Peer Information at Work: Evidence from a Field Experiment*

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Abstract

Providing workers with information about their coworkers' performance is a standard management tool, yet we know little about how such information should be designed and targeted across workers. We study this in a large-scale field experiment with 2,897 rideshare drivers. We first elicit workers' demand for peer information and document substantial heterogeneity: nearly half do not seek peer information in any performance-contingent scenario. These preferences are highly predictive of treatment effects. Peer information increases earnings by 3.7% among information-seeking workers but has no effect among workers who avoid it, while both groups respond similarly to monetary incentives. To identify the mechanism, we exploit random assignment of peer groups to estimate the causal effect of relative performance. We find strong asymmetries: learning that one is above the peer average increases unconditional earnings by 7.9%, while learning that one is below average reduces it by 3.1%. We find no evidence that peer information changes search behavior or productivity, suggesting it operates through social comparisons rather than social learning. Finally, we develop a theoretical framework to characterize the optimal information policy.

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1 Introduction

Peer information, defined as feedback about coworkers' output, earnings, or productivity, is a standard management tool for motivating workers. Firms routinely provide workers with information about peers' performance through rankings, dashboards, and performance reviews. Advances in workplace technologies now allow firms to deliver this feedback in real time and tailor it at scale, yet little is known about how it should be targeted across workers to improve performance.

The effects of peer information are theoretically ambiguous, as they depend on the underlying mechanisms through which workers interpret and respond to it (Lim, 2025). In particular, workers may differ in whether they value peer information in the first place. Existing empirical evidence from high-stakes field settings is also limited and mixed. Some studies find that peer information increases worker effort and performance, while others document negative or null effects (Blanes i Vidal and Nossol, 2011; Barankay, 2012; Wu and Liang, 2021; Ashraf, 2025). Together, these factors make it difficult to predict how workers will respond to peer information and, in turn, how firms should design effective feedback policies.

These considerations raise several important questions. Do workers seek or avoid peer information at work, and when they receive such information, does it motivate or discourage them? More broadly, how does peer information affect behavior across workers with different information preferences, through what mechanism does it operate, and what does this imply for the optimal design of workplace feedback policies?

We study these questions using a large-scale, high-stakes field experiment with 2,897 drivers in collaboration with a ride-hailing platform in Singapore. The experiment was implemented as part of a newly-designed six-week driver program, "*[Firm's name]* Insights," which aimed to help drivers better manage their work time and earnings and to which all registered drivers were invited to enroll. During the program, all participating drivers received semi-weekly earnings updates via email showing their own total trip earnings, together with a breakdown by utilization hours and implied hourly earnings.

In addition, each driver was randomly matched to a fixed "reference group" of 10 other drivers who typically worked similar hours. Some participating drivers received peer earnings information consisting of the corresponding average earnings, utilization hours, and hourly earnings of their reference group, whose members were not themselves part of the experiment. Because these reference groups were randomly assigned, the design generates exogenous variation in the peer earnings benchmarks that drivers observe. Prior to the study, the firm had not previously provided drivers with information about peers' earnings.

At baseline, we elicited drivers' preferences for receiving this peer information using a novel survey module adapted from the "strategy-method" approach of Butera et al. (2022). Drivers indicated whether they would like to receive peer earnings updates ("Yes," "Neutral," or "No") conditional on whether their past earnings were above, around, or below the average of their reference group. To make these choices incentive-compatible, drivers were given a small monetary bonus: choosing either to receive or not receive peer information required forgoing the bonus,

while choosing indifference resulted in random assignment at no cost. This procedure allows us to measure drivers' demand for peer information.

We then randomly assigned drivers to one of three information treatments that remained fixed throughout the six-week intervention period. Drivers in the Control group never received any information about their peer group's earnings. Drivers in the Peer Info group received peer earnings updates twice each week regardless of their stated preferences. Drivers in the Endogenous Info group received peer information (or not) depending on their stated preferences. Orthogonally to the information treatments, every driver was also randomly assigned to temporary monetary incentives on two separate days during the intervention period, corresponding to roughly a 10% increase in daily earnings. These incentives provide a money-metric benchmark for comparing the effects of peer information with standard monetary incentives.

We document three main sets of findings. First, there is substantial heterogeneity in workers' demand for peer information. Slightly more than half of drivers (52%) seek peer information in at least one performance-contingent scenario ("info-seeking"), while the remaining 48% never choose to receive it in any scenario ("non-info-seeking"). A rich set of observable characteristics, including demographics, baseline labor supply, and work patterns, has limited predictive power for these measured information preferences.

Second, elicited information preferences strongly predict subsequent labor-supply responses to peer earnings information. On average, peer information has a modest positive effect on the intensive margin, increasing daily earnings by 2.0%, but this average masks offsetting responses across drivers. In particular, peer information increases labor earnings by 3.7% among info-seeking drivers, while having no detectable effect on non-info-seeking drivers. By contrast, monetary incentives raise labor earnings by 25–28% for both groups, with no significant differences by information preference. A back-of-the-envelope calculation suggests that, when aggregated over a full week, the effect of peer information on unconditional earnings for info-seeking drivers is equivalent to an 8.3% increase in one day's earnings (approximately S$5.60, or US$4.40).

Third, we identify the mechanism through which peer information affects worker behavior. By randomly assigning drivers to peer group, we generate exogenous variation in the peer average earnings they observe and can therefore estimate the causal *earnings-gap response function*, which maps labor-supply changes to workers' relative earnings position from the peer average. The response is strongly asymmetric: learning that one is below average reduces subsequent earnings by 3.1%, whereas learning that one is above average increases earnings by 7.9%. These responses also vary systematically with workers' elicited information preferences. By contrast, we find little support for a peer learning channel. Using detailed trip-level GPS data, we show that peer information does not significantly change search behavior, driving efficiency and productivity. Taken together, the evidence points to social comparisons, with peer average earnings acting as a social reference point, rather than social learning.

These findings motivate our theoretical analysis of the optimal design of peer information. We develop a framework in which the platform chooses not only whether to provide peer information,

but also which peer benchmark to assign to each worker in order to maximize aggregate labor supply, subject to a credibility constraint. The central object for optimal design is the causal earnings-gap response function, which we identify and estimate in the experiment, and we derive theoretical results characterizing the optimal information policy under alternative assumptions on this response function.

The rest of the paper is organized as follows. Section 2 discusses our contributions to the literature. Section 3 describes the experimental design. Section 4 presents the experimental results and discusses mechanisms. Section 5 presents the theoretical framework. Section 6 concludes.

2 Related Literature

This paper relates to two strands of the literature that have largely developed separately. One studies social comparisons and peer effects in the workplace. Within this strand, a large body of work examines the effects of relative performance feedback on worker effort and productivity, both in the laboratory (e.g., Kuhnen and Tymula, 2012; Charness et al., 2014; Gill et al., 2019) and in the field (e.g., Blanes i Vidal and Nossol, 2011; Barankay, 2012; Wu and Liang, 2021). A related line of research studies productivity spillovers arising from workers' assignment to peer groups, either through random assignment or endogenous choice (e.g., Falk and Ichino, 2006; Mas and Moretti, 2009; Senn et al., 2023). The other strand studies the effects of pay transparency and pay inequality on employees' satisfaction, effort, and performance, often in settings where pay differences may be perceived as "unjustified" (e.g., Card et al., 2012; Breza et al., 2018; Cullen and Perez-Truglia, 2022).[1] Our setting lies at the intersection of these literatures. Ridesharing resembles a high-frequency piece-rate work environment, where drivers are paid per completed trip under the same underlying pricing algorithm. Any earnings differences are therefore "justified," arising because a driver works more hours and completes more trips or operates more productively. In our study, drivers receive information about the earnings of similar drivers in their reference group, making peer earnings information simultaneously a form of relative performance feedback and a form of pay disclosure.

Our paper contributes to the literature on social comparisons by offering a unified explanation to help reconcile the mixed effects of relative performance feedback: heterogeneity in workers' demand for peer information. Prior work has documented positive, null, and even negative effects, but has largely treated peer information as a "one-size-fits-all" intervention and not measured whether workers want to receive such information in the first place (Hannan et al., 2008; Eriksson et al., 2009; Blanes i Vidal and Nossol, 2011; Barankay, 2011, 2012; Kuhnen and Tymula, 2012; Charness et al., 2014; Huet-Vaughn, 2015; Azmat and Iriberri, 2016; Gjedrem, 2018; Gill et al., 2019; Wu and Liang, 2021; Ashraf, 2025). Along with our companion paper (Lim, 2025), we develop a portable methodology to measure these information preferences and validate its usefulness. In

[1] We follow Cullen (2024) in referring to all pay differences that cannot be explained by performance differences as "unjustified."

this paper, we provide the first evidence on workers' preferences for peer information in a high-stakes workplace environment. We show that workers differ substantially in whether they seek or avoid peer earnings information, and that these preferences are not merely descriptive but strongly predict subsequent labor-supply responses to the information. Together, this paper highlights that workers' information preferences are a missing, first-order primitive for understanding the effects of peer information, and provides a incentive-compatible method to elicit those preferences.

Our study also advances this literature by providing, to our knowledge, the first causal estimate of the *earnings-gap response function*, which describes how labor supply changes in response to workers learning how far ahead or behind their earnings are relative to the social reference point (in our case, peer average earnings). Estimating this function is empirically challenging because peer benchmarks are typically not randomly assigned, so workers' relative earnings position is endogenous. Existing work has therefore largely focused on the average effect of providing peer information. A notable exception is Gill et al. (2019), who estimate a rank response function in the lab by exploiting random tie-breaking of subjects with identical scores in a real-effort task. They find a "U-shaped" response, with subjects exerting most effort upon learning they are ranked first or last. By contrast, our field design overcomes this endogeneity problem by randomly assigning each driver to a reference group of ten similar peers (who are outside the experimental sample), thereby generating random variation in the peer average earnings that drivers observe and in the realized earnings gap (i.e. distance from one's earnings and the peer average). We leverage this variation to causally identify how labor supply responses depend on workers' relative earnings position. We show that workers with the same earnings respond asymmetrically to learning that they are earning more or less than their peers, and the shape of this response function differs systematically by workers' measured information preferences. More broadly, identifying this response function is important not only for understanding the behavioral effects of peer earnings information, but also for the optimal design of workplace information policies (i.e., determining which workers should receive information, and which peer benchmarks to display), a point we develop formally in our theoretical framework.

Our study also contributes to the pay transparency literature by showing that peer earnings disclosure can affect worker behavior even in a setting where fairness concerns about pay differentials are largely attenuated and opportunities for wage bargaining or career advancement are limited. Much of the existing literature studies work environments in which pay differentials may be perceived as "unjustified," making fairness concerns central to workers' responses to learning coworkers' pay. In their seminal work, Card et al. (2012) find that workers whose salaries are below the median of their peers have lower job satisfaction and higher job search intentions. More recently, Cullen and Perez-Truglia (2022) show that a higher perceived peer salary has a negative impact on worker effort and retention. By contrast, our setting resembles a piece-rate environment, in which peer earnings are especially informative about relative performance since higher earnings reflect higher effort (hours worked) or productivity (hourly earnings). We show that peer earnings disclosure still affects labor supply in such an environment, suggesting that the effects of pay

transparency extend beyond fairness concerns and can also operate through social comparisons over performance-based earnings, thereby linking the pay transparency literature to the literature on relative performance feedback at work.

Finally, our paper contributes to a growing literature within economics and operations management on understanding workers' labor supply decisions in platform-based markets. Existing work on ridesharing has examined how workers respond to financial incentives (Brandon et al., 2024; Allon et al., 2023), outside employment options (Caldwell and Oehlsen, 2023), the timing and flexibility of pay (Chen et al., 2025), and ratings or feedback about one's own driving behavior (Athey et al., 2019). We add to this literature by studying peer earnings information as a distinct platform lever for managing labor supply. In particular, we show that drivers increase hours worked and trips completed in response to such peer information. More broadly, our findings show that peer information can affect behavior in a high-stakes work environment and that these effects persist and do not attenuate throughout our six-week intervention period. By showing that drivers differ in whether they seek peer information, our results also speak to the welfare effects of non-pecuniary policy instruments (e.g., Allcott and Kessler, 2019; Butera et al., 2022) and highlight the potential gains from tailoring information by workers' preferences for welfare gains.

3 Rideshare Field Experiment

3.1 Study Context

Our study was conducted in collaboration with a ride-hailing platform based in Singapore. The company was interested in exploring new initiatives to better understand and support drivers by improving transparency and providing tools to help them manage their time at work and improve earnings.

In August 2025, drivers on the platform were invited via email to enroll in a new pilot program called "*[Firm's name]* Insights." Drivers were informed that they could receive exclusive updates and additional earnings opportunities, while all other aspects of work would remain unchanged. Participation in the program was entirely voluntary. At baseline, drivers signed up by completing an online survey and providing consent to participate.

In total, 3,135 drivers enrolled in the "*[Firm's name]* Insights" program. Of these, 200 drivers participated in an initial pilot and were excluded from the main experiment, and 38 drivers had their accounts deactivated prior to the program start date. The final experimental sample therefore comprises $N = 2{,}897$ active drivers.[2] The intervention period ran for six weeks, from September 22 to November 2, 2025. Afterward, drivers were invited to complete an endline survey in November 2025, and their administrative outcomes were observed for an additional six weeks following the intervention. We preregistered our design and analysis plan on the AEA RCT Registry (AEARCTR-

[2] As of the end of 2025, there were just over 60,000 private-hire drivers licensed to offer ride-hailing services in Singapore. Our experimental sample thus represents roughly 5% of the total licensed driver population, which is a conservative estimate as not all licensed drivers are necessarily active on any ride-hailing platform.

0016393).

3.2 Earnings Updates and Peer Group Construction

During the "*[Firm's name]* Insights" program, all participating drivers received semi-weekly email updates summarizing their own earnings performance. A mid-week update reported the earnings accumulated thus far in the current week, and an end-of-week update reported the total earnings for the completed week. Each update detailed their total trip earnings (excluding additional earnings incentives), with a breakdown of their total utilization hours and implied average hourly earnings. Utilization hours were defined as the total time spent traveling to a pickup and completing a trip through to drop-off.

In addition to these own earnings updates, drivers were informed that they might receive peer earnings updates during the program. We explained that they would be randomly matched to a "reference group" of 10 other drivers who typically worked similar hours. If selected, drivers would receive earnings information about their peer group. Specifically, they would observe their peer group's average total earnings (excluding additional earnings incentives), with the same breakdown of average utilization hours and average hourly earnings. This information would be delivered alongside their own earnings updates in the same semi-weekly emails, allowing drivers to compare their earnings performance and activity levels with those of similar peers. Figure 1 provides examples of the own earnings and peer earnings updates delivered to drivers during the program.

Peer groups were constructed by first computing each driver's average weekly utilization hours using administrative data from the two months prior to the intervention. Drivers were then binned according to these averages. Within each bin, drivers were randomly matched to 10 other drivers drawn from the same bin. Importantly, these reference drivers were drawn from outside the experimental sample. This design choice circumvents the reflection problem (Manski, 1993), ensuring that the peer earnings averages remain exogenous and are not contaminated by the treatment itself. It also isolates the effect of peer information from other potential drivers of behavior, such as second-order beliefs about being observed by peers and social image concerns (Butera et al., 2022). Peer group assignments remained fixed throughout the intervention period.

3.3 Information Preference Elicitation

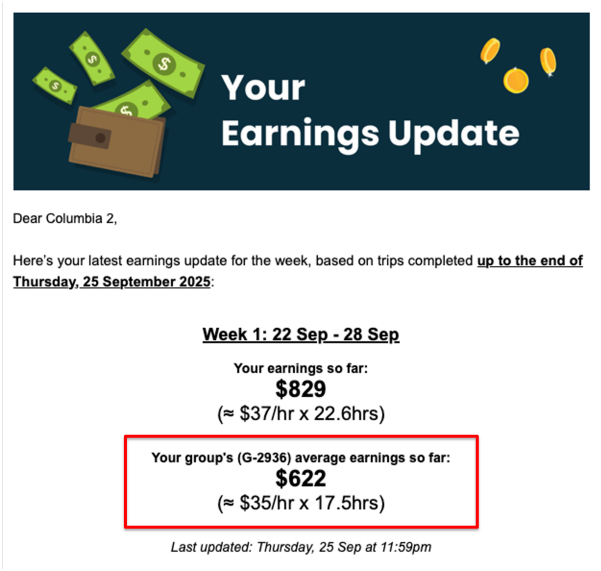
In the baseline survey, we elicited drivers' preferences for receiving peer earnings updates during the program. Using the strategy method, we asked drivers to indicate their choices conditional on their historical earnings performance relative to their peer group. Specifically, they considered three contingent scenarios: whether their historical weekly earnings were (i) above average, (ii) around average, or (iii) below average compared to the 10 similar drivers in their reference group. For each scenario, drivers chose whether they would like to receive peer earnings information by selecting "Yes," "Neutral," or "No." After making their selections, they were asked to provide a

Figure 1: Examples of Earnings Updates Delivered During the Program

(a) Own Earnings Update



(b) Own & Peer Earnings Update



Notes. Panel (a) displays an example of the own earnings update, detailing a driver's own earnings performance: total trip earnings (excluding incentives), utilization hours, and implied hourly earnings. Panel (b) displays the corresponding own & peer earnings update, which additionally reports the average total earnings, average utilization hours, and implied average hourly earnings of the driver's assigned reference group, comprising 10 other drivers who worked similar hours.

brief open-ended explanation for their choices. Appendix Figure A1 provides a screenshot of the survey module.

To incentivize truthful reporting, we implemented an incentive-compatible mechanism adapted from Lim (2025) and Butera et al. (2022). Drivers received an additional S$0.10 bonus on top of their survey incentive. The small monetary stake was utilized to distinguish strict preferences for information from indifference. With one-third probability, the driver's stated preference for the scenario matching their actual historical relative performance was implemented; otherwise, treatment assignment was random. If their matched choice was implemented and the driver had selected "Yes" (respectively, "No"), the driver forfeited the S$0.10 bonus and received (respectively, did not receive) peer earnings updates during the program. If the driver had selected "Neutral," they retained the bonus and their assignment was determined randomly.

Pilot testing with a small group of drivers prior to study recruitment suggested that survey instructions needed to be very simple and clear in this field setting. We therefore opted for this simplified elicitation procedure rather than implementing a full Becker-DeGroot-Marschak mechanism for measuring willingness-to-pay (Becker et al., 1964) to ensure comprehension and minimize survey attrition.

In addition to the information preference elicitation module, the baseline survey collected a rich set of driver characteristics including demographics, driving experience, and work patterns,

which we combine with administrative data to complement our analysis.

3.4 Experimental Design

Following the baseline recruitment survey and pilot phase, the main experiment involves 2,897 drivers and features two layers of randomization: a between-subject information treatment and a within-subject monetary incentive treatment. Figure 2 provides a schematic overview of the experimental design and timeline.

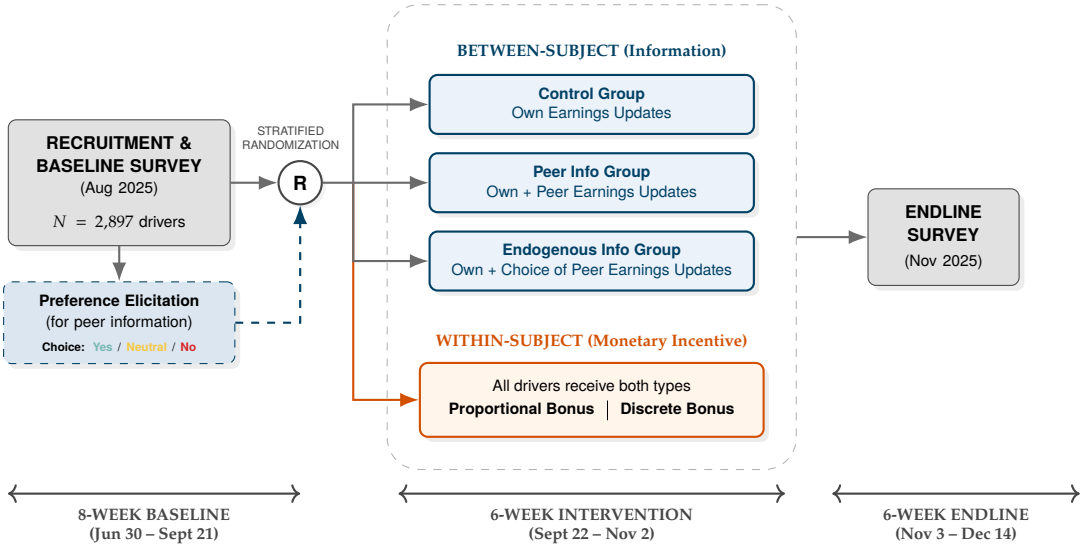
Information Treatments. Building on the information preference elicitation at baseline, the drivers were randomly assigned to one of three information conditions with equal probability: (1) **Control group**, where drivers received only their own earnings updates semi-weekly; (2) **Peer Info group**, where drivers received both their own earnings and their peer group's average earnings updates semi-weekly; and (3) **Endogenous Info group**, where drivers received their own earnings updates, but whether they additionally received peer earnings updates depended on their choice for the matched scenario. Treatment assignment was fixed throughout the intervention period, and randomization was stratified by baseline utilization hours and tenure.

Monetary Incentive Treatments. In addition to the information treatments, drivers were provided with additional earnings opportunities during the program. Each driver was assigned to two single-day monetary incentives during the intervention period. These featured two distinct incentive structures: (i) **Proportional Bonus**, where drivers earned 10% more on total trip earnings in a day; and (ii) **Discrete Bonus**, where they earned a fixed earnings bonus of S$21 for completing at least 10 trips in a day. The latter was calibrated so that the average payout was approximately the same as a 10% wage increase. These incentives were exclusively offered on Wednesdays but not announced beforehand. Drivers were only notified hours before the start of their scheduled incentive day. The specific weeks in which the respective bonuses were active were randomly assigned for each driver, guaranteeing at least one washout week between a driver's two incentive days.

3.5 Descriptives and Balance

Appendix Table A1 presents summary statistics and balance tests. Column 1 reports means and standard deviations for the full experimental sample. The average driver is 51 years old, has about 6 years of driver experience, and 12 years of education. Most drivers are male (93%), and 62% report driving as their full-time job. A typical driver works 6 days per week and 5 hours per day, earning an average of S$480 (approximately US$370) in a week. Columns 2 through 4 report the same statistics for the Control, Peer Info, and Endogenous Info groups, respectively. Column 5 reports the p-values from F-tests of joint equality of means across the three groups. Consistent

Figure 2: Experimental Design Schematic



Notes. This figure provides a schematic overview of the experimental design and timeline.

with successful randomization, baseline characteristics are well-balanced across groups, with no statistically significant differences (all p-values are well above 10%).

4 Experimental Results from the Field

4.1 Demand for Peer Earnings Information

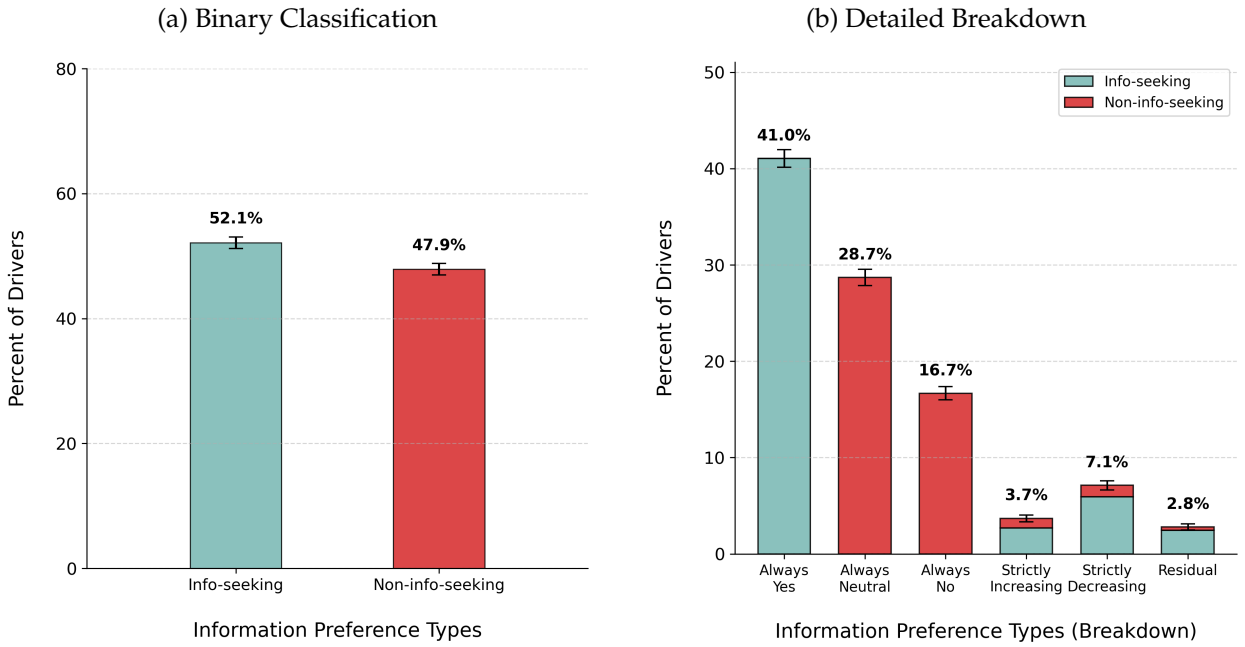
Information Preference Types. We begin by documenting drivers' demand for peer earnings information. Recall that drivers indicated whether they would like to receive peer earnings updates conditional on whether their historical weekly earnings were above, around, or below the average of their peer group. For the main analysis, we classify drivers into two binary preference types. Drivers who did not choose "Yes" in any of the three contingent scenarios are classified as non-information-seeking drivers (hereafter, non-info-seeking), whereas those who chose "Yes" in at least one scenario are classified as information-seeking drivers (hereafter, info-seeking).

Figure 3 displays the distribution of drivers' preference types. Panel A shows that slightly over half of the drivers (52.1%) are classified as info-seeking. Panel B provides a finer breakdown of these underlying types. The largest category (41.0%) consists of drivers who strictly prefer to receive peer information in all three scenarios ("Always Yes"). A further 28.7% always express indifference ("Always Neutral"), and 16.7% strictly avoid peer information in all scenarios ("Always No"). About 10% of drivers exhibit strictly monotonic preferences ("Strictly Increasing" and "Strictly Decreasing"), meaning they are more or less likely to seek information as their earnings performance improves relative to peer group. Note that these monotonic types are likely an underestimate since we did not elicit drivers' willingness-to-pay so there is loss in cardinal

information.

Taken together, the evidence points to substantial heterogeneity in drivers' demand for peer earnings information, and aligns with the findings of our companion paper studying Prolific workers in an online labor market (Lim, 2025). Our findings provide the first evidence of the distribution of information preferences among workers in a high-stakes field environment.

Figure 3: Distribution of Information Preferences



Notes. Panel (a) reports the share of drivers classified as non-information-seeking and information-seeking. Non-info-seeking drivers are those who never choose "Yes" in any of the three relative-performance scenarios (below, around, and above average relative to their peer group); information-seeking drivers are the complement. Panel (b) provides a finer breakdown into six mutually exclusive types: "Always Yes," "Always Neutral," and "Always No" refer to drivers who make the same choice across all three scenarios. "Strictly Increasing" "Strictly Decreasing" refer to drivers whose preferences strictly increase (decrease) with relative performance. The residual type includes all remaining drivers. The error bars display ± one standard error of the mean.

Correlates of Information Demand. We next assess the extent to which baseline characteristics predict drivers' information preferences. We estimate linear probability models for whether a driver is info-seeking using the same set of observables as in the balance tests, with progressively richer sets of controls. Appendix Table A2 reports the results. Overall, observable characteristics have limited predictive power. Even in the richest specification (Column 4), the model explains only a small fraction of the variation in information-seeking preferences, with an R^2 of 0.055. This suggests that drivers' demand for peer earnings information is not well explained by driver demographics, baseline labor supply, and work patterns.

That said, a few interesting patterns emerge. Female drivers are about 10 percentage points (pp) less likely to seek information, while more educated drivers are more likely to do so (around

3 pp per additional year of education). Drivers with longer tenure with the platform are also more likely to be info-seeking, though those with more years of driving experience are less likely to do so. By contrast, baseline labor supply measures (average weekly earnings and trips completed) are not significantly correlated with information preferences. Among self-reported measures, drivers who multi-home are about 9 pp more likely to seek information, and those who are part of social media driver groups are also more likely to do so. In sum, while some observable characteristics are correlated with peer information demand, a substantial share of the variation remains unexplained. Given that information preferences strongly predict responses to peer information (as we show below), this highlights the utility of directly eliciting such preferences, as they are not easily inferred from observables.[3]

Motives Underlying Information Demand. To better understand drivers' demand for peer earnings information, we examine their open-ended explanations for why they chose to seek or avoid such information. In the baseline survey, after drivers made contingent choices (Yes, Neutral, or No) for scenarios in which their historical earnings were above, around, or below the average earnings of their reference group, we asked: "Please tell us in a few words why you made the above choices." Based on these responses, we devise a coding scheme that classifies each explanation into one of eleven mutually exclusive categories. Table A3 presents the coding scheme with example responses for each category.

These categories fall into two main groups. The first group captures rationales for not seeking peer information. This includes responses indicating that peer earnings information is not relevant, useful, or worth paying for (**"Not Interested or Relevant"**); explicit statements that drivers prefer not to compare themselves with others (**"Do Not Wish to Compare"**); concerns that such comparisons may create stress or discouragement (**"Avoid Stress"**); as well as responses mentioning that they already have their own earnings targets (**"Own Target"**) or indicating indifference towards the information (**"Neutral"**). The second group captures motivations for seeking peer information, which fall into two broad themes. One relates to *social comparisons*, where drivers indicate using peer average earnings as a reference point to benchmark their performance (**"Benchmarking"**); to compare with other drivers (**"Comparison with Peers"**); or to motivate themselves to work harder (**"Motivation"**). The other relates to *social learning*, where drivers view peer information as useful for learning from peers about earnings opportunities or work strategies (**"Learning"**). The remaining responses reflect general curiosity or interest in staying informed about the platform (**"General Interest"**).

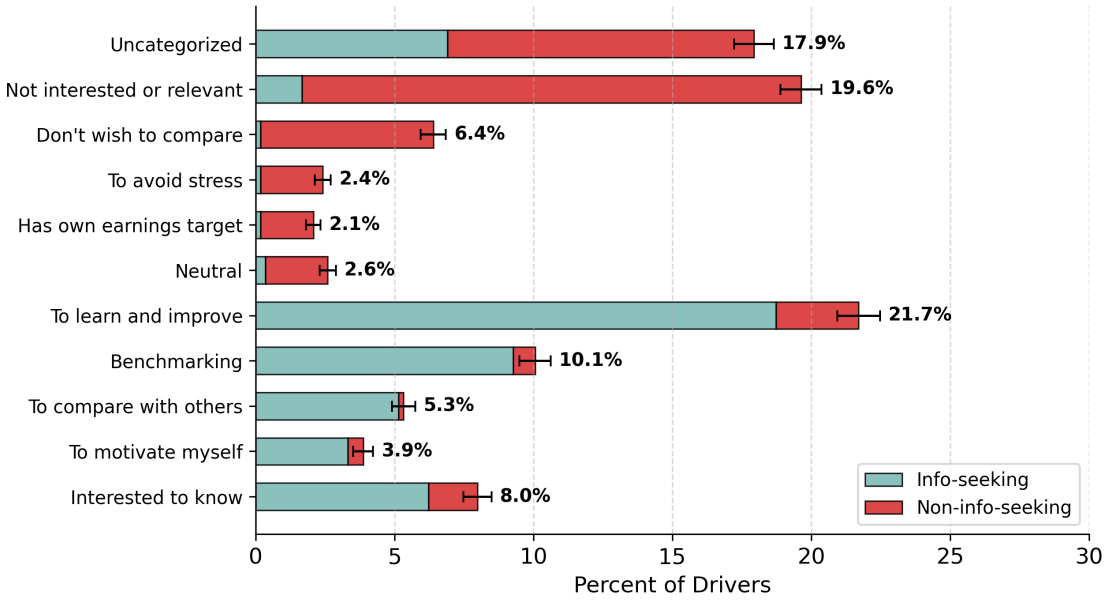
Figure 4 displays the distribution of the hand-coded responses by information preference type. First, drivers' stated motives align closely with their revealed preferences. Motives indicating a lack of demand for peer earnings information are almost exclusively provided by non-info-seeking drivers, while those consistent with seeking peer information are predominantly provided by info-

[3]This conclusion is robust to more flexible prediction methods. Using a tuned random forest classifier with the same set of observables, out-of-sample predictive performance remains weak (AUC = 0.65), indicating that information preferences are not well predicted even when allowing for non-linearities and interactions. See Appendix Figure A2.

seeking drivers. This alignment supports the validity of our information preference elicitation methodology, suggesting that the roughly even split between info-seeking and non-info-seeking drivers (Figure 3, Panel A) reflects genuine heterogeneity rather than random choice.

Among motives for not seeking peer information, the most common rationale is that it is not relevant or useful, accounting for 19.6% of responses. In addition, 8.8% of responses reflect a desire to avoid comparisons or the stress associated with them. In contrast, among motives for seeking peer information, the dominant motive is to learn from peers and improve earnings or work strategies, cited in 21.7% of responses. Social comparisons motives also account for a substantial share: 19.3% of responses indicate using peer information for benchmarking, comparing with others, or motivating oneself. Taken together, these patterns suggest that both social comparison and learning considerations are important drivers of information demand, providing evidence on the underlying mechanisms, which we discuss in more detail later.

Figure 4: Motives Underlying Information Choice



Notes. This figure presents the fraction of drivers citing different motives for seeking or avoiding peer earnings information. At baseline, after choosing whether they would like to receive peer earnings information across three contingent scenarios, drivers were asked to provide an open-ended explanation for their choices. Responses are hand-coded into one or more of eleven mutually exclusive categories (see Table A3 for details). The error bars display ± one standard error of the mean.

4.2 Impact of Peer Earnings Information on Labor Supply

Empirical Strategy. Hereafter, we restrict the analysis to drivers in the Control and Peer Info groups, for whom exposure to peer earnings information is randomly assigned. We first estimate the effects of peer information at the driver-day level using a two-way fixed effects specification:

$$y_{it} = \alpha_i + \delta_t + \beta \text{ PeerInfo}_{it} + \gamma \text{ Incentives}_{it} + \varepsilon_{it}, \quad (1)$$

where y_{it} denotes the outcome of interest for driver i on day t. α_i and δ_t represent driver and day fixed effects, respectively. PeerInfo_{it} is an indicator that equals one if driver i is assigned to receive peer earnings information and day t occurs after the first earnings update was delivered during the intervention period. Incentives_{it} is an indicator for whether driver i was assigned to a monetary incentive (either proportional or discrete bonus) on day t. ε_{it} is the random error term clustered at the driver level, which reflects the unit of randomization.

To test whether drivers' elicited information preferences predict their responses to peer information, we augment the above specification by interacting the treatment indicators with InfoSeeking_i and Non-InfoSeeking_i, indicators for info-seeking and non-info-seeking drivers, respectively:

$$\begin{aligned} y_{it} = \alpha_i + \delta_t + \beta_1 \left(\text{PeerInfo}_{it} \times \text{InfoSeeking}_i\right) + \beta_2 \left(\text{PeerInfo}_{it} \times \text{Non-InfoSeeking}_i\right) \\ + \gamma_1 \left(\text{Incentives}_{it} \times \text{InfoSeeking}_i\right) + \gamma_2 \left(\text{Incentives}_{it} \times \text{Non-InfoSeeking}_i\right) + \varepsilon_{it} \end{aligned} \tag{2}$$

The coefficient of interest β captures the average treatment effect of receiving peer earnings updates, and correspondingly, β_1 and β_2 capture the effects for info-seeking and non-info-seeking drivers, respectively. In addition, γ and the corresponding γ_1 and γ_2 measure the impact of monetary incentives (equivalent to a 10% wage increase on a given day), which we use to benchmark the magnitude of peer information effects.

Main Results. We first examine the impact of peer information and monetary incentives on the extensive and intensive margins of labor supply. The extensive margin captures whether a driver works on a given day (defined as accepting at least one trip regardless of completion status), while the intensive margin measures total daily earnings conditional on working.

Figure 5 plots the estimated effects on these two margins, both for the average treatment effect and separately by drivers' elicited information preferences. As shown in Panel A, peer information has no significant impact on the extensive margin: drivers are no more or less likely to log onto the platform to accept trip requests. In contrast, monetary incentives increase the probability of working by 2%, and this average effect is statistically significant ($p = .023$). This extensive margin response does not significantly differ by drivers' information preferences ($p = .664$).

Panel B reveals a different pattern for the intensive margin. On average, peer information increases daily earnings by S$2.14, though the effect is only marginally significant ($p = .094$). However, this masks meaningful heterogeneity across drivers' information preferences. Among info-seeking drivers, peer information increases daily earnings by S$3.94 (or 3.7% from baseline), an effect that is highly significant both statistically ($p = .01$) and economically. In contrast, peer information has no detectable effect among non-info-seeking drivers. The difference in treatment effects between the two groups is statistically significant ($p = .032$). As a benchmark, we observe that monetary incentives have a strong positive effect, increasing earnings by S$28.04 (or 26.0% from baseline). Strikingly, unlike the response to peer information, the response to monetary incentives does not significantly differ between info-seeking and non-info-seeking drivers ($p = .263$).

Taken together, these results demonstrate that our incentivized measure of information prefer-

ences strongly predict behavioral responses to peer earnings information. This heterogeneity may help reconcile the mixed field evidence in the literature on relative performance feedback (e.g., Barankay, 2011; Wu and Liang, 2021; Ashraf, 2025). When workers differ in their preferences for peer information, studies that do not account for such heterogeneity may estimate attenuated or different-signed average effects depending on the composition of workers who respond favorably to peer information and those who do not.

Having established that info-seeking drivers increase their total daily earnings in response to peer earnings information, we next unpack the margins underlying this intensive margin effect. Drivers could achieve higher earnings through two (non-mutually exclusive) channels: a labor supply channel by working longer hours and completing more trips, or a productivity channel by earning more per hour worked, such as by targeting high-surge areas or reducing deadheading time with improved search.

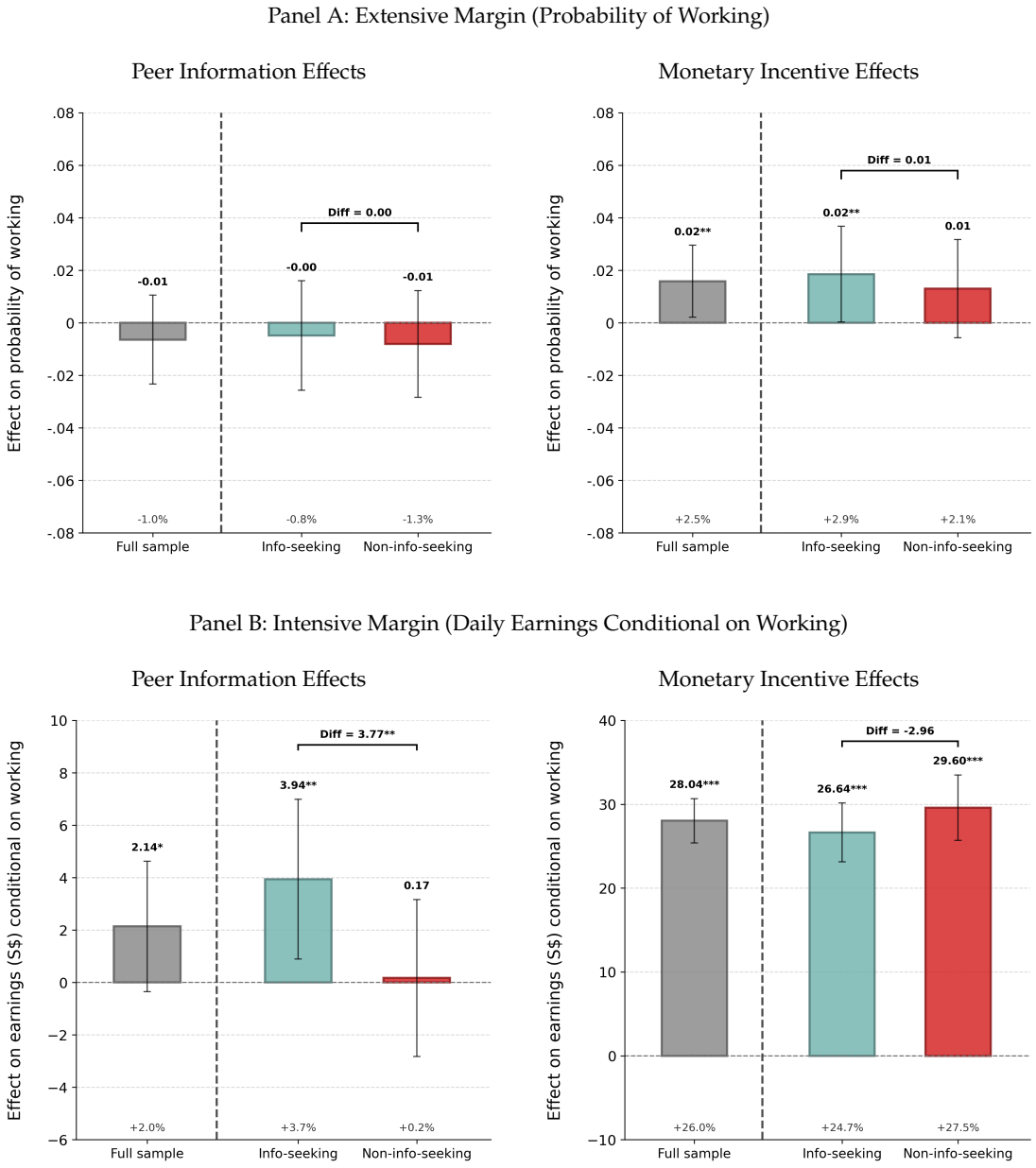
Table 1 presents the regression results for the full set of daily labor supply outcomes. Panel A estimates the baseline specification (1), while Panel B estimates the interacted specification (2). For ease of comparison, Columns 1 and 2 report the effects on the extensive margin and total daily earnings visualized in Figure 5. Columns 3 through 5 extend the intensive margin analysis to the underlying components: total trips completed, total active hours, and implied hourly earnings, the latter of which we use as a proxy for driver productivity.

Focusing first on the full sample (Panel A), peer information increases total trips completed by 0.16 and active hours worked by 0.06 per day. As with total earnings, these average effects are modest and only marginally significant ($p = .075$ and $p = .082$, respectively). Crucially, there is no significant effect on hourly earnings. Allowing these effects to vary by drivers' information preferences (Panel B) reveals a much clearer pattern. Among info-seeking drivers, peer information leads to an increase of 0.28 trips completed and 0.10 active hours per day, with both effects being highly significant ($p = .008$ and $p = .009$, respectively). Yet, even for these highly responsive drivers, peer information does not significantly change hourly earnings. Among the non-info-seeking drivers, we again observe no significant effect across all intensive margin outcomes.

We benchmark these effects against the monetary incentive treatments. On average, monetary incentives generate strong positive responses across all margins (Panel A), increasing trips completed by 1.59, active hours worked by 0.52, and hourly earnings by S$1.73/hr ($p < .001$ for all). Strikingly, while our elicited preferences strongly predict the differential response to peer information, they have no predictive power for the monetary incentives: both info-seekers and non-info-seekers respond similarly on all margins of labor supply.

Overall, the evidence suggests that the earnings response to peer information operates primarily through increased labor supply rather than higher productivity. Info-seeking drivers respond to the peer earnings updates by working harder, logging more hours and completing more trips on the platform. Furthermore, the sharp contrast between the information and incentive treatments suggests that non-info-seeking drivers are not simply disengaged or unresponsive to any

Figure 5: Treatment Effects on Extensive and Intensive Margins



Notes. This figure plots treatment effects on daily labor supply along the extensive and intensive margins. Panel A uses an indicator for working that day as the dependent variable, while Panel B uses daily earnings conditional on working. In each panel, the left graph reports effects of peer information and the right graph reports effects of monetary incentive. Within each graph, the first bar shows the average treatment effect from the baseline specification (1), while the second and third bars report effects for info-seeking and non-info-seeking drivers from the interacted specification (2). Percent values shown at the bottom of each bar are relative to the baseline mean. The error bars represent 95% confidence intervals.

interventions in general; rather, they are specifically not responding to peer information on average.

Table 1: Effects on Daily Labor Supply Outcomes

Dependent variable:	Extensive margin	Intensive margin			
	1 if working	Total earnings	Trips completed	Active hours	Hourly earnings
	(1)	(2)	(3)	(4)	(5)
Panel A: Average Treatment Effects (ATE)					
Peer Information (β)	-0.01	2.14*	0.16*	0.06*	-0.10
	(0.01)	(1.27)	(0.08)	(0.03)	(0.12)
Incentives (γ)	0.02**	28.04***	1.59***	0.52***	1.73***
	(0.01)	(1.35)	(0.09)	(0.03)	(0.18)
Panel B: ATE by Information Preferences					
Peer Information × Info-seeking (β_1)	-0.00	3.94**	0.28***	0.10***	-0.01
	(0.01)	(1.56)	(0.10)	(0.04)	(0.15)
Peer Information × Non-info-seeking (β_2)	-0.01	0.17	0.03	0.01	-0.20
	(0.01)	(1.53)	(0.10)	(0.04)	(0.14)
Incentives × Info-seeking (γ_1)	0.02**	26.64***	1.53***	0.50***	1.69***
	(0.01)	(1.79)	(0.12)	(0.04)	(0.23)
Incentives × Non-info-seeking (γ_2)	0.01	29.60***	1.66***	0.55***	1.77***
	(0.01)	(1.99)	(0.13)	(0.05)	(0.23)
Baseline mean	0.63	107.29	6.60	2.71	41.11
	(0.48)	(86.57)	(5.61)	(2.19)	(11.55)
p-values of tests of interest:					
Difference in peer information and incentive effects: $\beta = \gamma$	0.048	0.000	0.000	0.000	0.000
Peer information effect by preferences: $\beta_1 = \beta_2$	0.790	0.032	0.043	0.042	0.247
Incentive effect by preferences: $\gamma_1 = \gamma_2$	0.664	0.263	0.425	0.431	0.781
No. of observations	243,180	150,421	150,421	150,421	147,999
No. of workers	1,930	1,869	1,869	1,869	1,865

Notes. This table reports regression estimates of the effects of peer information and monetary incentives on daily labor supply outcomes. Panel A reports average treatment effects from estimating equation (1). Panel B reports heterogeneous effects by information preference type from estimating equation (2), where info-seeking drivers are those who choose to receive peer information in at least one contingent scenario. Column 1 uses all driver-days, while Columns 2 through 5 are estimated on working days only. All regressions include driver and date fixed effects, and standard errors clustered at the driver level are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Quantifying the Peer Information Effect. We close this subsection by benchmarking the peer information effect against the single-day monetary incentive using unconditional daily earnings (including zeros on non-working days) as the dependent variable. Recall the monetary incentive corresponds to approximately a 10% wage increase for that day. We focus this comparison on info-seeking drivers, since the above results show that, on average, non-info-seeking drivers do not respond to peer earnings information. Among info-seeking drivers, peer information increases daily earnings by S$2.29, while the monetary incentives increase earnings by S$19.38. Thus, on a per-day basis, the peer information effect amounts to roughly 12% of the response to a 10% wage increase. With two earnings updates over a typical week, the weekly effect of peer information is roughly equivalent to that of a 8.3% wage increase (approximately S$5.60, or US$4.40), assuming the effects scale linearly. Given that providing peer earnings updates entails essentially zero marginal cost for the platform, this magnitude suggests that peer information can be a cost-effective tool for influencing labor supply among info-seeking drivers who value such information.

4.3 Mechanisms

We next examine the mechanisms through which peer earnings information affects drivers' labor supply. The open-ended responses discussed in Subsection 4.1 point to two candidate mechanisms: *social comparisons* and *social learning*. These channels are not mutually exclusive, and we therefore present evidence on each in turn.

Social Comparisons. In models of social comparisons, individuals derive utility not only from their own outcomes but also from how their outcomes compare with those of others. In our setting, drivers receive email updates that prominently display the average earnings of their reference group alongside their own earnings. This makes the peer average earnings a natural and salient reference point that drivers use to evaluate their relative performance. If such comparisons are operative, responses to peer information may differ asymmetrically depending on whether drivers learn that they are earning more or less than their peers.[4]

Our experimental design allows a clean test of this mechanism. Each driver is randomly matched to a reference group of ten similar peers, generating random variation in the peer average earnings they observe, and therefore in their realized earnings gap relative to their reference group. We exploit this variation to examine how drivers causally respond to their relative earnings position.

We first examine whether responses differ depending on whether drivers learn they are above or below their peer group average. Specifically, we estimate the following specification for the full sample, as well as separately for the subsamples of info-seeking and non-info-seeking drivers:

$$\begin{aligned} y_{it} = \alpha_i + \delta_t + \beta_1 \left(\text{PeerInfo}_{it} \times \text{BelowAverage}_{it}\right) + \beta_2 \left(\text{PeerInfo}_{it} \times \text{AboveAverage}_{it}\right) \\ + \beta_3 \, \text{AboveAverage}_{it} + \beta_4 \, \text{OwnEarnings}_{it} + \beta_5 \left(\text{BaselineEarnings}_i \times \text{Post}_t\right) \\ + \gamma \, \text{Incentives}_{it} + \varepsilon_{it}, \end{aligned} \tag{3}$$

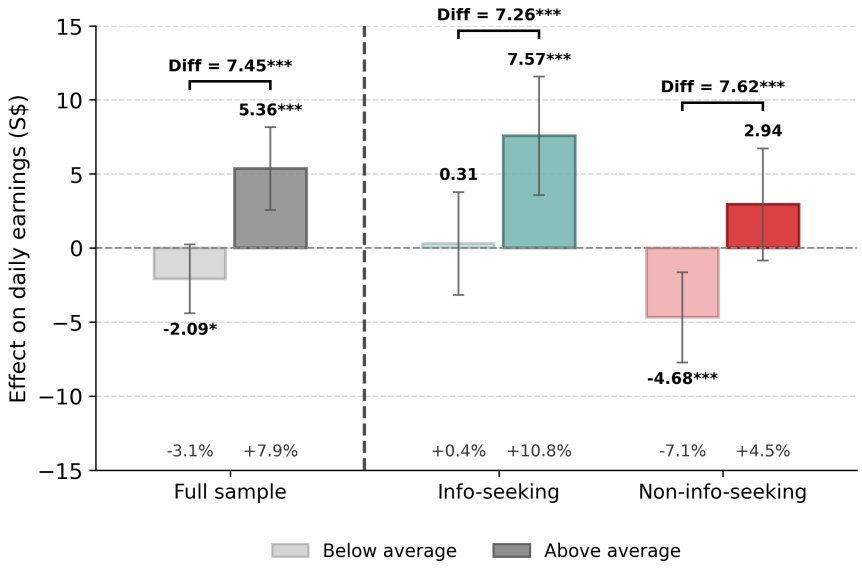
where y_{it} denotes total earnings for driver i on day t, including zeros to jointly capture both the extensive and intensive margins. BelowAverage_{it} and AboveAverage_{it} are indicators equal to one if driver i's earnings fall below or above the peer group average based on the most recent earnings update, and remain fixed until the next update. OwnEarnings_{it} denotes the driver's own earnings reported in the most recent update. $\text{BaselineEarnings}_i$ is the average daily earnings at baseline for driver i, and $\text{BaselineEarnings}_i \times \text{Post}_t$ controls for differential trends correlated with baseline earnings (e.g., regression to the mean). Here, β_1 captures the causal effect of peer information when drivers learn that they are below their peer group average, while β_2 captures the corresponding effect when they are above.

[4] Learning that one is below the reference point may induce effort increases, for example due to disadvantageous inequality aversion as in Fehr and Schmidt (1999), but may also reduce effort if it leads to discouragement or lower morale (e.g., Breza et al., 2018). In contrast, when individuals learn they are above the reference point, effort may increase due to status-seeking or competitive motives (e.g., Charness et al., 2010), or decrease due to advantageous inequality aversion.

Figure 6 presents the estimated effects. For the full sample, learning that one is below the peer group average marginally reduces daily earnings by S$2.09 (3.1% relative to baseline; $p = .079$). In contrast, learning that one is above the peer group average significantly increases daily earnings by S$5.36 (7.9% relative to baseline; $p < .001$). The difference between these two estimates is highly significant ($p < .001$), indicating a stark asymmetry in responses to learning about one's relative earnings position.

We also estimate these effects separately for info-seeking and non-info-seeking drivers. Among info-seeking drivers, there is no significant response when earnings fall below the peer average, whereas being above the peer average leads to a large increase in daily earnings of S$7.57 (10.8% relative to baseline; $p < 0.001$). In contrast, among non-info-seeking drivers, learning that one is below the peer average significantly reduces daily earnings by S$4.68 (7.1% relative to baseline; $p < 0.001$), while the effect of being above the peer average is positive but not significant. In both groups, the difference between the two treatment effects (β_1 and β_2) is highly statistically significant ($p < .001$).

Figure 6: Effects of Learning One's Relative Earnings Position



Notes. This figure reports the effects of peer information when drivers learn they are earning below versus above their peer group average earnings. The leftmost pair of bars reports estimates for the full sample; the other two pairs report estimates separately for info-seeking and non-info-seeking drivers. The coefficients come from estimating equation (3), which interacts peer information treatment with indicators for below-average and above-average earnings states. The error bars represent 95% confidence intervals.

We next examine how treatment effects vary across the distribution of the relative earnings gap. To flexibly characterize the causal response to relative earnings position, we compute the earnings gap (defined as the difference between a driver's own earnings and their peer group average) and partition observations into ten deciles. Figure A3 in the Appendix shows the distribution of realized earnings gaps. We then estimate a version of equation (3), replacing the above-/below-average

indicators with indicators for each earnings gap decile to allow the effect of peer information to vary non-parametrically across the distribution.

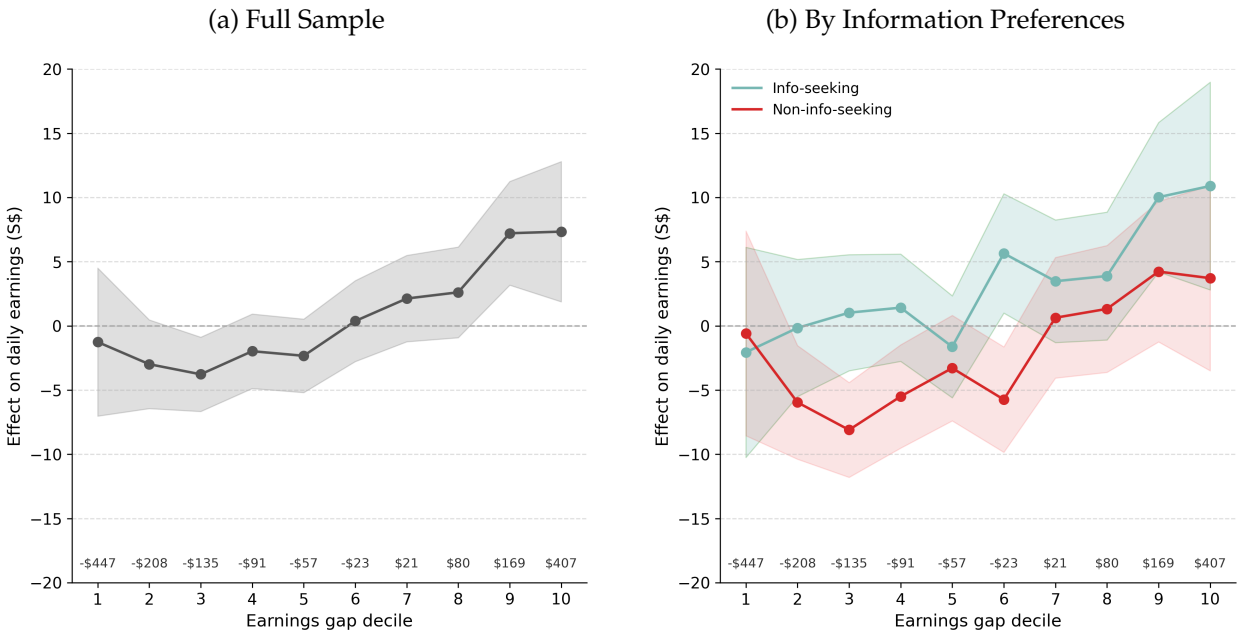
Figure 7 plots the estimated treatment effects by decile of the earnings gap distribution, with the average earnings gap for each bin reported above the x-axis. Panel A, which uses the full sample, reveals a roughly monotonically increasing pattern. For drivers facing a substantial negative earnings gap (deciles 1–5), treatment effects are consistently negative, though the 95% confidence intervals indicate these estimates are somewhat noisy. As the earnings gap narrows towards zero (decile 6), the treatment effect turns positive and continues to rise steadily across the upper deciles. Among drivers with positive earnings gaps (deciles 7–10), peer information leads to higher daily earnings, with effects reaching over S$7 for top deciles 9 and 10. Overall, the pattern is consistent with the above above-/below-average specification: learning that one is doing better than their peers increases labor earnings, while learning that one is doing worse than peers reduces earnings.

We also estimate these effects separately by information preference types, shown in Panel B. Among info-seeking drivers, the treatment effect is flat and statistically indistinguishable from zero when they fall well below the peer average earnings (deciles 1–5), but their response rises sharply with the earnings gap and is strongly positive in the upper deciles, when they are outperforming their peers. In contrast, non-info-seeking drivers exhibit significant negative treatment effects in the lower deciles. When non-info-seeking drivers learn they outperform their peers, their response to the information is positive but more muted compared to the info-seeking drivers. Together, these patterns suggest that responses to peer information depend not only on one's relative earnings performance but also on measured information preferences.

In summary, the asymmetric responses to peer information suggest that drivers' utility is directly affected by their relative earnings standing, consistent with models of social comparisons (e.g., Clark and Oswald, 1996; Card et al., 2012). The peer average earnings appears to act as a reference point against which drivers evaluate their earnings performance, even absent fairness concerns. In our setting, the patterns are consistent with competitive motives dominating when drivers are ahead of their peers (particularly among info-seekers), and discouragement or morale loss dominating when they fall behind (especially among non-info-seekers).

Social Learning. An alternative mechanism is social learning, whereby drivers use peer earnings information to update their beliefs about prevailing market conditions or their own production function. In our setting, drivers operate in a complex work environment in which earnings depend on multiple input dimensions, such as where to search for trips, whether to accept or reject trip requests, and when to work. Drivers may therefore not be fully informed about the "production technology" that maps these choices into earnings, and may fail to optimize along all relevant margins (e.g., Hanna et al., 2014). The peer information provided to drivers, consisting of average total earnings, hourly earnings, and utilization hours among similar drivers, serves as a signal about the achievable returns to supplying labor under prevailing conditions. For example, observing that peers achieve higher hourly earnings may lead a driver to infer that their current strategy

Figure 7: Treatment Effects Across the Relative Earnings Distribution



Notes. This figure plots the treatment effects of peer information across deciles of the realized relative earnings gap (i.e., own earnings minus peer group average earnings from the most recent update). Panel (a) reports estimate for the full sample, and Panel (b) reports estimates separately for info-seeking and non-info-seeking drivers. The coefficients come from estimating a flexible version of equation (3) that interacts peer information treatment with indicators for each earnings gap decile; labels right above the x-axis report the mean earnings gap (S$) in each decile. The shaded bands represent 95% confidence intervals.

is suboptimal, perhaps because they are searching in low-demand areas or using suboptimal trip acceptance thresholds. In response, drivers may experiment with alternative strategies to improve earnings and move closer to the production frontier. Indeed, recent evidence shows that platform workers can and do learn from peers to meaningfully improve productivity at work. For example, Tang (2024) document that new food delivery workers learn from their peers' past delivery experiences, reducing search time by around 10%.

To test this learning channel, we leverage detailed trip-level GPS data to examine whether drivers adjust their search behavior within each work shift in response to peer earnings information. We focus on three key behavioral margins: (1) spatial footprint, measured by the dispersion of a driver's pickup locations; (2) repositioning, measured by the share of trips originating in the central region of the city; and (3) trip selectivity, measured by the share of auto-accepted trips within a shift. In addition, we examine two complementary measures of driving productivity, average deadhead time and shift hourly earnings (excluding any earnings incentives). Under a learning interpretation, peer information should lead drivers to adjust these margins in ways that improve productivity. Throughout, we benchmark the effects of peer information against the effects of monetary incentives.

Table 2 presents the estimated effects. Focusing on the full sample (Panel A), peer information

has no statistically significant effects on any margin of search behavior or productivity. In contrast, monetary incentives lead to substantial changes along several margins. Drivers increase their spatial footprint by 0.17 kilometers ($p = .004$) and the share of auto-accepted trips by 1 pp ($p < .001$), while reducing average deadhead time by 4.76 minutes ($p < .001$) within each shift. These changes are accompanied by a decline in hourly earnings per shift (excluding incentives), suggesting that drivers may be trading off higher trip volume against trip quality. The pattern of results is consistent with drivers being less likely to "cherry-pick" (i.e., more willing to accept lower-value trips in terms of fares and locations) in response to monetary incentives, which reduces deadhead time and expands their spatial footprint.

In Panel B, we estimate heterogeneous effects by information preferences. Between the two groups, one would expect info-seeking drivers to be more likely to adjust their search behavior in response to peer information. However, we find consistently null effects for both info-seeking and non-info-seeking drivers across all margins. The only exception is a marginally significant but economically small reduction in deadhead time among info-seeking drivers.

Table 2: Effects on Search Behavior and Productivity

Dependent variable:	Search Behavior			Productivity	
	Mean dispersion of pickups (km) (1)	Share of trips in central region (2)	Share of trips auto-accepted (3)	Mean deadhead time (min) (4)	Hourly earnings (ex. incentives) (5)
Panel A: Average Treatment Effects (ATE)					
Peer Information (β)	0.04	-0.01	0.00	-0.69	-0.13
	(0.04)	(0.00)	(0.00)	(0.62)	(0.10)
Incentives (γ)	0.17***	0.01	0.01***	-4.76***	-0.87***
	(0.06)	(0.01)	(0.00)	(0.99)	(0.15)
Panel B: ATE by Information Preferences					
Peer Information × Info-seeking (β_1)	0.05	-0.01	0.00	-1.38*	-0.13
	(0.05)	(0.00)	(0.00)	(0.79)	(0.12)
Peer Information × Non-info-seeking (β_2)	0.04	-0.00	0.00	0.07	-0.12
	(0.05)	(0.00)	(0.00)	(0.73)	(0.12)
Incentives × Info-seeking (γ_1)	0.14*	0.00	0.01***	-4.86***	-0.87***
	(0.08)	(0.01)	(0.00)	(1.25)	(0.17)
Incentives × Non-info-seeking (γ_2)	0.19**	0.01	0.01***	-4.66***	-0.87***
	(0.08)	(0.01)	(0.00)	(1.31)	(0.21)
Baseline mean	3.97	0.41	0.04	44.90	40.27
	(3.10)	(0.37)	(0.13)	(46.91)	(8.71)
p-values of tests of interest:					
Difference in peer information and incentive effects: $\beta = \gamma$	0.077	0.095	0.138	0.000	0.000
Peer information effect by preferences: $\beta_1 = \beta_2$	0.834	0.627	0.931	0.095	0.944
Incentive effect by preferences: $\gamma_1 = \gamma_2$	0.581	0.301	0.620	0.900	0.982
No. of observations	167,129	168,117	169,344	135,233	135,233
No. of workers	1,864	1,864	1,866	1,818	1,818

Notes. This table reports regression estimates of the effects of peer information and monetary incentives on shift-level search behavior and productivity outcomes. Panel A reports average treatment effects, while Panel B reports heterogeneous effects by information preference type, where info-seeking drivers are those who choose to receive peer information in at least one contingent scenario. All regressions include driver, date, and time-of-day fixed effects, and standard errors clustered at the driver level are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To further probe this mechanism, we examine whether responses differ between drivers who explicitly cite learning-related motives in the baseline survey and those who do not. If peer

learning were at play, one would expect drivers who express a desire to learn from peers to be more likely to change their search behavior. Table A4 presents the results. Consistent with our main findings, we find no evidence of systematic changes in search behavior or productivity in response to peer information, even among drivers who explicitly cite learning-related motives for seeking information. Therefore, the evidence points to a limited role for peer learning, and is more consistent with drivers responding to peer earnings information through social comparisons with the peer average serving as a reference point.

4.4 Post-Intervention Dynamics

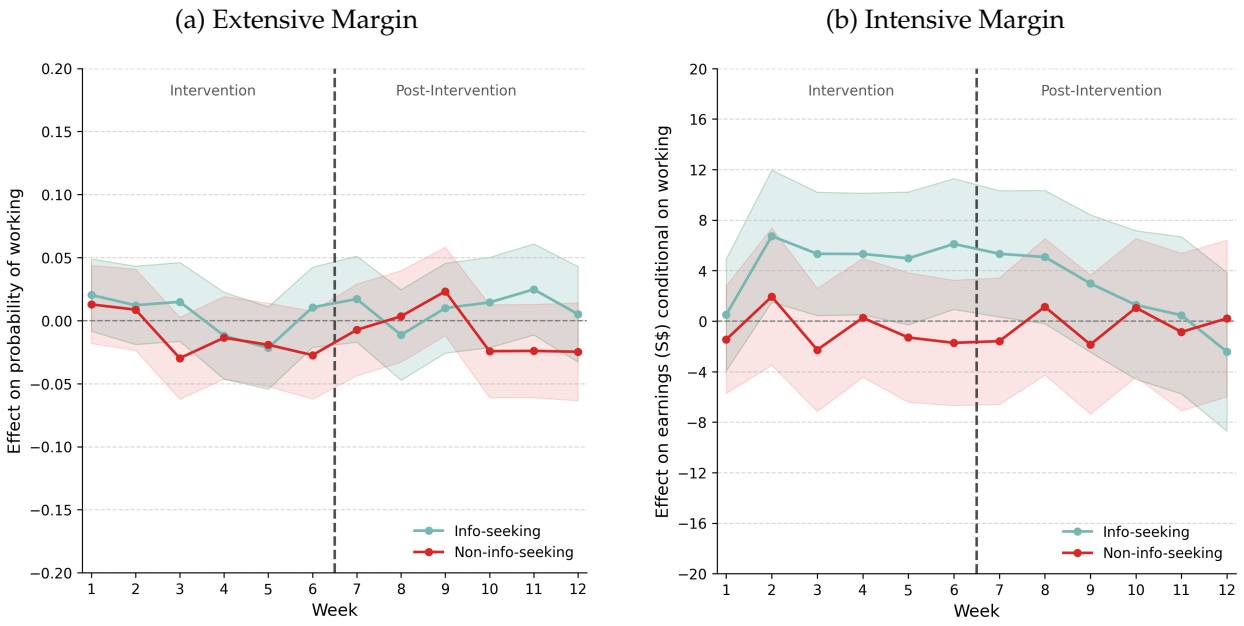
Finally, we examine how the effects of peer information evolve over time and whether they persist after the intervention ends. To study these dynamics, we estimate week-by-week treatment effects throughout both the intervention period (weeks 1–6) and the post-intervention period (weeks 7–12).

Figure 8 plots these estimates separately for info-seeking and non-info-seeking drivers. Panel A shows effects on the probability of working. We find no statistically significant effects on the extensive margin across all weeks, both during and after the intervention. Panel B shows effects on the intensive margin, measured by daily earnings conditional on working. During the intervention period, the provision of peer information significantly increases earnings for info-seeking drivers, and the effects are remarkably stable across weeks. Following the end of the intervention, the earnings effects for info-seeking drivers gradually return toward baseline. In the first two weeks after the intervention (weeks 7–8), earnings remain somewhat elevated, potentially reflecting the influence of the final earnings update received at the end of the intervention. However, these effects dissipate thereafter, and by week 9 we find no evidence of a persistent effect. In contrast, the effects for non-info-seeking drivers remain statistically indistinguishable from zero throughout.

Taken together, these temporal dynamics provide further evidence on the underlying mechanism. Under a social learning interpretation, one would expect changes in behavior to persist as drivers learn from peers to adopt better strategies and improve earnings over time. In contrast, the lack of persistence post-intervention is consistent with responses to peer information being driven by social comparisons, which attenuate once the information is no longer provided and drivers no longer have a salient reference point for comparison.

We next use this insight to study how a platform should optimally design peer information. Specifically, we develop a theoretical framework in which the platform chooses whether to provide information and which peer earnings benchmark to display, taking into account heterogeneity in drivers' responses to peer information, which depend on their relative earnings position.

Figure 8: Temporal Dynamics of Peer Information Effects



Notes. This figure reports week-by-week treatment effects of peer information over the intervention period (weeks 1–6) and post-intervention period (weeks 7–12), estimated separately for info-seeking and non-info-seeking drivers. Panel (a) uses an indicator for working that day (extensive margin), while Panel (b) uses daily earnings conditional on working (intensive margin) as the dependent variable. The estimates come from specifications with driver and date fixed effects, with standard errors clustered at the driver level. The shaded bands represent 95% confidence intervals. See Figure A4 in the Appendix for the analogous figure on the temporal dynamics of monetary incentive.

5 Optimal Design of Peer Information

5.1 Model Environment

We consider a platform populated by a continuum of drivers. Let F denote the cumulative distribution function of baseline earnings. We index drivers by their baseline earnings quantile rank $p \in [0,1]$ under F. Let $Q : [0,1] \to \mathbb{R}_+$ denote the associated quantile function $Q = F^{-1}$, which represents the baseline earnings of a driver at rank p.

Timing. Drivers first realize baseline earnings from a previous period. At the start of the current period, the platform provides peer information according to its information policy. After observing this information, drivers choose labor supply for the current period.

5.2 Information Policy

The platform designs an information mechanism to maximize aggregate labor supply. To capture the extensive margin (whether to provide peer information) and the intensive margin (which peer benchmark to display), we define an information policy as a pair (χ, q), where:

- $\chi : [0,1] \to \{0,1\}$ is the treatment indicator, where $\chi(p) = 1$ if a driver of baseline rank p receives peer information and $\chi(p) = 0$ otherwise;
- $q : [0,1] \to [0,1]$ is the assignment rule that maps a driver of rank p to a peer benchmark quantile $q(p)$.

Under this policy, a driver of rank p is assigned a peer earnings level of $Q\big(q(p)\big)$, which generates a latent earnings gap relative to their own baseline earnings: $g(p) = Q(p) - Q\big(q(p)\big)$. This earnings gap is revealed to the driver if they are treated with peer information (i.e. $\chi(p) = 1$).

5.3 Information Design Constraint

Any information policy (χ, q) chosen by the platform must satisfy an information design constraint, which we term the *global credibility constraint*. Formally, for any quantile rank $t \in [0,1]$, the total mass of drivers who are assigned a benchmark rank at or below the t-th quantile cannot exceed κt:

$$\int_0^1 \mathbb{1}\{q(p) \le t\}\, dp \le \kappa t, \quad \forall t \in [0,1] \tag{4}$$

for some parameter $\kappa \ge 1$, which limits how much the platform can oversample the same benchmark quantiles.

If $\kappa = 1$, the platform cannot oversample low benchmark quantiles. In particular, if the constraint binds for all t, then the distribution of assigned peer benchmarks exactly matches the population distribution. In this case, the assignment rule q is measure-preserving. Intuitively, the platform is truthful in the aggregate, where every driver's earnings are used as a benchmark for exactly one other driver in the population. If instead $\kappa > 1$, the platform has some allowance to distort this sampling, allowing it to reuse some benchmarks more frequently than they naturally occur.

5.4 Worker Preferences and Labor Supply

We microfound the labor supply response to peer information by modeling driver's utility as dependent on relative earnings, following the literature on social preferences and workplace comparisons (DellaVigna et al., 2022; Breza et al., 2018; Cullen and Perez-Truglia, 2022).

Consider a driver with treatment status $\chi \in \{0,1\}$ and a realized earnings gap g. The driver chooses hours h in the current week to maximize utility of the form:

$$U(h \mid g, \chi) = wh - C(h) + \chi M(g)h, \tag{5}$$

where $w > 0$ is the average hourly wage, and $C(h)$ is the cost of supplying hours that is strictly increasing and convex: $C'(h) > 0$ and $C''(h) > 0$ for all $h > 0$.

The additional term $M(g)$ captures the marginal shift in utility derived from peer comparisons:

$$M(g) = m - \gamma_- f_-(-g) \cdot \mathbb{1}\{g < 0\} + \gamma_+ f_+(g) \cdot \mathbb{1}\{g \geq 0\}, \tag{6}$$

where m represents a constant morale or attention shift simply from learning the earnings gap. γ_- and γ_+ capture the potentially asymmetric intensity of social preferences when a driver is behind or ahead of their peer earnings benchmark. $f_-, f_+ : \mathbb{R}_+ \to \mathbb{R}_+$ are increasing with $f_-(0) = f_+(0) = 0$.

Let $h(g, \chi)$ denote the optimal hours supplied by the driver. The first-order condition is:

$$w + \chi M(g) = C'(h(g, \chi)) \implies h(g, \chi) = (C')^{-1}\left(w + \chi M(g)\right) \tag{7}$$

Rewriting yields the "reduced-form" labor supply response function:

$$h(g, \chi) = \underbrace{(C')^{-1}(w)}_{h_0} + \chi \underbrace{\left[(C')^{-1}\big(w + M(g)\big) - (C')^{-1}(w)\right]}_{\tau(g)}, \tag{8}$$

where h_0 is the baseline hours supplied. We refer to $\tau(g)$ as the causal earnings gap response function. If a driver is not treated with peer information (i.e. $\chi = 0$), the latter term zeros out, and thus the labor supply response is exactly zero.

5.5 The Platform's Problem

Let $\mathcal{P}_\kappa$ denote the set of feasible information policies (χ, q) satisfying the global credibility constraint under a given $\kappa \geq 1$. The platform chooses an information policy $(\chi, q) \in \mathcal{P}_\kappa$ to maximize the aggregate hours supplied across the continuum of drivers. Since the baseline labor supply h_0 is independent of the information policy, maximizing total hours is equivalent to maximizing the aggregate causal earnings gap response:

$$\max_{(\chi,q)\in\mathcal{P}_\kappa} \int_0^1 \chi(p) \cdot \tau\big(Q(p) - Q(q(p))\big)\, dp \tag{9}$$

The solution to the platform's problem depends on the shape of the causal earnings response function, $\tau(\cdot)$. To establish a theoretical benchmark, we first characterize the optimal policy under a linear specification of the response function.

Linear Earnings Gap Response. Assume τ is linear in the earnings gap: $\tau(g) = \beta g$ for some parameter $\beta > 0$. The platform's objective simplifies to maximizing the aggregate earnings gap revealed to treated drivers: $\int_0^1 \chi(p) \cdot \big(Q(p) - Q(q(p))\big)\, dp$. We can then characterize the optimal policy as follows.

Proposition 1 (Optimal Policy Under Linearity) *Suppose $\tau(g) = \beta g$ with $\beta > 0$, and let Q be strictly increasing. For any credibility parameter $\kappa \geq 1$, an optimal information policy $(\chi^*, q^*) \in \mathcal{P}_\kappa$ takes the*

following form:

1. *(Extensive margin) There exists a treatment cutoff*

$$p^* = \frac{1}{\kappa + 1}$$

such that

$$\chi^*(p) = \begin{cases} 1 & \text{if } p \geq p^*, \\ 0 & \text{if } p < p^*. \end{cases}$$

That is, only the top fraction $\kappa/(\kappa+1)$ of drivers are treated with peer information.

2. *(Treated drivers) Treated drivers are assigned to the lowest feasible benchmark quantiles, saturating the global credibility constraint on the interval $\left[0, \frac{1-p^*}{\kappa}\right]$. The assignment $q^*(p)$ for $p \geq p^*$ is not uniquely determined as the platform is indifferent to how these lowest benchmarks are allocated among treated drivers.*

3. *(Untreated drivers) The assignment $q^*(p)$ for $p < p^*$ is not uniquely determined and can be chosen arbitrarily as long as the global credibility constraint is satisfied.*

To get intuition for this result, consider two special cases. If $\kappa = 1$, the platform treats exactly the top half of drivers with peer information ($p^* = \frac{1}{2}$), and assigns them to benchmark quantiles from the bottom half of the distribution. Crucially, the platform only cares about maximizing the aggregate earnings gap and is indifferent to exactly how the lowest benchmarks are distributed among the treated drivers. If $\kappa = \infty$, the platform treats all drivers ($p^* = 0$), and matches everyone to the bottom of the distribution ($q^*(p) = 0, \forall p$).

Remark 1 (Affine Response). If the causal earnings gap response function includes a constant term c such that $\tau(g) = \beta g + c$, the platform's problem remains additively separable. On the extensive margin, the fixed term c shifts the treatment cutoff p^*, which is now implicitly defined by the condition: $Q(p^*) + \frac{c}{\beta} = Q\left(\frac{1-p^*}{\kappa}\right)$. Intuitively, if simply receiving peer information generates a positive (negative) morale or attention effect independent of the earnings gap, this strictly lowers (raises) the cutoff p^*, expanding (shrinking) the pool of treated drivers. On the intensive margin, the platform remains indifferent to the exact assignment rule $q^*(p)$ among treated drivers as long as it saturates the global credibility constraint by allocating the lowest feasible benchmarks.

Earnings Gap Response with Diminishing Sensitivity. We now relax the linearity assumption to allow for diminishing sensitivity: τ is strictly concave for positive earnings gaps ($g > 0$). As we show, introducing curvature changes the platform's intensive margin problem and the optimal policy is characterized as follows:

Proposition 2 (Optimal Policy Under Diminishing Sensitivity) *Suppose the earnings gap response function is twice continuously differentiable, with $\tau(0) = 0$, $\tau'(g) > 0$ for all g, and is strictly concave in the domain of gains ($\tau''(g) < 0$ for $g > 0$). Let Q be continuously differentiable with $Q'(p) > 0$ for all p. For any credibility parameter $\kappa \geq 1$, an optimal information policy (χ^*, q^*) takes the following form:*

1. *(Extensive Margin) There exists a treatment cutoff $p^* \in (0, 1)$ implicitly defined by the condition:*

$$\tau\big(Q(p^*) - Q(0)\big) = \int_{p^*}^{1} \tau'\big(Q(p) - Q(q^*(p))\big) \cdot Q'\big(q^*(p)\big) \cdot \frac{1}{\kappa}\, dp,$$

   where $q^*(p)$ is the optimal assignment rule, such that

$$\chi^*(p) = \begin{cases} 1 & \text{if } p \geq p^*, \\ 0 & \text{if } p < p^*. \end{cases}$$

2. *(Treated drivers) Conditional on treatment ($p \geq p^*$), the optimal assignment rule $q^*(p)$ is strictly increasing and uniquely given by:*

$$q^*(p) = \frac{p - p^*}{\kappa}, \qquad \forall\ p \geq p^*$$

3. *(Untreated drivers) The assignment $q^*(p)$ for $p < p^*$ is not uniquely determined and can be chosen arbitrarily as long as the global credibility constraint is satisfied.*

The first-order condition in the above proposition equates the marginal cost and marginal benefit of excluding the marginal driver with peer information. The left-hand side captures the platform's loss in labor supply from not treating the marginal driver at rank p^* with peer information, who would otherwise be matched to the lowest feasible benchmark of $Q(0)$. The right-hand side captures the aggregate gain in labor supply from the remaining treated drivers ($p > p^*$), as excluding the marginal driver allows the platform to assign lower benchmarks to the infra-marginal mass of drivers while still satisfying the global credibility constraint.

Taken together, these results show that the platform's optimal information policy depends on the shape of the causal earnings-gap response function $\tau(g)$. In particular, the response function serves as a sufficient statistic for optimal design, determining both which workers should receive information, and how peer benchmarks should be assigned. The two propositions characterize the optimal information policy for maximizing aggregate labor supply under alternative assumptions about the earnings-gap response function, consistent with our empirical estimates.

6 Conclusion

This paper studies how firms should design and target peer information at work to motivate worker effort and performance. Using a large-scale field experiment with 2,897 rideshare drivers, we elicit workers' demand for peer earnings information, estimate its effects through randomized information provision, and exploit random assignment of peer groups to causally identify how workers respond to relative performance. The inclusion of monetary incentives further allows us to benchmark the magnitude of these effects.

Our findings show that workers are highly heterogeneous in their demand for peer information, with only 52% classified as "info-seeking." These elicited preferences are highly predictive of treatment effects. While the average effect of peer information is modest, it masks substantial heterogeneity by information preferences. Peer information increases daily earnings by nearly 4% among info-seeking drivers but has no detectable effect among non-info-seeking drivers, even though both groups respond similarly to monetary incentives. Taken together, these results provide a unifying explanation for the mixed evidence in the literature: studies that do not account for heterogeneity in information demand may aggregate offsetting responses across different worker types, and therefore recover attenuated or null average effects. More broadly, our findings highlight that workers' information preferences are a previously unmeasured source of heterogeneity that is first-order for understanding how workers respond to workplace feedback.

We further show that, even abstracting from preference heterogeneity, responses to peer information depend on workers' relative performance. Our design overcomes the key identification challenge by randomly assigning each driver to a reference group of ten similar drivers, which generates exogenous variation in the average peer earnings they observe, and therefore in realized earnings gaps. This allows us to provide, to our knowledge, the first causal estimate of the *earnings-gap response function*. We find that workers with the same earnings respond differently depending on whether they are above or below their peer group average, and that these responses vary systematically with elicited information preferences. Additional evidence indicates that peer information does not affect productivity or search behavior, consistent with social comparisons rather than social learning as the underlying mechanism.

In sum, our findings have direct implications for the design of workplace feedback policies. A uniform "one-size-fits-all" approach to providing the same peer information to all workers can generate muted average effects by masking substantial heterogeneity across workers. Instead, firms can improve labor supply by targeting peer information based on workers' preferences and by carefully choosing the reference groups used for comparison. Our theoretical framework formalizes this information design problem and characterizes the optimal information policy under alternative assumptions about the earnings-gap response function. More broadly, our results highlight information design as a key margin for improving worker effort and performance in modern workplaces, where firms increasingly have the ability to tailor feedback at scale.

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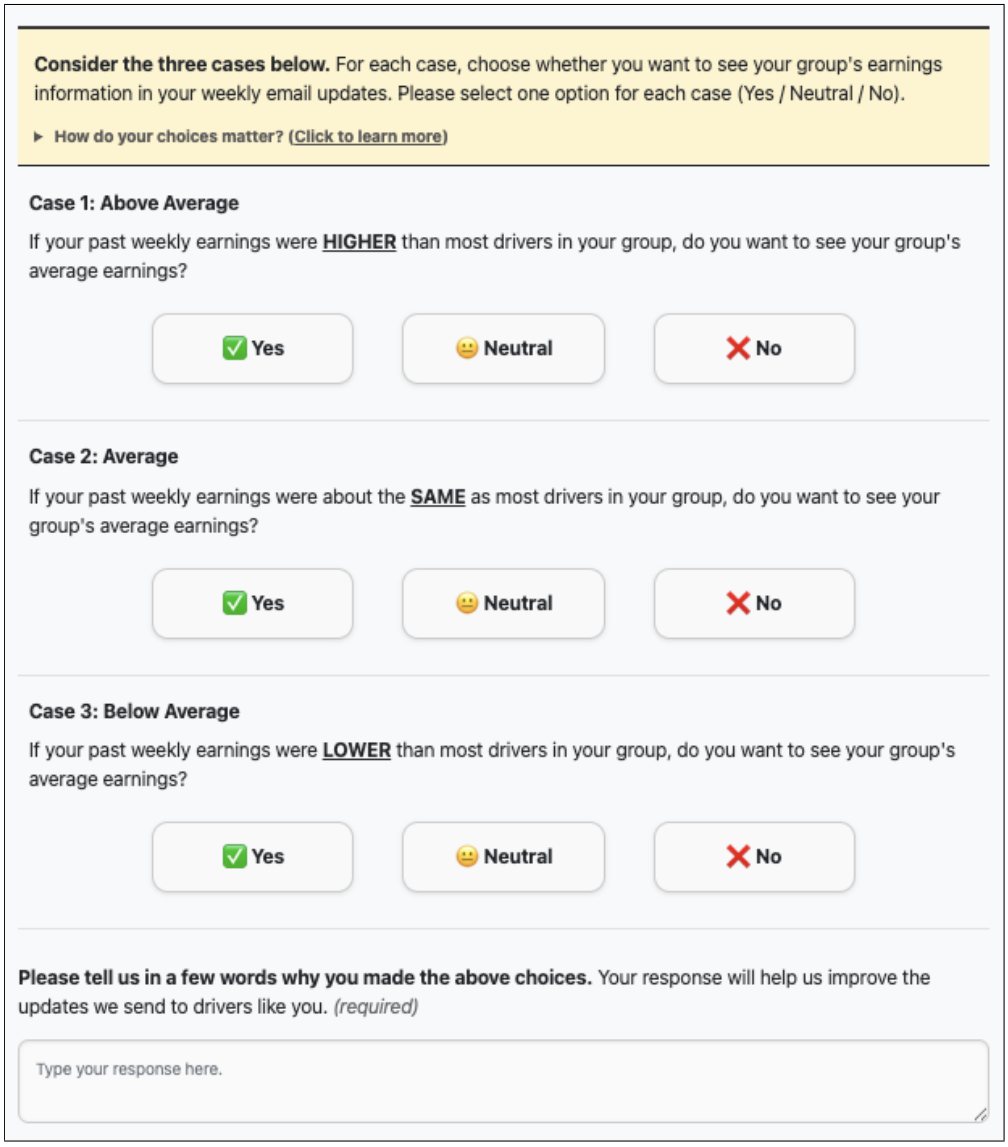
Tang, Y. (2024). To follow the crowd? benefits and costs of migrant networks. Technical report, Working Paper.

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Online Appendix

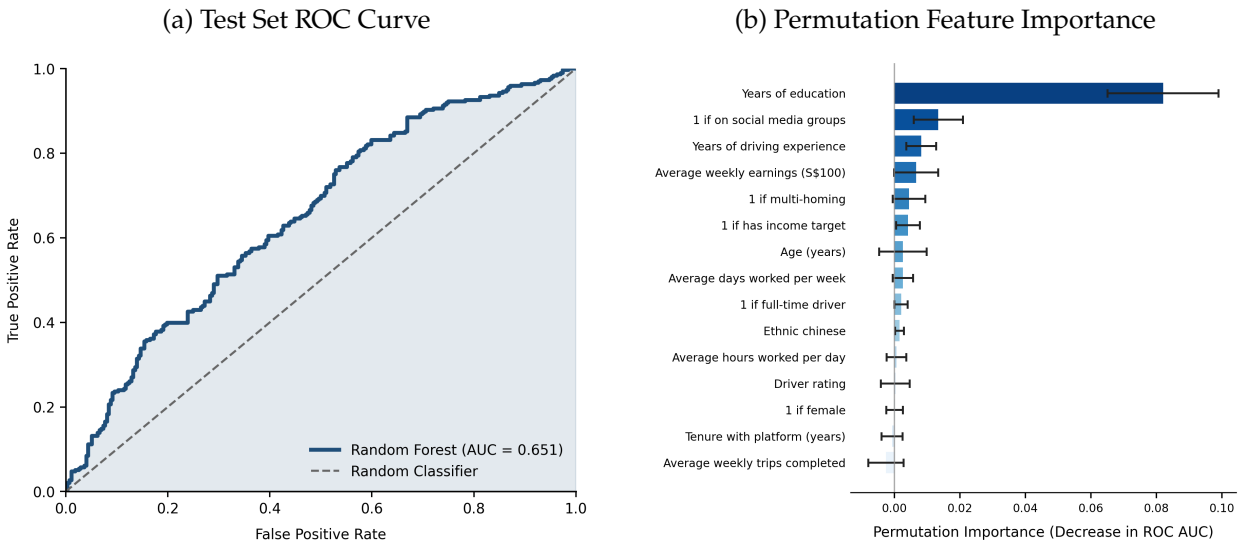
A. Supplementary Figures and Tables

Figure A1: Information Preference Elicitation



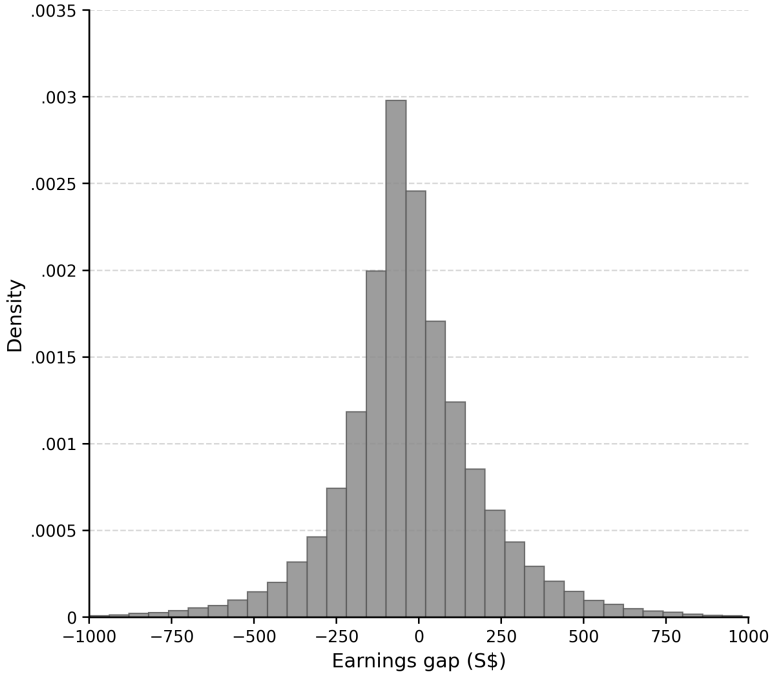
Notes. This figure shows the baseline survey module used to elicit drivers' preferences for receiving peer earnings information. Using a strategy-method approach, drivers choose "Yes," "Neutral," or "No" in three contingent scenarios: when their historical weekly earnings were above, around, or below their reference group average. After making these choices, drivers are asked to provide a brief open-ended explanation. To make elicitation incentive-compatible, with probability 1/3, the choice corresponding to the driver's realized relative-earnings scenario was implemented; otherwise, assignment to peer information was random. In the implemented scenario, selecting "Yes" (respectively, "No") means the driver receives (does not receive) peer information and forgoes a small bonus (S$0.10). Selecting "Neutral" allows the driver to keep the bonus, with receipt of peer information determined randomly.

Figure A2: Random Forest Classification of Information Preferences



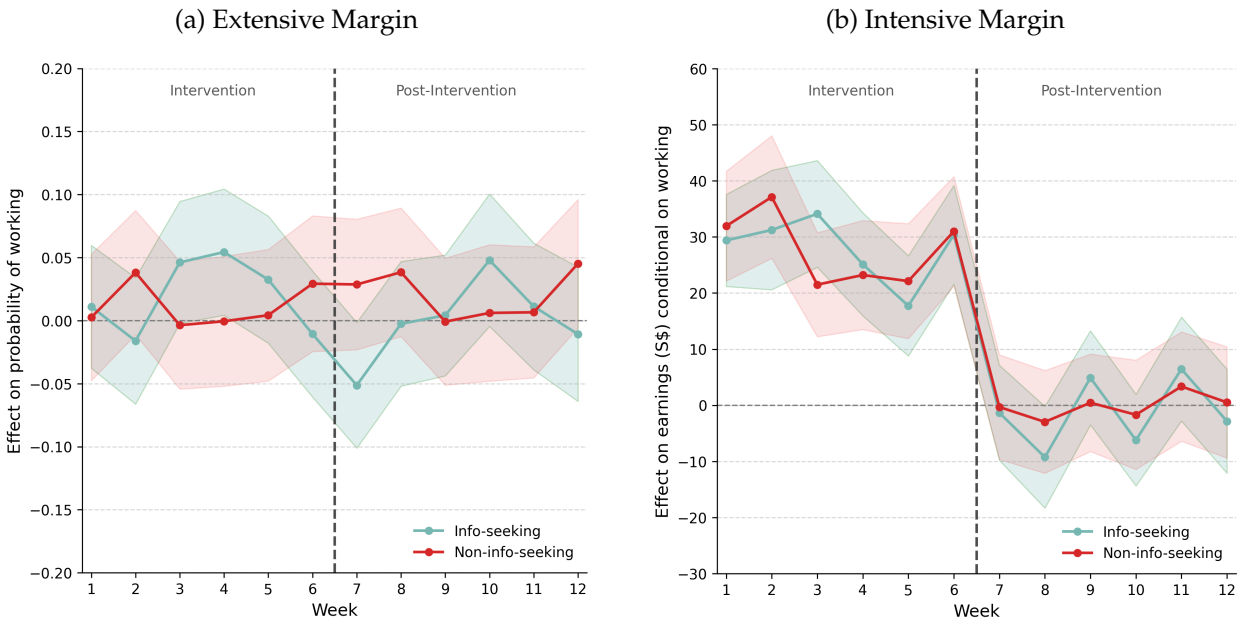
Notes. This figure reports out-of-sample predictive performance from a tuned random forest classifier that predicts whether a driver is info-seeking using the full set of baseline observables. Panel (a) shows the receiver operating characteristic (ROC) curve evaluated on a held-out test set, with an area under the curve (AUC) of 0.65, indicating weak predictive performance. Panel (b) reports permutation-based feature importance, measured as the average decrease in AUC when each variable is randomly permuted. Higher values indicate greater predictive importance. The error bars display ± one standard deviation across 30 permutation repeats.

Figure A3: Distribution of Relative Earnings Gaps



Notes. This figure plots the distribution of drivers' relative earnings gaps (S$), defined as own earnings minus peer group's average earnings realized from each earnings update. For readability, the histogram restricts to observations with earnings gaps between $[-1,000, 1,000]$, which accounts for 99.6% of the full sample.

Figure A4: Temporal Dynamics of Monetary Incentive Effects



Notes. This figure reports week-by-week treatment effects of monetary incentive over the intervention period (weeks 1–6) and post-intervention period (weeks 7–12), estimated separately for info-seeking and non-info-seeking drivers. Panel (a) uses an indicator for working that day (extensive margin), while Panel (b) uses daily earnings conditional on working (intensive margin) as the dependent variable. The estimates come from specifications with driver and date fixed effects, with standard errors clustered at the driver level. The shaded bands represent 95% confidence intervals. See Figure 8 in the main text for the analogous figure on the temporal dynamics of peer information.

Table A1: Sample Characteristics and Balance Tests

	Full Sample (1)	Control Group (2)	Peer Info Group (3)	Endogenous Info Group (4)	p-value (F-test) (5)
Panel A: Demographics					
Age (Years)	50.702	50.895	50.688	50.524	0.718
	(10.019)	(10.089)	(10.027)	(9.949)	
1 if Female	0.073	0.076	0.067	0.077	0.670
	(0.260)	(0.265)	(0.250)	(0.266)	
1 if Chinese (Ethnicity)	0.795	0.802	0.792	0.791	0.789
	(0.404)	(0.398)	(0.406)	(0.407)	
Years of Education	12.205	12.188	12.137	12.290	0.478
	(2.806)	(2.854)	(2.709)	(2.854)	
Panel B: Baseline Labor Supply on Platform					
Average Weekly Earnings (S$)	477.323	475.274	478.279	478.401	0.982
	(402.466)	(394.880)	(405.126)	(407.636)	
Average Weekly Trips Completed	30.134	29.633	30.381	30.384	0.781
	(27.018)	(25.943)	(27.561)	(27.531)	
Panel C: Driver Profile and Work Patterns					
Years of Driver Experience	6.057	6.014	6.252	5.905	0.417
	(5.904)	(5.854)	(6.117)	(5.735)	
Tenure With Platform (Years)	3.251	3.235	3.261	3.257	0.967
	(2.386)	(2.380)	(2.398)	(2.381)	
1 if Full-Time Driver	0.616	0.630	0.616	0.603	0.485
	(0.486)	(0.483)	(0.487)	(0.490)	
Average Hours Worked Per Day	5.414	5.456	5.384	5.402	0.548
	(1.495)	(1.482)	(1.523)	(1.481)	
Average Days Worked Per Week	5.814	5.799	5.856	5.787	0.433
	(1.242)	(1.247)	(1.194)	(1.285)	
Driver Rating (5-Point Scale)	4.951	4.953	4.951	4.950	0.701
	(0.079)	(0.077)	(0.082)	(0.077)	
Panel D: Other Self-Reported Measures					
1 if Multi-Homing	0.818	0.810	0.820	0.825	0.659
	(0.386)	(0.393)	(0.384)	(0.380)	
1 if Has Income Target	0.767	0.769	0.761	0.770	0.858
	(0.423)	(0.422)	(0.427)	(0.421)	
1 if on Social Media Driver Groups	0.523	0.530	0.530	0.510	0.590
	(0.500)	(0.499)	(0.499)	(0.500)	
No. of Observations	2,897	961	969	967	–

Notes. Columns (1) through (4) report means with standard deviations in parentheses for the full sample and each experimental group, respectively. Column (5) reports the p-value from an F-test of joint equality of means across the three groups.

Table A2: Correlates of Peer Information Demand

Dependent variable:	1 if classified as "info-seeking"			
	(1)	(2)	(3)	(4)
Demographics				
Age (Years)	-0.001	-0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
1 if Female	-0.096***	-0.090**	-0.092***	-0.091**
	(0.035)	(0.035)	(0.036)	(0.035)
1 if Chinese (Ethnicity)	0.016	0.011	0.007	-0.003
	(0.023)	(0.023)	(0.023)	(0.023)
Years of Education	0.030***	0.030***	0.030***	0.028***
	(0.003)	(0.003)	(0.004)	(0.004)
Baseline Labor Supply on Platform				
Average Weekly Earnings (S$100)		0.007	0.003	0.004
		(0.008)	(0.008)	(0.008)
Average Weekly Trips Completed		-0.000	0.000	0.000
		(0.001)	(0.001)	(0.001)
Driver Profile and Work Patterns				
Years of Driver Experience			-0.007***	-0.006***
			(0.002)	(0.002)
Tenure With Platform (Years)			0.012***	0.010**
			(0.004)	(0.004)
1 if Full-Time Driver			0.034	0.032
			(0.024)	(0.024)
Average Hours Worked Per Day			0.016**	0.011
			(0.008)	(0.008)
Average Days Worked Per Week			-0.008	-0.012
			(0.008)	(0.008)
Driver Rating (5-Point Scale)			-0.024	-0.031
			(0.119)	(0.120)
Other Self-Reported Measures				
1 if Multi-Homing				0.087***
				(0.025)
1 if Has Income Target				0.043*
				(0.022)
1 if on Social Media Driver Groups				0.072***
				(0.019)
R-squared	0.033	0.035	0.043	0.055
No. of Observations	2,897	2,897	2,840	2,840

Notes. This table reports correlates of information demand from linear probability models where the dependent variable equals one if a driver is classified as "info-seeking" (i.e., chooses to receive peer information in at least one contingent scenario). Robust standard errors in parentheses. The reduction in observations from Columns (3) to (4) reflects missing values in driver rating due to insufficient rated trips for a small subset of drivers. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Coding Scheme with Example Responses

Category	Explanation	Example
Unclassified	The participant's response was blank, unintelligible, off-topic, corrupted, or otherwise could not be meaningfully categorized.	"N/A"; "[response unclear]"; "[incomplete response]"
Not Interested or Relevant	The participant specified that they were not interested in knowing other drivers' earnings, or that the information was irrelevant, unnecessary, or not useful. This category also includes responses indicating that earnings should remain private, that they prefer not to know (when not related to stress), or that the information is not meaningful for their situation (e.g., working part-time).	"Other drivers' earnings are not relevant to me."; "That information is not useful for what I do."; "Earnings should remain private."; "Since I only work part-time it does not matter to me."
Do Not Wish to Compare	The participant specified that they do not want to compare their earnings with those of other drivers.	"I prefer not to compare my earnings with others."; "I do not want to compare myself with other drivers."; "I don't really compare myself to other drivers."
Avoid Stress	The participant specified that knowing other drivers' earnings could create stress, discouragement, or disappointment, or negatively affect their well-being.	"It would be discouraging if I saw that others earned much more."; "I prefer not to know because it could create unnecessary stress."; "I would rather focus on my work without that pressure."
Own Target	The participant specified that they rely on their own personal earnings goal or target to evaluate their performance, rather than information about other drivers' earnings.	"I already have my own daily earnings target."; "What matters is whether I meet my personal goal."; "I have a number in mind and that's what I stick to."
Neutral	The participant specified that they have no strong preference and would be comfortable either having or not having the information.	"Either option is fine for me."; "I do not have a preference."; "I'm okay with it either way, doesn't matter to me."
Learning	The participant specified that they would use the information to learn from others, adjust their driving strategy, improve their performance, or better understand market conditions in order to increase earnings.	"It could help me adjust when and where I choose to drive."; "I could learn from that information to improve my earnings."; "It would help me understand the market better."
Benchmarking	The participant specified that they would use average earnings as a benchmark, gauge, or reference point for evaluating their own performance, without explicitly emphasizing comparison with other drivers.	"It would give me a benchmark for how I am doing."; "I would like to know the average as a reference point."; "It would be good to know what most people are making."
Comparison with Peers	The participant specifically stated that they would like to compare their earnings with those of other drivers.	"I would like to know how my earnings compare with other drivers."; "It would be useful to see whether I earn more or less than others."; "I'd compare what I earn with what other drivers earn."
Motivation	The participant specified that the information would motivate them or encourage them to improve their performance or increase their earnings.	"Knowing the average would motivate me to do better."; "It would push me to work harder."; "It would make me want to do better."
General Interest	The participant specified that they were generally interested or curious to know the information without identifying a specific purpose.	"I would simply like to know."; "More information is always better."; "I'd be interested to see what that looks like."

Notes. This table provides an overview of the qualitative coding scheme used for categorizing drivers' open-ended responses.

Table A4: Effects on Search Behavior and Productivity by Learning Motives

Dependent variable:	Search Behavior			Productivity	
	Mean dispersion of pickups (km) (1)	Share of trips in central region (2)	Share of trips auto-accepted (3)	Mean deadhead time (min) (4)	Hourly earnings (ex. incentives) (5)
Panel A: Average Treatment Effects (ATE)					
Peer Information (β)	0.06	-0.00	0.00	-0.55	-0.19*
	(0.04)	(0.00)	(0.00)	(0.69)	(0.11)
Incentives (γ)	0.17***	0.01	0.01***	-6.07***	-0.93***
	(0.06)	(0.01)	(0.00)	(1.08)	(0.16)
Panel B: ATE by Learning Motives					
Peer Information × Learning motive (β_1)	0.07	0.00	0.00	-1.20	-0.03
	(0.06)	(0.01)	(0.00)	(1.09)	(0.19)
Peer Information × Non-learning motive (β_2)	0.05	-0.00	0.00	-0.30	-0.25**
	(0.05)	(0.00)	(0.00)	(0.74)	(0.12)
Incentives × Learning motive (γ_1)	0.20*	-0.00	0.00	-7.07***	-1.02***
	(0.11)	(0.01)	(0.00)	(1.75)	(0.28)
Incentives × Non-learning motive (γ_2)	0.16**	0.01	0.01***	-5.69***	-0.90***
	(0.07)	(0.01)	(0.00)	(1.21)	(0.19)
Baseline mean	3.91	0.42	0.03	45.05	40.44
	(3.10)	(0.37)	(0.13)	(47.26)	(8.85)
p-values of tests of interest:					
Difference in peer information and incentive effects: $\beta = \gamma$	0.132	0.250	0.104	0.000	0.000
Peer information effect by learning motives: $\beta_1 = \beta_2$	0.803	0.570	0.509	0.426	0.263
Incentive effect by learning motives: $\gamma_1 = \gamma_2$	0.743	0.358	0.298	0.470	0.682
No. of observations	135,782	136,600	137,641	109,491	109,491
No. of workers	1,519	1,519	1,520	1,484	1,484

Notes. This table reports regression estimates of the effects of peer information and monetary incentives on shift-level search behavior and productivity outcomes, using the sample of drivers with hand-coded motives that are not "uncategorized." Panel A reports average treatment effects estimated on this restricted sample. Panel B reports heterogeneous effects by whether the stated motive is learning-related. See Table A3 for the coding scheme. All regressions include driver, date, and time-of-day fixed effects, and standard errors clustered at the driver level are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B. Theoretical Appendix

Proof of Proposition 1. Under $\tau(g) = \beta g$ with $\beta > 0$, the platform's objective is to maximize the aggregate earnings gap among treated drivers:

$$\max_{(\chi,q)\in\mathcal{P}_\kappa} \beta \int_0^1 \chi(p) \cdot \big(Q(p) - Q(q(p))\big)\, dp$$

Let $M = \int_0^1 \chi(p)\, dp$ denote the mass of treated drivers. For any given M, the first component $\int_0^1 \chi(p)Q(p)\, dp$ is maximized by treating the highest-ranked drivers. Therefore, the treated set is $p \in [1 - M, 1]$.

Conditional on this treated set, the platform minimizes the aggregate benchmarks assigned to the treated drivers:

$$\int_{1-M}^1 Q(q(p))\, dp$$

Recall the platform faces the global credibility constraint:

$$\int_0^1 \mathbb{1}\{q(p) \le t\}\, dp \le \kappa t, \quad \forall t \in [0, 1]$$

The platform thus assigns the lowest possible benchmark quantiles to the treated mass M and assign the remaining, higher benchmark quantiles to the untreated mass $1 - M$. Since Q is strictly increasing, the lowest feasible assignment for treated drivers is achieved by saturating the credibility constraint and filling the interval $[0, M/\kappa]$ at density κ. This yields:

$$\int_{1-M}^1 Q(q(p))\, dp = \int_0^{M/\kappa} \kappa Q(t)\, dt$$

Dropping the multiplicative constant β, the platform's objective can therefore be written as a function of M:

$$V(M) = \int_{1-M}^1 Q(p)\, dp - \int_0^{M/\kappa} \kappa Q(t)\, dt$$

Differentiating with respect to M using Leibniz's rule yields:

$$V'(M) = Q(1 - M) - Q(M/\kappa)$$

Since Q is strictly increasing, the first-order condition implies $1 - M = \frac{M}{\kappa}$. Note that $W'(M)$ is strictly decreasing, so the FOC identifies the unique global optimum. Therefore, the optimal treated mass and corresponding cutoff are given by:

$$M^* = \frac{\kappa}{\kappa + 1}, \qquad p^* = 1 - M^* = \frac{1}{\kappa + 1}$$

To achieve this optimum, the platform assigns treated drivers ($p \ge p^*$) benchmark quantiles from the interval $[0, \frac{1-p^*}{\kappa}] = [0, p^*]$ such that the induced distribution of benchmarks has uniform density κ. Because the objective is linear, the platform is indifferent to the specific assignment rule $q^*(p)$ among treated drivers, provided it satisfies this distributional requirement.

Finally, since untreated drivers ($p < p^*$) do not enter the objective, their assignments $q^*(p)$ are

not uniquely determined, as long as they are mapped to the remaining benchmark quantiles in a way that satisfies the global credibility constraint. ■

Proof of Proposition 2. Let $M = \int_0^1 \chi(p)\,dp$ denote the mass of treated drivers. For any given M, the platform optimally treats the highest-ranked drivers, since the earnings gap response function τ is strictly increasing. As in the linear case, this implies a treatment cutoff $p^* = 1 - M$, such that:

$$\chi^*(p) = \begin{cases} 1 & \text{if } p \geq p^*, \\ 0 & \text{if } p < p^*. \end{cases}$$

Conditional on this treated set, the platform chooses an assignment rule $q(p)$ to maximize the aggregate earnings gap response:

$$\int_{1-M}^{1} \tau\big(Q(p) - Q(q(p))\big)\,dp$$

Because τ is strictly increasing, the platform seeks to minimize the assigned benchmark quantiles to treated drivers to maximize the earnings gaps. Therefore, the optimal policy saturates the global credibility constraint, assigning treated drivers benchmarks from the interval $[0, \frac{M}{\kappa}]$ at uniform density κ.

As τ is strictly concave in the domain of gains, the platform is no longer indifferent to the specific assignment rule $q^*(p)$ for treated drivers. Note that since $\tau(g) < 0$ for $g < 0$, an optimal policy will never assign a negative earnings gap to a treated driver, as the platform could strictly improve the objective by setting $\chi(p) = 0$ for such drivers. Hence, for treated drivers, any optimal assignment must satisfy $Q(p) \geq Q(q(p))$.

To determine how to allocate these benchmarks, let $v(p, q) = \tau\big(Q(p) - Q(q)\big)$. On the gains domain $g > 0$, the cross-partial derivative is:

$$\frac{\partial^2 v}{\partial p \partial q} = -\tau''\big(Q(p) - Q(q)\big) \cdot Q'(p) \cdot Q'(q) > 0,$$

since by assumption, $Q' > 0$ and τ is strictly concave in gains ($\tau'' < 0$ for $g > 0$). This implies that $v(p, q)$ is strictly supermodular in (p, q).

By standard assortative matching arguments, the optimal assignment rule $q^*(p)$ must be strictly increasing. The platform must assortatively match the treated drivers $p \in [p^*, 1]$ to the lowest feasible benchmarks on the interval $\left[0, \frac{1-p^*}{\kappa}\right]$ by saturating the global credibility constraint. This uniquely pins down the linear mapping:

$$q^*(p) = \frac{p - p^*}{\kappa}, \qquad \forall\ p \geq p^*$$

The platform's objective can then be written as a function of the cutoff p^*:

$$V(p^*) = \int_{p^*}^{1} \tau\left(Q(p) - Q\left(\frac{p - p^*}{\kappa}\right)\right) dp$$

Differentiating with respect to p^* using Leibniz's rule yields:

$$V'(p^*) = -\tau\big(Q(p^*) - Q(0)\big) + \frac{1}{\kappa}\int_{p^*}^{1} \tau'\big(Q(p) - Q(q^*(p))\big) \cdot Q'\big(q^*(p)\big)\, dp$$

Setting $V'(p^*) = 0$ yields the condition which implicitly defines p^*, as stated in the proposition.

To ensure an interior solution $p^* \in (0,1)$ exists, we evaluate the limits. As $p^* \to 1$, the integral vanishes, yielding $V'(1) = -\tau(Q(1) - Q(0)) < 0$. As $p^* \to 0$, the first term vanishes (since $\tau(0) = 0$), yielding $V'(0) = \frac{1}{\kappa}\int_0^1 \tau'(Q(p) - Q(\frac{p}{\kappa})) \cdot Q'(\frac{p}{\kappa})\, dp > 0$. Since $V'(p^*)$ is continuous, the Intermediate Value Theorem guarantees the existence of a cutoff $p^* \in (0,1)$ satisfying the first-order condition.

Finally, since untreated drivers ($p < p^*$) do not enter the objective, their assignments $q^*(p)$ are not uniquely determined, as in the linear case. ■