	Platform's expected revenue in the t-th period without and with the advanced matching technology
w_t^0, w_t^T	Worker's expected payoff in the t-th period without and with the advanced matching technology
$\mathcal{X}^{0,par}$, $\mathcal{X}^{T,par}$	Set of all first-period assignments that make the worker willing to participate in the second period for the case without and with the advanced matching technology

3.2 Model Results

We summarize the worker's participation decision in the following lemma.

Lemma 1. *If no advanced matching technology is used,*

- *when $c \leq \delta \frac{1}{5}(x_H + x_L)$, the worker always participates in the second period (i.e., $\mathcal{X}^{0,par} = \{x_H, x_L, 0\}$);*
- *when $\delta \frac{1}{5}(x_H + x_L) < c \leq \delta \frac{2}{5}(x_H + x_L)$, the worker participates in the second period iff $x_1 = x_H$ or $x_1 = x_L$ (i.e., $\mathcal{X}^{0,par} = \{x_H, x_L\}$);*
- *when $c > \delta \frac{2}{5}(x_H + x_L)$, the worker never participates in the second period (i.e., $\mathcal{X}^{0,par} = \emptyset$).*

If the advanced matching technology is used,

- *when* $c \leq \delta(\frac{x_H}{4} + \frac{3x_L}{20})$*, the worker always participates in the second period (i.e.,* $\mathcal{X}^{T,par} = \{x_H, x_L, 0\}$*);*
- *when* $\delta(\frac{x_H}{4} + \frac{3x_L}{20}) < c \leq \delta(\frac{x_H}{2} + \frac{x_L}{5})$*, the worker participates in the second period iff* $x_1 = x_H$ *or* $x_1 = x_L$ *(i.e.,* $\mathcal{X}^{T,par} = \{x_H, x_L\}$*);*
- *when* $\delta(\frac{x_H}{2} + \frac{x_L}{5}) < c \leq \delta(\frac{2}{3}x_H + \frac{x_L}{6})$*, the worker participates in the second period iff* $x_1 = x_H$ *(i.e.,* $\mathcal{X}^{T,par} = \{x_H\}$*);*
- *when* $c > \delta(\frac{2}{3}x_H + \frac{x_L}{6})$*, the worker never participates in the second period (i.e.,* $\mathcal{X}^{T,par} = \emptyset$*).*

Accordingly, when $x_H < 2x_L$ *and* $\delta(\frac{x_H}{2} + \frac{x_L}{5}) < c \leq \delta\frac{2}{5}(x_H + x_L)$*, the worker is less likely to participate in the second period when the advanced matching technology is used than when it is not (i.e.,* $\mathcal{X}_1^{T,par} \subset \mathcal{X}_1^{0,par}$*).*

The proofs of all our lemmas and propositions are in the Appendix. Lemma 1 not only provides the conditions for the worker to participate in the second period but also asserts that while the worker in general has a higher incentive to participate when the advanced matching technology is adopted because of its 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 or poor) are close to each other. In this case, $\mathcal{X}^{T,par} \subset \mathcal{X}^{0,par}$, which implies that the use of an advanced matching algorithm may undermine worker participation by revealing extra information in the technology-facilitated matching outcomes. Without the advanced matching technology, 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 as a good-match or a poor-match. However, when the advanced matching technology is used, a good match and a poor match can carry different information on the underlying demand probability. For example, if the worker is assigned to a poor-match employer, then she will infer that the underlying demand probability is low; otherwise, the platform would have assigned her to a good-match employer. In this case, she may leave the platform and take other opportunities in the second period, which will result in an expected revenue loss for the platform. This phenomenon is more prominent when good-match and poor-match job tasks do not differ significantly in value ($x_H < 2x_L$), such that the gain from a better match enabled by the technology will not dominate the expected loss, due to information revelation caused by the better matching technology. In addition, this extra information makes a difference to the platform's revenue only if the opportunity cost for the worker to participate is in a range of intermediate values such that a poor-match job in the first period is a good enough signal for the worker to participate when the advanced matching technology is absent, but not so when the advanced matching technology is in place.

We next examine how the platform's revenue, $\pi^l \equiv \pi_1^l + \pi_2^l$,[9] is affected by the adoption of the advanced matching technology. We first focus on the case when $\mathcal{X}^{T,par} \subset \mathcal{X}^{0,par}$, 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 the advanced matching technology), respectively. In these figures, the cases in which π_2^0 always equals 0 regardless of x_2 happen when the worker chooses not to participate on the platform in the second period, based on Lemma 1.

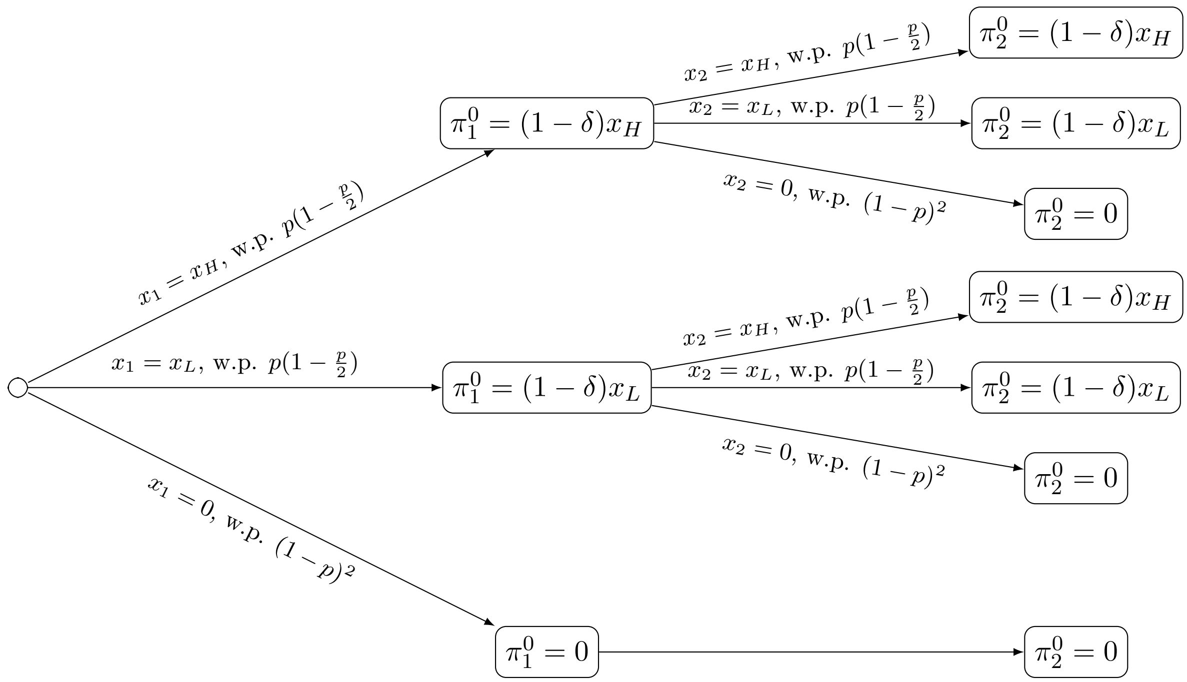


Figure 1: Platform revenue: when no matching technology is used

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

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

[9]We follow prior studies (e.g., Geng et al., 2022; Jiang et al., 2011; Jin et al., 2022) and do not include a discount factor in our two-period model. If we introduce a new parameter $\eta \in [0,1]$ as the discount factor, the condition for x_H in Proposition 1 will be changed to $x_H < \frac{10+11\eta}{10+4\eta}x_L$. It will not reduce to an empty set, as long as $\eta > 0$, suggesting that including a discount factor will not change our main results qualitatively.

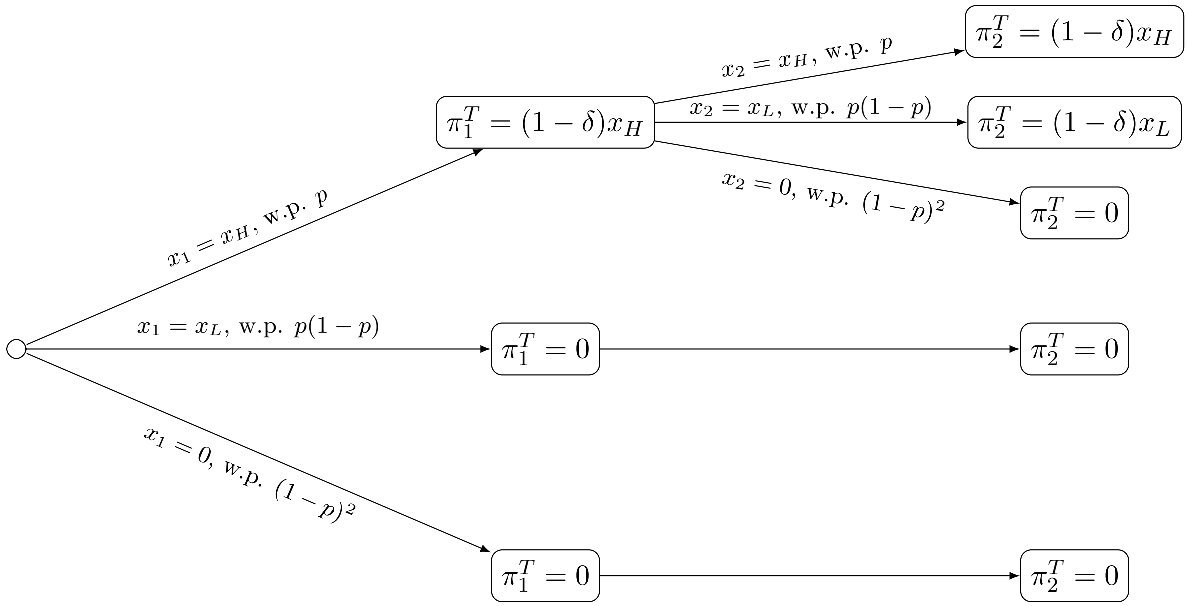


Figure 2: Platform revenue: when matching technology is used

for the case without the advanced matching technology, and

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

for the case with the advanced matching technology. 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 advanced matching technology, and

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

for the case with the advanced matching technology. In making these calculations, we assume 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 $\mathcal{X}^{T,par} \subset \mathcal{X}^{0,par}$. Following the same procedure, we can calculate the platform's ex ante expected revenue under all conditions as:

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

where $l \in \{T, 0\}$. We then compare the expected revenue of the gig-economy platform between the cases with and without the use of an advanced matching technology, and we summarize our results in the following proposition.

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

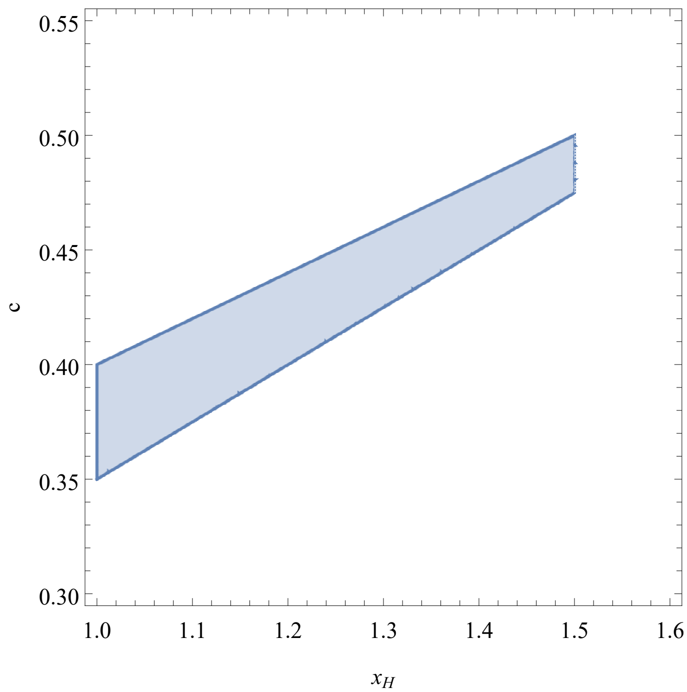


Figure 3: Parameter space for $\pi^{T*} < \pi^{0*}$ (shaded area)
Note: $x_L = 1$, $\delta = 0.5$

Proposition 1 asserts that the platform's expected revenue can be negatively affected by the use of an advanced matching technology, even if we do not consider any cost associated with developing the advanced matching technology.[10] Specifically, when the outside opportunity cost for a worker is intermediate and the values of different types of match are sufficiently close, then adopting an advanced matching technology will hurt the gig-economy platform's expected revenue, as illustrated in Figure 3.

The platform's expected revenue is affected by the use of an advanced matching technology in two ways. On the one hand, the use of the advanced matching technology can enhance the matching quality

[10] In our model, we can introduce a new parameter $\xi \in [0, 1]$ as the probability of a worker acting strategically to capture the scenario in which some workers may not act strategically and always participate in the second period, regardless of what they observe in the first period. With this new parameter, the condition for x_H in Proposition 1 changes to $x_H < \frac{20+\xi}{20-6\xi}x_L$. This condition does not shrink to an empty set as long as $\xi > 0$. In practice, we believe at least some workers act strategically (Cook et al., 2021). Thus, our results hold qualitatively.

when employers with different degrees of matching quality are present, yielding a higher expected revenue. We call this effect the *"matching enhancement effect"* of an advanced matching technology. On the other hand, strategic gig workers can potentially make use of the demand information revealed by assigned jobs in the first period, thereby changing their participation behavior. Specifically, as shown in Lemma 1, under certain conditions, the adoption of an advanced matching technology may undermine the participation of the worker compared to when the advanced matching technology is not adopted, leading to a potential expected revenue loss for the platform. We call this effect the *"information revelation effect"* of the advanced matching technology. The information revelation effect is, of course, not always detrimental and sometimes can work to the platform's benefit (e.g., when a good-match employer is assigned, indicating a strong demand condition). The overall impact of the advanced matching technology on the platform's expected revenue 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 when it is negative but dominated by the matching enhancement effect, the technology is instrumental to the gig-economy platform enabling better matching, which translates to higher revenue. When the opposite is true, however, the gig-economy platform's revenue could be lessened by the adoption of the advanced technology in matching as a result of an insufficient labor supply, even if we set aside the cost of developing and deploying the advanced matching technology.

Our model thus uncovers an important yet often-overlooked insight on how the revenue of a gig-economy platform that adopts a better technology to facilitate matching can be affected by gig workers' strategic reaction to demand information revealed by assigned job tasks. Our findings suggest that although the advanced matching technology effectively assigns 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-economy platform, if it further takes into account workers' strategic participation behavior. Specifically, this strategic participation behavior hurts the platform when a poor-match employer is assigned in the first period. In this case, workers' participation incentives are lower when the advanced matching technology is used than when the technology is not used. The information revelation effect here functions like an attribution effect from the workers' point of view: when a worker is assigned to a poor-match employer, she can attribute that match to either low demand or a poor matching system, until the adoption of the advanced matching technology 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 the advanced matching technology is absent compared to the case when the advanced matching technology 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 the advanced matching technology:

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

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 $F^T(p|x_1 = x_L)$, as shown in Figure 4.

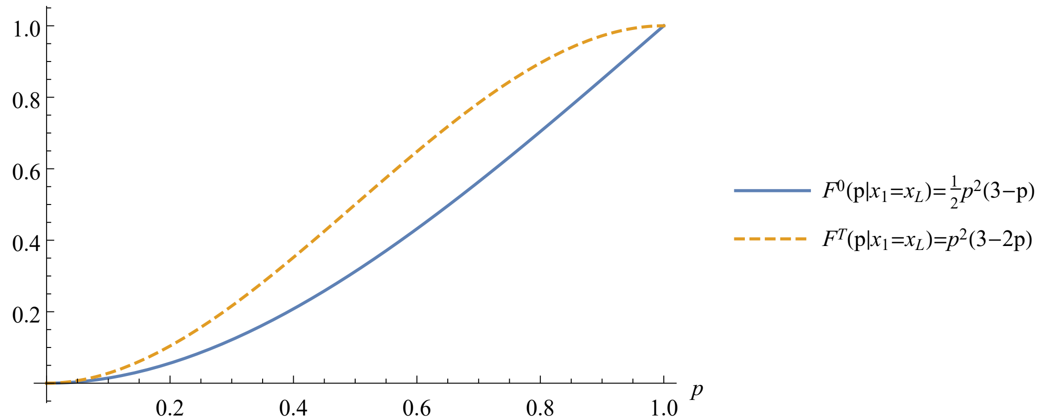


Figure 4: $F^0(p|x_1 = x_L)$ first-order stochastically dominates $F^T(p|x_1 = x_L)$

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

4 Extended Models

In this section, we conduct several model extensions to examine the robustness of our main result and derive additional insights with respect to adopting an advanced matching technology. Specifically, we extend our main model to cases in which (1) the platform can strategically adjust its commission rate based on whether an advanced matching technology is adopted, (2) a worker's opportunity cost is considered in the first period, (3) the advanced matching technology can identify the match (good or poor) accurately with some probability, (4) the opportunity cost of workers is endogenously determined by competition between platforms, and (5) the workers compete for job tasks.

4.1 Endogenous Revenue Sharing

In the main model, we consider a fixed commission rate (i.e., $1-\delta$) regardless of whether the advanced technology is used for matching. In this section, we investigate whether our key insights are robust if the platform can strategically tailor its commission rate according to its technology strategy. That is, given the matching technology applied, the platform can choose a different commission rate. Consistent with the business reality that the commission rate is typically set just once for all transactions, we assume that this commission rate $1-\delta$ (or equivalently, the revenue-sharing ratio with a δ proportion for the worker) is decided at the very beginning before demand is realized and remains the same in both periods.

Let δ^{0*} and δ^{T*} denote the optimal revenue-sharing ratio decided by the platform for the cases without and with the advanced matching technology, respectively. The platform's optimal revenue-sharing ratio and the corresponding expected revenues π^{0*}_{endo} and π^{T*}_{endo} are given by the following lemma.

Lemma 2. *When there is no advanced matching technology,*

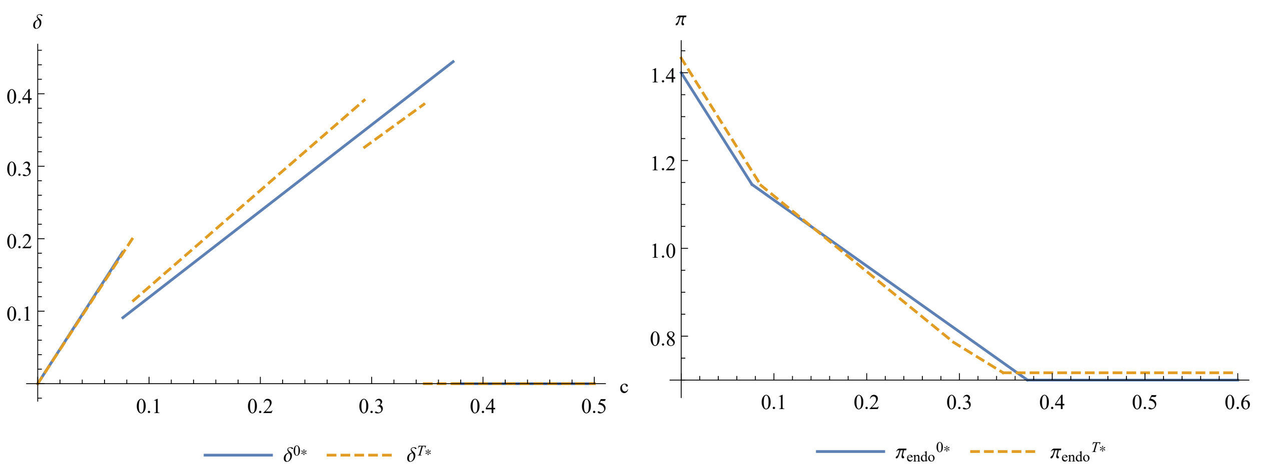
- *if* $c \leq c^0_1$*, the optimal revenue-sharing ratio is* $\delta^{0*} = \frac{5c}{x_H+x_L}$ *and the corresponding expected revenue is* $\pi^{0*}_{endo} = \frac{2x_H}{3} + \frac{2x_L}{3} - \frac{10c}{3}$*,*
- *if* $c^0_1 < c \leq c^0_2$*,* $\delta^{0*} = \frac{5c}{2(x_H+x_L)}$ *and* $\pi^{0*}_{endo} = \frac{3x_H}{5} + \frac{3x_L}{5} - \frac{3c}{2}$*,*

- *if* $c > c_2^0$, $\delta^{0*} = 0$ *and* $\pi_{endo}^{0*} = \frac{x_H}{3} + \frac{x_L}{3}$.

When the advanced matching technology is used,

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

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



(a) Revenue-Sharing Ratio (δ^{0*} and δ^{T*})

(b) Platform Revenue (π_{endo}^{0*} and π_{endo}^{T*})

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 the advanced matching technology is adopted, the worker might in fact get a larger proportion out of the total revenue when the advanced matching technology is adopted compared to when it is not (see Figure 5a). Conventional wisdom may suggest that, by using a better matching technology, the platform has more control over demand allocation and thus should have more bargaining power when setting commission rates, leading to a smaller δ or more severe "labor exploitation" from workers. In contrast, we find that because the information revelation effect of technology may undermine worker participation, the platform may have to increase the worker's share of revenue instead to motivate worker participation (i.e., it is possible that $\delta^{0*} < \delta^{T*}$). Accordingly, the application of the advanced matching technology may not necessarily lead to more severe exploitation as expected.

Figure 5b also implies that under some circumstances, adopting the advanced matching technology may still hurt the platform's revenue even when the revenue-sharing ratio is determined conditionally based on the use of matching technology. Proposition 2 gives a more comprehensive investigation of 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 matching technology, 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 the advanced matching technology than when it does not (i.e., $\pi^{T*}_{endo} < \pi^{0*}_{endo}$).*

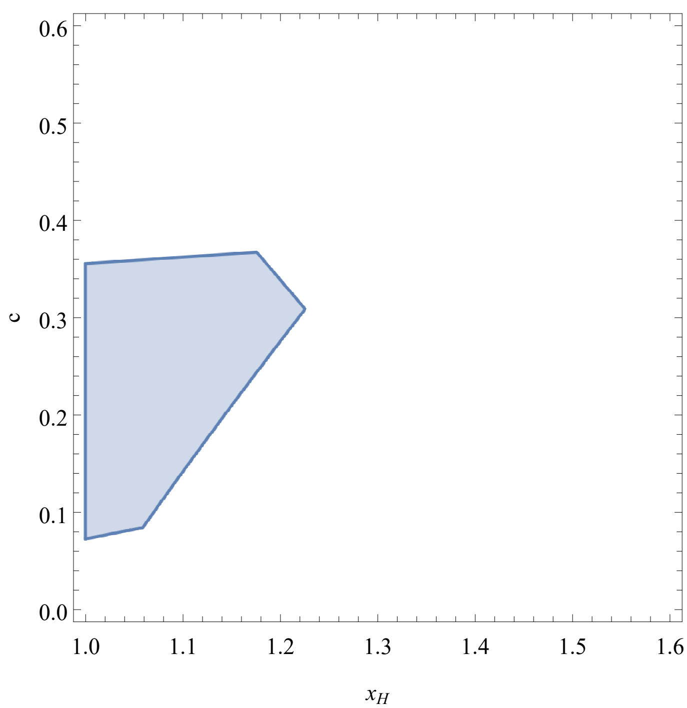


Figure 6: Parameter space for $\pi^{T*}_{endo} < \pi^{0*}_{endo}$ (shaded area)
Note: $x_L = 1$

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

4.2 Worker's First-Period Opportunity Cost

In the main model, we normalize the first-period opportunity cost to zero. In this section, we assume that a worker also incurs an opportunity cost βc in the first period, where $\beta \in [0, 1]$. Parameter β captures the extent to which a worker's opportunity cost of working on a gig-economy platform increases over time for the reasons discussed in Section 3.1. When $\beta = 1$, the opportunity cost is the same in the two periods. The worker evaluates her payoff before the first period and decides whether to participate in the first period. The worker's expected payoff if she participates in the first period, denoted by $w_1^{l,par}$, where $l \in \{T, 0\}$, is given by:

$$w_1^{l,par} \equiv (\mathbf{E}^l[w_1] - \beta c) + \mathbf{E}^l \left[\max\left\{0, \mathbf{E}^l[w_2|x_1] - c\right\}\right], \tag{15}$$

and the expected payoff if she does not participate ($w_1^{l,nopar}$) is given by:

$$w_1^{l,nopar} \equiv 0 + \max\left\{0, \mathbf{E}^l[w_2] - \beta c\right\}. \tag{16}$$

We note that the first term in each of these two equations indicates the first-period expected payoff, and the second term refers to the contingent second-period expected payoff; a worker can only observe the demand information in the first period if she participates. A worker participates in the first period if $w_1^{T,par} \geq w_1^{T,nopar}$ when the advanced matching technology is adopted, and does so if $w_1^{0,par} \geq w_1^{0,nopar}$ when the advanced matching technology is not adopted. Based upon the worker's first-period participation decision, we can follow a similar derivation of the platform's revenue as in our main model. We summarize our findings in the following proposition.

Proposition 3. *When the worker's first-period opportunity cost is βc, the parameter region of (x_H, x_L, c) such that $\pi^{T*} < \pi^{0*}$ always exists for any $\beta \in [0, 1]$. When $\beta \leq \frac{5}{6}$, the parameter region is the same as that in Proposition 1. When $\beta > \frac{5}{6}$, the area of such a parameter region shrinks as β increases.*

Proposition 3 shows that our main result – that adopting a better matching technology can backfire and negatively affect a gig-economy platform's revenue – remains robust, although this may happen in a smaller parameter region as the difference in opportunity cost between the two periods decreases. The intuition behind the sometimes reduced parameter region is that when the first-period opportunity cost is higher, there are more disadvantages associated with avoiding the advanced matching technology, because the worker's first-period participation constraint without the advanced technology is tighter than that with the technology. Therefore, a platform can find it harder to adopt a better matching technology. However, this region never disappears, even if the worker's first-period opportunity cost is the same as that in the second period ($\beta = 1$), confirming the robustness of our main result.

4.3 Imperfect Matching Technology

In our main model, we consider two extreme cases of matching, "random" matching and "perfect" matching, to illustrate adopting an advanced matching technology can reduce a gig-economy platform's revenue. We assume that when the advanced matching technology is adopted, as long as a good-match employer (x_H) is available in the market, he will be identified and assigned to a worker. In this extension, we relax this assumption and discuss the possibility of "imperfect" matching. To nest "random" and "perfect" matching as special cases, we introduce a new parameter k and specify the matching process as follows: when the good-match (x_H) and poor-match (x_L) employers are both available on the platform, the probability that x_H is identified and assigned to the worker is $\frac{1}{2} + k$, where $k \in [0, \frac{1}{2}]$ captures the probability of the matching technology identifying and assigning the good match accurately. It is clear that $k = 0$ is equivalent to a random matching, and $k = \frac{1}{2}$ is equivalent to a perfect matching. In other words, the main model compares the case when $k = 0$ to that when $k = \frac{1}{2}$. In what follows, we analyze the worker's participation decision and the platform's revenue when adopting a matching technology with the accuracy parameter k. We are interested in answering this question: will the platform's revenue always increase as the matching technology becomes more capable of identifying and assigning good matches?

We maintain all the other assumptions in our main model. Following a similar procedure as that in our main model, we can calculate the worker's expected payoff in the second period conditional upon observing the first-period job assignment, or $\mathbf{E}^k[w_2|x_1]$, where the superscript k indicates the matching technology accuracy. We argue that adopting a better matching technology can backfire because a worker's conditional expected payoff in the second period may be lower when the advanced matching technology is applied than when it is not. We note that this happens only when the first-period job assignment is a poor match ($x_1 = x_L$), so we focus on the case when $x_1 = x_L$ in the following lemma.

Lemma 3. *When a technology with matching accuracy k is adopted, the worker's expected payoff in the second period upon receiving a poor-match employer in the first period ($x_1 = x_L$) is given by:*

$$\mathbf{E}^k[w_2|x_1 = x_L] = \delta \frac{4(x_H + x_L) - 9kx_L - 6k^2(x_H - x_L)}{10(1-k)}. \tag{17}$$

Furthermore,

- *when $x_H \leq \frac{5}{4}x_L$, $\mathbf{E}^k[w_2|x_1 = x_L]$ decreases in k, and*
- *when $x_H > \frac{5}{4}x_L$, $\mathbf{E}^k[w_2|x_1 = x_L]$ first increases and then decreases in k, with the peak at*

$k = \hat{k} \equiv 1 - \sqrt{\frac{2x_H - x_L}{6(x_H - x_L)}}$.

Lemma 3 indicates that the shape of the relationship between the matching accuracy (i.e., k) and the worker's expected second-period payoff, given $x_1 = x_L$ (i.e., $\mathbf{E}^k[w_2|x_1 = x_L]$), can vary depending on the relative magnitude of x_H and x_L. We have several observations from this lemma. First, as the matching technology becomes more accurate, the worker's expected second-period payoff does not always increase (and may even decrease in some cases). This observation reflects the two countervailing effects of advanced technology adoption that we discussed in our main model: the positive matching enhancement effect and the negative information revelation effect. Because the matching enhancement effect is less significant when the difference between x_H and x_L is small ($x_H \leq \frac{5}{4}x_L$), there is a decreasing relationship between matching accuracy k and $\mathbf{E}^k[w_2|x_1 = x_L]$ in the first case of Lemma 3. Second, in both cases of Lemma 3, the effect of further technology improvement on $\mathbf{E}^k[w_2|x_1 = x_L]$ is negative if the accuracy of the matching technology is already high. This finding provides an interesting and somewhat counter-intuitive insight into a platform's technology strategy in that a platform may prefer a less-than-perfect matching technology, even if improving the technology's matching capability per se is costless. This insight will be formalized in Proposition 4. Third, if we compare $\mathbf{E}^{k=0}[w_2|x_1 = x_L]$ (random matching, or no advanced technology adoption) and $\mathbf{E}^{k=\frac{1}{2}}[w_2|x_1 = x_L]$ (perfect matching technology), then we return to our main model.

Due to the non-linear relationship between k and $\mathbf{E}^k[w_2|x_1 = x_L]$ when $x_H > \frac{5}{4}x_L$, depending on the size of the worker's opportunity cost c, her participation decision in the second period can be very complicated as the matching accuracy becomes higher. For the sake of tractability, we focus on the most interesting case when $c \in (\underline{c}, \overline{c})$, where $\underline{c} \equiv \max\left\{\mathbf{E}^{k=0}[w_2|x_1 = x_L], \mathbf{E}^{k=\frac{1}{2}}[w_2|x_1 = x_L]\right\}$ and $\overline{c} \equiv \mathbf{E}^{k=\hat{k}}[w_2|x_1 = x_L]$. Figure 7 illustrates this case, in which there exists $k_1 < k_2 < \frac{1}{2}$ such that $\mathbf{E}^k[w_2|x_1 = x_L] \geq c$ if $k_1 \leq k \leq k_2$ and $\mathbf{E}^k[w_2|x_1 = x_L] < c$ if $k < k_1$ or $k > k_2$. In other words, upon receiving x_L in the first period, the worker continues participating in the second period only when the matching technology is not too poor and not too advanced, which is a direct outcome of the matching enhancement and information revelation effects. Given such worker participation behavior, we can derive the platform's overall ex-ante expected revenue, denoted as π^k, and discuss how it will change as the matching accuracy improves, which we summarize in the following proposition.

Proposition 4. *When $x_H > \frac{5}{4}x_L$ and $c \in (\underline{c}, \overline{c})$, the platform's expected revenue π^k obtains its maximum at $k^* = k_2 < \frac{1}{2}$ if $c \leq \frac{\delta(46x_H - 31x_L)(5x_H + 2x_L)}{456x_H - 323x_L}$, and at $k^* = \frac{1}{2}$ otherwise.*

According to Proposition 4, as the accuracy of the matching technology increases, the platform will not necessarily benefit from this accuracy. This result echoes the findings in our main model in that the adoption of a perfect matching technology can backfire. Figure 8 illustrates the case in which the platform's maximum revenue is obtained when the matching accuracy is less than perfect.

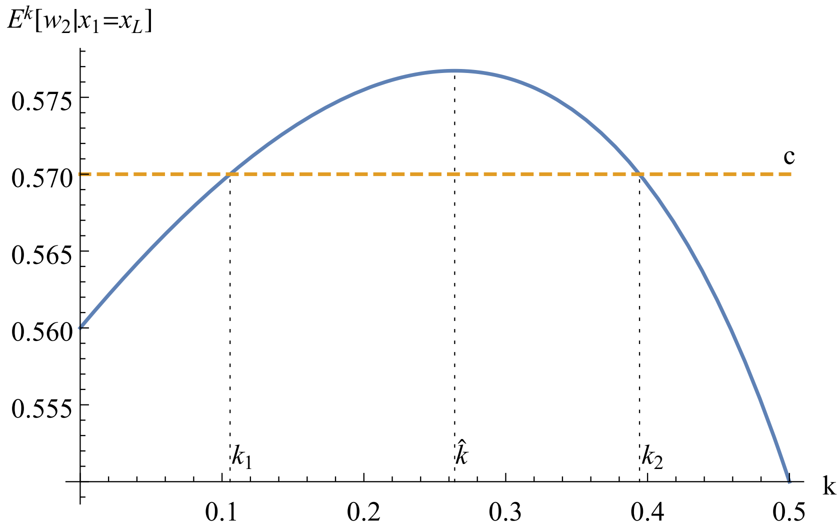


Figure 7: Relationship between $\mathbf{E}^k[w_2|x_1 = x_L]$ and k
Note: $x_H = 1.8$, $x_L = 1$, $c = 0.57$

In this case, the platform's expected revenue π^k increases in k for $k < k_2$, and there is a drop of π^k discontinuously at $k = k_2$. Although π^k again increases in k for $k > k_2$, the platform's revenue with the perfect technology ($k = \frac{1}{2}$) may not be as high as that when $k = k_2$.

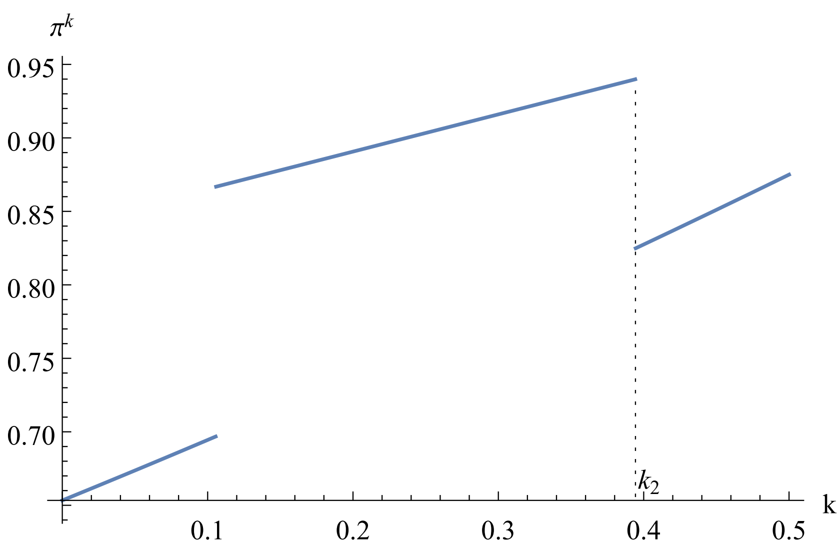


Figure 8: Platform revenue π^k and matching accuracy k
Note: $x_H = 1.8$, $x_L = 1$, $c = 0.57$

In addition, this analysis also sheds light on a platform's optimal technology choice. Our findings suggest that when a platform makes decisions to improve its level of matching accuracy for its matching technology, in addition to development or investment costs, the impact of this added improvement on both matching quality and workers' participation behavior needs to be taken into account. While it is typically not wise to forego any improvement and instead continue to use random matching, the platform may strategically refrain from pushing forward matching accuracy further even if doing so is cost free.

4.4 Endogenous Opportunity Cost from Platform Competition

In our main model, we assume the worker's opportunity cost to be given and exogenous. As mentioned, such opportunity costs can arise partly because a worker may switch to another competing platform. In this section, we focus on the role of platform competition and assume that the expected payoff on the competing platform is an opportunity cost for a worker; as a result, we normalize the worker's payoff from other outside options to 0.

We consider a focal gig-economy platform (i.e., the platform we consider in our main model) that has an advantage (or disadvantage) over a competing platform. We capture this advantage (or disadvantage) by parameter α, which can be either negative or positive and is the added utility that a worker obtains when choosing the focal platform. The focal platform is advantaged if $\alpha > 0$ and is disadvantaged if $\alpha < 0$. This parameter effectively captures considerations beyond the payoff from job tasks that may affect a worker's platform choice (Song et al., 2020; Chen and Guo, 2022), such as the focal platform's reputation and service quality relative to its competitor.

Similar to our main model, we consider a two-period game in which there is a worker and employers with potential job tasks on both platforms that are either a good match (x_H) or a poor match (x_L) for the worker. The probability that each employer appears is p on the focal platform and q on the competing platform. As in our main model, p and q capture the labor demand on the two platforms, respectively. The worker knows only the distribution of p and q and not their realized values. We also assume that the marginal distributions of p and q are both uniform distributions on $[0, 1]$.

In this extension, we further model the correlation between labor demands on the two platforms. This correlation is common knowledge to the platforms and the worker and is relevant to the worker when she infers her expected payoff from her observation on a given platform in the first period. Such correlation, in practice, can be either positive or negative. On the one hand, two platforms can compete with each other: given the constant total labor demand, if one platform has many employers at a given time, then the demand on the other platform may be low, suggesting a negative correlation. On the other hand, some factors, such as being located in similar temporal and geographical regions, could lead to commonalities and thus a positive correlation between the two demands. To capture this correlation, we introduce a joint distribution of p and q with marginal distributions as $U[0, 1]$. We denote the CDF of this joint distribution as $C(p, q)$, which is called a copula in statistics literature (e.g., Trivedi and Zimmer, 2007; Jaworski et al., 2010), and has the following upper and lower bounds (a.k.a. Fréchet-Hoeffding bounds):

$$\max\{p+q-1,0\} \leq C(p,q) \leq \min\{p,q\}.$$

It is easy to check that the upper bound corresponds to the case of a perfect positive correlation ($p = q$) while the lower bound corresponds to the case of a perfect negative correlation ($p = 1-q$) (e.g., Trivedi and Zimmer, 2007; Jaworski et al., 2010). To capture the full range of possible correlations, we specify the joint CDF of p and q as:

$$C(p,q) = \max\left\{p^{-\theta} + q^{-\theta} - 1, 0\right\}^{-\frac{1}{\theta}}, \tag{18}$$

which is also known as the Clayton copula (e.g., Trivedi and Zimmer, 2007; Jaworski et al., 2010). A parameter $\theta \in [-1,\infty)\backslash\{0\}$ is introduced here. When $\theta = -1$, we have the Fréchet-Hoeffding lower bound. As $\theta \to \infty$, the joint distribution approaches the Fréchet-Hoeffding upper bound, and as $\theta \to 0$, it approaches the case of independent p and q (e.g., Schmidt, 2007). In other words, as θ changes from -1 to 0 and to ∞, it captures the range from a perfect negative correlation, to independence, and to a perfect positive correlation.

Neither platform currently uses any advanced matching technology. We are interested in studying whether the focal platform has an incentive to adopt an advanced matching technology if it has a choice to do so, given the status quo. This question is essentially the same as the question we examine in our main model, except for the presence of a competing platform in this extension.

The timing of the game is as follows: (1) The focal platform decides whether to adopt the advanced matching technology, which is committed across both periods. (2) The worker then decides which platform to participate during the first period.[11] (3) The worker observes her assignment on platform of choice, gets the first-period payoff, and then decides either to stay on the same platform for the second period or switch to the other one if she believes she can earn more by doing so. (4) The worker's second-period payoff is realized.

Proposition 5. *When there is a competing platform and x_H is close to x_L, the focal platform's expected revenue is lower when it adopts the advanced matching technology than when it does not if $\alpha \in [0, \overline{\alpha})$ and $\theta \in (\underline{\theta}, \overline{\theta})$, where $\overline{\alpha} > 0$ and $\overline{\theta} > \underline{\theta} > 0$.*

Proposition 5 provides several important insights. First, we show that the key finding in our main model – that adopting a better matching technology may not always be beneficial to a gig-economy platform – still holds, although does so with boundary conditions in terms of the focal platform's

[11] For a tie-breaking rule, we assume that a worker will choose the focal platform if she is indifferent between the focal platform and the competing one.

advantage in other dimensions and the labor demand correlation between the two platforms in the market. Second, the focal platform should refrain from adopting a more advanced matching technology when it has an advantage over its competitor in other dimensions (e.g., reputation), but the advantage is not too large. Intuitively, if the focal platform has a disadvantage in other dimensions, it is already hard for it to attract users even in the first period, making the information revelation effect less prominent compared to the matching enhancement effect, which can help it attract additional demand. In this case, adopting a more advanced matching technology is profitable because it can compensate for the focal platform's disadvantage. On the other hand, when the focal platform has a sufficiently large advantage in other dimensions, we find that it should also adopt a more advanced matching technology because its advantage in other dimensions is large enough to offset the possible unintended negative information revelation effect from adopting the technology to prevent workers from switching to the competing platform. Third, strategically not adopting the advanced matching technology can be more profitable for the focal platform when the correlation between the labor demands of the two platforms is positive ($\theta > 0$) and is neither too large nor too small. The key intuition behind this result is related to when the possible negative information revelation effect is more significant, or when a worker has the incentive to switch from the focal platform after receiving a poor-match (x_L) in the first period. Clearly, a worker has no incentive to switch when the demand correlation is close to being perfect positive (i.e., there is no need to switch to a platform with similar demand but worse matching) or close to independence (i.e., there is no update about the demand on the other platform). However, the result that the worker is unlikely to leave upon receiving x_L when the demand correlation is negative is counterintuitive. Note that although receiving x_L is a worse signal than receiving x_H, it is still better than receiving no assignment. Therefore, if the demands on the two platforms, p and q, are negatively correlated, upon receiving x_L, then both the posterior probability of a very small q and that of a very large q increase. As a result, both the probability that an employer with x_H appears on the competing platform in the second period and the probability that no employer appears increase. However, the increase in the former probability cannot offset the increase in the latter when the worker evaluates the second-period payoff, because the job task with x_H may not be assigned even if it appears, given the lack of an advanced matching technology on the competing platform.

4.5 Interrelated Worker Demand

In our 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 workers may engage in labor competition. In this case, while a worker may not know that other workers potentially are serving the same demand, the platform considers all the workers who can potentially take these jobs when it matches employers and workers.

We next take this demand interrelation into account and focus on a representative case of two workers and four potential employers on the platform.[12] We first examine the case in which workers do not know that other workers are serving the same demand when this competition information is not revealed by the platform. Later in Section 5.2, we will examine how worker behavior and platform revenue are affected if the platform reveals this competition information to workers.

Each potential employer appears with a probability p, which again describes the demand condition (or the relative demand to supply). Among the four potential employers, two are a good match for the workers and generate a revenue of x_H, whereas the other two matches are poor and only generate a revenue of x_L. We derive the results for both when the two workers have homogeneous preferences (i.e., the same employer is considered as a good or poor match for both workers) and when the two workers' preferences are differentiated (i.e., one worker's good-match employer is the other worker's poor match).

In the presence of interrelated worker demand, the gig-economy platform still assigns jobs randomly when the advanced matching technology is not adopted, and assigns good-match employers to both workers whenever possible to maximize the revenue when the advanced matching technology is adopted. If the number of good-match employers appearing on the platform is lower than the number of workers, then 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., two workers but only one employer), then the two workers will be assigned to the employer with equal probability.

In the rest of this section, we discuss the workers' participation decisions and the platform's expected revenue if (1) the advanced matching technology is adopted and (2) no advanced matching technology is used, so we may show when a platform's adoption of the advanced matching technology can backfire, which demonstrates the robustness of our key insights with respect to worker competition. Let π^{0*}_{rela} and π^{T*}_{rela} denote the platform's expected revenue without and with the advanced matching technology when workers' demands are interrelated, respectively. Following the same analysis we used in Section 3, we find that our results are in line with those of the main model; we summarize these results in the following proposition.

Proposition 6. *Suppose workers' demands are interrelated.*

- *When workers have homogeneous preferences, the platform's expected revenue when it adopts the*

[12] 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.

advanced matching technology is lower than that without the technology ($\pi^{T*}_{rela} < \pi^{0*}_{rela}$) *if and only if* $x_H < \frac{215}{121}x_L$ *and* $\delta(\frac{4x_H}{7} + \frac{4x_L}{21}) < c \leq \delta(\frac{4x_H}{9} + \frac{4x_L}{9})$.

- *When workers have heterogeneous preferences, the platform's expected revenue when it adopts the advanced matching technology is lower than that without the technology* ($\pi^{T*}_{rela} < \pi^{0*}_{rela}$) *if and only if* $x_H < \frac{23}{22}x_L$ *and* $\delta(\frac{4x_H}{7} + \frac{4x_L}{21}) < c \leq \delta(\frac{4x_H}{9} + \frac{4x_L}{9})$.

Proposition 6 continues to show that adopting an advanced matching technology may hurt the platform's revenue 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 relative to x_L, the platform's ex-ante expected revenue can be even lower when it adopts an advanced matching technology than when it does not. This finding implies that the insights from our main model are robust to whether workers have independent demands or not.

We can also observe that compared to the case when workers' preferences are homogeneous, the region in which adopting the advanced matching technology hurts the platform shrinks when workers have heterogeneous preferences ($\frac{23}{22}x_L < \frac{215}{121}x_L$). This is because when workers' preferences are heterogeneous, the matching enhancement effect from adopting the advanced matching technology is stronger. This result indicates that a platform is less likely to be hurt by technology adoption if workers' preferences are more diversified.

5 Mitigating the Possible Negative Effect of Advanced Matching Technology by Actively Revealing Information

Our main model and extensions consistently show that using an advanced matching technology can sometimes hurt a platform's revenue. The anticipated benefit of the advanced matching technology is tenable only when the matching enhancement effect dominates the possible negative information revelation effect if the revealed demand information discourages worker participation. In practice, gig-economy platforms can reveal demand information to workers. For example, ride-hailing and delivery platforms provide workers with a "heat map" that reveals real-time demand in different areas of a city (Uber, 2021; Instacart, 2021; DoorDash, 2022). The use of surge pricing can also be considered a demand signal. As competition from workers targeting the same demand can affect job assignments, revealing competition information may also influence workers' interpretation of demand information carried by assigned jobs and thus worker participation. In this section, we examine two approaches – revealing demand information and revealing competition information directly to workers – that could mitigate the negative effect of matching technology for gig-economy platforms, and we compare the relative effectiveness of these two approaches. To analyze this competition information, we use our model from Section 4.5 with interrelated worker demand (and homogeneous worker preferences) as our benchmark.

5.1 Revealing Demand Information

When demand information is not directly revealed by the platform, 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. When this indirect inference leads to an unfavorable outcome, the platform could instead reveal the demand information directly to the worker.

We assume that the platform can commit to truthfully revealing demand information (i.e., p) to the worker.[13] The worker's participation decision in the second period then will simply depend on the revealed p, but not on the matching outcome in the first period because the inference for p is no longer needed. We consider the case when the platform adopts the advanced matching technology 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:

$$\delta \left(Pr^T_{worker}(x_2 = x_H|p)x_H + Pr^T_{worker}(x_2 = x_L|p)x_L \right) \geq c, \tag{19}$$

where $Pr^T_{worker}(x_2 = x_H|p)$ (or $Pr^T_{worker}(x_2 = x_L|p)$) is the probability that the worker *thinks* a good-match (or poor-match) employer is assigned to her with the advanced matching technology, whose expressions are in equation (A7) of the Appendix. In this case, the worker does not know the existence of the competitor, so she assumes she faces all four potential employers. Inequality (19) is equivalent to:

$$p > \overline{p} \equiv \frac{1}{2} \left(2 - \sqrt{2} \sqrt{\frac{\sqrt{(x_H + x_L)^2 - 4cx_L/\delta}}{x_L} - \frac{x_H}{x_L} + 1} \right). \tag{20}$$

In this case, the platform's revenue, denoted as π^{T*}_{RD}, is given by:

$$\begin{aligned} \pi^{T*}_{RD} = & \underbrace{(1-\delta) \int_0^1 [Pr^T_{actual}(x_1 = x_H|p)2x_H + Pr^T_{actual}(x_1 = x_L|p)2x_L]\, dp}_{\text{revenue from the first period}} \\ & + \underbrace{(1-\delta) \int_{\overline{p}}^1 [Pr^T_{actual}(x_2 = x_H|p)2x_H + Pr^T_{actual}(x_2 = x_L|p)2x_L]\, dp,}_{\text{revenue from the second period}} \end{aligned} \tag{21}$$

where $Pr^T_{actual}(x_t = x_H|p)$ (or $Pr^T_{actual}(x_t = x_L|p)$), $t = 1, 2$, is the *actual* probability that a good-match (or poor-match) employer is assigned to a worker with the advanced matching technology, whose

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

expressions are in equation (A9) of the Appendix. The platform cares about whether the potential negative effect brought about by the adoption of the advanced matching technology, as shown in Section 4.5, can be alleviated by truthfully revealing p (i.e., whether $\pi^{T*}_{RD} > \pi^{T*}_{rela}$). The following proposition answers this question.

Proposition 7. *If the platform's expected revenue is lower when it adopts the advanced matching technology than when it does not, then the platform adopting the technology is better off by truthfully revealing p to the worker (i.e., $\pi^{T*}_{RD} > \pi^{T*}_{rela}$), but it may still be worse off compared to the case without the use of the advanced matching technology (π^{T*}_{RD} may still be less than π^{0*}_{rela}).*

This proposition shows that when the information revelation effect works against the platform's benefit, the revealed demand information will mitigate the unfavorable information revelation effect of the advanced matching technology, which increases platform revenue (i.e., $\pi^{T*}_{RD} > \pi^{T*}$). However, in some cases when the demand condition is not good, revealing this information directly, even though it is better than letting the worker infer from the assigned matching outcome, still hurts platform revenue compared to when workers infer information from a randomly matched job assignment. Thus, we find that by truthfully revealing p, the platform may still be worse off compared to the case without the adoption of the advanced matching technology. Of course, the information revelation effect enabled by the advanced matching technology may sometimes work to the platform's benefit (e.g., over-optimistic demand expectations). When this happens, directly revealing demand information may hurt the platform's revenue as well. Therefore, whether to commit to direct demand revelation is a strategy that platforms need to consider thoughtfully.

5.2 Revealing Competition Information

In Section 4.5, we assume that workers are not aware of other workers competing for the same labor demand when this information is not revealed by the platform. In this section, however, we analyze what happens if the platform instead chooses to reveal the number of workers competing for the same demand to workers. In this case, each worker knows that other workers on the platform are competing for the same potential labor demand. When a worker infers demand information from the first-period job assignment, she takes into account the effect of competition on the type of 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 of the other worker's participation decision. We focus on the case in which the platform adopts the advanced technology for matching, as our interest is to examine whether revealing competition information can alleviate the possible negative effect of advanced technology adoption. We develop the symmetric Nash Equilibrium (mixed strategy allowed) in Lemma 4.

Lemma 4. *When the platform that adopts the advanced matching technology reveals competition information to workers who compete for the same potential demand, there exists in the following cases 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 workers' responses when competition information is revealed, we can calculate the expected revenue of the platform, denoted as π^{T*}_{RC}, and compare that to the revenue when no competition information is revealed in Section 4.5 (π^{T*}_{rela}). The following proposition gives the result of this comparison.

Proposition 8. *If the platform's expected revenue is lower when it adopts the advanced matching technology than when it does not, then the platform adopting the advanced matching technology is no worse off by revealing competition information to workers (i.e., $\pi^{T*}_{RC} \geq \pi^{T*}_{rela}$), but it may still be worse off compared to the case without the use of the advanced matching technology (π^{T*}_{RC} may still be less than π^{0*}_{rela}).*

Conventional wisdom suggests that revealing competition information to workers might discourage workers from continuing their work, as their expected payoff is less in the presence of competition from peers. However, our analysis suggests that this argument may not be universally true. There are two factors that a worker needs to consider when she is making the participation decision: (1) 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 induces a worker to think more positively about the labor demand after seeing that the first-period assignment is a poor match. This is because competition serves as another reason for not getting a good match in the first period, and thus a worker may not blame demand after being assigned to a poor-match employer in the first period, thereby mitigating the unfavorable information revelation effect in our main model.

Now that we have examined two possible approaches to mitigate the potential negative effect brought by advanced technology adoption, we next address the following question: which approach – revealing demand information, competition information, or both – is more effective in mitigating the possible 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 only revealing demand information.*

Corollary 1 offers two interesting observations. First, it indicates that revealing both demand and competition information is suboptimal for the platform. This is because when demand information is truthfully revealed to gig workers, they do not need to infer demand information from assigned jobs. Therefore, the issue of the 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 matching technology induces an unfavorable information revelation effect, revealing demand information is more effective than revealing competition information in mitigating this effect. In cases in which matching technology hurts the platform's revenue, a possible negative information revelation effect dominates the matching enhancement effect. While both approaches can mitigate this negative impact of matching technology, revealing competition information additionally discloses the presence of competition that workers might not have been aware of, thus discouraging them from participating as a result of competitive pressure.

6 Advanced Matching Technology and Welfare

In our previous sections, we have focused on the implications of advanced matching technology adoption on platform revenue. In this section, we analyze the impact of an advanced matching technology on worker surplus as well as the total welfare of the platform and the worker, which could be of interest to policy-makers. Investigating total welfare also allows us to examine whether the change in platform revenue results from the redistribution of welfare across different parties.

Equation (14) gives the expression for the platform's ex-ante expected revenue (π^{l*}). For worker surplus, two things are different. First, the worker gets a δ proportion of the total revenue, instead of $1 - \delta$ for the platform. Second, unlike the platform, which earns no revenue if the worker does not participate, the worker gets the value c from her outside option if she does not participate on the platform. Considering these two modifications for equation (14), we derive the worker's ex-ante expected surplus, denoted by w^{l*}, where $l \in \{0, T\}$, to be:

$$w^{l*} = \int_0^1 \sum_{x \in \{x_H, x_L, 0\}} Pr^l(x_1 = x|p)\Big(\delta x + \mathbf{1}_{\{x \notin \mathcal{X}^{l,par}\}} c + \mathbf{1}_{\{x \in \mathcal{X}^{l,par}\}} \sum_{x' \in \{x_H, x_L, 0\}} Pr^l(x_2 = x'|p)\delta x'\Big) dp. \tag{22}$$

The total welfare of the platform and the worker, denoted by TW^{l*}, where $l \in \{0, T\}$, is thus given by:

$$TW^{l*} = \pi^{l*} + w^{l*}. \tag{23}$$

We analyze both cases where the commission rate for workers (δ) is exogenously given and where the rate is endogenously decided by the platform. Our results and associated intuition are slightly different for the two cases. We summarize our results in the following proposition and Figure A6 in the Appendix.

Proposition 9. *Compared to the case when no advanced matching technology is adopted, the adoption of an advanced matching technology never reduces worker surplus if the commission rate is exogenously given, but may do so if the commission rate is endogenously decided by the platform. The adoption of the advanced matching technology may reduce the total welfare of the platform and the worker, regardless of whether the commission rate is exogenous or endogenous.*

In this proposition, we first find that worker surplus is always higher when a better matching technology is adopted than when it is not, if the commission rate is exogenous. This result is intuitive because the two effects associated with the introduction of matching technology (i.e., the matching enhancement and information revelation effects), both benefit the worker: the first effect improves the match and the second effect helps the worker makes a better participation decision. However, the result can be different if the commission rate is endogenously determined by the platform. In this case, the platform has another tool to respond to the worker's strategic behavior induced by the additional information that is revealed by the matching outcome, thus limiting the worker's surplus. Therefore, with an endogenous commission rate, worker surplus sometimes goes down due to the adoption of advanced matching technology. Furthermore, we find that the total welfare of the platform and the worker may decrease after the advanced matching technology is introduced. This suggests that the decrease in the platform's revenue is not merely a redistribution of the welfare. Even when the worker benefits from the adoption of advanced matching technology, the increase in worker surplus is sometimes not sufficient to compensate for a platform's revenue loss. These results suggest an inefficiency brought about by the worker's strategic behavior as a result of the advanced technology's information revelation effect, and we should consider this effect not only from the platform's perspective but also from the total welfare's perspective.

Figure A6 also provides an interesting observation. In the case of an exogenous commission rate, we find that in the region where the total welfare goes down when the advanced matching technology is adopted, the platform's revenue also decreases; that is, $TW^{T*} < TW^{0*}$ implies $\pi^{T*} < \pi^{0*}$. This is because the worker's surplus is never hurt in this case. This observation implies that a policy-maker may not need to provide additional incentives for the platform to improve welfare after introducing the advanced matching technology, as the platform already has an internal incentive to mitigate such a loss. However, when the platform adjusts its commission rate based on its matching technology's capability, in the region where total welfare goes down when the advanced matching technology is adopted, the platform's revenue does not necessarily decrease. This suggests that there may be a need for regulation on the commission rate or platform pricing policies to align the interest of the platform with what is good with respect to total welfare, such that the platform's decision to adopt the advanced matching technology will not hurt total welfare.

7 Concluding Remarks

As the gig economy is rapidly expanding, advanced technologies are being widely adopted to evaluate and assign job tasks more optimally to workers. This study provides a broader and more complete understanding of the landscape of interactions between human workers and technologies. It does so by formulating a modeling framework as a foundation to study the human-technology interactions in the context of gig-economy platforms; in these platforms, human workers can update their beliefs about uncertain labor demand revealed through matching outcomes in a Bayesian manner and decide whether to participate on the platforms. Contrary to the expectation that gig-economy platforms can always boost revenue substantially by utilizing a better matching technology to enhance matching quality between gig workers and employers, we show the conditions under which applying a better matching for managing human workers on platforms does not increase revenue. Our results are robust to alternative model assumptions regarding conditional revenue sharing and both platform and worker competitions. We also examine the optimal level of improvement in matching accuracy for gig-economy platforms, putting aside the cost consideration, and identify two approaches that can remedy the unanticipated effect of a better matching technology. Our study provides valuable insights regarding the overall impacts that the choice of matching technology and response to the matching technology by human workers can have on workplaces enabled by gig-economy platforms.

Advances in artificial intelligence (AI), especially those in machine learning algorithms and its subfield of deep learning, increasingly help transform business practices and the platform economy (Brynjolfsson et al., 2019; Lou and Wu, 2021; Zhou and Zou, 2022). Some speculate that a smart AI-enabled matching technology has learning capability and can consider the potential negative information revelation effect when assigning job tasks (e.g., intentionally assigning suboptimal job tasks to workers). However, unless the technology is permanently downgraded to a level that we find optimal in our model extension (in Section 4.3), misleading workers to believe in a matching quality that is lower than its actual state is unsustainable; for example, it could trigger distrust of workers on platform operations and increase worker churn. Gig workers have already expressed displeasure and aversion to being manipulated by AI or algorithms more broadly (Möhlmann and Henfridsson, 2019). Therefore, reputable platforms should not pursue strategies grounded in misperception and manipulation. Furthermore, AI can only process given information and cannot change demand conditions. In a market with low labor demand, there may simply be no good-match job tasks for AI to recommend. This inevitable choice, unfortunately, conveys information about the unfavorable demand condition. This negative information revelation effect driven by low labor demand cannot be fully alleviated by AI, even if AI anticipates workers' strategic behavior.

Theoretical Contributions: The literature has focused on platform-enabled market design to reduce transaction costs and efficiently use information to match employers and workers (Einav et al., 2016). Researchers are interested in studying how digital technologies can be used to motivate workers to contribute to the gig economy and enhance market efficiency (Fradkin, 2017; He et al., 2021; Horton, 2017). Recent developments in digital technologies, such as those in the area of data analytics and matching learning (or AI in general), have substantially enhanced the quality of worker-employer matching and gig-economy platforms' overall operational performance (Wu et al., 2019, 2020; Hitt et al., 2021). However, little attention is paid to possible unintended consequences and whether improved matching quality can indeed help platforms obtain higher revenue.

We contribute to the literature by revealing that a better matching technology, although enhancing the quality of matching between workers and employers, functions as a double-edged sword in the gig economy. To the best of our knowledge, our study is the first to provide a comprehensive model that systematically examines the impact and implications of adopting a better matching technology on a gig-economy platform. As technologies become more adept at processing information about the supply and demand of workers and their activities, information about labor demand, especially when it is low, can be unintentionally revealed to workers through their matching outcomes. This could encourage workers not to continue participating in the gig-economy platform as anticipated and thus lower platform revenue. Our model considers the crucial factors in decision making about a worker's participation in the platform; these factors include beliefs updated by information revealed in jobs assigned by matching technology through a Bayesian manner, expected payoffs associated with participation, and opportunity costs that can be influenced by platform competition.

In addition, we extend the emerging literature on algorithmic management in the gig economy. The findings derived from our model can deepen the understanding of the "good bad job" phenomenon linked to gig work empowered by algorithmic technologies. While 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, in addition to flexible work arrangements offered in the gig workplace (Cameron, 2020; Manyika et al., 2016). Our model leverages the notion of "algorithmic imaginary" to examine the perception of matching technologies by gig workers, as well as their behavior in making sense of information from the matching outcomes (Zhang et al., 2022). Thus, our model offers a more nuanced way to examine how gig workers can navigate the tension between job tasks assigned by a better matching technology and autonomy by strategically engaging with job tasks and using them to make informed participation decisions.

Boundary Conditions and Practical Implications: We next discuss the boundary conditions of our model and link them to reality. Our study also offer several practical implications for policy-makers and practitioners who use advanced matching technologies in the gig economy.

First, we caution gig-economy platforms about the unintended negative consequences of adopting a technology with better matching quality. A perfectly accurate matching technology is not necessarily optimal, even if costs to acquire or develop the technology are nominal. Such performance results from the possible negative information revelation effect as human workers interact with demand signals carried in assigned jobs from the platform's matching results. This negative impact likely occurs when different types of matches (i.e., "good-match" and "poor-match" job tasks) do not differ significantly in value to workers. For example, in the case of a food delivery platform in a small town where most restaurants are located fairly close to one another, a good match and a poor match do not differ too much in value; thus, the matching enhancement effect of the technology is not very significant. However, the information revelation effect can still occur when a driver receives a poor match, which could hurt the gig-economy platform's expected revenue. Even if the platform has enough market power to adjust its revenue split with its workers, applying advanced technologies such as AI for matching may still result in lower revenue for the platform. As technologies and their associated algorithms continue to improve their matching quality and capability, the adverse effect associated with a better matching technology that we identify in our study could even be amplified and, thus, should not be overlooked. Therefore, developing a matching system that can analyze all available information and exhibit superior matching performance is not always the best course of action for improving platform revenue. Gig-economy platforms that do not demonstrate an understanding of the advantages and disadvantages of matching technologies could misallocate valuable resources to conditions for which the technologies provide minimal benefits and possible negative consequences. To avoid these costly mistakes, platforms should adopt matching technologies more strategically, by taking into account their potential information revelation effect.

Second, in the presence of competition between platforms in the gig economy, we show that when a focal platform has a sufficiently large advantage over competitors in dimensions other than monetary compensation (e.g., reputation, service quality) or is disadvantaged in these dimensions, adopting a more advanced matching technology can be beneficial. For example, with respect to the market share of ride-hailing companies in the U.S.,[14] Uber accounts for over half of total market share and dominates Lyft in some cities (e.g., Houston)[15] In this case, Lyft can benefit from developing and adopting a better matching technology because it can compensate for its disadvantage in the areas in which Uber dominates. Whether Uber can benefit from a more advanced matching technology depends on whether Uber's advantage in other dimensions is large enough to offset the possible unintended negative information revelation effect from adopting technology to prevent workers from switching to a competing platform.

Third, gig-economy platforms should make efforts to attract workers with heterogeneous preferences, as we show that a platform is less likely to be hurt by adopting an advanced matching technology if workers' preferences are more diversified. In Uber's case, if riders and drivers are located in a scattered manner and drivers prefer riders closer to them, then different drivers may have heterogeneous preferences for riders. At the same time, it is also possible that drivers may homogeneously want to avoid picking up a rider in areas with heavy traffic. Our findings suggest that Uber is more likely to be hurt by adopting an advanced matching technology if the matching is mainly about avoiding heavy traffic rather than about reducing traveling distance.

Fourth, we provide immediately actionable guidance and show that gig-economy platforms adopting an advanced matching technology to match workers and their employers could directly disclose some information about labor supply and demand to workers in order to mitigate negative consequences caused by technology adoption. Platforms can benefit more from revealing demand information compared to worker competition information. In practice, we observe that gig-economy platforms provide workers with a "heat map" that reveals real-time demand in different areas of a city (Uber, 2021; Instacart, 2021; DoorDash, 2022), but they generally do not allow workers to see how many competing workers are near them, consistent with the optimal strategy that our results suggest. The information disclosure strategy could help workers better understand the labor market when they receive matching outcomes and decide whether to continue working for the platform or not.

Finally, we offer policy implications with respect to the total welfare of gig-economy platforms and

[14] See https://www.statista.com/statistics/910704/market-share-of-rideshare-companies-united-states/, accessed on January 16, 2023.

[15] See https://dfdnews.com/2021/08/19/uber-vs.-lyft-whos-tops-in-the-battle-of-u.s.-rideshare-companies/ and https://www.inc.com/business-insider/lyft-slowly-moves-in-on-uber-ride-sharing-market-dominance.html, accessed on January 16, 2023.

their workers, depending on whether the commission rate is exogenously or endogenously determined.[16] Based on our findings, policy-makers may not need to interfere if the commission rate is independent of the matching technology, as a platform's incentive to choose a strategy that also benefits total welfare is internalized. However, if a platform has sufficient market power to decide how the revenue is split between the platform and workers, then a regulation on the commission rate may be needed, since the incentive of the platform may not always be aligned with what is good for total welfare.

Overall, our insights from this study can enrich collective understandings of managing both intended and unintended outcomes derived from better matching technologies.

Limitations and Future Research Directions: This study has two limitations, which may indicate directions for future research. First, in our model extension, we examine endogenous opportunity costs, which can arise partly because a worker can switch to another competing platform. While our study is among the first to point out the potential downside of adopting an advanced matching technology in that scenario, future research can extend this consideration and further examine the dynamics of the competition, including how platforms can strategically decide whether to advance matching technology, assess the extent to which they advance the technology, and determine how to apply the technology in the matching process.

Second, we do not model strategic employers and thus do not consider their welfare explicitly in this study. We deliberately focus on the strategic behavior of workers instead of employers, because currently on gig-economy platforms, workers usually are more critical and have better outside options than employers.[17] That said, if we consider the strategic behavior of employers in our model, we anticipate that the two effects we examine in our main model can influence employers similarly to those for the platform. A key mechanism behind our main result is that under some circumstances, workers are more likely to leave the platform upon observing a poor match in the first period in the case when an advanced matching technology is adopted compared to the case when it is not, because of the extra information carried by better-matched outcomes. If we also model employers' participation decisions, they will also likely leave if they anticipate that workers will leave the platform, leaving an insufficient labor supply in the second period. In other words, when workers are inclined to leave,

[16]For some platforms in the gig economy, the commission rate has not changed frequently in the past few years. For example, Uber currently charges drivers 25% of total fares (See `https://www.uber.com/gh/en/drive/basics/tracking-your-earnings/`, accessed on January 16, 2023), which is the same as the rate in 2018, according to a report by Mishel (2018) claiming that "Uber takes a 25 percent commission from the fares after deducting a 'booking fee' per trip of roughly $1.55". Other web resources such as RideGuru (See `https://ride.guru/content/resources/driver-payout-take-home`, accessed on January 16, 2023) also offer information about relatively stable commission structures. Of course, we cannot exclude the possibility that some platforms may adjust their commission rates for various considerations. Thus, both cases (when the commission rate is both exogenously and endogenously determined) are considered in our study.

[17]See, for example, Marshall (2021). The platforms, as two-sided markets, enlarge themselves by subsidizing one side of the market and charging the other side the full price (Parker and Van Alstyne, 2005; Rochet and Tirole, 2006). Solon (2017) highlights that Uber could not operate without a critical mass of drivers, and the company provides about one-thousand-dollar sign-up and referral bonuses to attract workers. Workers are rewarded by dynamically priced fares paid by employers on the platforms as well.

employers are also likely to leave and earn a zero surplus, reinforcing the result in our main model. Future research can further validate our speculation by explicitly accounting for the role of employers as well as their interactions with employees and the platform, and hence investigate the impact of adopting an advanced matching technology on employer surplus.

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Appendix: Proofs

Proof of Lemma 1. Based on equations (7) and (9), we can immediately list the optimal participation decisions of the worker without and with the advanced matching technology as below:

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

and

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

To prove the other part of the lemma, we first note that:

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

and

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

This means that upon receiving x_H or 0 in the first period, the worker's expected payoff is higher when the advanced matching technology is adopted than when no advanced matching technology is adopted. Thus, the worker's participation in the second period when no advanced matching technology is adopted implies that worker's participation when the advanced matching technology is adopted. Or mathematically, $x_H \in \mathcal{X}^{0,par} \Rightarrow x_H \in \mathcal{X}^{T,par}$ and $0 \in \mathcal{X}^{0,par} \Rightarrow 0 \in \mathcal{X}^{T,par}$.

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

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

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

$$\delta\Pi_2^T(x_1 = x_L) < c \leq \delta\Pi_2^0(x_1 = x_L),$$

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 the advanced matching technology.

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

□

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 $\pi^{T*} \geq \pi^{0*}$. This is because if these conditions are not satisfied, we know that $\mathcal{X}^{0,par} \subseteq \mathcal{X}^{T,par}$. In addition, when the advanced matching technology is adopted (compared to when the advanced matching technology 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,

$$\begin{aligned}
\pi^{T*} &= (1-\delta)\int_0^1 \sum_{x\in\{x_H,x_L,0\}} Pr^T(x_1 = x)\Big(x + \mathbf{1}_{\{x\in\mathcal{X}^{T,par}\}}\sum_{x'\in\{x_H,x_L,0\}} Pr^T(x_2 = x')x'\Big)dp \\
&\geq (1-\delta)\int_0^1 \sum_{x\in\{x_H,x_L,0\}} Pr^T(x_1 = x)\Big(x + \mathbf{1}_{\{x\in\mathcal{X}^{0,par}\}}\sum_{x'\in\{x_H,x_L,0\}} Pr^T(x_2 = x')x'\Big)dp \\
&\geq (1-\delta)\int_0^1 \sum_{x\in\{x_H,x_L,0\}} Pr^0(x_1 = x)\Big(x + \mathbf{1}_{\{x\in\mathcal{X}^{0,par}\}}\sum_{x'\in\{x_H,x_L,0\}} Pr^0(x_2 = x')x'\Big)dp \\
&= \pi^{0*}.
\end{aligned}$$

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, π^{0*} and π^{T*} are given by equations (12) and (13), respectively. Then,

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

which is negative if and only if $x_H < \frac{3}{2}x_L$. This implies $\pi^{T*} < \pi^{0*}$ 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 $\pi^{T*} < \pi^{0*}$ 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

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

The only case for which $\mathcal{X}^{T,par} \subset \mathcal{X}^{0,par}$ 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 the advanced matching technology ($\pi^{T*} < \pi^{0*}$):

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

□

Proof of Lemma 2. When the platform can strategically choose the revenue-sharing parameter δ, 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 participating 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 the advanced matching technology, and $\delta^{T*} \in \{\frac{20c}{5x_H+3x_L}, \frac{10c}{5x_H+2x_L}, \frac{6c}{4x_H+x_L}, 0\}$ with the advanced matching technology. Which δ to choose depends on which one generates the highest revenue for the platform. Note that here the platform makes the following tradeoff: a smaller δ implies a higher $1-\delta$ and thus directly increases the revenue share for the platform, but a smaller δ also decreases the worker's participation and thus may indirectly decrease the platform's revenue.

Without the advanced matching technology, 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:

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

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:

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

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, we obtain the following:

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

We complete a similar analysis for the case with the advanced matching technology. The result is:

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

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

□

Proof of Proposition 2. Based on Lemma 2, when the profit sharing parameter δ is endogenously set by the platform, the platform's revenue without and with the adoption of the advanced matching technology is given below, respectively:

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

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

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

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

Therefore, with some algebraic calculation, since $x_L < x_H$, $\pi_{endo}^{T*} < \pi_{endo}^{0*}$ 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. Since $\mathbf{E}^l[w_1] = \delta\mathbf{E}^l[x_1] = \delta\mathbf{E}^l[x_2] = \mathbf{E}^l[w_2]$, where $l \in \{T, 0\}$, the condition that $w_1^{l,par} \geq w_1^{l,nopar}$ is equivalent to:

$$(\delta\mathbf{E}^l[x_1] - \beta c) + \mathbf{E}^l\left[\max\left\{0, \delta\mathbf{E}^l[x_2|x_1] - c\right\}\right] \geq \max\left\{0, \delta\mathbf{E}^l[x_1] - \beta c\right\}. \tag{A1}$$

If $\delta\mathbf{E}^l[x_1] - \beta c \geq 0$, inequality (A1) becomes $\mathbf{E}^l\left[\max\left\{0, \delta\mathbf{E}^l[x_2|x_1] - c\right\}\right] \geq 0$, which is naturally satisfied. If $\delta\mathbf{E}^l[x_1] - \beta c < 0$, inequality (A1) becomes $\delta\mathbf{E}^l[x_1] - \beta c + \mathbf{E}^l\left[\max\left\{0, \delta\mathbf{E}^l[x_2|x_1] - c\right\}\right] \geq 0$. Combining the two cases, we know that inequality (A1) is satisfied if and only if:

$$G^l(x_H, x_L, c, \delta) \equiv \delta\mathbf{E}^l[x_1] + \mathbf{E}^l\left[\max\left\{0, \delta\mathbf{E}^l[x_2|x_1] - c\right\}\right] \geq \beta c.$$

Given the expressions in equations (6)-(9), we can calculate $G^T(x_H, x_L, c, \delta)$ and $G^0(x_H, x_L, c, \delta)$, whose expressions are given by:

$$G^T(x_H, x_L, c, \delta) = \frac{1}{6}\Bigg(\max\left(0, \frac{\delta x_H}{2} + \frac{\delta x_L}{5} - c\right) + 2\max\left(0, \frac{\delta x_H}{4} + \frac{3\delta x_L}{20} - c\right)$$
$$+3\max\left(0, \frac{\delta}{6}(4x_H + x_L) - c\right) + 3\delta x_H + \delta x_L\Bigg),$$

and

$$G^0(x_H, x_L, c, \delta) = \frac{1}{3}\left(\max\left(0, \frac{1}{5}\delta(x_H + x_L) - c\right) + 2\max\left(0, \frac{2}{5}\delta(x_H + x_L) - c\right) + \delta(x_H + x_L)\right).$$

Under the parameter range $x_H > x_L > 0$, $c \geq 0$ and $0 < \delta < 1$, it is not hard to verify that $G^T(x_H, x_L, c, \delta) < G^0(x_H, x_L, c, \delta)$ never holds. (We verify this by using the `FindInstance` function in Mathematica.) In other words, we show that $G^T(x_H, x_L, c, \delta) \geq G^0(x_H, x_L, c, \delta)$. Therefore, $w_1^{0,par} \geq w_1^{0,nopar}$ implies $w_1^{T,par} \geq w_1^{T,nopar}$. That is, if the worker would like to participate in the first period when there is no advanced matching technology, then that worker must also do so when the technology is at use. In order to find the cases when $\pi^{T*} < \pi^{0*}$, it must be the case that in the first period the worker would like to participate in cases both with and without the matching technology. Therefore, a necessary condition for $\pi^{T*} < \pi^{0*}$ is that the worker would like to participate in the first period when there is no advanced matching technology. That is, compared to the case when the first-period opportunity cost is zero, $\pi^{T*} < \pi^{0*}$ requires an additional constraint: $w_1^{0,par} \geq w_1^{0,nopar}$, which is equivalent to:

$$\frac{1}{3}\left(\max\left(0, \frac{1}{5}\delta(x_H + x_L) - c\right) + 2\max\left(0, \frac{2}{5}\delta(x_H + x_L) - c\right) + \delta(x_H + x_L)\right) \geq \beta c. \quad \text{(A2)}$$

Note that in the main model where the first-period opportunity cost is zero, the condition for $\pi^{T*} < \pi^{0*}$ is $x_H < \frac{3}{2}x_L$ and $\delta(\frac{x_H}{2} + \frac{x_L}{5}) < c \leq \delta\frac{2}{5}(x_H + x_L)$ (from Proposition 1). Using this inequality, we can simplify (A2) as:

$$\frac{1}{3}\left(0 + 2\left(\frac{2}{5}\delta(x_H + x_L) - c\right) + \delta(x_H + x_L)\right) \geq \beta c,$$

or equivalently

$$c \leq \frac{9\delta(x_H + x_L)}{5(3\beta + 2)}. \quad \text{(A3)}$$

Therefore, the current condition for $\pi^{T*} < \pi^{0*}$ is $x_H < \frac{3}{2}x_L$ and

$$\delta(\frac{x_H}{2} + \frac{x_L}{5}) < c \leq \min\left\{\delta\frac{2}{5}(x_H + x_L), \frac{9\delta(x_H + x_L)}{5(3\beta + 2)}\right\}.$$

Note that when $\delta\frac{2}{5}(x_H + x_L) \leq \frac{9\delta(x_H+x_L)}{5(3\beta+2)}$ or equivalently $\beta \leq \frac{5}{6}$, the newly-added constraint does not bind, so the parameter region s.t. $\pi^{T*} < \pi^{0*}$ is the same as that in proposition 1. When $\beta > \frac{5}{6}$, the binding constraint becomes $c < \frac{9\delta(x_H+x_L)}{5(3\beta+2)}$. Clearly, $\frac{9\delta(x_H+x_L)}{5(3\beta+2)}$ is decreasing in β, which means the area of the parameter region s.t. $\pi^{T*} < \pi^{0*}$ shrinks as β increases. However, even if $\beta = 1$, we have:

$$\frac{9\delta(x_H+x_L)}{5(3\beta+2)} = \frac{9\delta(x_H+x_L)}{25} > \delta(\frac{x_H}{2} + \frac{x_L}{5}) \quad \text{when } x_H < \frac{8}{7}x_L.$$

Thus, the parameter region of (x_H, x_L, c) such that $\pi^{T*} < \pi^{0*}$ never shrinks to an empty set for any $\beta \in [0, 1]$. □

Proof of Lemma 3. Based on the setup that when the good-match (x_H) and poor-match (x_L) employers are both available on the platform, the probability that x_H is assigned to the worker is $\frac{1}{2} + k$, we have the following expressions for the likelihoods of $x_1 = x_H$, $x_1 = x_L$, and $x_1 = x_H$:

$$\begin{cases} Pr^k(x_1 = x_H|p) = p(1-p) + p^2\left(\frac{1}{2}+k\right) = \left(1-\frac{p}{2}\right)p + kp^2, \\ Pr^k(x_1 = x_L|p) = p(1-p) + p^2\left(\frac{1}{2}-k\right) = \left(1-\frac{p}{2}\right)p - kp^2, \\ Pr^k(x_1 = 0|p) = (1-p)^2. \end{cases} \tag{A4}$$

By Bayes' Rule, we have the posteriors as follows:

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

The expected revenue from the second period given p is given by:

$$\mathbf{E}^k[x_2|p] = x_H\left(kp^2 + \left(1-\frac{p}{2}\right)p\right) + x_L\left(p\left(1-\frac{p}{2}\right) - kp^2\right).$$

The worker's expected payoff from the second period given that x_L was assigned to the worker is thus given by:

$$\begin{aligned} \mathbf{E}^k[w_2|x_1 = x_L] &= \delta\mathbf{E}^k[x_2|x_1 = x_L] \\ &= \int_0^1 \mathbf{E}^k[x_2|p]f^k(p|x_1 = x_L)dp \\ &= \delta\frac{4(x_H+x_L) - 9kx_L - 6k^2(x_H-x_L)}{10(1-k)}. \end{aligned} \tag{A5}$$

Taking the first-order derivative of $\mathbf{E}^k[w_2|x_1 = x_L]$ w.r.t. k gives:

$$\frac{\partial\mathbf{E}^k[w_2|x_1 = x_L]}{\partial k} = \delta\frac{4x_H - 5x_L - 6k(2-k)(x_H-x_L)}{10(1-k)^2}.$$

We let $L(k) := 4x_H - 5x_L - 6k(2-k)(x_H - x_L)$. Clearly, we know that:

$$\text{sign}\left(\frac{\partial \mathbf{E}^k[w_2|x_1 = x_L]}{\partial k}\right) = \text{sign}\left(L(k)\right).$$

Since

$$\frac{\partial\left(L(k)\right)}{\partial k} = -12(x_H - x_L)(1-k) \leq 0,$$

we have $L(k)$ is decreasing in k for $k \in [0, \frac{1}{2}]$. In addition, we know that $L(\frac{1}{2}) = -\frac{1}{2}(x_H + x_L) < 0$.

If $L(0) \leq 0$ or $x_H \leq \frac{5}{4}x_L$, we know that $L(k) \leq L(0) \leq 0$, so $\frac{\partial \mathbf{E}^k[w_2|x_1 = x_L]}{\partial k} \leq 0$ or $\mathbf{E}^k[w_2|x_1 = x_L]$ is decreasing in k.

If $L(0) > 0$ or $x_H > \frac{5}{4}x_L$, we know that there exists $\hat{k} \in [0, \frac{1}{2}]$ such that $L(\hat{k}) = 0$ and $L(k) \gtrless 0$ for $k \lessgtr \hat{k}$. Therefore, $\mathbf{E}^k[w_2|x_1 = x_L]$ is increasing in k when $k < \hat{k}$ and decreasing in k when $k > \hat{k}$. Solving $L(\hat{k}) = 0$ gives $\hat{k} = 1 - \sqrt{\frac{2x_H - x_L}{6(x_H - x_L)}}$.

□

Proof of Proposition 4. Following a similar procedure as that for the derivation of equation (A5), we know that:

$$\mathbf{E}^k[w_2|x_1 = 0] = \delta\left(\frac{k(x_H - x_L)}{10} + \frac{x_H + x_L}{5}\right), \text{ and}$$
$$\mathbf{E}^k[w_2|x_1 = x_H] = \delta\left(\frac{(6k^2 + 9k + 4)\,x_H + (4 - 6k^2)\,x_L}{10(k+1)}\right).$$

$\mathbf{E}^k[w_2|x_1 = 0]$ is increasing in k since $(x_H - x_L) > 0$. When we take the first-order derivative of $\mathbf{E}^k[w_2|x_1 = x_H]$ w.r.t. k, we have:

$$\frac{\partial \mathbf{E}^k[w_2|x_1 = x_H]}{\partial k} = \frac{\delta}{10}\left(\frac{2x_L - x_H}{(k+1)^2} + 6(x_H - x_L)\right).$$

If $2x_L \geq x_H$, the above $\frac{\partial \mathbf{E}^k[w_2|x_1 = x_H]}{\partial k}$ is clearly positive. If $2x_L < x_H$, we have:

$$\frac{\partial \mathbf{E}^k[w_2|x_1 = x_H]}{\partial k} \geq \frac{\delta}{10}\left(\frac{2x_L - x_H}{(\frac{1}{2}+1)^2} + 6(x_H - x_L)\right) = \frac{2\delta}{9}(25x_H - 23x_L) > 0.$$

Therefore, $\mathbf{E}^k[w_2|x_1 = x_H]$ is also increasing in k.

From Lemma 3 we know that when $x_H > \frac{5}{4}x_L$, $\mathbf{E}^k[w_2|x_1 = x_L]$ is first increasing and then decreasing in k, with the peak at $k = \hat{k}$, which is $1 - \sqrt{\frac{2x_H - x_L}{6(x_H - x_L)}}$. Therefore, when $k \leq \hat{k}$, $\mathbf{E}^k[w_2|x_1 = x]$ is always increasing in k for $x \in \{x_H, x_L, 0\}$. Thus, for any matching technologies $k_1 < k_2 < \hat{k}$, if the worker continues to participate in the second period when $k = k_1$, then that worker must also participate when $k = k_2$. Therefore, the platform's revenue π^k will also increase in k.

When $k > \hat{k}$, $\mathbf{E}^k[w_2|x_1 = x]$ is increasing in k for $x \in \{x_H, 0\}$, but decreasing in k for $x = x_L$. Since $c \geq \underline{c} \geq \mathbf{E}^{k=\frac{1}{2}}[w_2|x_1 = x_L]$, there exists $\tilde{k} \in [\hat{k}, \frac{1}{2}]$ such that $\mathbf{E}^{\tilde{k}}[w_2|x_1 = x_L] = c$ and $\mathbf{E}^k[w_2|x_1 = x_L] \gtrless c$ when $k \lessgtr \tilde{k}$. That is, the worker participates in the second period when $x_1 = x_L$ if $k < \hat{k}$, and does not participate in the second period when $x_1 = x_L$ if $k > \hat{k}$.

For the case when $x_1 = x_H$, since $c \leq \bar{c} = \mathbf{E}^{k=\hat{k}}[w_2|x_1 = x_L] \leq \mathbf{E}^{k=\hat{k}}[w_2|x_1 = x_H] < \mathbf{E}^{k}[w_2|x_1 = x_H]$ for any $k > \hat{k}$, the worker always participates in the second period when $x_1 = x_H$, no matter what k is.

For the case when $x_1 = 0$, one can verify that:

$$\begin{aligned}\underline{c} - \mathbf{E}^{k=\frac{1}{2}}[w_2|x_1 = 0] &= \delta \left(\max\left\{ \frac{2(x_H + x_L)}{5}, \frac{x_H}{2} + \frac{x_L}{5} \right\} - \frac{3x_H}{10} \right) \\ &= \delta \left(\max\left\{ \frac{x_H}{10} + \frac{2x_L}{5}, \frac{(x_H + x_L)}{5} \right\} \right) > 0,\end{aligned}$$

so $c \geq \underline{c} > \mathbf{E}^{k=\frac{1}{2}}[w_2|x_1 = 0] > \mathbf{E}^{k}[w_2|x_1 = 0]$. Thus, the worker never participates in the second period when $x_1 = 0$, no matter what k is.

In sum, when $k > \hat{k}$, the platform's revenue is thus:

$$\pi^k = \begin{cases} \int_0^1 \sum_{x \in \{x_H, x_L, 0\}} Pr^k(x_1 = x|p) \Big((1-\delta)x + \mathbf{1}_{\{x \in \{x_H, x_L\}\}} \sum_{x' \in \{x_H, x_L, 0\}} Pr^k(x_2 = x'|p)(1-\delta)x' \Big) dp \\ \quad \text{if } \hat{k} < k \leq \tilde{k}, \\ \int_0^1 \sum_{x \in \{x_H, x_L, 0\}} Pr^k(x_1 = x|p) \Big((1-\delta)x + \mathbf{1}_{\{x \in \{x_H\}\}} \sum_{x' \in \{x_H, x_L, 0\}} Pr^k(x_2 = x'|p)(1-\delta)x' \Big) dp \\ \quad \text{if } k > \tilde{k}. \end{cases}$$

Comparing the expression for π^k when $\hat{k} < k \leq \tilde{k}$ and that when $k > \tilde{k}$, we notice that the former is always larger than the latter because there is a larger set in the indicator function in the former expression ($\mathbf{1}_{\{x \in \{x_H, x_L\}\}}$ vs. $\mathbf{1}_{\{x \in \{x_H\}\}}$) and $\sum_{x' \in \{x_H, x_L, 0\}} Pr^k(x_2 = x'|p)(1-\delta)x' > 0$. In other words, there is a drop of the value of π^k at $k = \tilde{k}$ s.t. $\pi^{\tilde{k}+\epsilon} < \pi^{\tilde{k}}$ for small $\epsilon > 0$. Plugging in the expressions of $Pr^k(x_1 = x|p)$ from equation (A4), we get:

$$\pi^k = \begin{cases} \frac{1}{30}(1-\delta)((19k + 18)x_H + (18 - 19k)x_L) & \text{if } \hat{k} < k \leq \tilde{k}, \\ \frac{1}{30}(1-\delta)((k+2)(6k+7)x_H - 2(k(3k+5) - 7)x_L) & \text{if } k > \tilde{k}. \end{cases}$$

Taking the first-order derivative w.r.t. k gives:

$$\frac{\partial \pi^k}{\partial k} = \begin{cases} \frac{1}{30}(1-\delta)(19(x_H - x_L)) > 0 & \text{if } \hat{k} < k \leq \tilde{k}, \\ \frac{1}{30}(1-\delta)(19x_H - 10x_L + 12k(x_H - x_L)) > 0 & \text{if } k > \tilde{k}, \end{cases}$$

so π^k is increasing in k for $k < \tilde{k}$ and $k > \tilde{k}$ separately.

Given the monotonicity of π^k w.r.t. k on $[0, \tilde{k}]$ and $(\tilde{k}, \frac{1}{2})$, the only two candidates for the optimal k are $\tilde{k}$ and $\frac{1}{2}$.

When $k = \frac{1}{2}$, $\pi^{k=\frac{1}{2}} = \frac{1}{30}(1-\delta)((\frac{1}{2}+2)(6(\frac{1}{2})+7)x_H - 2(\frac{1}{2}(3(\frac{1}{2})+5) - 7)x_L) = (1-\delta)(\frac{5x_H}{6} + \frac{x_L}{4})$.

When $k = \tilde{k}$, $\pi^{k=\tilde{k}} = \frac{1}{30}(1-\delta)((19\tilde{k} + 18)x_H + (18 - 19\tilde{k})x_L)$, where $\tilde{k}$ satisfies $c = \mathbf{E}^{\tilde{k}}[w_2|x_1 =$

$x_L] = \delta\frac{4(x_H+x_L)-9\tilde{k}x_L-6\tilde{k}^2(x_H-x_L)}{10(1-\tilde{k})}$.

Since $\mathbf{E}^k[w_2|x_1 = x_L]$ is decreasing in k, we know that if c is larger, then $\tilde{k}$ is smaller, and then $\pi^{k=\tilde{k}}$ is smaller. $\pi^{k=\frac{1}{2}}$ is independent of c. Therefore, $\pi^{k=\tilde{k}} \geq \pi^{k=\frac{1}{2}}$ if and only if $c \leq c^*$, where c^* satisfies:

$$\begin{cases} c^* = \delta\frac{4(x_H+x_L)-9\tilde{k}^*x_L-6(\tilde{k}^*)^2(x_H-x_L)}{10(1-\tilde{k}^*)} \\ \frac{1}{30}(1-\delta)((19\tilde{k}^*+18)x_H + (18-19\tilde{k}^*)x_L) = (1-\delta)(\frac{5x_H}{6} + \frac{x_L}{4}). \end{cases}$$

Solving for $\tilde{k}^*$ from the second equation ($\tilde{k}^* = \frac{7(2x_H-3x_L)}{38(x_H-x_L)}$) and then plugging it into the first equation give $c^* = \frac{\delta(46x_H-31x_L)(5x_H+2x_L)}{456x_H-323x_L}$. Thus, π^k obtains its maximum at $k = \tilde{k}$ if $c \leq \frac{\delta(46x_H-31x_L)(5x_H+2x_L)}{456x_H-323x_L}$, and at $k = \frac{1}{2}$ otherwise. □

Proof of Proposition 5. First, we will prove that if the advantage parameter $\alpha < 0$, adopting the advanced matching technology will never hurt the focal platform ($\pi^{T,f} \geq \pi^{0,f}$). When the technology is not adopted, the worker will not choose the focal platform but instead choose the competitor in the first period because the expected revenues of the two platforms are symmetric and also because that worker will incur a negative utility α from the focal platform. If adopting the technology will not let the worker choose the focal platform instead of the competitor in the first period, then the information revelation effect is irrelevant since the first-period information is not obtained from the focal platform anyway. Therefore, adopting the technology can never hurt the focal platform. If adopting the technology will let the worker choose the focal platform instead of the competitor in the first period, then:

$$\begin{aligned} \pi^{T,f} \geq & \int_0^1 (1-\delta)(px_H + p(1-p)x_L)dp \\ > & \int_0^1 (1-\delta)p(1-\frac{p}{2})(x_H+x_L)dp \\ \geq & \pi^{0,f}, \end{aligned}$$

where the first inequality holds because $\int_0^1(1-\delta)(px_H+p(1-p)x_L)dp$ is only the first-period revenue of the focal platform if it adopts the technology, which is apparently no less than the total revenue over two periods; the second inequality comes from the fact that $(px_H+p(1-p)x_L) - p(1-\frac{p}{2})(x_H+x_L) = \frac{p^2}{2}(x_H - x_L)$ and $x_H > x_L$; the third inequality holds because $\int_0^1(1-\delta)p(1-\frac{p}{2})(x_H+x_L)dp$ is the focal platform's revenue under the extreme assumption that the worker will always switch from the competitor to the focal platform in the second period.

We next examine the case when $\alpha \geq 0$ and the worker will thus choose the focal platform in the first period. The derivation is similar to the proof of Proposition 1. Since the marginal prior distribution of p is still $U[0,1]$, the worker's posterior expected payoffs from the focal platform are the same as those in the main model. In what follows, we use superscript "f" to denote the focal platform and "c" to denote the competing platform. By equations (7) and (9) and the fact that the worker obtains a δ proportion of the total revenue, we have the following expressions for the worker's posterior expected payoffs in the second period from the focal platform:

$$\begin{cases} \mathbf{E}^0[w_2^f|x_1 = x_H] = \delta\frac{2}{5}(x_H + x_L) + \alpha, \\ \mathbf{E}^0[w_2^f|x_1 = x_L] = \delta\frac{2}{5}(x_H + x_L) + \alpha, \\ \mathbf{E}^0[w_2^f|x_1 = 0] = \delta\frac{1}{5}(x_H + x_L) + \alpha, \end{cases}$$

for the case without the advanced matching technology and

$$\begin{cases} \mathbf{E}^T[w_2^f|x_1 = x_H] = \delta(\frac{2}{3}x_H + \frac{x_L}{6}) + \alpha, \\ \mathbf{E}^T[w_2^f|x_1 = x_L] = \delta(\frac{x_H}{2} + \frac{x_L}{5}) + \alpha, \\ \mathbf{E}^T[w_2^f|x_1 = 0] = \delta(\frac{x_H}{4} + \frac{3x_L}{20}) + \alpha, \end{cases}$$

for the case with the advanced matching technology.

Given the joint CDF of p, q as $C(p, q)$, we know the joint PDF of p, q is $c(p, q) = \frac{\partial^2 C(p,q)}{\partial p \partial q}$. We denote $C_q(p, q) := \frac{\partial C(p,q)}{\partial q}$, and by construction, $\frac{\partial C_q(p,q)}{\partial p} = c(p, q)$.

In the case when no advanced matching technology is applied, the worker's posterior distribution of q given that x_H was assigned in the first period (denoted by $f^0(q|x_1 = x_H)$) is given by:

$$\begin{aligned} f^0(q|x_1 = x_H) &= \int_0^1 f^0(p, q|x_1 = x_H)dp \\ &= \int_0^1 \frac{Pr^0(x_1 = x_H|p, q)c(p, q)}{\int_0^1 \int_0^1 Pr^0(x_1 = x_H|p, q)c(p, q)dqdp}dp \\ &= \int_0^1 \frac{Pr^0(x_1 = x_H|p)c(p, q)}{\int_0^1 \int_0^1 Pr^0(x_1 = x_H|p)c(p, q)dqdp}dp \\ &= \int_0^1 \frac{Pr^0(x_1 = x_H|p)c(p, q)}{\int_0^1 Pr^0(x_1 = x_H|p)dp}dp \\ &= 3\int_0^1 p(1 - \frac{p}{2})c(p, q)dp \\ &= 3\left(\frac{1}{2} - \int_0^1 (1 - p)C_q(p, q)\right). \end{aligned}$$

The second equation comes from Bayes' Rule. The third equation comes from the fact that the first-period revenue on the focal platform is independent of q. The fourth equation comes from the fact that $\int_0^1 c(p, q)dq = 1$ because the marginal distribution of p is $U[0, 1]$. The fifth equation is obtained by plugging in $Pr^0(x_1 = x_H|p) = p(1 - \frac{p}{2})$. The last equation comes from integration by parts.

Therefore, in the case when no advanced matching technology is applied, the worker's expected payoff in the second period from the competing platform given that x_H was assigned in the first period (denoted by $\mathbf{E}^0[w_2^c|x_1 = x_H]$) is given by:

$$\begin{aligned}
\mathbf{E}^0[w_2^c|x_1 = x_H] &= \delta \int_0^1 q(1-\frac{q}{2})(x_H + x_L) f^0(q|x_1 = x_H)dp \\
&= 3\delta(x_H + x_L) \int_0^1 \left(\frac{1}{2} - \int_0^1 (1-p)C_q(p,q)\right) q(1-\frac{q}{2})dq \\
&= 3\delta(x_H + x_L) \left[\int_0^1 \frac{q}{2}(1-\frac{q}{2})dq - \int_0^1 (1-p)\left(\int_0^1 q(1-\frac{q}{2})C_q(p,q)dq\right)dp\right] \\
&= 3\delta(x_H + x_L) \left[\frac{1}{6} - \int_0^1 (1-p)\left(\frac{p}{2} - \int_0^1 (1-q)C(p,q)dq\right)dp\right] \\
&= 3\delta(x_H + x_L) \left[\frac{1}{6} - \int_0^1 \frac{p}{2}(1-p)dp + \int_0^1 \int_0^1 (1-p)(1-q)C(p,q)dpdq\right] \\
&= 3\delta(x_H + x_L) \left[\frac{1}{12} + \int_0^1 \int_0^1 (1-p)(1-q)C(p,q)dpdq\right],
\end{aligned}$$

where the fourth equation again comes from integration by parts.

Similarly, we can calculate all the posterior expected payoff in the second period from the competing platform:

$$\begin{cases}
\mathbf{E}^0[w_2^c|x_1 = x_H] = 3\delta(x_H + x_L)\left[\frac{1}{12} + \int_0^1\int_0^1(1-p)(1-q)C(p,q)dpdq\right], \\
\mathbf{E}^0[w_2^c|x_1 = x_L] = 3\delta(x_H + x_L)\left[\frac{1}{12} + \int_0^1\int_0^1(1-p)(1-q)C(p,q)dpdq\right], \\
\mathbf{E}^0[w_2^c|x_1 = 0] = 6\delta(x_H + x_L)\left[\frac{1}{12} - \int_0^1\int_0^1(1-p)(1-q)C(p,q)dpdq\right],
\end{cases}$$

for the case without the advanced matching technology and

$$\begin{cases}
\mathbf{E}^T[w_2^c|x_1 = x_H] = 2\delta(x_H + x_L)\left[\frac{1}{12} + \int_0^1\int_0^1(1-q)C(p,q)dpdq\right], \\
\mathbf{E}^T[w_2^c|x_1 = x_L] = 6\delta(x_H + x_L)\left[\frac{1}{12} + \int_0^1\int_0^1(1-2p)(1-q)C(p,q)dpdq\right], \\
\mathbf{E}^T[w_2^c|x_1 = 0] = 6\delta(x_H + x_L)\left[\frac{1}{12} - \int_0^1\int_0^1(1-p)(1-q)C(p,q)dpdq\right],
\end{cases}$$

for the case with the advanced matching technology.

We now have all the expressions for the worker's expected payoff from the focal platform $\mathbf{E}^l[w_2^f|x_1 = x]$ and that from the competitor $\mathbf{E}^l[w_2^c|x_1 = x]$ where $l \in \{T, 0\}$ and $x \in \{x_H, x_L, 0\}$, so we may compare them point by point in theory. However, since the expression for $C(p,q)$ is mathematically too involved as part of an integrand and thus we are unable to derive an analytical solution, we rely on exhaustive numerical simulations for the remaining part of our proof. Since we are seeking cases when the platform's revenue is lower when the advanced matching technology is adopted than when it is not, we are interested in cases when the worker's expected payoff in the second period with the focal platform is lower than that with the competing platform when the technology is adopted, but the worker's expected payoff in the second period with the focal platform is higher than that with the competing platform when the technology is not adopted. In sum, we are seeking cases ($x \in \{x_H, x_L, 0\}$) when $\mathbf{E}^T[w_2^f|x_1 = x] < \mathbf{E}^T[w_2^c|x_1 = x]$ but $\mathbf{E}^0[w_2^f|x_1 = x] \geq \mathbf{E}^0[w_2^c|x_1 = x]$.

According to the insight from our main model, we know that such cases are more likely to happen when x_H is small enough or the matching enhancement effect is small enough. Therefore, we can investigate in the most extreme case when $x_H = x_L$ in our numerical simulation. If under this condition we can show $\mathbf{E}^T[w_2^f|x_1 = x] < \mathbf{E}^T[w_2^c|x_1 = x]$ and $\mathbf{E}^0[w_2^f|x_1 = x] \geq \mathbf{E}^0[w_2^c|x_1 = x]$ hold strictly, by continuity we can claim that as long as x_H is small enough, the inequalities are still true. In addition, without loss of any generality, we let $\delta = \frac{1}{2}$ and $x_L = 1$ in our numerical simulation. For the sake of simplicity, we first let $\alpha = 0$ and will show the case where $\alpha > 0$ in the latter part of the proof. For any given θ, we use the `NIntegrate` function in Mathematica to calculate the integrals in the expressions for $\mathbf{E}^l[w_2^c|x_1]$ and then create a plot with θ as the x-axis and $\mathbf{E}^l[w_2^c|x_1]$ together with the corresponding $\mathbf{E}^l[w_2^f|x_1]$ as the y-axis to compare them.

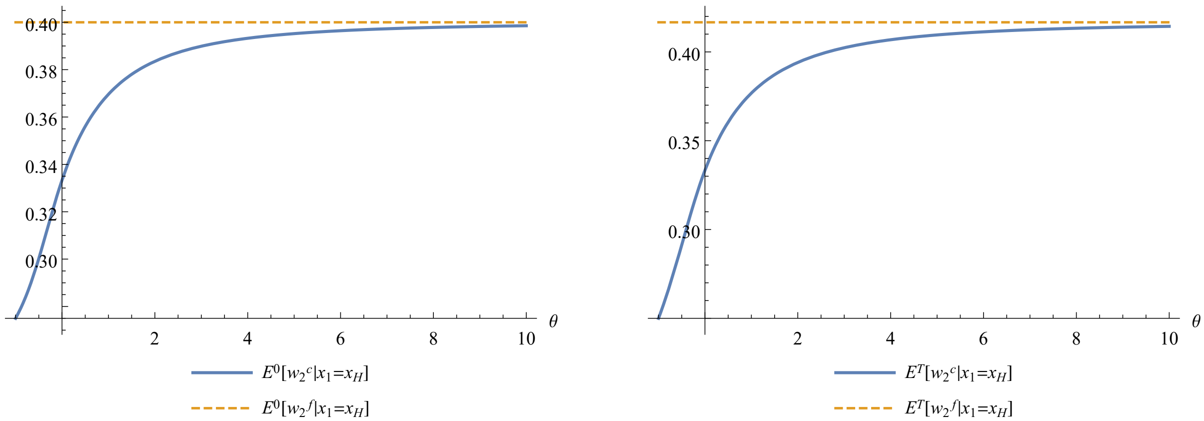


Figure A1: Comparing $\mathbf{E}^l[w_2^c|x_1 = x_H]$ and $\mathbf{E}^l[w_2^f|x_1 = x_H]$

First, we compare $\mathbf{E}^l[w_2^c|x_1 = x_H]$ and $\mathbf{E}^l[w_2^f|x_1 = x_H]$, where $l \in \{T, 0\}$. As plotted in Figure A1, we find that $\mathbf{E}^l[w_2^c|x_1 = x_H] < \mathbf{E}^l[w_2^f|x_1 = x_H]$ for any θ and $l \in \{T, 0\}$. Note that these figures are for the case when $\alpha = 0$. If $\alpha > 0$, the dashed line ($\mathbf{E}^l[w_2^f|x_1 = x_H]$) will go even higher by α, so $\mathbf{E}^l[w_2^c|x_1 = x_H] < \mathbf{E}^l[w_2^f|x_1 = x_H]$ still holds, which means that upon receiving x_H in the first period, the worker will always not switch.

We then compare $\mathbf{E}^l[w_2^c|x_1 = x_L]$ and $\mathbf{E}^l[w_2^f|x_1 = x_L]$, where $l \in \{T, 0\}$. Figure A2 plots out the comparison between $\mathbf{E}^l[w_2^c|x_1 = x_L]$ and $\mathbf{E}^l[w_2^f|x_1 = x_L]$. We can see from the figure that $\mathbf{E}^0[w_2^f|x_1 = x_L] > \mathbf{E}^0[w_2^c|x_1 = x_L]$ always holds for any θ, but $\mathbf{E}^0[w_2^f|x_1 = x_L] < \mathbf{E}^0[w_2^c|x_1 = x_L]$ for positive and large enough θ. We also know that $\mathbf{E}^0[w_2^f|x_1 = x_L] \to \mathbf{E}^0[w_2^c|x_1 = x_L]$ when $\theta \to \infty$ since in that case $p = q$ and thus the two platforms are symmetric. Note that this is for the case when $\alpha = 0$. If $\alpha > 0$, the flat line for $\mathbf{E}^0[w_2^f|x_1 = x_L]$ will increase by α relative to the curve for $\mathbf{E}^0[w_2^c|x_1 = x_L]$. Therefore, if α is not very large or $\alpha < \overline{\alpha}$, where $\overline{\alpha} = \max(\mathbf{E}^0[w_2^c|x_1 = x_L]) - \mathbf{E}^0[w_2^f|x_1 = x_L]$, the range for θ such that $\mathbf{E}^T[w_2^f|x_1 = x_L] < \mathbf{E}^T[w_2^c|x_1 = x_L]$ and $\mathbf{E}^0[w_2^f|x_1 = x_L] > \mathbf{E}^0[w_2^c|x_1 = x_L]$ should be $\theta \in (\underline{\theta}, \overline{\theta})$, where $0 < \underline{\theta} < \overline{\theta}$ and $\underline{\theta}$ and $\overline{\theta}$ are the two intersections of $\mathbf{E}^T[w_2^f|x_1 = x_L]$ (the dashed line in the figure) and $\mathbf{E}^T[w_2^c|x_1 = x_L]$ (the solid curve in the figure). If $\alpha \geq \overline{\alpha}$, then $\mathbf{E}^T[w_2^f|x_1 = x_L] \geq \mathbf{E}^T[w_2^c|x_1 = x_L]$ and $\mathbf{E}^0[w_2^f|x_1 = x_L] > \mathbf{E}^0[w_2^c|x_1 = x_L]$ always hold.

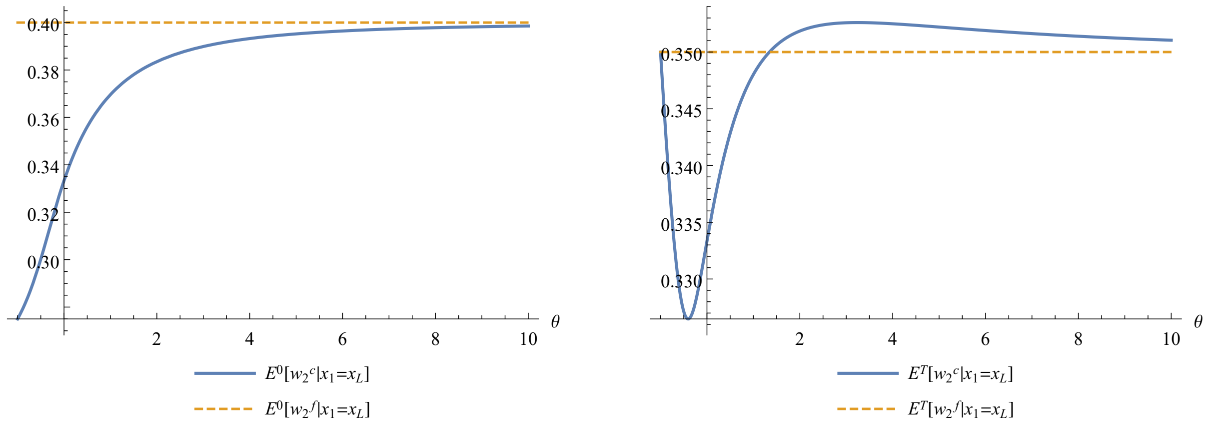


Figure A2: Comparing $\mathbf{E}^l[w_2^c|x_1 = x_L]$ and $\mathbf{E}^l[w_2^f|x_1 = x_L]$

So far, we have shown that when x_H is small enough, if $0 \leq \alpha < \overline{\alpha}$ and $0 < \underline{\theta} < \overline{\theta}$, upon receiving x_L in the first period, the worker will not switch if no advanced matching technology is adopted but will switch if the technology is adopted. Note that if the worker switches upon receiving $x_1 = x_L$, then that worker will also switch if $x_1 = 0$. Therefore, the focal platform's expected revenue when adopting the technology is given by:

$$\begin{aligned}
\pi^{T,f} &= \int_0^1 (1-\delta)\big[p(x_H + px_H + p(1-p)x_L) + p(1-p)x_L\big]dp \\
&= (1-\delta)(\frac{5}{6}x_H + \frac{x_L}{4}) \\
&\to (1-\delta)\frac{13}{12}x_L \text{ when } x_H \to x_L.
\end{aligned}$$

The focal platform's expected revenue when it does not adopt the technology $\pi^{0,f}$ satisfies:

$$\begin{aligned}
\pi^{0,f} &\geq \int_0^1 (1-\delta)\Big[p(1-\frac{p}{2})(x_H + p(1-\frac{p}{2})(x_H + x_L)) + p(1-\frac{p}{2})(x_L + p(1-\frac{p}{2})(x_H + x_L))\Big]dp \\
&= (1-\delta)\frac{3}{5}(x_H + x_L) \\
&\to (1-\delta)\frac{6}{5}x_L \text{ when } x_H \to x_L,
\end{aligned}$$

where the right-hand side of the first inequality assumes the worker will also switch upon receiving $x_1 = 0$ when the technology is not adopted. Thus, $\pi^{0,f} > \pi^{T,f}$ when $x_H \to x_L$, if $0 \leq \alpha < \overline{\alpha}$ and $0 < \underline{\theta} < \overline{\theta}$.

□

Proof of Proposition 6. **Homogeneous Worker Preferences.** We first consider the case when workers' preferences are homogeneous. Each worker does not know the existence of the other worker, so each worker will act as if she was the only worker in the market with four potential employers, two of which are x_H and two of which 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^l_{worker} where $l \in \{0, T\}$.

Without the advanced matching technology, we have by definition:

$$\begin{cases} Pr^0_{worker}(x_1 = x_H|p) = Pr^0_{worker}(x_2 = x_H|p) = \frac{1}{2}\left(1-(1-p)^4\right), \\ Pr^0_{worker}(x_1 = x_L|p) = Pr^0_{worker}(x_2 = x_L|p) = \frac{1}{2}\left(1-(1-p)^4\right), \\ Pr^0_{worker}(x_1 = 0|p) = Pr^0_{worker}(x_2 = 0|p) = (1-p)^4, \end{cases} \tag{A6}$$

and with the advanced matching technology (again, by definition):

$$\begin{cases} Pr^T_{worker}(x_1 = x_H|p) = Pr^T_{worker}(x_2 = x_H|p) = 1-(1-p)^2, \\ Pr^T_{worker}(x_1 = x_L|p) = Pr^T_{worker}(x_2 = x_L|p) = (1-p)^2\left(1-(1-p)^2\right), \\ Pr^T_{worker}(x_1 = 0|p) = Pr^T_{worker}(x_2 = 0|p) = (1-p)^4. \end{cases} \tag{A7}$$

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

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

and

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

The only case such that $\mathcal{X}^{T,par}_{rela} \subset \mathcal{X}^{0,par}_{rela}$ 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 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 employer. These likelihoods are denoted as Pr^l_{actual} where $l \in \{0, T\}$. By definition, we have:

When the advanced matching technology is not applied,

$$\begin{cases} Pr^0_{actual}(x_1=0|p)=Pr^0_{actual}(x_2=0|p)=\frac{1}{2}\binom{4}{1}p(1-p)^3+(1-p)^4=(1-p)^3(1+p), \\ Pr^0_{actual}(x_1=x_H|p)=Pr^0_{actual}(x_2=x_H|p)=\frac{1-Pr^0_{actual}(x_1=0|p)}{2}=\frac{p^4}{2}-p^3+p, \\ Pr^0_{actual}(x_1=x_L|p)=Pr^0_{actual}(x_2=x_L|p)=\frac{1-Pr^0_{actual}(x_1=0|p)}{2}=\frac{p^4}{2}-p^3+p, \end{cases} \tag{A8}$$

and when the advanced matching technology is applied,

$$\begin{cases} Pr^T_{actual}(x_1=0|p)=Pr^T_{actual}(x_2=0|p)=\frac{1}{2}\binom{4}{1}p(1-p)^3+(1-p)^4=(1-p)^3(1+p), \\ Pr^T_{actual}(x_1=x_H|p)=Pr^T_{actual}(x_2=x_H|p)=p, \\ Pr^T_{actual}(x_1=x_L|p)=Pr^T_{actual}(x_2=x_L|p)=1-p-(1-p)^3(1+p)=p^4-2p^3+p. \end{cases} \tag{A9}$$

The platform's revenue is given by:

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

Similar to the case when there were no interrelated workers, a necessary condition for $\pi^{T*}_{rela}<\pi^{0*}_{rela}$ is $\mathcal{X}^{T,par}_{rela}\subset\mathcal{X}^{0,par}_{rela}$, or $\delta\frac{4(3x_H+x_L)}{21}<c<\delta\frac{4(x_H+x_L)}{9}$. Under this condition, $\mathcal{X}^{T,par}_{rela}=\{x_H\}$ and $\mathcal{X}^{0,par}_{rela}=\{x_H,x_L\}$. Plugging in them into the platform's revenue, we can show under this condition we have:

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

Using some algebra, we have $\pi^{0*}_{rela}>\pi^{T*}_{rela}$ if $x_H<\frac{215}{121}x_L$.

In fact, we can calculate π^{T*}_{rela} and π^{0*}_{rela} under all conditions. The results are:

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

and

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

Heterogeneous Worker Preferences. We 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, $\mathcal{X}_{rela}^{T,par}$ and $\mathcal{X}_{rela}^{0,par}$ remain identical to the analysis above because this new setup does not change the worker's participation decision, as 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 employer when the advanced matching technology is not applied since the matching is randomly conducted. However, it does change the likelihoods when the advanced matching technology is applied. In this case, they are given by:

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

Again, a necessary condition for $\pi_{rela}^{T*} < \pi_{rela}^{0*}$ is $\mathcal{X}_{rela}^{T,par} \subset \mathcal{X}_{rela}^{0,par}$, or $\delta\frac{4(3x_H+x_L)}{21} < c \leq \delta\frac{4(x_H+x_L)}{9}$. Under this condition, $\mathcal{X}_{rela}^{T,par} = \{x_H\}$ and $\mathcal{X}_{rela}^{0,par} = \{x_H, x_L\}$. Plugging in them into the platform's revenue, we can show under this condition we have:

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

Using some algebra, we have $\pi_{rela}^{0*} > \pi_{rela}^{T*}$ if $x_H < \frac{23}{22}x_L$.

□

Proof of Proposition 7. As mentioned in Section 5.1, we can find the threshold $\overline{p}$ such that a worker participates by solving:

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

which gives:

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

Thus, the platform's revenue is:

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

Since this expression is mathematically too involved, we rely on a numerical exercise to show this proposition. We first note that δ is simply a scaling factor, since one can let $c' = \frac{c}{\delta}$ without loss of generality. The same argument applies to 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 δ and x_L. We take $\delta = 0.5$ and $x_L = 1$. Figure A3 below shows the region in which π_{RD}^{T*} is larger than, smaller than, or equal to π_{rela}^{T*} and π_{rela}^{0*}, where the x-axis is x_H and the y-axis is c. The whole region plotted out (non-white) is when the condition $\pi_{rela}^{T*} < \pi_{rela}^{0*}$

is satisfied. If there is no region with a certain color plotted in the figure, then it means that the condition indicated by the color never holds when $\pi^{T*}_{rela} < \pi^{0*}_{rela}$.

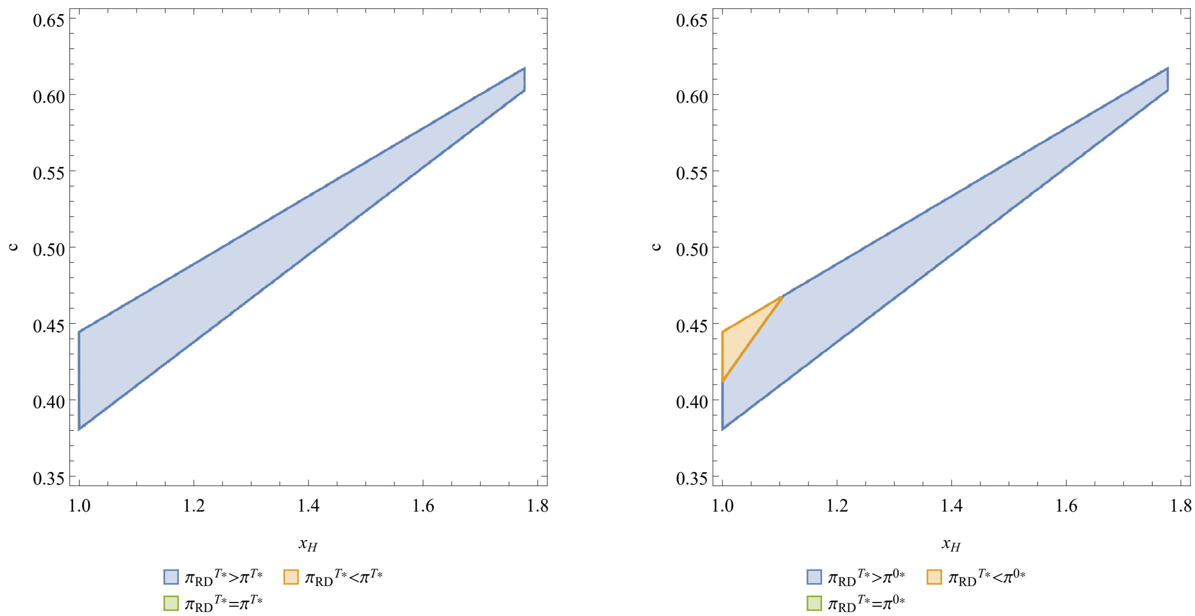


Figure A3: Revealing demand information when the advanced matching technology is facilitated
Note: $x_L = 1$, $\delta = 0.5$.

The numerical exercise shows that the platform adopting the advanced matching technology is better off by truthfully revealing p to the worker (i.e., $\pi^{T*}_{RD} > \pi^{T*}$), but it may still be worse off compared to not using the advanced matching technology (i.e., $\pi^{T*}_{RD} < \pi^{0*}$) for smaller x_H.

□

Proof of Lemma 4. 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:

$$\begin{cases} P^T_{x_H,single} = 1-(1-p)^2, \\ P^T_{x_L,single} = (1-p)^2\left(1-(1-p)^2\right), \\ P^T_{0,single} = (1-p)^4, \end{cases} \tag{A10}$$

when the advanced matching technology is facilitated, and are:

$$\begin{cases} P^0_{x_H,single} = \frac{1}{2}\left(1-(1-p)^4\right), \\ P^0_{x_L,single} = \frac{1}{2}\left(1-(1-p)^4\right), \\ P^0_{0,single} = (1-p)^4, \end{cases} \tag{A11}$$

when the advanced matching technology is not facilitated.

In each period, when two workers both participate, we 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 = "T" or "0" indicates the cases when the advanced matching technology is facilitated or not, respectively. We then have:

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

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 participate, we 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 $l \in \{T, 0\}$. Clearly, $P^l_{x,both} = \sum_{x' \in \{x_H,x_L,0\}} p^l_{x,x'}$. Then, when the advanced matching technology is facilitated, we have:

$$\begin{cases} P^T_{x_H,both} = p^2 + p(1-p)\left(1-(1-p)^2\right) + p(1-p)^3 = p, \\ P^T_{x_L,both} = p(1-p)(1-(1-p)^2) + p^2(1-p)^2 + p(1-p)^3 = p^4 - 2p^3 + p, \\ P^T_{0,both} = p(1-p)^3 + p(1-p)^3 + (1-p)^4 = (1-p)^3(1+p), \end{cases} \tag{A12}$$

and when the advanced matching technology is not facilitated, we have:

$$\begin{cases} P^0_{x_H,both} = \frac{1}{4}p^2(6-p(8-3p)) + \frac{1}{4}p^2(6-p(8-3p)) + p(1-p)^3 = \frac{p^4}{2} - p^3 + p, \\ P^0_{x_L,both} = \frac{1}{4}p^2(6-p(8-3p)) + \frac{1}{4}p^2(6-p(8-3p)) + p(1-p)^3 = \frac{p^4}{2} - p^3 + p, \\ P^0_{0,both} = p(1-p)^3 + p(1-p)^3 + (1-p)^4 = (1-p)^3(1+p), \end{cases} \tag{A13}$$

For any given p, we 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 $l \in \{T, 0\}$. Thus, by definition:

$$u^l_{both} = \delta(x_H P^l_{x_H,both} + x_L P^l_{x_L,both}), \tag{A14}$$

$$u^l_{single} = \delta(x_H P^l_{x_H,single} + x_L P^l_{x_L,single}). \tag{A15}$$

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

$$f^l_{RC}(p|x_1 = x) = \frac{P^l_{x,both}}{\int_0^1 P^l_{x,both}dp}. \tag{A16}$$

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 $l \in \{T, 0\}$. Then:

$$q^l_{x,x'} = \frac{p^l_{x,x'}}{P^l_{x,both}}. \tag{A17}$$

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:

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

Plugging in the values, this is equivalent to:

$$c \leq c_1, \text{ where } c_1 = \delta(\frac{2x_H}{9} + \frac{32x_L}{189}). \tag{A18}$$

Similarly, to 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:

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

as well as

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

Plugging in the values, this is equivalent to:

$$c_{21} < c \leq c_{22}, \text{ where } c_{21} = \delta(\frac{19x_H}{63} + \frac{23x_L}{126}), c_{22} = \delta(\frac{23x_H}{42} + \frac{5x_L}{21}). \tag{A19}$$

The conditions for the other two possible pure strategy equilibria can be found using 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 rather 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 $x_1 = x_L$, and with probability $\lambda_3 \in (0, 1)$ if $x_1 = 0$.

To get the values of λ_1, λ_2, and λ_3, we can leverage the revenue equivalence in a mixed strategy.

To find λ_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:

$$\int_0^1 ((\lambda_1 u^T_{both} + (1 - \lambda_1) u^T_{single}) q^T_{x_H,x_H} + u^T_{single} q^T_{x_H,x_L} + u^T_{single} q^T_{x_H,0}) f^T_{RC}(p|x_1 = x_H)) dp = c,$$

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 λ_2 and λ_3:

$$\int_0^1 (u^T_{both} q^T_{x_L,x_H} + (\lambda_2 u^T_{both} + (1-\lambda_2) u^T_{single}) q^T_{x_L,x_L} + u^T_{single} q^T_{x_L,0}) f^T_{RC}(p|x_1 = x_L) dp = c,$$

and

$$\int_0^1 (u^T_{both} q^T_{0,x_H} + u^T_{both} q^T_{0,x_L} + (\lambda_3 u^T_{both} + (1-\lambda_3) u^T_{single}) q^T_{0,0}) f^T_{RC}(p|x_1 = 0) dp = c,$$

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 8. In this proposition, we focus on the situation in which the platform's expected revenue when it facilitates the advanced matching technology is lower than that when there is no advanced matching technology ($\pi^{T*} < \pi^{0*}$). 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 using a similar procedure to the one we used to obtain Proposition 1.

Based on Lemma 4, when using the advanced matching technology, the profits with (π^{T*}_{RC}) and without (π^{T*}) revealing the competition information are respectively given by:

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

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

and

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

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

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

The profit when no advanced matching technology 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 $\pi_{rela}^{T*} < \pi_{rela}^{0*} \Leftrightarrow x_H < \frac{215}{121}x_L$ and $\delta(\frac{4x_H}{7}+\frac{4x_L}{21}) < c \leq \delta(\frac{4x_H}{9}+\frac{4x_L}{9})$,

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

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 A4. The whole region plotted out (non-white) is that for which the condition $\pi_{rela}^{T*} < \pi_{rela}^{0*}$ is satisfied. If there is no region with a certain color plotted in the figure, then it means that the condition indicated by the color never holds when $\pi_{rela}^{T*} < \pi_{rela}^{0*}$.

□

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 compare the two revealing strategies alone.

As mentioned in the proof of Proposition 7, the platform's revenue when demand information is revealed is $\pi_{RD}^{T*} = (1-\delta)\int_0^1 \left[p2x_H + (p^4-2p^3+p)2x_L\right]dp + (1-\delta)\int_{\overline{p}}^1 \left[p2x_H + (p^4-2p^3+p)2x_L\right]dp$, where $\overline{p} = \frac{1}{2}\left(2-\sqrt{2}\sqrt{\frac{\sqrt{(x_H+x_L)^2-4cx_L/\delta}}{x_L}-\frac{x_H}{x_L}+1}\right)$.

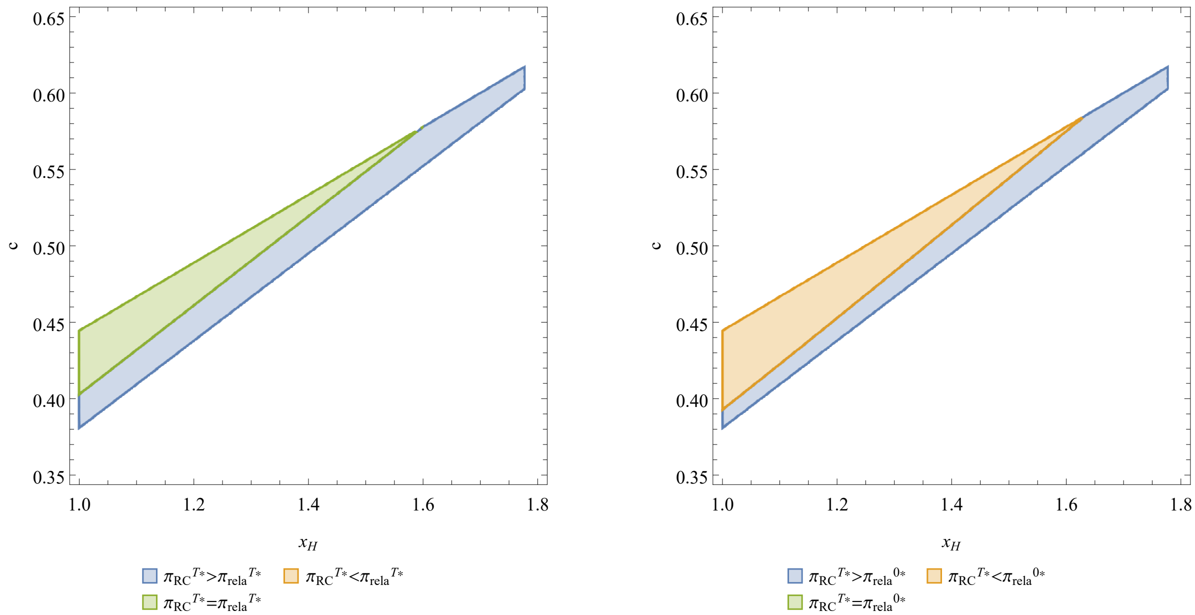


Figure A4: Revealing competition when the advanced matching technology is facilitated
Note: $x_L = 1$, $\delta = 0.5$.

Because this expression is mathematically too involved, we again rely on a numerical exercise to compare π^{T*}_{RD} and π^{T*}_{RC}, with $\delta = 0.5$ and $x_L = 1$ since δ and x_L are again simply scaling parameters. The result of the numerical exercise is summarized in Figure A5, in which the total region plotted out (non-white) represents the parameter space such that $\pi^{T*}_{rela} < \pi^{0*}_{rela}$ is satisfied. If there is no region with a certain color plotted in the figure, then it means that the condition indicated by the color never holds when $\pi^{T*}_{rela} < \pi^{0*}_{rela}$. We can see that within this entire region, $\pi^{T*}_{RD} > \pi^{T*}_{RC}$, which is what we claim in Corollary 1.

□

Proof of Proposition 9. We first consider the case when the commission rate (or parameter δ) is exogenous. From the proof of Lemma 1, we know that the set of all the first-period assignments that make the worker willing to participate in the second period is given by:

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

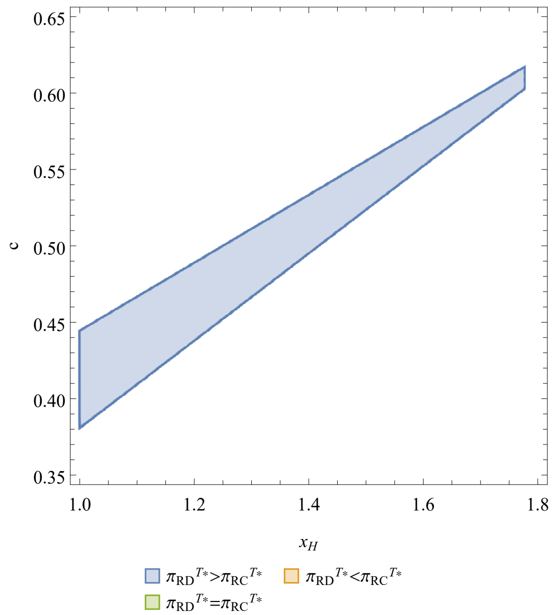


Figure A5: Revealing demand vs competition information
Note: $x_L = 1$, $\delta = 0.5$

and

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

Plugging these into equation (22) gives the worker's surplus as:

$$w^{0*} = \begin{cases} \delta\frac{2}{3}(x_H + x_L) - c & \text{if } c \leq \delta\frac{1}{5}(x_H + x_L), \\ \delta\frac{3}{5}(x_H + x_L) - \frac{2}{3}c & \text{if } \delta\frac{1}{5}(x_H + x_L) < c \leq \delta\frac{2}{5}(x_H + x_L), \\ \delta\frac{1}{3}(x_H + x_L) & \text{if } c > \delta\frac{2}{5}(x_H + x_L), \end{cases}$$

and

$$w^{T*} = \begin{cases} \delta(x_H + \frac{1}{3}x_L) - c & \text{if } c \leq \delta(\frac{x_H}{4} + \frac{3x_L}{20}), \\ \delta(\frac{11}{12}x_H + \frac{17}{60}x_L) - \frac{2}{3}c & \text{if } \delta(\frac{x_H}{4} + \frac{3x_L}{20}) < c \leq \delta(\frac{x_H}{2} + \frac{x_L}{5}), \\ \delta(\frac{5}{6}x_H + \frac{1}{4}x_L) - \frac{1}{2}c & \text{if } \delta(\frac{x_H}{2} + \frac{x_L}{5}) < c \leq \delta(\frac{2}{3}x_H + \frac{x_L}{6}), \\ \delta(\frac{1}{2}x_H + \frac{1}{6}x_L) & \text{if } c > \delta(\frac{2}{3}x_H + \frac{x_L}{6}). \end{cases}$$

First, we claim that if the conditions in Lemma 1 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, then it must be the case that $w^{T*} \geq w^{0*}$. This is because if these conditions are not satisfied, we know that $\mathcal{X}^{0,par} \subseteq \mathcal{X}^{T,par}$, and thus:

$$\begin{aligned}
w^{T*} &= \int_0^1 \sum_{x\in\{x_H,x_L,0\}} Pr^T(x_1 = x|p)\Big(\delta x + \mathbf{1}_{\{x\notin\mathcal{X}^{T,par}\}}c + \mathbf{1}_{\{x\in\mathcal{X}^{T,par}\}} \sum_{x'\in\{x_H,x_L,0\}} Pr^T(x_2 = x'|p)\delta x'\Big)dp \\
&\geq \int_0^1 \sum_{x\in\{x_H,x_L,0\}} Pr^T(x_1 = x|p)\Big(\delta x + \mathbf{1}_{\{x\notin\mathcal{X}^{0,par}\}}c + \mathbf{1}_{\{x\in\mathcal{X}^{0,par}\}} \sum_{x'\in\{x_H,x_L,0\}} Pr^T(x_2 = x'|p)\delta x'\Big)dp \\
&\geq \int_0^1 \sum_{x\in\{x_H,x_L,0\}} Pr^0(x_1 = x|p)\Big(\delta x + \mathbf{1}_{\{x\notin\mathcal{X}^{0,par}\}}c + \mathbf{1}_{\{x\in\mathcal{X}^{0,par}\}} \sum_{x'\in\{x_H,x_L,0\}} Pr^0(x_2 = x'|p)\delta x'\Big)dp \\
&= w^{0*}.
\end{aligned}$$

Here the first inequality comes from the fact that $c \leq \sum_{x'\in\{x_H,x_L,0\}} Pr^T(x_2 = x'|p)\delta x'$ whenever $x \in \mathcal{X}^{l,par}$, and $\mathcal{X}^{0,par} \subseteq \mathcal{X}^{T,par}$. The second inequality is because when the advanced matching technology is adopted (compared to when the advanced matching technology 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.

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, from the calculations above, w^{0*} and w^{T*} are given by:

$$\begin{aligned}
w^{0*} &= \delta\frac{3}{5}(x_H + x_L) - \frac{2}{3}c, \\
w^{T*} &= \delta(\frac{5}{6}x_H + \frac{1}{4}x_L) - \frac{1}{2}c.
\end{aligned}$$

Then, we have:

$$\begin{aligned}
w^{T*} - w^{0*} &= \Big[\delta(\frac{5}{6}x_H + \frac{1}{4}x_L) - \frac{1}{2}c\Big] - \Big[\delta\frac{3}{5}(x_H + x_L) - \frac{2}{3}c\Big] \\
&= \delta(\frac{7x_H}{30} - \frac{7x_L}{20}) + \frac{c}{6} \\
&> \delta(\frac{7x_H}{30} - \frac{7x_L}{20}) + \frac{\delta}{6}(\frac{x_H}{2} + \frac{x_L}{5}) \\
&= \delta\frac{19}{60}(x_H - x_L) > 0.
\end{aligned}$$

Therefore, $w^{T*} \geq w^{0*}$ is always satisfied.

Similarly, for the case when the commission rate (or parameter δ) is endogenously determined by the platform, we can calculate the worker's surplus in this case based on results from Lemma 2:

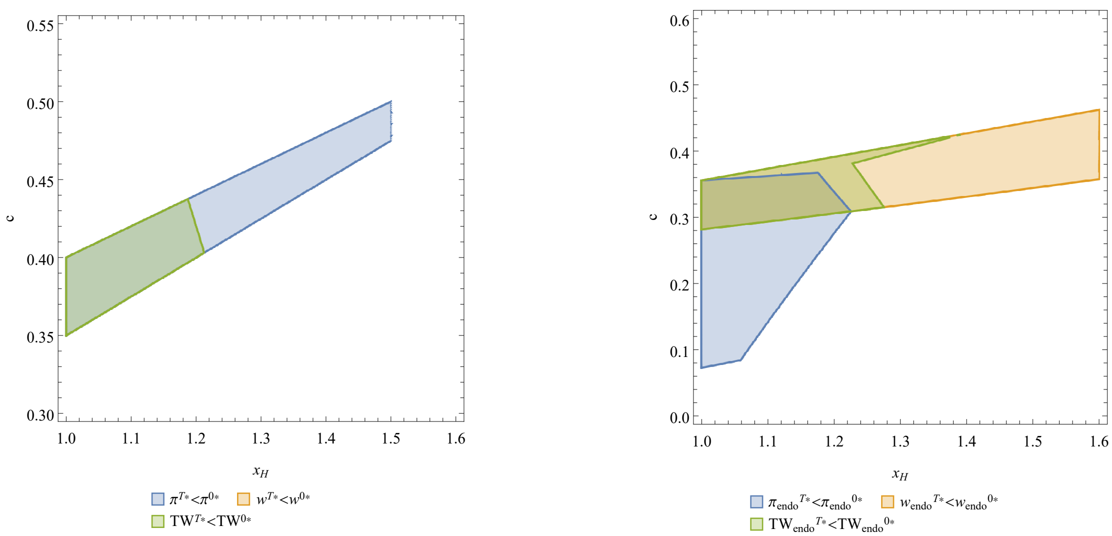
$$w^{0*}_{endo} = \begin{cases} \frac{7c}{3} & \text{if } c \leq c_1^0 \\ \frac{5c}{6} & \text{if } c_1^0 < c \leq c_2^0 \\ 0 & \text{if } c > c_2^0 \end{cases}$$

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

$$w_{endo}^{T*} = \begin{cases} \frac{c(45x_H+11x_L)}{15x_H+9x_L} & \text{if } c \leq c_1^T \\ \frac{c(35x_H+9x_L)}{30x_H+12x_L} & \text{if } c_1^T < c \leq c_2^T \\ \frac{c(3x_H+x_L)}{4x_H+x_L} & \text{if } c_2^T < c \leq c_3^T \\ 0 & \text{if } c > c_3^T \end{cases}$$

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

Finally, we show the possible existence of the worse-off outcome with the advanced matching technology based on our expressions and a numerical exercise by comparing TW^{0*} vs. TW^{T*}, as well as w_{endo}^{0*} vs. w_{endo}^{T*}, and TW_{endo}^{0*} vs. TW_{endo}^{T*}, with $\delta = 0.5$ (only when δ is exogenous) and $x_L = 1$ since δ and x_L are just scaling parameters. The result of the numerical exercise is summarized in Figure A6, and the existence of the blue and yellow regions implies that the proposition is proved.



(a) Exogenous commission rate, no orange region

(b) Endogenous commission rate

Figure A6: Advanced matching technology and worker surplus/total welfare
Note: $x_L = 1$

□