INSEAD The Business School for the World®

Working Paper

2026/23/STR

Impact of Referral Ties on Worker Earnings in the Gig Economy: Evidence from an On-Demand Delivery Platform in India

Devanshee Shukla
INSEAD, devanshee.shukla@insead.edu

Victoria Sevcenko
INSEAD, victoria.sevcenko@insead.edu

Jasjit Singh
INSEAD, jasjit.singh@insead.edu

April 9, 2026

With digital platform "gig" work expanding globally and providing livelihoods to millions of low-income workers in the Global South, understanding the drivers of these workers' earnings has become increasingly important. Whereas existing research emphasizes platform design and worker characteristics as drivers of gig worker earnings, we examine another potential driver that is understudied: their social connections with more experienced workers through referral ties. We argue that such referral ties can boost gig workers' earnings through information provision by the referrer. Analyzing proprietary data from an on-demand delivery platform in India, we find that referred workers earn 14.2% more per hour than a matched sample of non-referred workers. Using difference-in-differences estimation for better econometric identification, we find that following the referrer's exit, the referred worker's hourly earnings decline by 12.5%, erasing most of the referral premium and demonstrating that the above earnings effect depends on the referrer's continued presence on the platform. Additional analyses further support an information-exchange mechanism: (i) when the referrer is concurrently online, the referred workers earn more, complete more jobs per hour, and are able to position themselves closer to high-demand areas; and (ii) upon the referrer's exit, the referred workers experience most prominent earnings declines for the more information-sensitive earnings components, where the referrer's guidance would have helped the most. Our study thus demonstrates how the mechanism of information exchange through interpersonal networks might be important even in a gig setting, at least in the Global South, where formal channels of information are often underdeveloped.

Key words: Gig Economy; Digital Platforms; Referrals; Worker Earnings; Emerging Economies

We are grateful to the partner firm for providing access and support. We thank Aparajita Agarwal, Matthew Bidwell, and Evan Starr for helpful comments and suggestions. This paper also benefited from feedback at the AOM 2025 Meeting, People and Organizations Conference at Wharton, SMS 2025 Meeting, Strategic Human Capital Conference at Bocconi University, and seminar presentations at INSEAD.

1. INTRODUCTION

In recent years, digital platforms such as Uber, Upwork, and TaskRabbit have rapidly become a major form of employment for many workers (Kretschmer et al. 2022). Estimates suggest that between 154 and 435 million people—accounting for up to 12% of the global workforce—are currently involved in some form of platform-mediated "gig" work (Datta and Chen 2023). Gig work is expected to continue growing fast, particularly in emerging economies across the Global South, where tens of millions of low-income workers already depend on gig work as a major source of livelihood (Johnson et al. 2020, NITI Aayog 2022, Brailovskaya 2025). As a result, understanding what drives gig worker earnings is crucial, with empirical research on this issue being particularly limited from the Global South.

Much of the academic and public discourse portrays gig workers as atomistic independent contractors (Katz and Krueger 2019, Ravenelle 2019, Mas and Pallais 2020). This view explains gig worker earnings as largely a function of platform design, e.g., incentive structures, workflows, and algorithms (Chen et al. 2019, Rahman et al. 2023, Chung et al. 2024), and individual worker characteristics, e.g., intrinsic motivation, risk aversion, and preferences for flexibility (e.g., Hall and Krueger 2018, Cook et al. 2021). Where social connections are examined, they tend to be studied not for their direct impact on the individual worker's earnings, but for their contribution to either the worker's emotional well-being, such as reducing loneliness and providing meaning (Petriglieri et al. 2019, Cameron 2022) or their collective bargaining power aimed at improving working conditions (Rosenblat 2018, Maffie 2020). However, longstanding theories of labor markets and organizations suggest that work is often socially embedded, with social connections directly shaping access to and individual outcomes in jobs (Granovetter 1985, Fernandez et al. 2000). Yet, we know surprisingly little about how such connections shape worker earnings in the gig economy.

In this paper, we focus on a key channel through which social connections are known to influence worker outcomes in traditional employment—job referrals—and ask whether and how referrals might shape worker earnings even in the context of gig platforms. To accomplish this, we integrate the literatures on platform design and recruitment through referrals to develop a framework for understanding the potential impact of referrals on gig worker earnings. We argue that, while gig platforms lack the formal support structures of traditional employment, referral ties can partially substitute for this support by connecting a referred worker to someone who is already active on the platform, knows the referred worker's background, and is well positioned to provide personalized guidance. This guidance can range from helping the referred worker understand platform operations and develop effective strategies, to making sense of the opaque and frequently changing algorithmic systems governing task allocation, pricing, and rewards. Importantly, we argue that this informational role is not limited to the point of entry. Because platform conditions continuously evolve and workers have few alternative resources to make sense of these changes, a referrer who is actively navigating the same environment at the same time may remain a valuable source of information well beyond the initial onboarding period.

We test our predictions using proprietary data from one of the largest publicly listed food and parcel delivery platforms in India (henceforth 'GigRider'). GigRider was launched in 2015 and by 2022 had grown to engage over 200,000 delivery gig workers (henceforth 'couriers') based across 200 cities. The couriers use either motorbikes or bicycles to perform a range of delivery tasks, such as delivering restaurant food or groceries, and often work irregular part-time hours, common for platforms operating in the on-demand delivery sector. As a fast-growing venture in a competitive market (with typically four to six competitors in each of its locations), GigRider is critically dependent on signing up enough couriers and ensuring that they remain sufficiently productive. To do so, it employs a mix of referral incentives to encourage its existing couriers to also bring others they know as couriers, and incentive schemes that attempt to guide the couriers towards areas with high demand as demand shifts dynamically and unevenly over time for the different regions. The platform shared with us detailed order-level as well as courier-level proprietary data, which allowed us to construct a longitudinal dataset capturing weekly platform activity and average earnings per hour for 100,231 couriers who had joined GigRider between October 1, 2022, and June 30, 2023. Our dataset also includes additional information such as whether or not a given courier was referred (and if so, by whom and whether the referrer is still active on the platform), and several other time-invariant courier characteristics.

We use the above data to conduct three sets of analyses related to the role of referral ties. First, we examine evidence whether referral status is associated with greater courier earnings, a comparison we implement by analyzing a matched sample of referred and comparable non-referred couriers. Following exact matching to identify referred and non-referred couriers that are observationally identical on gender, vehicle ownership, geographic cluster, and entry cohort, we find that joining the platform via a referral is associated with higher hourly earnings: referred couriers earn on average about 14.2% more per hour than observationally comparable non-referred workers. However, while our matching approach improves comparability of the referred and non-referred couriers, given the possibility of unobserved selection effects, it does not allow for a strong causal interpretation of the role of referral ties in actually *driving* the referred courier's earnings. We therefore take this evidence as indicative and use it to motivate our subsequent analyses that strives for better econometric identification.

This leads to our second set of analyses, where we use a more rigorous approach to identifying the causal effect of referral ties using appropriate longitudinal models. Specifically, we identify cases of referred workers where the referrer exited the platform before the end of our observation window, which allows us to compare referred workers' earnings not only cross-sectionally but also before versus after the respective referrers' departures from the platform. Using a staggered difference-in-differences research design, we are able to compare earnings changes among referred couriers whose referrers have already exited the platform to those whose referrers are still on the platform. The results provide strong evidence that active referral ties, i.e., ties to referrers who are still active on the platform, may indeed meaningfully drive a referred courier's earnings: in our preferred econometric specification, referred couriers' hourly earnings on average decline by about 12.5% following their referrer's exit.

In our third set of analyses, we perform two additional tests to more directly examine whether information sharing between the referrers and referred couriers may be a key mechanism that helps drive the earnings effects for the referred couriers as documented above: (i) we examine whether the referred couriers' hourly earnings are higher when their referrers are also online in the same hours (which may improve the timeliness and relevance of the information they could provide); and (ii) we examine whether referrer departure disproportionately impacts couriers' earnings on more information-sensitive (i.e., difficult to understand), components of their compensation where input from referring peers could be particularly helpful. Our results are consistent with information exchange through referral ties being an important mechanism behind the observed results documented above: (i) referred couriers earn significantly more when their referrers are online in the same hours as they are, and are able to complete more orders and position themselves closer to high-demand areas in this scenario; and (ii) following their referrer's exit, a referred courier's compensation decline is especially large in the incentive pay components that are more information-sensitive, i.e., where referrers may be able to offer the most valuable guidance.

Our study makes three primary contributions. First, we extend research on gig worker earnings—an important issue given that gig work supports the livelihoods of tens of millions of people globally—by documenting referral ties as a novel and significant driver of earnings. Second, we extend the work on referral-based hiring from traditional employment settings to the gig economy, showing that by facilitating information exchange, referral ties have an important role to play for worker earnings even in this setting. Third, by examining low-income gig workers based in India, our study responds to recent calls by scholars for more empirical research set in understudied contexts from the Global South.

2. WORKER PERFORMANCE AND EARNINGS IN THE GIG ECONOMY

2.1 Existing Research on Platform-Mediated Gig Work

Platform-mediated gig work refers to work that is transacted (and often delivered) through digital platforms. Users (either organizations or individuals) request services or offer jobs—also known as "gigs"—that can be completed independently through flexible, short-term, and heterogeneous working arrangements. Algorithms or automated systems typically take on the majority of managerial functions (Kellogg et al. 2020), such as allocating jobs and tasks, evaluating or facilitating in the evaluation of worker performance, and making termination decisions (Griesbach et al. 2019, Duggan et al. 2020). Platforms can thus coordinate large numbers of geographically dispersed workers in highly efficient ways (Vallas and Schor 2020, Rahman 2021). In turn, workers typically have significant autonomy in choosing when, where and for how long to be available for work, and their compensation varies accordingly (Mas and Pallais 2017).

Prior work on the determinants of worker performance and earnings in the platform-mediated gig work context generally falls into two broad streams—platform characteristics and individual worker attributes—which we review next.

Platform characteristics

Digital labor platforms exercise considerable control over the labor process and hence worker behavior, effectively establishing the "rules of the game" that directly influence worker performance and consequently their earnings potential (Lee et al. 2015, Rosenblat and Stark 2016). The first dimension of platform design that prior research has documented as relevant is how the incentive structure is set up. Platforms design algorithms to set pricing schedules (Chen et al. 2019, Hall et al. 2021), alter the relationship between worker performance and pay (Filippas et al. 2020, Mas and Pallais 2020, Cook et al. 2021, Kaynar and Siddiq 2022, Ye et al. 2022, Ai et al. 2023), and introduce penalties and sanctions to discipline workers (Idug et al. 2023, Xu et al. 2023). These incentive structures directly affect workers' choices over when, where, and for how long to work, and thereby their earnings (Hall et al. 2021). For instance, Uber's surge pricing algorithm is known to affect driver earnings by shaping the spatial and temporal patterns of their labor supply (Chen and Sheldon 2016, Hall et al. 2021).

The second dimension of platform design that has been documented by prior research as relevant for worker performance and earnings is how the platform structures its workflows. Platform-specific features such as rating systems, monitoring mechanisms, task allocation algorithms, and scheduling flexibility create distinct work environments that shape worker strategies and performance outcomes (Gandini 2019, Wood et al. 2019, Chung et al. 2024). Platforms vary considerably in their degree of algorithmic control, the granularity and timing of feedback mechanisms, and the opportunities they provide for worker advancement (Rahman et al. 2023)—all of which impact individual performance and earnings potential.

The third dimension of platform design documented as relevant is the nature of its algorithmic management processes. Modern machine learning algorithms are often extremely complex, with their outcomes difficult to understand and explain even for their designers, let alone users (Burrell 2016, Ananny and Crawford 2018). Platforms keep these algorithms proprietary and may at times partly obscure their decision rules even from their own workers to protect their competitive advantage and prevent gaming behaviors (Kellogg et al. 2020, Bucher et al. 2024). As a result, workers often experience algorithmic management as confusing and opaque (Curchod et al. 2020, Kellogg et al. 2020). Most platforms also continuously update their algorithms to optimize performance and adapt to market conditions (Uber Technologies 2018, Koning et al. 2022, Rahman et al. 2023), making it even harder for workers to develop effective strategies that do not become quickly outdated (Curchod et al. 2020, Kellogg et al. 2020, Rahman 2021).

Individual worker attributes

Individual attributes of gig workers can also significantly influence their performance and earnings on a given platform. A substantial literature has documented heterogeneity in worker preferences, particularly regarding schedule flexibility and income targeting behaviors (Farber 2005, Hall and Krueger 2018, Chen et al. 2019, Koustas 2019). Workers exhibit varying preferences for when and how much to work, for example, with some workers displaying income-targeting behaviors while others following more consistent schedules (Camerer and Vepsalainen 1988, Crawford and Meng 2011).

Risk tolerance has emerged as another critical individual characteristic shaping gig economy participation and earnings. The income volatility inherent in platform-mediated work often attracts workers with higher risk tolerance and reduces the participation of more risk-averse individuals (Cook et al. 2021, Garin et al. 2024). Finally, workers' outside options, skill levels, and experience also contribute to performance and earnings differentials (Jarrahi and Sutherland 2019, Dube et al. 2020, Cook et al. 2021).

2.2 The Potential Impact of Referral Ties

Extending the focus beyond platform characteristics and individual workers' attributes, we argue that gig worker earnings might also be significantly affected by their social ties, paralleling longstanding theories of traditional labor markets and organizations suggesting that work carried out by employees is often socially embedded (Granovetter 1985, Fernandez et al. 2000), and that social connections can significantly shape not only access to job opportunities but also on-the-job performance and earnings of employees (Castilla 2005, Campero and Kacperczyk 2023).

One of the most consequential channels through which social connections shape worker outcomes in traditional employment—that is, a formal employer-employee relationship, involving regular compensation, managerial oversight, and access to organizational resources and colleagues—is job referrals, where new employees join an organization through their social ties with an existing employee (Fernandez et al. 2000, Castilla 2005, Burks et al. 2015, Schlachter and Pieper 2019). An estimated 69% of U.S. companies maintain formal employee referral programs, and 25–50% of employees in the U.S. and Europe report obtaining a job through a friend or family contact (Burks et al. 2015). Prior research documents that referred employees benefit from referrals because their referrers share informal knowledge about how to perform effectively, provide mentorship, facilitate introductions to peers, and offer guidance on navigating organizational norms and incentive structures (Fernandez and Weinberg 1997, Castilla 2005, Pieper 2015, Schlachter and Pieper 2019).

Gig platforms have increasingly adopted similar practices, offering referral bonuses and other incentives to encourage existing workers to recruit from their networks (e.g., Anyshift n.d., Sproutgigs n.d., Uber Technologies n.d., uParcel n.d.). However, it is not obvious whether referrals can function similarly in this context. Gig workers lack the formal organizational structures, managerial oversight, and co-located colleagues that facilitate knowledge sharing and post-referral monitoring in traditional employment. Moreover, gig platforms are typically designed and marketed as self-sufficient systems in which an individual worker, equipped with nothing more than the app, can successfully find work, complete tasks, and earn income without relying on colleagues, mentors, or other support structures (Rosenblat 2018, Vallas and Schor 2020). This raises the under-examined question of whether referrals can improve worker performance and earnings even in the gig economy context, and if so, through which mechanisms. We argue that referrals can indeed benefit gig workers in this way, even if some of the mechanisms driving these effects may be different compared to those in traditional employment.

Although gig platforms lack the formal support structures of traditional employment, a referral tie might at least partially substitute for such structures: it represents a connection between a new worker and someone who is already active on the platform, knows the referred worker's background, and may be able to provide personalized guidance to help boost the new worker's productivity. This guidance can range from helping the new worker onboard and familiarize with platform operations, to developing effective strategies to deal with the complex and frequently changing algorithmic systems governing task allocation, pricing and rewards (Rosenblat and Stark 2016, Möhlmann and Zalmanson 2017). Crucially, this informational role is not limited to the point of entry, as emphasized in the traditional employment literature (e.g., Premack and Wanous 1985, Campero and Kacperczyk 2023). Because platform conditions continuously evolve and workers have few alternative resources to make sense of these changes, a referrer who is actively navigating the same environment concurrently can remain a valuable source of guidance well beyond the initial onboarding period.

In sum, we propose that *referrals can positively affect gig worker earnings, and a key mechanism for this is the ongoing informational channel that the referral tie provides*. If this proposition is correct, we should observe the following empirical patterns. First, referred workers should earn more than non-referred workers on average. Second, this earnings advantage should be concentrated in periods when the referrer is also active on the platform and get attenuated after the referrer exits the platform. In other words, consistent with the idea that it is the ongoing relationship rather than the act of being referred that drives much of the benefits for the gig worker, the exit of a referrer should be associated with a decline in the referred worker's earnings as it disrupts use of the referral tie as a channel for information flow. We test these predictions in our empirical analyses, progressing from establishing the basic association between referrals and worker earnings to causally examining evidence of a disruptive effect of the referrer's exit on worker earnings.

3. EMPIRICAL CONTEXT AND DATA

Our empirical context is "GigRider", a publicly listed on-demand food- and parcel-delivery platform operating in over 200 cities across India. Independent gig workers sign up as couriers on the platform through a mobile application and decide for themselves when to log onto the platform and how long to stay signed in to accept jobs. Once a worker is online, a proprietary dispatch algorithm allocates delivery requests based on their geographic proximity and historical acceptance rates for orders assigned to them. Order tracking, performance evaluation, and payments are all handled automatically by the platform's algorithms, with little need for human oversight or supervision.

As a part of our research partnership, we were able to obtain access to fine-grained proprietary data on all of the platform's operations between October 1, 2022, and June 30, 2023. These include detailed information on each order completed during this 39-week observation window (e.g., the order number, the courier it was allocated to, the allocation timestamp, the distance the courier travelled to make the delivery, the delivery timestamp, etc.) as well as on each courier who completed at least one order during this period (e.g., the courier's id number, their gender and vehicle ownership, the date of their joining the platform, the geographic cluster they primarily operate in, their online hours, their order handling, their earnings for each hour of activity, etc.). Importantly, we also obtained detailed information on all referrals relevant for the above time period, i.e., for each courier in our data we know whether, and if so by whom, they were referred when joining the platform.

While new couriers also often sign up on their own, GigRider operates a referral program across all its geographic clusters. Existing couriers are given unique referral codes that they share with prospective joiners, who then enter them online during the process of signing up to be a courier on the platform. GigRider awards both the referrer and the new recruit a one-time “sign-on” bonus of between INR 500 and 2000, conditional on the recruit completing between 20 and 50 orders within the first 7 to 10 days, depending on the ongoing referral scheme.[1] Importantly, beyond the payment of referral bonuses, the platform’s algorithmic decisions do not use information about referral ties further in any way. In other words, the platform applies its algorithms uniformly across all couriers, with no differentiation based on whether they had entered through a referral or without one.

We use the fine-grained data on the orders and the couriers as described above to construct a longitudinal dataset for analysis in two steps. First, we restrict the set of couriers to be included in the dataset to the 100,231 couriers in our data who had joined GigRider on or after October 1, 2022—the start of our observation window—so that we observe each courier’s complete platform history from the point of entry. Second, for this set of couriers, we construct a panel dataset at the courier–week level by retaining only those weeks in which the respective courier was active, i.e., had logged into the platform to accept delivery orders at least once. Courier–weeks with zero activity for the focal courier are thus excluded from our final sample for analysis. The resulting panel is therefore unbalanced and comprises of 419,281 courier–week observations. In line with the platform’s definition of an “exit” event, we classify a given week as the week of the respective courier’s exit from the platform if it is the last week of activity for the courier in our data and there are at least two weeks between that week and the end of our observation window.

4. VARIABLE DEFINITION AND MATCHED SAMPLE CONSTRUCTION

4.1 Dependent Variable

A key performance metric GigRider tracks is couriers’ total weekly earnings. These weekly earnings are comprised of two components: order-level earnings and weekly incentive earnings. The order-level earnings include a base commission for each order as well as supplementary incentives such as festival surges, weather-based and distance-based bonuses, earnings from customer tips, and

[1] INR refers to the Indian Rupee. As of March 2026, 1 US dollar was equivalent to about INR 92. On average, couriers on the platform make about INR 1,543 per week.

deductions arising from penalties for platform-defined infractions. The weekly incentive earnings include additional incentive payments based on a courier's achievement of certain weekly targets and is referred to by the platform as "minimum guarantee" or MG for doing so. All earnings accrued during a week are calculated and credited to the couriers' accounts at the end of the week.

Importantly, unlike in traditional full-time employment settings, a courier's total earnings per week do not represent a comparable measure of earnings across workers or across weeks in a gig economy setting because of substantial cross-sectional and intertemporal variation in how many hours different workers choose to be active in a week. Therefore, prior work examining worker earnings in settings similar to ours (e.g., gig work in ride-hailing or deliveries) has relied on average earnings per hour worked rather than total weekly earnings of workers as the most relevant metric for comparison (Hall and Krueger 2018, Chen et al. 2019, Cook et al. 2021). Public statements by GigRider as well as our interviews with its senior managers confirmed that, like typical gig economy platforms, GigRider also did rely on average courier earnings per hour as a key metric to evaluate courier performance as well as to guide algorithmic optimization. Our main dependent variable for this study is therefore also *Hourly Earnings*—calculated by dividing the total (INR) compensation that the given courier received in a given week by the total hours during which they were online that week, either delivering orders or waiting for orders.

4.2 Explanatory and Control Variables

The key explanatory variable for our main analysis is *Referred*, which takes the value of 1 if a given courier had joined the platform as a result of a referral by another courier already on the platform, and 0 otherwise. Of the 100,231 couriers in our final sample for analysis, 12,811 (12.8%) had joined the platform through a referral. To facilitate more fine-grained analysis, we further break this variable into two time-varying indicator variables: *Referred with Referrer Present*, which takes the value of 1 if and only if the courier had joined through a referral *and* the referrer was still active on the platform in the given week, and *Referred with Referrer Exited*, which takes the value of 1 if and only if the courier had joined through a referral *and* the referrer had exited prior to the given week.

In some of our estimation models (that do not include courier fixed effects), we also include two (time invariant) courier characteristics as control variables: *Female*, which takes the value of 1 if the courier is female and 0 otherwise, and *Motorcycle Ownership*, which takes the value of 1 if the courier operates a motorcycle, and 0 otherwise (which typically implies that the courier operated a bicycle instead).[2] We also account for fixed effects for the current calendar *Week* for the focal observation to account for seasonality and any demand and supply fluctuations, *Geographic Area* to account for the courier's primary location of operation (similar to the U.S. ZIP codes and thus more fine-grained than the city), the *Week of Entry* capturing the calendar week in which the focal courier first joined the platform (measured as the number of weeks since October 1, 2022—the start of our observation window) to account for any entry cohort effects.

4.3 Summary Statistics and Matched Sample Construction

Table 1 presents summary statistics for observed characteristics of the 100,231 unique couriers in our sample (Panel A) as well as for relevant operational metrics and earnings statistics across the 419,281 courier-week observations in our dataset (Panel B). A comparison of the summary statistics for referred couriers (Column 2) versus non-referred couriers (Column 3) in Panel A shows that referred couriers are more likely to be *Female* (1.5% vs. 1.0%, $p < 0.01$), less likely to have *Motorcycle Ownership* (57.8% vs. 69.3%, $p < 0.01$), and more likely to be from an earlier *Week of Entry* (9.9 vs. 10.7, $p < 0.01$). A comparison of the same for Panel B further shows that the referred couriers on average work more *Total Hours* each week, complete more *Total Orders* each week, and have greater *Total Earnings* each week (all differences are statistically significant at $p < 0.01$). Turning in particular to our primary outcome measure, *Hourly Earnings*, referred couriers on average earn 146.5 INR per hour while non-referred couriers on average earn INR 127.2 per hour, which represents a significant difference of about 15.2% in *Hourly Earnings* ($p < 0.01$).[3]

[2] Naturally, couriers using a motorcycle can travel faster, enabling them to complete more orders per hour and hence achieve greater hourly earnings. But this variable can also be seen as a (partial) control for the socioeconomic status of a courier, since motorcycle ownership is significantly more expensive than bicycle ownership.

[3] Figures A1 and A2 in the Appendix show the full distribution of *Hourly Earnings*, both overall and disaggregated by the courier's referral status.

These summary statistics are consistent with the view that referral ties might have helped referred couriers increase their earnings. However, the analysis so far does not rule out the possibility of the pattern being driven purely by a selection effect instead, whereby referred couriers differ significantly from non-referred couriers already prior to joining the platform.

As a first step towards accounting for the potential selection effect mentioned above, we start by matching on the couriers' observable characteristics to construct a corresponding sample of non-referred couriers that can be considered more comparable to the referred courier sample. In particular, we implement a one-to-many exact matching procedure using *Female*, *Motorcycle Ownership*, *Week of Entry*, and *Geographic Area*. The resulting matched sample and the corresponding matching weights are used to report the summary statistics for the matched sample in Column 4 of Table 1. Comparing the summary statistics in Panel A across Columns 2, 3 and 4 of Table 1, we see that the matching procedure significantly improves balance on the variables employed. As expected, relative to the unmatched non-referred courier sample (Column 3), the matched non-referred courier sample (Column 4) more closely resembles the referred courier sample (Column 2) in terms of gender (now 1.3% vs. 1.5%, $p = 0.263$), motorcycle ownership (now 57.8% vs. 57.8%, $p = 0.967$), and week of entry (now 9.8 vs. 9.9, $p = 0.052$). Importantly, looking at Panel B, the difference between referred and non-referred couriers for our primary dependent variable, *Hourly Earnings*, increases rather than decreases once the matching process is employed (now INR 146.54 vs INR 121.30, $p < 0.01$).[4]

— INSERT TABLE 1 HERE —

Matching on observables reduces but does not eliminate a concern that the observed earnings gap between the referred and non-referred couriers might just reflect selection effects related to unobserved differences between the referred and non-referred couriers. Therefore, we complement our use of matching with a difference-in-differences analysis that can provide more credible causal identification.

[4] As Panel B also shows, this pattern is robust to using *Total Earnings* for the week as the measure for the couriers' earnings, with referred couriers earning significantly more than matched non-referred couriers, on average.

5. ECONOMETRIC APPROACH

In this section, we introduce our two complementary econometric approaches for formally examining the extent and nature of the link between referrals and worker performance. Our first econometric approach examines the association between a courier's referral status and performance through a multivariate regression model that uses the matched sample described in Section 4.3. Although this analysis employs our dataset that is at the courier-week level, this is essentially a pooled cross-sectional comparison that involves estimating the following regression on the matched sample and accordingly clustering the standard errors at the courier level:

$$Hourly\ Earnings_{it} = \beta_0 + \beta_1 Referred_i + \theta X_i + \delta_t + \gamma_c + \lambda_i + \varepsilon_{it} \tag{1}$$

where $Hourly\ Earnings_{it}$ represents the average hourly earnings for courier i in week t, *Referred* is an indicator variable for courier's referral status, and the vector X_i includes two controls—*Female* and *Motorcycle Ownership*. The model also includes relevant fixed effects: δ_t denotes *Week* fixed effects, γ_c denotes *Geographic Area* fixed effects, and λ_i denotes *Week of Entry* fixed effects. Our primary interest in carrying out this regression is in the sign, economic magnitude and statistical significance of the estimate for β_1, whose being positive and significant would indicate that referred couriers do indeed on average earn more per hour than their respective matched non-referred couriers.

Our second econometric approach employs a longitudinal difference-in-differences estimation approach to get at the question of whether the observed difference between earnings of the referred and the respective matched non-referred couriers in equation (1) represent a treatment effect that can be causally attributable to the referral ties. A cross-sectional comparison lacks a pre-treatment period—referred couriers are always referred, so selection and treatment are confounded by construction. We can, however, observe referred couriers losing their active tie when their referrer exits the platform. To the extent that the referral premium reflects a genuine treatment effect, it should diminish when the tie is severed. Our identification strategy exploits the fact that many referring couriers exit the platform before the end of our observation period, with referrer exit serving as a quasi-exogenous shock to the referred courier's active social connection.[5]

We start with the simplest way to implement the above idea by replacing *Referred* in Equation (1) by two time-varying indicator variables introduced earlier—*Referred with Referrer Present* and *Referred with Referrer Exited*—to estimate the following pooled regression model that more fully employs the full richness of our courier-week panel data than Equation (1):

$$\begin{aligned} \textit{Hourly Earnings}_{it} = \beta_0 + \beta_1(\textit{Referred with Referrer Present})_{it} \\ + \beta_2(\textit{Referred with Referrer Exited})_{it} + \theta X_i + \delta_t + \gamma_c + \lambda_i + \varepsilon_{it} \end{aligned} \tag{2}$$

where our interest is now in the sign, economic magnitude and statistical significance of the difference $\beta_1 - \beta_2$, which we expect to be positive and significant if referred couriers do indeed earn more as long as they have an active referral tie, i.e., their referrer is still active on the platform, than after the referrer has exited the platform.

Next, we refine the above approach by implementing a staggered difference-in-differences specification that employs two-way fixed effects for *Courier* and calendar *Week*. This specification still relies on the full sample of couriers but exploits within-courier changes in earnings of the referred couriers before versus after a referrer exits the platform. For non-referred couriers, the indicator *Referrer Exited* always remains zero, so these couriers serve as never-treated comparison units alongside referred couriers whose referrers have not yet exited. Specifically, we estimate the following two-way fixed effects (TWFE) model:

$$\textit{Hourly Earnings}_{it} = \alpha_i + \delta_t + \beta_1 \textit{Referrer Exited}_{it} + \varepsilon_{it} \tag{3}$$

where α_i represents the courier fixed effects (which absorb all time-invariant courier-level variables used in the previous equation), δ_t represents week fixed effects, and *Referrer Exited*$_{it}$ is an indicator equal to 1 after courier *i*'s referrer has exited the platform, and 0 otherwise. The coefficient β_1 now

[5] One specific concern might be that certain changes in platform policies or external demand might induce greater referrer exits as well as changes in referred couriers' earnings. However, if this were the case, we should expect referrer exits to cluster in particular weeks, which we do not see when we plot the distribution of referrer exits over time (see Figure A3 in the Appendix).

captures the average change in *Hourly Earnings* following tie disruption, i.e., the referrer's exit.

One remaining concern with the above model is that, because referrer exit occurs at different points in time across couriers, our TWFE estimation may combine effects across cohorts and over time, potentially biasing the estimation (De Chaisemartin and d'Haultfoeuille 2020, Goodman-Bacon 2021). To address this concern, we employ a refined difference-in-differences estimator developed by Callaway and Sant'Anna (2021), which accounts for this staggered timing of treatment. The approach, which we will refer to as CSDID, estimates treatment effects separately by cohort—defined in our case by the week of referrer exit—and compares treated couriers at each point in time only to couriers who are not yet treated. Formally, we estimate the average treatment on the treated (ATT) effect as:

$$\mathrm{ATT}(g,t) = \mathbb{E}\left[\textit{Hourly Earnings}_{it}(1) - \textit{Hourly Earnings}_{it}(0) \mid \mathrm{G}_i = g\right] \tag{4}$$

where $G_i = g$ indicates that courier i's referrer exits in week g. We aggregate cohort-specific effects across groups and time periods using the weighting scheme proposed by Callaway and Sant'Anna (2021) and implement their recommended doubly robust inverse-probability weighting approach. Standard errors are computed using a wild bootstrap with 1,000 replications, clustered at the courier level. All CSDID specifications use a ten-week window before and after referrer exit.

We estimate three versions of this model, progressively narrowing the control group. The first version includes all couriers as potential controls, so that referred couriers whose referrers have exited are compared to both non-referred couriers and referred couriers whose referrers have not yet exited or never exit during our sample period. The second version restricts the sample to referred couriers only, using those whose referrers have not yet exited or never exit during our sample period as controls. The third version, and our preferred specification, further restricts the sample to referred couriers whose referrers all eventually exit during our sample period, comparing referred couriers whose referrers already exited to referred couriers whose referrers have not yet exited. Because all couriers in this sample eventually experience referrer exit, treated and control couriers differ only in *when* their referrers leave rather than in *whether* they do, helping further mitigate concerns that the two groups may be compositionally different.

6. MAIN RESULTS

Table 2 reports estimates from multivariate analysis that employs our matched sample of referred and non-referred couriers to estimate equation (1). As shown in Column 1, referred couriers are found to earn an average of INR 17.27 more per hour than non-referred couriers, representing a 14.2% premium relative to the average hourly earnings of the matched sample of the non-referred couriers (INR 121.30 as per Column 4 of Table 1). Column 2 decomposes this effect using equation (2), distinguishing between referred couriers in the weeks in which their referrers are still active on the platform (*Referred with Referrer Present*) from the weeks following their referrer's exit, if any (*Referred with Referrer Exited*). Referred couriers with an active referrer earned INR 25.99 more per hour than the non-referred couriers, which represents a 21.4% premium relative to the average hourly earnings of the non-referred couriers. By contrast, referred couriers whose referrers had exited earned only INR 4.94 more per hour, representing just a 4.1% premium. The pooled difference-in-differences statistic is therefore INR 21.05 per hour, representing a 17.4% premium for having an active referral tie ($p < 0.01$). In other words, the earnings premium documented for the referred couriers in Column 1 is largely contingent on the referrer actually being active on the platform, since the premium largely disappears once the referrer exits and hence the referral tie is no longer active.[6]

— INSERT TABLE 2 HERE —

In Table 3, we move to estimation based on equations (3) and (4) to refine our prior difference-in-differences estimation by further exploiting the variation in the incidence and timing of the referrer's exit across the referred couriers. Column 1 presents the findings from implementing our two-way fixed effects (TWFE) specification from equation (3). This analysis still employs our full sample of couriers from Table 2. In other words, the treated couriers, i.e., referred couriers

[6] To assess robustness, we also re-estimated our models using alternative outcome definitions, including the natural logarithm of *Hourly Earnings*, *Total Earnings*, and the natural logarithm of *Total Earnings*. Across specifications, the estimation results remain qualitatively similar (see Table A1 in the Appendix).

whose referrers had already exited as of a given week, are still compared to a combination of referred couriers whose referrers had not yet exited, referred couriers whose referrers never exit during our sample period, as well as non-referred couriers. The TWFE estimate in Column 1 represents an economically and statistically significant decline of INR 20.34 ($p < 0.01$) in hourly earnings following referrer exit, i.e., following the disruption of an active referral tie, remarkably similar to our earlier pooled difference-in-differences estimate of INR 21.05 from Column 2 of Table 2.

To address limitations of the TWFE estimation described earlier, Column 2 of Table 3 reports estimates from our CSDID analysis based on equation (4) with all couriers (i.e., the control group includes all referred couriers whose referrers have not yet exited, whose referrers never exit during our sample period, as well as couriers who were not referred). The estimated decline from this analysis is INR 20.85, again remarkably similar to both our TWFE estimate in Column 1 and the pooled difference-in-differences estimate in Column 2 of Table 2. Next, Column 3 restricts the sample to only referred couriers, using referred couriers whose referrers have not yet exited or never exit during our sample period as the control group. The estimated effects become smaller, amounting to INR 15.78, but remain statistically significant ($p < 0.01$) and economically comparable to our results in the first two columns.

Finally, Column 4 reports our preferred specification that relies only on the sample of referred couriers whose referrers exit during our sample period. The estimated average treatment effect on the treated for this CSDID estimation is a decline of INR 16.01 per hour, which remains statistically significant ($p < 0.01$). Post-estimation calculations reveal that the average predicted value for *Hourly Earnings* for the treated couriers (i.e., the referred couriers whose referrers exited during our observation window) was INR 128.61 for the pre-treatment period (i.e., before the referrer's exit) and INR 112.60 for the post-treatment period (i.e., after the referrer's exit). The INR 16.01 drop between the two therefore represents a 12.5% decrease relative to the average predicted value of *Hourly Earnings* for the pre-treatment period. Another useful benchmark for interpreting the materiality of this drop in earnings is the raw statistic for the *Hourly Earnings* premium for referrals in the matched sample, which is INR 25.23 (calculated as the difference between its average values in Columns 2 and 4 in Table 1). Our CSDID estimate is thus economically significant and not too dissimilar from the overall referral premium that motivated our investigation in the first place.

We also present in Figure 1 the detailed event-study estimates for the estimation in Column 4 of Table 3, plotting treatment effects by event timing (weeks relative to referrer exit, starting with zero in the week immediately preceding exit). The pre-exit coefficients, which are useful to assess whether the earnings were trending differentially even prior to exit, are small and statistically indistinguishable from zero. The post-exit coefficients indicate that hourly earnings decline sharply for about five weeks before stabilizing to be persistently lower at approximately INR 25 per hour below the pre-exit level.[7,8]

— INSERT TABLE 3 AND FIGURE 1 HERE —

In sum, across all variants of our difference-in-differences examination in Tables 2 and 3, we consistently find strong evidence that referrer exit is associated with a persistent decline in referred couriers' hourly earnings. The economic magnitude of this drop is substantial and lies in the range of INR 16–21 per hour, depending on the exact difference-in-differences model and the comparison sample employed. In other words, the evidence is more consistent with a genuine treatment effect of active referral ties than with a premium driven purely by selection at the recruiting stage.

7. FURTHER EXPLORATION OF MECHANISMS

We now further investigate our proposed mechanism of information-sharing as a key driver of the treatment effect documented above. First, if referred couriers benefit from real-time information sharing with their referrers, then the effect should be stronger when both couriers are concurrently active on the platform, i.e., greater temporal overlap in their activity should lead to a greater earnings boost for the referred courier. Second, we examine the operational channel through which this

[7] One might also ask whether our effects might be driven by selective attrition across couriers following referrer exit: if more productive couriers exit sooner after referrer exit, estimates of post-exit earnings decline may reflect differential attrition rather than treatment. We checked for this by restricting the referred courier sample to those who remain active for at least ten weeks following referrer exit. The results, reported in Table A2 and Figure A4 in the Appendix, remain robust and economically similar to the main CSDID results (a decline of INR 22.76).

[8] Event-study estimates from our TWFE specification from before and from alternative CSDID comparison groups described below exhibit similar dynamics and are available from the authors upon request.

occurs, testing whether concurrent activity helps referred couriers complete more orders and position themselves closer to high-demand pick-up locations. Third, we examine whether the referrer's presence on the platform is particularly beneficial for enhancing compensation components for which information sharing can indeed be expected to help more. We describe each set of tests in turn next.

Association Between Weekly Activity Overlap and Hourly Earnings.

We first examine whether referred couriers earn more in the weeks when they spend more hours concurrently active with their referrer. For each referred courier–week, we estimate:

$$\begin{aligned} \textit{Hourly Earnings}_{it} = \beta_0 + \beta_1(\textit{Weekly Overlap Hours})_{it} + \beta_2(\textit{Total Referred Hours})_{it} \\ + \beta_3(\textit{Total Referring Hours})_{it} + \delta_t + \alpha_i + \varepsilon_{it} \end{aligned} \tag{5}$$

where *Weekly Overlap Hours*$_{it}$ is the total number of hours in week t when courier i and their referrer are simultaneously online. The model controls for the referred and referring courier's total hours worked that week as *Total Referred Hours* and *Total Referring Hours*, respectively (though the results are not sensitive to doing so), α_i captures courier fixed effects, and δ_t captures the calendar *Week* fixed effects. As in our earlier models, the standard errors are clustered at the courier level.

Table 4 reports the estimates from this specification: Each additional hour of weekly overlap is indeed associated with a INR 0.63 increase in hourly earnings—about 0.5% of the mean *Hourly Earnings* of referred couriers in the sample. In other words, given that referred couriers on average have 5.5 overlapping hours per week with their referrer, a doubling of the overlapping hours from this initial baseline would be associated with a 2.5% increase in hourly earnings.

— INSERT TABLE 4 HERE —

Association Between Hourly Activity Overlap and Operational Outcomes.

To understand how activity overlap between the referred and the referring couriers translates into better operational performance (that drives the higher hourly earnings), we next construct and employ a more fine-grained dataset where the unit of analysis is now the courier-hour (rather than courier-week). This allows us to examine how hour-by-hour concurrent activity affects two operational performance metrics critical for the referred courier's earnings: the number of orders completed (*Number of Orders*), and the average distance to the order pickup point (*Distance to Pickup*), a proxy for being able to locate close to high-demand areas. We estimate the following equation, where we use Y to denote either of the two operational outcomes mentioned above:

$$\begin{aligned} Y_{ith} = \beta_0 + \beta_1 (Overlap)_{ith} + \beta_2 (Total\ Referred\ Hours)_{it} \\ + \beta_3 (Total\ Referring\ Hours)_{it} + \delta_t + \alpha_i + \eta_h + \varepsilon_{ith} \end{aligned} \tag{6}$$

where i indexes referred couriers, t indexes weeks and h indexes the cumulative hour within the week (taking values from 1 to 168, i.e., 24×7). $Overlap_{ith}$ equals 1 if the referred courier i and their referrer were both active during the hour h within the week t, and is 0 otherwise. We also control for the total number of hours each courier worked during that week so that the overlap effect is not driven by differences in how much they worked overall. Courier fixed effects (α_i) absorb time-invariant heterogeneity across couriers, week fixed effects (δ_t) absorb platform-wide temporal shocks common to all couriers in a given week, and hour-of-week fixed effects (η_h) absorb any systematic variation across the 168 hours of the week. Standard errors are clustered at the courier level.

Table 5 shows that overlap improves performance on both of our dependent variables capturing a courier's hourly operational outcomes. Across the 2,124,385 courier-hour observations analyzed, the referred couriers average 1.92 orders per hour, with average pickup distance of 1.60 km (see Table A3 in the Appendix). Concurrent activity increases orders by 0.070 per hour (a 3.6% increase relative to the average) and reduces pickup distance by 0.022 km (a 1.4% decrease relative to the average). In summary, the estimated effects are consistent with real-time information sharing helping referred couriers position themselves more effectively to access orders, which may help explain their higher earnings.[9]

[9] We also carried out exploratory interviews with 70 couriers to learn more about their experience of working on the

— INSERT TABLE 5 HERE —

Decomposing the Effect of Referrer Exit Across Earnings Components.

If referrers help couriers navigate complex pay rules, then the effects of referrer exit should be particularly pronounced for earnings components whose payout structure is more complex and harder to interpret, and where information sharing with the referrer is therefore most valuable. Based on our interviews with couriers, discussions with the platform's managers, and direct examination of the platform's pay schedules (see Figure A5 in the Appendix for an example), we treat three of the platform's five pay components as relatively more complex and challenging to interpret: minimum guarantee (MG) pay, order pay, and penalties.

MG pay is governed by multi-tiered weekly thresholds that vary by shift, time window, and order type, with eligibility contingent on conditions such as minimum order counts, cancellation rules, and time-of-day requirements. While these parameters are displayed in the platform's app, their payout implications are complex and often difficult for couriers to understand. Order pay can be similarly complex, as it depends on multiple algorithmically combined factors—including distance slabs, demand conditions, and order sequencing—without a clear or stable mapping from observable effort to compensation. Finally, penalties are applied through rules that are often communicated only ex post, making their incidence difficult to predict or avoid.

In contrast, incentives (e.g., explicitly stated surge or festival bonuses) and customer tips are typically more straightforward and less amenable to strategic navigation. Incentives have clearly specified eligibility criteria and payout formulas, leaving little room for interpretation. Tips, while uncertain ex ante, depend on customer discretion rather than platform rules. As a result, there is relatively little a courier can do to systematically influence them through their knowledge of how the platform works.

Based on the above reasoning, we decompose *Hourly Earnings* into *Information-Sensitive*

platform. Several couriers explained how real-time information exchange about demand conditions and positioning across zones often helped their performance. One courier explained, "We work in different areas and share which zones are getting more orders" (Courier 1). Others emphasized the role of co-presence in calibrating work intensity and timing decisions: "My roommates see my phone—login times, targets, earnings—and decide when and where to start" (Courier 2).

Earnings per Hour (minimum guarantee, order-level earnings or penalties) and *Other Earnings per Hour* (incentives or tips). We then use our CSDID estimation approach to estimate component-specific treatment effects by referrer exit cohort, comparing referred couriers whose referrers exit to those whose referrers have not yet exited. Table 6 shows a clear divergence across earnings components. *Information-Sensitive Earnings per Hour* decline by INR 13.80—about 12% of mean pre-exit total information-sensitive earnings—and this effect is statistically significant ($p < 0.01$). In contrast, *Other Earnings per Hour* decline modestly by INR 0.38 following referrer exit, with the effect not being statistically significant. This pattern suggests that referrers primarily help couriers navigate the more complex components of platform compensation, where platform know-how matters most, rather than earnings components where additional information may have little effect.[10]

— INSERT TABLE 6 HERE —

8. DISCUSSION

With gig work on digital platforms expanding globally and providing livelihoods to tens of millions of low-income workers in emerging markets, understanding what drives gig worker earnings is increasingly important. In this paper, we argue that referral ties can increase workers' earnings even in the gig economy context by providing access to informal support and information relevant for worker performance in platform-mediated work. Our pooled cross-sectional results suggest that referred couriers earn 14.2% more per hour than observationally similar non-referred couriers. Difference-in-differences models relying on referrer exits as quasi-exogenous events find results consistent with the above observation: when a referrer leaves, their referred workers' earnings drop by 12.5% (in our preferred estimation model), erasing much of the earnings premium relative to non-referred couriers. We also find evidence consistent with real-time information exchange being an important underlying mechanism driving workers' performance: couriers earn more per hour,

[10] In our exploratory interviews, couriers suggested that more experienced peers indeed often helped them interpret complex compensation rules, such as for meeting MG thresholds and achieving certain pay adjustments. As one noted, "We share how to complete the order target quickly to get the MG" (Courier 3). Some non-referred couriers reported learning about such rules only after experiencing unexpected payout outcomes: "Nobody told me about the targets or bonuses. I only understood after my payout was low" (Courier 4). These accounts are consistent with the idea that social ties may help couriers navigate complex pay components.

complete more orders and position themselves closer to high-demand locations when their referrers are online in the same hour, and earnings declines following referrer exit are concentrated in more complex and information-sensitive compensation components.

Our study makes several contributions to extant literatures. First, we extend the work on gig worker performance and earnings (Spreitzer et al. 2017, Cropanzano et al. 2023) by incorporating social ties via referrals as an important driver. Prior literature on the drivers of worker performance often focuses on the characteristics of platforms (Rietveld and Eggers 2018, Chung et al. 2024) and worker attributes (Chen et al. 2019, Collins et al. 2019, Angrist et al. 2021, Katsnelson and Oberholzer-Gee 2021, Cameron 2022, Datta and Chen 2023). To the extent that social networks among platform workers are discussed, they are often viewed as a means of improving workers' emotional wellbeing (Petriglieri et al. 2019, Cameron 2022) and collective bargaining power (Rosenblat 2018, Maffie 2020). To the best of our knowledge, prior work has not examined how social ties may also help improve worker performance and earnings on the platform. Our findings suggest that workers may benefit from explicitly trying to grow their social networks on the platform.

Second, we also extend the work on referral-based hiring to the gig economy (Fernandez et al. 2000, Castilla 2005, Burks et al. 2015, Campero and Kacperczyk 2023). The gig context represents an extreme case of an organization with high physical dispersion of workers, no managerial oversight, little ability to monitor the workers who are referred, and high levels of turnover. This raises the question of whether referrals work at all in this context, and if so, through which mechanisms. We show that referrals do increase worker earnings even in this context, and identify a mechanism that differs from those emphasized in existing work from traditional employment settings. Existing research often emphasizes initial transfers of knowledge that can benefit referred workers at the point of entry into the organization (e.g., Premack and Wanous 1985, Wanous et al. 1992, Campero and Kacperczyk 2023), but the value of which may depreciate over time (e.g., Castilla 2005, Pieper 2015). In contrast, we uncover a novel mechanism of real-time information sharing that benefits the referred worker throughout their tenure as long as the referrer remains active on the platform.

Third, by examining worker performance in India—an emerging economy in the Global

South where the gig sector is growing rapidly and employing millions of people (NITI Aayog 2022)—we respond to calls by strategy scholars for more research from understudied populations from such emerging market settings. Much of the extant work on the gig economy focuses on developed Western economies, where workers often have access to alternative employment and wider informational resources (Hall and Krueger 2018, Koustas 2019, Curchod et al. 2020, Angrist et al. 2021, Cameron 2022). However, in many emerging economies, gig workers often rely on such work as the primary source of livelihood (NITI Aayog 2022, Datta and Chen 2023) and have access to fewer resources to navigate the complex platform rules that govern their earnings (Koo and Eesley 2021). In such contexts, interpersonal information channels such as the referral ties we study may be especially consequential for worker outcomes.

However, our study is not without limitations. First, we examine our research question in the context of a single on-demand delivery platform. We believe the conditions at this platform should generalize to others—it is app-based, largely algorithmically managed, and relies on individual incentives that are similar to other ride-hailing and delivery platforms such as Uber and Lyft. Yet, the specific nature of GigRider's incentive systems—how complex they are, how often they change, the type of onboarding and ongoing support that the platform provides—may be particular to this platform. Future work may therefore fruitfully examine how referrals impact earnings on other platforms.

Second, our study is set in a single country, India. While we have data on more than 200 cities, the strength and nature of social ties in this context may differ from those in other countries. Platform workers in India are often migrants from smaller towns and villages, and communication among them may be hindered by the considerable linguistic diversity across regions. Together, these factors may produce smaller and more fragmented, but potentially also more intensive and supportive networks than workers may have if they spent their entire lives in the same city and/or spoke the same language. Future research may therefore fruitfully explore how variation in these dimensions across different contexts may shape the effectiveness of referral-based systems in platform settings.

Third, our core findings rely on the quasi-exogenous timing of referrer departure. While we argue that the exact timing of referrer departure is unlikely to be endogenous to referred workers' future performance, and we perform additional robustness checks to help address concerns regarding common shocks to earnings and selective attrition among referred workers, we cannot fully rule out that some unobserved factor jointly drives both referrer departure and the subsequent decline in referred workers' earnings. Future research using alternative identification strategies, such as randomized control trials, could help address this limitation.

9. CONCLUSION

In conclusion, our study demonstrates that referral programs in the gig economy may serve not only as a recruitment mechanism as emphasized in prior work on traditional employment but also as an ongoing performance and earnings support system for gig workers. We show that referred workers systematically earn more than their non-referred counterparts, but these advantages diminish when referrers exit the platform, suggesting treatment effects involving social ties that transmit valuable information well beyond initial recruitment. These findings have important implications for platform design and worker strategies. Platforms seeking to improve worker performance might benefit from taking the role of social ties between gig workers seriously, such as by moving beyond simple referral bonuses to develop systems that help sustain worker networks and facilitate peer-to-peer information exchange. Workers, in turn, may gain from actively building and maintaining connections with other platform participants. More broadly, our results suggest that treating gig work as purely atomized, individual labor overlooks the significant social infrastructure that underlies successful platform participation in the gig economy.

REFERENCES

Ai W, Chen Y, Mei Q, Ye J, Zhang L (2023) Putting teams into the gig economy: A field experiment at a ride-sharing platform. *Management Sci.* 69(9):5336–5353.

Ananny M, Crawford K (2018) Seeing without knowing: Limitations of the transparency ideal and its application to algorithmic accountability. *New Media & Soc.* 20(3):973–989.

Angrist JD, Caldwell S, Hall JV (2021) Uber versus Taxi: A driver's eye view. *Amer. Econom. J.: Appl. Econom.* 13(3):272–308.

Anyshift (n.d.) Find highest paid top-rated gig jobs in Houston, TX now. Accessed December 1, 2025, https://www.anyshift.com/business-referral-shifter.

Brailovskaya V (2025) Digital labor gig economy from the worker's perspective: A literature review. Report, IDinsight.

Bucher E, Schou PK, Waldkirch M (2024) Just another voice in the crowd? Investigating digital voice formation in the gig economy. *Acad. Management Discoveries* 10(3):488–511.

Burks SV, Cowgill B, Hoffman M, Housman M (2015) The value of hiring through employee referrals. *Quart. J. Econom.* 130(2):805–839.

Burrell J (2016) How the machine 'thinks': Understanding opacity in machine learning algorithms. *Big Data & Soc.* 3(1):1–12, URL http://dx.doi.org/10.1177/2053951715622512.

Callaway B, Sant'Anna PH (2021) Difference-in-differences with multiple time periods. *J. Econometrics* 225(2):200–230.

Camerer C, Vepsalainen A (1988) The economic efficiency of corporate culture. *Strategic Management J.* 9(S1):115–126.

Cameron LD (2022) "Making out" while driving: Relational and efficiency games in the gig economy. *Organ. Sci.* 33(1):231–252.

Campero S, Kacperczyk A (2023) Network referrals and self-presentation in the high-tech labor market. *Organ. Sci.* 35(3):1023–1044, URL http://dx.doi.org/10.1287/orsc.2022.16674.

Castilla EJ (2005) Social networks and employee performance in a call center. *Amer. J. Sociol.* 110(5):1243–1283.

Chen MK, Chevalier JA, Rossi PE, Oehlsen E (2019) The value of flexible work: Evidence from Uber drivers. *J. Political Econom.* 127(6):2735–2794.

Chen MK, Sheldon M (2016) Dynamic pricing in a labor market: Surge pricing and flexible work on the Uber platform, working paper, University of California, Los Angeles.

Chung HD, Zhou YM, Ethiraj S (2024) Platform governance in the presence of within-complementor interdependencies: Evidence from the rideshare industry. *Management Sci.* 70(2):799–814.

Collins B, Garin A, Jackson E, Koustas D, Payne M (2019) Is gig work replacing traditional employment? Evidence from two decades of tax returns, working paper, Russell Sage Foundation, New York.

Cook C, Diamond R, Hall JV, List JA, Oyer P (2021) The gender earnings gap in the gig economy: Evidence from over a million rideshare drivers. *Rev. Econom. Stud.* 88(5):2210–2238.

Crawford VP, Meng J (2011) New York city cab drivers' labor supply revisited: Reference-dependent preferences with rational-expectations targets for hours and income. *Amer. Econom. Rev.* 101(5):1912–1932.

Cropanzano R, Keplinger K, Lambert BK, Caza B, Ashford SJ (2023) The organizational psychology of gig work: An integrative conceptual review. *J. Appl. Psych.* 108(3):492–519.

Curchod C, Patriotta G, Cohen L, Neysen N (2020) Working for an algorithm: Power asymmetries and agency in online work settings. *Admin. Sci. Quart.* 65(3):644–676.

Datta N, Chen R (2023) *Working Without Borders: The Promise and Peril of Online Gig Work* (Washington, DC: World Bank).

De Chaisemartin C, d'Haultfoeuille X (2020) Two-way fixed effects estimators with heterogeneous treatment effects. *Amer. Econom. Rev.* 110(9):2964–2996.

Dube A, Jacobs J, Naidu S, Suri S (2020) Monopsony in online labor markets. *Amer. Econom. Rev.: Insights* 2(1):33–46.

Duggan J, Sherman U, Carbery R, McDonnell A (2020) Algorithmic management and app-work in the gig economy: A research agenda for employment relations and HRM. *Human Resource Management J.* 30(1):114–132.

Farber HS (2005) Is tomorrow another day? The labor supply of New York city cabdrivers. *J. Political Econom.* 113(1):46–82.

Fernandez RM, Castilla EJ, Moore P (2000) Social capital at work: Networks and employment at a phone center. *Amer. J. Sociol.* 105(5):1288–1356.

Fernandez RM, Weinberg N (1997) Sifting and sorting: Personal contacts and hiring in a retail bank. *Amer. Sociol. Rev.* 62(6):883–902.

Filippas A, Horton JJ, Zeckhauser RJ (2020) Owning, using, and renting: Some simple economics of the "sharing economy". *Management Sci.* 66(9):4152–4172.

Gandini A (2019) Labour process theory and the gig economy. *Human Relations* 72(6):1039–1056.

Garin A, Jackson E, Koustas D, Miller A (2024) The evolution of platform gig work, 2012–2023, working paper, National Bureau of Economic Research, Cambridge, MA.

Goodman-Bacon A (2021) Difference-in-differences with variation in treatment timing. *J. Econometrics* 225(2):254–277.

Granovetter M (1985) Economic action and social structure: The problem of embeddedness. *Amer. J. Sociol.* 91(3):481–510.

Griesbach K, Reich A, Elliott-Negri L, Milkman R (2019) Algorithmic control in platform food delivery work. *Socius* 5:1–15, URL http://dx.doi.org/10.1177/2378023119870041.

Hall JV, Horton JJ, Knoepfle DT (2021) Pricing in designed markets: The case of ride-sharing, working paper.

Hall JV, Krueger AB (2018) An analysis of the labor market for Uber's driver-partners in the United States. *ILR Rev.* 71(3):705–732.

Idug Y, Niranjan S, Manuj I, Gligor D, Ogden J (2023) Do ride-hailing drivers' psychological behaviors influence operational performance? *Internat. J. Oper. Production Management* 43(12):2055–2079.

Jarrahi MH, Sutherland W (2019) Algorithmic management and algorithmic competencies: Understanding and appropriating algorithms in gig work. *Information in Contemporary Society*, 578–589 (Cham, Switzerland: Springer International Publishing).

Johnson C, Bester H, Janse Van Vuuren P, Dunn M (2020) Africa's digital platforms: Trends report. Technical report, Cenfri, Cape Town, South Africa, URL https://cenfri.org/wp-content/uploads/Africas-digital-platforms-trends-report.pdf.

Katsnelson L, Oberholzer-Gee F (2021) Being the boss: Gig workers' value of flexible work, working paper, Harvard Business School, Boston.

Katz LF, Krueger AB (2019) Understanding trends in alternative work arrangements in the United States. *RSF: Russell Sage Found. J. Soc. Sci.* 5(5):132–146.

Kaynar N, Siddiq A (2022) Estimating effects of incentive contracts in online labor platforms. *Management Sci.* 69(4):2106–2126.

Kellogg KC, Valentine MA, Christin A (2020) Algorithms at work: The new contested terrain of control. *Acad. Management Ann.* 14(1):366–410.

Koning R, Hasan S, Chatterji A (2022) Experimentation and start-up performance: Evidence from A/B testing. *Management Sci.* 68(9):6434–6453.

Koo W, Eesley C (2021) Platform governance and the rural–urban divide: Sellers' responses to design change. *Strategic Management J.* 42:941–967.

Koustas DK (2019) What do big data tell us about why people take gig economy jobs? *AEA Papers Proc.* 109:367–371.

Kretschmer T, Leiponen A, Schilling M, Vasudeva G (2022) Platform ecosystems as meta-organizations: Implications for platform strategies. *Strategic Management J.* 43(3):405–424.

Lee MK, Kusbit D, Metsky E, Dabbish L (2015) Working with machines: The impact of algorithmic and data-driven management on human workers. *Proc. 33rd Annual ACM Conf. Human Factors in Computing Systems*, 1603–1612 (Seoul, Republic of Korea: ACM), URL http://dx.doi.org/10.1145/2702123.2702548.

Maffie MD (2020) The role of digital communities in organizing gig workers. *Indust. Relations* 59(1):123–149.

Mas A, Pallais A (2017) Valuing alternative work arrangements. *Amer. Econom. Rev.* 107(12):3722–3759.

Mas A, Pallais A (2020) Alternative work arrangements. *Annual Rev. Econom.* 12(1):631–658.

Möhlmann M, Zalmanson L (2017) Hands on the wheel: Navigating algorithmic management and Uber drivers' autonomy. *Proceedings of the Thirty Eighth International Conference on Information Systems (ICIS 2017)*, 1–17 (Seoul, South Korea).

NITI Aayog (2022) India's booming gig and platform economy. Policy brief, NITI Aayog, Government of India, New Delhi.

Petriglieri G, Ashford SJ, Wrzesniewski A (2019) Agony and ecstasy in the gig economy: Cultivating holding environments for precarious and personalized work identities. *Admin. Sci. Quart.* 64(1):124–170.

Pieper JR (2015) Uncovering the nuances of referral hiring: How referrer characteristics affect referral hires' performance and likelihood of voluntary turnover. *Personnel Psych.* 68(4):811–858.

Premack SL, Wanous JP (1985) A meta-analysis of realistic job preview experiments. *J. Appl. Psych.* 70(4):706–719.

Rahman HA (2021) The invisible cage: Workers' reactivity to opaque algorithmic evaluations. *Admin. Sci. Quart.* 66(4):945–988.

Rahman HA, Weiss T, Karunakaran A (2023) The experimental hand: How platform-based experimentation reconfigures worker autonomy. *Acad. Management J.* 66(6):1803–1830.

Ravenelle AJ (2019) "We're not uber:" control, autonomy, and entrepreneurship in the gig economy. *J. Managerial Psych.* 34(4):269–285.

Rietveld J, Eggers JP (2018) Demand heterogeneity in platform markets: Implications for complementors. *Organ. Sci.* 29(2):304–322.

Rosenblat A (2018) *Uberland: How Algorithms Are Rewriting the Rules of Work* (Oakland, CA: University of California Press).

Rosenblat A, Stark L (2016) Algorithmic labor and information asymmetries: A case study of Uber's drivers. *Internat. J. Comm.* 10:3758–3784.

Schlachter SD, Pieper JR (2019) Employee referral hiring in organizations: An integrative conceptual review, model, and agenda for future research. *J. Appl. Psych.* 104(11):1325–1346.

Spreitzer GM, Cameron L, Garrett L (2017) Alternative work arrangements: Two images of the new world of work. *Annual Rev. Organ. Psych. Organ. Behav.* 4(1):473–499.

Sproutgigs (n.d.) Hire freelancers to help with small gigs for your business. Accessed December 1, 2025, https://sproutgigs.com/referral-program.php.

Uber Technologies (2018) Under the hood of Uber's experimentation platform. Accessed November 10, 2025, https://www.uber.com/en-SG/blog/xp/.

Uber Technologies (n.d.) How referrals work. Accessed December 1, 2025, https://www.uber.com/us/en/drive/basics/how-referrals-work/.

uParcel (n.d.) Your easiest way to deliver. Accessed December 1, 2025, https://www.uparcel.sg/blog/entry?blog_url=10-agent-referral-programme.

Vallas S, Schor JB (2020) What do platforms do? Understanding the gig economy. *Annual Rev. Sociol.* 46(1):273–294.

Wanous JP, Poland TD, Premack SL, Davis KS (1992) The effects of met expectations on newcomer attitudes and behaviors: A review and meta-analysis. *J. Appl. Psych.* 77(3):288–297.

Wood AJ, Graham M, Lehdonvirta V, Hjorth I (2019) Good gig, bad gig: Autonomy and algorithmic control in the global gig economy. *Work, Employment Soc.* 33(1):56–75.

Xu Y, Lu B, Ghose A, Dai H, Zhou W (2023) The interplay of earnings, ratings, and penalties on sharing platforms: An empirical investigation. *Management Sci.* 70(5):3077–3095, URL http://dx.doi.org/10.1287/mnsc.2023.4761.

Ye T, Ai W, Chen Y, Mei Q, Ye J, Zhang L (2022) Virtual teams in a gig economy. *Proc. Natl. Acad. Sci.* 119(51):e2206580119.

TABLES

Table 1: Summary Statistics

	(1)	(2)	(3)	(4)	(5)
	Full Sample (Unmatched)	Referred Couriers	Non-referred Couriers (Unmatched)	Non-referred Couriers (Matched)	Full Sample (Matched)
Panel A: Courier sample and characteristics					
Female	0.011	0.015	0.010	0.013	0.013
	(0.104)	(0.122)	(0.101)	(0.115)	(0.115)
Motorcycle Ownership	0.678	0.578	0.693	0.578	0.578
	(0.467)	(0.494)	(0.461)	(0.494)	(0.494)
Week of Entry	10.636	9.912	10.743	9.796	9.810
	(7.669)	(6.211)	(7.856)	(6.226)	(6.223)
Unique Couriers	100,231	12,811	87,420	84,369	97,180
Panel B: Operational metrics and earnings across courier-weeks					
Total Hours	12.273	18.481	10.791	10.728	12.300
	(14.231)	(17.094)	(13.028)	(13.100)	(14.346)
Total Orders	30.745	47.652	26.711	26.743	30.981
	(39.784)	(50.638)	(35.554)	(36.272)	(40.491)
Total Earnings	1,543.434	2,479.957	1,319.942	1,294.747	1,535.087
	(2,241.414)	(2,892.419)	(1,991.766)	(1,984.588)	(2,250.440)
Hourly Earnings	130.930	146.535	127.206	121.302	126.425
	(299.462)	(308.062)	(297.252)	(258.279)	(269.380)
Observations	419,281	80,780	338,501	334,795	415,575

Notes. This table presents means and standard deviations by referral status for couriers. The sample includes 100,231 unique couriers observed over a 39-week period from October 1, 2022, to June 30, 2023. Panel A reports time-invariant courier characteristics at the unique courier level, while Panel B reports performance and earnings at the courier-week level. Column 1 reports statistics for the full sample, Column 2 for referred couriers, Column 3 for all non-referred couriers, and Column 4 for exact-match weighted non-referred couriers matched to referred couriers. The matching procedure uses exact matching on *Female*, *Motorcycle Ownership*, *Week of Entry*, and *Geographic Area*. The matched sample in Column 4 contains 3,706 fewer courier-week observations than the unmatched non-referred sample in Column 3, corresponding to a reduction of approximately 1.1%. This limited attrition reflects the use of exact matching on discrete, largely complete variables with few missing values. Column 5 pools referred couriers (Column 2) with their exact-matched non-referred counterparts (Column 4) to form the full matched sample used as the estimation sample in the subsequent regression analyses. All mean differences between referred and non-referred couriers (unmatched) are statistically significant at the 1% level. Standard deviations are shown in parentheses.

Table 2: Association between Referral Status and Hourly Earnings

	(1)	(2)
Dependent Variable	*Hourly Earnings*	*Hourly Earnings*
Estimation Method	Pooled OLS	Pooled OLS
Sample	Full Sample (Matched)	Full Sample (Matched)
Referred	17.269***	
	(1.761)	
Referred with Referrer Present		25.986***
		(2.590)
Referred with Referrer Exited		4.937***
		(1.757)
Female	14.518*	14.644*
	(7.485)	(7.487)
Motorcycle Ownership	46.402***	46.226***
	(1.992)	(1.983)
Constant	96.169***	96.290***
	(1.104)	(1.099)
Adjusted R^2	0.076	0.076
Observations	413,371	413,371
Unique Couriers	92,954	92,954
Week Fixed Effects	Yes	Yes
Geographic Area Fixed Effects	Yes	Yes
Week of Entry Fixed Effects	Yes	Yes

Notes. This table reports OLS regression estimates from the matched sample examining the association between referral status, referrer presence, and *Hourly Earnings*. The unit of observation is the courier-week. *Hourly Earnings* is computed by dividing the total (INR) compensation that the courier received in a given week by their total online hours during which they were either delivering or waiting for orders that week. In column 1, *Referred* equals 1 for couriers who joined via a referral. In column 2, *Referred with Referrer Present* equals 1 for courier-weeks in which the referred courier's referrer is still active on the platform, and *Referred with Referrer Exited* equals 1 for courier-weeks in which the referrer has exited. The omitted category is non-referred couriers. Couriers are matched exactly on *Female*, *Motorcycle Ownership*, *Geographic Area*, and *Week of Entry*, and regressions are estimated on the matched sample using analytic weights. The regression sample ($N = 413{,}371$) is slightly smaller than the matched descriptive sample ($N = 415{,}575$) because fixed effects estimation automatically drops courier-weeks with insufficient within-group variation for the fixed effects included in the specification. All specifications include fixed effects for calendar *Week*, *Geographic Area*, and *Week of Entry*. Standard errors clustered at the courier level are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: Difference-in-Differences Estimates of the Effect of Referrer Exit on Hourly Earnings

	(1)	(2)	(3)	(4)
Dependent Variable	*Hourly Earnings*	*Hourly Earnings*	*Hourly Earnings*	*Hourly Earnings*
Estimation Method	TWFE	CSDID	CSDID	CSDID
Sample	All couriers	All couriers	Referred	Referred
Comparison Group	Referrer not yet exited + never exited + non-referred	Referrer not yet exited + never exited + non-referred	Referrer not yet exited + never exited	Referrer not yet exited
ATT	-20.341^{***}	-20.853^{***}	-15.782^{***}	-16.005^{***}
	(1.374)	(1.605)	(1.921)	(1.908)
95% CI	[−23.03, −17.65]	[−24.00, −17.71]	[−19.55, −12.01]	[−19.75, −12.26]
Observations	419,281	419,281	80,739	80,739
Unique Couriers	92,954	95,147	12,615	12,615
Treated Couriers	3,708	3,708	3,708	3,708
Week Fixed Effects	Yes	Yes	Yes	Yes
Courier Fixed Effects	Yes	Yes	Yes	Yes

Notes. This table reports difference-in-differences estimates of the effect of referrer exit on *Hourly Earnings*. The unit of observation is the courier-week. *Hourly Earnings* is computed by dividing the total (INR) compensation that the courier received in a given week by their total online hours during which they were either delivering or waiting for orders that week. A courier is classified as having exited if they remain inactive for 14 consecutive days and do not return to the platform for the remainder of the observation window. Column 1 reports estimates from a two-way fixed effects (TWFE) specification estimated on the full sample of couriers, where referred couriers whose referrers have exited are compared to all other couriers including non-referred couriers who are never treated. Standard errors in Column 1 are clustered at the courier level. Columns 2–4 report estimates using the Callaway and Sant'Anna (2021) difference-in-differences estimator with doubly robust inverse probability weighting. Column 2 uses the full sample, where non-referred couriers serve as additional never-treated controls alongside referred couriers whose referrers have not yet exited. Column 3 restricts the sample to referred couriers, with the control group comprising referred couriers whose referrers never exit as well as those whose referrers have not yet exited. Column 4 further restricts the control group to referred couriers whose referrers have not yet exited in the same calendar week. Standard errors in Columns 2–4 are computed using wild bootstrap with 1,000 replications to account for within-courier dependence.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: Association between Weekly Activity Overlap and Hourly Earnings

	(1)
Dependent Variable	*Hourly Earnings*
Estimation Method	OLS
Sample	Referred Couriers
Weekly Overlap Hours	0.630^{***}
	(0.118)
Total Referred Hours	-0.336^{***}
	(0.049)
Total Referring Hours	-0.324^{***}
	(0.085)
Adjusted R^2	0.382
Observations	75,001
Unique Couriers	10,763
Week Fixed Effects	Yes
Courier Fixed Effects	Yes

Notes. This table examines whether referred couriers earn more in weeks when they spend more hours concurrently active with their referrer on the platform. The unit of observation is the courier-week. The dependent variable is *Hourly Earnings*, computed by dividing the total (INR) compensation that the courier received in a given week by their total online hours during which they were either delivering or waiting for orders that week. The sample is restricted to referred couriers in weeks in which a courier signed into their account on the platform to accept orders at least once during that week ($N = 75{,}001$). *Weekly Overlap Hours* is the total number of hours in a given week when the referred courier and their referrer are simultaneously online on the platform. The model controls for the referred and referring courier's total hours worked that week as *Total Referred Hours* and *Total Referring Hours*, respectively. All specifications include calendar *Week* fixed effects (absorbing platform-wide temporal shocks) and *Courier* fixed effects (controlling for time-invariant courier characteristics). The regression sample is smaller than the descriptive statistics sample (Table 1: $N = 80{,}780$) because fixed effects estimation automatically drops singleton observations (courier-weeks with insufficient within-group variation). Standard errors clustered at the courier level are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Association between Hourly Activity Overlap and Operational Outcomes

	(1)	(2)
Dependent Variable	*Number of Orders*	*Distance to Pickup*
Estimation Method	OLS	OLS
Sample	Referred Couriers	Referred Couriers
Overlap	0.0695^{***}	-0.0218^{***}
	(0.0034)	(0.0027)
Total Referred Hours	0.0016^{***}	-0.0000
	(0.0001)	(0.0001)
Total Referring Hours	-0.0003^{*}	0.0002
	(0.0001)	(0.0002)
Adjusted R^2	0.339	0.224
Observations	2,124,385	2,056,749
Unique Couriers	12,223	12,223
Week Fixed Effects	Yes	Yes
Courier Fixed Effects	Yes	Yes
Hour-of-Week Fixed Effects	Yes	Yes

Notes. This table examines whether temporal overlap between referred couriers and their referrers affects operational outcomes. The unit of observation is the courier-hour, restricted to hours when the referred courier was actively working on the platform during the study period. *Number of Orders* is the count of orders completed by the referred courier in that hour. *Distance to Pickup* is the average distance (in kilometers) from the courier's location to the restaurant for orders received in that hour. All models include calendar *Week* fixed effects (absorbing week-level shocks), *Courier* fixed effects (controlling for time-invariant courier characteristics), and *Hour-of-Week* fixed effects (absorbing systematic variation across the 168 hours of the week). Standard errors clustered at the courier level are in parentheses. Column 1 includes all hours when referred couriers were actively working. Column 2 further restricts to hours where the courier received at least one order. *Overlap* equals 1 if both the referred courier and their referrer were actively working on the platform during that specific hour. *Total Referred Hours* is the total number of hours the referred courier worked that week. *Total Referring Hours* is the total number of hours the referrer worked that week. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

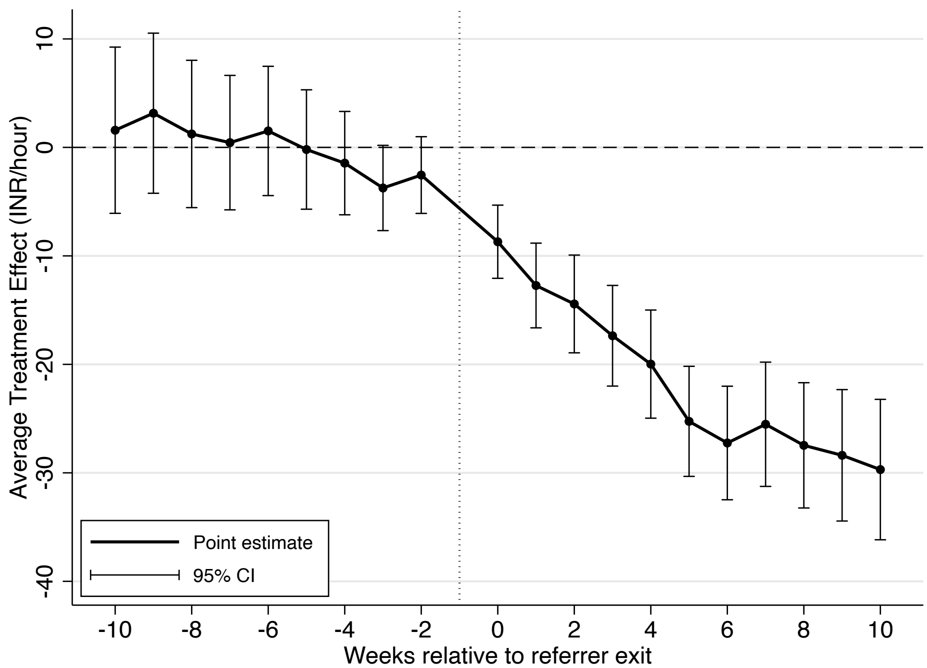
Table 6: Difference-in-Differences Estimates of the Effect of Referrer Exit on Earnings Components

	(1)	(2)
Dependent Variable	*Information-sensitive Earnings per Hour*	*Other Earnings per Hour*
Estimation Method	CSDID	CSDID
Sample	Referred Couriers	Referred Couriers
Comparison Group	Referrer not yet exited	Referrer not yet exited
ATT	-13.804^{***}	-0.382
	(1.675)	(0.248)
95% CI	$[-17.087, -10.521]$	$[-0.868, 0.104]$
Observations	80,739	80,739
Unique Couriers	12,615	12,615
Treated Couriers	3,708	3,708
Week Fixed Effects	Yes	Yes
Courier Fixed Effects	Yes	Yes

Notes. This table reports difference-in-differences estimates of the effect of referrer exit on information-sensitive and other components of hourly earnings. The unit of observation is the courier-week. Estimates are obtained using the Callaway and Sant'Anna (2021) difference-in-differences estimator with doubly robust inverse probability weighting. A courier is classified as having exited if they remain inactive for 14 consecutive days and do not return to the platform for the remainder of the observation window. The sample is restricted to referred couriers, and the control group comprises referred couriers whose referrers have not yet exited in the same calendar week. Standard errors are computed using wild bootstrap with 1,000 replications to account for within-courier dependence. *Information-Sensitive Earnings per Hour* includes minimum guarantee pay, order pay, and penalties. *Other Earnings per Hour* includes incentive pay and tips. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

FIGURES

Figure 1: Event Study Plot for Hourly Earnings around Referrer Exit



Notes. This figure plots event-study estimates from a difference-in-differences design using the Callaway and Sant'Anna (2021) estimator. The sample is restricted to referred couriers. Treatment is defined as the week in which a courier's referrer exits the platform. At each event time, treated couriers are compared to referred couriers whose referrers have not yet exited. Coefficients are normalized relative to the week immediately preceding referrer exit (week -1), which serves as the omitted reference period. Vertical bars indicate 95% confidence intervals based on wild bootstrap standard errors clustered at the courier level.

SUPPLEMENTARY APPENDIX (ONLINE)

Table A1: Association between Referral Status and Courier Earnings: Alternative Earnings Measures

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	*Log Hourly Earnings*	*Total Earnings*	*Log Total Earnings*	*Log Hourly Earnings*	*Total Earnings*	*Log Total Earnings*
Estimation Method	OLS	OLS	OLS	OLS	OLS	OLS
Sample	Full Sample (Matched)	Full Sample (Matched)	Full Sample (Matched)	Full Sample (Matched)	Full Sample (Matched)	Full Sample (Matched)
Referred	0.157***	1005.020***	0.864***			
	(0.004)	(27.861)	(0.012)			
Referred with Referrer Present				0.173***	1019.175***	0.915***
				(0.005)	(32.583)	(0.014)
Referred with Referrer Exited				0.135***	984.997***	0.792***
				(0.005)	(43.125)	(0.017)
Female	0.032	37.745	0.005	0.032	37.950	0.006
	(0.022)	(101.652)	(0.073)	(0.022)	(101.652)	(0.073)
Motorcycle Ownership	0.338***	666.466***	0.469***	0.338***	666.181***	0.468***
	(0.004)	(21.722)	(0.013)	(0.004)	(21.751)	(0.013)
Constant	4.344***	950.949***	5.893***	4.344***	951.144***	5.894***
	(0.004)	(14.301)	(0.011)	(0.004)	(14.330)	(0.011)
Adjusted R^2	0.193	0.184	0.168	0.193	0.184	0.168
Observations	413,371	413,371	413,371	413,371	413,371	413,371
Unique Couriers	92,954	92,954	92,954	92,954	92,954	92,954
Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Week of Entry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table reports regression estimates from the matched sample examining the association between referral status, referrer presence, and courier productivity. The unit of observation is courier-week. The dependent variables are *Log Hourly Earnings* (columns 1 and 4), *Total Earnings* (columns 2 and 5), and *Log Total Earnings* (columns 3 and 6). *Log Hourly Earnings* is the natural logarithm of *Hourly Earnings*. *Total Earnings* is the total weekly earnings for courier-weeks when the courier was online. *Log Total Earnings* is the natural logarithm of total weekly pay. In columns 1–3, *Referred* equals 1 for couriers who joined via a referral. In columns 4–6, *Referred with Referrer Present* equals 1 for courier-weeks in which the referred courier's referrer is still active on the platform, and *Referred with Referrer Exited* equals 1 for courier-weeks in which the referrer has exited. The omitted category is non-referred couriers. Couriers are matched exactly on *Female, Motorcycle Ownership, Geographic Area, and Week of Entry*, and regressions are estimated on the matched sample using analytic weights. All specifications include fixed effects for *Geographic Area, Week, and Week of Entry*. Standard errors clustered at the courier level are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A2: Difference-in-Differences Estimates of the Effect of Referrer Exit on Hourly Earnings: Survivorship Robustness Check

	(1)
Dependent Variable	*Hourly Earnings*
Estimation Method	CSDID
Sample	Referred Couriers (active $\geq$10 weeks post-exit)
Comparison Group	Referrer not yet exited
ATT	-22.763^{***}
	(2.279)
95% CI	[-27.111, -18.180]
Observations	138,858
Unique Couriers	11,232
Treated Couriers	1,495
Week Fixed Effects	Yes
Courier Fixed Effects	Yes

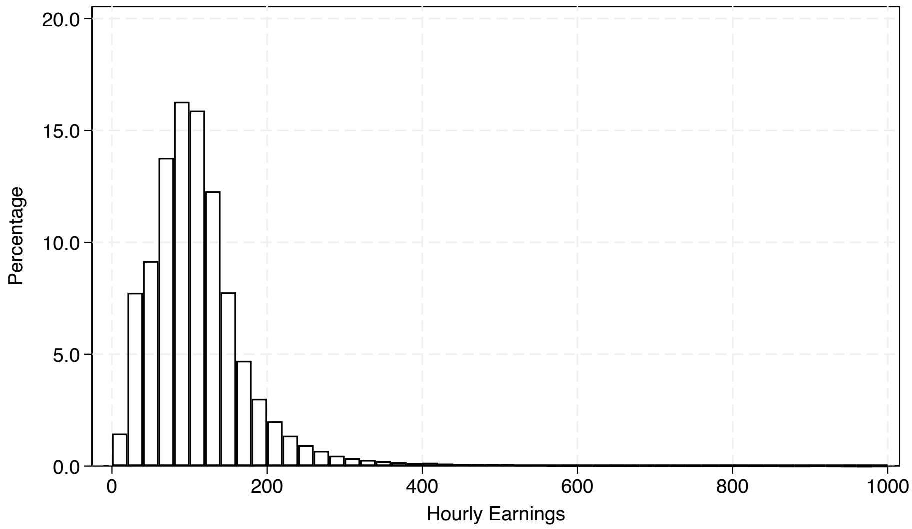
Notes. This table reports average treatment effects on the treated (ATT) estimated using the Callaway and Sant'Anna (2021) difference-in-differences estimator. A courier is classified as having exited if they remain inactive for 14 consecutive days and do not return to the platform for the remainder of the observation window. The sample is restricted to referred couriers whose referrer exits by week 36 and who remain active on the platform for at least 10 consecutive weeks following referrer exit. This restriction ensures that post-exit outcomes are observed for the full 10-week window given the platform's 14-day exit buffer. The control group comprises referred couriers whose referrers have not yet exited in the same calendar week. Standard errors are computed using wild bootstrap with 1,000 replications to account for within-courier dependence. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A3: Summary Statistics for Hourly Activity Overlap Analysis

Variable	N	Mean	SD
Number of Orders	2,124,385	1.922	1.161
Distance to Pickup	2,124,385	1.603	1.029
Overlap	2,124,385	0.205	0.404
Total Referred Hours	2,124,385	44.558	25.127
Total Referring Hours	2,124,385	12.620	20.359

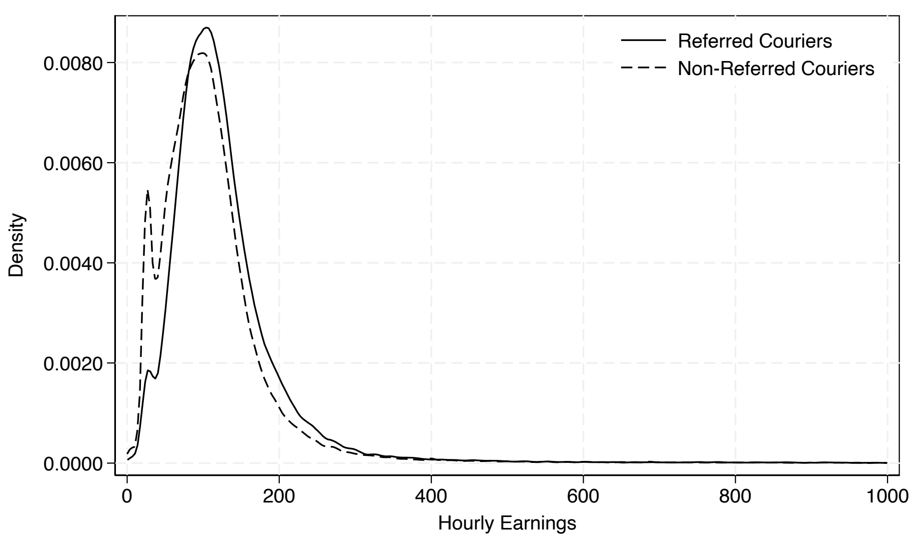
Notes. This table presents summary statistics for the hourly overlap analysis in Table 5. The unit of observation is the courier-hour, representing each hour that a referred courier was actively working on the platform during the study period. *Number of Orders* is the count of orders completed by the referred courier in that hour. *Distance to Pickup* measures the average distance (in kilometers) from the courier's location to the restaurant for orders received in that hour. *Overlap* is a binary indicator equal to 1 if both the referred courier and their referrer were actively working on the platform during that hour. *Total Referred Hours* is the total number of hours the referred courier was active that week. *Total Referring Hours* is the total number of hours the referrer was active that week.

Figure A1: Distribution of Hourly Earnings



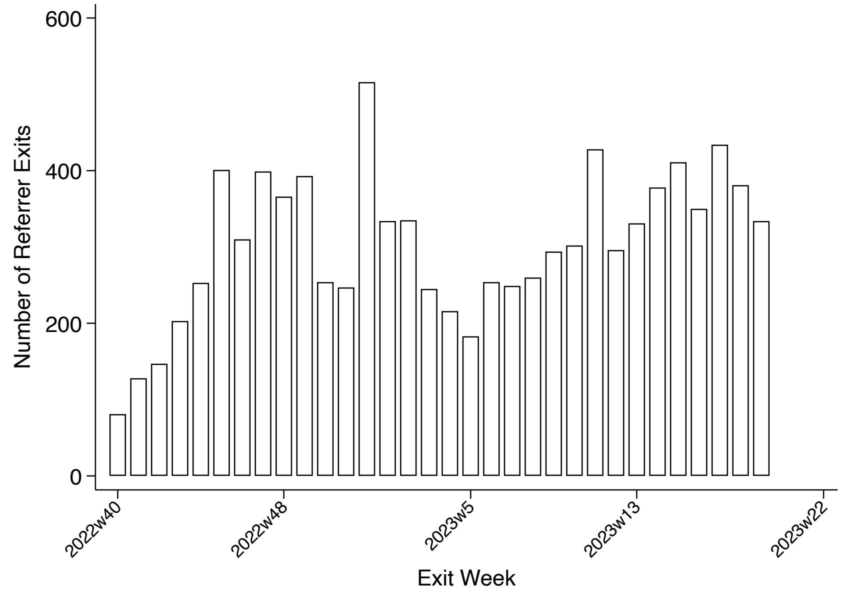
Notes. This figure shows the distribution of *Hourly Earnings* across all courier-week observations. *Hourly Earnings* is defined as the total (INR) compensation that a courier received in a given week divided by their total online hours during which they were either delivering or waiting for orders that week.

Figure A2: Distribution of Hourly Earnings by Referral Status



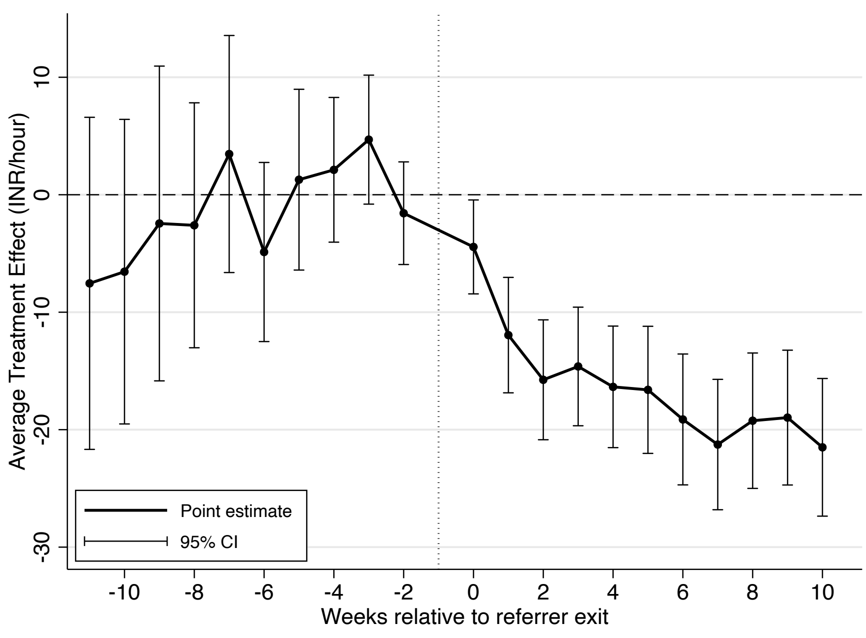
Notes. This figure plots kernel density estimates of *Hourly Earnings* separately for referred and non-referred couriers. *Referred* takes the value of 1 if a courier joined the platform through a referral by another courier already on the platform, and 0 otherwise.

Figure A3: Distribution of Referrer Exit Weeks



Notes. This figure shows the distribution of referrer exits over time. Each bar represents the number of referrers who exit in a given calendar week during our observation window. A courier is classified as having exited if they remain inactive for 14 consecutive days and do not return to the platform for the remainder of the observation window.

Figure A4: Event Study Plot for Hourly Earnings: Survivorship Robustness Check



Notes. This figure plots event-study estimates from a difference-in-differences design using the Callaway and Sant'Anna (2021) estimator. The sample is restricted to referred couriers whose referrer exits by week 36 and who remain active for at least 10 consecutive weeks following referrer exit; treated couriers are compared to those whose referrers have not yet exited. Coefficients are normalized relative to week -1. Vertical bars indicate 95% confidence intervals based on wild bootstrap standard errors.

Figure A5: Example of Platform Pay Schedule

MARKETPLACE

SUPER KINGS

Base pay per order

Day	Full Day
Monday - Sunday	₹ 29

Distance Pay

First Mile (FM)	> 2Km	₹ 4 Per Km (upto ₹20)
Last Mile (LM)	> 2.5Km - 4Km	₹ 6 Per Km
	> 4Km - 10Km	₹ 8 Per Km
	> 10Km	₹ 15 Per Km (upto ₹200)

Daily Slab-based Minimum Guarantee

MG Points	*Monday - Sunday*
>=32	₹ 2,000
29-31	₹ 1,500
24-28	₹ 1,200
18-23	₹ 900
12-17	₹ 550
6-11	₹ 250

Conditions ***Mon - Fri***
>=6 Orders in DinnerLn (7PM to 3AM) and No Order Cancellation or Fake Delivery
Offer valid for Super Kings

Conditions ***Sat & Sun***
>=8 Orders in DinnerLn (7PM to 3AM) and No Order Cancellation or Fake Delivery
Offer valid for Super Kings

Dinner MG (Dinner + LN)

Dinner MG (Dinner + LN) - Monday to Sunday

₹225	₹350	₹450	₹550	₹750	₹1,000
5-6 MG Points	7-8 MG Points	9-10 MG Points	11-13 MG Points	14-15 MG Points	>=16 MG Points

Conditions
No Order Cancellation or Fake Delivery
Offer valid for Super Kings