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The Dual Effects of Team Contest Design on On-Demand Service Work Schedules

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Emerging on-demand service platforms (OSPs) have recently embraced teamwork as a strategy for stimulating workers' productivity and mediating temporal supply and demand imbalances. This research investigates the team contest scheme design problem considering work schedules. Introducing teams on OSPs creates a hierarchical single-leader multi-follower game. The leader (platform) establishes rewards and intra-team revenue-sharing rules for distributing workers' payoffs. Each follower (team) competes with others by coordinating the schedules of its team members to maximize the total expected utility. The concurrence of inter-team competition and intra-team coordination causes dual effects, which are captured by an equilibrium analysis of the followers' game. To align the platform's interest with workers' heterogeneous working-time preferences, we propose a profit-maximizing contest scheme consisting of a winner's reward and time-varying payments. A novel algorithm that combines Bayesian optimization, duality, and a penalty method solves the optimal scheme in the non-convex equilibrium-constrained problem. Our results indicate that teamwork is a useful strategy with limitations. Under the proposed scheme, team contest always benefits workers. Intra-team coordination helps teams strategically mitigate the negative externalities caused by over-competition among workers. For the platform, the optimal scheme can direct teams' schedules toward more profitable market equilibria when workers have inaccurate perceptions of the market.

Key words: On-demand service platforms, Team contest, Contest scheme design, Market equilibrium

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1. Introduction

On-demand service platforms (OSPs) recently implemented a new supply management strategy that organizes workers into teams and makes them compete with each other. For example, ride-hailing platform DiDi Chuxing launched a "virtual team" program where teams atop the leaderboard received bonuses (Ai et al. 2019; Zhang et al. 2019). Field experiments revealed that this team-based operational strategy improved drivers' productivity significantly, leading to an average increase of 33.8% in the number of completed orders and a 27.4% increase in drivers' income. Some food delivery platforms divided service areas into multiple stations whose leaders were responsible for instructing couriers to compete for orders (Chan 2021). The last example is mapping platforms that integrated several ride-hailing companies into a single-access system (Zhou et al. 2021). Allowing workers from several companies to compete for customers accessed via the same application inherently transforms the integrator model into an extended form of team contests. Compared to the case with fully self-scheduled workers, the behavioral benefits of implementing team contests are evident, including establishing team identity, increasing cooperation between workers, and stimulating productivity (Ai et al. 2019). However, the managerial implications of team contests on OSPs have not been thoroughly investigated due to the "*dual effects*" – *intra-team coordination* and *inter-team competition.*

First, the presence of teams enables intra-team coordination on work schedules, which offers a novel method for correcting the temporal supply and demand mismatches. Demand for service on OSPs, such as ride-hailing trips (He 2021) and food deliveries (Tong et al. 2020), is frequently volatile. Meanwhile, labor supply on OSPs depends on the proportion of active workers, which highly depends on their working-time preferences. As many workers on OSPs are part-time workers, they enjoy the flexibility of scheduling their working hours (Chen, Rossi, et al. 2019; Mukhopadhyay and Chatwin 2020). Furthermore, *self-scheduled workers* may have inaccurate perceptions of market conditions (Dong et al. 2021) because their decisions are made independently with limited social connections or knowledge of others (Glavin et al. 2021). Consequently, workers might not respond to the platform as expected, contributing to significant discrepancies between supply and demand during peak hours (Shen 2019; Wu et al. 2021). After implementing the team-based operations, intra-team work schedules can be conducted by (a) allowing workers within each team to interchange information on working-time preferences, and (b) coordinating team members' individual schedule decisions to maximize the total expected utility. The impacts of implementing localized coordination on the equilibrium state have been investigated in the machine scheduling problem (Immorlica et al. 2009), in which demands are assumed to be fixed and known a priori.

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However, OSPs are two-sided markets in which the realized demand depends on the instantaneous labor supply. On the other hand, previous studies observed the spontaneous coordination among workers in two-sided markets. For example, taxi drivers coordinate their shifts or service locations to maximize their revenue (Shehory and Kraus 1999). Drivers on ride-hailing platforms colluded for a lack of service providers and exploited surge prices (Tripathy et al. 2022). Nevertheless, the team-based coordination on work schedules has not been rigorously described or analyzed.

Second, with all teams vying for the same pool of customers, inter-team competition becomes inevitable. This can be further escalated into a contest by the platform that offers additional incentives for completed orders, as is performed in Ai et al. (2019). In literature, game theory is often used to describe the strategic interactions between workers and to delineate the contest outcomes by the notion of market equilibrium (Fu and Wu 2019). Inter-team competition on OSPs differs from previous studies in three ways: (a) OSPs serve as intermediaries in the two-sided markets that usually exhibit cross-network effects on both demand and supply (Armstrong 2006; Rochet and Tirole 2006). As a result, the inter-team competition is less likely to be a zero-sum game; (b) Aggregate models that project from individuals' performances to each team's winning probability may overlook the temporal dimension of contest design, while work schedule play a central role in this context; (c) The decision-makers follow a hierarchical structure such that the intra-team work schedules directly determine each team's contest outcomes. In contrast, workers in other economic contests, e.g., collective rent-seeking, make their decisions simultaneously and independently (Nitzan 1991; Baik and Lee 2007).

A central task for the platform, with teams present, resides in devising optimal contest schemes to align teams' work schedules with the platform's interests, by taking advantage of the above dual effects. This study proposes a *platform-centric contest scheme* and characterizes the corresponding market equilibrium on OSPs. The contest scheme consists of three components, (a) a *winner's reward*, which is commonly used in practice (Nalebuff and Stiglitz 1983; Ai et al. 2019), is awarded to the team with the most completed orders, (b) the *intra-team revenue-sharing rules* (Nitzan and Ueda 2011; Baik and Lee 2007; Kobayashi and Konishi 2021) guarantee workers' *individual rationality*, meaning that each worker's utility from joining a designated team is greater than that of the fully self-scheduling case, and (c) the *attraction weights*, which are tailored to account for the temporal imbalance of supply and demand and act as important parameters in intra-team revenue-sharing rules. To this extent, we expect to direct the market equilibria toward the platform's interests with reduced supply-demand imbalances.

The procedure of team contests on OSPs is illustrated in Figure 1. Workers have been organized into teams before the platform declares a platform-centric scheme. Next, all teams observing the contest scheme will simultaneously conduct intra-team coordination on workers' schedules to maximize the total utility in inter-team competition while ensuring workers' participation constraints. In the end, the platform announces the winning team. Each team distributes its revenue from completed orders plus the winner's reward among team members.

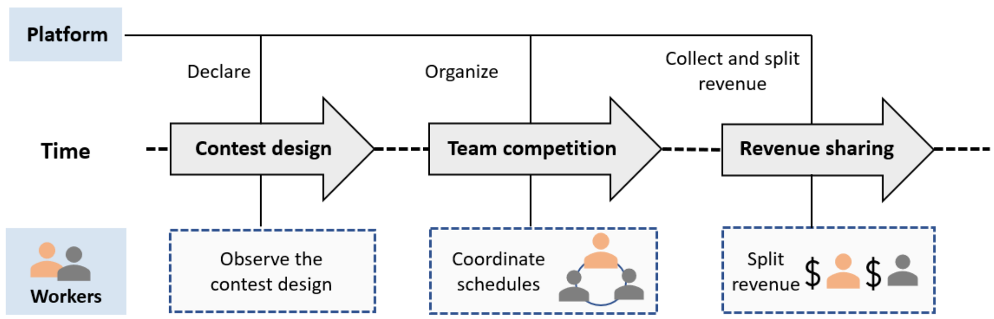


Figure 1 **Timeline of events for team contests on OSPs**

Objectives and Methodology. Considering the dual effects and the hierarchical structure on OSPs, we model the *contest scheme design problem* as a single-leader multi-follower game. A platform is the leader who designs the contest scheme to guide the lower-level market equilibrium. Teams are strategic followers who decide intra-team schedules responding to the upper-level contest scheme, other teams' strategies, and the team members' participation constraints. Our main objectives are (a) characterizing the optimal platform-centric scheme and (b) identifying key factors that impact the scheme decisions and contest outcomes at equilibrium. The goal of this research is to explore why and under what conditions using teams can enhance OSPs' profitability and workers' expected utility compared to the status quo market with self-scheduled workers.

To model this hierarchical game, we first model the intra-team scheduling coordination as an optimization problem where each team's total utility and feasible schedules are affected by other teams' decisions. On that premise, the market equilibrium under a particular scheme is characterized by *quasi-variational inequalities* (QVI). Next, we formally introduce the platform-centric contest scheme, which optimizes the winner's reward and period-specific attraction weights simultaneously to maximize the platform's total profit. Assembling all these elements, we formulate the platform-centric contest scheme design problem as a *mathematical programming with equilibrium constraints* (MPEC) program. However, solving the optimal contest scheme in this game is technically challenging. An algorithm integrating Bayesian optimization, penalty, and duality methods is developed to solve the global optimal platform-centric scheme.

Main Contributions. Our contributions are as follows:

1. By utilizing a flow approximation for scheduling decisions, we simplify the hierarchical contest scheme design problem to an MPEC formulation, which would otherwise be intractable when there are a large number of workers. The modeling methodology developed here can be used in other incentive research on OSPs.

2. Due to the difficulty of computing the optimal strategy for a single-leader multi-follower game, we develop an efficient algorithm that combines Bayesian optimization with QVI-based algorithms. This work provides the groundwork for implementing team-based strategies on OSPs.

3. Our findings suggest that the effectiveness of team contests may be overstated when intra-team coordination is not considered. It complements empirical studies in an attempt to provide a more complete understanding of the value of team-based operations.

Main Results. We list our main results as follows:

1. Team contests with the optimal platform-centric scheme can overcome the temporal misalignment between supply and demand.

2. The effectiveness of team contests depends on workers' perception accuracy toward their scheduling utility before they join teams. When workers have inaccurate perceptions, implementing team contests benefits the platform and workers. Otherwise, it may lead to a loss of profit for the platform.

3. The intra-team heterogeneity in workers' working-time preferences is critical in determining the optimal platform-centric scheme.

4. The platform benefits from the increasing number of teams with a diminishing marginal return.

Paper Organization. The rest of the paper is organized as follows. Section 2 overviews the market setting and the contest scheme design problem. Section 3 models the market equilibrium incorporating both workers' intra-team coordination and inter-team competition. The QVI for characterizing market equilibria and the corresponding solution algorithm are presented. Section 4 formally introduces and models the platform-centric contest scheme design problem. The algorithm for computing the optimal scheme is developed. Section 5 numerically evaluates the impact of teamwork from both the platform's and workers' perspectives. Section 6 discusses more model variants and conducts a sensitivity analysis for more insights on factors impacting contest scheme design and contest outcomes. The paper concludes with the main findings and future works.

2. Problem Overview

2.1. Market Setting

Consider a monopolistic platform that deploys a team contest strategy in a two-sided market. To serve the time-varying market demand, we divide the planning horizon into a sequence of time periods $T = \{1, 2, ..., t, ..T_0\}$. The analysis of contest scheme design and market equilibrium focuses on the long-term average steady state of the market. The settings of supply and demand are outlined as follows:

Supply side. The supply sides consist of K types of workers who are heterogeneous in their working-time preferences, as indicated by their service cost per period c^{kt}. We characterize a worker type by a vector $\boldsymbol{c^k} = (c^{kt})_{t=1}^{T_0} \in \mathbb{R}^{T_0}$. Prior to the competition, workers are grouped into a set of teams denoted as $J = \{1, ..., i, j, .., J_0\}$, and the numbers of workers per team are the same. The composition of team j is predetermined and is captured by a tuple $\{N_j^k\}_{k \in K}$, where N_j^k is the number of the k-type workers in team j. Each team consists of a leader and several team members. A team leader has the authority to coordinate the schedules of team members, namely their working hours during the planning horizon. Teams compete with each other for service orders and the winner's reward R by making intra-team coordination decisions.

Throughout the paper, we use the supply of active workers per period N_j^{kt}, i.e., the number of workers in the working state, as a representation of team j's collective scheduling decisions for the k-type workers. For each period $t \in T$, let $N_j^t = \sum_{k \in K} N_j^{kt}$ denote the total supply of active workers provided by team j. The vector $\boldsymbol{N^t} = (N_j^t)_{j=1}^{J_0} \in \mathbb{R}^{J_0}$ represents the supply of active workers from all teams during period t.

Demand side. Customers send service requests to the platform and are then matched with active workers. The potential demand, or the maximum number of service requests that can be made by customers, varies with time periods and is denoted as Q_0^t for $t \in T$. For a given Q_0^t, the demand served per period q^t depends on the supply of active workers $\boldsymbol{N^t}$ and is prescribed as

$$q^t(\boldsymbol{N^t}) = F_q(\boldsymbol{N^t} | Q_0^t), \quad \forall t \in T. \tag{1}$$

Without loss of generality, we assume that the function $F_q(\cdot)$ is twice differentiable. Equation (1) captures the cross-side network effects in two-sided markets. That is, the number of participants on the demand side depends on the number of participants on the supply side and vice versa (Armstrong 2006; Rochet and Tirole 2006). Since on-demand service markets generally exhibit positive cross-side network effects (Rochet and Tirole 2006), the served demand is supposed to increase continually with the supply of active workers from each team, i.e., $\partial q^t / \partial N_j^t > 0$ for $t \in T$ and $j \in J$.

A team's service output in competition depends on the platform's matching policy. Suppose that the platform treats all teams and workers equally in matching. Then, for each period $t \in T$, team j's service output q_j^t is directly proportional to its supply of active workers relative to the total supply of active workers in all teams:

$$q_j^t(N_j^t, \boldsymbol{N_{-j}^t}) = q^t(\boldsymbol{N^t}) \cdot \frac{N_j^t}{\sum_{i \in J} N_i^t}, \quad \forall t \in T, \quad j \in J. \tag{2}$$

where the vector $\boldsymbol{N^t_{-j}} = (N_i^t) \in \mathbb{R}^{(|J|-1)}$ represents the supply of active workers from all teams in period t except team j. Equation (2) suggests that the per-period service output of each team increases with its own active workers' supply but decreases with the supply of other teams.

Competition rules. We consider team contests with complete information. Anticipating teams' responses, a platform designs the contest scheme to steer the market toward a more profitable equilibrium. Observing the contest scheme, each team leader simultaneously determines the team schedules to maximize the total utility of its team members during the competition while ensuring their individual rationality. Following common practice (Ye et al. 2020), we measure a team's performance by its total service output over the entire planning horizon, i.e., $\sum_{t\in T} q_j^t$ for $j \in J$. In each period $t \in T$, the platform pays a team w^t for each completed order. At the end of the competition, the team with the best performance receives a winner's reward R, and each team member receives a positive share of the team revenue based on the declared attraction weights and revenue-sharing rules. In the long run, the competition could be implemented repeatedly, with each round determining a winning team. In an average sense, a team's probability of winning the reward is determined by a Tullock contest success function (Tullock 2001) so that it is defined as $\sum_{t\in T} q_j^t / \sum_{i\in J}\sum_{t\in T} q_i^t$ for any team $j \in J$.

2.2. Hierarchical Structure of the Contest Scheme Design Problem

Figure 2 represents the hierarchical single-leader multi-follower structure of the contest scheme design problem on OSPs. The platform is the profit-maximizing leader, and each team is a follower. The leader designs the contest scheme to influence teams' decisions and the resulted market equilibrium. Each follower solves a coordinated scheduling problem considering other teams' actions in competition.

The two levels of decision-making are intertwined. At the upper level, the platform designs the contest by considering teams' scheduling decisions under the winner's award and their impact on demand. At the lower level, a team leader who maximizes team utility needs to take both the inter-team competition and workers' time preferences for service into consideration. On the one hand, the scheduling decisions depend on both the winner's reward and other teams' decisions. On the other hand, intra-team coordination should guarantee individual rationality, meaning that all workers are better off under the coordinated schedules than under the self-scheduling status quo. This links a worker's utility to the attraction weights in revenue-sharing rules and her team's performance in competition. Due to the hierarchical structure, finding the optimal contest scheme is challenging by its very nature.

The model presented later follows the hierarchical structure described above. Specifically, Section 3 models the followers' game and characterizes the lower-level market equilibrium. Section 4 models the upper-level contest scheme design problem.

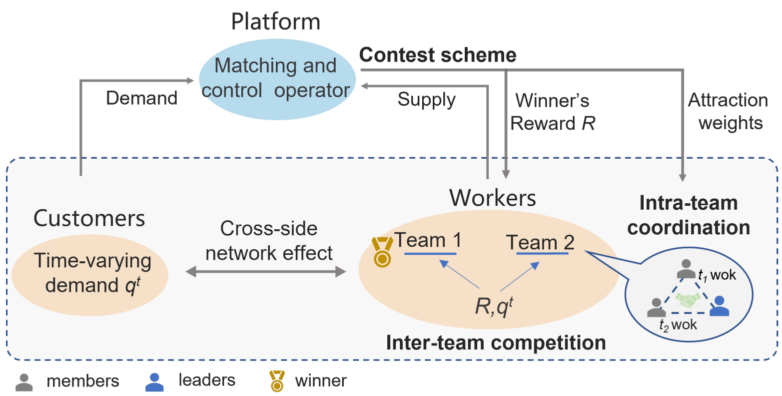


Figure 2 **Model setting and framework**

3. Market Equilibrium Model under Team Contests

In this section, we present the market equilibrium model under team contests and its solution algorithm. We first introduce a time-expanded network over which we could represent workers' schedules as traversing flows. Then, we develop utility functions and model intra-team coordination as a network flow optimization problem. We will show how each team's scheduling decisions correlate with the contest scheme and the decisions of other teams. At the end of this section, we formally define the market equilibrium and present the equivalent formulation along with a solution algorithm. The notations and acronyms used throughout this paper are summarized in Table EC.1 in Appendix A.

3.1. Workers' Schedule Approximate Representation

We use a time-expanded network (Zha, Yin, and Du 2018) to capture workers' schedules over the planning horizon. A time-expanded network is denoted as $G(V,A)$, where V is the set of nodes and A is the set of links representing workers' states between each pair of nodes (Figure 3). All schedules begin with a common "Start" node and terminate at an "End" node, indicating the beginning and end of the planning horizon, respectively.

Specifically, the planning horizon is divided into T_0 periods of equal length. In each time step, a work node in the set V_1 and an auxiliary rest node in the set V_1' are used to distinguish workers' being working and resting, respectively. Workers in a work node could traverse to the next work node by providing on-demand services, or to the rest node for a temporary rest. Workers in a rest node can go to the adjacent work node at the same time step or to the next rest node, which means they return to work or continue resting, respectively.

The link set A consists of five mutually exclusive subsets. The links connecting two work nodes belong to the working link set T, as the previously defined period set. The sets $A1-A4$ contain links indicating the start of the planning horizon, work-rest transition, rest, and the end of the planning horizon, respectively. Customers' service demand only appears on the working links.

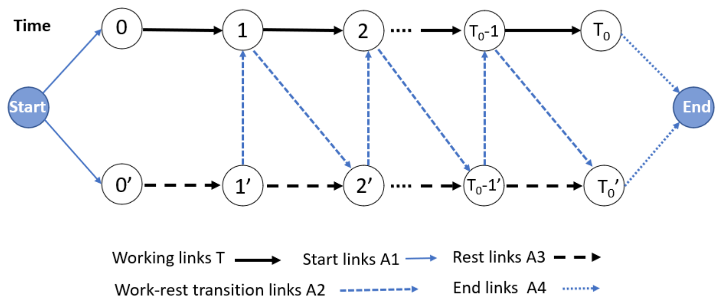


Figure 3 Time-expanded network

A path from 'Start' to 'End' denotes a worker's schedule: start ($A1$), work (T), work-rest transition ($A2$), rest ($A3$), end ($A4$).

In a time-expanded network, a worker's schedule can be represented by a path from the "Start" node to the "End" node. For example, the path "$Start \to 0 \to 2 \to 3' \to 4' \to 4 \ldots \to T_0 \to End$" means that a worker starts working at time step 0 and takes a break at time step 2 after working two periods. Then, the worker returns to work at time step 4 until the end of the planning horizon. For a k-type worker, the cost traversing a working link t equals her service cost per period c^{kt}. Workers incur no revenue or cost over other non-working links. Each worker's profit over a link is the difference between her revenue and service cost.

Let P denote the set of all paths from the "Start" node to the "End" node. Suppose that the supply of workers is infinitesimal. Then, the flow along a path $p \in P$ represents the number of workers who follow the schedule defined by path p. Throughout the paper, we denote f_j^{kp} as the flow of k-type workers in team j whose schedules are along path p. Hence, the collective schedules of all workers in team j can be represented by a vector $\boldsymbol{f_j} = (f_j^{kp}) \in \mathbb{R}^{(|K| \times |P|)}$. The fractional path flow can be interpreted as the result of the mixed scheduling strategy adopted by team leaders. In each period, the team j's supply of k-type active workers N_j^{kt} is essentially the flow across each link $t \in T$. From the network topology, $N_j^{kt} = \sum_{p \in P} f_j^{kp} \cdot \delta_t^p$ where δ_t^p equals 1 if the link t lies on path p, and 0 otherwise. Recall that a team's service output per period is a function of active workers' supply $\boldsymbol{N^t}$ (equation (2)), a time-expanded network links a team's performance to its scheduling decision $\boldsymbol{f_j}$.

3.2. Team Strategy: Intra-team Schedule Coordination

Using a time-expanded network, the intra-team coordination problem is equivalent to assigning heterogeneous types of team members to different paths such that the team utility is maximized and workers are individual rational. The feasible path flow pattern constitutes a team's strategy profile, and the resulted network flow model is a proxy for the workers' scheduling model. Given a contest scheme, the following specifies the utility of teams and individual workers.

Team utility with workers' schedules and the winner's reward. In competition, a team's revenue R_j comes from two sources, serving customers and winning rewards. Since teams receive w^t per completed order in period t, a team's total revenue from serving customers is $\sum_{t\in T} w^t q_j^t(N_j^t, \boldsymbol{N_{-j}^t})$ for $j \in J$. The expected reward of team j is computed by the defined Tullock contest success function $\sum_{t\in T} q_j^t / \sum_{t\in T} q^t$ and the winner's reward R. To summarize, given the winner's reward R, team j's revenue R_j is:

$$R_j(\boldsymbol{N}, R) = \sum_{t\in T} w^t q_j^t(N_j^t, \boldsymbol{N_{-j}^t}) + R \cdot \frac{\sum_{t\in T} q_j^t}{\sum_{t\in T} q^t(\boldsymbol{N^t})}, \quad \forall j \in J. \tag{3}$$

where the vector $\boldsymbol{N} = (\boldsymbol{N^t})_{t=1}^{T_0} \in \mathbb{R}^{(|J|\times|T|)}$ denotes the supply of active workers during the entire planning horizon.

Let U_j be the total utility of all members in team j. For $j \in J$, U_j is defined as the difference between total team revenue R_j and total labor costs, which is a function of its team schedule $\boldsymbol{f_j}$, other teams' supply $\boldsymbol{N_{-j}} = (\boldsymbol{N_{-j}^t})_{t=1}^{T_0}$ and the winner's reward R:

$$U_j(\boldsymbol{f_j}, \boldsymbol{N_{-j}}, R) = R_j(\boldsymbol{N}, R) - \sum_{k\in K}\sum_{t\in T} c^{kt} \cdot N_j^{kt} - c_h \sum_{k\in K}\sum_{p\in P} f_j^{kp} \cdot (h^p)^\nu, \quad \forall j \in J, \tag{4}$$

where the term $\sum_{k\in K}\sum_{t\in T} c^{kt} \cdot N_j^{kt}$ represents the total period-specific service costs and $c_h \sum_{k\in K}\sum_{p\in P} f_j^{kp}$ represents the cost associated with the cumulative labor hours h^p. Here, $h^p = \sum_{t\in T} \delta_t^p$, δ_t^p equals 1 if the working period t lies on path p, and 0 otherwise; c_h is a cost parameter for amounting labor hours, and ν represents workers' degree of aversion to working duration.

Individual worker's utility with revenue-sharing rules. The revenue of each worker depends on the revenue of her team and how it is allocated among team members. In intra-team scheduling, each team leader is a decision-maker who decides the strategy profile for each type of workers and allocates the team revenue based on the declared intra-team revenue-sharing rules. Notice that there are multiple paths, so each worker will follow a mixed strategy profile. Since workers of the same type adopt the same mixed scheduling strategy, they gain identical average revenue in the long run. The following formally defines the intra-team revenue-sharing rules:

DEFINITION 1 (INTRA-TEAM REVENUE-SHARING RULES). A set of intra-team sharing rules F_m defines a mapping from teams' supply inputs $\boldsymbol{N}$ to a team- and type-specific worker's revenue $\hat{r}_j^k$, i.e., $F_m : \boldsymbol{N} \to \hat{r}_j^k$ with the team revenue conservation property $\sum_{k\in K}\sum_{j\in J} N_j^k \hat{r}_j^k = R_j(\boldsymbol{N}, R)$ for each team $j \in J$.

We denote a contest scheme as (R, F_m) for brevity. Given intra-team sharing rules F_m for team $j \in J$, each k-type worker's utility u_j^k is defined as her revenue minus the average labor cost:

$$u_j^k(\boldsymbol{f_j}, \boldsymbol{N_{-j}}, R|F_m) = \hat{r}_j^k(\boldsymbol{N}, R|F_m) - \frac{1}{N_j^k}\left(\sum_{t\in T} c^{kt} N_j^{kt} + c_h \sum_{p\in P} f_j^{kp} \cdot (h^p)^\nu\right), \quad \forall j \in J, k \in K, \tag{5}$$

where the term $\left(\sum_{t\in T} c^{kt} N_j^{kt} + c_h \sum_{p\in P} f_j^{kp} \cdot (h^p)^\nu\right)$ is the total labor cost of k-type workers in team j. The average labor cost results from the assumption of intra-team equal treatment.

Intra-team coordination model. Given a contest scheme (R, F_m) and the active workers' supply from other teams $\boldsymbol{N}_{-j}$, a leader in team j decides its members' schedules $\boldsymbol{f_j}$ to maximize the team's utility U_j. For each team $j \in J$, we model the intra-team coordination problem as the following flow optimization problem based on the prescribed utility of teams and individuals:

$$\max_{\boldsymbol{f_j}} \quad U_j(\boldsymbol{f_j}, \boldsymbol{N_{-j}}, R), \tag{6a}$$

$$\text{s.t.} \quad \sum_{p\in P} f_j^{kp} = N_j^k, \quad \forall k \in K, \tag{6b}$$

$$f_j^{kp} \geq 0, \quad \forall k \in K, p \in P, \tag{6c}$$

$$u_j^k(\boldsymbol{f_j}, \boldsymbol{N_{-j}}, R | F_m) \geq u_0^k, \quad \forall k \in K. \tag{6d}$$

where constraint (6b) denotes flow conservation condition for each worker type; constraint (6c) defines the flow to be non-negative; constraint (6d) essentially represents the aforementioned IR constraint. (6d) states that each worker will be better off by joining a team and gets a utility no less than u_0^k, the utility under self-scheduling without teams. Here, u_0^k is an exogenous parameter for each worker type $k \in K$. Note that the supply of active workers $\boldsymbol{N_{-j}}$ in (6d) is derived from the schedules of all teams except team j. Thus, considering IR constraint (6d) makes the feasible set of a team's schedules $\boldsymbol{f_j}$ dependent on its rivals' decisions $\boldsymbol{f_{-j}}$.

3.3. Market Equilibrium Definition and Formulation

Given a contest scheme, the team contest could be captured by a non-cooperative game. Each team is a strategic player and solves the intra-team coordination problem (6). For this game, the market equilibrium can be formally defined as follows:

Definition 2 (Market equilibrium under team contests). Given the team composition $\{N_j^k\}$ for each team $j \in J$, the market equilibrium defines a stationary state where no team can gain a higher team utility by unilaterally changing its team members' schedules without violating IR constraints.

The above definition leads to a generalized Nash equilibrium (GNE) because each team's feasible set of intra-team schedules depends on the decisions of other teams. Mathematically, given a contest scheme (R, F_m), GNE is to find a vector $\boldsymbol{f}^* = (\boldsymbol{f_j^*})_{j\in J}$, such that $\boldsymbol{f_j}^*$ is the optimal solution of the intra-team coordination problem (6) with $\boldsymbol{N_{-j}}$ fixed at $\boldsymbol{N_{-j}^*}$:

$$U_j(\boldsymbol{f_j^*}, \boldsymbol{N_{-j}^*}, R) \geq U_j(\boldsymbol{f_j}, \boldsymbol{N_{-j}^*}, R) \quad \forall j \in J, \boldsymbol{f_j} \in \boldsymbol{\mathcal{M}_j}(\boldsymbol{N_{-j}^*}, R, F_m), \tag{7}$$

where $\boldsymbol{\mathcal{M}_j}(\boldsymbol{N^*_{-j}}, R, F_m)$ is the feasible set of team j's schedules. Specifically, this set is defined by (6b)-(6d) and can be expressed as $\boldsymbol{\mathcal{M}_j}(\boldsymbol{N^*_{-j}}, R, F_m) = \{\boldsymbol{f_j} | \sum_{p\in P} f_j^{kp} = N_j^k, f_j^{kp} \geq 0, u_j^k(\boldsymbol{f_j}, \boldsymbol{N^*_{-j}}, R|F_m) \geq u_0^k\}$.

Characterizing the equilibrium defined by (7) is equivalent to scheduling workers according to the solutions of the following QVI:

$$\sum_j L_j(\boldsymbol{f_j^*})^T(\boldsymbol{f_j} - \boldsymbol{f_j^*}) \geq 0, \quad \forall \boldsymbol{f_j} \in \boldsymbol{\mathcal{M}_j}(\boldsymbol{N^*_{-j}}, R, F_m). \tag{8}$$

Here, L_j is a function of $\boldsymbol{f_j}$, defined by $L_j(\boldsymbol{f_j}) = -\nabla_{f_j^{kp}} U_j(\boldsymbol{f_j}, \boldsymbol{N^*_{-j}}, R)$ for $j \in J$.

Note that the defined GNE assumes fixed team compositions and ensures that workers join teams by imposing IR constraints. The flexibility of workers to choose their teams is not considered here. This simplification applies when workers have limited knowledge about each other and are offered a one-shot joining option for a particular team. For instance, the ride-hailing platform DiDi Chuxing assigns team members to team leaders via a recommendation-based system, which exempts team members from making team choices (Zhang et al. 2019). More flexible settings that allow workers to choose their teams and the associated considerations such as workers' incentive compatibility are left for future research. Furthermore, some platforms may overlook workers' willingness to participate and have the authority to assign workers directly to teams (Rokicki et al. 2015; Lei 2021). In this situation, the equilibrium analysis could relax IR constraint (6d) as $u_j^k \geq 0$. Thus, workers are only guaranteed non-negative utility for providing services in teams.

3.4. Solution Algorithm for Market Equilibrium

Solving the QVI defined by (8) is challenging because the feasible sets of intra-team schedules are interdependent among teams. We develop a *penalty-duality-based solution algorithm* by (a) disentangling this interdependence of feasible sets and transforming QVI into a sequence of *variational inequalities* (VIs); (b) solving the resulting VIs via duality theory.

The first step applies an *iterative penalty method* introduced by Pang and Fukushima (2005). In each iteration m, this method converts IR constraints (6d) to be a part of each team's objective via penalty terms. Mathematically, we introduce $g_j^k(\boldsymbol{f_j}, \boldsymbol{N_{-j}}, R, F_m)$ to denote the utility loss for k-type workers after joining team j, i.e., $g_j^k(\boldsymbol{f_j}, \boldsymbol{N_{-j}}, R, F_m) = N_j^k u_0^k - N_j^k u_j^k(\boldsymbol{f_j}, \boldsymbol{N_{-j}}, R|F_m)$. Note that when $g_j^k \leq 0$, the k-type workers are individually rational in joining team j. The penalty terms for team j are then defined as quadratic functions of g_j^k for $k \in K$. With that, each team takes the active workers' supply from other teams $\boldsymbol{N_{-j}}$ as a given vector and solves the intra-team coordination problem (6) with the objective (6a) replaced by:

$$\min_{\boldsymbol{f_j}} \quad -U_j(\boldsymbol{f_j}, \boldsymbol{N_{-j}}, R) + \frac{1}{2\rho^{(m)}} \sum_{k\in K} \left(\left[\mu_j^{k(m)} + \rho^{(m)} \cdot g_j^k(\boldsymbol{f_j}, \boldsymbol{N_{-j}}, R, F_m) \right]^+ \right)^2. \tag{9}$$

where the operator $[x]^+$ stands for $\max(0,x)$; ρ and μ_j^k are parameters that are updated in each iteration m. The parameter ρ satisfies $\rho^{(m+1)} > \rho^{(m)}$ and tends to ∞. The parameter μ_k^j is bounded and updated by the rule $\mu_j^{k(m+1)} = \left[\mu_j^{k(m)} + \rho^{(m)} \cdot g_j^k\right]^+$ for $j \in J, k \in K$. Thereafter, g_j^k is short for $g_j^k(\boldsymbol{f_j}, \boldsymbol{N_{-j}}, R, F_m)$ for notation simplification.

By penalizing the IR constraints (6d), the remaining constraints (6b) and (6c) redefine the feasible set of intra-team schedules for each team. Since these sets are independent of each other and are nonempty polyhedral, each iteration m essentially solves a Nash equilibrium that has a VI formulation $\sum_{j\in J}(\boldsymbol{f_j} - \boldsymbol{f_j}^*)^T \left(L_j(\boldsymbol{f_j}) + \sum_{k'\in K} \left[\mu_j^{k'(m)} + \rho^{(m)} \cdot g_j^{k'}\right]^+ \cdot \nabla_{f_{jp}^k} g_j^{k'} \right) \geq 0$ for $\boldsymbol{f_j}$ in the redefined feasible set.

Since the above VI possesses an asymmetric Jacobian matrix on its feasible set, it could not be easily handled by commercial solvers. Therefore, we apply a *duality-based method* (Aghassi et al. 2006) to reformulate the above VI as an optimization problem. The basic idea is as follows. Because the redefined feasible set for each team is a polyhedron, solving the above VI is equivalent to minimizing a linear program parameterized by $\boldsymbol{f}^*$. By strong duality, $\boldsymbol{f}^*$ optimizes the linear program if the optimal objective is equal to that of its dual problem. The duality-based method solves the above VI by minimizing the duality gap with respect to the primal variables $\boldsymbol{f}$ and the dual variables $(\boldsymbol{\lambda_j})_{j=1}^{J_0}$:

$$\min_{\boldsymbol{f},\boldsymbol{\lambda_j}} \quad z_{VI} = \sum_j \boldsymbol{f_j}^T \left(L_j(\boldsymbol{f_j}) + \sum_{k'\in K} \left[\mu_j^{k'(m)} + \rho^{(m)} \cdot g_j^{k'}\right]^+ \cdot \nabla_{f_{jp}^k} g_j^{k'} \right) - \sum_j \boldsymbol{\lambda_j}^T \boldsymbol{N_j^0}, \tag{10a}$$

$$\text{s.t.} \quad \boldsymbol{A_j}^T \boldsymbol{\lambda_j} \leq L_j(\boldsymbol{f_j}) + \sum_{k'\in K} \left[\mu_j^{k'(m)} + \rho^{(m)} \cdot g_j^{k'}\right]^+ \cdot \nabla_{f_{jp}^k} g_j^{k'}, \quad \forall j \in J, \tag{10b}$$

$$\boldsymbol{A_j} \boldsymbol{f_j} = \boldsymbol{N_j^0}. \quad \forall j \in J, \tag{10c}$$

$$\boldsymbol{f_j} \geq 0, \quad \forall j \in J. \tag{10d}$$

Here, for each team $j \in J$, $\boldsymbol{\lambda_j} = (\lambda_j^k)_{k=1}^{K_0} \in \mathbb{R}^{|K|}$ represents the vector of the multipliers for the flow conservation constraints (6b), and $\boldsymbol{A_j}$ is the corresponding $|K|$-by-$(|K| \times |P|)$ coefficient matrix for (6b); $\boldsymbol{N_j^0} = (N_j^k)_{k=1}^{K_0} \in \mathbb{R}^{|K|}$ denotes the composition of team j; z_{VI} is the value of the objective function (10a). By duality theory, $z_{VI} \geq 0$ and the equality holds at the VI's solution.

In summary, the penalty-duality-based solution algorithm solves the QVI (8) by solving a sequence of penalized VIs whose solutions are derived by (10). Appendix B details the solution algorithm.

4. Platform-Centric Contest Scheme Design

The fact that contest schemes affect team schedules gives the platform control over the market equilibrium and contest outcomes. This section examines the design of the platform-centric scheme. We first detail this contest scheme and then formulate the hierarchical contest scheme design problem as an MPEC program. An algorithm for computing the global optimal platform-centric contest scheme is presented.

4.1. Overview of Platform-Centric Contest Scheme

Allocating the revenue of a team based on each member's relative effort is a common practice for teamwork (Skaperdas 1998; Nitzan 1991; Fu and Wu 2019). A platform-centric contest scheme extends this idea to the multi-period setting. Specifically, it motivates teams with a winner's reward R and allocates team revenue based on each worker's relative supply contribution throughout the planning horizon. Instead of treating each period equally, this scheme induces workers to serve more customers during high-demand periods via period-specific attraction weights $\boldsymbol{\gamma}$ that are defined as follows:

Definition 3 (Attraction weights). Attraction weights $\boldsymbol{\gamma} = (\gamma^t)_{t=1}^{T_0} \in \mathbb{R}^{|T|}$ refer to a vector of normalized non-negative weights γ^t that a platform assigned to each working period $t \in T$.

Given the winner's reward R and attraction weights $\boldsymbol{\gamma}$, the revenue share of each worker type equals the share of the corresponding active workers' supply weighted by attraction weights over the entire planning horizon. More specifically, the revenue of a k-type worker in team j is:

$$\hat{r}_j^k(\boldsymbol{N}, R|\boldsymbol{\gamma}) = \frac{\sum_{t\in T} \gamma^t \cdot N_j^{kt}}{\sum_{k'\in K}\sum_{t\in T} \gamma^t \cdot N_j^{k't}} \cdot \frac{R_j(\boldsymbol{N}, R)}{N_j^k}, \quad \forall j \in J, k \in K, \tag{11}$$

where the team revenue $R_j(\boldsymbol{N}, R)$ is specified by equation (3), and attraction weights $\boldsymbol{\gamma}$ satisfy the normalization requirement $\sum_{t\in T} \gamma^t = 1$. Equation (11) defines the aforementioned intra-team revenue-sharing rules F_m. Following the equations (5) and (11), given the winner's reward R and attraction weights $\boldsymbol{\gamma}$, the utility of a k-type worker in team j is:

$$u_j^k(\boldsymbol{f_j}, \boldsymbol{N_{-j}}, R|\boldsymbol{\gamma}) = \frac{\sum_{t\in T} \gamma^t \cdot N_j^{kt}}{\sum_{k'\in K}\sum_{t\in T} \gamma^t \cdot N_j^{k't}} \cdot \frac{R_j}{N_j^k} - \frac{1}{N_j^k} \cdot \left(\sum_{t\in T} c^{kt} N_j^{kt} + c_h \sum_{p\in P} f_j^{kp} \cdot (h^p)^{\nu} \right), \quad \forall j \in J, k \in K. \tag{12}$$

By introducing attraction weights, we aim to dynamically balance supply and time-varying demand to promote the platform's profit. Figure 4 illustrates this point with an example of two types of workers. Type 1 workers prefer to work during low-demand period 2, while the opposite holds for Type 2 workers. Without teams, workers choose their schedules following their time preferences. Suppose that these two types of workers form a team and period 1 is assigned a higher attraction weight than period 2. If Type 1 workers keep the same schedules as before, they will experience lower earnings than under self-scheduling. Thus, to ensure workers' individual rationality, the team leader will assign both types of workers to work in high-demand period 1.

This work adopts the above platform-centric contest scheme for three reasons. First, implementing a lump-sum winner's reward is a well-recognized policy for motivating workers (Ai et al. 2019).

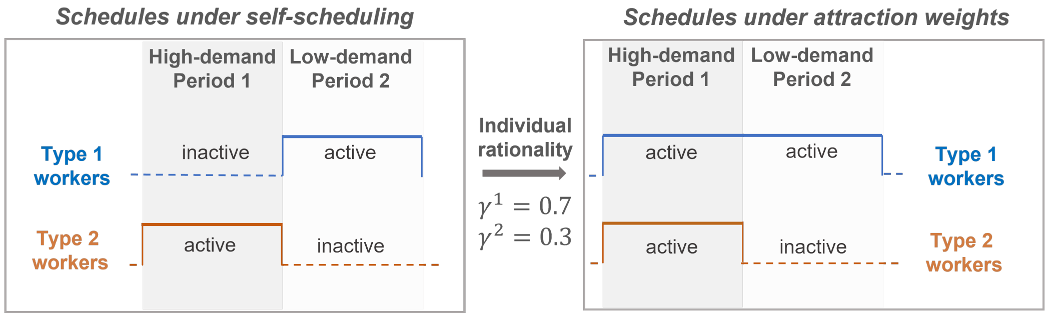


Figure 4 An explanation on the mechanism of attraction weights

Second, period-specific attraction weight can be viewed as a dynamic pricing policy, which has been proved useful for balancing supply and demand on OSPs (Zha, Yin, and Du 2018; Chen and Sheldon 2016). Third, a platform-centric scheme is flexible yet simple, which is a major requirement of any reward scheme (Nalebuff and Stiglitz 1983). Since attraction weights apply to workers' collective efforts, a platform-centric scheme could allocate workers' payoffs without tracking individual schedules.

4.2. The Platform-Centric Contest Scheme Design

4.2.1. Contest scheme design formulation. As discussed in Section 2, the contest scheme design problem can be modeled as a single-leader multi-follower game. Given a platform-centric contest scheme $(R, \boldsymbol{\gamma})$, the followers' problem may admit multiple equilibria. For exploring the potential of team contests, we assume that the platform has the authority to select the *best* equilibrium:

Assumption 1. *The platform has the power to select the equilibrium with the highest profit if multiple market equilibria coexist.*

Designing a platform-centric contest scheme is to find the optimal winner's reward R and attraction weights γ such that the platform's profit is maximized at equilibrium. Mathematically, with assumption 1, we model this hierarchical contest scheme design problem as the following MPEC program:

$$\max_{\boldsymbol{\gamma}, R} \max_{\boldsymbol{f}} \quad \sum_{t \in T} p^t \cdot q^t(\boldsymbol{N^t}) - R, \tag{13a}$$

$$\text{s.t.} \quad 0 \le \gamma^t \le 1, \quad \sum_{t \in T} \gamma^t = 1, \tag{13b}$$

$$R \ge 0, \tag{13c}$$

$$\boldsymbol{f} \in \mathcal{S}(R, \boldsymbol{\gamma}). \tag{13d}$$

where $\mathcal{S}(R, \boldsymbol{\gamma})$ stands for the solution set of the QVI defined by (8) for a given platform-centric scheme $(R, \boldsymbol{\gamma})$. In objective function (13a), the parameter p^t represents the per-unit service profit obtained by the platform during period t. More specifically, p^t equals the service price charged to customers in period t minus workers' wage per completed order w^t. There, the second 'max' operator comes from assumption 1 that the equilibrium with the highest profit is selected under a given contest scheme. Constraint (13b) specifies the normalization requirement for attraction weights $\boldsymbol{\gamma}$, and constraint (13c) ensures that the winner's reward R is non-negative. Constraint (13d) states that workers' schedules $\boldsymbol{f}$ constitute feasible solutions if they support the market equilibrium under team contests. The following proposition shows that the problem (13) is feasible:

Proposition 1. *[Feasibility of the platform-centric contest scheme design problem] There exists at least one feasible contest scheme $(R, \boldsymbol{\gamma})$ to problem (13), under which the market equilibrium exists.*

Readers can refer to Appendix C.1 for the proof of Proposition 1.

4.2.2. Solving the optimal platform-centric contest scheme. Solving the contest scheme design problem (13) is challenging as it is constrained by parameterized QVI. In essence, the followers' game is nonlinear, nonconvex, and intractable. Consequently, teams' best responses to the upper-level decision $(R, \boldsymbol{\gamma})$ may lead to a disjunctive feasible set. Furthermore, finding a global solution to an MPEC program is in general computationally expensive.

We propose an algorithm combining the market equilibrium algorithm and multiple starting points search to compute the global optimal platform-centric scheme. The main idea is to convert problem (13) into a general nonlinear optimization problem for the local optimal solution, and then find the best scheme by continuously exploring new local searches. The former task is completed using the penalty-duality-based algorithm discussed in Section 3.4, and the latter is conducted using Bayesian optimization.

Specifically, the penalty-duality-based algorithm suggests that the schedules satisfying equilibrium constraint (13d) could be derived by solving a sequence of optimization problems (10). Therefore, we replace constraint (13d) with the optimization problem (10). Since problem (10) has an objective function value $z_{VI} \geq 0$ and the equality holds at the equilibrium solution, we move z_{VI} to the upper-level objective (13a) by applying a large positive penalty parameter η. With that, solving the contest scheme design problem (13) is transformed into solving a sequence of the following single-level optimization problem:

$$\begin{aligned} \max_{\boldsymbol{\gamma}, R\geq 0} \max_{(\boldsymbol{f}, \boldsymbol{\lambda_j})} \quad & \sum_t p^t \cdot q^t(\boldsymbol{N^t}) - R - \eta \cdot z_{VI}(\boldsymbol{f}, \boldsymbol{\lambda_j}), \\ \text{s.t.} \quad & (13b), (10b), (10c), (10d). \end{aligned} \tag{14}$$

Problem (14) is a nonlinear and nonconvex optimization problem. With specified initial values for decision variables, (14) can be solved iteratively by commercial solvers for a local optimal solution. To obtain a global optimal solution, we introduce Bayesian optimization which is a powerful approach for solving black-box global optimization problems (Frazier 2018). Here, Bayesian optimization explores the feasible set of decisions variables and locates the initial values leading to the best local solution. Figure 5 summarizes the entire solution procedure. Appendix C.2 details the solution algorithm and briefly introduces Bayesian optimization. Note that the algorithm designed is flexible enough to solve a variety of contest schemes in hierarchical single-leader multi-follower games, which is of significance itself to game theorists.

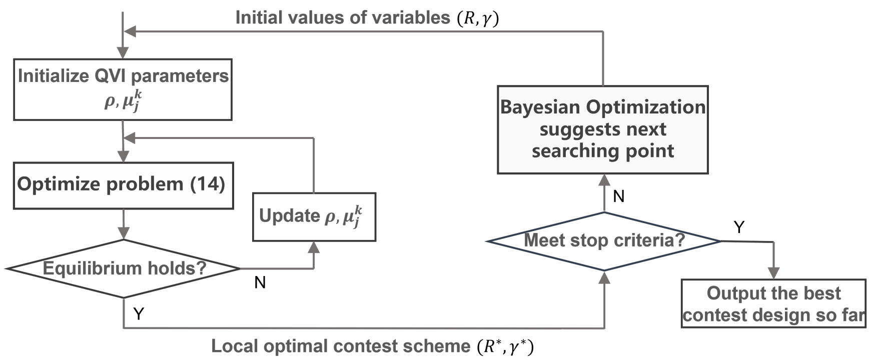


Figure 5 **Solution procedure for solving the optimal platform-centric contest scheme**

5. Numerical Experiments and Discussion

In this section, we aim to numerically evaluate the effectiveness of teamwork under the proposed contest scheme. We first specify the parametric setting of numerical experiments and a self-scheduling benchmark used throughout the section. Utilizing the previously-mentioned algorithms, the numerical example draws implications for the platform and workers. The results focus on the competition between two symmetric teams, and more flexible settings such as varying team compositions and multi-team competition will be discussed in Section 6.

5.1. Numerical Setup and Benchmark Specification

5.1.1. Numerical setup. Consider a four-period planning horizon $T = \{1,2,3,4\}$, and let the first two periods denote *morning* periods and the last two denote *afternoon* periods. Given that the morning periods are peak hours, the potential demand quantities are $\{Q_0^t\} = \{500,500,300,300\}$ (requests/hour). The served demand per period in (1) is assumed to follow an exponential function (Yang et al. 2010):

$$q^t(\boldsymbol{N^t}) = Q_0^t \cdot \exp(-\frac{\alpha}{\sum_{j\in J} N_j^t}), \quad \forall t \in T. \tag{15}$$

The parameter α captures the sensitivity of demand to the supply of active workers. The term $\alpha/\sum_{j\in J} N_j^t$ refers to a measure of service quality, e.g., the average waiting time customers wait to be served. The numerical example sets $\alpha = 50(\text{hour}^{-1})$.

Worker type and team compositions. 120 workers are evenly divided into two types, *Type 1* and *Type 2* workers. The former group, also termed the *afternoon* workers, prefers to work during the afternoon periods with service costs $\boldsymbol{c^1} = \{50, 50, 30, 30\}(\$/\text{hour})$. The latter group, also termed the *morning* workers, prefers to work during the morning periods with $\boldsymbol{c^2} = \{30, 30, 50, 50\}(\$/\text{hour})$. For both types, workers' aversion degree to working duration is set as $\nu = 2$ and the associated cost parameter is $c_h = 2(\$/\text{hour}^2)$.

Team compositions are predetermined. We begin with the simplest setting where two teams of equal team size and *symmetric team compositions* compete against each other. The symmetric team composition means that two teams have the same distribution of worker types, i.e., $N_i^k = N_j^k$ for $i, j \in J$ and $k \in K$. The *asymmetric teams* divide workers of two types unevenly into two teams for evaluating the impact of team compositions on the contest outcome.

Service price setting. As per completed order, the platform charges customers higher fares during the peak periods. The platform charges an average fare of \$30 per request in the morning periods and \$25 per request in the afternoon periods. According to the current practice (Chen, Rossi, et al. 2019), workers receive 80% of the fare, while the platform collects the remaining 20%. The above revenue-sharing rate remains the same with or without team contests.

The above parameters are either from empirical studies or selected for illustration purposes only. Nonetheless, the managerial insights are general and have been validated through sensitivity analysis. These parameters can be calibrated using real-world data based on the circumstances of specific platforms.

5.1.2. Self-scheduling benchmark. We consider the *fully self-scheduling* case as a benchmark, in which each worker independently schedules her daily work hours. Since individual workers have only partial information about their coworkers without communication, we model their scheduling decisions by including randomness in their perception of the scheduling utility (Sheffi 1985). It then contributes to a k-type worker's *perceived utility* toward a schedule V_k^p, consisting of the real utility u_k^p and a random perception error term ξ^p, i.e., $V_k^p = \theta \cdot u_k^p + \xi^p$ for $p \in P$. Every k-type worker seeks to maximize her perceived utility when choosing her work schedule, and the probability distribution over her choices is derived from a discrete choice model. θ is a positive parameter that indicates the dispersion among workers with respect to their perceived utility. The smaller value of θ indicates a larger variance in workers' perceptions. Thereafter, we call θ the *perception intensive parameter*. Note that as team participation improves intra-team information sharing, θ is higher in each team's perceived utility. We implicitly assume that the workers have perfect information in the setting with only two teams.

Throughout the experiments, the random terms ξ_p for different paths are supposed to be independently and identically distributed Gumbel variables (Sheffi 1985). The value of θ ranges from a fairly small number indicating workers select schedules randomly, to a positive number indicating that workers uniformly choose the schedules to obtain the highest real utility. The self-scheduling benchmark is computed at an equilibrium state where no worker can improve her perceived utility by unilaterally changing her schedule. The computation uses the same parameter settings as that used for teams, such as the setting of prices and service costs. Whenever multiple equilibria coexist, the equilibrium with the highest platform's profit is selected. Appendix D details the mathematical formulation of this benchmark.

The fully self-scheduling benchmark serves two purposes. First, this benchmark reflects the status quo market across a wide range of platforms. Team-based incentive policies are expected to outperform the self-scheduling benchmark. Second, the equilibrium self-scheduling utility u_0^k is input for the IR constraint (6d) when solving the optimal contest scheme and the corresponding market equilibrium. In the benchmark, u_0^k is the expectation of real utility for k-type workers across all chosen schedules at equilibrium.

5.2. Results on Platform-Centric Contest Scheme with Teams

The following presents the results of the competition between two symmetric teams. The optimal platform-centric scheme, including the optimal winner's reward and attraction weights, are presented. The key factors affecting the contest outcomes are discussed.

5.2.1. Optimal platform-centric scheme and workers' schedules. For two symmetric team contests, the optimal winner's reward is zero in all situations of worker perception accuracy. This is expected and is explained by the winner's reward's marginal effect. A further discussion of this point is provided in Section 6.3.

Figure 6 illustrates that the optimal attraction weights are consistent with the potential market demand. Morning peak periods have consistently higher attraction weights than those non-peak afternoon periods. Furthermore, the optimal attraction weights are insensitive to workers' perception accuracy.

To investigate the effect of attraction weights on workers' schedules in equilibrium, we compare the supply of active workers under the fully self-scheduling benchmark and the optimal platform-centric scheme. To show whether increasing attraction weights for peak periods attracts more workers, we also examine a platform-centric scheme in which four periods are assigned the same attraction weight $\gamma^t = 0.25$ and the winner's reward R is set as zero in accordance with the optimal

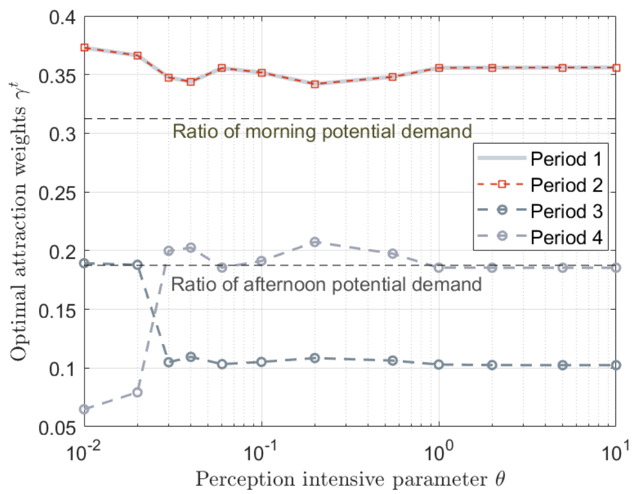


Figure 6 **The optimal attraction weights**

scheme. The results in Figure 7 lead to three observations. First, the optimal platform-centric scheme provides the highest supply of active workers during morning peak periods. Second, despite that the attraction weights are suboptimal in the platform-centric scheme of $\gamma^t = 0.25$, it exceeds the self-scheduling benchmark regarding the total supply of active workers. Third, compared to the case where all periods are equally weighted, assigning higher attraction weights to the peak periods stimulates some Type 1 workers to switch from their preferred periods in the afternoon to the peak periods in the morning. These observations support the adoption of attraction weights as a supply-demand balancing policy.

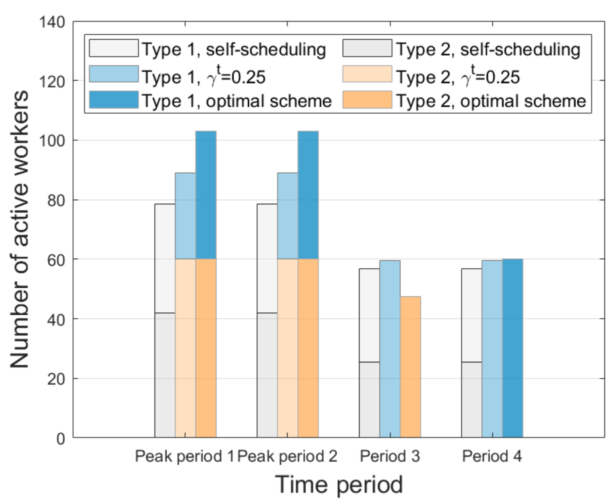


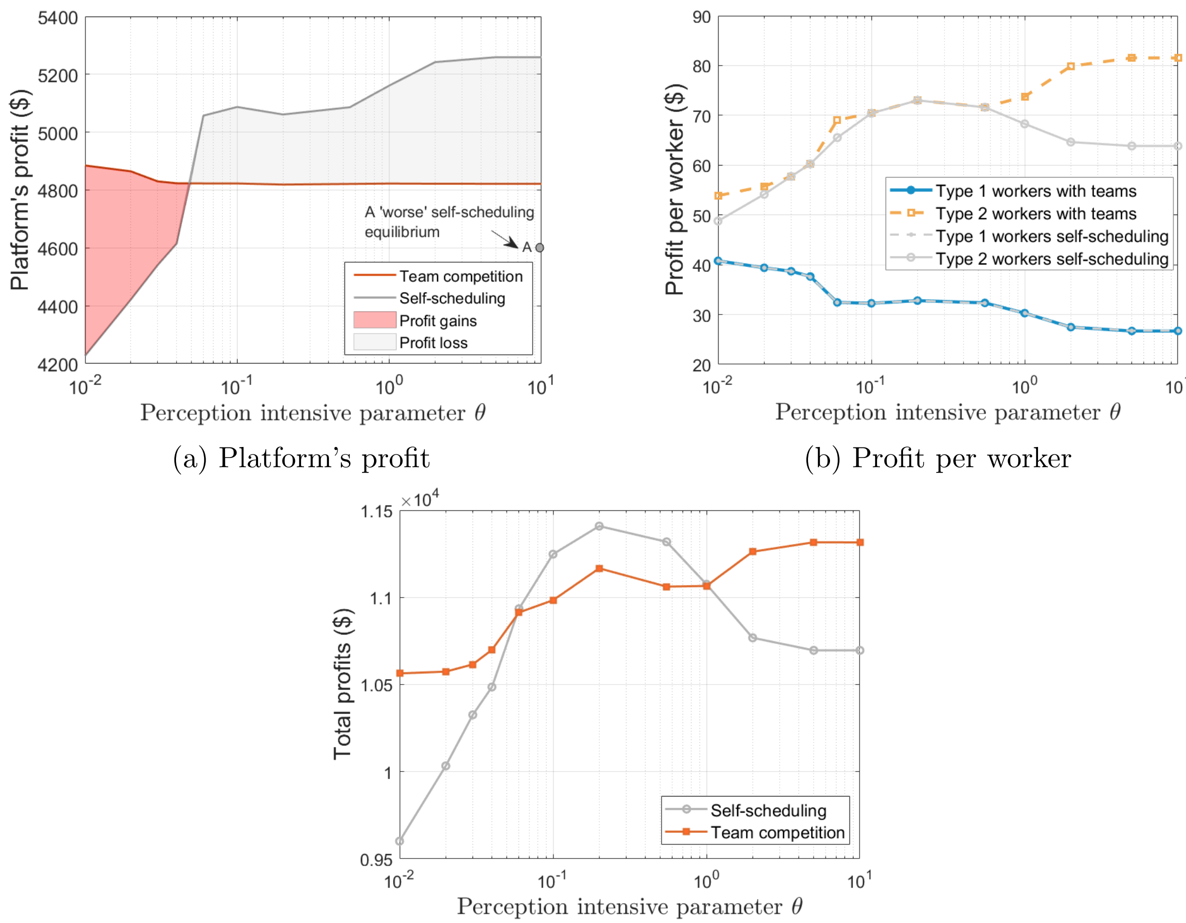
Figure 7 **Workers' schedules under self-scheduling and team contest ($\theta = 0.02$)**

5.2.2. Impacts of team contests on the platform and workers. The *platform's profit* and *profit per worker* at equilibrium are two critical performance measures in this symmetric team setting and self-scheduling benchmark. With team contests, the equilibrium responses to the optimal platform-centric contest scheme. The former measure is calculated by equation (13a). The latter equals the worker's real utility, which is u_j^k under intra-team scheduling and u_0^k under the fully self-scheduling benchmark.

Figure 8a summarizes the platform's profit per different market settings. Under the fully self-scheduling benchmark, the platform's profit increases with the perception intensive parameter θ. By contrast, the platform's profit under team contests remains stable despite fluctuations in workers' self-scheduling utility. When workers perceive their scheduling utility less accurately, the platform gains higher profit under team contests than under the fully self-scheduling benchmark. This benefit arises from intra-team information sharing, which reduces workers' randomness in choosing work schedules. Due to the dominance of workers' intra-team coordination over the inter-team competition, when workers have more accurate information about their utility, the platform's profit in the benchmark exceeds that under team contests. This is because, with an accurate perception of profitable hours, more self-scheduled workers will jam into these periods to compete with each other. The concentration of active workers' supply consequently intensifies the competition and reduces the total workers' utility. With the help of teamwork, team leaders can maximize the team's collected utility by avoiding this over-competition effect in scheduling workers. Therefore, the intra-team coordination contradicts the platform's intention to promote competition for higher profits, which is beneficial for achieving the welfare maximization objective.

One may question the rationale for team contest as it could generate less profit than the self-scheduling benchmark. Note that all these comparisons are based on the principle of "selecting the best equilibrium". However, the platform cannot always control which self-scheduling equilibrium to be reached while the team contest policy manages to do so. To show this difference, the point "A" in Figure 8a exemplifies a *worse* self-scheduling equilibrium, at which a platform obtains a much lower profit than that with teams. Therefore, team contest is a critical strategy to reduce the risk of converging into a low-profit market equilibrium.

Figure 8b shows that the profit per worker under team contests is no less than that under fully self-scheduling by the virtue of the IR constraint. The improvement in the workers' profits depends on their perception accuracy as well as their types. In this case study, morning (Type 2) workers earn more than afternoon (Type 1) workers in all scenarios because the former group has lower service costs during high-revenue peak periods. While Type 1 workers receive the same profits as in the benchmark, Type 2 workers gain higher profits after joining teams even when they perceive their scheduling utility accurately.



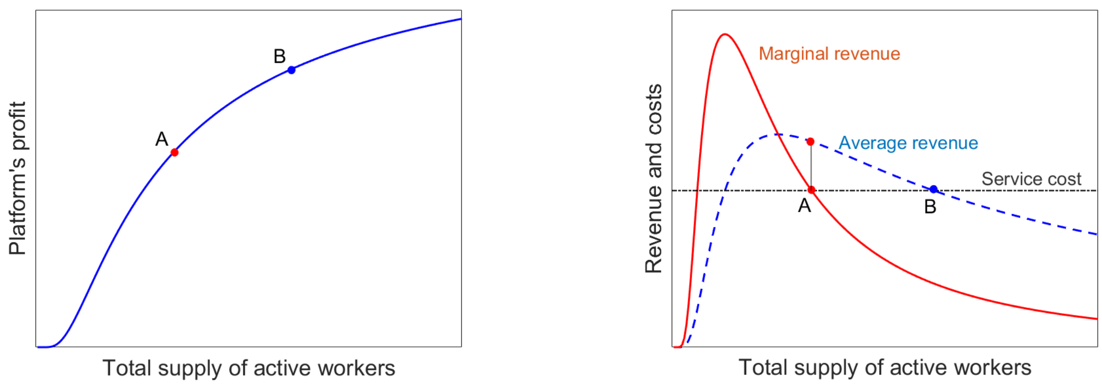
(a) Platform's profit (b) Profit per worker

(c) Total profit of the platform and workers

Figure 8 Profit gains from the team contests

Team contests have inconsistent impacts on the platform and workers in Figures 8a and 8b when θ is large. Workers achieve greater profits under team contests than under self-scheduling while the platform does not. A portion of increased total profit is transferred from the platform to workers (Figure 8c). This is mainly because the mitigated over-competition among self-interested workers owing to intra-team coordination.

An illustrative one-period example can explain this observation. Following the demand function (15), Figure 9 sketches the platform's profit and a typical worker's revenue and service cost regarding the supply of active workers. For this one-period example, workers' marginal service cost equals their per-unit service cost. With a sufficient number of workers, if all workers are self-scheduled, they would enter the market to provide services until their average profit reaches zero (Zha, Yin, and Yang 2016), leading to a high level of active workers' supply (point B in Figure 9b). However, after forming a common-interested team, the leader considers the marginal effect that a worker exerts on the entire team (Hu and Treich 2014). This results in a lower level of active workers' supply as in point A and positive profit per worker. With teamwork, the reduced competition among workers undermines the platform (Figure 9a). In our numerical example, such an effect is more obvious when workers' perception becomes more accurate and explains the profit loss for the platform as shown in Figure 8a.



(a) Platform's profit (b) Workers' revenue and costs

Figure 9 Intra-team coordination mitigates over-competition among workers

In summary, the designed contest scheme for team contests always benefits workers. The platform should carefully check the workers' perception accuracy, which affects the power of intra-team coordination on the final contest outcome. As workers' perception accuracy increases, the platform should balance the effects of intra-team coordination and inter-team competition to avoid the loss of profit caused by the dominance of the former factor.

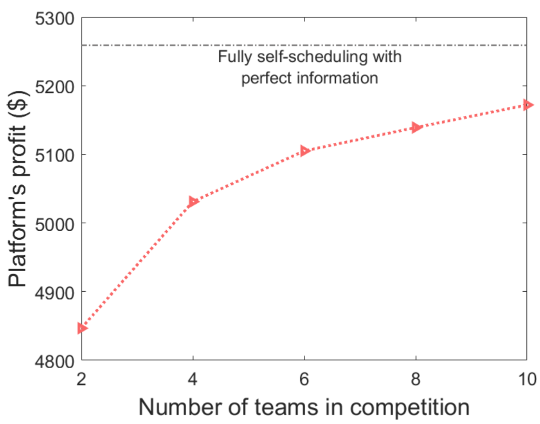
6. Model Variants and Sensitivity Analysis

This section provides more insights into factors that impact the platform's contest design decisions and contest outcomes. Section 6.1 discusses the multi-team contests with a large number of teams. Section 6.2 relaxes the symmetric team assumption and examines how the intra-team heterogeneity from both team compositions and team members' working-time preferences affects the competition. Section 6.3 explores the mutual influences between the winner's reward and attraction weights in the platform-centric contest scheme.

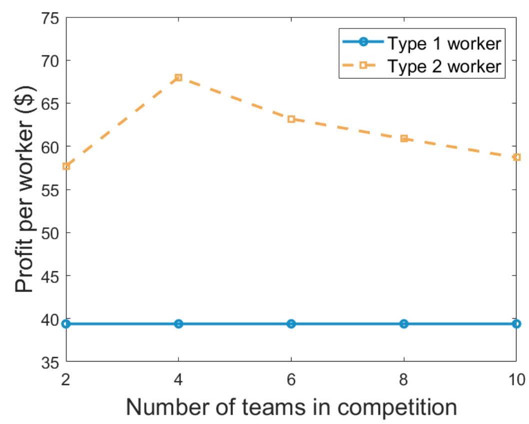
6.1. Multi-team Contests on OSPs

We extend the number of teams from two to ten to explore the impacts of splitting workers into more teams. We alter the team size while maintaining the total number of workers and the symmetric team setting. We set the perception intensive parameter $\theta = 0.02$ to compute the self-scheduling utility. The general conclusions also apply to other values of θ.

Figure 10a shows that the platform benefits from the increased number of teams. As the number of teams increases, each team becomes more "selfish" in seeking to maximize their utility despite potential externalities to other teams. As a result of the intensified competition, teams will summon more active workers to compete for service orders. The increased active workers' supply thus produces a higher profit for the platform, which approaches the profit generated by fully self-scheduled workers with perfect information. However, the effectiveness of splitting workers into more teams has diminishing marginal benefit to the platform.



(a) Platform's profit



(b) Profit per worker

Figure 10 Profits of the platform and workers with the number of teams

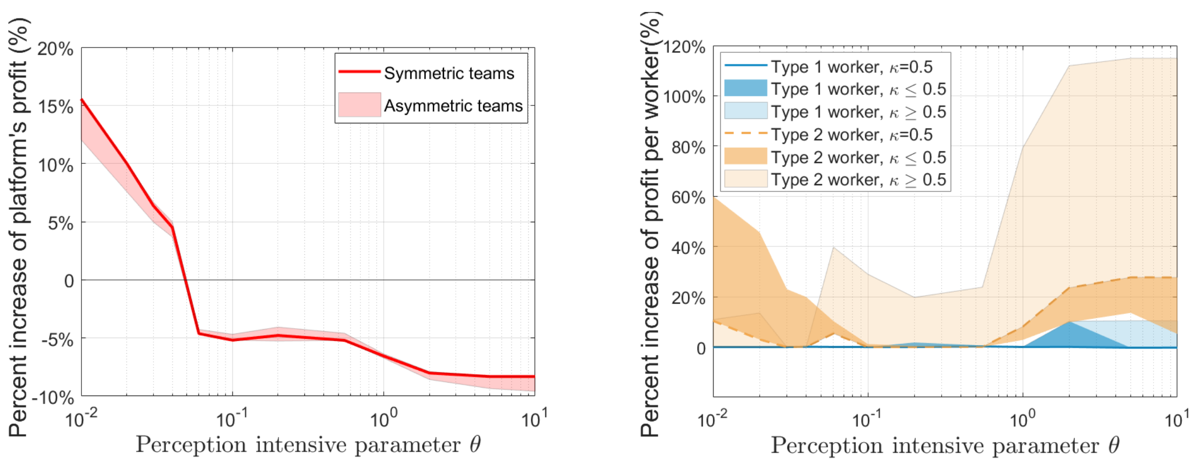
The impact of multi-team contests on workers differs based on their types (see Figure 10b). In this example, Type 1 workers receive the same profit as under the self-scheduling benchmark, regardless of the number of teams. By contrast, the impact of multi-team contests on Type 2 workers is undetermined.

6.2. Intra-team Heterogeneity

Previous studies indicate that intra-team heterogeneity greatly impacts contest outcomes (Ye et al. 2020). This subsection examines the impact of intra-team heterogeneity from team compositions and working-time preferences. The former measures team diversity regarding worker types while the latter measures the degree of differences between two types of workers.

6.2.1. Team compositions. To examine the influence of team compositions on contest outcomes, we vary the worker type distribution in teams while maintaining a fixed number of workers. Specifically, in Team 1, κ denotes the ratio of Type 1 workers in one of the two teams (Team 1), and the ratio of Type 2 workers is $1-\kappa$. Correspondingly, the ratios of the two types in Team 2, are $1-\kappa$ and κ, respectively. The team compositions are varied by changing the value of κ from 0 to 1 with a step size of 0.1. When κ equals 0.5, it is equivalent to the symmetric team setting. Other values of κ lead to asymmetric team settings. Here, we focus on how symmetric and asymmetric team settings impact the contest outcome.

Our numerical results indicate that team composition has a non-monotonic effect on market equilibrium. Figure 11 combines the results for various values of κ, as shown in the shaded area. The results are presented in terms of percentage increase in the platform's profit and the profit per worker compared to those under the self-scheduling benchmark. Despite the change in team compositions, the conclusion that team contests improve the platform's profit when workers have less accurate perceptions remains valid (Figure 11a). Interestingly, while workers are better off in all situations compared to the self-scheduling benchmark, the difference in profit per worker is type-dependent (Figure 11b). Symmetric teams do not appear to have any significant disadvantages over other team compositions for Type 1 workers. Since the cost of switching from their preferred afternoon to morning periods dominates the incremental incomes, these workers do not benefit too much from the team contest regardless of team compositions. This finding does not necessarily apply to Type 2 workers, for whom staying in symmetrical teams is significantly less profitable than staying in certain asymmetrical teams. The more Type 2 workers, who prefer to work in the morning periods with the smaller value of κ, the less fluctuation in their profitability when their perceptions are accurate. These observations highlight the difficulty of determining the best team composition, given the platform's and workers' disparate influences.



(a) Percent increase of the platform's profit (b) Percent increase of profit per worker

Figure 11 **Percent increase of profits with team compositions and perception accuracy**

6.2.2. Workers' heterogeneous working-time preferences. Because attraction weights are designed to balance supply and time-varying demand, the optimal contest design will certainly be influenced by workers' time preferences. We investigate the impacts of working-time preferences on the optimal attraction weights considering two factors. (a) Because Type 1 (afternoon) workers' time preferences are less compatible with the peak hours, it is more costly to incentivize them to reschedule. Hence, the experiment varies their service cost distribution and keeps a constant total service cost of \$160. Specifically, Type 1 workers' service cost varies from 40 (\$/hour) to 80 (\$/hour) per morning period. The remaining cost is evenly distributed to afternoon periods. The service cost distribution for Type 2 (morning) workers remains unchanged. Consequently, the higher service cost experienced by Type 1 workers during morning periods indicates a higher degree of heterogeneity among team members. (b) Type 1 workers' ratio κ in Team 1 is changed to accommodate various team compositions stated in Section 6.2.1.

For demonstration purposes, workers' perception accuracy takes $\theta = 0.02$ when calculating the self-scheduling utility of workers. Figure 12 shows that the degree of heterogeneity in workers' working-time preferences significantly impacts the values of optimal attraction weights. When Type 1 workers encounter minimal service costs in the morning, team members' preferred working hours are broadly similar. As a result, the platform assigns high attraction weights to the morning peak periods. On the contrary, when Type 1 workers face high costs in the morning, they shift to work in the afternoon periods. In this case, the platform assigns a great proportion of attraction weights to low-demand afternoon periods regardless of team compositions. This contradicts our purpose of raising the attractiveness of peak periods. The explanation is that attraction weights $\boldsymbol{\gamma}$ are period-specific but independent of worker types. When Type 1 workers strongly prefer to work in the afternoon, implementing high attraction weights in the morning cannot ensure workers' individual rationality. These results suggest that period-specific attraction weights only apply to situations where team members' working-time preferences are not substantially different.

6.3. Interdependence between the Winner's Reward and Attraction Weights

Investigating the relationship between the winner's reward and attraction weights at optimality is nontrivial, largely because the platform might not have complete control over both policies in practice. We examine the mutual influence between the winner's reward and attraction weights by fixing one design element and solving problem (13) for the other one. Figure 13 presents the results, which include all team compositions stated in Section 6.2.1. When computing the results of Figure 13b, we set the attraction weights of two morning (afternoon) periods equal. Workers' perception intensive parameter takes $\theta = 0.02$ when calculating the self-scheduling utility of workers.

Figure 13a illustrates how the optimal attraction weights change with the winner's reward R, which is treated as an input parameter in this case. We combine the results from all team compositions because there is no clear correlation between them and the values of attraction weights. Overall, the optimal attraction weights for the morning peak periods increase with the winner's reward and decrease for the afternoon periods. Figure 13b suggests that attraction weights and

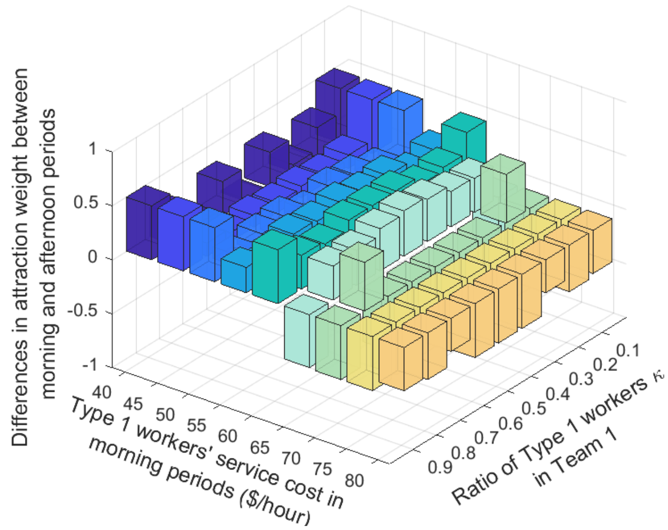
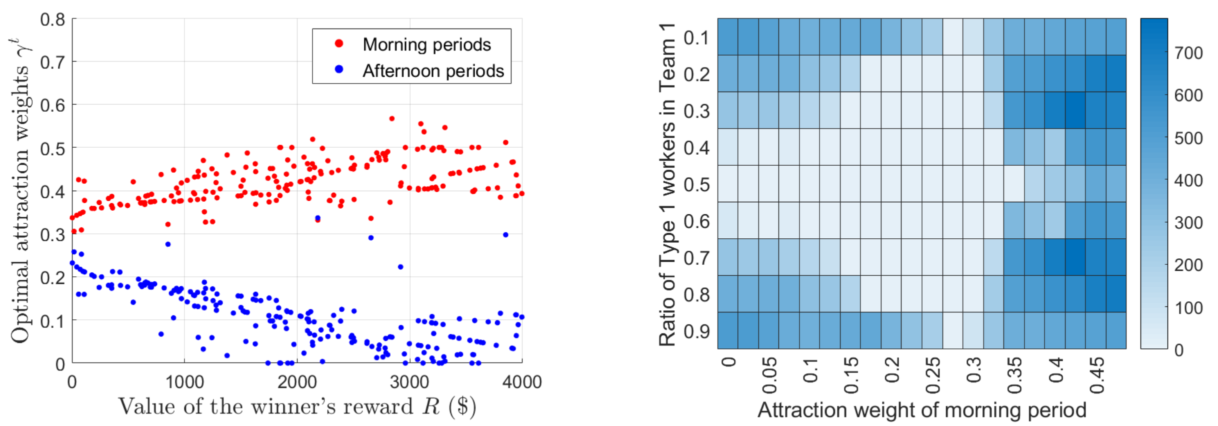


Figure 12 **Peak and non-peak periods' attraction weights different with Type 1 workers' service costs and ratios**

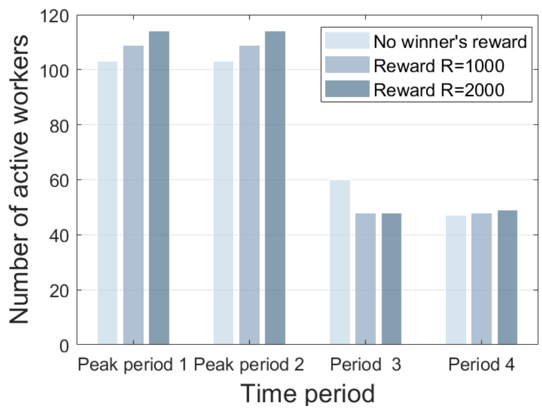


(a) Optimal attraction weights change with winner's reward
(b) The optimal winner's reward changes with attraction weights

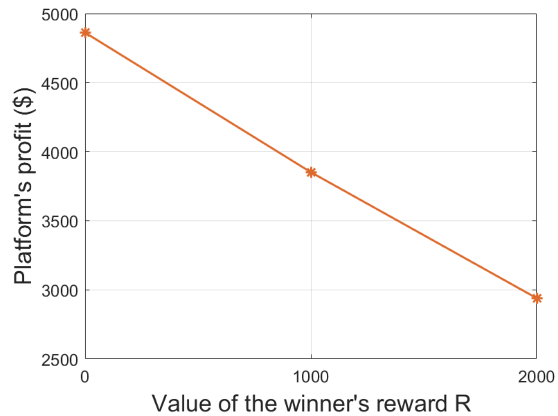
Figure 13 **The mutual influence between attractions weights and the winner's reward**

team compositions significantly impact the optimal winner's reward. To this extent, using non-optimal attraction weights incurs an external reward, which can be avoided by applying symmetric team compositions. Overall, Figure 13 indicates that attraction weights and the winner's reward are strongly correlated.

When the platform lacks complete control over both the winner's reward and attraction weights, it is critical to choose the most effective design component. After demonstrating the effectiveness of attraction weights in Section 5.2, this section investigates the effects of the winner's reward on alleviating supply-demand imbalances and on the platform's profitability. Figure 14 compares the number of active workers and the platform's total profit at equilibrium when the winner's reward is set to be $0, $1000, and $2000, respectively. Here, the platform only optimizes the attraction weights. Figure 14a shows that increasing the amount of reward attracts more workers during peak periods. On the opposite, this policy incurs additional costs, reducing the benefit from the external reward, and leaving the platform with a loss of profit (Figure 14b). These results and those in Section 5.2 suggest that attraction weights are more effective than the winner's reward in directing the market equilibrium in the platform's favor.



(a) The supply of active workers



(b) Platform's daily profit

Figure 14 The supply of active workers and the platform's profit with the winner's reward (symmetric teams)

7. Conclusion

Team contest design has the potential to balance supply and demand on OSPs. This paper develops an integrated model for aligning work schedules with fluctuating service demand. In a hierarchical single-leader multi-follower game, the contest scheme utilizes the dual effects of inter-team competition and intra-team scheduling coordination. The lower-level intra-team coordination problem solves the workers' schedules by network flow optimization. QVI is used to quantify the market equilibrium with heterogeneous working-time preferences. The upper-level problem considers a platform-centric scheme that combines a winner's reward to incentivize finishing more orders and period-specific attraction weights to balance supply and demand. In-depth numerical experiments evaluate the impact of team contests on the platform and its workers and identify critical factors affecting the optimal scheme. This work draws the following managerial insights:

1. The optimal platform-centric contest scheme with a winner's reward and attraction weights can alleviate temporal supply-demand imbalances and steer the market toward more advantageous equilibria. Attraction weights are more effective than the winner's reward at increasing the platform's profit.

2. While team contest benefits all workers, its impacts on the platform rely on workers' perceptions of their utilities prior to joining teams. The platform benefits more from the team contest when workers' perception accuracy is lower.

3. There is a discrepancy between dual effects as enhancing the intra-team coordination will weaken inter-team competition. The team's scheduling decisions benefit its workers at the expense of misaligning labor supply with the platform's profit-maximizing objectives.

4. Splitting workers into multiple teams increases profit for the platform but the marginal return is diminishing.

5. Supply and demand can be balanced through the use of attraction weights only when workers within a team have less heterogeneous working-time preferences.

Our study identifies several potential directions for future research. First, we assume predetermined team compositions throughout the analysis. A future direction is to consider workers' flexibility to choose teams and optimize team compositions and the contest scheme in tandem. Optimizing team compositions is more complicated than current models, mainly because decentralized team assignment introduces combinatorial complexity into the decision-making process. Second, workers are assumed to report their types (e.g., per-period service cost) truthfully to the team leader. Investigating incentive-compatible contest scheme designs is an interesting extension. Finally, our conclusions are derived from numerical experiments that employ hypothetical instances due to a lack of available data. Empirically validating our models and results will be an intriguing future research direction.

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Proofs and Supplementary Materials

Appendix A Summary of Major Notation

Table EC.1: Summary of major notation

Notation	Description
Sets	
J	The set of teams;
T	The set of periods;
K	The type space of workers;
P	The path set over a time-expanded network;
$\boldsymbol{\mathcal{M}_j}$	The feasible set of team j's intra-team schedules;
$\mathcal{S}(R,\boldsymbol{\gamma})$	Solution set of QVI parameterized by the contest scheme $(R,\boldsymbol{\gamma})$.
Variables of intra-team coordination problem	
U_j	The utility of team j (\$);
R_j	The revenue of team j (\$);
q_j^t	Service output of team j in period t (requests/hour);
q^t	Served demand in period t (requests/hour);
N_j^{kt}	Supply of k-type active workers from team j in period t (/hour);
N_j^t	Supply of active workers from team j in period t (/hour), vector $\boldsymbol{N^t}=(N_j^t)_{j=1}^{J_0}$;
f_j^{kp}	Flow along path p of k-type workers from team j, vector $\boldsymbol{f_j}=(f_j^{kp})_{k\in K,p\in P}$;
u_j^k	Utility of a k-type worker in team j (\$).
Variables of contest scheme design problem	
R	The winner's reward (\$);
γ^t	Attraction weight of period t, vector $\boldsymbol{\gamma}=(\gamma^t)_{t=1}^{T_0}$;
λ_j^k	Lagrangian multiplier for constraint (6b), vector $\boldsymbol{\lambda_j}=(\lambda_j^k)_{k=1}^{K_0}$;
$\boldsymbol{f}$	$(\boldsymbol{f_j})_{j=1}^{J_0}$, the scheduling plans of all teams.
Parameters	
Q_0^t	Potential demand in period t (requests/hour);
N_j^k	The number of k-type workers in team j, vector $\boldsymbol{N_j^0}=(N_j^k)_{k=1}^{K_0}$;
c^{kt}	The service cost of k-type workers in period t(\$/hour), vector $\boldsymbol{c^k}=(c^{kt})_{t=1}^{T_0}$;
p^t	Per unit service profit in period t (\$/request);
w^t	Workers' earning per completed service order (\$/request);
h^p	Working hours along path p (hour);
c_h	Cost parameter for amounting working hours;
ν	Workers' degree of aversion to working duration;
δ_t^p	Parameter indicating whether period t lies in path p;
u_0^k	A k-type worker's utility under self-scheduling (\$).
Other vectors	
$\boldsymbol{N_{-j}^t}$	(N_j^t), supply from all teams other than j in period t, vector $\boldsymbol{N_{-j}}=(\boldsymbol{N_j^t})_{t=1}^{T_0}$;
$\boldsymbol{N}$	$(\boldsymbol{N^t})_{t=1}^{T_0}$, supply of active workers during the entire planning horizon;
$L_j(\boldsymbol{f_j})$	The derivative of $-U_j$ with respect to $\boldsymbol{f_j}$.
Acronyms	
OSPs	On-demand service platforms;
IR	Individual rationality;
GNE	Generalized Nash equilibrium.
QVI	Quasi-variational inequalities;
VI	Variational inequalities;
MPEC	Mathematical programming with equilibrium constraints.

Appendix B Supplementary Materials for Section 3

Algorithm 1: A penalty-duality-based algorithm for market equilibrium

Result: Scheduling plans of all teams at market equilibrium $\boldsymbol{f}^*$;

Set iteration counter $m=0$, initialize parameters μ_j^k, ρ and an error tolerance ϵ;

Solve optimization problem (10) for the optimal schedule $\boldsymbol{f}^{*(0)}$;

while *there exists* (k,j) *such that* $g_j^k(\boldsymbol{f_j}^{*(m)}, \boldsymbol{N}_{-j}^{t(m)}, R, F_m) > \epsilon$ **do**

  Update μ_j^k and ρ by setting $\mu_j^{k(m+1)} = \left[\mu_j^{k(m)} + \rho^{(m)} \cdot g_j^k\right]^+$ and $\rho^{(m+1)} > \rho^{(m)}$;

  Solve optimization problem (10) for the optimal solution $\boldsymbol{f}^{*(m+1)}$;

  Set $\boldsymbol{f}^{*(m+1)} \to \boldsymbol{f}^{*(m)}$, $\mu_j^{k(m+1)} \to \mu_j^{k(m)}$, $\rho^{(m+1)} \to \rho^{(m)}$;

end

Output the converged scheduling plans of all teams $\boldsymbol{f}^{*(m)}$.

Appendix C Supplementary Materials for Section 4

C.1 Feasibility of the platform-centric contest scheme design problem

Proposition 1. *[Feasibility of the platform-centric contest scheme design problem] There exists at least one feasible contest scheme* $(R,\boldsymbol{\gamma})$ *to problem* (13)*, under which the market equilibrium exists.*

Proving Proposition 1 is equivalent to proving that there exists at least one non-negative solution $(R,\boldsymbol{\gamma})$ such that the normalization constraint (13b) is satisfied and the QVI's solution set $\mathcal{S}(R,\boldsymbol{\gamma})$ is nonempty. In this proof, we first remove IR constraint (6d) from intra-team coordination problem (6) and transform the QVI defined by (8) into the following VI:

$$\sum_j L_j(\boldsymbol{f_j^*})^T(\boldsymbol{f_j} - \boldsymbol{f_j^*}) \geq 0, \quad \forall \boldsymbol{f_j} \in \boldsymbol{\mathcal{M}_j}. \tag{E1}$$

where the feasible set of each team's schedules is $\boldsymbol{\mathcal{M}_j} = \{\boldsymbol{f_j} | \sum_{p\in P} f_j^{kp} = N_j^k, f_j^{kp} \geq 0\}$ and is independent of other teams' decisions. After proving the solution existence to the above VI (Lemma EC.1), we complete the proof by showing that there is a contest scheme $(R,\boldsymbol{\gamma})$ that satisfies constraint (13b) and that $\mathcal{S}(R,\boldsymbol{\gamma})$ coincides with the solution set of the above VI.

Lemma EC.1. *There exist solutions to the VI problem* (E1)*.*

The feasible set $\boldsymbol{\mathcal{M}}$ that defines the VI problem (E1) is the Cartesian product of the feasible set for each team $j \in J$, i.e., $\boldsymbol{\mathcal{M}} = \prod_{j=1}^{J_0} \boldsymbol{\mathcal{M}_j}$. Since $\boldsymbol{\mathcal{M}_j}$ is a nonempty, closed and bounded polyhedron, the set $\boldsymbol{\mathcal{M}}$ is compact. Furthermore, because the solutions to the VI also belong to $\boldsymbol{\mathcal{M}}$, the VI problem (E1) essentially defines a mapping from $\boldsymbol{\mathcal{M}}$ to the set itself.

Next, we demonstrate that the function $L_j(\boldsymbol{f_j})$ that defines the VI problem (E1) is continuous with variables $\boldsymbol{f_j}$. For each team $j \in J$, the partial derivative of team utility U_j with respect to a specific path flow f_j^{kp} is as follows:

$$\frac{\partial U_j(\boldsymbol{f_j}, \boldsymbol{N_{-j}}, R)}{\partial f_j^{kp}} = \sum_{t\in T} w^t \cdot \frac{\partial q_j^t}{\partial N_j^t} \cdot \delta_t^p + R \cdot \Phi_j - \sum_{t\in T} c^{kt} \cdot \delta_t^p - c_h \cdot (h^p)^\nu, \quad \forall k \in K, p \in P, \tag{E2}$$

where the team utility $U_j(\boldsymbol{f_j}, \boldsymbol{N_{-j}}, R)$ is specified by equation (4); the term Φ_j comes from the Tullock contest success function in equation (3) and is derived as follows:

$$\Phi_j = \frac{1}{\sum_{t\in T} q^t} \cdot \left(\sum_{t\in T} \frac{\partial q_j^t}{\partial N_j^t} \cdot \delta_t^p \right) - \frac{\sum_{t\in T} q_j^t}{(\sum_{t\in T} q^t)^2} \cdot \left(\sum_{t\in T} \sum_{i\neq j} \frac{\partial q_i^t}{\partial N_j^t} \cdot \delta_t^p \right), \quad \forall j \in J. \tag{E3}$$

By equation (E2), $\partial U_j(\boldsymbol{f_j}, \boldsymbol{N_{-j}}, R)/\partial f_j^{kp}$ is a continuous function of f_j^{kp} because the demand function $F_q(\cdot)$ is twice differentiable (equation (1)) and the link flow N_j^t continuously changes with the path flow f_j^{kp}. Therefore, the function $L_j(\boldsymbol{f_j}) = -\nabla_{f_j^{kp}} U_j(\boldsymbol{f_j}, \boldsymbol{N_{-j}}, R)$ defines a continuous mapping from $\boldsymbol{\mathcal{M}_j}$ into $\mathbb{R}^{(|K|\times|P|)}$ for each team $j \in J$.

Based on Brouwer's fixed-point theorem and Theorem 3.1 from Harker and Pang (1990), the above conclusions on compact $\boldsymbol{\mathcal{M}}$ and continuous $L_j(\boldsymbol{f_j})$ imply that there exist solutions to the VI defined by (E1). □

Next, we show that there exists a feasible solution $(R, \boldsymbol{\gamma})$ to the platform-centric contest scheme design problem (13). For simplicity, we select an attraction weight $\gamma^t = 1/|T|$ for period $t \in T$, where $|T|$ is the cardinality of the period set T. The normalization constraint (13b) is automatically satisfied.

Following equation (12), a k-type worker's utility under the platform-centric scheme $(R, 1/|T|)$ is as follows:

$$u_j^k(\boldsymbol{f_j}, \boldsymbol{N_{-j}}, R|\frac{1}{|T|}) = \frac{\sum_{t\in T} N_j^{kt}}{\sum_{k\in K}\sum_{t\in T} N_j^{kt}} \cdot \frac{R_j}{N_j^k} - \frac{1}{N_j^k} \cdot \left(\sum_{t\in T} c^{kt} N_j^{kt} + c_h \sum_{p\in P} f_j^{kp} \cdot (h^p)^\nu \right), \quad \forall j \in J, k \in K. \tag{E4}$$

where the team revenue R_j is given by

$$R_j = \sum_{t\in T} w^t q_j^t(N_j^t, \boldsymbol{N_{-j}^t}) + R \cdot \frac{\sum_{t\in T} q_j^t}{\sum_{t\in T} q^t(\boldsymbol{N^t})}, \quad \forall j \in J. \tag{E5}$$

Fixing workers' schedules $(\boldsymbol{f_j})_{j\in J}$ and active workers' supply $(\boldsymbol{N^t})_{t\in T}$ at one solution of the VI defined by (E1), a k-type worker's utility u_j^k continually increases with the winner's reward R. Thus, there must exist a non-negative reward $\hat{R}$ such that the IR constraints $u_j^k(\boldsymbol{f_j}, \boldsymbol{N_{-j}}, \hat{R}) > u_0^k$ hold for each worker type $k \in K$ and each team $j \in J$. With that, IR constraint (6d) could be safely dropped in deriving the optimal solutions to intra-team coordination problem (6). Consequently, the QVI defined by (8) becomes the VI as shown in (E1), giving back $(\boldsymbol{f_j})_{j\in J}$ as a solution in the set $\mathcal{S}(R, \boldsymbol{\gamma})$. Therefore, the contest scheme $(\hat{R}, 1/|T|)$ is a feasible solution to the contest scheme design problem (13). □

C.2 Global optimization for the optimal contest scheme design

Bayesian optimization (BO) is a powerful approach for solving black-box derivative-free global optimization problems (Frazier 2018). In the absence of an exact objective function form, BO approximates it with a probabilistic surrogate model and then performs the optimization. More specifically, BO treats the objective function as a random function and applies a prior measure to it. With each sample drawn from the objective function, a posterior distribution is then computed to better approximate the objective. To determine the next sampling point, an acquisition function is optimized based on the posterior distribution. The acquisition function combines exploration and exploitation in its search for a new point. There, exploration means searching toward unexplored regions with high predicted uncertainty. By contrast, exploitation focuses on sampling where the surrogate model predicts a favorable outcome. Typically, Bo applies to optimization problems with simple feasible sets and dimensions less than 20.

To solve the optimal contest scheme with BO, we use the commonly adopted Gaussian process as the surrogate model. The sampling points are determined by an acquisition function called "expected-improvement-plus" function. This acquisition function evaluates a point based on the expected improvement in the objective function value. It avoids regions from being over-exploited to escape a local optimum and is a typical choice of BO. In programming, we set the exploration ratio at 0.6. As a stop criterion, BO is set to evaluate the objective function no more than 50 times. Throughout numerical experiments, the function 'bayeopt' in Matlab is used to implement BO.

Algorithm 2: Solution algorithm for the optimal platform-centric contest scheme

Result: The global optimal platform-centric contest scheme $(R^*, \boldsymbol{\gamma}^*)$ and the scheduling plans of all teams at market equilibrium $\boldsymbol{f}^*$;

Initialize suggested searching points $(R^{(0)}, \boldsymbol{\gamma}^{(0)})$, penalty parameter η, and an error tolerance ϵ;

while *BO does not reach the maximum number of objective function evaluations* **do**

  Set iteration counter $m = 0$, initialize parameters μ_j^k and ρ;

  Solve problem (14) for a local optimal solution $(R^{*(m)}, \boldsymbol{\gamma}^{*(m)}, \boldsymbol{f}^{*(m)})$;

  while $z_{VI}^{*(m)} > \epsilon$ **do**

    Update μ_j^k and ρ by setting $\mu_j^{k(m+1)} = \left[\mu_j^{k(m)} + \rho^{(m)} \cdot g_j^k\right]^+$, $\rho^{(m+1)} > \rho^{(m)}$;

    Solve problem (14) for a local optimal solution $(R^{*(m+1)}, \boldsymbol{\gamma}^{*(m+1)}, \boldsymbol{f}^{*(m+1)})$;

    Set $\boldsymbol{f_j}^{*(m+1)} \to \boldsymbol{f_j}^{*(m)}$, $\mu_j^{k(m+1)} \to \mu_j^{k(m)}$, $\rho^{(m+1)} \to \rho^{(m)}$;

  end

  Output the local optimal solution $(R^{*(m)}, \boldsymbol{\gamma}^{*(m)}, \boldsymbol{f}^{*(m)})$ and the objective function value of problem (14);

  Seek the next suggested searching point $(R_0, \boldsymbol{\gamma_0})$ via BO;

end

Output the best local solution so far $(R^*, \boldsymbol{\gamma}^*, \boldsymbol{f}^*)$.;

Appendix D Supplementary Materials for Section 5

Fully self-scheduling benchmark. Under fully self-scheduling, each worker makes scheduling decisions independently to maximize her perceived utility. Thus, a k-type worker chooses schedule p only if $\theta u_k^p + \xi^p \geq$

$\theta u_k^{p'} + \xi^{p'}$ for all $p' \in P$. Here, θ measures the dispersion among workers regarding their perceived utility. When θ is small, the random term ξ^p and the deterministic term $\theta \cdot u_k^p$ are comparable, indicating a large variance in workers' perceptions. By contrast, a large value of θ makes the deterministic term a dominant one, which implies a small perception variance among workers. Using the discrete choice model, the probability that a k-type worker would choose schedule p is given by $\mathbb{P}^{kp} = \mathbb{P}[\theta u_k^p + \xi^p \geq \theta u_k^{p'} + \xi^{p'}, \forall p' \in P]$. Assume that the random terms follow identical and independent Gumbel distributions, we have $\mathbb{P}^{kp} = \frac{\exp\left(\theta \cdot u_k^p\right)}{\sum_{p' \in P} \exp\left(\theta \cdot u_k^{p'}\right)}$. At equilibrium, no worker can gain a higher perceived utility by unilaterally changing her working schedule. Plugging in the above scheduling choice model, the equilibrium flow $\boldsymbol{f}$ can be obtained by solving the following fixed-point problem:

$$f^{kp} = \mathbb{P}^{kp}(\boldsymbol{f}) \cdot \sum_{j \in J} N_j^k, \quad \mathbb{P}^{kp}(\boldsymbol{f}) = \frac{\exp\left(\theta \cdot u_k^p(\boldsymbol{f})\right)}{\sum_{p' \in P} \exp\left(\theta \cdot u_k^{p'}(\boldsymbol{f})\right)}, \quad \forall p \in P, k \in K. \tag{E6}$$

When $\theta \to 0$, workers will take each possible schedule with an equal probability. At equilibrium, workers are evenly distributed over all paths. When $\theta \to +\infty$, all workers choose the schedule yielding the highest real utility u_k^p. For a given value of θ, the self-scheduling utility is calculated as $u_0^k = \sum_{p \in P} \mathbb{P}^{kp} \cdot u_k^p$ for each worker type $k \in K$.