The Rise of Riders: Digital Platforms, Targeted Matching, and Job Creation

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Abstract: *In recent years, gig economy jobs—particularly those of food delivery and ride-hailing drivers—have rapidly emerged as a significant force in the labor market, reflecting the deep integration of China's digital and real economies. This paper examines how digital platforms that support the gig economy exercise directionality and dominance in labor matching, where the platform dictates which consumers workers serve, rather than allowing independent choice. While this platform-led matching may appear to limit consumer and worker autonomy, it actually arises from the platform's central role in information flow and its technological capabilities, serving as a foundation for the platform's ability to create large-scale employment through cross-side network effects. Using a theoretical model that integrates digital platforms, labor markets, and product markets, the paper explores how the efficiency of targeted matching affects employment creation. In the early stages of gig economy development, when targeted matching efficiency is low, improvements in assignment efficiency lead to a net increase in gig employment, worker income, and overall social welfare. However, in the later stages, as targeted matching efficiency improves, the potential for monopoly abuse by incumbent platforms may trigger a crowding-out effect, leading to unemployment, income inequality between platforms and workers, and higher commission fees. While fostering competition within platform markets offers benefits, policymakers should avoid excessively low entry barriers, as these can negatively impact incumbent platforms' decisions regarding labor, pricing, and technology investment.*

Keywords: *Gig economy; digital-real integration; platform regulation; competitive market*

JEL Classification Codes: L20, L86

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1. Introduction

Since the 20th National Congress of the Communist Party of China (CPC) has adopted an employment-first strategy, both the annual Central Economic Work Conference and the government work report have consistently emphasized the need to stabilize and expand employment. Amid the growing

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integration of digital and traditional economies, flexible employment forms—such as food delivery riders, couriers, ride-hailing drivers, and online domestic service workers—have seen rapid growth, outpacing traditional sectors in job creation and becoming a key driver of employment opportunities. For example, Meituan's Corporate Social Responsibility Report states that, by December 2022, the platform employed 6.24 million delivery personnel, a 235.25% increase from 2.95 million in June 2020. Similarly, data from the National Ride-Hailing Regulatory Information Interaction Platform indicates that the number of licensed ride-hailing drivers nationwide rose from 3.49 million in June 2021 to 5.79 million in June 2023, marking a 165.76% increase, with ride-hailing now by far surpassing traditional taxis in market share.

How can digital platforms like Didi and Meituan generate large-scale employment in such a short period? One explanation lies in the cross-side network effects inherent in platform economies: the welfare of demand-side individuals rises as supply-side participation increases, while supply-side welfare improves with growing demand-side engagement. This reciprocal relationship between supply and demand facilitates a rapid expansion in transaction volumes (Rysman, 2009; Evans & Schmalensee, 2016). For instance, in the case of ride-hailing, an increase in passengers using the platform attracts more riders, while a larger driver base, in turn, draws more passengers. These cross-side network effects enable ride-hailing platforms to swiftly build an extensive base of users and riders.

However, this is not the full picture. Traditional taxis (or taxi companies) also function as platforms and exhibit cross-side network effects. Specifically, as more people take taxis, the incentive for individuals to become taxi riders increases, and the subsequent growth in the driver base attracts more passengers. So, why can ride-hailing platforms create such a large number of jobs in such a short time, despite the taxi market being well-established? One explanation lies in the stronger cross-side network effects of ride-hailing platforms compared to traditional taxis, which results in a more significant job creation effect. The enhanced network effects of ride-hailing platforms can be attributed to their higher efficiency in matching supply and demand—i.e., lower transaction costs—compared to traditional taxis. This increased assignment efficiency stems from the platforms' ability to leverage digital technologies extensively. In other words, it is the higher level of digitization that enables the gig economy, built on digital platforms, to thrive.

While digital technology offers significant potential, it is not a panacea, and numerous instances of unsuccessful digital transformations underscore this reality. In the context of the gig economy and the digital platforms that underpin it, digital technology plays an indispensable role in effectively creating a substantial number of jobs. To understand this, it is essential to conduct an in-depth analysis of the work processes of gig workers and the mechanisms through which digital platforms facilitate these processes. Using the example of food delivery riders, we can illustrate the unique nature of the gig economy, characterized by the job creation sequence: "identification of supply and demand information → platform-order matching→ continuous performance of tasks by workers → attraction of new participants". The most critical element in this sequence is the platform-order matching process.

A Typical Case of Platform Targeted Matching: Food Delivery Riders

In traditional food delivery models, a delivery rider seeking to offer their services must wait around restaurants. However, this system presents several challenges. The number of consumers a restaurant can serve is limited, and both the timing and location of consumer orders are randomly distributed. As a result, food delivery work opportunities are fragmented and highly uncertain, making the job less appealing to workers.

With the rise of digital platforms like Meituan and Ele.me, however, the matching process between food delivery riders and consumers has undergone a profound transformation. When consumers place food orders via mobile apps, they not only provide the platform with dining information, but also enable the platform to aggregate multiple orders from adjacent areas (such as nearby streets or communities). The platform then uses GPS to track the location of riders, selecting the most suitable one via a specific *algorithm and assigning them the integrated delivery tasks. In this targeted matching model, the efficiency of the platform's matching process is crucial: when it is highly efficient, riders spend less time waiting for job opportunities, leading to an increase in deliveries per unit of time. This, in turn, makes the role of food delivery driver more attractive as a viable (gig) occupation. As more riders join the platform, consumer demand rises, which, in turn, attracts even more riders, triggering a cycle of growth. These cross-side network effects, in turn, contribute significantly to job creation.*

Digital platforms supporting the gig economy engage in direct work allocation during transaction matching, rather than allowing consumers or workers to make independent choices, which has never existed in traditional platform models. For instance, when consumers shop on Taobao, they independently choose the store; when using Alipay for payments, they select their recipients; and users of the Windows operating system choose which software to install. In contrast, platforms like Meituan and Didi first aggregate multi-directional information from various parties before assigning specific workers to serve particular consumers.

The platform-led targeted matching is not intended to deprive the right to choice of consumers and workers. Instead, it arises from the platform's role as an information aggregator and its ability to leverage algorithms that facilitate highly efficient matching. The cross-side network effects of ride-hailing services, for example, are stronger than those of traditional taxis, not simply because of the greater use of digital technology, but because digital technology has fundamentally transformed the matching process. This transformation enables platforms to conduct targeted matching of labor services, greatly enhancing efficiency. In this sense, the targeted matching function of digital platforms acts as both an accelerator and catalyst for the cross-side network effect within the platform model. However, this does not imply that targeted matching is a flawless mechanism. Under specific conditions, platform-led targeted matching may give rise to other issues, highlighting the importance of proactive government regulation.

This paper develops a theoretical model based on the food delivery ecosystem, encompassing food delivery platforms, online and offline restaurants, workers, and consumers. Using this model, the paper examines the impact and underlying mechanisms of changes in targeted matching efficiency—an indicator of digital technology advancement—on several outcomes, including the employment creation function of food delivery platforms, the number and income of riders, total social welfare, its distribution, and the potential role of government intervention in both the labor and product markets. The model presented here has the following key features: (1) It illustrates how the targeted matching mechanism of food delivery platforms links online restaurants, riders, and consumers; (2) It captures the cross-side network effects arising from this targeted matching mechanism in a simplified form; (3) It incorporates the labor market and endogenizes the gig employment decisions of workers; and (4) It explores the important interactions between the labor market and product market, considering both prices (rider wages and online order prices) and quantities (rider employment and online order volume).

Research has shown that the targeted matching efficiency of digital platforms exerts both an *inclusion effect* and a *crowding-out effect* on gig employment. On the one hand, as digital technology advances and targeted matching efficiency improves, the value that riders can generate increases, incentivizing platforms to hire more riders. This constitutes the inclusion effect. On the other hand, increased assignment efficiency also means that riders become more dependent on the platform, and, in some cases, it reduces the number of riders needed to fulfill a given number of orders. In this context, platforms may have an incentive to "replace workers with technology", leading to the *crowding-out effect*. The relative magnitude of these two effects depends on the level of development of digital technology, and by extension, the efficiency of targeted matching. In the early stages of gig economy development, when digital technology is still maturing, the inclusion effect generally outweighs the crowding-out effect, resulting in an ongoing increase in the equilibrium employment of riders.

However, as digital technology matures and the gig economy progresses to its middle and later stages, the crowding-out effect of enhanced targeted matching efficiency begins to surpass the inclusion effect. Under these conditions, while further increases in targeted matching efficiency may boost the number of orders on food delivery platforms, they will simultaneously reduce the platform's demand for riders, potentially leading to unemployment.

The welfare analysis results indicate that, regardless of whether the gig economy is in its early or late stages of development, improving the efficiency of targeted matching consistently contributes to an increase in total social welfare. This provides a theoretical foundation for the continued promotion of digital technological advancements and business innovations based on the platform model. However, workers do not always benefit proportionally from the gains arising from technological progress and platform innovation. Since the platform controls almost all the information and decision-making power necessary for targeted matching, the distribution of social welfare is largely determined by the platform in the absence of government intervention. Notably, as targeted matching efficiency improves, the share of total welfare allocated to the rider group follows a pattern of initially increasing and then decreasing. In other words, once digital technology reaches a certain level of sophistication and the gig economy attains a substantial scale, the majority of the welfare gains are captured by the digital platform, rather than by the workers themselves.

The primary cause of the aforementioned issues is the tendency of incumbent platforms to exploit their monopoly position. Research has shown that, in the absence of government regulation, a monopolistic food delivery platform tends to impose commission fees on online restaurants—essentially, customer acquisition costs—that exceed the socially optimal level. These excessively high fees force online restaurants to raise their prices in order to cover the costs, which in turn reduces consumer demand for online orders. As a result, while advances in digital technology may increase the overall order volume on food delivery platforms, the growth rate of orders remains sub-optimal compared to the socially optimal level, leading to a lower-than-optimal number of riders being employed. In other words, although the cross-side network effect driven by the targeted matching mechanism generates substantial employment demand, the actual employment creation effect remains underutilized relative to the social optimum. Furthermore, in the later stages of gig economy development, the crowding-out effect of digital technology on labor employment significantly outweighs the inclusion effect of increased online economic activity. In the absence of government intervention, technological advancements may actually exacerbate the gap between the actual and ideal employment levels.

The government can mitigate the various issues arising from platform monopolies by fostering competitive markets. In the model, the introduction of a potential entrant creates competitive pressure on incumbent platforms, and the government can influence market competitiveness by adjusting the entry threshold (or entry cost). Research has shown that building a competitive market can lead to positive outcomes, such as reducing the commission fees imposed by platforms on merchants and increasing the rider workforce. However, the entry threshold should not be set too low. When the threshold falls below a certain critical level, further reductions can result in a loss of social welfare. Additionally, if digital platforms are free to choose the targeted matching efficiency they wish to achieve—and thus, their corresponding level of technology investment—the incumbent platform's R&D investment in targeted matching may either be excessive or insufficient relative to the socially optimal level. The government's regulation of the entry threshold can significantly influence the platform's technology investment decisions. If the entry threshold is too high, it may fail to create sufficient competitive pressure on the incumbent platform. Conversely, if the threshold is too low, it could lead to either excessive or insufficient investment by the incumbent platform. It can be theoretically demonstrated that there is an optimal entry threshold that maximizes social welfare. This optimal threshold is dynamic and varies depending on factors such as labor risk, the R&D costs of the targeted matching mechanism, and other parameters. Therefore, the government's role is not only to build a competitive market but also to adjust the entry threshold in a timely and appropriate manner based on changing factors, thereby regulating market dynamics and ensuring that the employment and welfare-enhancing effects of digitalization and platformization are fully realized.

The potential marginal contributions and innovations of this paper are reflected in the following aspects:

(1) This paper introduces an targeted matching mechanism for digital platforms to explain the rapid growth of the gig economy and its operational dynamics within the context of the integration between the digital and real economies[1]. While existing literature on the gig economy generally attributes its rapid development to the "natural" effects of cross-side network effects, it tends to overlook the pivotal role and mechanisms by which digital platforms shape the gig economy, particularly in terms of work allocation. Given the fragmented nature of gig work, efficient matching between workers and consumers is essential to ensure a continuous flow of work opportunities. This matching requires the direct involvement of digital platforms, which possess information advantages, in orchestrating the targeted matching process. Only through such platform-driven coordination can the cross-side network effect be fully leveraged, enabling the swift creation of substantial employment opportunities.

(2) This paper further underscores the necessity of regulating platform monopolies to fully realize the potential for expanding rider employment. To sustain the growth of gig economy jobs, the inclusion effect of digital platform-order matching on labor employment must outweigh the crowding-out effect. However, when digital platforms hold a monopoly position and engage in monopoly pricing of commission fees—particularly in the later stages of digital technology development—excessively high commission fees not only impose a financial burden on online merchants but also increase costs for consumers. This, in turn, can stifle demand, ultimately leading to stagnation or even a decline in rider employment.

(3) This paper demonstrates that a competitive market environment, when made freely accessible, can effectively mitigate the issues arising from platform monopolies. However, this is contingent upon the government's careful regulation of the platform market's entry threshold. If the entry threshold is set too high, the threat of competition becomes negligible, failing to curb the incumbent platform's monopoly behavior. Conversely, if the entry threshold is too low, it may distort the incumbent platform's labor employment decisions and other operational aspects, ultimately leading to a loss in social welfare.

The structure of the remainder of the paper is as follows: Section 2 reviews and critiques the existing literature; Section 3 constructs a theoretical model that includes food delivery platforms, online and offline restaurants, workers, and consumers; Section 4 presents an equilibrium analysis of both the product and labor markets; Section 5 examines the impact of targeted matching efficiency on equilibrium outcomes and welfare distribution; Section 6 explores the effects of platform monopolies on commission pricing, labor employment, and welfare distribution; Section 7 analyzes the governance role of competitive markets in mitigating the risks associated with platform monopolies; Section 8 investigates the implications of digital platforms independently determining their desired targeted matching efficiency; Section 9 extends the discussion on how to maximize the employment creation potential of digital platforms; and finally, Section 10 concludes the paper.

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[1] The targeted matching mechanism proposed in this paper also offers an explanation for the rapid growth of the short video industry. While it may seem that mobile users independently select which short videos to watch, in reality, their choices are shaped by the targeted matching and targeted recommendations provided by short video platforms. These platforms possess comprehensive data on both videos and users, enabling them to tailor content to individual preferences. By effectively matching videos with users, the platforms reduce search costs, facilitate the continued activation of cross-side network effects, and thereby contribute to the industry's rapid expansion. However, unlike food delivery and ride-hailing platforms, which primarily rely on location-based matching, short video platforms face the additional challenge of multi-dimensional matching. This involves aligning user preferences, video content, and other factors, making the process of targeted matching more complex.

2. Literature Review

2.1 Two-Sided Market Theory

The gig economy, exemplified by digital platform employment, represents a distinct form of two-sided (or multi-sided) market. A "two-sided market" refers to a market structure mediated by a platform that serves both the supply and demand sides, facilitating transactions of products or services between users on each side (Rochet and Tirole, 2003; Evans, 2003; Wright, 2004; Armstrong, 2006). Existing literature on two-sided market theory often attributes the growth of employment in digital platforms to the natural effects of cross-side network dynamics. Specifically, cross-side network effects in such markets suggest that the value of the platform's products or services increases as the number of users on both the supply and demand sides grows (Roson, 2005). This, in turn, attracts more consumers and workers, leading to large-scale job creation (Bogliacino et al., 2020). While this perspective highlights the role of cross-side network effects in job creation, it oversimplifies the process by neglecting the underlying preconditions necessary for digital platforms to generate employment, as well as the critical need for government regulation.

Compared with the job creation function of platforms, traditional two-sided market theory focuses more on the strategic actions platforms take under cross-side network effects. Because of these effects, once a platform's supply and demand sides reach a certain size, the cost for any individual to switch platforms becomes very high (Farrell & Klemperer, 2007). This makes the platform economy susceptible to a "winner-takes-all" dynamic: the largest platform on both sides will likely dominate the entire market, leaving other platforms with minimal market share or forcing them out entirely (Katz & Shapiro, 1994; Besen and Farrell, 1994; Caillaud and Jullien, 2003). This gives platforms an incentive to strengthen their monopoly power through strategic pricing, exclusionary tactics, and other means. With strategic pricing, the fees a platform charges one user group influence that group's willingness to use the platform and, due to cross-side network effects, subsequently affect the number of users on the other side (Rochet & Tirole, 2003; Armstrong, 2006; Ji, 2006; Xu et al., 2006; Cheng and Sun, 2006; Wang and Xin, 2008). Regarding exclusionary tactics, platforms can prevent users from joining competing platforms by using exclusive contracts, effectively squeezing out competitors (Fudenberg and Tirole, 2000; Armstrong & Wright, 2007; Mantena et al., 2010). This paper examines how digital platform monopoly pricing in the product market affects labor employment. While this is a form of strategic platform behavior, unlike existing literature, this paper demonstrates that the net effect of such pricing on labor employment changes dynamically with the efficiency of targeted matching[2].

2.2 The Gig Economy

Similar to two-sided market theory, research on the gig economy often views the rapid expansion of gig employment as an inevitable outcome in the digital economy. Specifically, the unique advantages of digital platforms—such as their data capabilities, algorithms, and other technological features—are seen as key drivers of industrial transformation and the evolution of business models. As a result, the demand for diverse, flexible forms of employment and positions has surged, aiming to meet both immediate and

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[2] Beyond traditional two-sided market theory, other studies focus specifically on the digital platform economy. These studies primarily address two aspects: First, the evolution of the digital platform economy (Helfat and Raubitschek, 2018; Barlow et al., 2019; Garud et al., 2022; Khanagha et al., 2022; Panico and Cennamo, 2022; Tang and Chi, 2013; Liu, 2015; Wang and Zhang, 2017; Zhu et al., 2019). For example, Panico and Cennamo (2022) argue that consumer preferences for platform market share and platform supply-side innovation play an important role in value creation within the platform economy. Second, the governance of the digital platform economy (Lu and Zhang, 2014; Zhen, 2017; Xiao, 2020). For instance, Xiao (2020) finds that there is a value co-destruction phenomenon in the platform economy. This phenomenon is the result of platform leadership failure, and the governance of this phenomenon requires the platform leadership to be positioned from commercial platform leadership to responsible platform leadership.

non-standard product or service needs (De Stefano, 2016; Li & Zhou, 2022; Guo, 2023). Within this context, scholars, both Chinese and international, typically explore the nature of gig work, the structure of labor relations, the potential risks associated with gig employment, and the regulatory challenges posed by its rapid growth[3].

From the perspective of the nature of gig work, practitioners' work opportunities are directly tied to consumer demand for products or services, making it a quintessential form of "on-demand labor". Furthermore, the task-based employment model central to gig work means that workers do not engage in long-term formal contracts with those they serve. In other words, once a worker completes a specific task within a designated time frame, their interaction with the consumer ends (Friedman, 2014; Mas & Pallais, 2020).

Regarding labor relations within the gig economy, the subordinate relationship between gig workers and digital platforms remains a subject of debate (Kaine & Josserand, 2019). Some scholars, emphasizing work autonomy, argue that although digital platforms help gig workers find work opportunities, practitioners retain the ability to independently set their working hours, positioning them as "self-employed" or "independent contractors". From this perspective, no formal employment relationship exists between workers and digital platforms, which at most entails a cooperative arrangement (Chen, 2021). In contrast, other scholars highlight the labor control exerted by digital platforms, noting that platforms monitor and direct workers through algorithms while using customer feedback, rankings, and ratings systems to compel workers to remain online for extended periods. As such, platforms act as "shadow employers" for gig workers (Friedman, 2014; Gandini, 2019; Rahman, 2021; Xia & Ding, 2024).

In terms of the potential risks associated with gig work, the unpredictability of work opportunities and income presents a stark contrast to traditional, fixed employment, leading to challenges in achieving a stable work-life balance (Doucette & Brandford, 2019; Warren, 2021). Additionally, algorithmic control places workers in high-pressure, high-risk situations, often resulting in excessive work intensity (Wei & Liu, 2023; Pei et al., 2024). Further complicating matters, gig workers often lack sufficient social security and are typically unable to access vocational training, limiting opportunities for both vertical career advancement and cross-industry mobility at an affordable cost (Kost et al., 2019). In light of these issues, existing literature advocates for the establishment of a labor rights protection framework tailored to digital gig employment, with a particular emphasis on clarifying the labor relationship between digital platforms and gig workers. This includes defining the various dimensions of subordination—be it personal, economic, or organizational (Li & Zhou, 2022; Xiao, 2021)[4].

Existing research enhances our understanding of the gig economy and offers valuable insights for labor rights protection in the digital age. However, these studies often assume that digital platforms inherently create employment opportunities without exploring the underlying mechanisms. In contrast, this paper examines how the efficiency of targeted matching influences labor employment, highlighting both inclusion and crowding-out effects. While the literature on technological innovations like artificial intelligence (AI) and industrial robots also discusses their dual impact on employment, these studies suggest that the positive effects of technological innovation on job creation are more evident in the long run (Acemoglu & Restrepo, 2018, 2020; Chen and Qin, 2022). This paper, however, finds that the

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[3] Other scholars discuss the economic impact of the gig economy. For example, Barrios et al. (2022) and Mo and Li (2022) find that the gig economy has a substitution relationship with entrepreneurial activity, and the gig economy promotes high-quality development of the entrepreneurial market by crowding out low-quality, subsistence-level entrepreneurial activity.

[4] Scholars have also examined the challenges that emerging gig economy models pose to tax systems and their governance, suggesting the development of a robust personal income tax framework and stronger tax compliance obligations for online gig platforms (Cai et al., 2022; Sun et al., 2022).

inclusion effect of targeted matching efficiency on labor employment is more immediate. This difference likely stems from the digital platform economy's greater capacity to rapidly absorb and integrate technological advancements. In traditional industries, unlocking the potential benefits of technological innovations—such as artificial intelligence and industrial robotics—within the conventional economy necessitates extensive digitalization and intelligent transformation, a process that demands prolonged and cumulative effort.

3. Model Description

Consider a Hotelling linear market (Figure 1) that includes businesses, consumers, digital platforms, and workers. Among them, businesses are divided into online businesses that have access to the platform and offline businesses that do not have access to the platform. They are located at the left and right ends of the Hotelling market, produce products of the same quality, and compete on price in the product market[5]. For ease of understanding and expression, it is assumed that the businesses here are restaurants. The online business is referred to as Restaurant 1, which has access to digital platforms represented by Meituan and Ele.me and only provides online ordering services; the offline business is referred to as Restaurant 2, which does not have access to digital platforms and only provides offline consumption.

The different operating models determine the following two differences between the two restaurants: (1) The two restaurants have different customer acquisition costs. Since the platform provides online restaurants with the opportunity to be "searched for" by consumers, for Restaurant 1, which has access to the online platform, for every meal sold, it needs to pay the platform a commission fee (is determined by the platform, see below for details). This is not only the cost for Restaurant 1 to acquire customers through the platform, but also equivalent to the service fee charged by the platform to Restaurant 1. Restaurant 2 does not have access to the platform, so it does not need to pay commission fees. However, Restaurant 2 also has to pay costs to attract customers, such as laying advertising materials offline. Without loss of generality, this paper sets the customer acquisition cost for Restaurant 2 for every meal sold as (exogenously given).

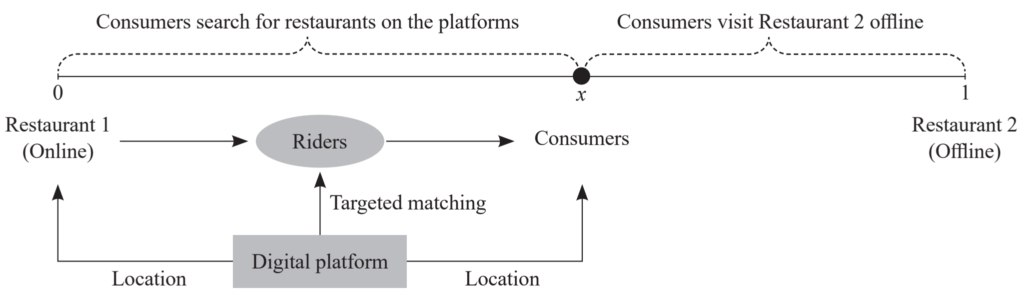

Figure 1: Hotelling Linear Market

The two restaurants have different delivery methods. Unlike consumers who need to go to Restaurant 2 for dine-in, if consumers order takeaway from Restaurant 1 online, the digital platform

[5] In reality, the competitive landscape between restaurants is more complex. Online restaurants, in addition to delivery services, can also offer dine-in options. Offline restaurants, which previously only offered dine-in service, can also choose to join digital platforms and provide delivery services. Furthermore, online and offline restaurants exhibit heterogeneity in product quality, product positioning, and other aspects. However, considering that this paper aims to analyze the job creation function of the targeted matching mechanism and its underlying principles, and that factors such as product differences and competitive models between restaurants are not directly related to the job creation function of targeted matching efficiency, this paper simplifies the theoretical modeling of these aspects.

will select a rider and assign the task of picking up and delivering the meal to the rider. This is called the digital platform's targeted matching between workers and consumers. The delivery fee for takeaway delivery is the income source of takeaway riders. To simplify the mathematical derivation, it is assumed that the price p_1 paid by consumers to Restaurant 1 includes the delivery fee paid to the takeaway rider. The delivery fee is transferred to the platform when Restaurant 1 pays the commission fee f to the platform, and finally paid to the rider by the platform in the form of wages according to the total workload of each rider. In addition, within the model framework of this paper, the targeted matching mechanism of the digital platform helps riders identify multiple orders from adjacent geographical areas (such as the same street or community) at the same time, thus increasing the number of deliveries made by the same rider per unit of time. Therefore, the total income of the rider depends on the hourly wage, working hours and the targeted matching efficiency of the digital platform[6]. Riders decide their working hours based on the cost and benefit of their work, which reflects the flexibility of the gig work of riders. This will be described in detail below[7].

Given the differences between the two restaurants outlined above, the following sections specifically explore the consumer's dining choices, the decision-making behaviors of the restaurants and the digital platform, as well as the riders' willingness to supply labor.

3.1 Product Market

On the demand side, a total of 1 consumer is evenly distributed on a linear market with a density of 1. These consumers each have a consumption demand of 1 unit of food and need to choose whether to order takeaway from online Restaurant 1 or dine in at offline Restaurant 2. We use the location of the consumer in the market $x \in [0,1]$ to identify different consumers, and the utility function of consumer x dining in different restaurants can be expressed as:

$$u(x) = \begin{cases} u_1 = \theta - p_1 - (t + x - aL), \text{if consumer chooses Restaurant 1} \\ u_2 = \theta - p_2 - (t + 1 - x), \text{if consumer chooses Restaurant 2} \end{cases} \tag{1}$$

Where $\theta \in \Re^+$ represents the utility a consumer derives from purchasing a meal. Let θ be sufficiently large such that consumers always purchase one unit of food. p_1 and p_2 are the purchase costs for ordering food online and dining offline, respectively. $t + x - aL$ and $t + 1 - x$ represent the time costs for consumers waiting for food delivery and going to the restaurant without platform assistance[8]. Specifically, considering that the distance between consumers and restaurants is the main factor affecting purchase time, this paper, without loss of generality, assumes that whether consumers go to Restaurant 1 or Restaurant 2, there is not only a base distance (or base time cost) $t \geq 1$, but also additional time cost for their specific location (the specific magnitude of x). That is, the actual time costs for consumers going to Restaurant 1 and Restaurant 2 are $t + x$ and $t + 1 - x$, respectively. At this time, even for consumers at $x = 0 (x = 1)$ who are closest to Restaurant 1 (Restaurant 2), they still need to consume time cost to dine

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[6] In reality, the key difference between hourly wages and piece-rate wages lies in the uncertainty (or variability) of the number of deliveries a rider makes within a unit of time. For example, the number of deliveries made by different riders within a unit of time may vary depending on their degree of diligence and work experience. However, in order to explain the impact of the targeted matching mechanism on labor employment with the simplest possible model, this paper does not consider the individual heterogeneity of riders in terms of diligence, work experience, etc., but only focuses on the impact of targeted matching efficiency on the number of deliveries within a unit of time. Therefore, there is a definite conversion relationship between hourly wages and piece-rate wages within the scope of this paper.

[7] In theory, delivery distance can impact riders' wages. However, given that riders typically operate within a service radius of 3 kilometers, a fixed basic service fee is applied, with no additional distance charges. As a result, we simplify the delivery fee model, implicitly assuming that the delivery distance among riders does not vary significantly. This assumption aligns with the typical characteristics of business districts and residential communities in food delivery services. Should distance-based delivery fees be incorporated into the model in future research, attention would need to be given to the dynamic programming challenges posed by the varying time and spatial factors affecting both riders and consumers.

[8] The implicit assumption here is that the time cost per unit distance is normalized to 1.

at Restaurant 1 (Restaurant 2)[9]. Furthermore, for Restaurant 1, which has access to the digital platform, the digital platform not only helps restaurants and consumers find each other more conveniently, but also can assign riders to pick up and deliver food through targeted matching, saving consumers' time for purchasing meals and food delivery. Therefore, the time cost for consumers ordering takeaway online from Restaurant 1 using the digital platform decreases from $t+x$ (going to the restaurant in person) to $t+x-aL$ (waiting for takeaway delivery)[10].

Note that aL represents the time cost saved by the targeted matching mechanism for consumers, which consists of the following two parts: 1) the number of takeaway riders L. Holding other conditions constant, as the number of riders increases, more labor is involved in takeaway delivery, and the waiting time for consumers decreases accordingly, so consumer welfare increases; 2) the targeted matching efficiency of the digital platform a. Holding the number of riders constant, the targeted matching mechanism of the digital platform affects the work efficiency of workers, thus changing the number of meals that each rider can deliver per unit time. The larger the value of a, the higher the targeted matching efficiency, the higher the delivery frequency of riders, and the more conducive it is to reducing the time cost of takeaway delivery[11]. In the following section, we first consider the case of exogenously given , where the targeted matching efficiency mainly depends on the level of development of digital technology and is not controlled by the platform; and then consider the case of endogenously given a, that is, the digital platform can independently decide the targeted matching efficiency it hopes to achieve and the corresponding technical investment.

Given the utility function in Equation (1), the market boundary between the two restaurants is determined by the location of the marginal consumer in the market. The marginal consumer can obtain the same utility by choosing either restaurant. Let $u_1 = u_2$, and we can obtain the location of the marginal consumer $\frac{1-p_1+p_2+aL}{2}$. Correspondingly, consumers to the left and right of this location choose Restaurant 1 and Restaurant 2 for consumption, respectively. The demand functions for Restaurant 1 and Restaurant 2 are:

$$Q_1 = \frac{1-p_1+p_2+aL}{2} \tag{2}$$

$$Q_2 = \frac{1+p_1-p_2-aL}{2} \tag{3}$$

With consumer demand established, the two restaurants engage in price competition. Their respective profit functions are:

$$\pi_1 \equiv \Pi_1(p_1,p_2) = (p_1-f)\cdot Q_1(p_1,p_2) \tag{4}$$

$$\pi_2 \equiv \Pi_2(p_1,p_2) = (p_2-c)\cdot Q_2(p_1,p_2) \tag{5}$$

The profit function for the digital platform is:

$$\pi_p \equiv \Pi_p(f) = f\cdot Q_1 - w\cdot L - F \tag{6}$$

In Equation (6), $f\cdot Q_1$ represents the digital platform's total revenue from matching services, derived from the commission fees collected from Restaurant 1. The platform incurs two types of costs: 1) total

[9] It is important to note that x=0 (x=1) does not mean that consumers have no time cost when purchasing meals at Restaurant 1 (Restaurant 2). Rather, it indicates that this consumer is the one closest to Restaurant 1 (or Restaurant 2), and the time cost of purchasing meals is the smallest. In addition to being expressed as a base distance, t can also be understood as the meal preparation time, etc.

[10] A more rigorous approach would involve a parameter k such that the time for the number of riders L saved is given by kaL. However, for the sake of parsimony, we normalize k to 1

[11] Note that aL represents the cross-side network effect of workers on consumers, specifically, how the number of workers influences individual consumer utility. Furthermore, with a fixed number of workers, the magnitude of this effect depends on the efficiency a of targeted matching.

rider wages wL, as the platform employs and pays wage w to riders hired from the labor market;[12] and 2) the platform's cost of investment F in digital technologies, such as the development of the digital system. This paper will consider both exogenously given F and endogenously determined $F = F(a)$ sequentially.

3.2 Labor Market

In the labor market, workers make labor supply decisions to maximize their utility. Consider a labor market with a continuum of identical workers. For simplicity, the number of workers is normalized to 1 (e.g., representing 100 million workers). The optimization problem for any worker is:

$$\max_{C,L^s} U = C^{\frac{1}{2}} - \beta L^s (1+ra) \tag{7}$$

$$s.t.\, C - wL^s \leq 0 \tag{8}$$

In Equation (7), C represents the worker's consumption, and L^s represents the working hours the worker invests in the gig work as a delivery rider. $U(C,L^s)$ satisfies $\frac{\partial U(\cdot)}{\partial C} > 0$, $\frac{\partial^2 U(\cdot)}{\partial C^2} < 0$, that is, the worker's utility increases with the amount of consumption, but the marginal utility decreases. $\beta L^s(1+ra)$ is the labor cost of a worker engaged in the occupation as a rider, which can be decomposed into two parts: 1) the direct cost of labor. The longer the worker's working hours L^s, the higher the labor cost. 2) Labor risks, such as the risk of traffic accidents, etc. This paper uses $ra>0$ to describe the labor risk per unit of working hours, where r is the (work) risk coefficient, which is determined by the characteristics of the work; a is the targeted matching efficiency, which also represents the number of working hours of the worker per unit time. With the increase in the number of working hours (delivery frequency), the worker's labor risk also increases. ra reflects the negative impact of the platform's use of digital technology to control the rider's labor process—the so-called "digital control" (Chen, 2020). $\beta>1$ is a cost coefficient. The constraint condition is the worker's budget constraint, that is, the worker's consumption cannot exceed the total income determined by the hourly wage w and working hours L^s.[13]

In equilibrium, $C=wL^s$. Substituting this into Equation (7) and applying the first-order condition $\frac{\partial U}{\partial L^s} = 0$ yields the worker's labor supply:

$$L^s = \frac{w}{4\beta^2(1+ra)^2} \tag{9}$$

Here, we provide a special explanation of the meaning of L^s. According to the above, L^s represents the working hours a worker invests in the occupation of a rider. The implicit assumption is that, in addition to working as a rider, workers can also engage in other occupations (however, to simplify the model, this paper does not introduce another occupation and consider the mutual substitution relationship between different occupations), which reflects the flexibility of the occupation of a takeaway rider. Furthermore, since this paper normalizes the number of workers to 1, L^s also represents the total time all workers are employed in the takeaway market. Based on this, this paper can equate L^s with the number of riders.[14] To simplify and unify the concepts in the context, unless otherwise specified, L^s represents the number of riders by default in the following sections.

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[12] In practice, consumers pay delivery fees per order. For mathematical simplicity, we assume that the price p_1 consumers pay Restaurant 1 includes the delivery fee, which is then passed on to the platform as part of the commission fee f. The platform subsequently pays this amount to the riders.

[13] Three points should be noted here: 1) The hourly wage w herein represents the compensation a worker receives for delivering a orders within a given time unit. Consequently, the worker's piece-rate wage is w/a. 2) This model simplifies the effect of delivery distance on rider wages w by assuming that riders primarily operate within a base mileage range, with negligible distance variations between deliveries. 3) While workers may have other income sources, for simplicity, this analysis focuses solely on earnings from delivery services.

[14] For instance, with 100 million workers in the labor market, L^S=0.3 implies a total investment of 30 million labor hours in rider positions, equivalent to 30 million full-time riders.

3.3 Time Sequence of the Game

The game unfolds in three stages, as illustrated in Figure 2.

Stage 1: The platform invests F in developing the digital system, and Restaurant 1 onboards onto the platform.

Stage 2: The platform determines the number of riders to employ (L^D) and the commission fee f levied on Restaurant 1.

Stage 3: The two restaurants then compete on price, consumers make their purchase decisions, and the platform dispatches riders to deliver meals from Restaurant 1. Consumers choosing Restaurant 2 pick up their orders on their own.

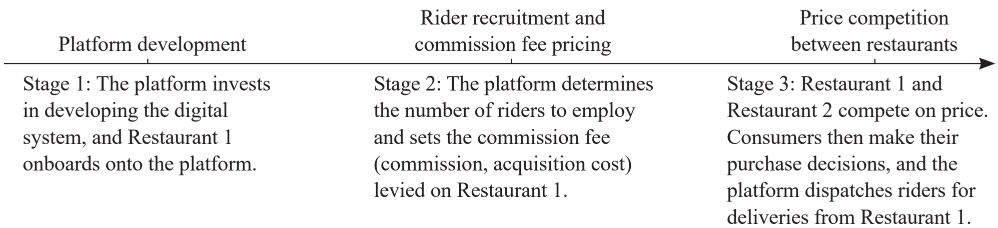

Figure 2: Time Sequence of the Game

The theoretical model in this paper has the following differences and characteristics compared with the traditional Hotelling model. 1) The cross-side network effect is introduced into the Hotelling model in a relatively concise form, thereby portraying the process and effect of mutual influence and mutual creation between supply (including product supply and labor supply) and demand (including product demand and labor demand). 2) By introducing an targeted matching mechanism, the process of the platform using digital technology to identify and match multi-stakeholder information (including consumers, restaurants, and riders, etc.) is portrayed, thereby adding the labor market to the model and placing the labor market and the product market in the same theoretical framework. Table 1 summarizes the main variables involved in the theoretical model and their economic meanings.

Table 1: Key Variables and Their Economic Interpretations

Variable Type	Decision-maker(s)	Variable	Economic Interpretation
Endogenous	Digital platform	f	The commission fee charged by the digital platform to online restaurants, representing the platform's commission fee or the online restaurant's unit customer acquisition cost.
	Digital platform and workers	L	The number of riders employed by the digital platform, which also represents workers' labor hours.
	Digital platform and workers	w	Workers' wage level.
	Workers	C	Workers' consumption, which is a function of their labor hours and wages
	Restaurant	p_1	Restaurant 's product price, $i=1.2$.
	Consumers	Q_1	Restaurant 's market demand, $i=1.2$.
Exogenous before endogenous	Digital platform	a	The digital platform's targeted matching efficiency, $a\in[0,2\sqrt{2}\beta]$.
		$F/F(a)$	The digital platform's R&D cost.
Exogenous	/	θ	Consumers' consumption utility.
		c	The offline restaurant's customer acquisition cost
		β	The worker's cost coefficient, where $\beta>1$.
		r	The worker's risk coefficient per unit of labor.

4. Equilibrium Analysis

We employ backward induction to determine the game's equilibrium. We first analyze price competition and market equilibrium in the product market between the two restaurants, followed by the platform's commission fee and labor decisions.

4.1 Price Competition between Restaurant 1 and Restaurant 2

In Stage 3, Restaurants 1 and 2 simultaneously set prices to maximize profits. Their respective optimization problems are:

$$\max_{p_1} \pi_1 = (p_1 - f)Q_1(p_1, p_2) \tag{10}$$

$$\max_{p_2} \pi_2 = (p_2 - c)Q_1(p_1, p_2) \tag{11}$$

Solving the first-order conditions $\frac{\partial \pi_i}{\partial p_i} = 0$, with $i = 1,2$, yields the following pricing strategies for the two restaurants:

$$p_1 = \frac{3 + aL + 2f + c}{3} \tag{12}$$

$$p_2 = \frac{3 - aL + f + 2c}{3} \tag{13}$$

Substituting (12) and (13) into (2) and (3) yields the demand functions for Restaurants 1 and 2:

$$Q_1 = \frac{3 + c + aL - f}{6} \tag{14}$$

$$Q_2 = \frac{3 - c - aL + f}{6} \tag{15}$$

As can be learned from the expressions of p_1 and Q_1 shown in Equations (12) and (14), as a and L increase, even if Restaurant 1 increases prices, demand remains strong due to the increased efficiency and rider workforce, assuming other variables remain constant. This is because the improved assignment efficiency a and increased rider workforce L dramatically enhance delivery efficiency, attracting more online orders. In short, the targeted matching mechanism, powered by advancements in digital technology, makes Restaurant 1 significantly more appealing to consumers. Furthermore, a reduction in the platform's commission fee f leads Restaurant 1 to lower prices p_1, further stimulating demand, holding other conditions constant. However, under equilibrium, both the platform's commission fee and labor demand L are endogenous to assignment efficiency a. We will subsequently analyze the equilibrium values of f and L and their relationship with a.

4.2 Digital Platform Decision

The digital platform determines the commission fee f charged to the restaurant and the number of riders L^D to employ in order to maximize profit. Given the worker's labor supply function in Equation (9), $L^S = \frac{w}{4\beta^2(1+ra)^2}$, the platform must set the wage at $w^* = w^*(L^D) = 4\beta^2(1+ra)^2 \cdot L^D$ to attract the desired number of riders L^D, so that worker's labor supply equates the desired workforce, i.e., L^S=L^D. Thus, the platform's optimization problem is:

$$\max_{f, L^D} \pi_p = f \cdot Q_1 - w^*(L^D) \cdot L^D - F \tag{16}$$

$$s.t.\, aL^D \geq Q_1 \tag{17}$$

Equation (17) establishes the "sufficient matching" condition between the labor and product markets. Specifically, it ensures that the platform's riders have sufficient capacity to fulfill all online orders, preventing situations where orders are placed but not delivered. Targeted matching efficiency increases the number of deliveries per rider per unit time, thus determining the riders' maximum delivery capacity. Therefore, aL reflects the maximum amount of food, and $aL \geq Q_1$ means the maximum amount of food all riders employed by the digital platform can deliver cannot be lower than the order volume of online restaurants. Only in this way can the platform have the ability to fully meet consumers' delivery needs for online orders, and there will be no situation where consumers place orders but no riders deliver them.[15]

Substituting $Q_1(f, L^D) = \dfrac{3+c+aL^D-f}{6}$ into (16) yields the following Lagrangian function:

$$\max_{f, L^D} \mathcal{L} = f \cdot Q_1(f, L^D) - w^*(L^D) \cdot L^D - F + \lambda(aL^D - Q_1(f, L^D)) \tag{18}$$

Based on the first-order conditions $\dfrac{\partial \mathcal{L}}{\partial f} = 0$, $\dfrac{\partial \mathcal{L}}{\partial L} = 0$, and $\dfrac{\partial \mathcal{L}}{\partial \lambda} = 0$, we can obtain the commission fee and number of riders at the equilibrium condition:[16]

$$f^* = \frac{(3+c) \cdot [8\beta^2(1+ra)^2 + 5a^2]}{8\beta^2(1+ra)^2 + 10a^2} \tag{19}$$

$$L^* = \frac{(3+c) \cdot a}{8\beta^2(1+ra)^2 + 10a^2} \tag{20}$$

Substituting (19) into (9) yields the equilibrium hourly wage level:

$$w^* = \frac{4\beta^2(1+ra)^2 \cdot (3+c)a}{8\beta^2(1+ra)^2 + 10a^2} \tag{21}$$

Substituting (19) and (21) into (7) yields the rider's equilibrium utility:

$$U(C^*, L^*) = \frac{\beta(1+ra) \cdot (3+c)a}{8\beta^2(1+ra)^2 + 10a^2} \tag{22}$$

5. Dynamic Effects of Advances in Digital Technology

This section analyzes the influence of targeted matching efficiency a on equilibrium outcomes, assuming that this efficiency a is exogenously determined and not controlled by the platform. Here, reflects the advancement of digital technologies (e.g., GPS, AI). A smaller indicates an earlier stage of development, while a larger a signifies a more mature technological landscape. Thus, a represents both the efficiency of targeted matching and the level of digital technology development.

5.1 Digital Technology and Labor Market

Building upon the equilibrium solutions from Part 3, as illustrated in Figure 3, the numerical simulation demonstrate how targeted matching efficiency a affects the equilibrium number of riders and

[15] If this were not the case, it would imply that some consumers' delivery needs remain unmet. Anticipating this, rational consumers would then forgo online ordering. Consequently, the platform would forfeit the associated revenue. In essence, the platform can only fully capitalize on online ordering revenue if it can satisfy total market demand for delivery.

[16] The implicit technical assumption is that . This assumption ensures a corner solution to the optimization problem, meaning the solution lies on the constraint boundary.

their wage levels (Equations 20 and 21). The simulation demonstrates that both the equilibrium number of riders and their wages initially rise and subsequently fall with increasing targeted matching efficiency. This occurs because targeted matching efficiency exerts two opposing influences on labor demand. First, higher assignment efficiency reduces the number of riders needed to fulfill a given order volume (Q_1), thus decreasing the platform's labor demand. Given the exogeneity of a at this stage, this efficiency is primarily a function of digital technology's advancement. We term this the "crowd-out effect" of digital technology (or targeted matching) on labor. Second, greater assignment efficiency enhances consumer utility from Restaurant 1 orders, leading to increased demand. Consequently, the platform hires more riders to meet this demand, increasing both equilibrium employment and wages. This is the "draw-in effect" of digital technology on labor.

The numerical simulation in Figure 3 further demonstrates that the relative strength of these two effects systematically varies across different stages of the gig economy and digital technology development. In the nascent gig economy, where digital technology is still developing, targeted matching efficiency is relatively low. Here, the "draw-in" effect outweighs the "crowd-out" effect, and increasing assignment efficiency drives employment and rider wages upward. However, as digital technology advances and assignment efficiency surpasses a threshold, the "crowd-out" effect dominates. Consequently, further increases in assignment efficiency not only fail to generate additional employment but may even lead to unemployment and wage stagnation for existing riders. Empirically, this manifests as a point where the growth in rider employment and wages plateaus, or even declines, despite potential for further growth. As we will show, this is not due to market saturation but rather the platform's pricing strategies. Based on this, Proposition 1 is obtained:

Proposition 1: Holding all other variables constant, with increasing targeted matching efficiency , both rider numbers and wages initially increase and subsequently decrease.

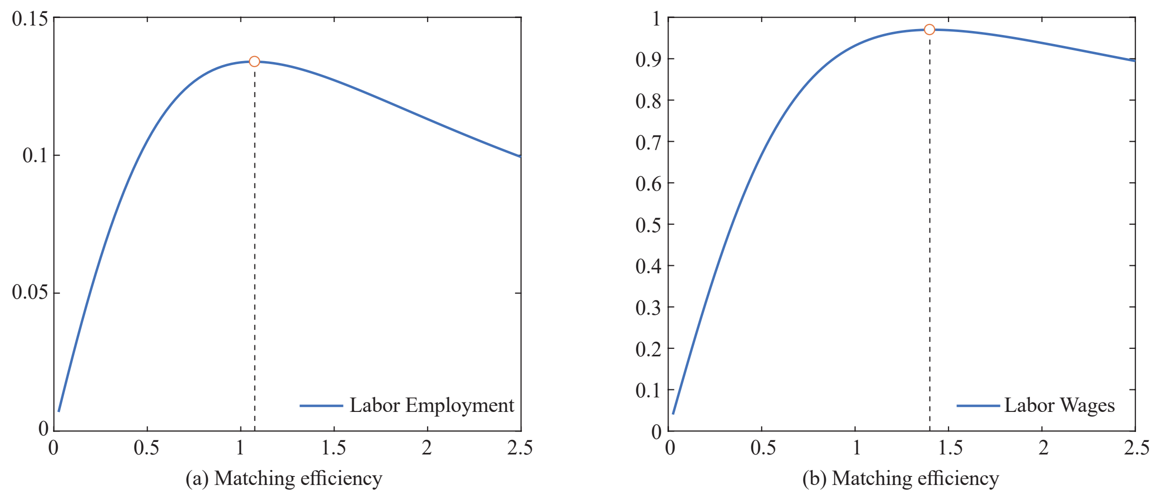

Figure 3: Impact of Targeted Matching Efficiency on the Number of Riders and Wage Levels

Note: Compiled by the authors. The parameter settings for the exogenous variables in the numerical simulation process are θ=6, c=0.2, β=1.2, r=0.1, F=0.1, a∈[0.2.5].

5.2 Digital Technology Progress and the Product Market

This section examines how targeted matching efficiency influences various prices within the product market. Figure 4 shows the results of the numerical simulation.

First, we focus on the commission fee f charged by the digital platform to Restaurant 1. The results show that the commission fee charged to Restaurant 1 decreases as the targeted matching efficiency increases (dashed line). The reason why the commission fee f becomes cheaper is mainly due to the reduction in the marginal cost of delivery services brought about by the improvement of targeted matching efficiency. To explain the economic logic behind this, the platform's profit is re-expressed here as $\pi_p = f \cdot Q_1 - \frac{w^*}{a} \cdot Q_1 - F$, where, under equilibrium conditions, marginal revenue $MR(Q_1)=f^*$ equals marginal cost $MC(Q_1)=\frac{w^*}{a}$. Among them, a represents the number of orders delivered by a rider, and correspondingly, $\frac{w^*}{a}$ represents the wage cost of delivering an order.

According to $w^{*}{''}(a) < 0$, with the increase in targeted matching efficiency , the marginal cost of delivery orders $\frac{w^*}{a}$ decreases, resulting in marginal profit being greater than zero, that is, $MR-MC>0$. At this time, the increase in order volume Q_1 can bring incremental profits to the platform. Combined with Equation (14), if the platform wants to increase the sales Q_1 of Restaurant 1, it mainly achieves this by lowering the commission fee f^*. Therefore, the platform will reduce f^* to a level where the marginal revenue and marginal cost are just equal, that is, $MR=MC$. In other words, with the increase in targeted matching efficiency a, the potential profit space of the takeaway industry increases, and if the platform wants to transform the potential profit into actual profit, it must help Restaurant 1 sell more meals. To do this, it is necessary to reduce the commission fee f^*, which in turn will prompt Restaurant 1 to lower prices p_1, and then sell more meals.

We now turn to the product prices of the two restaurants, p_1 and p_2. The simulation shows that Restaurant 1's product price p_1 also decreases with increasing targeted matching efficiency (solid line). This is primarily because the lower commission fee, a result of digital technology advancements, further reduces Restaurant 1's operating costs, enabling them to compete with lower prices and capture a larger market share. Consequently, Restaurant 2, to remain competitive, is forced to lower its price as well (dashed line).

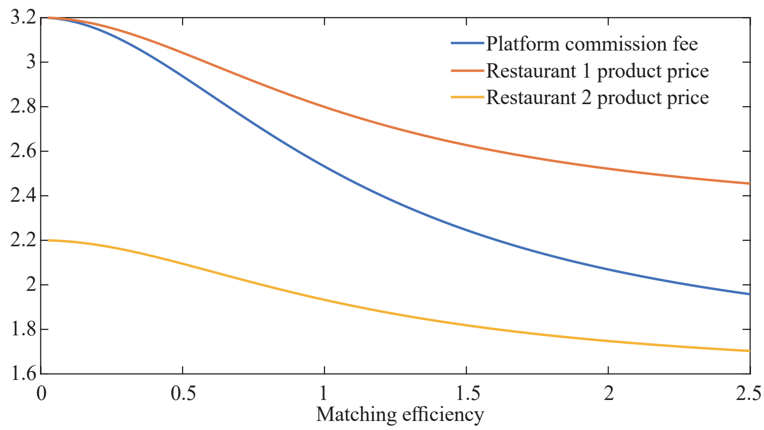

Figure 4: Impact of Targeted Matching Efficiency on Commission Fees and Meal Prices

Note: Compiled by the authors. The parameter settings for the exogenous variables in the numerical simulation process are θ=6, c=0.2, β=1.2, r=0.1, F=0.1, a∈[0.2.5].

Within the current framework, the digital platform enjoys a monopoly: 1) Restaurant 1 is dependent on the platform for customer acquisition (search traffic) and delivery services; 2) Consumers rely on the platform for information regarding Restaurant 1 and access to delivery services; 3) Workers are limited to platform employment for flexible work opportunities. Consequently, the platform possesses monopoly pricing power over both commission fees f and rider wages , influencing the product price p_1 of Restaurant 1 and the product price p_2 of Restaurant 2. Nevertheless, increased assignment efficiency driven by technological advancements still leads to lower commission fees and product prices, highlighting the crucial role of digital technology and targeted matching in reducing market frictions and enhancing efficiency. However, this does not imply a perfect market structure, as discussed below.

5.3 Welfare Analysis

Building upon the preceding equilibrium analysis, this section investigates the effect of digital platform's targeted matching efficiency on welfare. We analyze how targeted matching efficiency affects the welfare of individual economic agents and aggregate social welfare, further considering the distribution of this welfare to assess the potential for distributional inequality arising from technological advancements.

(1) Worker Welfare. In this paper, worker welfare refers to rider welfare $U(C^*,L^*)$, which represents the total utility of all riders. Figure 5 numerically simulates the relationship between rider welfare $U(C^*,L^*)$ and targeted matching efficiency a. The results show that with the improvement of the digital platform's targeted matching efficiency, worker welfare first increases and then decreases, specifically as follows: Combined with Proposition 1, in the early stage of the development of the gig economy, the level of development of digital technology is also relatively low. At this time, the draw-in effect of digital technology on labor is stronger than the crowd-out effect. In this stage, although the labor cost of riders increases with the increase in working hours, due to the increase in wages w^*, the increase in consumption level C^* ultimately exceeds the increase in labor costs.

Therefore, the welfare level of riders increases with the targeted matching efficiency a. With the continuous development of the gig economy, digital technology gradually matures and makes the targeted matching efficiency a exceed a certain critical value. After that, the crowd-out effect of digital technology on labor will be stronger than the draw-in effect, that is, the increase in a will lead to a decrease in equilibrium labor employment L^*. At this time, although the labor cost decreases with the decrease in working hours, the labor wage w^* also decreases with the increase in a, which in turn leads to a decrease in rider income. Overall, the decline in rider income exceeds the decline in labor costs. Hence, the welfare level of riders decreases with the targeted matching efficiency a. The above conclusions can be summarized as Proposition 2.

Proposition 2: With other conditions constant, as the targeted matching efficiency a of the digital platform increases, worker welfare $U(C^*, L^*)$ initially increases and subsequently decreases.

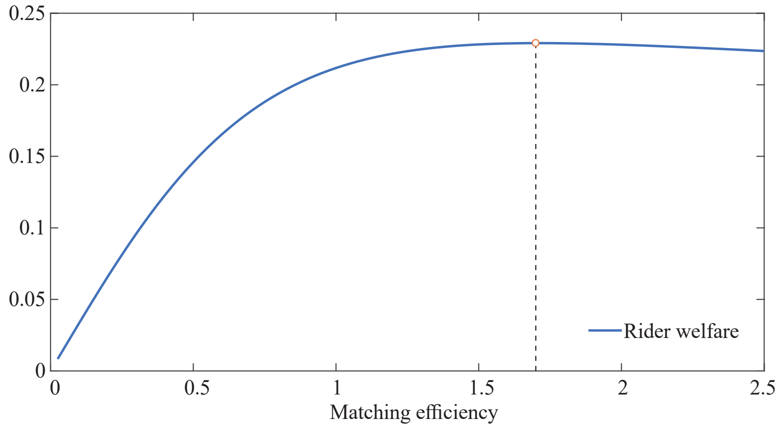

Figure 5: Impact of Targeted Matching Efficiency on Rider Welfare

Note: Compiled by the authors. The parameter settings for the exogenous variables in the numerical simulation process are θ=6, c=0.2, β=1.2, r=0.1, F=0.1, a∈[0.2.5].

(2) Welfare Levels of Product Market Participants. The digital platform's monopoly pricing power dictates that changes in assignment efficiency influence the welfare of product market participants via the commission fee. Figure 6 illustrates the effect of assignment efficiency on the profits of Restaurant 1, Restaurant 2, the platform, and consumer welfare. As assignment efficiency increases, the platform lowers the commission fee f for Restaurant 1, bolstering its price competitiveness and expanding its online market share, thus increasing Restaurant 1's profits (Figure 6a). Simultaneously, consumers

benefit from lower transaction costs and prices, leading to increased welfare (Figure 6d). Growing online order volume also boosts platform profits (Figure 6c). Conversely, Restaurant 2 faces mounting pressure. First, improved online delivery efficiency draws customers to Restaurant 1. Second, Restaurant 1's price advantage further erodes Restaurant 2's market share, leading to declining profits (Figure 6b).

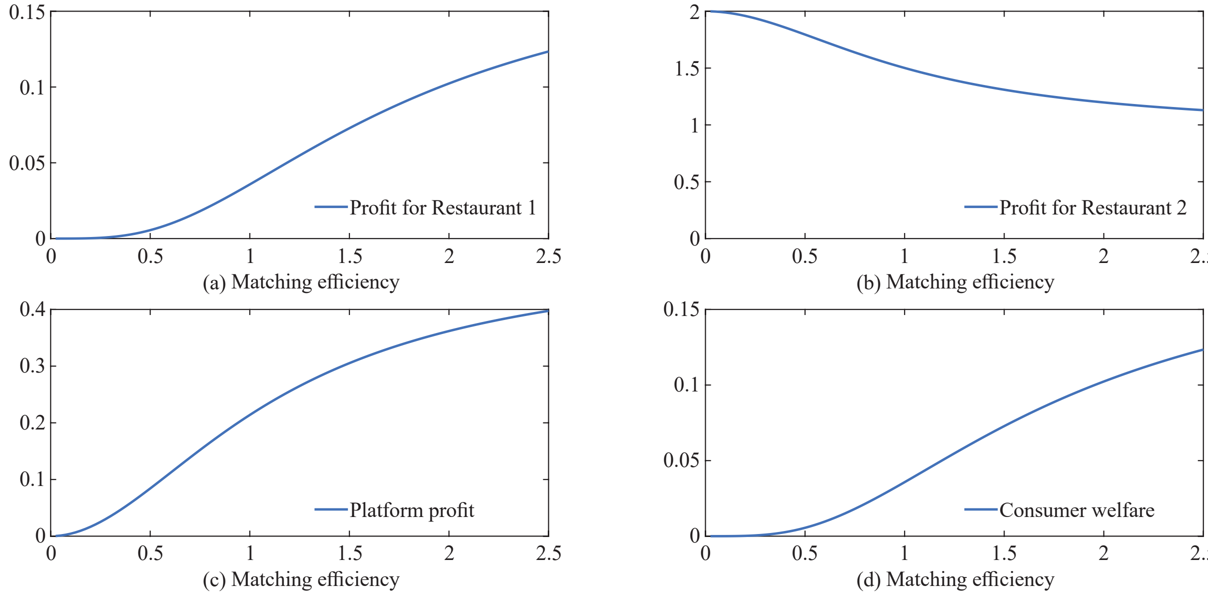

Figure 6: Impact of Targeted Matching Efficiency on the Welfare of Product Market Participants

Note: Compiled by the authors. The parameters for the exogenous variables in the numerical simulation are set as: θ=6, c=0.2, β=1.2, r=0.1, F=0.1, a∈[0.2.5].

(3) Total Social Welfare and its Distribution. Here, we further analyze the impact of targeted matching efficiency on total social welfare. Total social welfare is the sum of consumer utility U_C, rider utility $U(C^*, L^*)$, platform profit (π_p), and total restaurant profit $\sum \pi_i$, i=1,2, i.e.:

$$SW=U^C+U(C^*, L^*)+\pi_p+\pi_1+\pi_2 \tag{23}$$

In Equation (23), $U_C=\int_0^{Q_1}[\theta-p_1-(x-aL^*)]dx+\int_{Q_1}^{1}[\theta-p_2-(1-x)]dx$. Figure 7a numerically simulates Equation (23). The simulation shows that total social welfare increases with the platform's targeted matching efficiency. As shown in the previous analysis, the increase in total social welfare stems primarily from two sources. First, in the labor market, increased assignment efficiency within a specific range enhances worker utility. Second, in the product market, higher assignment efficiency provides consumers with more convenient delivery and lower prices, while also boosting profits for both the platform and Restaurant 1. These two effects are sufficiently strong that, despite reduced profits for Restaurant 2, the overall benefits of increased assignment efficiency prevail[17].

A question that needs further clarification is whether the welfare distribution among different economic actors is fair? This paper uses the proportion of welfare of different economic actors in total social welfare to reflect the distribution of total social welfare. Figure 7b performs a numerical simulation of this. In addition, Figure 7c separately plots the welfare share of riders and the digital

[17] As digital technologies evolve, the efficiency of targeted matching improves, often resulting in a decline in rider welfare. However, the gains in market efficiency typically outweigh the riders' utility losses in the labor market. As a result, overall social welfare generally increases.

platform to more intuitively compare the welfare distribution between the two. It can be found that with the improvement of targeted matching efficiency, the welfare share of Restaurant 1 maintains an upward trend (dashed line in Figure 7b), but the welfare share of Restaurant 2 continues to decline (cross line in Figure 7b), which reflects the crowding out of the offline economy by the online economy, indicating that total social welfare is more distributed to the online economy. However, it is worth noting that the degree of benefit of different online economic participants is different: although the welfare share of the digital platform, Restaurant 1, and consumers are all increasing, the welfare share of riders shows a trend of first rising and then falling (dashed line in Figure 7b and 7c). The reason is that when digital technology enters a mature stage and the gig economy develops to a certain level, the improvement of targeted matching efficiency not only crowds out labor, causing unemployment problems, but also enables the digital platform to use its monopoly position in the labor market to transfer more of the profits from online consumption to itself rather than riders, triggering the problem of distributional inequity.

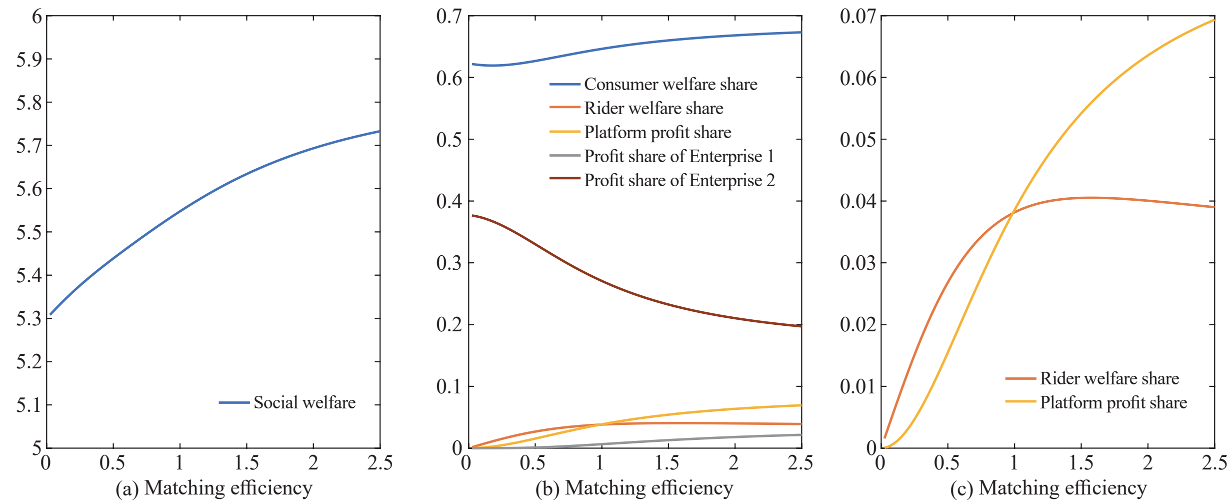

Figure 7: Impact of Targeted Matching Efficiency on Overall Social Welfare and Welfare Distribution

Note: Compiled by the authors. The parameter settings for the exogenous variables in the numerical simulation process are θ=6, c=0.2, β=1.2, r=0.1, F=0.1, a∈[0.2.5].

6. Potential Harms of Platform Monopolies

To further demonstrate the potential harms of platform monopolies, this section compares the commission fees and labor employment volume when digital platforms abuse their monopoly position with the socially optimal situation.[18]

6.1 Socially Optimal Commission Fees and Labor Employment

If the government were to set commission fees and make labor employment decisions with the goal of maximizing overall social welfare, it would consider not only the profits of digital platforms , but also the welfare of consumers, workers, and both restaurants. Therefore, the government's optimization problem is:

[18] This section first solves for the socially optimal commission fee and labor employment volume, and then compares it with the case where the platform abuses its monopoly position.

$$\max_{f,L^D} SW = U^C + U(C,L^S) + \pi_p + \pi_1 + \pi_2 \tag{24}$$

$$s.t.\, aL^D \geq Q_1 \tag{25}$$

The social welfare function in Equation (24) can be further expressed as $SW=\theta+Q_1(\mathrm{f},L^D)[aL^D-Q_1(\mathrm{f},L^D)+1+\mathrm{c}]-\frac{1}{2}-\mathrm{c}-\mathrm{F}+\beta(1+ra)L^D-4\beta^2(1+ra)^2L_D^2$, where $Q_1(\mathrm{f},L^D)=\frac{3+aL^D-f+c}{6}$. The constraint condition in Equation (25) is also the matching condition that the number of riders sufficiently meets the delivery needs of consumers.

Let $\lambda \geq 0$ be the Lagrange multiplier for the matching condition, then the corresponding Lagrange function is expressed as:

$$\max_{f,L^D} \mathcal{L}=SW+\lambda(aL^D-Q_1(f,L^D)) \tag{26}$$

Based on the first-order conditions, $\frac{\partial\mathcal{L}}{\partial f}=0$, $\frac{\partial\mathcal{L}}{\partial L}=0$, and $\frac{\partial\mathcal{L}}{\partial\lambda}=0$, the socially optimal commission fee and labor employment volume can be obtained:

$$f^{FB} = 3+c-\frac{5a[\beta(1+ra)+a(1+c)]}{8\beta^2(1+ra)^2} \tag{27}$$

$$L^{FB} = \frac{\beta(1+ra)+a(1+c)}{8\beta^2(1+ra)^2} \tag{28}$$

Substituting Equation (28) into Equation (9), the socially optimal hourly wage can be obtained:

$$w^{FB} = \frac{\beta(1+ra)+a(1+c)}{2} \tag{29}$$

Further substituting Equations (28) and (29) into Equation (7), the rider's utility under the socially optimal conditions can be obtained:

$$U(C^*,L^*) = \frac{\beta(1+ra)+a(1+c)}{8\beta(1+ra)} \tag{30}$$

6.2 Welfare Loss Due to Monopolistic Platform

Based on the analysis results from the previous section, this section compares the equilibrium outcomes under platform monopoly and socially optimal conditions from three perspectives: the product market, the labor market, and overall social welfare.

(1) Product Market. Figure 8 numerically simulates the commission fees under both platform monopoly and socially optimal conditions. The results show that when the efficiency of targeted matching mainly depends on the level of digital technology development, if the platform uses its monopoly position to engage in monopoly pricing, then $f^*>f^{FB}$. That is, the commission fee f^* it charges is significantly higher than the socially optimal situation, which constitutes a price distortion (Figure 8a). Moreover, with the improvement of the level of digital technology, the problem of price distortion continues to worsen (Figure 8b), that is, $\frac{\partial(f^*-f^{FB})}{\partial a}>0$.

The rationale behind this trend is as follows: From a social welfare perspective, the more advanced the stage of digital technology development, the greater the efficiency of digital platforms' targeted matching, which directly enhances product market transaction efficiency. To fully realize the economic potential of this mechanism, it is crucial to incentivize online ordering by consumers Q_1, primarily through substantial reductions in platform commission fees, represented by $\frac{\partial f^{FB}}{\partial a} < 0$. However, digital platforms, while recognizing that lower commission fees can expand online order volume, also understand that this reduces their commission revenue from online restaurants. Consequently, their commission fee reductions consistently fall short of the socially optimal level. This discrepancy is particularly evident in the later stages of digital technology development. Platforms recognize that highly efficient targeted matching is sufficient to attract a large consumer base for online ordering, diminishing concerns about the negative impact of higher commission fees on order volume Q_1. Therefore, they choose to significantly inflate prices beyond the socially optimal level, expressed as $\frac{\partial f^*}{\partial a} < 0$. but $\left|\frac{\partial f^{FB}}{\partial a}\right| < \left|\frac{\partial f^{FB}}{\partial a}\right|$. Consequently, the more advanced the digital technology, the more severe the price distortion of commission fees when platforms abuse their monopoly power, and the greater the need for government market regulation of these platforms.

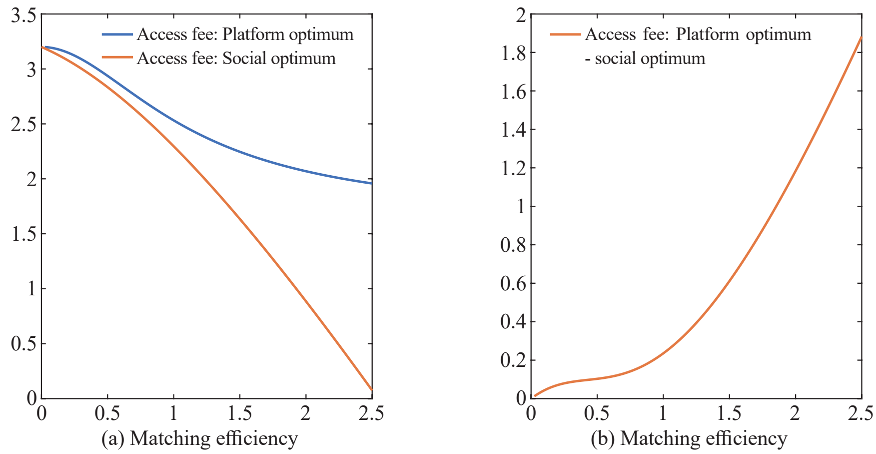

Figure 8: Impact of Monopolistic Platform on Commission Fees

Note: Compiled by the authors. The parameter settings for the exogenous variables in the numerical simulation process are θ=6, c=0.2, β=1.2, r=0.1, F=0.1, a∈[0.2.5].

Figure 9 numerically simulates online order volume under both platform monopoly and socially optimal conditions. The results reveal that the price distortion of commission fees further reduces online restaurant order volume below the socially optimal level (Figure 9a). This order volume gap widens with increasing targeted assignment efficiency (Figure 9b, which presents the inverse indicator of this gap $Q_1^* - Q_1^{FB}$), as shown by $Q_1^* < Q_1^{FB}$ and $\frac{\partial (Q_1^* - Q_1^{FB})}{\partial a} < 0$. While the increasing efficiency of targeted matching, driven by digital technology advancements, enhances the competitiveness of online ordering, driving an upward trend in order volume regardless of commission fee price distortions (i.e., $\frac{\partial Q_1^{FB}}{\partial a} > 0$ and $\frac{\partial Q_1^*}{\partial a} > 0$), the magnitude of this growth is significantly affected by platform behavior.

If platforms voluntarily lowered commission fees to the socially optimal level, online ordering would offer the dual benefits of high transaction efficiency and low prices, maximizing consumer participation and allowing them to fully benefit from the improved efficiency driven by technological advancements, the platform's multi-sided market structure, and the targeted matching mechanism. However, when platforms exploit their monopoly power, the resulting commission fee price distortion increases online restaurant operating costs, forcing them to raise prices—a move that diminishes the attractiveness of online ordering. Consequently, the reduction in online diners limits the realization of the platform's network effects and assignment efficiency, further constraining online order volume growth (i.e., $\frac{\partial Q_1^{FB}}{\partial a} > \frac{\partial Q_1^*}{\partial a} > 0$). This effect is amplified in later stages of digital technology (or gig economy) development, where the more severe commission fee price distortion widens the order volume gap (i.e., $\frac{\partial (Q_1^{FB} - \partial Q_1^*)}{\partial a} > 0$).

These results show that while digital technology improves the efficiency of food delivery, monopolistic platforms distort the distribution of the resulting benefits, capturing a share that would otherwise accrue to consumers and online restaurants, and thus preventing the maximization of the technology's potential.

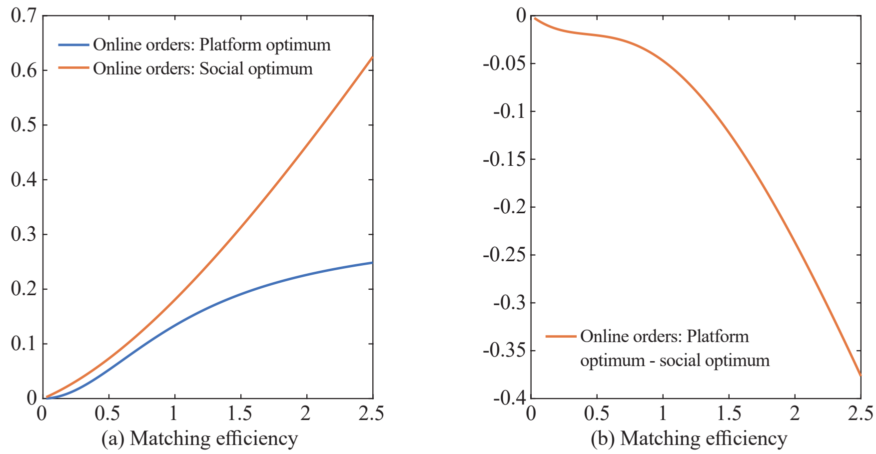

Figure 9: Impact of Monopolistic Platform on Online Orders

Note: Compiled by the authors. The parameter settings for the exogenous variables in the numerical simulation process are θ=6, c=0.2, β=1.2, r=0.1, F=0.1, a∈[0.2.5].

(2) Labor Market. Figure 10 numerically simulates labor employment under both platform monopoly and socially optimal conditions. Comparing the two scenarios reveals that the order volume gap for online restaurants suppresses the demand for riders by digital platforms, resulting in equilibrium labor employment L^* falling below the socially optimal level L^{FB} (Figure 10a), creating an employment gap of $L^{FB} - L^*$. Furthermore, Figure 10b shows that the employment gap exhibits a U-shaped pattern of first decreasing and then increasing.

The reason behind this is: With the development of digital technology, if the commission fee can be maintained at the socially optimal level, the gradually increasing efficiency of targeted matching and the moderate commission fee will jointly promote the rapid growth of online order volume. The resulting demand for labor can always exceed the crowding-out effect of digital technology on food delivery riders, resulting in a continuous increase in the equilibrium number of riders, that is, $\frac{\partial L^{FB}}{\partial a} > 0$. However, when digital platforms abuse their monopoly position to engage in monopoly pricing, the growth rate of online order volume becomes relatively slow due to excessively high commission fees. In this case, only in the early stage of digital technology development, when the crowding-out effect of digital technology on riders is relatively weak, can the incremental orders brought by the efficiency of targeted matching expand the labor demand of digital platforms for food delivery riders and narrow the employment gap in the labor market. On the contrary, when digital technology develops to a certain stage, the crowding-out effect of digital technology on riders far exceeds the absorption effect of order volume on food delivery riders, causing the employment gap in the labor market to increase instead of decreasing.

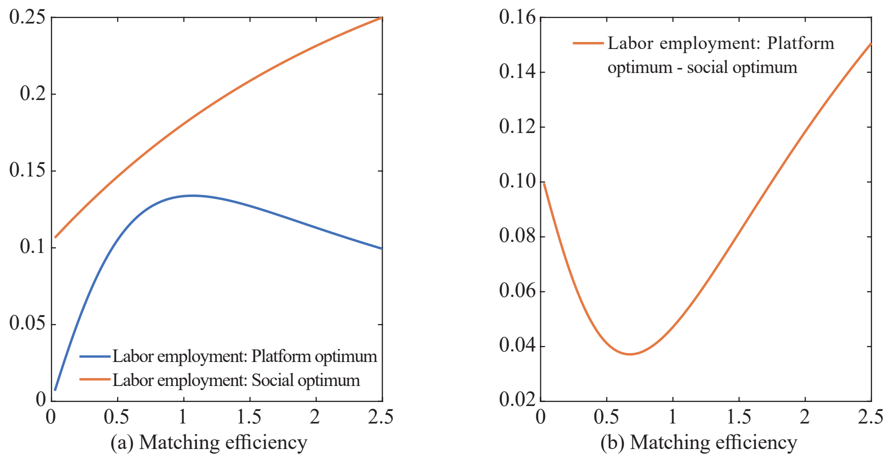

Figure 10: Impact of Monopolistic Platform on Labor Employment

Note: Compiled by the authors. The parameter settings for the exogenous variables in the numerical simulation process are θ=6, c=0.2, β=1.2, r=0.1, F=0.1, a∈[0.2.5].

(3) Social Welfare. Figures 11a and 11b numerically simulate overall social welfare under both platform monopoly and socially optimal conditions. Compared to the socially optimal scenario, when digital platforms abuse their monopoly power by charging online restaurants exorbitant commission fees, it not only leads to a net loss in overall social welfare (Figure 11a), but the welfare gap also exhibits a U-shaped pattern, first decreasing and then increasing, as digital technology develops (Figure 11b). From the expression for social welfare $SW=\theta+Q_1(f,L^D)[aL^D-Q_1(f,L^D)+1+c]-\frac{1}{2}-c-F+\beta(1+ra)L^D-4\beta^2(1+ra)^2L_D^2$ and $aL^D=Q_1(f,L^D)$ under the equilibrium conditions, we know that during the development of digital technology, overall social welfare is mainly affected by two factors: First, how many consumers can benefit from the platform's targeted matching mechanism, i.e., $Q_1(f,L^D)$; and second, the net effect of worker welfare and labor costs $\beta(1+ra)L^D-4\beta^2(1+ra)^2L_D^2$.

In the early stage of digital technology development, the number of consumers ordering online is not large, and the welfare gap caused by platform monopoly pricing is not significant. At the same time, the marginal employment absorption effect of digital technology progress is very large, and a small improvement in the efficiency of targeted matching can create many jobs and improve worker welfare. Therefore, in the early stage of digital technology development, the improvement of technology level helps to narrow the welfare gap. However, when digital technology develops to a certain stage, not only does the gap between the actual number of online orders and the socially optimal level become larger, but the crowding-out effect of digital technology on labor employment also becomes more obvious. In this case, the improvement of digital technology level instead expands the gap in overall social welfare.

Building on the analysis presented in Figures 11a and 11b, Figure 11c decomposes the welfare gaps for different stakeholders. If digital platforms abuse their monopoly power, online restaurants face increasingly severe price distortions in commission fees as digital technology advances. These elevated fees then diminish restaurant profits through two primary channels: reduced order profit margins and weakened market competitiveness. Consequently, the welfare gap for online restaurants increases with the level of digital technology development. For consumers, the distorted commission fees prevent some potential online food delivery users from accessing the service, keeping them in the traditional offline market. This not only indicates that the cross-side network effect of the online market falls short of the socially optimal level but also reflects insufficient competition in the product market, resulting in welfare losses for both online and offline consumers. Therefore, the consumer welfare gap also increases with the level of digital technology development. Regarding workers (delivery riders), the employment gap caused by price distortions leads to both reduced job opportunities and lower wages compared to the socially optimal scenario, creating a welfare gap. This gap increasingly widens in the later stages of digital technology development (or the gig economy).

Extending the analysis of Figures 11a and 11b, Figure 11d examines the proportion of the overall social welfare gap attributable to different stakeholders, thereby identifying the primary sources of welfare loss. When digital technology is nascent, and consequently, the targeted assignment efficiency of digital platforms is low (approaching 0 on the x-axis of Figure 11d), workers experience the largest welfare gap. This is because, in the early stages of digital technology development, the benefits provided by digital platforms to online restaurants and consumers are limited. Consequently, the degree of commission fee distortion, and its negative impact on these groups, is also minimal. However, worker welfare, particularly job opportunities, is intrinsically linked to online order volume and targeted assignment efficiency. Therefore, even with low assignment efficiency, workers still face a substantial welfare gap. As digital technology advances and assignment efficiency improves (moving rightward on the x-axis of Figure 11d), the welfare gaps for online restaurants and consumers surpass that of workers. This shift occurs because, once digital technology reaches a certain stage of development, online restaurants and consumers become significantly more reliant on digital platforms. If platforms then exploit this dependence by increasing commission fees, it creates substantial welfare losses for these two groups. Thus, as digital technology matures, the overall social welfare gap increasingly concentrates among online restaurants and consumers.

Comparing the results in Figures 7 and 11 reveals that while the targeted matching mechanism does improve the welfare of online restaurants, consumers, and workers (Figure 7) when digital platforms engage in monopoly pricing, the extent of these welfare gains falls short of the socially optimal level (Figure 11). The policy implication is that governments should focus not only on the welfare levels of market participants (and the disparities in welfare levels among them) but also on the gap between participants' actual welfare levels and the welfare possibility frontier (the highest level achievable under ideal conditions), ensuring that market participants fully benefit from the dividends of digital technology development. The following discussion will address how governments can prevent incumbent platforms from abusing their monopoly power by ensuring platform contestability (or ease of entry).

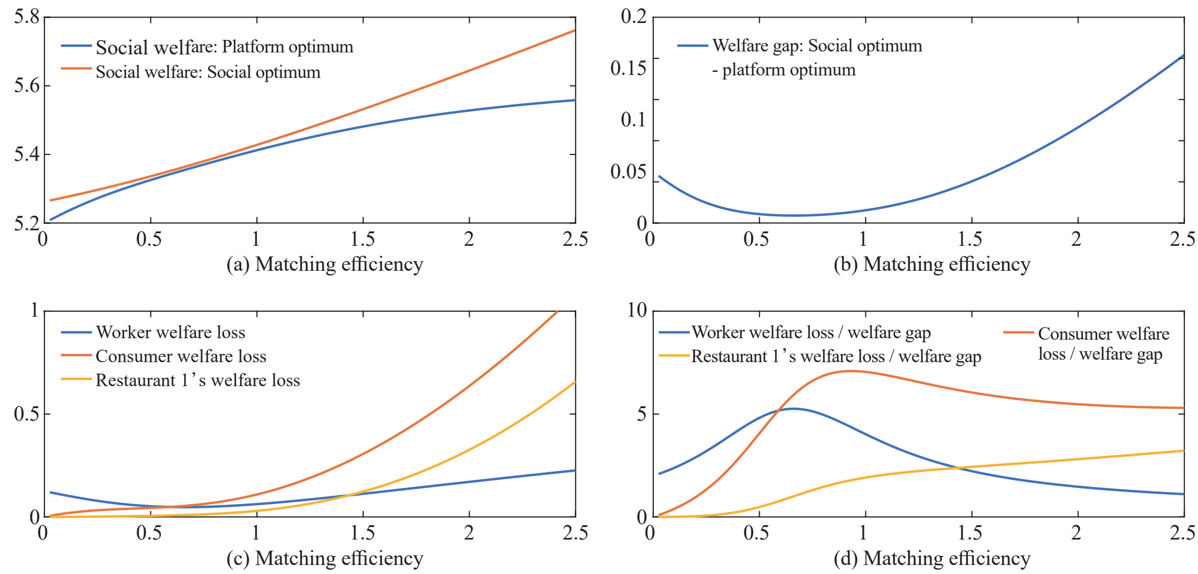

Figure 11: Monopolistic Platform and Social Welfare Loss

Note: Compiled by the authors. The parameter settings for the exogenous variables in the numerical simulation process are θ=6, c=0.2, β=1.2, r=0.1, F=0.1, a∈[0.2.5].

7. Contestable Market

This section explores how the government can mitigate the adverse effects of incumbent platform monopolies by fostering and influencing contestable markets. Here, a contestable market refers to a digital platform market with a potential entrant, denoted as E (hereinafter referred to as the "potential platform"), which can incur a cost to enter the market and compete with the incumbent platform for online restaurant partnerships. According to contestable market theory, the potential platform evaluates the profitability and feasibility of market entry based on the incumbent platform's pricing. Consequently, when the incumbent platform recognizes the competitive pressure from the potential entrant, it will proactively adjust its commission fees to deter market entry. Specifically:[19]

The strategic interaction between the incumbent platform and the potential entrant unfolds in two stages. In the first stage, the incumbent platform determines both its commission fee f and its labor employment level L. Crucially, to proactively mitigate competitive pressure, the incumbent considers not only its own profit maximization but also how its commission fee will influence the potential entrant's market entry decision. In the second stage, the potential entrant observes the incumbent's commission fee f and, based on this, assesses its maximum potential profit upon entering the market $\overline{E}_e$. This potential profit is then compared to the entry cost T to determine whether market entry is worthwhile[20]. Throughout this process, even if the potential entrant ultimately decides against entering the market, it must, given the incumbent's commission fee f, formulate a corresponding fee structure f_e^* to ensure its own profit maximization should it choose to enter. This can be represented as $f_e^*=argmax\, f_e$ $E_e[f_e, Q_e(f_e, f)]$, where $E_e[f_e, Q_e(f_e, f)]$ represents the potential entrant's profit, which is a function of the commission fee f_e and demand $Q_e(f_e, f)$[21]. Therefore, the potential entrant's maximum profit upon entering the market is $\overline{E}_e=E_e(f_e^* \backslash f)=E_e[f_e^*, Q_e(f_e^*, f)]$.

Based on the above assumptions, f_e^* represents the potential platform's optimal response given the incumbent platform's price level f, while $Q_e(f_e^*, f)$ represents the optimal response of online restaurants given specific commission fees f_e^* and f. Consequently, the potential platform's maximum profit upon market entry $\overline{E}_e$ is also a function of the incumbent platform's commission fee f. Furthermore, considering the framework of contestable market theory, the potential and incumbent platforms are engaged in a mutually substitutable competitive relationship within the digital platform market. The potential platform's demand and the incumbent platform's price level should satisfy $\frac{\partial Q_e(f_e^*, f)}{\partial f} > 0$, which can further demonstrate $\frac{\partial \overline{E}_e}{\partial f} > 0$[22]. Therefore, without loss of generality, the potential platform E's maximum profit upon market entry is denoted as $\overline{E}_e(f)$, where $\overline{E}_e'(f) > 0$.

7.1 Regulatory Effects of Contestable Markets

In a contestable market, an incumbent digital platform, when setting commission fees, considers

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[19] For a review of the assumptions and basic concepts of contestable market theory, see Zhang Hongfeng (2008), Lü Rongsheng et al. (2009), and other related studies.

[20] When $\overline{E}_e \le T$, potential platform E chooses not to enter the market; conversely, it would have entered.

[21] Once the potential platform enters the market, the online restaurant will evaluate its commission fees in comparison to those of the incumbent platform. Based on this comparison, the restaurant will determine the extent to which it will onboard onto the new platform. As a result, demand for the potential platform is influenced by both its own commission pricing and the pricing structure of the incumbent platform.

[22] It can be proven that when $\frac{\partial Q_e(f_e^*, f)}{\partial f} > 0$, $\frac{\partial \overline{E}_e}{\partial f} > 0$; and when $\frac{\partial Q_e(f_e^*, f)}{\partial f} < 0$, $\frac{\partial \overline{E}_e}{\partial f} > 0$. Relating this to the microeconomic definitions of complementary and substitute goods, if $\frac{\partial Q_e(f_e, f)}{\partial f} < 0$, it implies that the incumbent and potential platforms' products or services are complementary. However, contestable market theory focuses on the potential competitive relationship between incumbents and entrants, and therefore considers the case of substitutes. Consequently, the potential platform's profit upon market entry should increase with the incumbent platform's commission fee.

not only its own profit maximization but also how lowering those fees can deter potential platform entry. The incumbent platform's optimization problem can then be expressed as:

$$\max_{f,L^D} \pi_p = f \cdot Q_1(f, L^D) - w^*(L^D) \cdot L^D - F \tag{31}$$

$$s.t. \begin{cases} aL \geq Q_1 \\ \overline{E}_e(f) \leq T \end{cases} \tag{32}$$

Equation (31) represents the incumbent platform's profit function. The two constraints in Equation (32) are, respectively, the assignment condition ensuring that the labor market sufficiently meets product market demand, and the constraint preventing platform E from entering the market.

Let $\lambda_1 \geq 0$ and $\lambda_2 \geq 0$ be the Lagrange multipliers for the two constraints in Equation (32). Then, the Lagrangian function for the aforementioned optimization problem can be expressed as:

$$\max_{f,L^D} \mathcal{L} = f \cdot Q_1(f, L^D) - w^*(L^D) \cdot L^D - F + \lambda_1(aL^D - Q_1(f, L^D)) + \lambda_2[\mathrm{T} - \overline{E}_e(f)] \tag{33}$$

From the first-order conditions $\frac{\partial \mathcal{L}}{\partial f} = 0$, $\frac{\partial \mathcal{L}}{\partial L} = 0$, $\frac{\partial \mathcal{L}}{\partial \lambda_1} = 0$, and , $\frac{\partial \mathcal{L}}{\partial \lambda_2} = 0$, we can obtain:

$$\frac{\partial \mathcal{L}}{\partial f} = \frac{3 + c + aL - 2f}{6} + \frac{\lambda_1}{6} - \lambda_2 = 0 \tag{34}$$

$$\frac{\partial \mathcal{L}}{\partial L} = \frac{af}{6} - 8\beta^2 L(1 + ra)^2 + \frac{5a\lambda_1}{6} = 0 \tag{35}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_1} = \frac{5aL - 3 - c + f}{6} = 0 \tag{36}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_2} = \overline{E}_e^{-1}(T) - f = 0 \tag{37}$$

It is readily apparent that the incumbent platform will only adjust its commission fee pricing in response to potential competitive pressure when both Lagrange multipliers satisfy $\lambda_1 > 0$ and $\lambda_2 > 0$. Therefore, a prerequisite for government regulation of commission fees through contestable markets is that the entry cost to the platform market cannot be excessively high, specifically $\overline{E}_e^{-1}(T) \leq \min \left\{ \frac{(3+c) \cdot [8\beta^2(1+ra)^2 + 5a^2]}{8\beta^2(1+ra)^2 + 10a^2}, \frac{(3+c) \cdot 8\beta^2(1+ra)^2}{8\beta^2(1+ra)^2 + \frac{5}{6a^2}} \right\}$. Otherwise, regardless of whether the incumbent platform's commission fee is high or low, potential entrants will invariably be deterred by the prohibitively high entry barrier, precluding any competitive threat to the incumbent.

When the potential entrant's entry cost meets the aforementioned requirement, the equilibrium commission fee and labor employment volume are:

$$f^c = \overline{E}_e^{-1}(T) \tag{38}$$

$$L^c = \frac{3 - \overline{E}_e^{-1}(T) + c}{5a} \tag{39}$$

Equation (39) demonstrates that $\frac{\partial f^c}{\partial T} > 0$, indicating that lower entry costs for potential entrants are conducive to reducing the commission fees charged to online restaurants by incumbent platforms (Figure 12). The rationale behind this is that when the platform market is contestable, the incumbent platform must lower its commission fees to deter potential entry, ensuring that platform E cannot obtain sufficient profit to offset its entry costs should it choose to enter. Furthermore, the lower the entry cost for platform E, the greater the potential competitive pressure faced by the incumbent platform, incentivizing it to reduce commission fees even further.

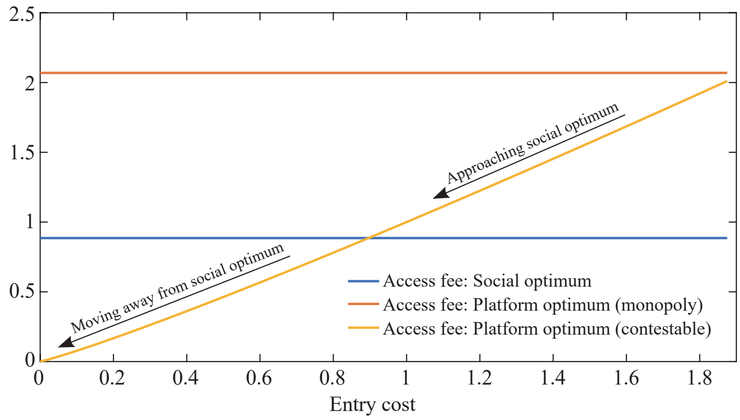

Figure 12: Impact of Entry Costs on Commission Fees

Note: Compiled by the authors. The parameter settings for the exogenous variables in the numerical simulation process are θ=6, c=0.2, β=1.2, r=0.1, F=0.1, a∈[0.2.5].

7.2 The Optimal Entry Cost

Furthermore, if the entry cost to the platform market is too low, the commission fees set by the incumbent platform in response to potential competition will fall below the socially optimal level (see the region to the left of the x-axis in Figure 12). While this may attract more consumers to order food online, it intensifies the platform's labor employment cost pressures, potentially leading to new welfare losses. Therefore, an optimal entry cost T^C exists such that the commission fees charged by the digital platform to online restaurants precisely meet the socially optimal requirement, thereby maximizing social welfare. This optimal entry cost is the one that satisfies $\overline{E}_e^{-1}(T^C) = f^{FB} = 3 + c - \frac{5a[\beta(1+ra)+a(1+c)]}{8\beta^2(1+ra)^2}$.

Figure 13 further simulates the comparative static relationship between T^C, targeted matching efficiency a, and labor risk r. The results indicate that, holding other conditions constant, as the level of digital technology (the gig economy) increases, or in gig industries with lower labor risk, governments have a greater need to reduce entry costs to platform markets to strengthen market contestability, as shown by $\frac{\partial T^C}{\partial a} < 0$ and $\frac{\partial T^C}{\partial r} > 0$. This is because, as digital technology advances and drives improvements in targeted assignment efficiency, the gig economy's dependence on digital platforms increases, correspondingly increasing the potential risk of monopoly. Therefore, the necessity of establishing contestable markets also increases. Furthermore, in gig industries with lower per-unit labor risk, it is important to encourage more participation from underutilized labor. To achieve this, governments must strengthen the contestability of platform markets to mitigate the negative impact of commission fee distortions on job creation. The above conclusions can be summarized as Proposition 3.

Proposition 3: When governments utilize contestable markets to prevent digital platforms from abusing their monopoly power, the entry cost to platform markets should be neither too low nor too high, but rather at an optimal level T^C.

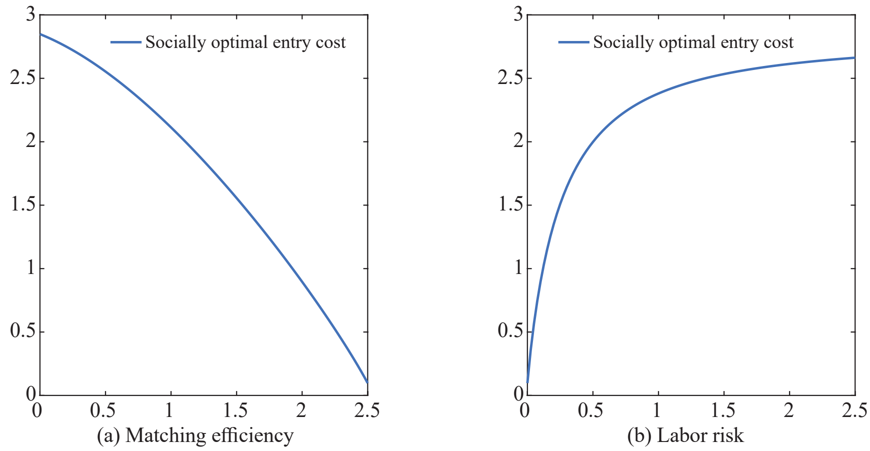

Figure 13: The Optimal Entry Cost

Note: Compiled by the authors. The parameter settings for the exogenous variables in the numerical simulation are θ=6, c=0.2, β=1.2, r=0.1, F=0.1, a∈[0.2.5].

8. Further Analysis: Endogenous Digital Platform Technology Investment

The preceding analysis, assuming exogenously determined targeted assignment efficiency (or, equivalently, that digital platforms have limited ability to influence assignment efficiency), explored the potential harms of platform monopolies and the regulatory effects of contestable markets. Building on this foundation, this section examines how the incumbent platform's technology investments, relative to the socially optimal level, change when platforms achieve a level of R&D capability that allows them to endogenously choose targeted matching efficiency and corresponding technology investments, i.e., endogenous . This analysis considers two distinct market structures: closed and contestable.

8.1 Technology Investment under Monopoly

This subsection compares technology investment decisions driven by platform profit maximization versus those driven by social welfare maximization, assuming a closed platform market. The respective optimization problems correspond to Equations (18) and (26) in the baseline model. However, the key difference here is that, when digital platforms can endogenously choose targeted assignment efficiency, R&D costs are no longer fixed but become a function of the chosen assignment efficiency $F=F(a)$. Furthermore, to capture the characteristic of R&D costs increasing and marginally increasing with the level of technology investment, we assume $F(a)=\frac{1}{2}ha^2$, where h>0.

Substituting $F(a)=\frac{1}{2}ha^2$ into Equations (18) and (26), and solving the resulting optimization problems, yields the first-order conditions for platform profit maximization and social optimality:

$$\frac{(3+c)^2 8\beta^2(1+ra)a}{[\beta^2(1+ra)^2+10a^2]^2}-ha=0 \tag{40}$$

$$\frac{\beta(1+ra)+a(1+c)}{8\beta^2(1+ra)^2}\times\frac{1+c}{1+ra}-ha=0 \tag{41}$$

Comparing the equilibrium solutions from Equations (40) and (41) reveals that when the platform market is closed, allowing digital platforms to abuse their monopoly power, their R&D investment in targeted matching mechanisms can be either insufficient or excessive, as detailed below:

The numerical simulation in Figure 14 illustrates that when digital platforms exploit their monopoly position, they tend to under-invest in technology when labor risk is low and over-invest when labor risk is high. From a social welfare perspective, while targeted matching mechanisms can enhance job creation, they also increase workers' labor risk *r*, particularly when the per-unit labor risk coefficient is high. Therefore, digital platforms should reduce R&D investment in targeted matching mechanisms when labor risk is high and only pursue significant investment in technology development when labor risk is low.

However, digital platforms focus primarily on how labor risk affects workers' willingness to engage. When the per-unit labor risk coefficient is high, workers' willingness to work decreases. To attract workers to food delivery, platforms must boost R&D investment in targeted matching mechanisms, ensuring that riders' delivery volumes per unit of time are sufficiently large. This increased job availability and higher income potential help improve workers' willingness to participate. On the other hand, when the per-unit labor risk coefficient is low, workers are more willing to work. In such cases, even without increased R&D investment, the platform can still attract workers to the gig economy of food delivery. Consequently, the platform lacks the internal incentive to invest heavily in technology, leading to under-investment.

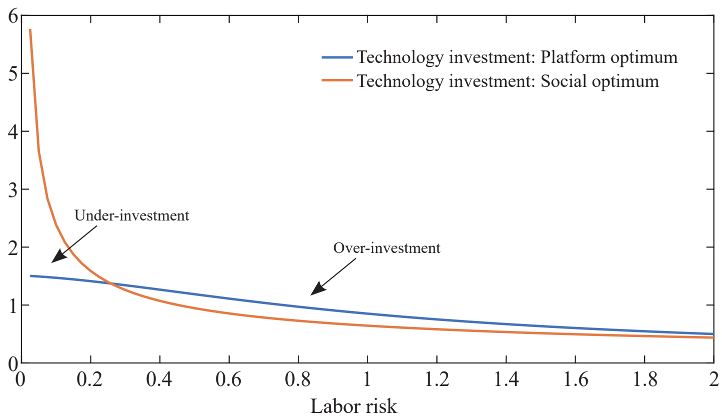

Figure 14: Platform Monopoly and Technology Investment: Influence of Labor Risk

Note: Compiled by the authors. The parameter settings for the exogenous variables in the numerical simulation are θ=6, c=0.2, β=1.2, h=0.1, r∈[0.025.2].

The numerical simulation in Figure 15 shows that when digital platforms exploit their monopoly power, they tend to under-invest in R&D when costs are either very low or very high, but over-invest when costs are at an intermediate level. From a social welfare perspective, to maximize the economic benefits of targeted matching mechanisms—especially in terms of efficiency gains and job creation—while keeping costs manageable, digital platforms should increase their investment in such mechanisms when R&D costs are low.

However, from the platform's standpoint, even though lower R&D costs for targeted matching mechanisms can significantly enhance social welfare, the platform's incremental profit represents only a small fraction of these welfare gains. As a result, the platform has little incentive to invest in these mechanisms. On the other hand, when R&D costs are exceptionally high, digital platforms face significant cost pressures, which result in under-investment in targeted matching mechanisms, falling short of the socially optimal level.

When R&D costs are neither too high nor too low, digital platforms can both afford the investment and shift part of the cost burden to online restaurants and consumers by increasing commission fees. Under these conditions, the platform's technology investment in targeted matching mechanisms tends to exceed the socially optimal level.

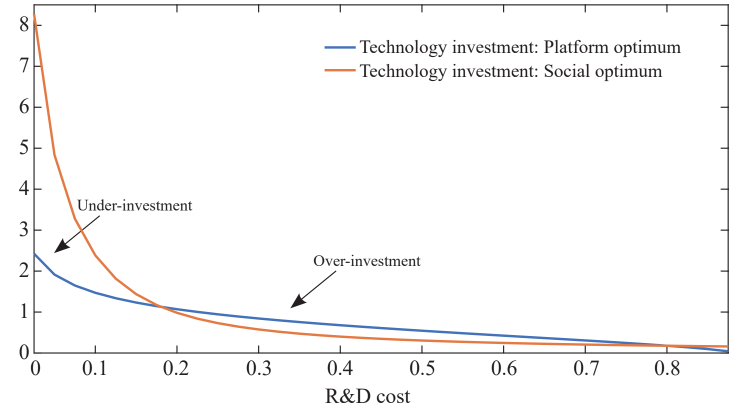

Figure 15: Platform Monopoly and Technology Investment: Influence of R&D Costs

Note: Compiled by the authors. The parameter settings for the exogenous variables in the numerical simulation are θ=6, c=0.2, β=1.2, r=0.1, h∈[0.025.0.875].

The numerical simulation in Figure 16 shows that when digital platforms exploit their monopoly power, they tend to over-invest in R&D when competitors' customer acquisition costs are low, and under-invest when those costs are high. From a social welfare perspective, platforms should focus on developing targeted matching mechanisms when offline restaurants' customer acquisition costs c are high. This would not only improve the efficiency of traditional restaurant services and create new job opportunities but also generate more profit for both platforms and online restaurants. On the other hand, when offline restaurants' customer acquisition costs are low, the potential for improving traditional restaurant services is limited, and platforms should scale back their R&D investment in targeted matching mechanisms to save on development costs.

However, platforms' actual behavior diverges from this socially optimal strategy. When offline restaurants' customer acquisition costs are low, competition between online and offline restaurants intensifies. To secure higher commission revenue, digital platforms tend to over-invest in digital technologies to help online restaurants gain a competitive edge. Conversely, when offline restaurants' customer acquisition costs are high, reducing platforms' R&D investment does not substantially harm the competitive advantage of online restaurants. In this case, platforms lack the incentive to aggressively develop targeted matching mechanisms, leading to under-investment.

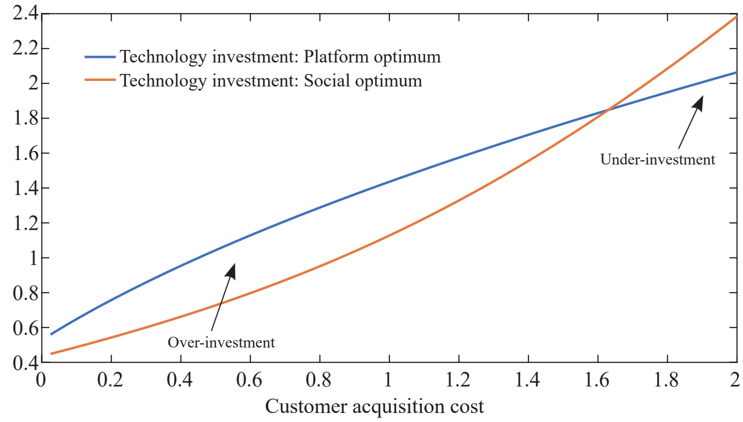

Figure 16: Platform Monopoly and Technology Investment: Influence of Customer Acquisition Costs

Note: Compiled by the authors. The parameter settings for the exogenous variables in the numerical simulation are θ=6, β=1.2, r=0.1, h=0.1, c∈[0.025.2].

8.2 Optimal Entry Cost under Endogenous Technology Investment

Next, consider the technology investment of digital platforms in contestable markets. The digital platform's optimization problem is consistent with Equation (33), and the corresponding first-order conditions are:

$$\frac{f^C L^C}{6} - 8\beta^2(1+ra)[L^C]^2\frac{3-\overline{E}_e^{-1}(T)+c}{a}\lambda_1 - ha = 0 \tag{42}$$

In Equation (42), $f^C = \overline{E}_e^{-1}(T)$, $L^C = \dfrac{3-\overline{E}_e^{-1}(T)+c}{5a}$, $\lambda_1 = \dfrac{8\beta^2(1+ra)^2}{25a^2}(3+c) - \left[\dfrac{8\beta^2(1+ra)^2}{25a^2} + \dfrac{1}{30}\right]$ $\overline{E}_e^{-1}(T)$.

Figure 17 simulates the first-order derivative of Equation (33) with respect to a under varying entry costs T. The intersection points of the resulting curves with the 0-axis represent the optimal technology investment levels. The results show that as entry costs decrease (corresponding to the curves shifting upwards in Figure 17), the digital platform's technology investment approaches the socially optimal level (corresponding to the intersection points gradually approaching the black solid dot representing the social optimum in Figure 17). However, once entry costs fall below a certain threshold, further reductions in platform market entry costs actually cause the digital platform's technology investment to deviate from the social optimum again (the rightmost intersection point in Figure 17 moves away from the black solid dot). Therefore, when governments attempt to mitigate the negative consequences of platform monopolies by fostering contestable markets, entry costs should be neither too low nor too high, but rather maintained within a moderate range.

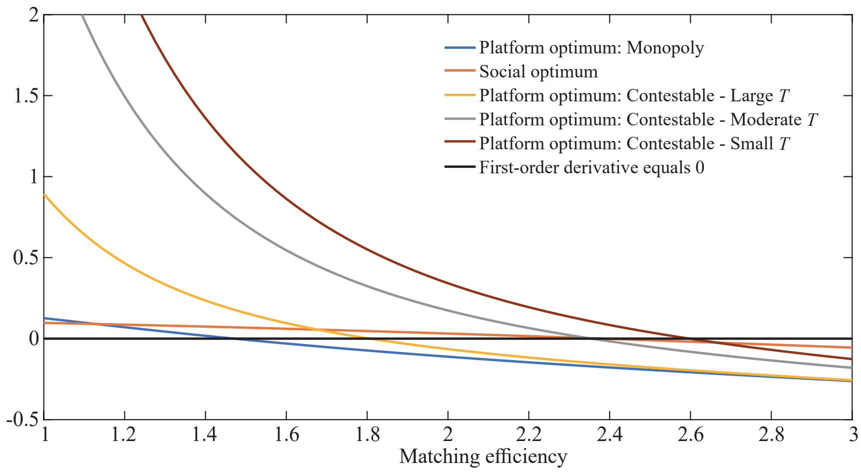

Figure 17: Impact of Entry Costs on Technology Investment

Note: Compiled by the authors. The parameter settings for the exogenous variables in the numerical simulation are θ=6, c=0.2, β=1.2, r=0.1, h=0.1.

Figure 18 illustrates the comparative static relationships between entry costs T^C, labor risk r, and R&D costs h. The findings indicate that, holding other factors constant, entry costs rise as both the per-unit labor risk coefficient r and R&D costs h increase. When the per-unit labor risk coefficient is low, the government does not need to be overly concerned about the potential risks of digital control. Additionally, when R&D costs for targeted matching mechanisms are low, the government can harness these mechanisms to enhance the efficiency and job creation in the traditional economy at a reduced cost, making significant technology development feasible. In these scenarios, the optimal government strategy is to reduce entry costs in the platform market. This, in turn, forces platforms to lower their commission fees, thereby encouraging expansion in the online food ordering market through technological innovation to discover new revenue sources.

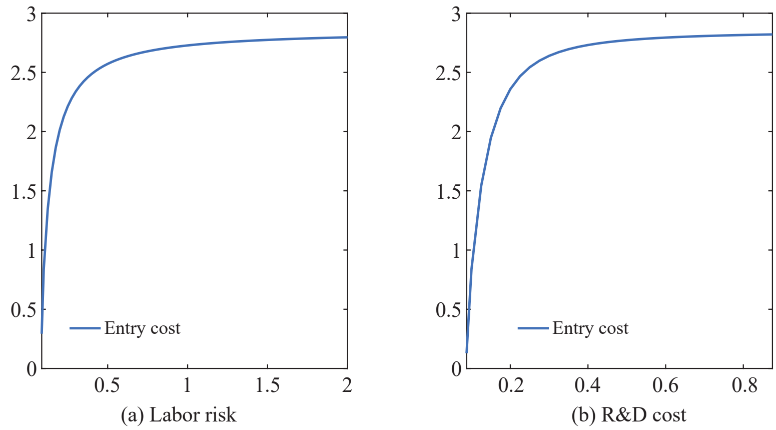

Figure 18: Determinants of the Optimal Entry Cost

Note: Compiled by the authors. In the numerical simulation for the left panel, the parameter settings for the exogenous variables are θ=6, c=0.2, β=1.2, h=0.1, r∈[0.025.2]. In the numerical simulation for the right panel, the parameter settings for the exogenous variables are θ=6, c=0.2, β=1.2, r=0.1, h∈[0.025.0.875]

9. Extended Discussion

This section extends the discussion on how to fully utilize the job-creation function of digital platforms by integrating the theoretical model of this paper with the government's regulatory documents on the gig economy.

9.1 Commission Fees

A fundamental prerequisite for safeguarding the labor rights of gig workers is ensuring they receive reasonable compensation. However, in practice, some digital platforms impose exorbitant commission rates on gig workers, resulting in actual earnings far below the service fees nominally paid by consumers. To address this issue, governments are mandating that platforms establish reasonable commission rates and publicly disclose their pricing rules.

Our theoretical model provides two key insights into why governments should regulate the commission fees charged by digital platforms. First, while the previous model focused primarily on the commission fees platforms charge online restaurants, rather than gig workers, it demonstrated the negative effects of commission fees on labor employment and wages. Specifically, even without accounting for the commissions taken from delivery riders, the model showed that monopoly pricing of commission fees by platforms would decrease the attractiveness of online ordering for consumers, ultimately leading to fewer job opportunities for gig workers. This highlights the importance of regulating not only the commissions that platforms charge workers but also those levied on merchants, in order to fully protect the labor rights of platform employees.

Second, future research could expand on this model to further investigate the potential impact of wage commissions. Specifically, if the model were to account for the commission rates that digital platforms charge workers, riders' nominal wages would appear higher than their actual earnings. The effect of these commission rates on worker welfare hinges on whether workers have rational expectations about the commission structure. If workers can accurately anticipate the commission rate, they will base their labor supply decisions on their real earnings, leading to no significant changes in labor supply or welfare. However, if workers are unaware of or misunderstand the commission rules, they may fall victim to a "wage illusion" — perceiving inflated nominal wages and, as a result, increasing their labor supply. This could lead to a reduction in their real wages and expose them to the risk of overwork. This highlights why governments require digital platforms to publicly disclose commission structures.

Transparency is essential to avoid the welfare losses caused by wage illusion.

If the model includes the commission rate that digital platforms charge workers, riders' nominal wages will appear higher than their actual earnings. The effect of the commission rate on worker welfare depends on whether workers have rational expectations about these commission rules. If workers can anticipate the platform's commission rate, they will base their labor supply decisions on their actual take-home pay. In this case, their willingness to work will remain relatively unchanged, and no significant welfare loss will occur.

However, if workers are unaware of the commission rules, they may be subject to the "wage illusion" of inflated nominal wages and increase their labor supply. This can result in a reduction in their real wages due to increased labor supply, and they may also face the risk of overwork. This highlights the importance of government regulations requiring digital platforms to disclose their commission rates to workers. Transparency in this regard helps prevent welf`are losses caused by wage illusion.

9.2 Labor Insurance

Unlike traditional fixed employment, which is protected by a social insurance system, such as unemployment insurance and work injury insurance, workers in the digital platform economy—like food delivery riders and ride-hailing drivers—generally lack adequate occupational safety and security. This is partly due to the fact that gig employment does not fully fit within the traditional social insurance framework. Additionally, digital platforms often lack the incentive to provide social insurance for their workers. In this context, macro-level policies propose the creation of a comprehensive social insurance system tailored to the characteristics of new forms of employment, while also encouraging digital platforms to implement an "insurance for all" system.

The theoretical model in this paper also applies to discussions on the necessity and feasibility of labor insurance. Regarding necessity, the model illustrates how labor risk affects the labor market by reducing workers' willingness to supply labor. To attract gig workers, digital platforms must raise wages, which in turn increases labor costs. This discourages platforms from hiring a large workforce, limiting their job creation potential.

As for feasibility, when digital platforms mitigate labor risk by providing insurance, their unit labor costs shift from solely wage expenses to a combination of wages and insurance costs. While platforms may worry about increased operational expenses, reducing labor risk actually boosts workers' willingness to participate, making recruitment easier. If labor insurance costs remain manageable, the total unit labor cost—including insurance—will be lower than operating without it, incentivizing platforms to hire more riders for food delivery services.

Moreover, as consumers anticipate a larger delivery workforce, cross-side network effects further drive demand for online food orders, creating additional job opportunities. In short, when labor insurance costs are controlled, digital platforms are more likely to offer coverage for food delivery riders, enhancing both workforce participation and the job creation benefits of targeted matching mechanisms.

9.3 Algorithm Governance

Digital platforms rely on targeted matching between consumers and workers, using precise control and algorithmic management that grants them a level of authority over workers exceeding that of traditional fixed employment. For example, platforms calculate estimated delivery times based on factors such as distance and order time, then impose rewards and penalties on delivery drivers based on their on-time delivery rates. While this system is designed to improve efficiency and reduce consumer wait times, the platforms' control over algorithmic rules—combined with their opacity—allows them to enforce stringent conditions that compress delivery times.

As a result, while platforms meet consumer demand for instant meal services, they also trap delivery drivers in an invisible cage of time constraints. Some drivers, under pressure to meet these demands, are even forced to resort to risky behaviors, such as violating traffic rules.

To prevent digital platform employment from being dictated entirely by algorithms, greater focus is needed on algorithmic governance. Feasible measures include clarifying fairness and compliance in algorithm design, holding platforms accountable for the negative consequences of unreasonable algorithmic designs, and protecting workers' rights to be informed about and to refuse algorithmic rules.

10. Concluding Remarks

As a prime example of the deep integration between digital technology and the real economy, the gig economy—anchored in digital platforms—has not only revolutionized traditional economic activities but also emerged as a catalyst for new professions, labor absorption, and socio-economic progress. This paper develops a theoretical model of the gig economy, incorporating digital platforms, online and offline sellers, workers, and consumers, to examine the internal mechanisms through which digital platforms generate large-scale employment. Additionally, it explores the evolving trends in worker welfare across various stages of the gig economy's development.

This paper finds that the key to digital platforms' sustained job creation lies in their unique targeted matching mechanism. Unlike traditional platforms that primarily act as intermediaries for information and transactions, digital platforms leverage their ability to precisely identify supply and demand information to actively manage worker allocation. Instead of workers or consumers determining service recipients, the platform itself makes these decisions.

This digital technology-driven, platform-centered, and highly targeted matching method maximizes the continuity of labor services while amplifying the cross-side network effects of the platform economy. It plays a crucial role in fostering new occupations, expanding employment opportunities, and enhancing worker welfare.

However, the study also reveals that the relative balance between job creation and job displacement shifts at different stages of gig economy development. In later stages, if dominant platforms exploit their market power to impose monopolistic pricing, gig employment opportunities may stagnate or even decline. This could further exacerbate income inequality between platforms and workers, undermining the long-term benefits of digital platform employment.

Based on the findings of this paper, the following policy recommendations are proposed:

First, uphold the principle of "technological neutrality" to continuously advance digital technology, support the sustainable development of the gig economy, and closely monitor the evolving impact of digital platforms on job creation and overall social welfare distribution. The employment-generating potential of digital platforms relies on an efficient targeted matching mechanism. To maximize their role in stabilizing and expanding employment, it is essential to strengthen fundamental digital research, achieve breakthroughs in core technologies, optimize algorithms, and enhance computing power.

In particular, for globally optimized targeted matching, digital platforms must not only model the dynamic spatial distribution of consumers and workers and account for behavioral uncertainties but also develop algorithmic systems for dynamic path planning, global optimization, and batch matching. Furthermore, to enable digital platforms to access the foundational data necessary for precise matching, the government may selectively open or permit the collection and use of certain user data under strict data security and privacy protection measures.

However, it is important to recognize that the impact of digital technological advancements on employment varies across different stages of gig economy development. Additionally, different market participants may not equally or fully benefit from technological progress. Therefore, government regulation of digital platforms in the gig economy should focus on two key aspects: first, the relative welfare levels of different market participants, and second, the extent to which each participant's actual welfare level aligns with the socially optimal level. Ensuring both the fairness and adequacy of welfare distribution should be a priority.

Second, in light of the principle of adapting to specific conditions and times, contestability of the platform market should be maintained within a reasonable range to ensure that workers fully benefit from the digital dividends created by the deep integration of digital and real economies.

This study finds that if platform market entry barriers are too high—eliminating contestability—the job creation potential of digital platforms cannot be fully realized. In particular, as digital technology advances and the gig economy reaches a certain scale, job growth may shift from expansion to gradual decline, leaving some workers unemployed. However, this decline is not due to a lack of opportunities in the gig economy itself but rather the monopolistic practices of incumbent platforms.

To ensure that gig economy employment continues to grow in step with digital progress, the government should regulate platform market entry thresholds based on industry-specific labor risks, the complexity of targeted matching mechanisms, and other relevant factors.

On one hand, enhancing digital infrastructure, promoting the research and diffusion of general-purpose digital technologies, and expanding digital talent training can help lower excessive entry barriers. These measures can also prevent incumbent platforms from engaging in “killer acquisitions” to eliminate potential competitors.

On the other hand, entry requirements should not be too lenient (e.g., overly relaxed qualification reviews), as this could encourage incumbent platforms to maintain their dominance through predatory pricing rather than through technological innovation and business model improvements. Such practices could ultimately harm gig workers, online merchants, consumers, and other stakeholders by leading to new welfare losses.

Third, it is crucial to recognize the evolving nature of the labor-employment relationship in the digital economy and further enhance the labor rights protection system. In the current digital gig economy, this relationship exhibits two key characteristics:

(1) Digital platforms continuously collect and monitor worker data in an all-encompassing, real-time, and end-to-end manner. While this is essential for efficient targeted matching, it also raises concerns about algorithmic capture. To prevent issues such as the misalignment between labor intensity and income, or between labor risk and protection due to algorithmic control, it is necessary to establish a comprehensive algorithm governance system. This should include safeguarding workers’ rights to transparency and refusal of algorithmic rules, granting them greater autonomy and control, and ensuring algorithmic fairness and compliance.

(2) Gig economy employment is characterized by short-term, non-contractual work, offering flexibility and convenience. However, this model also limits workers’ career development opportunities and makes it difficult for some to access essential social security and insurance benefits available to formal employees. To address these challenges, vocational training, pension schemes, and medical insurance programs for gig workers should be strengthened. Enhancing these protections will encourage greater participation in the gig economy while maximizing its job creation potential and cross-side network effects.

References:

Acemoglu D., Restrepo P. Artificial Intelligence, Automation, and Work in the Economics of Artificial Intelligence: An Agenda[J]. NBER Working Paper, 2018.

Acemoglu D., Restrepo P. Robots and Jobs: Evidence from US Labor Markets[J]. Journal of Political Economy, 2020(6): 2188-2244.

Armstrong M. Competition in Two-Sided Markets[J]. RAND Journal of Economics, 2006(3): 668-691.

Armstrong M., Wright J. Two-Sided Markets, Competitive Bottle Necks and Exclusive Contracts[J]. Economic Theory, 2007(2): 353-380.

Barlow M. A., Verhaal J. C., and Angus R. W. Optimal Distinctiveness, Strategic Categorization, and Product Market Entry on the Google Play App Platform[J]. Strategic Management Journal, 2019(8): 1219-1242.

Barrios J. M., Hochberg Y. V., Yi H. Launching with a Parachute: The Gig Economy and New Business Formation[J]. Journal of Financial Economics[J], 2022(1): 22-43.

Besen S. M., Farrell J. Choosing How to Compete: Strategies and Tactics in Standardization[J]. Journal of Economic Perspectives, 1994(2): 117-131.

Bogliacino F., Codagnone C., Cirillo V. et al. Quantity and Quality of Work in the Platform Economy[J]. Working Paper, 2020.

Cai C., Yan J. J., Cai Y. W. Tax Policy Applications and Tax Governance Strategies of a Gig Economy[J]. Taxation Research, 2022(2): 72-80.

Caillaud B., Jullien B. Chicken & Egg: Competition Among Intermediation Service Providers[J]. RAND Journal of Economics, 2003(2): 309-328.

Chen D., Qin Z. Y. Artificial Intelligence and Inclusive Growth: Evidence from International Robot Data[J]. Economic Research Journal, 2022(4): 85-102.

Chen L. Labor Order under Digital Control: A Study on the Labor Control of Take-out Platform Riders[J]. Sociological Studies, 2020 (6): 113-135.

Chen W. Theoretical Construction of Employment Relationship Governance on Internet Platform: Comparison and Reflection of Three Theoretical Perspectives[J]. Social Science, 2021(10): 80-86.

Cheng G. S., Sun W. J. A Study on Operating Mechanism and Regulation of Bankcard Industry[J]. Studies of International Finance, 2006(1): 39-46.

Doucette M. H., Bradford W. D. Dual job holding and the gig economy: Allocation of Effort across Primary and Gig Jobs[J]. Southern Economic Journal, 2019(4): 1217-1242.

Evans D. S. Some Empirical Aspects of Multi-Sided Platform Industries[J]. Review of Network Economics, 2003(3): 191-209.

Evans D. S., Schmalensee R. Matchmakers: The New Economics of Multisided Platforms[M]. Boston, Harvard Business Review Press, 2016.

Farrell J., Klemperer P. Coordination and Lock-In: Competition with Switching Costs and Network Effects[J]. Handbook of Industrial Organization, 2007(6): 1967-2072.

Friedman G. Workers without Employers: Shadow Corporations and the Rise of the Gig Economy[J]. Review of Keynesian Economics, 2014(2): 171-188.

Fudenberg D., Tirole J. Preemption and Rent Equalization in the Adoption of New Technology[J]. Review of Economic Studies, 2000(3): 383-401.

Gandini A. Labour Process Theory and the Gig Economy[J]. Human relations, 2019(6): 1039-1056.

Garud R., Kumaraswamy A., Roberts A., Xu L. Liminal Movement by Digital Platform Based Sharing Economy Ventures: The Case of Uber Technologies[J]. Strategic Management Journal, 2022(3): 447-475.

Guo C. X. The Trends, Characteristics, and Effects of Industrial Organization Evolution in the Digital Economy Era[J]. Chinese Rural Economy, 2023(10): 2-25.

Helfat C. E., Raubitschek R. S. Dynamic and Integrative Capabilities for Profiting from Innovation in Digital Platform Based Ecosystems[J]. Research Policy, 2018(8): 1391-1399.

Ji H. L. Research of Pricing Mode of Two-sided Markets[J]. Industrial Economics Research, 2006(4): 11-20.

Kaine S., Josserand E. The Organisation and Experience of Work in the Gig Economy[J]. Journal of Industrial Relations, 2019(4): 479-501.

Katz M. L., Shapiro C. Systems Competition and Network Effects[J]. Journal of Economic Perspectives, 1994(2): 93-115.

Khanagha S., Ansari S., Paroutis S., and Oviedo L. Mutualism and the Dynamics of New Platform Creation: A Study of Cisco and Fog Computing[J]. Strategic Management Journal, 2022(3): 476-506.

Kost D., Fieseler C., Wong S. I. Boundaryless Careers in the Gig Economy: An Oxymoron? [J]. Human Resource Management Journal, 2020(1): 100-113.

Li L. X., Zhou L. S. Platform Economy, Labor Market, and Income Distribution: Recent Trend and Policy Options[J]. International Economic Review, 2022(2): 46-59.

Liu J. P. Dual Model of Enterprise Growth: The Platform for Growth and Its Internal Mechanism[J]. China Industrial Economics, 2015(6): 148-160.

Lu W. G., Zhang X. Z. The Method for Defining the Abuse of Market Dominance in Two-sided Market: The Monopoly Case of Broadband in China[J]. China Industrial Economics, 2014(2): 122-134.

Lyu R. S., Luo Y., Chen J. Competitive Market Theory and Regulation of Natural Monopoly Industries in China[J]. Economic Perspectives, 2009(9): 49-52.

Mantena R., Sankaranarayanan R., Viswanathan S. Platform-Based Information Goods: The Economics of Exclusivity[J]. Decision Support Systems, 2010(1): 79-92.

Mas A., Pallais A. Alternative Work Arrangements[J]. Annual Review of Economics, 2020(12): 631-658.

Mo Y. Q., Li L. X. Gig Economy and Entrepreneurship: Evidence from the Entry of Food Delivery Platforms[J]. Management World, 2022(2): 31-45.

Panico C., Cennamo C. User Preferences and Strategic Interactions in Platform Ecosystems[J]. Strategic Management Journal, 2022(3): 507-529.

Rahman H. A. The Invisible Cage: Workers' Reactivity to Opaque Algorithmic Evaluations[J]. Administrative Science Quarterly, 2021 (4): 945-988.

Rochet, J. C., Tirole J. Platform Competition in Two-Sided Markets[J]. Journal of the European Economic Association, 2003(4): 990-1029.

Roson R., Two-Sided Markets: A Tentative Survey[J]. Review of Network Economics, 2005(2): 142-160.

Rysman M., The Economics of Two-Sided Markets[J]. Journal of Economic Perspectives, 2009(3): 125-143.

Stefano V. D. The Rise of the 'Just-In Time Workforce': On Demand Work, Crowdwork, and Labor Protection in the Gig Economy[J]. Comparative Labor Law and Policy Journal, 2016(3): 461-471.

Sun Z.,Yang S., Huo F. Y. Tax Administration of the Internet Gig Economy: Theory, Logic and Prospect[J]. Public Finance Research, 2022(2): 118-129.

Tang F. C.,Chi K. P. Research on Pricing Strategy of Online Group Buying in Two-sided Network[J]. Chinese Journal of Management Science, 2013(3): 185-192.

Wang X. H., Zhang Q. L. The Construction of the E-commerce Platform Reputation: From the Perspective of the Value Co-creation between Platform Enterprise and Sellers[J]. China Industrial Economics, 2017(11): 174-192.

Wang Z. H., Xin Z. H. The Effects of the Platform Matching Technique upon Pricing of Two- sided Markets[J]. Journal of Beijing Institute of Technology (Social Science Edition): 2008(3): 57-60.

Warren T., Work–Life Balance and Gig Work: 'Where are We Now' and 'Where to Next' with the Work-Life Balance Agenda?[J]. Journal of Industrial Relations, 2021(4): 522-545.

Wright J. One-Sided Logic in Two-Sided Markets[J]. Review of Network Economics, 2004 (1): 44-64.

Xia Z. X., Ding S. H. Redefining Digital Platform Work: Labor Relations or Partnership? Insights from Survey Data[J]. Comparative Economic and Social Systems, 2024(1): 107-116.

Xiao H. J. Responsible Platform Leadership: Structural Governance of Platform Value Co-destruction[J]. China Industrial Economics, 2020(7): 174-192.

Xiao Z. Theoretical Explanation and System Construction of Subordination Criteria for Labor Relationship Identification[J]. Legal Science Monthly, 2021(2): 160-176.

Xu L., Chen H. M., Pan X J. Consumer Multi party Holding Behavior and Compatibility Selection of Manufacturers: A Discussion Based on the Bilateral Market Theory[J]. World Economics, 2006(12): 28-40.

Zhang H. F. Governance of Natural Monopoly Industries: A Perspective Based on Competition Theory under Regulatory Framework[J]. Economic Review, 2008(1): 93-99.

Zhen Y. K. Research on New Policy of Ride-hailing Regulations[J]. China Industrial Economics, 2017(8): 81-99.

Zhu X. H., Chen H. S., Zhang T. Effectiveness of the Front-line Regulation of the Chinese Stock Exchanges: Evidence from Comment Letters[J]. Management World, 2019(3): 142-156.