Humans Are Not Machines: The Behavioral Impact of Queueing Design on Service Time

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Abstract:

Using behavioral experiments, we study the impact of queue design on worker productivity in service systems that involve human servers. Specifically, we consider two queue design features: *queue structure*, which can either be parallel queues (multiple queues with a dedicated server per queue) or a single queue (a pooled queue served by multiple servers); and *queue-length visibility*, which can provide either full or blocked visibility. We find that 1) the single-queue structure slows down the servers, illustrating a drawback of pooling; and 2) poor visibility of the queue length slows down the servers; however, this effect may be mitigated, or even reversed, by pay schemes that incentivize the servers for fast performance. We provide additional managerial insights by isolating two behavioral drivers behind these results–task interdependence and saliency of feedback.

Keywords: Behavioral Operations, Queueing Systems, Service Time, Real Effort Experiments

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∗This work was supported by grants from the Robert H. Brethen Operations Management Institute at the Whitman School of Management.

1 Introduction

In service systems, managers are constantly seeking ways to improve customers' experience by reducing service waiting times. Service windows, such as those at banks, post offices, motor vehicle offices, and delicatessens, are known for single-queue structures (a pooled queue served by multiple servers). Retail companies such as TJ Maxx, Hannaford, and Target have implemented or experimented with a single-queue, "next available" checkout policy with varying degrees of success (Hauss, 2008; Helms, 2011; Fantasia, 2009). Nevertheless, parallel queues are still common practice for many service environments in which servers have face-to-face contact with customers and with other servers (e.g., retail stores, ticket booths, security gates, fast food restaurants, etc.). Similarly, direct job assignments can be found in service systems in which the servers have no direct contact with either customers or other servers (e.g., technical support centers pre-assign tickets to specific agents), effectively creating a parallel-queues policy, so it is critical to consider both queue structures when studying worker productivity.

Bendoly et al. (2010) suggest that various behavioral factors impact worker productivity. They point out the need for rigorous research on several research questions, including: (1) given that a single queue has higher and more obvious task interdependence, which leads to dispensability of individual effort and, therefore, to reduced effort (Williams et al., 1981), does this *task interdependence* affect server speed? and (2) given that there is higher-quality feedback and a direct relationship with every customer in parallel queues than in single queues, does this *salient feedback* affect server speed?

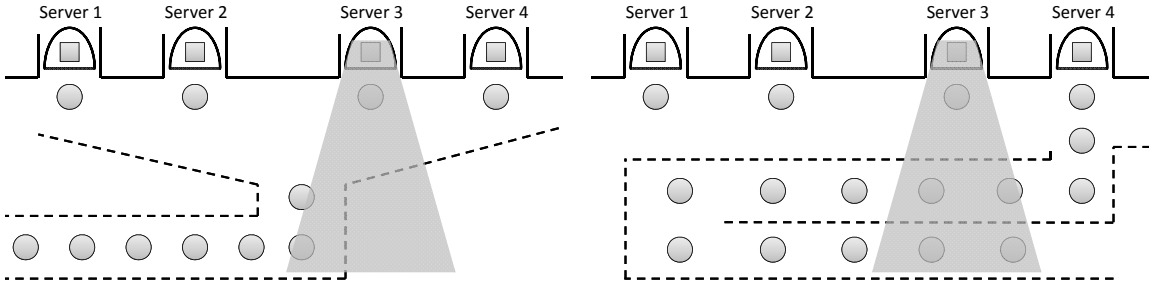
In this study, we focus on two aspects of queue design that impact *task interdependence* and *salient feedback*: queue structure and queue-length visibility. Queue structure is represented by single-queue and parallel-queues environments. Queue-length visibility (hereafter "queue visibility") is represented by the availability of feedback about the length of the queue, which we explore at two levels: full visibility (good feedback) and blocked visibility (poor feedback).

Based on prior research, the single-queue structure has both higher feedback and lower perceived interdependence relative to the parallel-queues structure and, therefore, should induce lower comparative effort (Bendoly et al., 2010). However, a direct comparison of these two systems does not allow us to identify which behavioral mechanism (task interdependence or saliency of feedback) drives this reduction in effort. Thus, to determine the marginal impact of feedback compared to interdependence, we also study these systems when both have low feedback (controlled by visibility). Any performance difference observed between single- and parallel-queues structures under equally poor feedback would indicate that workers are affected by the interdependence of the task. Meanwhile, the relative change from this baseline when comparing the two structures under full visibility would be the marginal impact of salient feedback. In order to isolate the variables of interest and reduce the potential variability inherent in real-world experiments, we perform experiments in controlled, simulated environments, in which subjects work with computerized co-workers to face a computer-generated stream of customers in a grocery-store cashier setting.

Queue visibility provides a tool to manipulate feedback. Moreover, the issue of visibility is

a real-world concern for service management. We spoke with managers at a ticketing booth for athletic events about queue-design choices and observed the dynamics of the queues at the booth (which we tested in both parallel- and single-queue structures in a pilot study for a related field experiment). Based on these observations, we find the following challenge of physical queue design: the physical structure of the queue environment may block visibility of longer queues due to high barriers—e.g., queues that extend behind walls or fences—or due to the position of the service provider relative to the queue, resulting in partial (or blocked) visibility.

For example, as Figure 1 illustrates, the arrangement of the single queue may affect the amount of feedback that servers receive through visibility of the queue length. In Figure 1(a), Server 3 has a limited view of the queue and does not have information about the true queue length. In contrast, in Figure 1(b), the same server has a better view of the queue and has better information about the queue length.

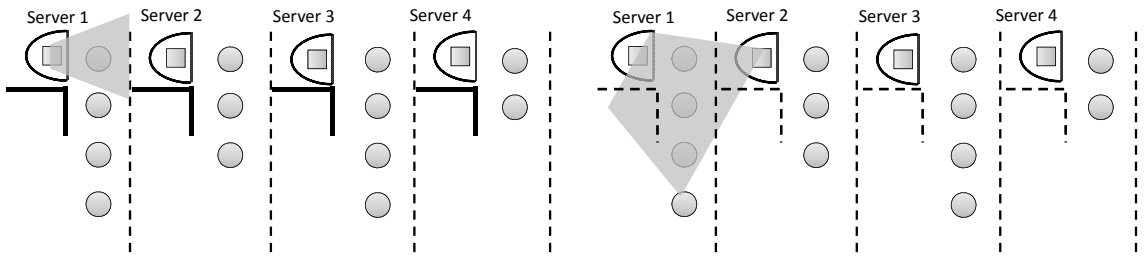


(a) Blocked visibility.

(b) Good (full) visibility.

Figure 1: Physical design of the single-queue system may impact cashiers' queue visibility.

Similarly, in the parallel-queues system, as illustrated in Figure 2, the presence of toll merchandise displays (represented by bold, thick lines on the diagram) next to the cashiers' terminals can block their visibility of the queue. Removing these objects may improve visibility of the queue length. Blocked visibility decreases availability of feedback and, consequently, may impact workers' performance. Based on research by Schultz et al. (1998), who find that workers in a serial task speed up or slow down when they can better measure the amount of work to be done, feedback quality or the lack of feedback could influence server motivation. Understanding the effect of visibility on worker speed provides valuable insights for the physical design of the service area.



(a) Blocked visibility.

(b) Good (full) visibility.

Figure 2: Physical design of the parallel-queues system may impact queue visibility for the cashiers.

This paper contributes to the literature by exploring the impact of queue structure and queue visibility on servers' behavior and providing important managerial insights for designing queueing systems. Our findings are rigorous in several ways: 1) We focus on nondiscretionary tasks—*i.e.,* tasks in which the servers do not have discretion in the number and quality of activities to perform for the customer. We focus on a nondiscretionary task because it removes the trade-off between service quality and speed (Hopp et al., 2007; Wickelgren, 1977; Anand et al., 2011). Examples of nondiscretionary tasks include processing shopping carts in a grocery setting; selling tickets at box offices; collecting money at toll booths; and other tasks that have structured procedures for completion. 2) We fix the average arrival rate within each treatment in order to stabilize the load. The load can affect servers' behavior (Delasay et al., 2015), and we want to minimize this effect. We then perform a robustness check with a lowered average arrival rate and confirm that our results are still present. 3) We automate co-workers to standardize or reduce social biases from interpersonal group dynamics (Mas and Moretti, 2009; Bandiera et al., 2010; Schultz et al., 2010), while still allowing for the effects of an interdependent task. We perform a robustness check to ensure that subjects are aware of the computerized behavior of their co-workers and the results are not due to mistaken assumptions about co-worker reactions. Thus, we isolate the two behavioral factors—task interdependence (controlled by queue structure) and saliency of feedback (controlled by both queue structure and queue visibility)—so that we may consider their role in servers' performance.

Our results challenge the commonly accepted assumptions about worker speed being the same in each queue structure. We find that servers work faster in a parallel-queues environment than in a single-queue system. Analytical research on queueing theory may benefit from incorporating this effect into its assumptions. We also find that poor queue visibility affects servers' performance in both structures; however, this result depends on the incentive scheme.

Our paper proceeds as follows. In Section 2, we summarize the relevant literature and develop our hypotheses. Section 3 describes our experimental design. In Section 4, we provide a summary of our data, including visual representations of the data. In Section 5, we present our data analysis and results. Finally, in Section 6, we provide managerial insights and conclude.

2 Literature Review and Hypotheses Development

The research questions posed in Bendoly et al. (2010) indicate a need to consider both task interdependence and feedback. In this section, we provide an overview of the literature underlying these factors and form the two main hypotheses of our paper. Additionally, we consider studies that focus on effort in groups and/or queueing settings to provide additional foundation for the experimental assumptions made in our study.

Working in groups changes the perception of output relative to effort. Williams et al. (1981) attribute the reduction in workers' individual effort in a group setting—as opposed to an individual setting–to social loafing, and Karau and Williams (1993) summarize several theories that have been proposed to explain the phenomenon. One of these theories, dispensability of effort, is closely related to our study: it is driven by task interdependence, which is present in the single-queue environment. In such an environment, the servers work collectively to clear the customer queue, and, hence, individual effort is dispensable, which is consistent with the hypotheses of Bendoly et al. (2010). Pearce and Gregersen (1991) explain that workers feel less responsibility for the task due to interdependence, and Kidwell and Bennett (1993) claim that "[g]reater task interdependence will be positively related to propensity to withhold effort." (Hypothesis 8, page 446)

Note that this interdependence is present regardless of the visibility of the other servers; and it may be present regardless of whether the workload is shared with a human server, a machine, or a virtual co-worker because it is about the shared effort across the pool of co-workers, not social pressure. In a parallel-queues system, because servers have their own queues, their performance has a direct impact on the speed at which their line moves. Moreover, the servers face every customer who joins their queue. If customers join the shortest queue, each server also influences the total workload of other servers, but servers are likely to view their queue as their responsibility. In contrast, in the single-queue environment, servers work together to process one common queue, and, thus, the impact of each individual's effort is less apparent. In both approaches, the work is collective, in that the workers jointly manage the final goal of processing all incoming customers. However, the interdependence makes the collective nature more clear in the single-queue than in the parallel-queues system (Bendoly et al., 2010). Because co-workers are known to be pre-programmed computers, we emphasize that this study is about the task interdependence mechanism, not about the more general concepts of social loafing. We can now state our first hypothesis:

Hypothesis 1 (Impact of queue structure) *Servers work faster in the queueing environment in which customers are aligned into multiple parallel queues instead of a single pooled queue.*

Separate from the various concepts of social loafing, control theory, discussed in the behavioral literature, tells us that workers use feedback about their actual performance relative to a goal to self-regulate behavior (Donovan, 2001; Bendoly et al., 2010). Schultz et al. (2003) and Powell and Schultz (2004) find that workers adjust their speeds more when feedback about performance becomes more salient, such as when low-inventory buffers allow observation of fast and slow points in a production line. Goal setting in conjunction with feedback leads to performance improvements

(Erez, 1977), but feedback alone can also lead to improvements (Latham and Locke, 1991). This feedback can take the form of monitoring the changes to work-in-process, where the ability to view changes in inventory levels changes worker behavior (Schultz et al., 2003; Powell and Schultz, 2004). That is, the visibility of the workload affects worker effort, leading to our second hypothesis:

Hypothesis 2 (Impact of queue visibility) *Servers work more slowly in a queueing environment with blocked (poor) queue visibility than in an environment with full (good) visibility.*

Note that both behavioral mechanisms, task interdependence and feedback, suggest a slower server performance in a single-queue structure: relative to parallel queues, the single-queue structure has higher task interdependence and lower feedback, both leading to a reduction in effort. Hence, observing a decrease in service rate in the single-queue structure does not indicate which behavioral mechanism is causing the decreased effort. Manipulating visibility of the system allows us to disentangle the impact: under blocked visibility, there is no feedback in either single- or parallel-queue structures. Thus, observing a slowdown in service rate in a single-queue system under blocked visibility indicates that the task interdependence mechanism is causing the slowdown. If the slowdown is observed only under good visibility, the slowdown is caused by the feedback mechanism.

Clearly, effort exerted by servers also depends on the provided rewards. Based on transaction cost economics (Williamson, 1975; Jones, 1984), we know that "employees have strong incentives to shirk and no incentive to improve performance unless task conditions allow them to demonstrate discrete performance contributions and to obtain related rewards" (Kidwell and Bennett, 1993, p. 445). Gilbert and Weng (1998) explore the impact of rewards in a related setting with pooled queue structures. In an analytical study on compensation and workload allocation, they find reduced benefit from pooling when two competing symmetric employees set a costly effort level, are compensated per customer, and compete with other servers for tasks. In our behavioral work, we also explore the effect of compensation on effort by including an incentive structure factor with two payment schemes: flat payment and pay-for-performance.

By studying dispensability of effort driven by task interdependence and saliency of feedback, we focus on structural drivers of effort reduction that occur without social interaction. However, there are other drivers of effort reduction in group settings that arise from social and strategic interactions between human co-workers. Such interactions have been addressed by, for example, Mas and Moretti (2009), who find that a worker's productivity improves when a highly productive employee is introduced into a group of parallel-queues workers. This occurs when there is a previous relationship, and the workers know that the faster employee can see them. Similar results show that workers are affected by peer relationships within their teams, such as friendships and enmities (Bandiera et al., 2010). Several studies show that individuals will converge to the average—such that fast workers slow down and slow workers speed up—a pattern known as equity theory (Schultz et al., 1998, 1999, 2010). Most of these studies are done in conjunctive (serial) tasks in which one subject's output depends on another upstream teammate's output. Schultz et al. (2010) present

evidence supporting equity theory in an additive task with a common buffer, which is similar to a single-queue setting. Additional interpersonal issues are tied to the physical structure and design of the queue and affect our subjects: dehumanization of teammates via lack of physical presence (Alnuaimi et al., 2010), framing of bonuses (Hossain and List, 2012), etc. In our study, all subjects had the same degree of physical separation from their computerized co-workers that had equal processing speeds on average and all payments occurred at the end to control for possible interpersonal issues and focus on queue structure and queue visibility rather than on peer effects.

A number of previous studies show that servers can adjust their service speed in response to the environment, rather than working at a stationary average speed (as early analytical work assumed). This includes reacting to the type of task, the work load, and the pay structure. Analytical work finds that the value of queue pooling is reduced when servers have discretion over the number or quality of tasks to perform for a given customer (*i.e.,* discretionary tasks) (Cachon and Zhang, 2007; Jouini et al., 2008; Debo et al., 2008; Hopp et al., 2007, 2009). Behavioral studies show that when tasks are discretionary, workers will speed up or slow down to keep up or to appear busy with a higher load, as necessary, particularly to meet external incentives (Tan and Netessine, 2014; Oliva and Sterman, 2001; Hasija et al., 2010). While discretion is an interesting factor, our study was concerned primarily with the impact of the queue design on server performance. Therefore, to minimize the effect of discretion, we focus on nondiscretionary tasks, which are very common in practice (checking out customers in a grocery setting, selling tickets, processing registration information, etc). Additionally, Joustra et al. (2010) show analytically that pooling is ineffective when merging distinct customer types, so all of our customers have comparable carts. Finally, in studying environmental factors in queueing systems, previous studies find that load can affect service rates (see Delasay et al. 2015 for a detailed summary). We set the queue parameters so that all subjects in a treatment face similar average arrival rates, and we test our study under both high and low load.

Our research is most closely related to the empirical work of Song et al. (2015) and Wang and Zhou (2015). Song et al. (2015) examine the impact of queue pooling in a healthcare setting. They find that patient length-of-stay is ten-percent shorter when physicians are assigned patients under a parallel (dedicated-queue) system, compared to when the physicians work together under a pooled (single-queue) system. This indicates that workers slow down when working with a single queue, as opposed to parallel-queues. The healthcare environment, however, has highly variable customer care requirements that are further compounded by the nature of discretionary task completion, meaning that service providers have discretion over the number of tasks to perform for a given patient. Wang and Zhou (2015) study parallel queues and single queues running simultaneously in a grocery store and find empirical evidence that workers slow down in pooled queues. These results support our first hypothesis in complex empirical settings.

Our study contributes to this literature by testing our hypotheses through a controlled laboratory experiment, which allows us not only to demonstrate the slowdown effect in a single-queue structure, but also to separate the behavioral mechanisms behind the servers' slowdown: task

interdependence and feedback availability. Identifying which mechanism is causing the servers' slowdown guides managers in selecting remedial actions.

3 Experimental Design

To test our hypotheses, we created a computer-simulated retail environment. Subjects participated in the experiment by playing the role of a cashier whose task is to process the shopping carts of incoming customers. The subjects worked as a part of a group of four cashiers in which the three other cashiers were computer-simulated. Each customer arriving for service brought a cart containing five grocery items with different prices, ranging from \$1 to \$5 in whole units (see Figure 3).

The subjects' task was to move each of five sliders to a value corresponding to the price of each grocery item and then to click the "Submit Cart" button. Sliders have been used in past research and are considered real-effort tasks (Gill and Prowse, 2011). These five sliders corresponded to the five items in the cart and moved in increments of \$0.10 from \$0 to \$6; this range ensured that the extreme values of price were not at the end of the slider, and, thus, all item prices were similarly difficult to set correctly. By design, all the grocery items had different prices, so that the subjects could not use the position of one slider as a reference point for aligning the adjacent slider. The permutations of prices were pre-generated randomly and then presented to all subjects in identical sequences to control for the difficulty of task. The simulator did not let subjects process carts inaccurately: the "Submit Cart" button became active only when all the prices were set correctly. We recorded the time between the customer's arrival to the server and the clicking of the "Submit Cart" button, which gave us a measure of service time.

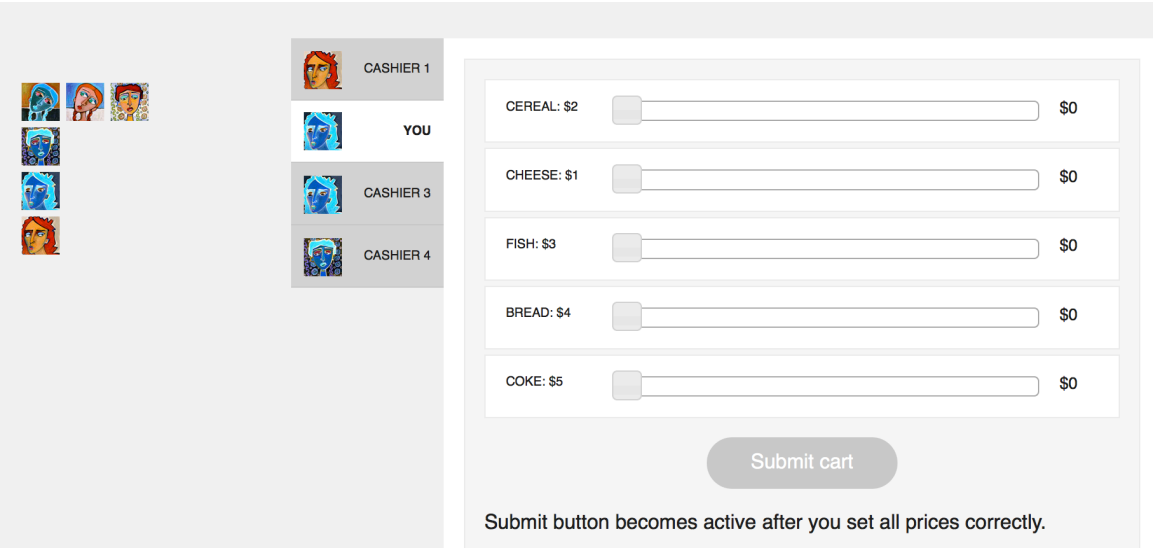


Figure 3: Sample Screen for the treatment with Single Queue and Full Visibility.

All the other cashiers were computerized and served customers according to a pre-programmed

process. Their service time for each customer was a random time set to ten seconds plus an exponential random variable with a mean of ten seconds. We selected this distribution after examining data from our pilot studies, in which we measured the subjects' service time (the plot of service time distribution from the pilot data is presented in Figure 9 in the Appendix, Section 7.3). Computer-simulated customers arrived for service according to a Poisson process with a mean inter-arrival time of 5.5 seconds. In the single-queue treatment, arriving customers joined the single queue; in the parallel-queues treatment, arriving customers observed the system and joined the shortest queue, with ties broken randomly. Customer jockeying is an important attribute of many real-world queues; however, because we did not have a well-developed model for customer jockeying behavior and because our main focus was on the server behavior, we omitted this aspect from the current study. Note that while customers already in the system did not jockey between the queues, the arriving customers always joined the shortest queue; this led to a distribution of customers that was fairly balanced among the queues during the experiment. Hence, we assumed that adding jockeying would not make a large change to the balance of load among the queues.[1] The simulator was initialized with customers already present in the queue to make sure that the subjects could immediately start working and that the system would achieve steady state relatively quickly. In the single-queue setting: one customer at each server and eight customers in the shared queue (for a total of 12 customers: 8 waiting and 4 in service); in the parallel-queues setting: one customer at each server and three customers in each queue (for a total of 16 customers: 12 waiting and 4 in service). To calibrate the parameters (arrival rate, service time of computerized servers, and initial queue length parameters), we simulated our experiment with different values and assessed the evolution of average queue length and average utilization in the system during the ten-minute experimental round. We then chose values for which each system could achieve the steady state within the allocated time for a variety of potential participants' service times (as evidenced by the plots in Figure 4) and for which the two queue structures had similar utilization (as evidenced by the plots of the average server's utilization in Figure 12 in the Appendix).

[1] We demonstrate this in Figure 13 in the Appendix, which shows the distribution of queue length assuming jockeying next to the distribution of queue length assuming that customers join the shortest queue, as implemented in our study.

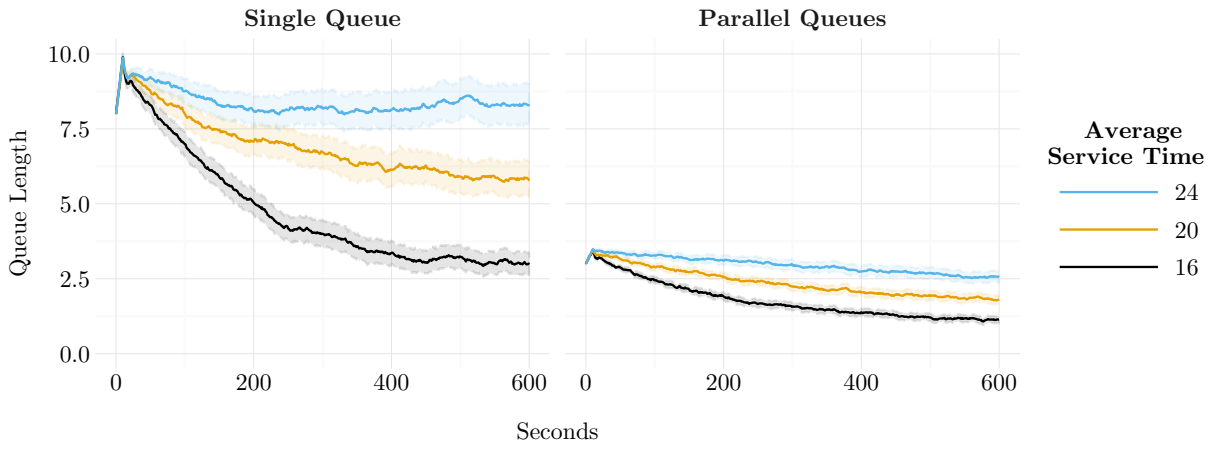


Figure 4: Average queue length during the ten-minute service interval. *Notes*: Queue length averaged across 500 simulations of a ten-minute interval. Service times of the three computer servers are fixed at ten plus an exponential random variable with a mean of ten. The *Average Service Time* of the fourth server is varied, assuming the same additive structure, to investigate the possible effect of the behavioral server with different service time on the queue length. For example, the service time of 16 in this figure corresponds to ten plus an exponential random variable with a mean of six. Customers arrived according to an exponential random variable with a mean of 5.5. *Single queue* was initialized with one customer at each server and eight customers in the pooled queue. The queue-length variable for the single queue measures the average number of customers in the pooled queue. *Parallel queues* was initialized with one customer at each server and three customers in each queue. The queue-length variable for the parallel queues measures the average number of customers in the line in front of the simulated behavioral agent.

3.1 Subject pools

We conducted our experiments on two populations. For the first population, we conducted our experiment in the behavioral lab at a large private university in the Northeastern United States. For the second population, we ran the experiment online, using Amazon Mechanical Turk, henceforth referred to as *M-Turk*. M-Turk is well supported as a subject pool in social-science experiments, particularly for tasks with limited expertise requirements (Berinsky et al., 2012; Buhrmester et al., 2011; Rand, 2012; Goodman et al., 2012; Paolacci et al., 2010). For example, Paolacci et al. (2010) compare the results of M-Turk workers to those of traditional lab-recruitment subjects across several studies and show that "[w]orkers in Mechanical Turk exhibit the classic heuristics and biases and pay attention to directions at least as much as subjects from traditional sources" (p. 417), indicating that M-Turk is a comparable and reliable source of experimental subject recruitment when compared to undergraduate lab-based recruitment.

Each population has its benefit. In the lab setting, we get a relatively homogeneous population and expect less noise associated with a difference in working conditions (type of equipment, Internet connection, etc.). In the M-Turk setting, we have access to a relatively heterogeneous population that potentially has a smaller "experimenter effect" (Paolacci et al., 2010) and is known to have a lower incidence of compensatory equalization or demoralization (Horton et al., 2011). Further, the incentive of M-Turk subjects to complete the experiment, particularly for the flat-pay incentive

scheme, may be closer to the real-world workers' incentive in many practical settings. Specifically, subjects may be worried about their reputation and their ability to get future jobs because they may be affected by the low rankings received on M-Turk from the experiment requesters.

3.2 Experimental flow

The experiment proceeded in the same manner for both populations. First, all subjects were exposed to a series of instruction screens that provided a description of the experimental environment and task, as well as a visual example of the experiment (see Section 7.1 in the Appendix for a complete set of instructions). Each subject then completed a two-minute training session to become familiar with the interface and sliders. After this training, the subjects completed a ten-minute round of the experiment. At the end of the experiment, the subjects completed an exit survey from which we collected demographic information, information regarding subjects' managerial experience, and, for the M-Turk population, information on the type of input device (external mouse, touchpad, touchscreen) the subjects used to move the sliders. Finally, the subjects received payment. Each subject was allowed to participate in the experiment only once.

3.3 Incentive settings

To capture different practical settings, we ran the experiments under two different incentive settings: Flat Pay, by which all subjects received a fixed payment for completing the experiment regardless of their performance (e.g., student employees at a university athletics ticketing booth who receive a fixed hourly wage); and Per Cart, by which subjects received a small fixed pay and a bonus per each completed cart (e.g., cashiers at a retail store who have incentives based on items scanned per minute). We explained the Per Cart payment scheme to the participants in the following way:

> *You will earn \$0.25 (\$0.04 on M-Turk) for each customer that you successfully submit. Thus, if you complete ten customers, you will earn \$2.50 (\$0.40) in addition to the \$2.00 (\$0.50) participation payment.*

Then, we checked that the subjects understood the payment scheme by having them compute the payoff for a sample scenario. In the case of a wrong answer, we repeated the instructions and had them compute the payoff again until they answered correctly.

The subjects in the M-Turk population were paid \$1.25 for participation in the 30-minute experiment regardless of their performance in the Flat Pay setting, and a fixed fee of \$0.50 in the Per Cart setting plus \$0.04 per each completed cart, with an average total payoff of \$1.47.[2] The subjects in the lab population were paid \$5.00 for participation in the 30-minute experiment regardless of their performance in the Flat Pay setting, and a fixed fee of \$2.00 in the Per Cart setting plus \$0.25 per each completed cart, with an average payoff of \$9.65.

[2]This was a relatively high pay rate for M-Turk subjects (typical rates are \$0.10–0.50 per study with a typical rate of \$1.40 per hour (Horton and Chilton, 2010)).

3.4 Experimental treatments

We differentiate between two types of factors involved in our study: the main experimental factors that impacted the actual design of the system; and factors that allowed us to address various practical settings. All the factors are summarized in Table 1.

	Factor 1 **Queue Structure**	Factor 2 **Queue Visibility**	Factor 3 **Incentives**	Factor 4 **Population**
Levels	Single Queue Parallel Queues	Full Blocked	Flat Per Cart	Lab M-Turk
	Factors impacting design of the queueing system		Factors controlling for heterogeneous environments	

Table 1: Summary of Factors.

Two main experimental factors impact the design of the queueing system and directly address Hypotheses 1 and 2: **Factor 1 - Queue Structure** with two levels (Single Queue and Parallel Queues); and **Factor 2 - Queue Visibility** with two levels (Full Visibility and Blocked Visibility). The difference between these treatments in our study was reflected in the visual representation of the queueing environment in the computer-simulated store. Given the main factors outlined above, we had four different visual representations of the system. Figure 3 shows a sample screen for the Single Queue treatment with Full Visibility. Screenshots of other treatments are shown in Figure 8 in the Appendix.

In addition to the two factors that impacted the design of the queueing systems, we included two factors that helped us assess the behavioral impacts of Factors 1 and 2 in heterogeneous environments. **Factor 3 - Incentive Setting** captured two practical payment schemes that are observed in retail and service environments: the Flat Pay incentive setting covers scenarios in which employees get paid a fixed wage regardless of their performance; the Per Cart incentive setting covers scenarios in which employees get incentives based on their performance (in our implementation, subjects got a bonus per each completed cart). Finally, **Factor 4 - Subject Population** with two levels (Lab and M-Turk) allowed us to test our hypotheses on a heterogeneous population. To sum up, we had a 2x2 design of the main experimental factors within a 2x2 framework of incentive setting and population combinations, for a total of 16 experimental cells.

3.5 Participants

For the lab experiment, we recruited 248 subjects at a large public university in the Northeastern U.S.: 46.0% of the subjects were female, 53.6% male, and the rest did not disclose their gender. Their ages ranged from 19 to 49, with a mean of 21.7 and a median of 21.

For the online experiment, we recruited subjects on M-Turk from the pool of U.S.-based workers with at least 70% positive feedback and 50 successfully completed prior tasks to ensure relatively

experienced computer users. Of the 481 unique subjects who completed the experiments on M-Turk, 54.3% were female, 44.4% male, and the rest did not disclose their gender. Their ages ranged from 19 to 51, with a mean of 34.1 and a median of 33.

4 Data Description

We obtained 729 complete observations across all treatments.[3] These observations are broken down by treatments and summarized in Table 2. We checked the results for unique user identification codes (both lab and M-Turk) and unique IP addresses (M-Turk) and eliminated any duplicates. Therefore, our reported observations do not include three lab subjects and seven M-Turk subjects who completed the study twice (20 total observations).

		Lab		M-Turk		
		Blocked Visibility	Full Visibility	Blocked Visibility	Full Visibility	Total
Flat	Parallel	28	27	60	53	168
	Single	27	28	62	60	177
Per Cart	Parallel	37	32	63	59	191
	Single	37	32	65	59	193
	Total	129	119	250	231	729

Table 2: Count of observations used in analysis.

For each subject, we collected data on all completed carts during the ten-minute round. The number of carts completed ranged from 1 to 67, with an average number of 29.72 and a standard deviation of 7.79. For further analysis, we included only the subset of carts that were completed in the second half of the experiment for two main reasons: we want to focus on the period when (1) the system is in steady-state and (2) the learning effects have subsided. We confirm that the system achieves the steady-state halfway through the experiment using our simulation plots (Figure 4). To confirm that the learning effect has subsided by the second half of the experiment, we plot the average transaction time per cart over time. Since all subjects completed a different number of carts, to capture the behavior in the second half of the carts, we broke the carts completed into percentiles for each subject. We then computed the average transaction time per cart across subjects for each percentile and plotted it in Figure 5.

[3]Some M-Turk subjects started the experiment, but quit before finishing; such observations are incomplete and, hence, are not included in the total count.

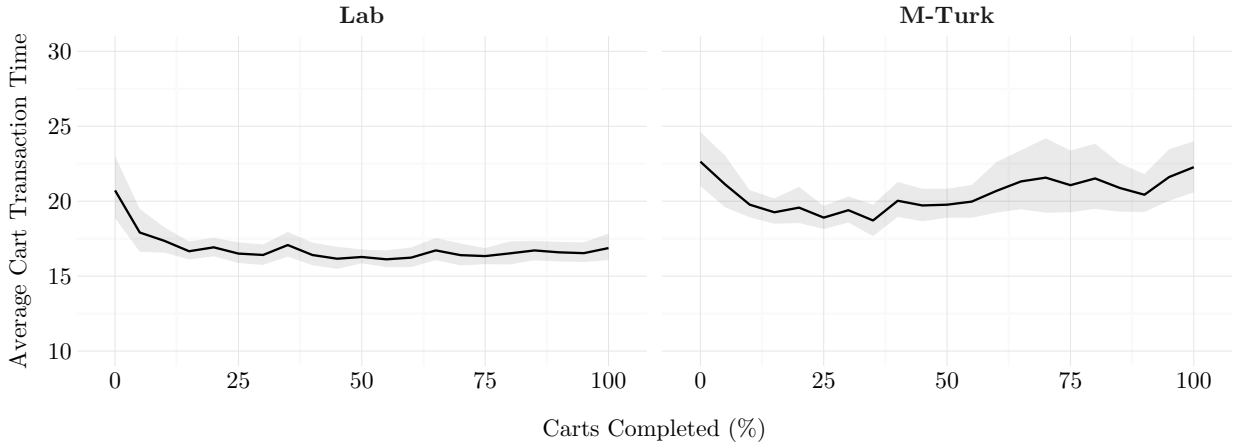


Figure 5: Analysis of Learning Effects. *Notes*: For each subject carts are sorted from 1 to the last cart completed. Then a step function is created with % on the x-axis and transaction time per cart on the y-axis. For example, if a subject completed 10 carts with transaction times of 10 for the first cart, 11 for the second carts, and so on, then the step function will have 11 from 0% to 10%, 12 from 10% to 20%, and so on. Then, we take an average over all subjects at % values of 0, 5, 10, etc. Shaded region represent bootstrapped 95% confidence bands.

As indicated by the plots in Figure 5, the main learning effect happens during the first quartile. Hence, for each user, we took the subset of carts that were completed in the second half of the experiment. The beginning of the second half of the experiment for each user was approximated by the cart number that followed the quotient of the division of the total number of completed carts by two. We then calculated the median service time and the variance of service time over the selected subset of carts for each user. In the Appendix, we also perform robustness checks by performing analysis using the average service time measure computed over the second half of carts and using median service time measure computed over all submitted carts to demonstrate that the results are robust (see Section 7.4).

Figure 6 presents the cumulative distributions of the Median Service Time aggregated by each of the four factors. There are several points worth noting. First, the distribution of the median service time under the Parallel-Queues setting is to the left of the distribution of the median service time under the Single-Queue setting, indicating that the distribution in the Parallel-Queues setting is stochastically smaller, and the subjects are working faster in the Parallel-Queues setting. This observation is consistent with our intuition about Hypothesis 1. While the ordering of distributions stays consistent over the whole domain, the size of the difference between the cumulative probability curves varies with the distribution percentile. For example, in the comparison of distributions under different queue structures, the difference between the curves at the 25^{th} percentile is smaller than the effect at the 50^{th} and 75^{th} percentiles, indicating that the effect is smaller for the faster than for the slower servers.

Second, when examining the comparison of distributions for different levels of queue visibility, we notice that while the Full Visibility curve is to the left of Blocked Visibility, the difference

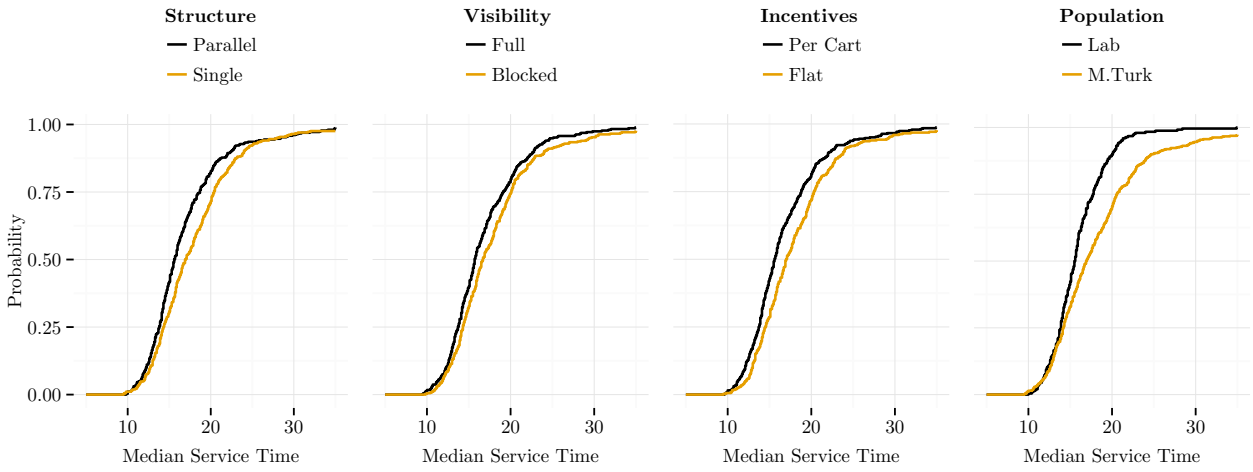


Figure 6: Cumulative Distribution Function of Median Service Time by Treatment.

between the curves is relatively small. While the direction is consistent with our intuition regarding Hypothesis 2, it is not clear whether the difference is significant. This may be due to the fact that we aggregated data across all other factors in these distribution plots. We will look at the disaggregated data below.

Third, we observe that compensating the subjects per completed cart made the subjects work faster, as evidenced by the difference between the curves for Flat Pay and Per Cart treatments. This is intuitive as subjects were trying to earn a higher payoff under the Per Cart treatment. Finally, subjects worked faster in the lab environment than on M-Turk, which is, again, intuitive, as the subjects in the lab were "working" in a minimal-distraction environment and were focused on a single task. Moreover, there may have been a more prominent "experimenter effect" in the lab environment, which could have provided an intrinsic incentive to work faster, consistent with Horton et al. (2011). Next, we present the disaggregated box plots of our data to assess potential interaction effects.

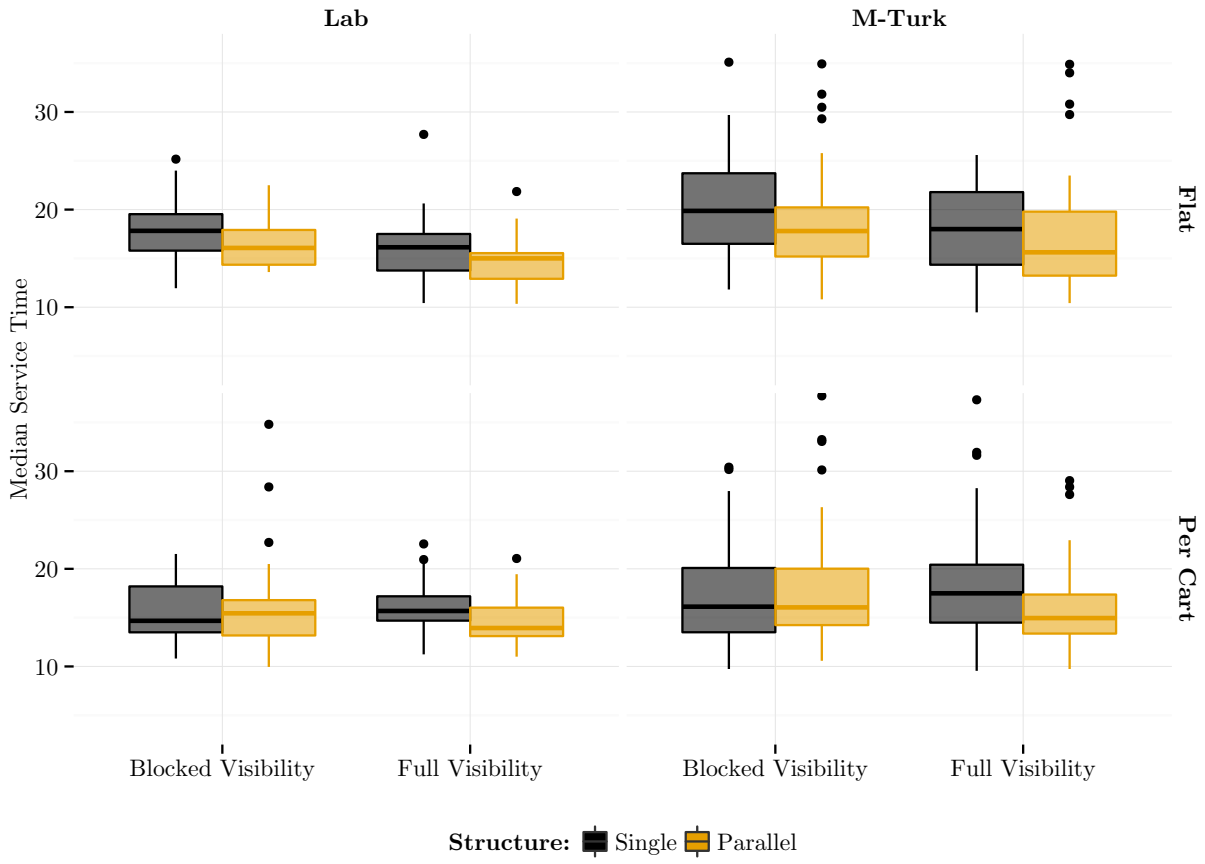


Figure 7: Box plots of Median Service Time.

Figure 7 presents box plots of median service time for all treatments.[4] In addition to the comparison insights already observed from the aggregate distribution plots, the disaggregated box plots allow us to look at potential interaction effects between different treatments. We make several observations that are not apparent from the earlier analysis:

1. There is little to no difference between Blocked and Full Visibility in the Single-Queue structure under Per Cart incentive setting. This observation is consistent with our expectation that the feedback is low in Single-Queue structures: since the feedback is already low in Single Queue, blocking visibility, which reduces the feedback from low to none, has little impact.

2. There is little to no difference between Single and Parallel Queue structures under Blocked Visibility and Per Cart incentive setting, indicating that the feedback mechanism is necessary to make a difference between the structures under the Per Cart incentive setting.

3. The median service time under the Parallel-Queues structure looks consistently lower than the median service time under the Single-Queue structure in all four cells that have Full Visibility.

[4]The dots on the box plot indicate outliers.

These observations provide us with initial intuition and direction. We now switch to a statistical analysis of our data to rigorously test our hypotheses and to quantify the results.

5 Data Analysis

We perform our analysis in several steps. First, in Section 5.1, we look for support of our hypotheses by comparing the 50^{th} percentiles of the median service time under different treatments. To capture potential interaction effects, we perform the tests separately for every combination of the other three factors. For example, to address Hypothesis 1, we perform eight comparisons for each combination of Factors 2, 3, and 4. Since distribution plots presented above (Figure 6) hint at potential differences in the comparisons of the tail behavior, we performed the same tests to compare the 25^{th} and 75^{th} percentiles of the median service time. Next, in Section 5.2, we compare the variance of service time per subject across treatments to study whether our factors had an impact on the variability of each subject's performance. In Section 5.3, we report results of our regression analysis, which combined all factors and included control variables. Finally, in Section 5.4, we present several robustness checks that confirm that our results hold in the systems with lower average load and with alternative experimental instructions.

Upon examination of Q-Q plots of our data (Figure 10 in Section 7.3 of the Appendix), we find that the disaggregated data did not satisfy the normality assumption; thus, rather than using standard analysis techniques, such as ANOVA, we performed non-parametric permutation tests (Fisher, 1935). Permutation tests are non-parametric randomization tests, in which the distribution of the test statistic is obtained through random permutation of treatment (or group) labels among observations (Phipson and Smyth, 2010; Good, 2013). Then, the $p-value$ is obtained by comparing the actual test statistic to the constructed distribution. Thus, an advantage of a permutation test is that no assumptions, beyond the assumption that observations are independent and identically distributed under the null hypothesis, are necessary (Phipson and Smyth, 2010).

In practice, when the number of observations is large, obtaining all possible permutations is not feasible. Instead, a common approach is to consider a random subset of all possible permutations (Phipson and Smyth, 2010; Ernst, 2004). We follow the common implementation and randomly draw $m = 10,000$ permutations for each test performed in this paper.

For example, consider the Blocked/M-Turk/Per Cart/Single treatment, which had 63 observations and Blocked/M-Turk/Per Cart/Parallel treatment, which had 65 observations (from Table 2). Thus, we had 63 observations labeled S and 65 labeled P, for a total of 128. We now describe the steps performed for obtaining the $p - values$.[5] Let us denote the statistic of interest for the original data as $d_{original}$ (e.g., difference of medians). Under the null hypotheses, the labels are interchangeable among subjects; therefore, in order to construct the empirical distribution of the test statistic under the null hypothesis, we first obtain 10,000 random permutations of these labels.

[5]There are two approaches for obtaining random subsets of permutations: randomly drawn without replacement and randomly drawn with replacement. For simplicity of implementation, we consider the second approach and report the conservative p-values in the paper.

Next, for each permutation, we obtain the statistic of interest, d_{permut} and find a number of permutations, b, for which the statistic of interest exceeds or is equal to $d_{original}$. Finally, we obtain the $p - value$ as $p = \frac{b+1}{m+1}$ (Phipson and Smyth, 2010; Ernst, 2004).

5.1 Analysis of Median Service Time

We compared the 25^{th}, 50^{th}, and 75^{th} percentiles of the median service time between treatments to find statistical support for our hypotheses. In Table 3, for each of the 16 treatment cells, we report the 50^{th} percentile of the Median Service Time with bootstrapped standard error in parentheses. We performed non-parametric permutation tests to check for the differences in 50^{th} percentiles between treatments, as described above, and reported the direction and its significance.

		Lab			M-Turk		
		Blocked Visibility		Full Visibility	Blocked Visibility		Full Visibility
Flat	Parallel	16.07 (0.93)	$>$ **	15 (0.52)	17.8 (0.64)	$>$ **	15.63 (0.75)
		$\wedge$ *		$\wedge$ **	$\wedge$ **		$\wedge$ **
	Single	17.82 (0.86)	$>$ **	16.14 (0.66)	19.87 (0.85)	$>$ *	18 (0.97)
Per Cart	Parallel	15.44 (0.48)	$>$ *	13.94 (0.58)	16.05 (0.53)	$>$ *	14.96 (0.5)
		$\vee$		$\wedge$***	$\wedge$		$\wedge$***
	Single	14.68 (0.65)	$<$ *	15.68 (0.35)	16.12 (0.92)	$<$	17.49 (1.03)

Table 3: 50^{th} percentiles of Median Service Times with bootstrapped standard errors in parentheses and comparisons between treatments. *Notes*: *** indicates significance at 1% level, ** – 5% level, * – 10% level.

Regarding queue structure, we find strong support for Hypothesis 1 in the Flat Pay incentive setting: we observe statistically significant lower service time (indicating better performance) in the Parallel-Queues than in the Single-Queue structure for both queue length visibility levels and both populations. In the Per Cart setting, interestingly, we observe a different behavior: the difference in service time between Parallel-Queues and Single-Queue structures is significant under Full Visibility, but not significant under Blocked Visibility. This observation indicates the difference in drivers behind observed reduction of effort: in Flat Pay, the reduction of effort is caused by the task interdependence mechanism, while in the Per Cart setting, the reduction of effort is caused by the lack of feedback.

Regarding queue visibility, we find strong support for Hypothesis 2, again in the Flat incentive setting: we observe statistically significant higher service time (indicating worse performance) in the Blocked Visibility than in the Full Visibility setting for both queue structure levels and both populations. In Single Queue, poor feedback exacerbated the already low feedback, but we also find that Parallel-Queues performance declined as the feedback decreased. Thus, we can conclude that poor visibility reduced the effort level in the Flat Pay treatment.

The impact of visibility manipulation in the Per Cart incentive setting with Single Queue deserves special attention: we observe that, in the lab population, the effect of visibility went in the opposite direction than predicted by Hypothesis 2. That is, Blocked Visibility *sped up* the servers. This may be explained as follows: in the presence of per cart incentives, the subjects tried to complete as many carts as possible. Without knowledge of how many potential customers were present, the subjects tried to work as fast as possible to "steal" as many customers as possible from the other servers, consistent with Gilbert and Weng (1998).

Next, we performed a similar analysis for 25^{th} and 75^{th} percentiles of the median service time distribution to assess whether our observations hold for slower and faster subjects. The results are presented in Table 4.

(a) 25^{th} percentile of the Median Service Times by Treatment (Fast servers)

		Lab			M-Turk		
		Blocked Visibility		Full Visibility	Blocked Visibility		Full Visibility
Flat	Parallel	14.35 (0.37)	$>^{***}$	12.91 (0.71)	15.19 (0.69)	$>^{**}$	13.23 (0.48)
		$\wedge^{**}$		$\wedge$	$\wedge^{*}$		$\wedge^{*}$
	Single	15.8 (0.52)	$>^{*}$	13.76 (0.92)	16.49 (0.64)	$>^{**}$	14.35 (0.84)
Per Cart	Parallel	13.18 (0.82)	$>$	13.11 (0.44)	14.24 (0.54)	$>$	13.37 (0.42)
		$\wedge$		$\wedge^{***}$	$\vee$		$\wedge^{**}$
	Single	13.5 (0.35)	$<^{**}$	14.69 (0.53)	13.5 (0.5)	$<^{*}$	14.49 (0.46)

(b) 75^{th} percentile of the Median Service Times by Treatment (Slow servers)

		Lab			M-Turk		
		Blocked Visibility		Full Visibility	Blocked Visibility		Full Visibility
Flat	Parallel	17.92 (0.66)	$>^{**}$	15.54 (0.42)	20.22 (0.84)	$>$	19.79 (1.2)
		$\wedge^{*}$		$\wedge^{**}$	$\wedge^{**}$		$\wedge$
	Single	19.53 (0.66)	$>^{*}$	17.5 (1.07)	23.72 (1.59)	$>^{**}$	21.79 (0.8)
Per Cart	Parallel	16.79 (0.8)	$>$	16.02 (0.83)	20.02 (1.23)	$>^{**}$	17.37 (0.82)
		$\wedge$		$\wedge$	$\wedge$		$\wedge^{**}$
	Single	18.2 (0.98)	$>$	17.19 (0.81)	20.09 (0.93)	$<$	20.42 (1.14)

Table 4: 25^{th} and 75^{th} percentiles of Median Service Times with bootstrapped standard errors in parentheses and tests of differences between treatments. *Notes*: *** indicates significance at 1% level, ** – 5% level, * – 10% level.

In the Flat Pay incentive setting, we observe similar results across all percentiles: subjects' median service times were lower under the Parallel-Queues structure and higher under Blocked Visibility. In the Per Cart incentive setting, the difference between queue structures was significant only under Full Visibility, which is consistent with the earlier observation about the 50^{th} percentile. Finally, we note that in the Per Cart incentive setting, queue visibility had weaker (or no) effect for

some combinations, and, moreover, the result in the Single-Queue setting where Blocked Visibility sped up the servers is not observed for slow servers (75^{th} percentile). One potential explanation for this change at the sub-group level may be that the "slow workers" did not have many motivated people. Understanding the individual factors that led to this difference in behavior between sub-groups requires future research.

5.2 Analysis of Variance of Service Time per Subject

In addition to studying the difference in median service times, we analyzed the difference in variance of service times per subject. As the queue design and/or incentive setting changed in the queueing system, we observed the changes in medians as indicated in Section 5.1; however, if such manipulations increased variability of service time, this increase may have negated (or even counterweighted) the benefit obtained by the decrease in median service time, making the system performance worse. Hence, we want to understand the changes in variance. Similar to the approach used for the median service times comparisons, we performed the non-parametric permutation tests to compare the means of variance of service time under different treatments, and we report the test results in Table 5.

		Lab			M-Turk		
		Blocked Visibility		Full Visibility	Blocked Visibility		Full Visibility
Flat	Parallel	10.9 (1.8)	$>$	9.1 (1.9)	601.6 (358.7)	$>$	234.5 (115.5)
		$\wedge$		$\wedge$	$\wedge$		$\wedge$
	Single	25.6 (15.5)	$>$	21.6 (11.4)	632.3 (365.2)	$>$	268.4 (161.3)
Per Cart	Parallel	24.4 (12.8)	$>$	21 (14.4)	67.9 (41.3)	$<$	72.1 (44.2)
		$\vee$		$\vee$	$\wedge$		$\vee$
	Single	9 (1.3)	$<$	16.5 (5.8)	73.3 (43.9)	$>$	62.6 (31.1)

Table 5: Means of Variance of Service Time with standard errors in parentheses and tests of differences between treatments. *Notes*: *** indicates significance at 1% level, ** – 5% level, * – 10% level.

First, we note that the variances were higher in the M-Turk population than in the Lab: This is intuitive, as the subjects were more focused on their task in the Lab environment and had potentially fewer distractions than in the M-Turk environment. We also observe that for all treatments within either population, there were no notable differences between the variances under different treatments, indicating that while changes to the queueing design shifted the distribution of service time, as evidenced in Section 5.1, they did not affect the variability of service time.

5.3 Regression Analysis

Finally, we performed regression analysis to capture the joint impact of queue structure, queue visibility, and incentive setting on the median service time, and to control for other factors that

could potentially have impacted our results. Since control variables and the variances were different in the Lab and M-Turk populations, we performed the regression separately for each population. We define the variables used in specifying the regression models in Table 6.

Variable Name	Definition
i	Subject ID;
$\mathbf{P}arallel_i \in \{0,1\}$	1 indicates a Parallel Queues treatment for Subject i;
$\mathbf{B}locked_i \in \{0,1\}$	1 indicates a Blocked Visibility treatment for Subject i;
$\mathbf{I}ncentivized_i \in \{0,1\}$	1 indicates a Per Cart incentive treatment for Subject i;
$\boldsymbol{X_i}$	a vector of interactions for Subject i;
$\boldsymbol{C_i^j}$	a vector of all control variables for Subject i in Population j, $j \in \{M, L\}$;
MST_i	median service time for Subject i.

Table 6: Variable definitions for the regression analysis.

We now specify the model with all interaction effects ($\boldsymbol{\beta^{jI}}$ is a vector of coefficients associated with interaction effects for population $j \in \{L, M\}$ indicating Lab or M-Turk, and $\boldsymbol{X}$ contains interaction terms) and control variables ($\boldsymbol{\beta^{jC}}$ is a vector of coefficients associated with control effects for population $j \in \{L, M\}$ and $\boldsymbol{C}^j$ contains all control variables) for the following regression analysis. $\boldsymbol{C}^L$ consists of gender (binary indicator with 1 representing male subjects), age (binary indicator with 1 representing subjects born after 1990), and managerial experience (binary indicator with 1 representing having managerial experience). In the M-Turk population, there was heterogeneity in the devices used to complete the experiment. Thus, in addition to the controls in $\boldsymbol{C}^L$, we controlled for the device type, distinguishing among external mouse, touchpad, and touchscreen. We excluded seven subjects who did not provide answers to all the questions that addressed our control variables.

For each population $j \in \{L, M\}$, the regression model was:

$$MST_i = \beta_0^j + \beta_1^j Parallel_i + \beta_2^j Blocked_i + \beta_3^j Incentivized_i + \boldsymbol{\beta^{jI} X} + \boldsymbol{\beta^{jC} C^j} + \epsilon_i. \tag{1}$$

As evidenced by the box plots of our data (Figure 7), there were multiple outliers, which skewed the distribution and violated the assumption of normality. Therefore, we used the robust regression approach and found MM-estimators using the *robustbase* package in R. This robust regression approach finds estimators that minimize the influence function, which captures the joint impact of residuals (see Yohai (1987) for details). We summarize regression results for the model in Equation 1 in Table 7: in the reported model, we include only the significant interaction term. Results of the full model containing all potential interaction effects are presented in the Appendix in Table 12.

	Lab					M-Turk				
	Estimate	Std. Error	t val.	p val.		Estimate	Std. Error	t val.	p val.	
P*arallel*	-0.939	0.344	-2.732	0.007	***	-1.53	0.371	-4.126	0	***
B*locked*	1.564	0.465	3.366	0.001	***	1.695	0.549	3.085	0.002	***
I*ncentivized*	0.062	0.465	0.134	0.894		-0.68	0.497	-1.368	0.172	
B×I	-1.471	0.665	-2.213	0.028	**	-1.326	0.733	-1.809	0.071	*
Born≥1990	-1.362	0.443	-3.075	0.002	***	-2.156	0.437	-4.937	0	***
Male	-1.179	0.347	-3.398	0.001	***	-1.707	0.374	-4.56	0	***
Managerial	0.372	0.443	0.838	0.403		0.512	0.406	1.26	0.208	
TouchPad						1.746	0.388	4.5	0	***
TouchScreen						2.121	1.073	1.976	0.049	**
Constant				17.347		Constant			17.883	
DF				238		DF			465	
Res.S.E.				2.525		Res.S.E.			3.839	
Adj.R^2				0.135		Adj.R^2			0.201	

Table 7: Robust regression results with significant interaction term. *Notes*: *** indicates significance at 1% level, ** – 5% level, * – 10% level.

Both models are significant and explain approximately 14 percent and 20 percent of the variation in median service time, in Lab and M-Turk populations, respectively. The results support our observations obtained in Section 5.1: for example, relative to the base setting of Single Queue, Full Visibility with Flat Pay incentive setting, we observe a statistically significant service time decrease (corresponding to a better performance) due to Parallel-Queues structure and service time increase (corresponding to a worse performance) due to Blocked Visibility. Moreover, we observe a significant interaction effect between incentives and visibility, which is consistent with our observations based on the box plot in Figure 7 and the results in Table 3. In addition, we observe that several control variables played an important role in determining the service time in the experiment: for example, younger subjects and male subjects worked faster, and subjects working with a touchpad or touchscreen instead of an external mouse worked more slowly.

5.4 Robustness Checks

5.4.1 Low Load

Recent research demonstrates that service time is impacted by the load (or the queue length) of the system (e.g., Delasay et al. (2015)). Within the scope of our research questions, it is interesting to see whether the effect of behavioral factors was impacted by the load and whether our results still hold if the server had plenty of idle time and, hence, frequently stopped/resumed and observed the system empty. To test for this, we ran additional experiments with a lower average arrival rate, which resulted in a lower average queue length and lower utilization for workers (see Figure 12 in the Appendix).

We again recruited subjects on M-Turk from the pool of U.S.-based workers with at least

70% positive feedback and 50 successfully completed prior tasks to ensure relatively experienced computer users. From the total of 487 unique subjects who completed the experiments on M-Turk, 48.3% were male, 51.7% were female, and the rest did not disclose their gender. Their ages ranged from 19 to 51, with a mean of 33.3 and a median of 31. We report the results of the median service time comparisons using permutation tests in Table 8.

(a) Number of Observations

		Blocked Visibility	Full Visibility
Flat	Parallel	59	60
	Single	64	63
Per Cart	Parallel	57	62
	Single	63	59

(b) 50^{th} % of the Median Service Time

		Blocked Visibility		Full Visibility
Flat	Parallel	17.86 (0.66)	$>$ *	16.43 (0.73)
		$\wedge$ *		$\wedge$ *
	Single	18.98 (0.74)	$>$	17.98 (1.15)
Per Cart	Parallel	16.79 (0.72)	$>$ **	14.86 (0.64)
		$\vee$		$\wedge$ *
	Single	15.9 (0.54)	$<$	16.14 (0.65)

(c) 25^{th}% of the Median Service Time

		Blocked Visibility		Full Visibility
Flat	Parallel	15.06 (0.8)	$>$ *	13.63 (0.7)
		$\wedge$		$\wedge$ *
	Single	15.52 (0.68)	$>$	14.92 (0.92)
Per Cart	Parallel	13.73 (0.84)	$>$ *	12.88 (0.35)
		$\wedge$		$\wedge$
	Single	13.82 (0.59)	$>$	13.06 (0.55)

(d) 75^{th} % of the Median Service Time

		Blocked Visibility		Full Visibility
Flat	Parallel	20.08 (0.98)	$<$	20.68 (0.99)
		$\wedge$ *		$\wedge$ *
	Single	22.39 (1.14)	$<$	22.82 (1.41)
Per Cart	Parallel	18.62 (0.9)	$>$	17.7 (0.88)
		$\vee$		$\wedge$
	Single	18.61 (0.62)	$<$	18.79 (0.96)

Table 8: Performance measures for the experiments with low arrival rate. *Notes*: *** indicates significance at 1% level, ** – 5% level, * – 10% level.

Low load reduced the impact of the queue design variables that we studied. Under low load, the utilization was lower (about 80%; see Figure 12 in the Appendix for details), indicating that the subjects observed the system with no customers in the queue more frequently than in the high load setting. When the subjects observed other servers being idle, they knew that there were no customers waiting in the system regardless of the visibility setting. Hence, we expected the effect of visibility to become less pronounced in a low load setting. Similarly, we expected the effect of queue structure to be lower under low load since the two systems appeared similar to the subjects when the waiting area was empty (which happened more frequently under the low load). Indeed, we observe that the effect was less pronounced under low load; however, the effects of speed-up due to Parallel Queues and slowdown due to Blocked Visibility are still present and are consistent with the results under high load.

5.4.2 Computerized Servers Emphasized

In this section, we describe a robustness check in which we emphasized to the subjects that the computerized servers were programmed to not react to the subjects' behavior. In particular, we explained to the subjects:

> *On average, every computerized server spends 20 seconds per customer; however, exact times spent on different customers may vary. The service pace is steady, i.e. the servers do not slowdown or speed-up during the course of the experiment. Service times were pre-programmed ahead of time and cannot be affected by any actions taken during the experiment.*

We checked the subjects' understanding by asking them about the average service time of the other workers, to which 95.6% of the subjects responded correctly. We performed this robustness check on M-Turk with a Flat Pay incentive setting and with High Load, making the outcome comparable to the results in the top-right cell of Tables 3 and 4. We recruited 200 subjects and obtained 195 complete observations.

(a) Number of Observations

	Original	Robustness Check
Parallel	53	99
Single	60	96

(b) 50^{th} % of the Median Service Time

Original		Robustness Check
15.63 (0.78)	>	15.15 (0.37)
∧ **		∧ **
18 (0.88)	>	16.78 (0.95)

(c) CDF of the Median Service Time for the Robustness Check.

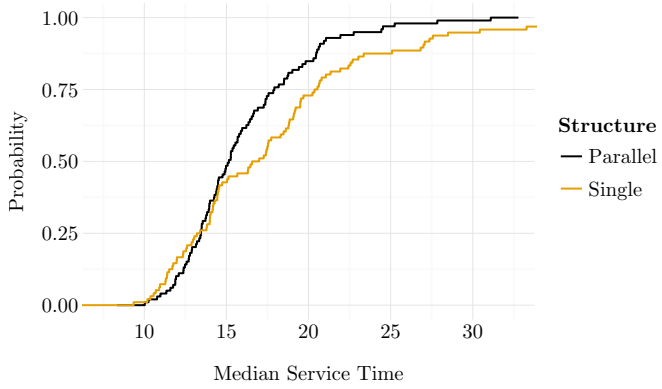


Table 9: Emphasizing details about computerized servers. *Notes*: Data collected on M-Turk under the Full Visibility setting. Bootstrapped standard errors are in parentheses. Tests are carried out using non-parametric permutation approach as in Section 5.1. *** indicates significance at 1% level, ** – 5% level, * – 10% level.

We find that, first, the service times did not change after the change in instructions and, second, consistent with our earlier results, servers sped up in the Parallel-Queues structure relative to the Single-Queue structure (Table 9). Thus, our results are shown to be robust.

6 Conclusion

The results of our study indicate that the physical layout of the service environment can influence worker effort and, hence, the system's overall performance. Specifically, we show that the median service time is higher in single-queue structures than in parallel-queues. From a managerial standpoint, when choosing to transition to single-queue structures, one has to be aware of the potential slowdown of servers; otherwise, the managers can overestimate the increase in performance after the move and fail to meet service goals.

We show that the behavioral mechanism that causes this slowdown depends on the payment scheme. In queueing systems in which servers are compensated regardless of their performance (flat pay incentive setting), the slowdown of servers is driven by task interdependence. In practice, this implies that in order to prevent (or mitigate) this slowdown, the managers have to focus on decreasing the task interdependence or decreasing effort dispensability. In queueing systems in which servers are compensated for performance (per cart incentive setting), the slowdown is driven by the feedback availability. Thus, to mitigate the slowdown, the managers have to focus on increasing feedback (for example, by providing real-time information about the queue to the servers or explicitly monitoring individual performances).

Within each structure, queue visibility plays an important role: in most settings, blocked visibility increases service time (decreasing performance); hence, managers of such systems may want to manipulate feedback to improve performance. Improvement of feedback can come from adjusting the physical layout of the queue to reduce visibility barriers (e.g., lowering the height of display cases) or adding visibility enhancements (e.g., mirrors or video displays of the line or electronic displays of customer movement within the store). However, when servers are compensated for performance (per cart incentive setting) in the single-queue structure, blocking visibility may lead to improved performance.

Across the literature on worker behavior and queueing theory, we have explored the separate effects of feedback and task interdependence as drivers of performance for parallel and single queues. These findings add to the body of work on the impact of the work environment on employees' behavior. More specifically, within the queueing theory literature, we consider non-discretionary tasks across environmental factors. To isolate feedback and interdependence as the variables of interest, we have controlled for many additional factors, including group size, interpersonal dynamics, cart complexities, and relative speed of co-workers. Incorporating these real-world complexities into the future research would further enrich the understanding of how output and performance are driven by the physical and personal design of work teams.

Finally, the impact of worker slowdown on customer satisfaction requires further analysis. Overall, the slower worker speed under single queues or low visibility may result in lower customer satisfaction, but not necessarily. In settings in which customers are not concerned about speed, but, rather, prefer a slower and more-personalized service, the result of server slowdown may lead to an increase in customer satisfaction. This area of research, as proposed by Bendoly et al. (2010), requires further investigation. Another important consideration in selecting the queue structure

is fairness as perceived by customers: social justice would favor single-queue systems due to the first-come-first-serve order of serving customers. Exploring customer perceptions regarding queue structure and corresponding changes in service time also requires further study.

References

Alnuaimi, O. A., L. P. Robert, L. M. Maruping. 2010. Team size, dispersion, and social loafing in technology-supported teams: A perspective on the theory of moral disengagement. *Journal of Management Information Systems* **27**(1) 203–230.

Anand, K. S., M Fazıl Paç, S. Veeraraghavan, et al. 2011. Quality–speed conundrum: Tradeoffs in customer-intensive services. *Management Science* **57**(1) 40–56.

Bandiera, O., I. Barankay, I. Rasul. 2010. Social incentives in the workplace. *The Review of Economic Studies* **77**(2) 417–458.

Bendoly, E., R. Croson, P. Goncalves, K. L Schutlz. 2010. Bodies of knowledge for research in behavioral operations. *Production and Operations Management* **19**(4) 434–452.

Berinsky, A. J., G. A. Huber, G. S. Lenz. 2012. Evaluating online labor markets for experimental research: Amazon.com's Mechanical Turk. *Political Analysis* **20**(3) 351–368.

Buhrmester, M, T. Kwang, S. D. Gosling. 2011. Amazon's Mechanical Turk: A new source of inexpensive, yet high-quality, data? *Perspectives on Psychological Science* **6**(3) 3–5.

Cachon, G., F. Zhang. 2007. Obtaining fast service in a queueing system via performance-based allocation of demand. *Management Science* **53**(3) 408–420.

Debo, L., B. Toktay, L. N. Van Wassenhove. 2008. Queueing for expert services. *Management Science* **54**(8) 1497–1512.

Delasay, M., A. Ingolfsson, B. Kolfal, K. Schultz. 2015. Load effect on service times. Working Paper.

Donovan, J. J. 2001. Work motivation. N. Anderson, D. S. Ones, H. K. Sinangil, C. Viswesvaran, eds., *Handbook of Industrial work and Organizational Psychology*, vol. 2. Sage, London, 53–76.

Erez, M. 1977. Feedback: A necessary condition for the goal setting-performance relationship. *Journal of Applied Psychology* **62**(5) 624.

Ernst, M. D. 2004. Permutation methods: a basis for exact inference. *Statistical Science* **19**(4) 676–685.

Fantasia, R. 2009. Move up to the head of the line: Hannaford market tests managing cart traffic at the register. TimesUnion.com. 1 August, 2009.

Fisher, R.A. 1935. *The Design of Experiments*. 3rd ed. Oliver & Boyd, London.

Gilbert, S. M., Z. K. Weng. 1998. Incentive effects favor nonconsolidating queues in a service system: The principal–agent perspective. *Management Science* **44**(12) 1662–1669.

Gill, D., V. L. Prowse. 2011. A novel computerized real effort task based on sliders. Working Paper, Econstor.

Good, P. 2013. *Permutation tests: a practical guide to resampling methods for testing hypotheses*. Springer Science & Business Media.

Goodman, J. K., C. E. Cryder, A. Cheema. 2012. Data collection in a flat world: The strengths and weaknesses of Mechanical-Turk samples. *Journal of Behavioral Decision Making* **26** 213–224.

Hasija, S., E. Pinker, R. A. Shumsky. 2010. Work expands to fill the time available: Capacity estimation and staffing under Parkinson's law. *Manufacturing & Service Operations Management* **12**(1) 1–18.

Hauss, D. 2008. Queue science helps retailers recover revenue at checkout. RetailTouchpoints.com. 8 August, 2008.

Helms, M. 2011. Minneapolis Target store's new checkout system 'test' raises customer hackles – and questions. MinnPost.com. 22 November 2011.

Hopp, W. J., S. Iravani, F. Liu. 2009. Managing white-collar work: An operations-oriented survey. *Production and Operations Management* **18**(1) 1–32.

Hopp, W. J., S. Iravani, G. Y. Yuen. 2007. Operations systems with discretionary task completion. *Management Science* **53**(1) 61–77.

Horton, J., L. Chilton. 2010. The labor economics of paid crowdsourcing. *Proceedings of the 11th ACM Conference on Electronic Commerce*. EC '10, ACM, New York, NY, USA, 209–218.

Horton, J. J, D. G Rand, R. J Zeckhauser. 2011. The online laboratory: conducting experiments inareallabormarket. *Experimental Economics* **14**(3) 399–425.

Hossain, T., J. A List. 2012. The behavioralist visits the factory: Increasing productivity using simple framing manipulations. *Management Science* **58**(12) 2151–2167.

Jones, G. R. 1984. Task visibility, free riding, and shirking: Explaining the effect of structure and technology on employee behavior. *Academy of Management Review* **9**(4) 684–695.

Jouini, O., Y. Dallery, R. Nait-Abdallah. 2008. Analysis of the impact of team-based organizations in call center management. *Management Science* **54**(2) 400–414.

Joustra, P. E., E. Van der Sluis, N. M. Van Dijk. 2010. To pool or not to pool in hospitals: a theoretical and practical comparison for a radiotherapy outpatient department. *Annals of Operations Research* **178**(1) 77–89.

Karau, S. J., K. D. Williams. 1993. Social loafing: A meta-analytic review and theoretical integration. *Journal of Personality and Social Psychology* **65**(4) 681–706.

Kidwell, R. E., N. Bennett. 1993. Employee propensity to withhold effort: A conceptual model to intersect three avenues of research. *Academy of management review* **18**(3) 429–456.

Latham, G. P., E. A. Locke. 1991. Self-regulation through goal setting. *Organizational behavior and human decision processes* **50**(2) 212–247.

Mas, A., E. Moretti. 2009. Peers at work. *American Economic Review* **99**(1) 112–145.

Oliva, R., J. D. Sterman. 2001. Cutting corners and working overtime: Quality erosion in the service industry. *Management Science* **47**(7) 894–914.

Paolacci, G., J. Chandler, P. G. Ipeirotis. 2010. Running experiments on Amazon Mechanical Turk. *Judgment and Decision Making* **5**(5) 411–419.

Pearce, J. L., H. B. Gregersen. 1991. Task interdependence and extrarole behavior: A test of the mediating effects of felt responsibility. *Journal of Applied Psychology* **76**(6) 838.

Phipson, B., G. K. Smyth. 2010. Permutation p-values should never be zero: calculating exact p-values when permutations are randomly drawn. *Statistical applications in genetics and molecular biology* **9**(1).

Powell, S. G., K. L. Schultz. 2004. Throughput in serial lines with state-dependent behavior. *Management Science* **50**(8) 1095–1105.

Rand, D. G. 2012. The promise of Mechanical Turk: How online labor markets can help theorists run behavioral experiments. *Journal of Theoretical Biology* **299** 172 – 179.

Schultz, K. L, D. C Juran, J. W Boudreau. 1999. The effects of low inventory on the development of productivity norms. *Management Science* **45**(12) 1664–1678.

Schultz, K. L, D. C Juran, J. W Boudreau, J. O McClain, J. L Thomas. 1998. Modeling and worker motivation in JIT production systems. *Management Science* **44**(12-part-1) 1595–1607.

Schultz, K. L., J. O. McClain, J. L. Thomas. 2003. Overcoming the dark side of worker flexibility. *Journal of Operations Management* **21**(1) 81–92.

Schultz, K. L., T. Schoenherr, D. Nembhard. 2010. An example and a proposal concerning the correlation of worker processing times in parallel tasks. *Management Science* **56**(1) 176–191.

Song, H., A. Tucker, K. L. Murrell. 2015. The diseconomies of queue pooling: An empirical investigation of emergency department length of stay. *Management Science* **61**(12) 3032–3053.

Tan, F., S. Netessine. 2014. The implications of worker behavior for staffing decisions: Empirical evidence and best practices. *Cornell Hospitality Quarterly* forthcoming.

Wang, J., Y. Zhou. 2015. Social loafing and queue driven speedup: Evidence from a supermarket. Working Paper.

Wickelgren, W. A. 1977. Speed–accuracy tradeoff and information processing dynamics. *Acta Psychologica* **41** 67–85.

Williams, K., S. G Harkins, B. Latané. 1981. Identifiability as a deterrant to social loafing: Two cheering experiments. *Journal of Personality and Social Psychology* **40**(2) 303.

Williamson, O. E. 1975. Markets and hierarchies. *New York* 26–30.

Yohai, V. J. 1987. High breakdown-point and high efficiency robust estimates for regression. *The Annals of Statistics* **15**(2) 642–656.

7 Appendix

7.1 Experimental Instructions

Welcome: "Thank you for your participation today. This task should take 20 minutes. You will earn [X] for your time today. Your responses will be used to do academic research. We appreciate you taking your time and giving this your full consideration." *Subjects then create a unique user ID. Consent is confirmed.*

Next, subjects are asked to fill out a questionnaire, which includes questions about managerial experience, gender, age, marital status, children, education, time in the United States, and input device type.

Training: "You will be completing a 2 minute training period on the next screen." *Subjects are presented with the animated training screen.* "This is an individual task which will give you practice before you participate in the study task in later screens."

"You will be acting as a cashier in a grocery store. Your customers each have five items in their cart. To process a customer's order, slide each bar to match the listed price. Once all items are entered, click submit button to move to the next cart. The "Submit Cart" button will remain inactive until you correctly set all 5 prices. This training period is to ensure you can do the mechanics of the task on your machine. The screen will auto-advance after 2 minutes." *Upon completion, subjects verify that training screens loaded. If they do not, they can repeat training.*

Task Instructions: *Instructions for each treatment follow.*

Per Cart treatment: "The training period is complete. The actual task is about to begin. You will earn [rate] for each customer that you successfully submit. Thus if you complete 10 customers, you will earn [bonus] in addition to the [flat payment]. Please indicate that you read the following by correctly answering: If you complete X carts, how much will you earn as a bonus?" *Forced response.*

Flat Pay: "That completes your training on the software. You will now work a ten minute shift in the grocery store. When the shift is over you will be asked several questions about your experience. "

M-Turk: "Then you will receive a completion code to submit to M-Turk to claim payment."

Lab: "Then you will get a printed receipt for payment."

Parallel: "Reminder, the task will last 10 minutes, and when it is over you will be asked several questions about your experience. You will now be working in a group with 3 other computerized servers. As customers arrive to the checkout area, they choose the line that currently has the fewest customers and wait in that line. Each server has his or her own line."

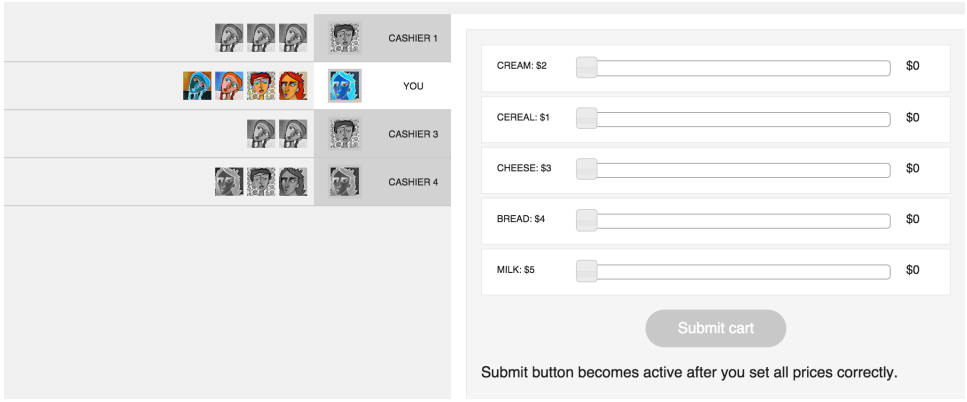
Single: "Reminder, the task will last 10 minutes, and when it is over you will be asked several questions about your experience. You will now be working in a group with 3 other computerized servers. As customers arrive to the checkout area, they join a single group line and then go to the next available server when their turn comes."

Blocked Visibility: "You can see part, but not all of the line as it wraps behind a fence."

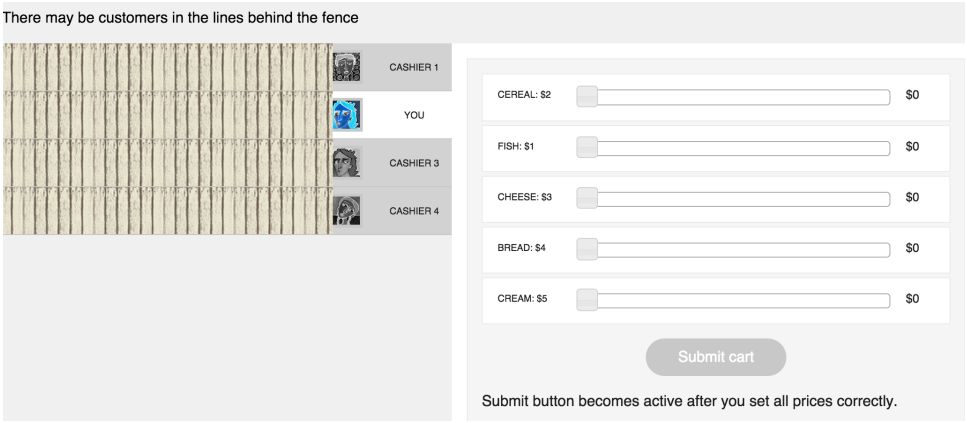
All: "You will be awarded your payment upon completion of one 10 minute shift and some short surveys. Please answer the following questions to indicate your understanding" *Subjects are presented with an animated sample screen. Next, subjects are asked questions about how the customers wait in line and number of co-workers.*

Exit Surveys: *Subjects were then assessed for questions of self-efficacy, group cohesion and perception, locus-of-control, as well as manipulation checks regarding the number of servers, the type of co-workers (human or computerized), queue structure, items per cart, and their perception of relative service time.*

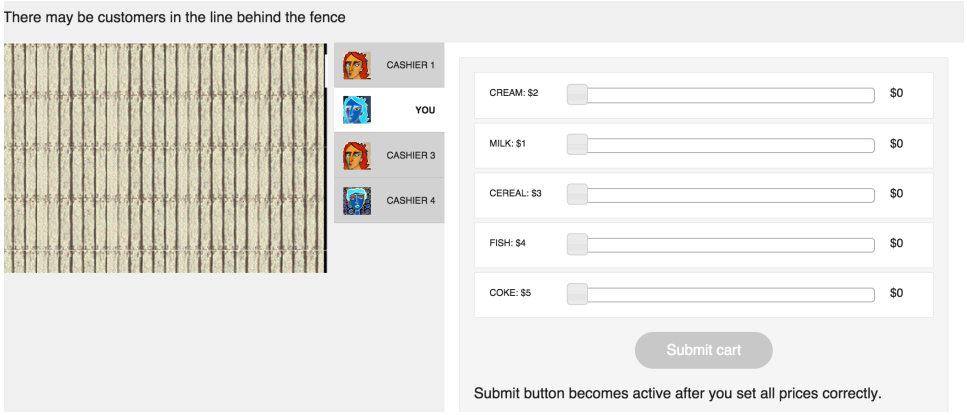
7.2 Screenshots of Different Treatments



(a) Parallel Queues, Full Visibility.



(b) Parallel Queues, Blocked Visibility.



(c) Single Queue, Blocked Visibility.

Figure 8: Screenshots of simulation in different treatments.

7.3 Supplemental Figures

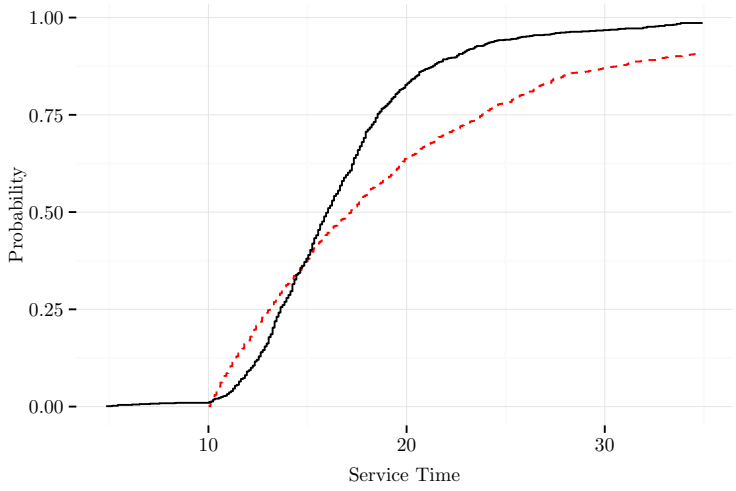


Figure 9: Empirical distribution of service times from a pilot study. *Notes*: The pilot was conducted in the lab and involved a four-server setup similar to that in the current experiment. Empirical distribution is solid black. Dashed Red is the distribution associated with a service time of ten plus an exponential random variable with a mean of ten. The red dashed line represents the distribution of service times used for the computerized servers.

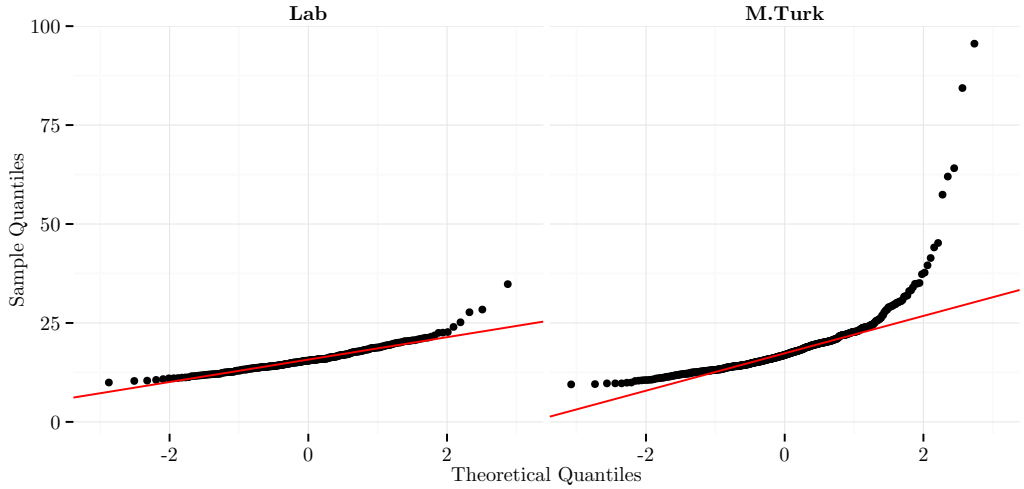


Figure 10: Q-Q Plot of Median Service Time

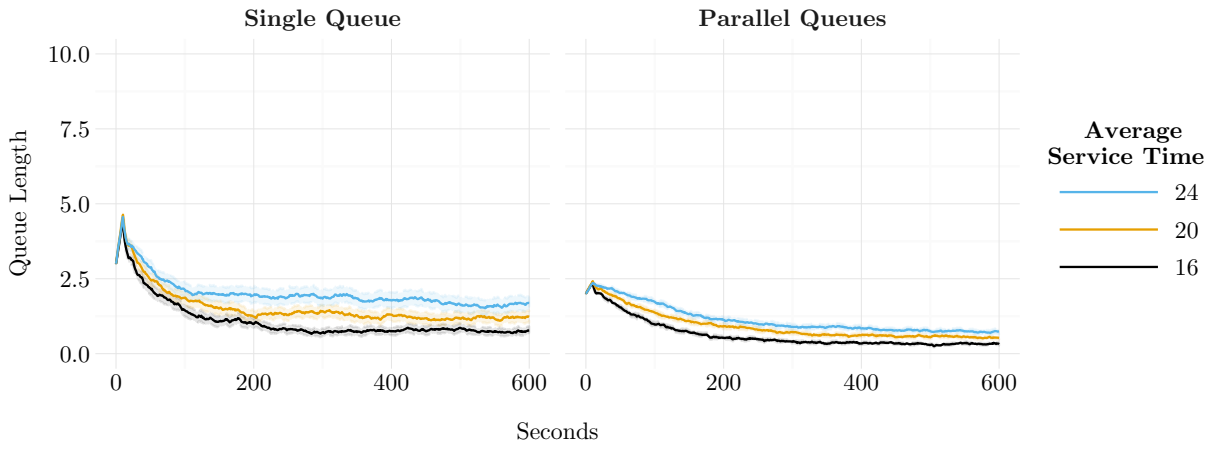
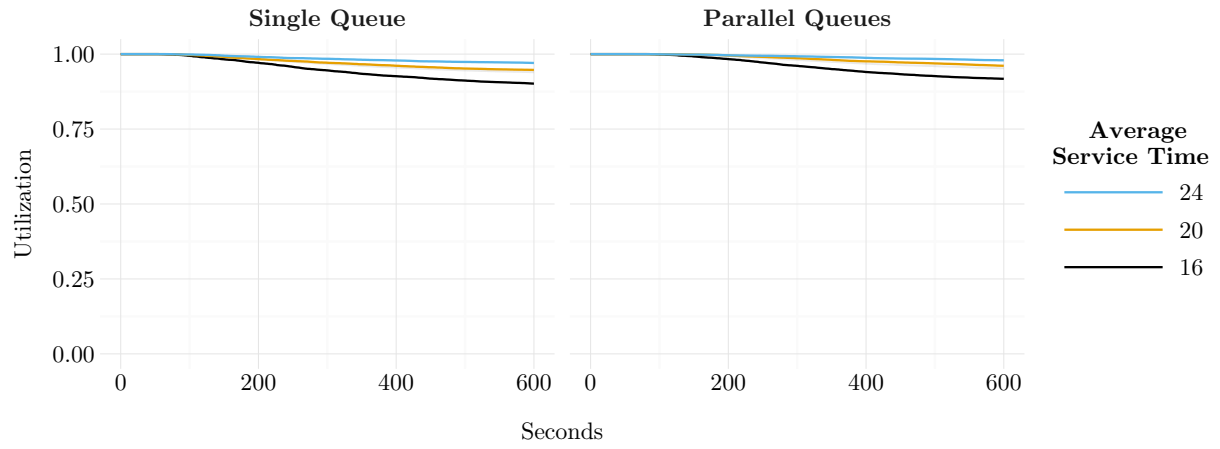
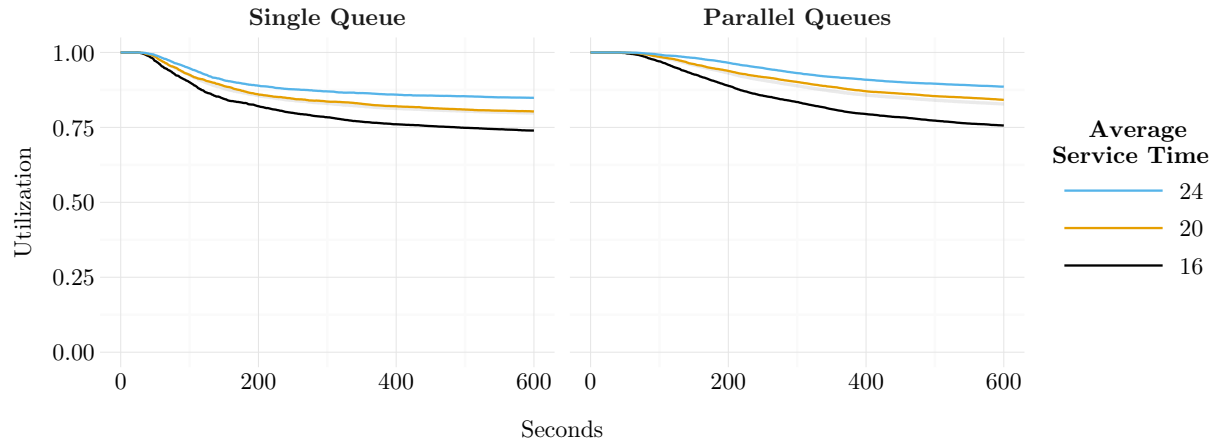


Figure 11: Average queue length during the ten-minute service interval for the low load. *Notes*: Queue length averaged across 500 simulations of a ten-minute interval. Service times of the three computer servers are fixed at ten plus an exponential random variable with a mean of ten. The *Average Service Time* of the fourth server is varied, assuming the same additive structure, to investigate the possible effect of the behavioral server with different service time on the queue length. For example, the service time of 16 in this figure corresponds to ten plus an exponential random variable with a mean of six. Customers arrived according to an exponential random variable with a mean of 6.5. *Single queue* was initialized with one customer at each server and three customers in the pooled queue. The queue-length variable for the single queue measures the average number of customers in the pooled queue. *Parallel queues* was initialized with one customer at each server and two customers in each queue. The queue-length variable for the parallel queues measures the average number of customers in the line in front of the simulated behavioral agent.



(a) High Load



(b) Low Load

Figure 12: Average server utilization during the ten-minute service interval. *Notes*: Server utilization averaged across 500 simulations of a ten-minute interval. Service times of the three computerized servers are fixed at ten plus an exponential random variable with mean of ten. The *Average Service Time* of the fourth server is varied, assuming the same additive structure, to investigate possible effect of a human server with different service times on the utilization. For example, the service time of 16 in this figure corresponds to ten plus an exponential random variable with mean of six. The Utilization variable measures the average utilization of the simulated human agent. **(a)** Customers arrive according to an exponential random variable with a mean of 5.5. *Single queue* starts with one customer at each server and eight customers in the pooled queue. *Parallel queues* start with one customer at each server and three customers in each queue. **(b)** Customers arrive according to an exponential random variable with a mean of 6.5. *Single queue* starts with one customer at each server and three customers in the pooled queue. *Parallel queues* start with one customer at each server and two customers in each queue.

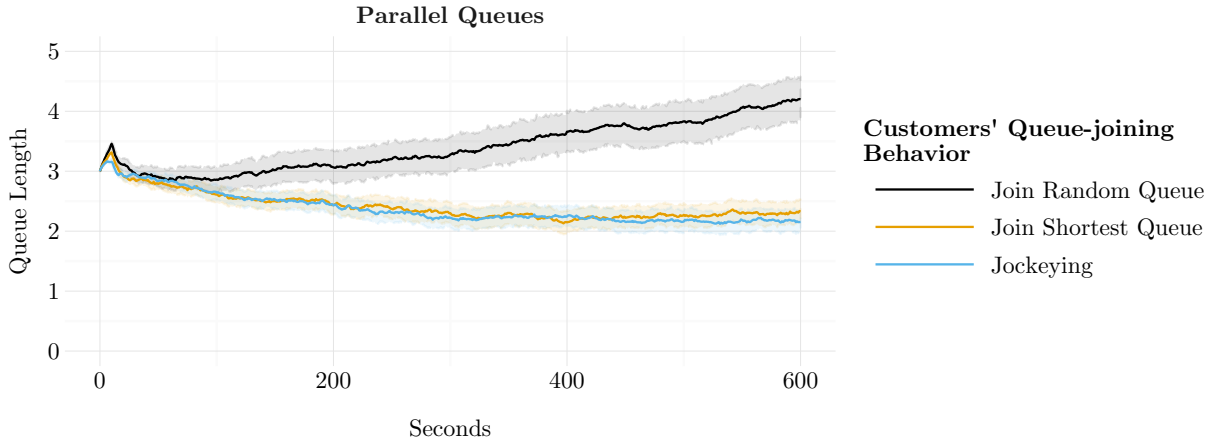


Figure 13: Average queue length depending on customers' queue-joining behavior. *Notes*: Queue length averaged across 500 simulations of a ten-minute interval for the high load setting. Service times of the three computerized servers are fixed at ten plus an exponential random variable with a mean of ten. The service time of the fourth server is also fixed, assuming the same additive structure, at ten plus an exponential random variable with a mean of six. Customers arrive according to an exponential random variable with a mean of 5.5. *Parallel queues* start with one customer at each server and three customers in each queue. The *Queue Length* variable for the parallel queues measures the average number of customers in the line in front of the simulated behavioral agent, depending on the queue-joining behavior.

7.4 Supplemental Tables

7.4.1 Robustness Check: Average Service Time

For robustness, we perform our means and 50th percentile comparison tests using Average Service Time measure:

(a) Mean of the Average Service Times by Treatment (Second Half of Carts)

		Lab			M-Turk		
		Blocked Visibility		Full Visibility	Blocked Visibility		Full Visibility
Flat	Parallel	18.59 (0.55)	>***	16.25 (0.43)	23.8 (1.81)	>	22.42 (2.71)
		∧ *		∧***	∧ **		∧
	Single	19.8 (0.76)	>	18.51 (0.91)	28.85 (2.61)	>***	24.04 (0.88)
Per Cart	Parallel	17.09 (0.86)	>	16.23 (0.94)	20.5 (0.9)	> *	18.14 (0.72)
		∧		∧ *	∧		∧ **
	Single	18.51 (1.11)	>	17.59 (0.9)	22.07 (1.49)	>	20.62 (1.45)

(b) 50^{th} % the Average Service Times by Treatment (Second Half of Carts)

		Blocked Visibility		Full Visibility	Blocked Visibility		Full Visibility
Flat	Parallel	14.95 (0.43)	>***	13.53 (0.83)	15.9 (0.77)	> *	14.58 (0.56)
		∧ *		∧	∧ **		∧ *
	Single	16.21 (0.66)	>	14.16 (1)	17.49 (1.14)	> *	16.09 (0.64)
Per Cart	Parallel	13.49 (0.84)	>	13.18 (0.42)	14.27 (0.58)	>	13.69 (0.54)
		∧		∧ **	∨		∧***
	Single	13.85 (0.34)	<	14.43 (0.47)	13.7 (0.54)	< *	15.29 (0.55)

Table 10: Differences in means and 50^{th} percentiles of Average Service Times between treatments. *Notes*: (a,b) - measures are calculated based on the second half of processed carts. *** indicates significance at 1% level, ** – 5% level, * – 10% level.

7.4.2 Robustness Check: All Carts

For robustness, we perform our robust regression analysis using all data (i.e. without excluding the first half of carts) and report the results in Table 11.

	Lab					**M-Turk**				
	Estimate	Std. Error	t val.	p val.		Estimate	Std. Error	t val.	p val.	
P*arallel*	-0.891	0.303	-2.941	0.004	***	-1.415	0.366	-3.867	0	***
B*locked*	1.463	0.42	3.48	0.001	***	1.545	0.542	2.852	0.005	***
I*ncentivized*	-0.205	0.422	-0.486	0.627		-0.635	0.511	-1.241	0.215	
B×I	-1.07	0.6	-1.783	0.076	*	-1.388	0.720	-1.928	0.054	*
Born≥1990	-1.303	0.421	-3.097	0.002	***	-1.930	0.419	-4.600	0	***
Male	-1.207	0.313	-3.855	0	***	-1.672	0.367	-4.559	0	***
Managerial	0.153	0.394	0.389	0.698		0.806	0.398	2.027	0.043	**
TouchPad						1.764	0.377	4.679	0	***
TouchScreen						3.141	1.208	2.600	0.010	***
Constant				17.537		Constant			17.74	
Robust Res.S.E.				2.294		Robust Res.S.E.			3.618	
Adj.R^2				0.1604		Adj.R^2			0.2134	

Table 11: Robust regression results based on the Median Service Time for all processed carts. *Notes*: *** indicates significance at 1% level, ** – 5% level, * – 10% level.

7.4.3 Full Regression Model

Robust regression model with all interaction terms.

	Lab					M-Turk				
	Estimate	Std. Error	t val.	p val.		Estimate	Std. Error	t val.	p val.	
P*arallel*	-1.176	0.595	-1.730	0.085	*	-2.023	0.771	-2.626	0.009	***
B*locked*	1.286	0.680	1.768	0.078	*	1.763	0.883	1.996	0.047	**
I*ncentivized*	0.276	0.727	0.387	0.699		-0.725	0.772	-0.939	0.348	
P×B	0.534	0.935	0.571	0.569		-0.083	1.100	-0.075	0.940	
P×I	-0.430	0.929	-0.463	0.644		0.116	1.004	0.116	0.908	
B×I	-1.805	0.992	-1.820	0.070	*	-2.287	1.135	-2.014	0.045	**
P×B×I	0.726	1.356	0.536	0.593		1.791	1.448	1.237	0.217	
Born≥1990	-1.407	0.432	-3.255	0.001	***	-2.113	0.437	-4.836	0.000	***
Male	-1.229	0.352	-3.494	0.001	***	-1.731	0.370	-4.679	0.000	***
Managerial	0.328	0.453	0.724	0.470		0.478	0.403	1.186	0.236	
TouchPad						1.709	0.388	4.404	0.000	***
TouchScreen						2.147	0.997	2.153	0.032	**
Constant				17.528		Constant			18.143	
DF				235		DF			462	
Res.S.E.				2.399		Res.S.E.			3.778	
Adj.R^2				0.171		Adj.R^2			0.208	

Table 12: Robust regression results with all interactions based on the Median Service Time for the second half of processed carts. *Notes*: *** indicates significance at 1% level, ** – 5% level, * – 10% level.