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**Nonparametric Estimation of Matching Efficiency and
Elasticity in a Spot Gig Work Platform: 2019–2023**

Hayato Kanayama
Waseda University

Suguru Otani
University of Tokyo

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Abstract

This paper provides new evidence on spot gig work platforms for unemployed workers searching for occupations with minimal educational or experience requirements in Japan. Using proprietary data from a private online spot work matching platform, Timee, it examines trends in key variables such as the numbers of unemployed users, vacancies, hires, and labor market tightness. The study compares these trends with part-time worker data from the public employment platform, Hello Work. The private platform shows a significant market expansion from December 2019 to December 2023. Applying a novel nonparametric approach, the paper finds greater variability in efficiency and higher elasticity, with elasticity with respect to the number of users fluctuating from below 0.7 to above 1.5, and elasticity with respect to the number of vacancies often exceeding 1.0, which is higher than Hello Work. Lastly, the study highlights less geographical heterogeneity of the spot work compared to Hello Work.

Keywords: matching function, matching efficiency, matching elasticity, gig worker, spot work

JEL code: E24, J61, J62, J64

1 Introduction

The gig economy, characterized by temporary, contract, and freelance online jobs rather than permanent positions, has experienced rapid growth in recent years. An increasing proportion of freelance workers are now matched with customers through online platforms. By analyzing the number of open projects and tasks on a sample of such platforms, [Kässi and Lehdonvirta](#)

*ha13yato@toki.waseda.jp Graduate School of Economics, Waseda University.

†suguru.otani@e.u-tokyo.ac.jp, Market Design Center, Department of Economics, The University of Tokyo
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(2018) find that the demand for online gig work increased by approximately 21% from 2016 to 2018. According to *Freelance Forward 2023* reported by Upwork, the share of professionals freelancing increased to nearly 64 million Americans, making up 38% of the U.S. workforce in 2023.¹ Despite the significance of the gig economy, research directly analyzing the structure and efficiency of gig labor markets remains limited, especially in comparison to traditional labor markets facilitated by public job search platforms.

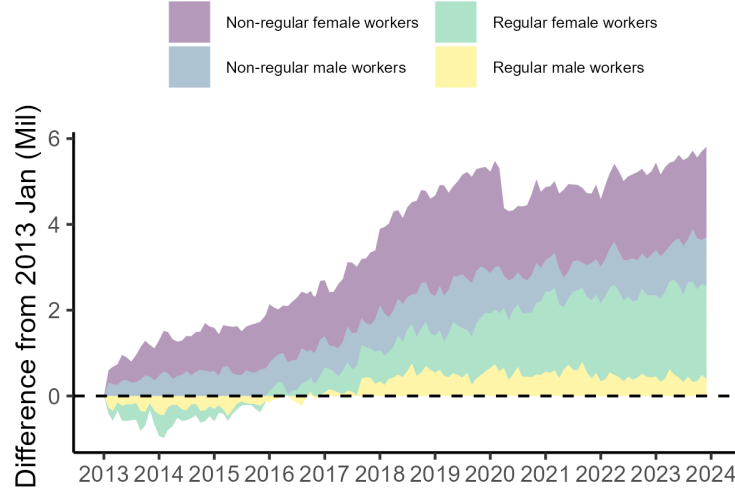
This paper contributes to the literature by providing the first systematic analysis of a spot gig worker labor market, distinguishing it from traditional labor markets and other segments of the gig economy. We focus on labor market matching efficiency and elasticities within spot work platforms that cater to unemployed workers seeking flexible, short-term jobs requiring minimal education or experience. Using proprietary aggregate data from a private online spot work matching platform, Timee, in Japan, we document key trends and compare these to public-sector employment services. The significance of spot work markets has expanded considerably from 2013 to 2024, as shown in Panels (a) and (b) of Figure 1. First, we analyze trends in core aggregate variables, including the number of unemployed users, vacancies, hires, and labor market tightness (i.e., the ratio of vacancies to unemployed users). To benchmark our findings against the public-sector labor market, we incorporate data from the “Report on Employment Service” (*Shokugyo Antei Gyomu Tokei*), which provides insights into part-time employment trends facilitated through Hello Work, Japan’s public employment platform. This comparison sheds light on the structural differences between private and public job-matching mechanisms in Japan.

First, we document the rapid expansion of the spot labor market on the private platform between December 2019 and December 2023. The number of registered users, predominantly unemployed individuals actively seeking spot work, exhibits a gradual increase, while the number of vacancies surges—particularly after 2022—leading to a rise in labor market tightness. Hiring activity escalates significantly around 2020, reflecting a sharp rise in successful job matches. Additionally, the job finding rate surpasses 1.0, indicating that active users frequently secure multiple spot jobs per month. Meanwhile, the worker finding rate remains stable at around 0.8, showing that 80% of spot jobs are successfully filled, reinforcing the platform’s effectiveness in facilitating rapid job matching.

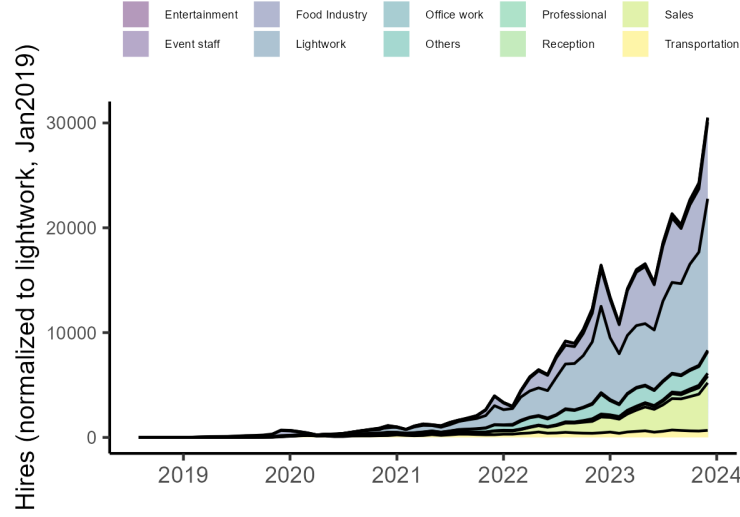
Second, we estimate the matching function and recover matching efficiency and elasticities using the novel nonparametric approach developed by Lange and Papageorgiou (2020). Our results reveal striking differences between private and public job-matching mechanisms. For Hello Work, matching efficiency remains relatively stable, fluctuating within a narrow range without notable trends. In contrast, the private platform exhibits a marked rise in matching efficiency, peaking around May 2023, coinciding with Japan’s peak holiday season, Golden Week. Differences also emerge in matching elasticities: while Hello Work’s elasticity with respect to unemployment hovers around 0.4 and its vacancy elasticity around 0.6, the private platform demonstrates significantly higher variation. Unemployment elasticity fluctuates between 0.7 and 1.5, and vacancy elasticity frequently exceeds 1.0, reflecting a dynamic and highly responsive matching process.

Lastly, we examine prefecture-level trends, focusing on Aichi, Osaka, and Tokyo—Japan’s

¹<https://www.upwork.com/research/freelance-forward-2023-research-report>: Accessed on September 19, 2024.



(a) Hires, Labor force survey



(b) Hires, Spot work platform

Figure 1: Changes of employment. National vs Spot work platform

Note: Panel (a) illustrates the time series of job changes in Japan, standardized to January 2013. The colored areas represent changes within specific worker groups. This graph is derived from data provided by the Economic Survey conducted by the Japanese Cabinet Office (details available at <https://www5.cao.go.jp/keizai3/2024/0802wp-keizai/setsume-e2024.pdf>, accessed September 19, 2024). Panel (b) presents the time series of hires on the platform, standardized to January 2019 for confidentiality purposes. The vertical axis represents the relative number of hires compared to January 2019. The filled areas depict the number of matched spot workers across various job categories as defined by the respective companies.

three largest metropolitan areas. Tokyo, the country's most extensive labor market, exhibits consistently higher matching efficiency than Osaka and Aichi. However, matching elasticities show similar trends across regions, suggesting lower geographical heterogeneity in spot work

matching compared to Hello Work. This may be attributed to the app-based nature of job matching, which ensures uniform accessibility across regions.

This study lays the foundation for understanding the economic mechanisms governing spot gig work, extending labor economics research beyond traditional and even broader gig economy studies. By shedding light on the distinct characteristics of spot work platforms and their efficiency in labor market matching, we offer novel insights into a rapidly evolving segment of the labor market.

1.1 Related literature

First, this paper contributes to the empirical literature on estimating the matching function, a fundamental component in macroeconomic models. We examine the trend of matching efficiency in Japanese labor markets via an online spot work matching platform nonparametrically using a novel approach (Lange and Papageorgiou 2020), which shows how to nonparametrically identify the matching function and estimate the matching function allowing for unobserved matching efficacy, without imposing the usual independence assumption between matching efficiency and search on either side of the labor market, allowing for multiple types of jobseekers. Lange and Papageorgiou (2020) highlight positive correlations between efficiency and market structure such as tightness and so on, which induces a positive bias in the estimates of the vacancy elasticity whenever unobserved matching efficacy is not controlled for, as is the case in the traditional Cobb-Douglas matching function with constant elasticity parameters.²

In the context of Japanese labor markets, Otani (2024b) estimates matching efficiency and mismatch in the off-the-job search administrative worker-vacancy-matching platform via Public Employment Security Offices, known as Hello-work. The paper finds a declining trend in matching efficiency, consistent with decreasing job and worker finding rates. The implied match elasticity with respect to unemployment is 0.5-0.9, whereas the implied match elasticity with respect to vacancies is between -0.4 and 0.4. Applying the same approach to proprietary data, Otani (2024a) estimates matching efficiency and elasticity in the on-the-job search scouting platform for high-skill employed workers, operated by a private firm in Japan, and compares these with Hello-work full-time ones. This paper complements the above findings. A series of papers overview the Japanese labor markets in the 2010s and 2020s and provide empirical evidence on matching efficiency, elasticity, and mismatch.

Second, our paper contributes to a nascent literature on alternative work arrangements in labor economics (Mas and Pallais 2020), which are closely related to spot work markets. The key difference between spot work and classical work is the frequency and flexibility of labor supply and demand. This paper is the first to estimate matching efficiency and

²Using administrative data of users and vacancies, Petrongolo and Pissarides (2001) summarize the early aggregate studies based on a Cobb-Douglas matching function with the flow of hires on the left-hand side and the stock of unemployment and job vacancies on the right-hand. In short, the match elasticity with respect to unemployment is in the range 0.5–0.7. In the context of Japanese labor markets, Otani (2024b) uses the nonparametric approach and updates the existing findings reported in Kano and Ohta (2005), Kambayashi and Ueno (2006), Sasaki (2008), and Higashi (2018) which use the traditional Cobb-Douglas matching function with geographical and occupational category fixed effects to capture geographical and occupational heterogeneity, which are also useful for comparison with other countries’ results reported in Bernstein *et al.* (2022) and Petrongolo and Pissarides (2001).

elasticity to the number of registered workers and spot vacancies on the online spot work platform highlighting the key difference from the public part-time worker-job matching platform. Alternative work arrangements based on spot platforms are growing rapidly in a labor markets. [Katz and Krueger \(2019\)](#) focus on alternative work arrangements defined as temporary help agency workers, on-call workers, contract workers, and independent contractors in the United States from 2005 to 2015. They provide evidence of an increase in these workers but online platform workers, such as “Uber” and “Task Rabbit” represented only 0.5% of the all in 2015. By contrast, [Kässi and Lehdonvirta \(2018\)](#) show that the demand for online labor markets was increased by 21% from 2015 to 2018.³

Focusing on the important feature of search and matching environment, some transportation industries such as taxi ([Frechette et al. 2019](#), [Buchholz 2022](#), [Lehe and Pandey 2022](#)), ride-sharing like Uber ([Guda and Subramanian 2019](#), [Rosaia 2020](#), [Castillo 2023](#), [Castillo et al. 2024](#)), bulk shipping ([Brancaccio et al. 2020](#), [2023](#)) are well studied. These studies describe models to explain why inefficiencies occur in the search and matching of sellers and buyers. However, to our knowledge, there is less literature about the overall features in the spot labor markets where the labor force on customer service, sales, and cleaning service is demanded and this is the first article to investigate the matching efficiency in these markets.

Third, this paper contributes to the growing literature on online job search platforms. The analysis of job matching within actual market institutions has gained prominence with the increasing availability of data from job advertising platforms ([Autor 2019](#)).⁴ Much of the literature examines application-level or vacancy-level behavior to capture search behavior and wage elasticity. For instance, [Faberman and Kudlyak \(2019\)](#) use proprietary application-level data from an online job search engine to investigate the relationship between search intensity and search duration, focusing on lower-skill, hourly jobs for both employed and unemployed workers. Similarly, [Kambayashi et al. \(2025\)](#) estimate elasticities of application, interview attendance, and offer acceptance with respect to posted wages using detailed process-level data for high-skill workers and firms on private job search platforms in Japan. In contrast, this paper takes a broader macro-level view, evaluating the efficiency of the private matching platform itself. To our knowledge, this is the first paper to estimate matching efficiency and elasticity in an online spot work matching platform, providing relatively longer-term insights into private online job search trends and complementing the micro-level studies mentioned above.

³Utilizing the unique features, empirical literature characterizes the relationship between labor supply and compensation scheme ([Chen et al. 2019](#), [Angrist et al. 2021](#), [Hall et al. 2021](#), [Butschek et al. 2022](#)) and gender wage gap ([Cullen et al. 2018](#), [Cook et al. 2021](#), [Adams-Prassl et al. 2023](#)). [Angrist et al. \(2021\)](#) have the randomized experiment using the “Uber” service to compare the value of the proportional compensation scheme offered by ride-share companies with taxi compensation. [Butschek et al. \(2022\)](#) implement a field experiment in the gig economy to confirm worker’s intrinsic motivation affect the relationship between performance and the compensation scheme.

⁴For example, studies such as [Kuhn and Skuterud \(2004\)](#), [Kuhn and Mansour \(2014\)](#), and [Kroft and Pope \(2014\)](#) use data focused solely on worker status, while papers like [Kuhn and Shen \(2013\)](#), [Hershbein and Kahn \(2018\)](#), [Brown and Matsa \(2016\)](#), and [Azar et al. \(2020\)](#) focus exclusively on vacancy data. Other studies, such as [Banfi and Villena-Roldan \(2019\)](#), [Marinescu and Rathelot \(2018\)](#), [Marinescu and Wolthoff \(2020\)](#), and [Azar et al. \(2022\)](#) utilize data that captures both worker and vacancy information.

2 Data

2.1 Data source

First, we use the Report on Employment Service (*Shokugyo Antei Gyomu Tokei*) for the month-level aggregate data from December 2019 to December 2023 to capture the trends of matchings between unemployed workers and vacancies via a conventional platform. These datasets include the number of job openings, job seekers, and successful job placements, primarily sourced from the Ministry of Health, Labour and Welfare (MHLW) of Japan, which publishes monthly reports and statistical data on the Public Employment Security Office, commonly known as Hello Work. Hello Work is a government-operated institution in Japan as a conventional platform that provides job seekers with employment counseling, job placement services, and vocational training, playing a critical role in Japan’s labor market. The data is often used as in [Kano and Ohta \(2005\)](#), [Kambayashi and Ueno \(2006\)](#), [Sasaki \(2008\)](#), [Kambayashi \(2013\)](#), [Higashi \(2018\)](#), and [Kawata and Sato \(2021\)](#). In particular, [Shibata \(2020\)](#) estimates the traditional Cobb-Douglas matching function, whereas [Otani \(2024b\)](#) estimates the nonparametric matching function. In this study, we focus on part-time workers in the Hello Work for a reasonable comparison. The period for our dataset is selected to be a consistent timeframe with the following platform data.

Second, we utilize proprietary data from a private company, Timee, that operates a spot-worker matching platform in Japan to analyze the trends in matchings between part-time spot workers and vacancies. Unlike Hello Work, the platform operates as an on-demand staffing platform designed to connect businesses with temporary workers for short-term jobs. The primary users of the platform are unemployed individuals seeking flexible, task-based employment rather than long-term positions. Workers can register on the platform app for free and immediately gain access to job offers from various companies, with the platform streamlining the process of matching workers with available shifts across industries such as food, retail, and logistics.

The platform’s business model allows workers to browse and accept jobs without the need for a traditional hiring process. Instead of charging a subscription fee, the platform earns revenue through fees paid by the businesses utilizing the service. This arrangement benefits both companies and workers by offering flexible, short-term employment opportunities while avoiding the formalities and commitments of long-term contracts. The platform’s simplicity and immediacy are its main draws for workers looking to fit employment around their schedules.

Several remarks are noteworthy. First, active job seekers on the platform are defined as registered workers who have activated the Timee app within a given month. Second, unlike Hello Work, where job seekers must enter part-time contracts for a set period and then leave the platform, active job seekers on Timee can match with multiple spot vacancies in a month. Third, while registered workers may use the platform for spot work as a side job, the number of such cases is small, so we do not differentiate these workers in the analysis.

Panel (b) in [Figure 1](#) shows a diverse range of job categories, with Entertainment, Food Industry, and Office Work occupying significant shares. Other categories like Event Staff, Light Work, and Professional roles also contribute to the platform’s job distribution, albeit to a lesser extent. This surge suggests a growing reliance on the spot work platform for flexible

employment opportunities, particularly in sectors like Entertainment and Food Industry. The steady rise across multiple categories implies an expanding spot labor market, reflecting a broadening acceptance and utilization of on-demand work arrangements in Japan.

2.2 Trend comparison

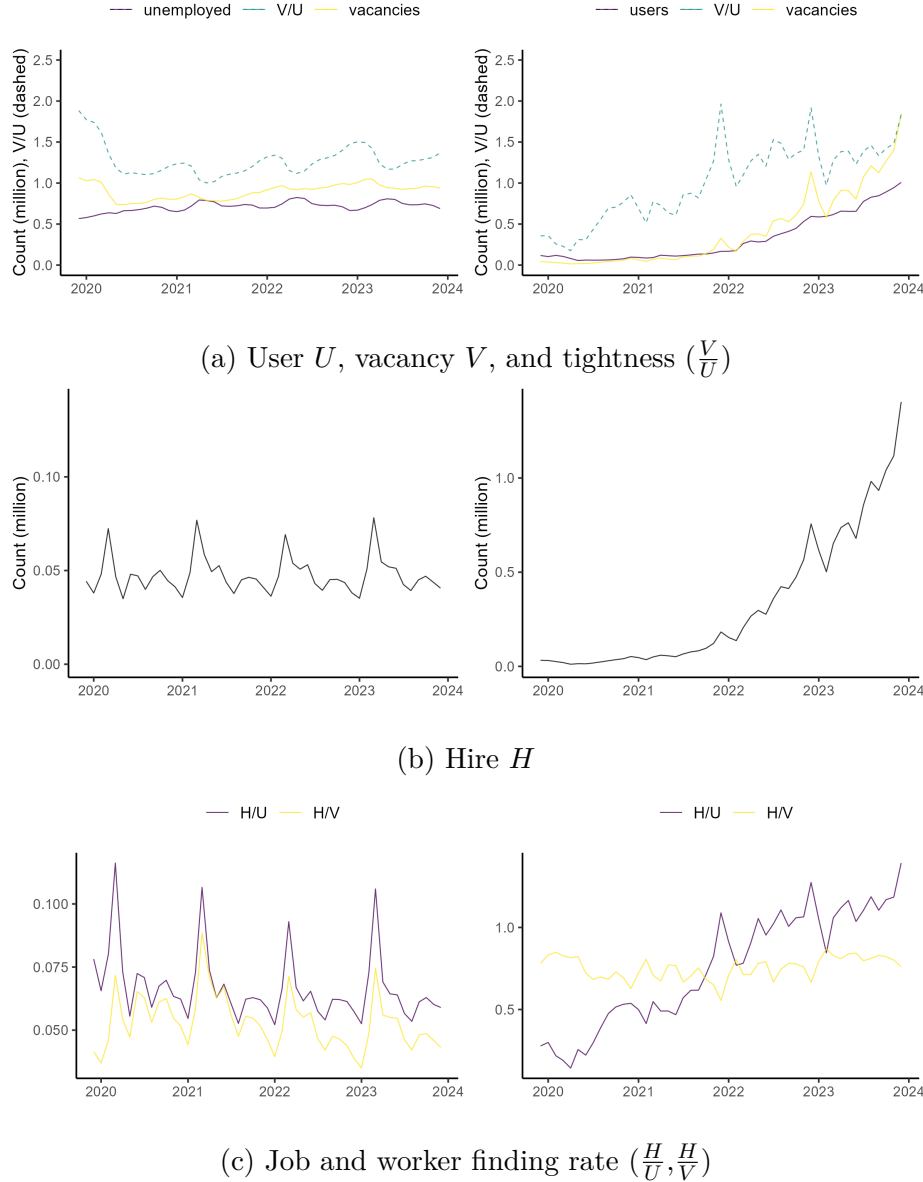


Figure 2: Trends of key variables: Hello Work part-time (left) vs platform (right) 2019-2023

Figure 2 provides a comparative analysis of labor market dynamics between the Hello Work public employment platform (left panel) and a private spot work platform (right panel) from December 2019 to December 2023.

First, We discuss the left panel of Hello Work for part-time workers and jobs. In panel (a), the number of unemployed individuals remains stable over the observed period, hovering around 0.8 million. Vacancies and tightness (V/U) show stable trends. Panel (b) shows that the hiring count through Hello Work remains low, with a small oscillating pattern throughout the period. This stable but limited hiring activity suggests that the platform may face constraints or inefficiencies in increasing the job match rate for part-time workers. In panel (c), the job and worker finding rates (H/U and H/V) exhibit a gradual decline over time, suggesting reduced effectiveness in matching job seekers with available vacancies via Hello Work. This decline might reflect a growing preference for alternative job search methods such as the spot-work platform.

In contrast, the right panels reflect the dynamics of the private platform, where a distinctive pattern emerges. Unlike Hello Work’s part-time flow from unemployed to employed, workers on this platform do not automatically leave after securing a match, which keeps a larger pool of active users. The number of registered users increases gradually, while the number of vacancies rises sharply, especially post-2022, leading to a notable rise in labor market tightness (V/U). This reflects an expanding demand for spot employment opportunities. The hiring count in panel (b) shows a rapid upward trajectory starting around 2022, underscoring a marked increase in successful matches.

Panel (c) illustrates the job and worker finding rates (H/U and H/V), highlighting significant differences compared to Hello Work. The job finding rate (H/U) continues to rise, reaching values close to 1.3, indicating that each worker matches with multiple vacancies per month. On the other hand, the worker finding rate (H/V) remains stable around 0.8, suggesting that 80% of the available jobs are successfully filled. This pattern demonstrates the platform’s increasing efficiency in matching workers to vacancies. It indicates a maturing spot labor market that still exhibits strong growth.

3 Model

Our primary focus is on analyzing matching efficiency and matching elasticity in relation to the number of registered workers and available vacancies in the labor market, facilitated by an online spot work matching platform operated by Timee in Japan. A matching function derived from search models is central to labor economics.⁵ This function is based on the premise of random search from both sides of the labor market, where job seekers represent labor supply and firms posting vacancies represent labor demand.

To estimate the matching function and recover matching efficiency, we adopt the novel approach proposed by [Lange and Papageorgiou \(2020\)](#).⁶ This approach addresses two critical issues: the endogeneity of matching efficiency ([Borowczyk-Martins et al. 2013](#)) and the limitations of the Cobb-Douglas specification, which assumes constant matching elasticity. To overcome these challenges, [Lange and Papageorgiou \(2020\)](#) propose a nonparametric identification and estimation framework for matching efficiency, under specific conditions that will be explored later in this paper.

⁵See [Pissarides \(2000\)](#), [Petrongolo and Pissarides \(2001\)](#), and [Rogerson et al. \(2005\)](#) for further reference.

⁶[Lange and Papageorgiou \(2020\)](#) also integrate search effort ([Mukoyama et al. 2018](#)) and a recruitment intensity index ([Davis et al. 2013](#)).

Let (A, U, V) denote random variables while realizations are subscripted by time t . We define that $m_t(\cdot, \cdot)$ maps period- t unemployed workers U_t , per-capita search efficacy/matching efficiency of the unemployed workers A_t , and vacancies V_t into hires H_t . Let assume that V and A are independent conditional on U , that is $V \perp A|U$. Let also assume that the matching function $m(AU, V) : \mathbb{R}_+^2 \rightarrow \mathbb{R}$ has constant returns to scale (CRS). Then, by applying nonparametric identification results of [Matzkin \(2003\)](#), Proposition 1 of [Lange and Papageorgiou \(2020\)](#) proves that $G(H, U, V)$ identifies $F(A, U)$ and $m(AU, V) : \mathbb{R}_+^2 \rightarrow \mathbb{R}_+$ up to a normalization of A at one point denoted as A_0 of the support of (A, U, V)

4 Estimation

Following [Lange and Papageorgiou \(2020\)](#), we begin by estimating $F(A_0|U)$ across the support of U . To achieve this, we use the distribution of hires conditional on users, U , and observed vacancies, V . Specifically, we have:

$$F(A_0|\psi U_0) = G_{H|U,V}(\psi H_0|\psi U_0, \psi V_0) \quad \text{for any arbitrary scalar } \psi,$$

$$F(\psi A_0|\lambda U_0) = G_{H|U,V}(\psi H_0|\lambda U_0, \psi V_0) \quad \text{where } \lambda > 0 \text{ is a scaling factor,}$$

where $F(A_0|\psi U_0)$ and $G_{H|U,V}$ represent the respective conditional distributions. By varying the parameters (ψ, λ) , we can trace out $F(A|U)$ across the entire support of (A, U) .

Given that our data is finite, we rely on an estimate of $G_{H|U,V}$ for the constructive estimator. Consider an arbitrary point (H_τ, U_τ, V_τ) . To obtain $G(H_\tau|U_\tau, V_\tau)$, we calculate the proportion of observations with fewer hires than H_τ , taken from observations proximate to (U_τ, V_τ) in the (U, V) -space. In practice, this is done by averaging across all observations, assigning smaller weights to those with values (U_t, V_t) distant from (U_τ, V_τ) via a kernel that discounts distant observations. The resulting estimate is expressed as:

$$F(\psi A_0|\lambda U_0) = G_{H|U,V}(\psi H_0|\lambda U_0, \psi V_0),$$

$$\hat{F}(\psi A_0|\lambda U_0) = \sum 1(H_t < \psi H_0) \kappa(U_t, V_t, \lambda U_0, \psi V_0),$$

where $\kappa(\cdot)$ denotes a bivariate normal kernel with bandwidth 0.01.

Once the distribution function $F(A|U)$ is recovered, we invert $F(A_t|U_t)$ to derive A_t for all observations in the dataset, using:

$$A_t = F^{-1}(G(H_t|U_t, V_t)|U_t),$$

Finally, we recover the matching function as:

$$m(A_t, U_t) = G^{-1}(F(A_t|U_t)|U_t).$$

To compute matching elasticities, we employ a linear regression, projecting hires onto the values of vacancies and users, interacted with implied matching efficiency. The resulting estimates approximate the derivatives of the matching function with respect to vacancies

and users, interacted with implied matching efficiency. This provides an estimate of the elasticity of the matching function.⁷

5 Results

5.1 Matching efficiency and elasticity in the platform

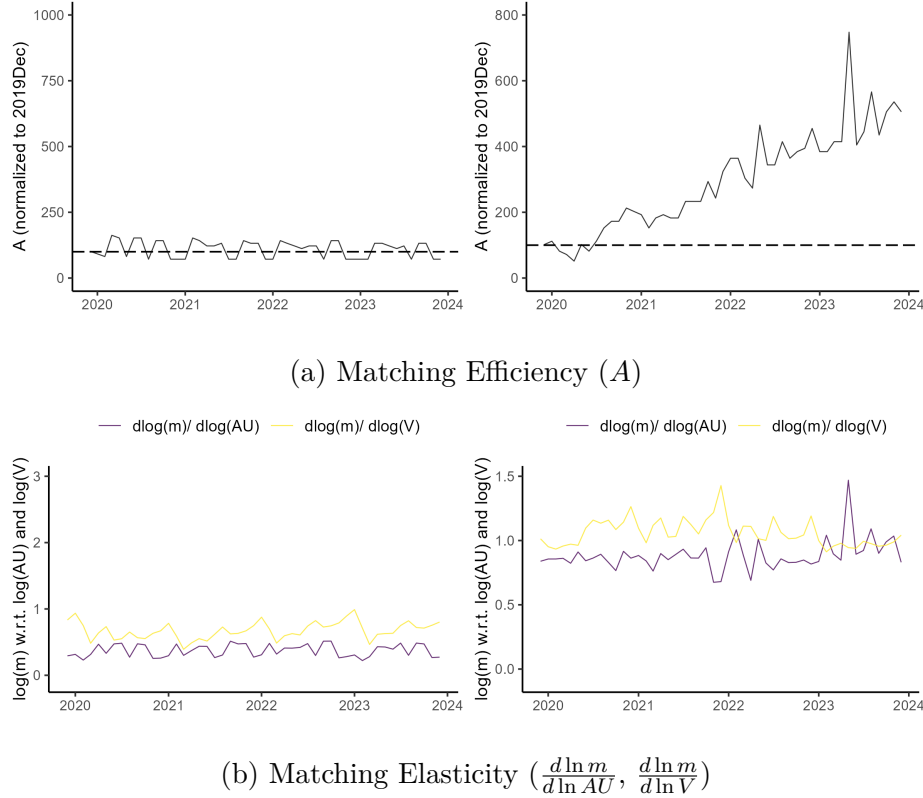


Figure 3: Hello Work full-time vs platform 2019-2023

Note: For confidentiality reasons, we normalize the efficiency to 2019 December for each platform.

Figure 3 illustrates the trends in matching efficiency normalized to December 2019 and matching elasticity for both the Hello Work public employment platform (left panels) and a private platform (right panels) from December 2019 to December 2023. In panel (a), the matching efficiency for Hello Work part-time remains relatively stable around the baseline, fluctuating within a narrow range without any significant upward or downward trends. In contrast, the private platform shows a markedly different pattern, with matching efficiency experiencing sharp increases, peaking around May 2023, reaching values of nearly 700, which implies that the efficiency is seven times larger than the initial period in December 2019.

⁷The matching elasticity with respect to users $\frac{d \log m(AU,V)}{d \log U} = \frac{dm(AU,V)}{dU} \frac{U}{H} = \frac{dm(AU,V)}{dAU} \frac{dAU}{dU} \frac{U}{H} = \frac{dm(AU,V)}{dAU} \frac{AU}{H}$ is obtained from the regression coefficient of H on AU and multiplying it by $\frac{AU}{H}$.

Panel (b) presents the matching elasticity with respect to unemployment interacted with estimated efficiency and vacancies for both platforms. For Hello Work, the elasticity with respect to unemployment remains consistently around 0.4, suggesting that changes in unemployment have a moderate impact on the number of matches. The elasticity with respect to vacancies for Hello Work fluctuates around 0.6, indicating that the platform’s matching process is more responsive to changes in vacancies than to unemployment. This pattern suggests a relatively balanced sensitivity to labor market conditions, although the responsiveness remains moderate.⁸

The private platform exhibits more variability in both matching efficiency and elasticity. The elasticity with respect to the number of users interacted with efficiency on the private platform shows greater fluctuations, ranging from below 0.7 to 1.5, with notable peaks around 2023. This suggests that the platform’s matching efficiency is more sensitive than Hello Work’s. The elasticity with respect to vacancies on the private platform also shows a volatile trend, with values consistently higher than those observed for Hello Work, frequently exceeding 1.0. Overall, the private platform displays higher volatility and sensitivity in both matching efficiency and elasticity compared to the more stable yet less dynamic public platform.

5.2 Prefecture-level matching efficiency and elasticity in the platform

Figure 4 illustrates prefecture-level labor market trends across the three representative prefectures – Aichi, Osaka, and Tokyo – which are the centers of the three metropolitan areas in Japan. For confidentiality reasons, the y-axis in the following figures reflects values relative to the baseline set by Tokyo in December 2019. Panels (a) and (b) display user and vacancy levels across Aichi, Osaka, and Tokyo, with Tokyo consistently leading in both categories. The growth in Tokyo is especially steep in terms of vacancies, where it surpasses the levels seen in the other two prefectures after 2022, demonstrating Tokyo’s rapid labor market expansion. The hiring trend in panel (c) mirrors these patterns, with Tokyo showing a dramatic rise in successful matches, followed by Osaka and Aichi.

Panel (d) displays matching efficiency across the regions, with Tokyo exhibiting fluctuating but generally higher matching efficiency, especially during the peaks in 2023. Aichi and Osaka demonstrate lower efficiency in the initial period, followed by a significant increase over time. Panels (e) and (f) show matching elasticities with respect to users and vacancies, respectively. The elasticities related to both users and vacancies exhibit consistent patterns, with only slight variations across regions. This suggests less geographical heterogeneity in the spot work platform compared to Hello Work.

⁸The estimated elasticities differ from those reported in Otani (2024b), likely due to the differing lengths of time horizons considered. Specifically, Otani (2024b) includes data from 1972 to 2013, a period covering economic booms and busts, which captures a broader range of labor market dynamics.

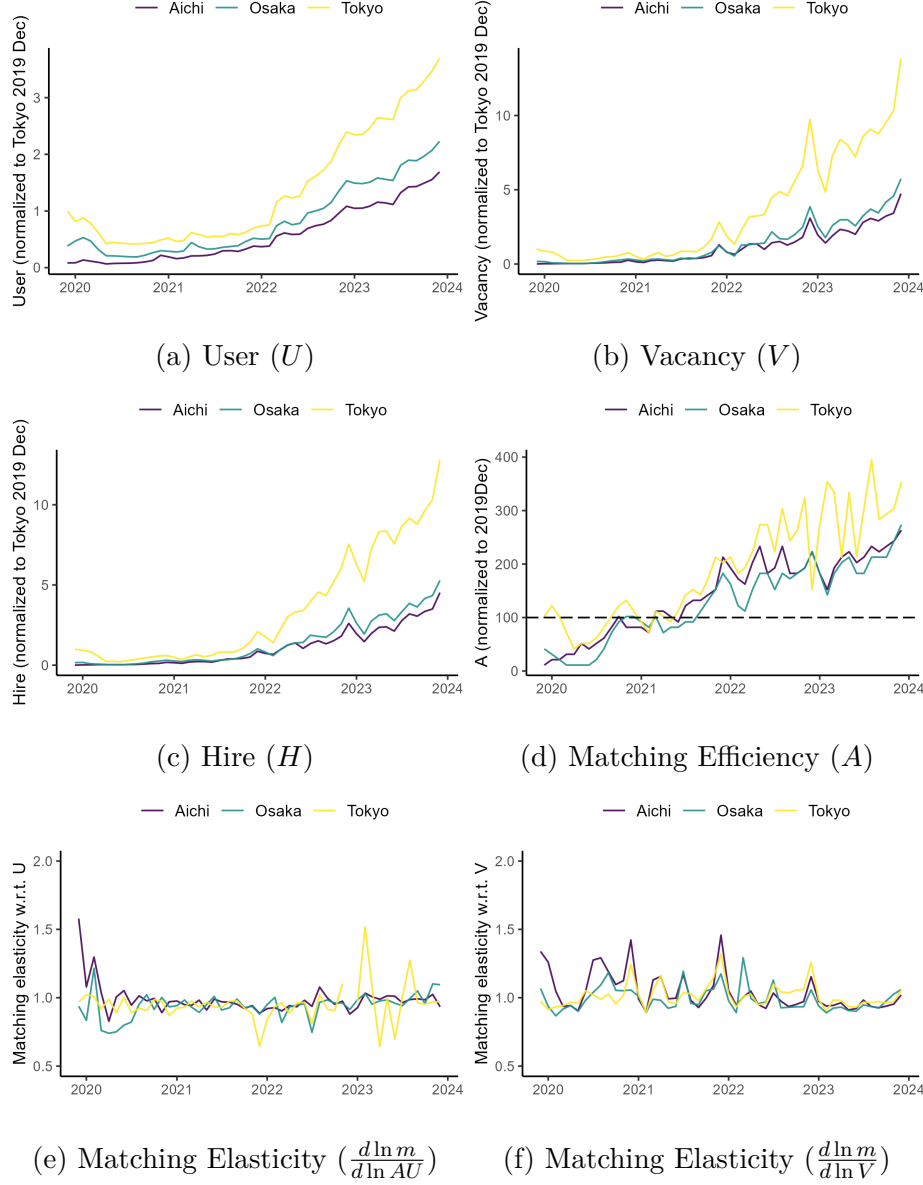


Figure 4: Hello Work full-time vs platform 2019-2024

Note: For confidentiality reasons, we normalize the level of the y-axis in Panels (a)-(c) to the information of January 2019 Tokyo.

6 Conclusion

This study reveals significant differences in labor market dynamics between the private online spot work platform and the public employment platform, Hello Work, in Japan. The private platform demonstrates a rapid expansion in part-time spot employment from December 2019 to December 2023, with a notable increase in registered users and a sharp rise in vacancies, particularly after 2022. We find that the private platform has become increasingly effective in facilitating job matches, achieving a worker finding rate where 80% of spot jobs are filled,

reflecting its growing influence in the part-time labor market.

By employing a novel nonparametric approach, the study estimates the matching function, highlighting clear distinctions in matching efficiency and elasticity between the two platforms. For Hello Work, matching efficiency remains stable around the baseline, with elasticity concerning unemployment around 0.4 and vacancies around 0.6, suggesting moderate sensitivity to labor market changes. In contrast, the private platform exhibits higher volatility, with matching efficiency peaking in 2023. The elasticity with respect to the number of users fluctuates between 0.7 and 1.5, while the elasticity concerning vacancies often exceeds 1.0. This greater variability indicates that the private platform is more sensitive and dynamic in response to labor market conditions. At the prefecture level, Tokyo’s labor market shows the highest matching efficiency, while the elasticities related to both users and vacancies exhibit consistent patterns, with only slight variations across regions, suggesting less geographical heterogeneity in the spot work platform compared to Hello Work.

This study offers macroeconomic implications and serves as a foundational step toward understanding labor market dynamics at the micro-level. Future research will explore the behaviors of individuals on both the labor demand and supply sides and their interactions that drive aggregate patterns. This approach will enable a more detailed analysis of the mechanisms underpinning labor market functioning.

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