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Last Place Aversion in Queues

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Abstract:
This paper documents the effects of last place aversion in queues and its implications for customer experiences and behaviors, as well as for operating performance. An observational analysis of customers queuing at a grocery store, and four online field studies in which participants waited in virtual queues, revealed that waiting in last place diminishes wait satisfaction while increasing the probabilities of switching and abandoning queues, with detrimental implications for service capacity. The research suggests that last place aversion can lead to maladaptive customer behaviors – switching behaviors that increase wait times, and abandoning when the benefits of waiting are most pronounced. The results indicate that this behavior is partially explained by the inability to make a downward social comparison; namely, when no one is behind a queuing individual, that person is less certain that continuing to wait is worthwhile. Furthermore, this paper provides evidence that queue transparency is an effective service design lever that managers can use to reduce the deleterious effects of last place aversion in queues. When people can't see that they're in last place, the behavioral effects of last place aversion are nullified, and when they can see that they're not in last place, the tendency to renege is greatly diminished. Finally, a system-level experiment, in which pairs of queues were created and analyzed, reveals that when the effects of last place aversion are addressed, overall abandonment decreases, such that with equivalent arrival and service rates, total service capacity can be increased.

[Keywords: Behavioral operations, queues, reference effects, last place aversion, transparency]

1. Introduction

Queues are everywhere. We stand in them at airports, banks, coffee shops, deli counters, gas stations, grocery stores, hospitals, hotels, nightclubs, restaurants, ticket stands, and practically anywhere else that service is physically delivered. We wait in virtual queues as well – when we call customer support, hail an on-demand service, or order food online. By one estimate, Americans spend 37 billion hours waiting in queues each year (Stone 2012), which equates to roughly 118 hours for every man, woman, and child in the country. Since the practice of waiting one's turn and the discipline of first-come, first-served are social norms that are instilled in us at a very young age, we have reason to be repelled by long queues – the more people ahead of us, the longer we'll have to wait for service (Little 1961). However, the results of this paper indicate that it's not just how long the line is in front of us, but also how short the line is behind us – in particular, *whether we're in last place* – that intensifies the pain of waiting and influences our behaviors in queues, with adverse performance consequences for service operations.

Recent research has shown that people are "last place averse," altering their preferences and behaviors in order to avoid being in last place (Kuziemko et al. 2014). This tendency has been shown in laboratory experiments and in survey data, illustrating how last place aversion affects preferences over redistribution. For example, people making just above the minimum wage are the most likely to oppose increasing it, since doing so could cause them to fall into last place themselves (Kuziemko et al. 2014). In many contexts, last place is ambiguous, since it is difficult to assess where in a distribution an individual perceives herself to be, and which distribution is at the top of mind. However, every queue has an end, and with it, an identifiable individual who is in last place. Research on last place aversion in queues, therefore, holds important promise for the field of operations management. To the extent that an aversion to being in last place alters our preferences and behaviors, then the fleeting period of time that individuals spend at the end of the line might cause them to behave in ways that are myopic for themselves and counterproductive for the operation. Moreover, the observability of who is last in queues makes the last-place individual a ready target for operational interventions designed to diminish their pain of waiting, making insights on last place aversion actionable for practitioners.

This paper contributes to the operations literature by documenting the customer and system-level effects of last place aversion in queues, distinguishing it from other drivers of queuing performance. At the customer level, this paper shows that after controlling for other factors, queuing in last place can diminish wait satisfaction, while increasing the probabilities of switching and reneging – behaviors that can be maladaptive for customers in the sense that they undermine outcomes.

Individuals in last place were found to be more than twice as likely than others waiting for service to switch queues, after controlling for other factors that should rationally influence the decision to switch, such as the relative states and service rates of both queues, and in the absence of visual information that could aid them in forecasting which line might be faster. Indeed, last place participants who switched queues were found to wait longer on average than those who did not, and as a consequence reported being less satisfied with their waiting experiences. Similarly, after controlling for other factors, individuals in last place who had the most to gain from waiting were found to be more than five times more likely to abandon queues than those waiting in other parts of the line – behavior that in practice undermines customer utility and firm profits. The results provide evidence that this tendency to renege is due in part to the last place individual's inability to make a downward social comparison, raising the question, "if nobody is willing to wait longer than me, then is staying in this queue worthwhile?" Consistently, the results further show how queue transparency can be used as an effective design lever to stave off the negative effects of last place aversion in queues. For example, the results suggest that a call center that emphasizes what's taking place in front of the customer when they are in last place, and that additionally reveals the growing queue behind them when they're not, should see a reduction in defections.

Finally, the paper demonstrates that these customer-level effects have important system-level consequences. Experimentally eliminating the effects of last place aversion in the final study, by ensuring that no waiting participant ever perceives themselves to be in last place, reduces defections by 43.5%. With equivalent arrival and service rates, queues without last place aversion sustained a higher peak capacity and longer wait times, resulting in 12.5% more people being served over time. Taken together, these results reveal last place aversion to be a consequential and systematic bias that undermines the experiences and behaviors of customers, and the performance of queueing systems, which can be proactively managed through operational design.

2. The psychology of queuing and last place aversion

Although queuing is only the gateway to many service operations, it can wield considerable influence over how services are experienced, or whether they are experienced at all. Queuing imposes psychological costs on customers (Carmon, Shanthikumar, and Carmon 1995), with stress building as a marginally increasing function of the wait time (Osuna 1985). Consequently, the nature and duration of a customer's wait is an important driver of service satisfaction and loyalty (Taylor 1994; Hui and Tse 1996). Moreover, the dynamics of the queues encountered by customers influence their competing impulses to abandon or persist in the interaction, affecting customer utility and firm profitability. Experimental evidence suggests that customers often make suboptimal abandonment decisions – staying too long in queues they should have abandoned, and abandoning queues in which they should have remained (Janakiraman, Meyer, and Hoch 2011). Hence, understanding the drivers of customers' experiences and behaviors in queues is of vital significance to operations management.

A considerable stream of research on the psychology of queuing has enumerated situational and design-based factors that influence the experiences and behaviors of customers in queues, offering the promise that waiting experiences can be improved and customer abandonment can be reduced through active management (Allon and Kremer 2019; Chase and Dasu 2001; Cook et al. 2002; Norman 2009). Since people treat their time as a precious commodity (Becker 1965) and are risk averse in their decisions regarding its use (Leclerc, Schmidtt, and Dubé 1995), this research has largely focused on how to set conditions that diminish the perceived costs and maximize the perceived benefits of waiting. No prior work in this rich stream of literature has directly explored how the perceptual and behavioral implications of being last in queues may differ discontinuously from the implications of occupying other positions in the line. However, it's plausible that the costs of waiting are never higher, and the perceived benefits are never lower than when one is in last place.

From a cost perspective, the visual cue of a long line in front of the last place customer makes the costs of waiting salient, and is a particularly potent driver of abandonment (Lu, Olivares, and Schilkrut 2013). Even if the queue discipline is just, the inability of the newest arrival to know when each party in front of them arrived, and how the queue formed, may trigger concerns about the inequity of relative throughput times (Zhou and Soman 2008). Moreover, having observed and acquired the least information about the queue's dynamics, last place customers are likely to experience the most uncertainty about the wait duration, while perceiving the least evidence of their progress, amplifying anxiety and exacerbating their perceptions of the cost of waiting (Osuna 1985).

The perceived benefits of waiting may feel similarly unfavorable at the end of the line. Operational transparency, enabling customers to observe the service process, has been shown to increase customer perceptions of service value and reduce their sensitivity to waiting (Buell, Kim, and Tsay 2017; Buell and Norton 2011). Since in physical queuing environments the service process typically resides at the head of a line, it's often the case that the last place customer lacks operational transparency, undermining their perceptions of the benefits of waiting for service. Furthermore, although a long queue ahead may signal that the service is worth waiting for (Kremer and Debo 2013; Lu, Olivares, and Schilkrut 2013; Debo, Parlour, and Rajan 2012; Veeraraghavan and Debo 2009), the absence of anyone with a subordinated position in the line means there's no visible evidence that anyone's willing to wait as long as the last place customer.

Consistent with these observations, although no prior work has systematically investigated the impact of last place aversion in queues, the number of people behind in a line has been shown to influence abandonment probabilities. In a series of experiments, Zhou and Soman (2003) demonstrate that customers are sensitive to the number of people in line behind them, and that as the number of people behind increases, the affective state of the customer rises, which in turn causes them to be less likely to renege (Zhou and Soman 2003). The authors highlight downward social comparisons as an explanation for the effect, which builds on a rich stream of the social psychology literature. People compare themselves to others in social situations (Festinger 1954; Buunk and Gibbons 2007), and those experiencing negative affect can enhance their subjective wellbeing by comparing themselves to someone who is less fortunate than they are (Wills 1981). Related ideas have also been explored in the operations literature, where behind-averse and ahead-seeking behaviors have been shown to have distinct implications for how systems should be designed to optimize performance and utility (Roels and Su 2014).

To the extent that downward social comparisons improve affect and diminish abandonments, one might expect that the complete inability to make a downward social comparison may cause those in last place to feel the pain of waiting especially acutely, yielding a discontinuity that leads to behaviors that differ from others waiting near the end of the line. Prior research of customers waiting in queues suggests that such a discontinuity might exist – for example, people in last place in a line are least likely to accept a payment to allow someone to enter the line in front of them (Oberholzer-Gee 2006). The presence of such a discontinuity could be practically consequential, as a readily-identifiable last place customer could be targeted with systematic interventions to improve their experience and the performance of the service operation.

This proposition, that customer experiences and behaviors may vary discontinuously at the end of a queue, is consistent with recent behavioral economics research that shows people are last place averse. People are more likely to accept risky gambles, are less likely to exhibit generosity, and are more likely to support policies that are against their own best interests, when doing so gets them out of, or helps them avoid, being in last place (Kuziemko et al. 2014). Furthermore, the notion of last place aversion is consistent with behavioral patterns empirically observed in other non-queuing contexts. For example, emergency room doctors who receive public relative performance feedback are most likely to improve when it becomes transparent that their patients' average length of stay is at the bottom of the distribution relative to those of the patients of their colleagues (Song et al. 2015). Diners in restaurants exhibit an aversion to ordering the cheapest wine on the menu – with preferences clustering around the second cheapest option (McFadden 1999). The pain of rejection stings most when one is picked last in gym class (Weir 2012).

Likewise, it is reasonable to hypothesize that the phenomenon of last place aversion will carry over to queues, resulting in discontinuously aversive experiences for last place customers:

> *Hypothesis 1 (H1):* Relative to those who occupy other positions in the queue, individuals in last place are less satisfied with their wait after controlling for other factors that influence the experience of waiting.

If being in last place leads to waits that are acutely dissatisfying, one can further hypothesize that individuals queuing in last place will be more likely to engage in maladaptive behaviors while they wait:

Hypothesis 2 (H2): Relative to those who occupy other positions in the queue, individuals in last place are more likely to switch queues after controlling for other factors that would influence the decision to switch.

Hypothesis 3 (H3): Relative to those who occupy other positions in the queue, individuals in last place are more likely to abandon queues after controlling for other factors that would influence the decision to abandon.

To the extent that last place aversion influences the experiences and behaviors of queuing customers, diminishing their satisfaction and reducing the probability that they will remain in the queue, one can hypothesize by extension that its individual-level effects will propagate, having system-level consequences that hinder service performance:

Hypothesis 4 (H4): Last place aversion reduces the capacity of queues to serve customers.

3. Presentation of field studies

Through five field studies, conducted in physical and virtual queuing environments, this paper provides evidence of the impact of last place aversion on the experiences and behaviors of people waiting in queues, and the resulting consequences for service performance. In many contexts, 'last place' is an equivocal concept, but in queues, it is readily identifiable. A person is defined to be in last place when there is no one behind them in the queue, and the studies that follow explore the differential effects of being last, relative to other positions, on peoples' perceptions and behaviors, and on queue and service performance.

Study 1 is an observational analysis of the behavior of 284 customers awaiting service in a grocery store checkout lane. Studies 2-5 leverage an online queuing environment, which enabled the manipulation and careful instrumentation of dynamics experienced and exhibited by queuing individuals. Study 2 explores the effects of last place aversion on queuing perceptions. Study 3 investigates how last place aversion affects switching behaviors and subsequent queuing experiences. Study 4 analyzes how last place aversion in queues affects reneging behaviors, tests the moderating roles of queue transparency and discretion, and explores the perception that waiting is worthwhile as an underlying behavioral mechanism for the effects of last place aversion in queues. Study 5 explores the system-level consequences of last place aversion for queue and service performance. In the presentation of each of the studies that follow, the paper reports how sample sizes were determined, all data exclusions, all manipulations, and all measures collected (Simmons, Nelson, and Simonsohn 2012).

3.1 Study 1: Observational Analysis

As an initial test of the conjecture that last place aversion substantively affects queuing behavior, 284 customers awaiting service in a grocery store checkout lane were observed. Over a five-hour period, the study focused on a single, centrally located queue, which had adjacent lanes on either side, which for the duration of the observational period were continuously open and providing service (**Figure 1**). The sample represents all customers who joined the queue during the period of observation. Of particular interest was under which conditions would customers switch from the focal queue to a non-focal one – and in particular, whether being in last place would prove to be a significant factor.

Figure 1: Setting and queue orientation for observational analysis (Study 1).

3.1.1. Data. Data were collected on the hour, minute, and second that each customer joined the focal queue, completed the checkout process, and if applicable, switched to a non-focal queue. Using these three data points from consecutive customer observations, the state of the queue for each second of each customer's queuing experience was imputed. The resulting 24,210 customer-second level observations included the number of seconds since the customer joined the queue, a running tally of the time the clerk had spent processing the current customer, the cycle time of the last customer to be served, the number of people ahead of the customer in the queue, the number of people behind the customer in the queue, and whether the customer was in last place.

The analysis focused on behaviors during the 9,440 observations in which customers were waiting for service, but had not yet received it. On average, these waiting customers had 1.48 people in front of them in line (*SD* = 0.850) and 0.47 people behind them (*SD* = 0.850). Customers who didn't switch queues (*N* = 139) spent an average of 124.36 seconds in line (*SD* = 77.14), 53.57 seconds waiting for service (*SD* = 49.80) and 70.79 seconds being served (*SD* = 51.68). Customers who did switch queues (*N* = 71), did so after waiting an average of 26.28 seconds (*SD* = 40.83).

3.1.2. Empirical strategy. As depicted in Equation (1), switching probabilities, $\Pr\left(SWITCH_{i,t}\right)$, for customer *i* at second *t* were modeled as a function of positional and queue-related factors, using a random effects logistic regression to account for heterogeneous customer types, and with robust standard errors clustered by customer, to address serial correlation:

$$\Pr\left(SWITCH_{i,t}\right) = f\left(\begin{array}{l} LAST_{i,t} + AHEAD_{i,t} + AHEAD^2{}_{i,t} + BEHIND_{i,t} + WAIT_{i,t} + \\ WAIT^2{}_{i,t} + CURRENT_{i,t} + CURRENT^2{}_{i,t} + CYCLE_{i,t} + \epsilon_{i,t} \end{array}\right) \quad (1)$$

In the specification above, $LAST_{i,t}$ is an indicator variable denoting whether the customer was in last place. $AHEAD_{i,t}$, $AHEAD^2{}_{i,t}$, and $BEHIND_{i,t}$ are continuous variables, counting the number of customers ahead and behind the customer, respectively. $WAIT_{i,t}$ and $WAIT^2{}_{i,t}$ denote the number of seconds since the focal customer entered the queue. $CURRENT_{i,t}$ and $CURRENT^2{}_{i,t}$ represent the elapsed processing time, in seconds, for the customer currently receiving service. $CYCLE_{i,t}$ denotes the cycle time of the most recent customer to complete service. Of particular interest was whether, after controlling for other factors, customers in last place would be more likely to switch to a non-focal queue than customers waiting in other parts of the queue.

3.1.3. Analysis and results. **Table 1** reveals that the pattern of results from this observational analysis is consistent with prior theory and empirical results about customer dynamics in queues. Column 1 demonstrates that consistent with the sunk cost fallacy, the longer customers waited, the less likely they were to switch from the focal queue (β=-0.026, $P < 0.01$), though at a diminishing rate (β=0.0001, $P < 0.01$). Customers were more likely to switch queues when there were more people in front of them (β=1.107, $P < 0.05$), but at a decreasing rate (β=-0.203, $P < 0.05$). Customers appeared insensitive to current customer processing time (β=-0.008, P = NS), except in the case of unusually long duration customers (β=0.00004, $P < 0.05$). The cycle time of the queue, measured as the processing time of the most recent customer to complete service, had an insignificant effect on customer switching probabilities (β=0.001, P= NS), which may be attributable in this queuing environment to the observability and variability of the service process.

The results suggest that current customer processing time likely served as a more salient indicator for customers of how fast the line was moving at any given time.

	(1)	(2)	(3)
	Pr(Switch)	Pr(Switch)	Pr(Switch)
Last place indicator		0.499	1.369**
		(0.938)	(0.596)
Number behind customer	-1.085**	-0.712	
	(0.449)	(0.712)	
Number ahead of customer	1.107**	1.088**	1.044**
	(0.504)	(0.506)	(0.498)
Number ahead of customer^2	-0.203**	-0.199**	-0.188**
	(0.097)	(0.097)	(0.095)
Wait time	-0.026***	-0.026***	-0.027***
	(0.007)	(0.007)	(0.008)
Wait time^2	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Current processing time	-0.008	-0.008	-0.008
	(0.006)	(0.006)	(0.006)
Current processing time^2	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)
Cycle time	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)
Constant	-5.059***	-5.536***	-6.347***
	(0.607)	(1.069)	(0.859)
Observations	9,440	9,440	9,440
Number of customers	210	210	210

Table 1: Probability of switching queues increases when customers are in "last place" (Study 1). All models are estimated with random effects logistic regression and robust standard errors, clustered by customer, are shown in parentheses. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively.

Consistent with prior research (Zhou and Soman 2003), customers were less likely to switch when there were more people behind them in the queue (β=-1.085, $P < 0.05$). Column 2 reveals that adding an indicator variable for whether the customer was in last place diminishes this effect to insignificance (β=-0.712, $P = 0.317$). Crucially, and in line with the proposition that individuals exhibit last place aversion in queues, Column 3 reveals that this effect was strongest when customers were in last place (β=1.369, $P < 0.05$). A marginal effects analysis of the specification in Column 3 reveals that, controlling for other factors, customers were 3.9 times more likely at any second to switch queues when they were in last place relative to when they were not, yielding a striking cumulative effect. Of the 71 customers who switched, 65 did so when they were in last place, 5 did so with a single person behind them, and 1 did so with two people behind them. No customers switched queues with more than two customers behind them.

Although these results are consistent with the presence of last place aversion in queues, owing to the short average length of the focal queue, there was a strong correlation between the numbers of people behind each customer and being in last place (ρ = -0.82). Additionally, it could be the case that the presence of merchandise displays and other customers impeded the switching behavior of all but those who were in last place, serving as an alternative explanation for the patterns observed. Moreover, the lack of instrumentation of the performance of the non-focal queues does not enable a direct test of whether the switching behaviors observed are rational or maladaptive. Consequently, to cleanly differentiate the effect of last place aversion from the linear effect of the number of customers behind, to rule out alternative explanations for the switching patterns observed, and to test whether the behaviors engendered by being last in queues are rational or maladaptive, further analysis was required.

3.2 Study 2: Queue Perceptions (H1)

Study 1 revealed that there is a behavioral tendency for customers to switch queues when they are in last place, hinting that being in last place may have a substantive effect on customer experiences, independent of other queuing dynamics. Study 2 explores the effect of last place aversion on customer experiences – specifically, on how being in last place affects customer perceptions of wait duration and wait time satisfaction. To do so, participants were recruited online to wait in an actual queue to complete a five-question survey. As such, this online experiment, and the others that follow, served as field tests of the experiences and behaviors of people waiting in actual queues, but the digital nature of these experiments facilitated higher fidelity data collection and better experimental control than could be achieved with physical queuing environments.

Importantly, apart from the experimental manipulations of interest, which where applicable are described in detail in the methods sections of each of the studies that follow, these digital queues were allowed to evolve naturally, in accordance with the behaviors of the people waiting in them. This behavioral variation is instrumented and controlled for in the econometric specifications presented, which facilitates clean identification of the effects of interest and high internal validity, but the natural evolution that is afforded by studying actual queues, rather than simulated ones, leads to greater external validity of the results that follow.

3.2.1 Participants. 301 participants (40.2% female, M_{age}=34.67, *SD*=11.50) completed this experiment on the Amazon Mechanical Turk platform in exchange for 50 cents (Buhrmester, Kwang, and Gosling 2011; Mason and Suri 2012). Participants were recruited to take part in a five-question survey, and were informed that completing the survey would take 2-5 minutes.

3.2.2 Design and procedure. As each participant arrived and completed the informed consent process, they were directed to join a first-come, first-served virtual queue to answer a five-question survey. In order to manage their wait duration, each virtual queue's capacity was capped at a maximum of six participants. When the sixth participant was assigned to a particular queue, the queue was closed to new arrivals, and a new queue was opened. This design feature ensured that participants never waited for more than five other participants to complete the survey. It also ensured as-if random variation in participants' relative positions in the queue. The target sample size of 300 participants was chosen in order to capture observations of at least 50 participants who experienced the full duration of their wait in last place.

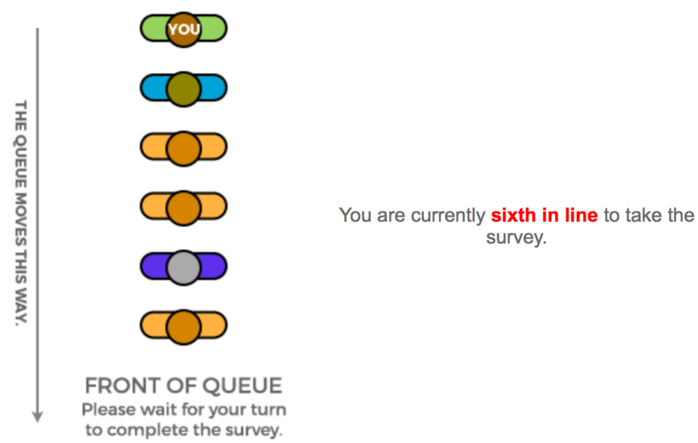


Figure 2: Queue display for virtual field study. Participants were able to see their own position in the queue, as well as those of other participants, tracking the queue state in real time.

As participants waited to complete the survey, they were able to observe their current position and progress in the queue, depicted from above, progressing from the top to the bottom of the screen (**Figure 2**). Each participant's current position in the queue was represented pictorially, as well as in words – for example, "You are currently fourth in line to take the survey." Each participant saw himself or herself represented as one of six randomly selected, stylized icons, depicting the head and shoulders of a person standing in line with the word "YOU" superimposed on top of it. Other participants were represented with similar randomly selected icons that varied by color. Throughout the experiment, each participant's avatar was consistently represented to others in their queue.

Participants were directed to take the survey when the participant in front of them in the queue completed it. The average participant spent 35.49 seconds responding to the survey questions, but some participants lingered for far longer (*SD* = 96.11 seconds). In order to manage the experiment duration for participants waiting behind particularly slow respondents, the experiment also allowed the next participant in line to advance if the person taking the survey had spent more than 60 seconds responding. 93.36% of participants completed the survey in less than 60 seconds.

While participants were waiting for their turn to take the survey, a digital display of the queue faithfully represented their progress. If a participant surfed away from the experiment, other participants in the queue observed their departure, and those waiting behind the departing participant advanced in the queue. Similarly, as participants in the front of the queue exited to take the survey, their departure was visible to the participants waiting behind them. When the queue updated, the graphical and textual representations of their position in the queue were updated too.

3.2.3 Independent measures. As participants waited to complete the survey, data were recorded every ten seconds on the number of participants in front of them in the queue (M = 1.82, SD = 0.93), the average number of participants behind them in the queue (M = 1.32, SD = 1.07), whether they were in last place (M = 0.44, SD = 1.07), and the number of seconds that had elapsed since they joined the queue. Given that the objective of this experiment was to test how positional and queue-related factors influence how people perceive and experience waiting, these data were aggregated to the queuing experience level, so as to best characterize the distinct nature of each participant's wait. The maximum number of people each participant experienced in front of them in the queue (e.g., the queue length at arrival) (M = 2.47, SD = 1.71) and behind them in the queue (M = 1.89, SD = 1.52) were encoded, and an indicator variable was created noting which participants spent the entirety of their waits in last place (M = 0.24, SD = 0.43). The amount of time each participant waited in the queue (M = 58.82 seconds, SD = 37.02 seconds), and the average cycle time of the queue in which each participant waited (M = 35.49, SD = 39.13) was also captured.

3.2.4 Survey measures. After waiting in the queue, participants were asked to rate their wait satisfaction, "Please rate your overall satisfaction with the length of your wait, on a scale of 1-7 (1= extremely dissatisfied; 7 = Extremely satisfied)," (M = 4.34, SD = 1.64) and to estimate the duration of their wait, "Please estimate how long you waited to take the survey (in seconds)," (M = 82.93, SD = 65.45). Due to the nature of the free text response field, this average was skewed upward by outliers. The maximum wait time experienced by any participant in this study was 195 seconds. Participants whose estimates exceeded 900 seconds (N = 2), where there existed a discontinuous break in wait time estimates, were excluded from the analysis, though the results are substantively similar if all observations are included. Participants were also asked to report their gender, their year of birth, and the highest level of education they had completed. Participants who left survey questions blank (N = 3) were also excluded, resulting in a final sample of 296 participants (40.9% female, M_{age}=34.63, SD=11.49).

3.2.5 Empirical strategy. As depicted in Equation 2, ex-post perceptions of the queue – participants' perceptions of how long they waited, and how satisfied they were with their wait – were modeled cross-sectionally as a function of positional and queue-related dynamics they experienced during their wait:

$$PERCEPTIONS_i = f\begin{pmatrix} LAST_i + AHEAD_i + AHEAD^2{}_i + \\ BEHIND_i + BEHIND^2{}_i + WAIT_i + \\ CYCLE_i + LAST_i \times WAIT_i + X_i + \epsilon_i \end{pmatrix} \tag{2}$$

In the above specification, $LAST_i$ is an indicator variable denoting whether the participant spent the full duration of their wait in last place. $AHEAD_i$ and $AHEAD^2{}_i$, and $BEHIND_i$ and $BEHIND^2{}_i$ captured the non-linear effect of the maximum number of people ahead and behind the participant during their waiting experience, $WAIT_i$ captured the total duration of their wait, and $CYCLE_i$ captured the average cycle time of the queue in which they waited. $LAST_i \times WAIT_i$ captures the interaction between waiting in last place and the duration of the wait – to determine whether the effects of last place aversion on perceptions depends on the amount of time one waits in last place. Finally, X_i represents a vector of control variables, denoting the participant's gender, age, and level of education. Controlling for these factors, participants who spent their queuing experience in last place were hypothesized to be less satisfied than those who waited in other parts of the queue, which serves as the test of H1.

3.2.6 Analysis and results. Wait estimates and wait satisfaction were modeled using OLS regression with robust standard errors. As shown in **Table 2**, Column 1, the proportion of time a participant spent in last place had no effect on their estimate of the duration of their wait (β = 4.990, P = 0.647), suggesting that being in last place does not make a wait feel longer. The most significant predictor of a participant's estimate of their wait time was the actual duration of their wait (β = 1.266, P < 0.01). Notably, participants in this setting overestimated the time they spent waiting in line, indicated by the coefficient on wait time being greater than 1 (F(1,287)=6.57, P=0.01). A rich stream of empirical queuing literature has found that people both overestimate and underestimate wait times (for an excellent review, see Allon and Kremer, 2019), but that overestimation, consistent with what is observed here, is often the norm when waits are unoccupied and delay announcements are not provided, as was the case in Study 2. Interestingly, controlling for other factors, the average cycle time of the queue had a negative and significant relationship with perceived wait time (β = -0.134, P = 0.05). Perhaps the salience of spending more time engaged in the service process at the front of a queue dampens perceptions of the amount of time one waited to be served, after the actual duration of their wait has been controlled.

Columns 2-3 begin to disentangle the determinants of wait time satisfaction. Column 2 shows that satisfaction is negatively affected by the duration of the wait ($\beta s < -0.15$, $Ps < 0.01$). In Column 2, participants reported marginally lower levels of satisfaction when there had been more people ahead of them in the queue ($\beta = -0.164$, $P < 0.10$), and when there had been more people behind them in the queue ($\beta = -0.146$, $P < 0.10$). Column 3 demonstrates the non-linearity of these effects. Controlling for other factors, participants were less satisfied with their wait when there had been more people in front of them ($\beta = -0.634$, $P < 0.01$), but at a decreasing rate ($\beta = 0.113$, $P < 0.01$). Moreover, consistent with prior research on downward social comparison (Zhou and Soman 2003), participants reported higher levels of satisfaction when there were more people behind them in the queue ($\beta = 0.722$, $P < 0.01$), but this effect too was attenuated as the number of people behind the participant increased ($\beta = -0.183$, $P < 0.01$). In both specifications, the average cycle time of the queue proved to be an insignificant determinant of satisfaction, likely owing to its strong mathematical dependence on the number of people in front of the focal participant, and the wait duration that participant experienced ($\beta s < 0.003$, $Ps > 0.213$) (Little 1961).

Importantly, Column 4 demonstrates that this non-linear effect of the number of people behind the participant on wait time satisfaction was attributable to last place aversion. Introducing an indicator variable for participants who spent the duration of their wait in last place revealed a negative, and marginally significant relationship with wait satisfaction ($\beta = -0.900$, $P < 0.10$), while reducing the binomial coefficients on the number of people behind the participant to insignificance, ($\beta = 0.061$, $P = 0.89$) and ($\beta = -0.068$, $P = 0.43$), respectively. Column 5 shows that after controlling for whether the participant spent the duration of their wait in last place, the effect of the number of customers behind is better modeled as a linear term. Interestingly, that term reveals that once a waiting participant is no longer in last place, having a second and third and fourth person waiting behind her actually *diminishes* her satisfaction ($\beta = -0.297$, $P < 0.01$). Perhaps once a person is able to make a downward social comparison, because they are no longer in last place, the effect of adding incrementally more people behind them in the line serves to reduce satisfaction by making the number of people waiting, and in turn, the wait itself, more salient. This pattern of results is consistent with the idea that the absence of a target for downward social comparison may be the psychological process that explains the aversive effects of last place aversion in queues. Once a person is no longer in last place, however, a growing queue behind may simply serve as a reminder of the inability of the service process to keep up with arrivals.

	(1)	(2)	(3)	(4)	(5)	(6)
	Wait Estimate	Wait Satisfaction	Wait Satisfaction	Wait Satisfaction	Wait Satisfaction	Wait Satisfaction
Wait time	1.266***	-0.015***	-0.018***	-0.018***	-0.017***	-0.025***
	(0.104)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Always in last place	4.990			-0.900*	-1.190***	-2.078***
	(10.890)			(0.468)	(0.273)	(0.425)
Always in last place × wait time						0.016**
						(0.007)
Maximum number ahead	-4.679	-0.164*	-0.634***	-0.603***	-0.528***	-0.146
	(3.209)	(0.099)	(0.171)	(0.177)	(0.178)	(0.258)
Maximum number ahead^2			0.113***	0.107***	0.089**	0.009
			(0.038)	(0.039)	(0.038)	(0.052)
Maximum number behind	-1.506	-0.146*	0.722***	0.061	-0.297***	-0.359***
	(3.712)	(0.082)	(0.242)	(0.447)	(0.090)	(0.090)
Maximum number behind^2			-0.183***	-0.068		
			(0.051)	(0.086)		
Cycle time	-0.134**	0.003	0.002	0.003	0.003	0.003
	(0.068)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female indicator	4.519	0.221	0.183	0.168	0.169	0.174
	(6.094)	(0.179)	(0.178)	(0.177)	(0.176)	(0.175)
Age	0.399	0.018**	0.018**	0.017**	0.016**	0.019**
	(0.364)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Education	1.032	-0.058	-0.070	-0.071	-0.070	-0.066
	(2.369)	(0.067)	(0.066)	(0.065)	(0.064)	(0.064)
Constant	7.406	5.307***	5.115***	5.920***	6.216***	6.426***
	(19.388)	(0.485)	(0.496)	(0.623)	(0.473)	(0.465)
Observations	296	296	296	296	296	296
Adjusted R-squared	0.398	0.186	0.212	0.219	0.220	0.237

Table 2: Estimate of wait time is unaffected by the proportion of time a participant spent in last place, but their wait satisfaction is negatively affected by the amount of time they spent in last place (Study 2). All models are estimated with OLS regression and robust standard errors, are shown in parentheses. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively.

After removing the non-linear term from the model, as described above, the negative relationship between waiting in last place and satisfaction with the wait intensifies considerably. Controlling for other factors, participants who spent the duration of their wait in last place reported wait time satisfaction that was 25.8% lower on average than participants who were not in last place (β = -1.190, $P < 0.01$). This result offers support for H1, and distinguishes the effects of last place aversion from the linear effect of the number of people waiting behind in a queue.

These results are interesting, since the sizable effects of last place aversion persist after controlling for the time the participant waited in the line to complete the survey. This suggests that being in last place is, in and of itself, what's diminishing customer experiences – not the prolonged wait duration that's associated with being in last place. What's more, these effects are particularly interesting because of their magnitude. The drop in wait time satisfaction experienced by a last place participant is the same as the drop experienced by participants who waited 70 additional seconds to take the survey – the equivalent of waiting behind two additional people. The results suggest that from a satisfaction perspective, participants would rather wait in a substantively longer queue to avoid waiting in last place. Of the effects reported so far, this is the first indication that last place aversion may lead to maladaptive behaviors, in the sense that a preference for waiting longer to avoid waiting in last place is an apparent deviation from rationality.

To test whether the pain of waiting in last place intensifies or diminishes as time progresses, Column 6 incorporates an interaction term between the participant's total wait duration and the indicator of whether they spent the entirety of their wait in last place. The results suggest that although wait satisfaction diminishes for everyone who experiences longer waits, the differential negative impact of being in last place on satisfaction is most detrimental for short waits (β = -2.08, $P < 0.01$), and its negative effects diminish over time (β = 0.016, $P < 0.05$). Practically speaking, this result suggests that interventions that target last place individuals early in their waits might be the most fruitful for improving waiting experiences, and perhaps for forestalling counterproductive switching and reneging behaviors.

These results highlight one way that last place aversion in queues may reduce customer satisfaction. Consistent with H1, the mere circumstance of waiting in last place, which is neither under the control of the customer nor the firm, is enough to meaningfully diminish wait satisfaction. The studies that follow investigate how and why the negative experiences attributed to being in last place may translate to behaviors that might further affect service performance for customers and firms alike. In particular, they explore the effects of last place aversion on switching and reneging behaviors – the customer choices to switch from one queue to another, or to opt out of the queue and forgo the service altogether. They also investigate the promise of a managerial intervention – queue transparency – for attenuating the negative effects of last place aversion in queues – as well as the effect of last place aversion on the capacity of queuing systems.

3.3 Study 3: Last place aversion and switching behavior (H2)

Study 2 highlighted how controlling for other factors, peoples' queuing satisfaction is substantively affected by being in last place. Study 3 replicates the conditions of the observational analysis from Study 1 in the online queuing environment, to investigate the effects of last place aversion on customer switching behaviors, and those switching behaviors' subsequent effects on customer experiences of the service.

Replicating Study 1 in the online queuing environment provides better experimental control over the conditions and higher fidelity data than could be captured in a physical queuing environment. These features facilitate the elimination of alternative explanations for the pattern of effects in Study 1. For example, lengthening the line permits more statistical power to disentangle the effect of last place aversion on switching behavior from the linear effect of the number of people behind a person in the queue. Moreover, the virtual queuing environment lacks any physical barriers (e.g., magazine racks, merchandise displays, shopping carts, shoppers, etc.) that may have impeded customers from switching among queues in the grocery store environment of Study 1.

Just as importantly, however, better instrumentation of all facets of the virtual queuing environment afford an opportunity to determine whether last place-induced switching may be rational or maladaptive. For example, the ability to continuously observe and document the status of both the focal and alternative queues allows us to track whether last place participants who switch do so advantageously. Relatedly, the lack of observability into the service process in the virtual queuing environment removes contextual cues that may in physical queuing environments facilitate strategic switching with the expectation of being served sooner, controlling away a rational explanation for last place-induced switching. Moreover, the virtual queuing environment enables the tracking of switching behavior and survey completion time of every participant "standing" in each line, which facilitates counterfactual analyses that were not possible in Study 1 (e.g., How long would this participant have waited if she had not switched queues, provided those ahead of her did not switch? Did switching make her better off?). Finally, participants can be directly surveyed in the virtual queuing environment, enabling Study 3 to build on Studies 1 and 2 by investigating how last place aversion affects switching behaviors and, in turn, queuing experiences. By facilitating an analysis of whether last place-induced switching improves or worsens the objective and subjective experiences of participants, the virtual queuing environment enables the assessment of whether the patterns of behavior we observe in response to being in last place are rational or maladaptive. If last place aversion-related behaviors are maladaptive, then operational design interventions that forestall them may hold promise for jointly improving customer experiences and firm performance.

3.3.1 Participants. 302 participants (41.7% female, M_{age}=35.08, *SD*=10.63) completed this study on the Amazon Mechanical Turk platform in exchange for 50 cents. Participants were recruited using the same language as Study 2.

3.3.2 Design and procedure. Study 3 replicated the design of Study 2 with four important modifications. First, upon completing the informed consent process, participants were asked not to surf away from the experiment while waiting in line. They were notified, "when your turn comes, you must click a button within 10 seconds to progress to the survey, or you will be disqualified from the HIT [and will not receive payment]." This step was added in an attempt to reduce the number of people who would disengage from the queue by opening a separate browser window and surfing to a different website while they waited. Such disengagement would censor the degree of switching that could be observed through the experiment. In physical queuing environments, a participant's continued presence is required to maintain one's place in line, and ultimately, to receive service. Hence, requiring a participant's continued presence in the virtual queuing environment is appropriately consistent.

Accordingly, the intended sample size for Study 3 was increased to 360 participants in anticipation of losing more participants due to this more stringent attention check. Although 369 participants completed the online informed consent process and joined a queue, 43 participants (11.7%) dropped out of the study by means of a connectivity issue, or by closing the browser window while waiting in the queue, and an additional 24 participants (6.5%) were disqualified when they failed to click the button to proceed to the survey within 10 seconds. Data from the remaining 302 participants were analyzed.

Second, after completing the informed consent process and reading the notification, participants joined the shorter of two queues in a paired queue system (**Figure 3A**). As before, each queue was allowed to reach a maximum of 6 participants. When both queues reached a maximum number of participants, a new paired queue system was opened to accommodate the new arrivals. However, unlike Study 2, when a queue fell below 6 participants, due either to participants quitting the queue or advancing through the survey, that queue was again eligible to accept new arrivals. Each new arrival was automatically added to the shortest available queue across all systems, resulting in the true-to-life queuing dynamic of new customers arriving perpetually.

Third, in order to accommodate a greater number of participants on the screen, and to facilitate social comparisons within and across queues, the way participants were presented to one another in the virtual environment was revised. The queue was inverted so that it progressed from the bottom of the screen to the top, and the variety and realism of the avatars was increased. Each participant saw themselves represented as a yellow circle, with the word "YOU" superimposed over the top of it. Other participants were represented with one of 41 randomly-assigned avatars, each representing different races, ages, and genders. Throughout the experiment, each participant's avatar was consistently represented to the other participants in their queue.

Fourth and finally, unlike Study 2, participants were given the opportunity to switch between the paired queues. If a participant desired to switch to the other queue, they could do so by clicking a green circular button at the end of the opposing queue that was labeled, "Move Here." Clicking the button would result in being placed at the end of the opposing queue, a behavior that served in the experiment as the indicator of switching queues. Importantly, as in physical environments, if a participant switched queues, they would lose their place in line, if there was another participant already behind them, or if a new participant subsequently arrived.

3.3.3 Independent measures. As in Study 2, while participants waited to complete the survey, data were recorded every ten seconds on the number of participants in front of them in the queue (M = 1.86, SD = 1.58), the number of participants behind them in the queue (M = 1.51, SD = 1.50), whether they were in last place (M = 0.37, SD = 0.48), and the number of seconds that had elapsed since they joined the queue. Participants waited in the queues for an average of 91.12 seconds (SD = 78.21 seconds) before progressing to the survey. Moreover, every ten seconds the status of the opposing queue was recorded. Participants might logically choose to switch to the opposing queue if it was shorter than the queue in front of them. Hence, a "paired queue advantage" metric was generated that designated whether the number of people in the opposing queue was less than the number of people in front of the participant in their current queue (M = 0.29, SD = 0.45).

Additionally, the cycle time of both the focal and opposing queues were measured, using the processing time for the last participant to receive service, in order to control for the relative pace of the queues (M = 23.89, SD = 10.19, and M = 23.58, SD = 10.44, respectively). Incorporating these lagged indicators results in dropping observations from participants waiting before the first person served in a queue received service, though the results are substantively similar if cycle time controls are not included and all observations are analyzed.

A.

B.

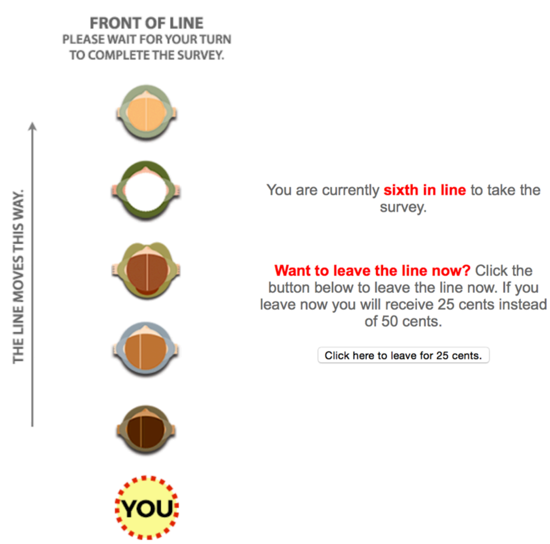


Figure 3: Queue displays for virtual field experiments (Studies 3-5). Study 3 explored how relative queue position affected switching behavior (Panel A). Study 4 investigated how relative queue position affected defection from the queue (Panel B). Study 5 resembled the design of Study 4 (Panel B), except that in treatment conditions, digital confederates were added behind each waiting participant in order to nullify the effects of last place aversion by ensuring that no participant perceived themselves to be in last place.

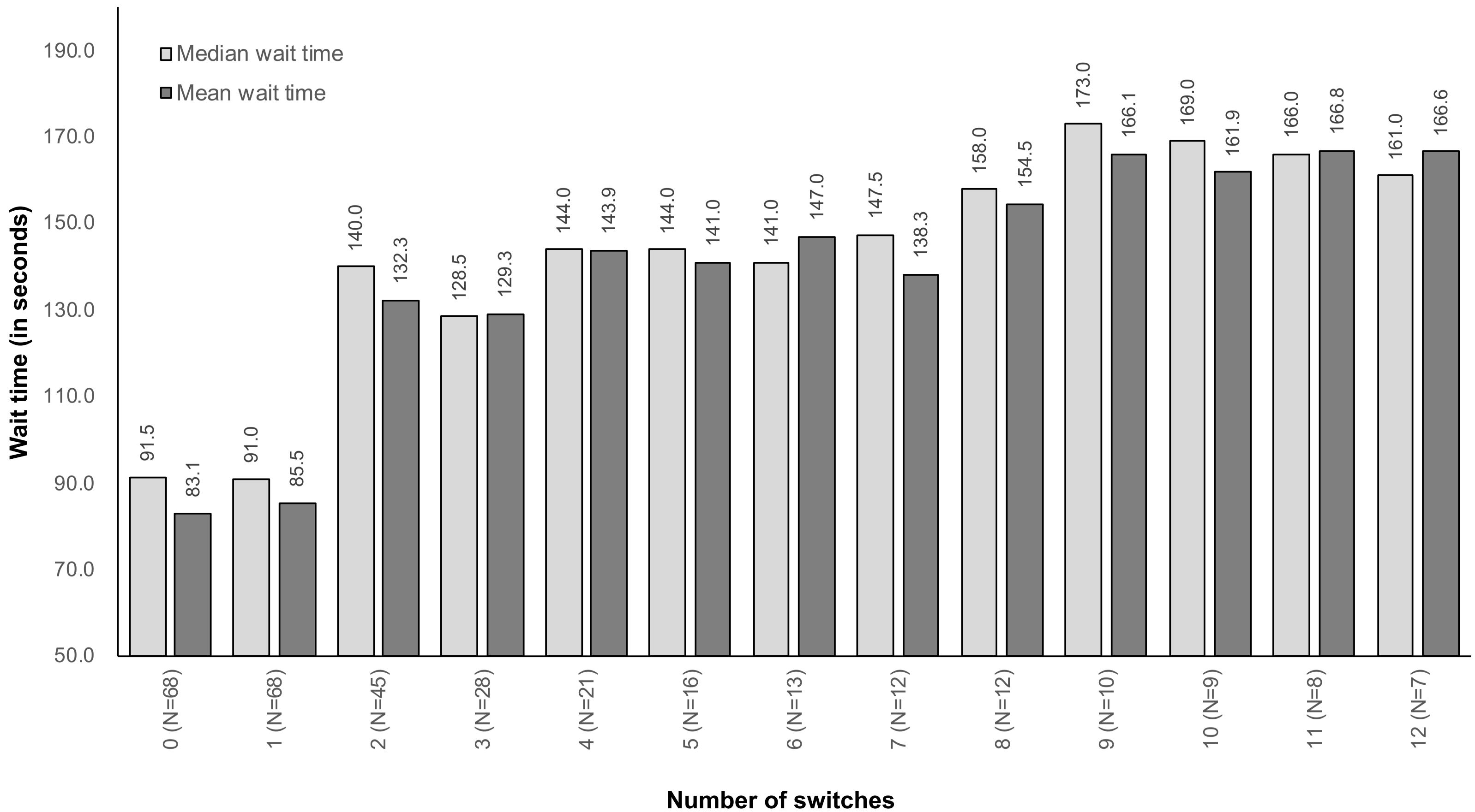


Figure 4: Switching queues increases the mean and median expected wait times of switchers (Study 3). Each pair of column graphs shows the mean and median number of seconds the switcher would have waited to take the survey if they had not switched again, calculated as the sum of the service times exhibited by participants in front of the switcher in line, plus imputed transition times, immediately prior to making the switch. N = 68 participants chose to switch at least once, N = 45 participants chose to switch at least twice, N = 28 participants chose to switch at least three times, etc. The pattern of results shows that, in general, the choice to switch in this context, where participants lacked transparency into the service process and visual information that could be used to forecast the relative speed of other participants, did not tend to reduce expected wait times.

3.3.4 Dependent Measures. The key dependent measure for this study was whether the participant chose to switch queues during a particular ten-second window. Consistent with the observational results in Study 1 and H2, the hypothesis underlying Study 3 was that controlling for other factors, participants would be more likely to switch queues when they were in last place. The average participant switched queues 1.28 times during their wait (*SD* = 5.58). For our primary analysis, we focus on participants who switched queues 12 or fewer times, which excludes (*N* = 5) participants, who switched a disproportionate number of times (*M* = 39.4, *SD* = 16.24). However, all presented results are substantively similar if all observations are included, or if stricter cutoffs are imposed.

As a secondary dependent measure, the total queuing times for participants were captured. Being in last place was hypothesized to increase the probability of switching behavior, which in turn was predicted to extend the duration of a participant's wait. Participants who did not switch queues (*N* = 234) waited an average of 77.30 seconds to take the survey (*SD* = 68.08). Participants who did switch queues (*N* = 68) waited an average of 138.69 seconds (*SD* = 91.66). Of course, the fact that switchers waited longer for service does not necessarily mean that switching was irrational. The virtual queuing environment made it possible to track the behavior and survey time of every individual within the paired queue system, and to impute an average transition time between survey participants, such that for every switch made by a participant, a counterfactual could be calculated reconstructing the wait time the participant would have had if she *and those in front of her* had not switched queues. Owing to the prevalence of switching, these counterfactuals are, hence, overestimated. Had no queue switching occurred, participants (*N* = 302) would have waited an average of 78.85 seconds (*SD* = 58.33 seconds) before taking the survey. Participants who chose not to switch (*N* = 234) would have waited an average of 77.63 seconds (*SD* = 59.93 seconds), and participants who chose to switch would have waited an average of 83.06 seconds (*SD* = 52.67 seconds), wait times that are statistically indistinguishable ($T(300)=0.675$, $P=0.50$). However, in general, each additional switch by a participant tended to result in nominally longer wait times (**Figure 4**), suggesting that switching behavior may have been costly. To test whether last place-induced switching may have been maladaptive, the total queuing time for each participant is modelled as a function of whether they switched, controlling for how long they would have waited had they not switched.

3.3.5 Survey Measures. As with Study 2, participants were asked to rate their wait satisfaction, "Please rate your overall satisfaction with the length of your wait, on a scale of 1-7 (1= extremely dissatisfied; 7 = extremely satisfied)," (*M* = 4.39, *SD* = 1.70) and to estimate the duration of their wait, "Please estimate how long you waited to take the survey (in seconds)," (*M* = 99.84, *SD* = 90.61). Participants were also asked to report their gender, their year of birth, and the highest level of education they had completed.

3.3.6 Empirical approach. As depicted in Equation (3), switching probabilities, $\Pr\left(SWITCH_{i,t}\right)$, for participant *i* during time period *t* were modeled as a function of positional and queue-related factors, using a random effects logistic regression with robust standard errors clustered by participant, as follows:

$$\Pr\left(SWITCH_{i,t}\right)=f\begin{pmatrix} LAST_{i,t}+AHEAD_{i,t}+BEHIND_{i,t}+ \\ WAIT_{i,t}+CYCLE_{i,t}+PCYCLE_{i,t}+ \\ PADV_{i,t}+REMAINING_{i,t}+X_{i}+\epsilon_{i,t} \end{pmatrix} \tag{3}$$

As in previous analyses, in the specification above, $LAST_{i,t}$ is an indicator variable denoting whether the participant was in last place, $AHEAD_{i,t}$ and $BEHIND_{i,t}$ count the number of participants ahead and behind the participant in the queue, $WAIT_{i,t}$ controls for how long the participant has been waiting in the queue, and $CYCLE_{i,t}$ indicates the current cycle time of the queue, measured as the service time of the last participant to complete the survey. Additionally, to account for rational reasons that participants might switch queues, the cycle time of the paired queue, $PCYCLE_{i,t}$, and an indicator variable denoting whether the paired queue is shorter than the line in front of the participant, such that it would appear an advantage to switch, $PADV_{i,t}$, are also included. Finally, a measure indicating the number of seconds remaining before the waiting participant would receive service if they don't switch lines, $REMAINING_{i,t}$, is included, as well as a vector of participant-level control variables, X_{i}.

To test whether the switching engendered by last place aversion may be maladaptive, in the sense that it can worsen peoples' objective and perceived waiting experiences, its effects on total wait times and wait satisfaction are additionally modelled. In Equation 4, queuing experiences of participant *i*, $EXPERIENCE_{i}$, are modelled in a cross-sectional, OLS regression as a function of indicator variables for whether the participant switched while in last place, $LASTSWITCH_{i}$, or otherwise, $OTHERSWITCH_{i}$; a count of the number of people ahead of the participant when he or she first joined the line, $FIRSTAHEAD_{i}$, and the sum of the service times for each of the participants initially waiting in front of the participant, $PREDWAIT_{i}$, a prediction of the participant's anticipated service time if no participants in the queue switched.

$$EXPERIENCE_{i}=f\begin{pmatrix} LASTSWITCH_{i}+OTHERSWITCH_{i}+ \\ FIRSTAHEAD_{i}+PREDWAIT_{i}+X_{i}+\epsilon_{i} \end{pmatrix} \tag{4}$$

By controlling for the state of the queue when the participant arrives, the coefficients on $LASTSWITCH_{i}$ and $OTHERSWITCH_{i}$ partial out the effect of the choice to switch on wait times and satisfaction, holding constant what the objective experience of the participant would have been in the absence of switching. Positional and queue-related aspects of the wait that extend beyond the initial state of the queue each participant encountered are excluded from this cross-sectional analysis, since they are endogenous with the choice to switch. If switching while in last place is a rational, experience-enhancing behavior, we should expect to see that switching will lead to reduced wait times or increased satisfaction. If instead it is maladaptive, we should expect to see switchers experiencing longer waits and reporting lower levels of satisfaction, after controlling for what their experiences would have been in the absence of switching.

3.3.7 Analysis and Results. In **Table 3**, Column 1 corroborates the results from Study 1 by showing that, controlling for other factors, people are more likely to switch queues when they are in last place (β = 1.108, $P < 0.05$). Column 2 demonstrates that these results persist after controlling for the state of the alternative queue. Although people are 56% more likely to switch when the other line is shorter (β = 0.650, $P < 0.05$), they are 2.34 times more likely to switch when they are in last place (β = 1.133, $P < 0.05$), offering support for H2.

Conventional wisdom suggests that switching is a rational behavior used by people to get through lines faster. That is, if a person intuits that their line is slower than the alternative, they will switch to reduce their overall wait. However, the virtual queuing environment used for this study hinders the ability of participants to act strategically in this regard. The complete inability to observe the arrival and service processes of both queues, and the impossibility of forecasting differences in the likely processing speeds of others in the queue, significantly reduces the expected advantage from switching. Moreover, because the virtual queuing environment used in this study affords the reliable calculation of counterfactuals, it is possible to directly test whether people are more likely to switch when their wait would have been longer, and whether the impulse to switch results in a shorter wait. Column 3 reveals that controlling for other factors, the time actually remaining in a person's wait is not a significant predictor of whether they will switch to an alternative queue (β = 0.006, $P = 0.38$), but being in last place is predictive of switching (β = 1.148, $P < 0.05$), as is whether there would be fewer people ahead in the opposing queue (β = 0.654, $P < 0.05$), and whether there are fewer people behind in the current queue (β = -0.560, $P < 0.10$). These results suggest that when all factors are considered, the switching decision is driven more by observable positional considerations than by peoples' ability to intuit the remaining duration of their wait.

Columns 4-5 investigate the effects of these switching behaviors on total wait duration and wait time satisfaction. Column 4 shows that people who switch at least once in Study 3 while in last place waited an average of 27.11 seconds longer to take the survey than people who did not switch (β = 27.107 $P < 0.01$), and that, owing to their lost positional advantage, people who switched while not in last place waited even longer (β = 41.672 $P < 0.01$). These results suggest that from an objective standpoint, the increased switching engendered by being in last place can be maladaptive, in the sense that it can result in longer waits. Column 5 shows that controlling for other factors, people who faced longer waits (β = -0.010 $P <$

0.01) and had more people waiting in front of them when they joined the queue (β = -0.197 P < 0.01) exhibited lower levels of wait satisfaction. However, even controlling for these factors, people who switched while in last place reported being 15% less satisfied with their waits than people who decided not to switch (β = -0.674 P < 0.05) People who switched while waiting in other parts of the queue exhibited insignificant declines in satisfaction (β = -0.479 P = 0.27).

	(1)	(2)	(3)	(4)	(5)
	Pr(Switch)	Pr(Switch)	Pr(Switch)	Total wait	Wait satisfaction
Last place indicator	1.108**	1.133**	1.148**		
	(0.495)	(0.523)	(0.523)		
Time remaining$_t$			0.006		
			(0.007)		
Last place switch indicator				27.107***	-0.674**
				(7.017)	(0.302)
Other switch indicator				41.672***	-0.479
				(11.194)	(0.429)
Initial number ahead				0.754	-0.197*
				(2.388)	(0.118)
Imputed wait time without switching				1.053***	-0.010***
				(0.077)	(0.004)
Time since joining queue	-0.014**	-0.014**	-0.014**		
	(0.006)	(0.006)	(0.007)		
Number ahead	0.055	-0.044	-0.195		
	(0.103)	(0.110)	(0.203)		
Number behind	-0.470*	-0.570*	-0.560*		
	(0.280)	(0.307)	(0.311)		
Cycle time	-0.018	-0.012	-0.011		
	(0.013)	(0.013)	(0.014)		
Paired queue cycle time		-0.022	-0.024*		
		(0.014)	(0.014)		
Paired queue advantage		0.650**	0.654**		
		(0.260)	(0.257)		
Female indicator	-0.540	-0.499	-0.518	0.663	0.423***
	(0.386)	(0.391)	(0.396)	(3.109)	(0.163)
Age	-0.063***	-0.063***	-0.065***	-0.053	-0.003
	(0.019)	(0.020)	(0.022)	(0.118)	(0.007)
Education	-0.008	0.046	0.046	0.932	-0.068
	(0.129)	(0.133)	(0.135)	(0.919)	(0.058)
Constant	-0.639	-0.395	-0.514	-7.881	5.977***
	(1.096)	(1.166)	(1.144)	(6.499)	(0.352)
Observations	2,613	2,566	2,566	297	296
Model type	RE Logit	RE Logit	RE Logit	OLS	OLS
Adjusted R-squared				0.872	0.365
Number of participants	227	220	220	297	296

Table 3: Being in last place significantly increases switching behavior, and switching prolongs wait duration, undermining satisfaction (Study 3). Columns 1-3 are estimated with random effects logistic models. Columns 4-5 are estimated with OLS. Robust standard errors, clustered at the individual level, are shown in parentheses in Columns 1-3. Robust standard errors are shown in parentheses in Columns 4-5. Columns 4-5 have a diminished number of observations because one participant didn't answer the wait satisfaction question. Adjusted R-squared metrics cannot be calculated for random effects logistic models, and are accordingly not provided in Columns 1-3 *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively.

Building on Study 2, these results highlight a second way that last place aversion in queues substantively affects customer service performance. The diminished satisfaction that arises from being in last place can translate to switching behaviors, which can in turn further prolong waits, exacerbating diminished wait time satisfaction. Adding insult to injury, not only did switching prolong total wait duration, last place participants who switched wound up spending more than twice as much time in last place on average – up from 20.90 seconds (SD = 25.93) to 50.46 seconds (SD = 33.66) ($T(295) = 7.19$, $P < 0.01$). These dynamics lend support to the idea that the behaviors emanating from last place aversion in queues are maladaptive, in that they substantively worsen customers' queuing experiences.

3.4 Study 4: Last place aversion and reneging behavior (H3)

Study 4 explores the effects of last place aversion on reneging behaviors – the choice to quit a line and forgo a service altogether. To the extent that being in last place diminishes customer experiences, as hypothesized in H3, queuing individuals may be most likely to give up on the line when they are in last place. Although quitting while in last place means the participant forgoes the service for which they are queuing, such behavior may be rational if it applies disproportionately to discretionary queues – where the service delivered isn't worth the wait. Study 4 explores this possibility – investigating the moderating role of completion utility on last place-induced reneging. Moreover, Study 4 investigates downward social comparison as a potential mechanism explaining the effects of last place aversion on reneging behavior, by studying whether being in last place makes people perceive a service to be less worthwhile. Finally, Study 4 explores the impact of queue transparency, a service design choice that may be used by managers in some circumstances to combat the deleterious effects of last place aversion on service performance. If last place aversion drives reneging behaviors in queues, transparency into one's relative position may increase abandonment when participants can see that they are in last place and it may reduce abandonment when participants can see that they're not.

3.4.1 Participants: 1,429 participants (50.5% female, M_{age}=36.45, SD=11.61) completed this study on the Amazon Mechanical Turk platform in exchange for 50 cents. Participants were recruited using the same language as in the prior online studies.

3.4.2 Design and Procedure: Study 4 replicated the design of the previous online studies, returning to a single queue with a capped capacity of six participants. Unlike the prior studies, the design of Study 4 formally allowed participants to abandon the queue without surfing away from the experiment. Beneath the textual description of the participant's current status in the queue was included an additional instruction that invited participants to leave the line early in exchange for a reduced level of compensation (**Figure 3B**). The degree to which waiting in the queue was discretionary was manipulated by offering different levels of compensation to participants who chose to renege – ranging in ten cent increments from 5 cents to 45 cents. When a low level of compensation was offered for abandoning, the incremental compensation for completing the survey was relatively high, mimicking service scenarios in which waiting for service is less discretionary – such as completing a necessary banking transaction or mailing a time-sensitive package at the post office. Conversely, when a high level of compensation was offered for abandoning, the incremental compensation for completing the survey was relatively low, mimicking service scenarios in which waiting for service is more discretionary – such as ordering a dessert item at a cafe or buying a non-mandatory product at a convenience store. Participants read “Want to leave the line now? Click the button below to leave the line now. If you leave now, you will receive [5, 15, 25, 35, 45] cents instead of 50 cents.”

Study 4 additionally manipulated queue transparency, whether or not participants could see the queue itself. In the transparent condition, participants saw both the pictorial and textual representations of their current position in the queue. In the non-transparent condition, participants only saw the textual representation of their current position in the queue. Importantly, although the textual representation presented information about how many participants were ahead in the queue, for example, “You are currently fourth in line to take the survey,” it presented no information about the status of the queue behind the participant; crucially, whether the participant was in last place.

Since there were ten conditions in this study, a recruiting target of 1,200 participants who did not renege from the queue was established. The aim of this strategy was to yield a minimum of 20 observations per rank per condition from participants who did not renege, plus additional observations from participants who chose to renege – offering sufficient power for the analysis.

3.4.3 Independent measures. As in the previous online studies, while participants waited to complete the survey, data were recorded every ten seconds on the number of participants in front of them in the queue (M = 1.47, SD = 1.49), the number of participants behind them in the queue (M = 0.99, SD = 1.16), whether they were in last place (M = 0.47, SD = 0.50), and the number of seconds that had elapsed since they joined the queue. The 240 participants who reneged did so after waiting an average of 15.94 seconds (SD = 22.29 seconds). The remaining 1,189 participants, who did not abandon the queue, waited for an average of 75.00 seconds (SD = 54.67 seconds) before progressing to the survey. Queue cycle times were also measured, as the average processing time for the participants served by each queue (M = 26.39 seconds, SD = 5.63 seconds).

3.4.4 Dependent Measures. The focal dependent measure for this study was whether the participant chose to renege from the queue. Study 4 was designed to test the hypothesis that controlling for other factors, people would be more likely to renege when they were in last place. Indeed, of the 240 participants who reneged, 146 (60.8%) did so when they were in last place.

3.4.5 Survey Measures. As with Studies 2 and 3, participants who waited in the queue were asked to rate their wait satisfaction, "Please rate your overall satisfaction with the length of your wait, on a scale of 1-7 (1= Extremely dissatisfied; 7 = Extremely satisfied)," (M = 4.36, SD = 1.70). Unlike the previous studies, participants who waited and participants who reneged were additionally asked to rate the degree to which they agreed or disagreed with the statement, "It was worth my time to wait in the line I just experienced," on a scale of 1-7 (1 = Strongly disagree; 7 = Strongly agree). Participants were also asked to report their gender, their year of birth, and the highest level of education they had completed.

3.4.6. Empirical approach. As depicted in Equation 5, the probability that participant i would renege at time t, $\Pr\left(RENEGE_{i,t}\right)$, was modelled as a function of positional and queue-related factors using a random effects logistic regression with robust standard errors clustered at the participant level:

$$\Pr\left(RENEGE_{i,t}\right) = f\begin{pmatrix} LAST_{i,t} + TRANS_{i} + LAST_{i,t} \times TRANS_{i} + COMP_{i} + \\ TRANS_{i} \times COMP_{i} + LAST_{i,t} \times TRANS_{i} \times COMP_{i} + AHEAD_{i,t} + \\ AHEAD^{2}_{i,t} + BEHIND_{i,t} + WAIT_{i,t} + CYCLE_{i,t} + X_{i} + \epsilon_{i,t} \end{pmatrix} \tag{5}$$

In the equation above, $LAST_{i,t}$ serves as an indicator variable for whether the participant is in last place, and in this specification captures whether participants who can't see they are in last place are more likely to defect. If queue transparency is an effective design lever for reducing last place customer defection, this coefficient should be insignificantly different from zero. $TRANS_{i}$ is an indicator variable denoting whether the queue was transparent to the participant, and in turn, whether seeing when they were not in last place had an effect on reneging behavior. $LAST_{i,t} \times TRANS_{i}$ measures whether the effect of being in last place has a differential effect when there's queue transparency. Since we should only expect the effects of last place aversion to affect a person's behavior when they can see they are in last place, this interaction term serves as our focal variable for testing H3, that last place aversion will increase reneging behavior. $COMP_{i}$ indicates the level of compensation the participant was offered to quit the queue, with higher levels of compensation leading to a more discretionary queuing environment. $TRANS_{i} \times COMP_{i}$ measures whether the effects of queue transparency on defection depend on how discretionary the wait is. Finally, $LAST_{i,t} \times TRANS_{i} \times COMP_{i}$ denotes whether the effects of last place aversion depend on the completion utility of the service. A positive coefficient would be consistent with the idea that last place-induced switching is rational, since it would indicate that last place participants are more likely to renege, when they are queuing for less valuable services. Such a behavior would be rational in that it would suggest people are strategically opting out of waiting for a less valuable service before they invest too much time in the queue. A negative coefficient would indicate that last place-induced reneging is maladaptive, in that it is causing people to quit the queue when they have more to gain from receiving the service. As in previous studies, $AHEAD_{i,t}$, $AHEAD^{2}_{i,t}$, $BEHIND_{i,t}$, $WAIT_{i,t}$, and $CYCLE_{i,t}$ accounted for the number of participants ahead and behind in the queue, the elapsed wait time, and the cycle time of the most recent participant to receive service.

In order to test the idea that people in last place, who can see that no one has lined up behind them for service, perceive the wait to be systematically less worthwhile, $WORTH_i$, in turn, driving an increased probability of reneging, $\Pr(RENEGE_i)$, cross-sectional Equations 6 and 7 are estimated with robust standard errors. Equation 6 models drivers of perceptions of the worth of waiting using OLS regression, and equation 7 models drivers of the probability of reneging using logistic regression.

$$WORTH_i = f\begin{pmatrix} LAST_i + AHEAD_i + AHEAD^2{}_i + BEHIND_i + \\ WAIT_i + CYCLE_i + COMP_i + RENEGE_i + X_i + \epsilon_i \end{pmatrix} \tag{6}$$

$$\Pr(RENEGE_i) = f\begin{pmatrix} LAST_i + AHEAD_i + AHEAD^2{}_i + BEHIND_i + \\ WAIT_i + CYCLE_i + COMP_i + WORTH_i + X_i + \epsilon_i \end{pmatrix} \tag{7}$$

The cross-sectional models above follow the data aggregation strategy used in Study 2. $LAST_i$ is an indicator variable denoting whether the participant was always in last place, $AHEAD_i$, $AHEAD^2{}_i$, and $BEHIND_i$ model the maximum number of people ahead and behind the participant during their queuing experience. $WAIT_i$ captures the amount of time the participant spent in the queue, $CYCLE_i$ controls for the cycle time of the queue, $COMP_i$ controls for the amount of compensation participants are being offered to quit the queue, and $WORTH_i$ captures the participant's perceptions that waiting in the queue was worthwhile. If after controlling for these other factors, differential perceptions of the worth of waiting explain the decision of last place participants to quit, it would lend further support to the idea that last place aversion can lead to maladaptive queuing behaviors. Such a result would suggest that the mere fact of being in last place causes people to perceive that the service for which they are queuing is less valuable – despite the fact that being last neither influences the value of the service itself, nor the duration of one's wait to receive it.

3.4.6 Analysis and Results. In **Table 4**, Column 1 examines data for the subsample of participants who experienced queue transparency. It shows that when the queue was transparent, controlling for other factors, under low levels of compensation for quitting, participants were more likely to renege from the queue when they were in last place ($\beta = 2.638$, $P < 0.01$), offering support for H3. Unsurprisingly, participants exhibited an increased willingness to defect when the compensation for defecting was higher ($\beta = 0.128$, $P < 0.01$). Interestingly however, an interaction exists wherein participants who received more attractive compensation for reneging were less prone to reneging when they were in last place ($\beta = -0.093$, $P < 0.01$). When the least attractive compensation for quitting was offered (5 cents), participants in last place were 5.9 times more likely to renege than participants in other parts of the line. When a median level of compensation for quitting was offered (25 cents), participants in last place were only 24% more likely to quit the queue than those in other parts of the line. Participants in last place were no more nor less likely to quit than those who were not in last place when an above-median level of compensation was offered for leaving the line. This pattern of results lends additional support to the idea that last place aversion may lead to maladaptive queuing behaviors in that it disproportionately drives people to abandon queues in circumstances when waiting might be more valuable.

Column 2 replicates the analysis for participants in the non-transparent condition. The results reveal that in the absence of queue transparency, when participants could not see that they were in last place, the effects of being in last place on reneging from the queue were insignificant ($\beta = 0.668$, $P = 0.453$). Column 3 extends the analysis for the full sample of participants. The results again reveal that in the absence of queue transparency, the effects of last place aversion on reneging behavior were nullified ($\beta = 0.479$, $P = 0.512$). Queue transparency marginally reduced the probability of reneging from the queue ($\beta = -1.774$, $P < 0.10$), but there exists a significant interaction, wherein participants who were able to observe that they were in last place were significantly more likely to renege ($\beta = 2.518$, $P < 0.05$). This pattern is interesting, in that it suggests that queue transparency has a contingent effect on reneging: seeing that one is not in last place reduces the probability of reneging, while seeing that one is in last place increases the probability of reneging. Consistent with the earlier results, the three-way interaction of transparency, last place, and compensation for quitting the queue is significant and negative ($\beta = -0.078$, $P < 0.05$), lending converging evidence that last place aversion can lead to maladaptive queuing behavior. Seeing that one is in last place has a disproportionate effect on reneging when queueing for services that are more valuable.

These results have important practical implications. First, they reveal that last place aversion not only adversely affects the experiences of waiting customers in ways that may diminish their satisfaction with the service, but also their behaviors, in ways that stand to undermine the performance of the service itself. Controlling for other factors, participants who were in last place were more likely to quit the line, giving up on the service entirely. Second, the results suggest that the effects may be most significant in less discretionary queuing contexts, where the cost of abandonment may be more severe for the customer. It should be noted that these results do not speak to behaviors in non-discretionary queuing environments, wherein completion utility is so high (and/or abandonment disutility is so high) as to preclude reneging. In such environments, it seems reasonable to assume that the benefits of waiting (and/or the high costs of quitting) would outweigh the pain of last place aversion, though this question remains an opportunity for future research. Finally, these results highlight queue transparency as a lever that may be used to reduce customer defections due to last place aversion. For example, since queue transparency reduces defections when people are not in last place, but increases defections when people are in last place, managers of a call center may be well served by providing information to customers about the state of the queue in front of them until a queue has accumulated behind them. Thereafter, the call center might transition to providing transparency about the shrinking line ahead, *and* the growing line behind.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Pr(Renege)	Pr(Renege)	Pr(Renege)	Worth waiting	Worth waiting	Pr(Renege)	Pr(Renege)
Last place indicator	2.638***	0.668	0.479	-0.792***	-0.100	1.481**	1.046
	(1.022)	(0.891)	(0.729)	(0.212)	(0.200)	(0.675)	(0.816)
Renege indicator					-2.601***		
					(0.232)		
Worth waiting							-1.034***
							(0.178)
Transparency			-1.774*				
			(0.992)				
Transparency x last place			2.518**				
			(1.114)				
Compensation to quit	0.128***	0.095***	0.080***	-0.021***	-0.016***	0.048***	0.036**
	(0.033)	(0.020)	(0.023)	(0.004)	(0.004)	(0.014)	(0.016)
Compensation x last place	-0.093***	-0.018	-0.015				
	(0.029)	(0.022)	(0.019)				
Transparency x compensation			0.046*				
			(0.027)				
Transparency x last place x compensation			-0.078**				
			(0.031)				
Number ahead	0.174*	-0.058	0.053	-1.485***	-0.442*	4.009***	3.019***
	(0.105)	(0.107)	(0.066)	(0.248)	(0.234)	(0.630)	(0.714)
Number ahead^2				0.222***	0.063*	-0.612***	-0.471***
				(0.034)	(0.033)	(0.086)	(0.100)
Number behind	-0.038	0.145	0.066	-0.064	-0.108*	-0.058	-0.348
	(0.209)	(0.188)	(0.131)	(0.067)	(0.059)	(0.199)	(0.242)
Time since joining queue	-0.017	-0.017***	-0.020***	0.005***	-0.006***	-0.067***	-0.078***
	(0.011)	(0.005)	(0.006)	(0.001)	(0.002)	(0.009)	(0.012)
Cycle time	-0.017	-0.046	-0.029	0.013	0.010	-0.080***	-0.068**
	(0.034)	(0.044)	(0.025)	(0.012)	(0.009)	(0.027)	(0.029)
Female indicator	-0.773*	-0.887**	-0.742***	0.280**	0.223**	-0.382	-0.064
	(0.419)	(0.371)	(0.273)	(0.122)	(0.109)	(0.349)	(0.396)
Age	0.002	-0.001	0.001	0.017***	0.017***	0.001	0.017
	(0.017)	(0.016)	(0.010)	(0.005)	(0.004)	(0.016)	(0.016)
Education	0.015	-0.023	0.005	-0.023	-0.001	0.184	0.078
	(0.127)	(0.150)	(0.089)	(0.045)	(0.041)	(0.129)	(0.131)
Constant	-7.964***	-6.274***	-5.696***	6.494***	6.193***	-4.070***	2.696
	(2.134)	(1.640)	(1.383)	(0.601)	(0.499)	(1.505)	(1.884)
Observations	4,963	5,244	10,207	670	670	670	670
Number of participants	665	753	1,418	670	670	670	670
Model selection	RE Logit	RE Logit	RE Logit	OLS	OLS	Logit	Logit
Sample selection	Transparent	Non-transparent	Full sample	Transparent	Transparent	Transparent	Transparent
Pseudo/Adjusted R-squared				0.166	0.331	0.578	0.719

Table 4: Reneging behavior is significantly increased by being in last place (Study 4). Columns 1-3 are estimated with random effects logistic models. Columns 4-5 are estimated with OLS models. Columns 6-7 are estimated with logistic models. Adjusted R-squared measures are provided for Columns 4-5 and Pseudo R-squared measures are provided for Columns 6-7. Such metrics cannot be calculated for random effects logistic models, and are accordingly not provided in Columns 1-3. All models are estimated with robust standard errors, which are shown in parentheses, with Columns 1-3 clustered at the individual level. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively.

Why does last place aversion in queues lead to reneging? Columns 4-7 test perceptions of the worth of waiting as a potential mechanism. This potential mechanism is related to the idea of downward social comparison. Intuitively, the last place participant, who sees that no one is willing to wait longer for the service than he or she is, may question whether continuing to wait is worthwhile. Since transparency is a requirement for one to know his or her relative position, these tests focus on the subsample of participants who experienced transparent waits. Column 4 shows that participants who spent the duration of their wait in last place reported lower perceptions of the worth of waiting (β = -0.792; P < 0.01). Column 5 shows that these diminished perceptions of the worth of waiting were especially acute among those who chose to renege from the queue (β = -2.601, P < 0.01), and that after accounting for people who reneged, those who persisted in last place did not report perceptions that were significantly diminished (β = -0.100, P = 0.615).

Columns 6-7 provide converging evidence. The columns reveal that controlling for the perceptions of the worth of waiting diminishes the relationship between being in last place and reneging. Being in last place is positively associated with reneging (β = 1.481, P < 0.05). Perceptions of the worth of waiting are negatively associated with reneging (β = -1.034, P < 0.01), and controlling for these perceptions drops the strength of the relationship between being in last place and reneging to insignificance (β = 1.046, P = 0.200).

A causal mediation analysis that accounted for the alternating specifications of the mediator and outcome variables (Hicks and Tingley 2011; Imai, Keele, and Tingley 2010) revealed that the average causal mediation effect, the change in the probability of defecting from the queue that was due to being in last place's reduction in the perceptions of the worth of waiting, was 0.0443 (95% confidence interval: 0.0186, 0.0763) relative to a total effect of 0.1025 (95% confidence interval: 0.0055, .2179). Diminished perceptions of the worth of waiting explained 43.5% of the total effect of being in last place on the probability of quitting the queue. These results are consistent with the idea that part of what may drive the effect of last place aversion in queues is the absence of a target for downward social comparison. When there is no one who is worse off, the last place individual is left feeling uncertain about whether waiting in the queue itself is worthwhile and may choose to defect in response.

3.4 Study 5: Last place aversion and service performance (H4)

Studies 1-4 have provided evidence of the individual-level effects of last place aversion on customers. An open question is whether these individual-level effects propagate such that they have system-level consequences. Study 5 addresses this question by comparing the performance of paired treatment and control queues, formed contemporaneously, manipulated such that participants waiting in the treatment queue never feel as though they are in last place. This design enables a direct investigation of whether last place aversion hinders the capacity of service systems, as hypothesized in H4.

3.5.1 Participants: 444 participants (44.3% female, M_{age}=38.59, SD=11.79) completed this study on the Amazon Mechanical Turk platform in exchange for 25 cents, with an opportunity to earn a 50-cent bonus for waiting in a queue.

3.5.2 Design and Procedure: Study 5 replicated the design of Study 4, with six differences. First, all queues in Study 5 were transparent. Second, instead of recruiting participants to engage in a study that paid 50 cents for completion, and offering lower amounts to participants who chose to quit the queue, participants were recruited to engage in a study that paid 25 cents for completion, and were offered a bonus of 50 cents if they decided to remain in the queue – mimicking a scenario from Study 4 in which waiting for service should be rationally worthwhile. Third, rather than forming one queue at a time, as in previous studies, Study 5 was coded to form pairs of queues simultaneously, with each new arrival being added in alternating fashion to a treatment or control queue within a paired system. This approach ensured that arrival rates between paired queues were practically identical (**Figure 5**). Fourth, instead of assigning each participant a randomly-chosen avatar, each paired queue system used the same avatars to represent people who arrived in the same order. This design choice ensured that from the outset, each paired queue looked as similar as possible to the participants. Fifth, data were collected every five seconds instead of every ten.

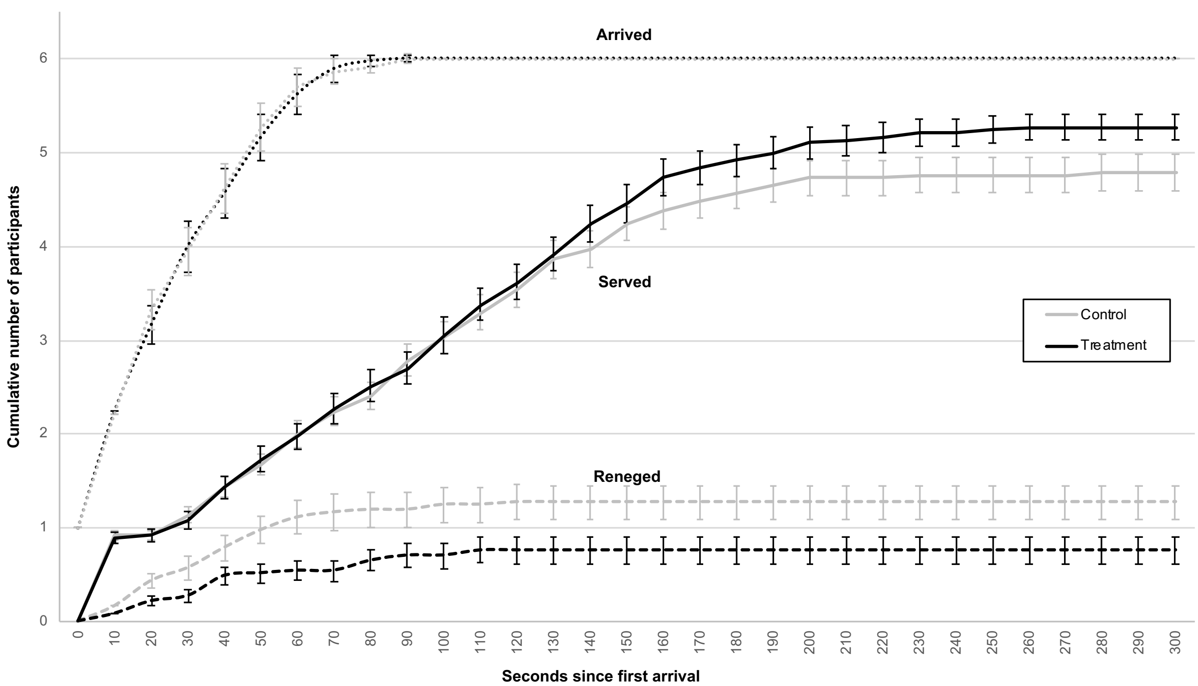


Figure 5: Cumulative counts of participants who arrived, reneged, and were served over time (Study 5). Black lines represent treatment queues, where digital confederates were used to ensure participants never felt as though they were in last place. Grey lines represent paired queues without this treatment. Fewer participants reneged and more participants were served in the treatment queues, suggesting that addressing last place aversion has the potential to increase service capacity. Standard errors are plotted for each series.

Sixth, and most importantly, the treatment queue in each paired queue system was manipulated so that no participant ever viewed themselves to be in last place. Specifically, each participant in a treatment queue saw the queue represented exactly as it was, except with an extra person shown waiting behind them. This digital confederate was represented by a randomly-chosen avatar. These digital confederates were shown as though they arrived immediately after the participant, and they never defected for the duration of the participant's wait. Others who arrived after, were shown to be waiting in the queue behind the digital confederate. Critically, each participant could only see their own digital confederate, so from each participant's perspective, the line they were waiting in was exactly one person longer than it was in actuality, and that extra person was waiting immediately behind them. This manipulation was designed to ensure that no participant in a treatment queue ever perceived they were waiting in last place.

Since there were two conditions in this study, assigned at the queue level, a target of 30 queues per condition was established ex-ante, for the purpose of making queue-level comparisons. In order to ensure comparable arrival processes for the paired queues, an exclusion criterion was devised wherein all participants in a queue pair had to arrive within the same 90-second interval. Allowing too much arrival time dispersion would lead to disparities in the formation of the paired queues, reducing their length and their comparability, and would compromise the believability of the experimental manipulation by making the proximate arrival and persistence of the digital confederates seem less likely. Data collection proceeded until at least 30 queue pairs had been collected that satisfied these criteria. The resulting sample included 37 queue pairs, composed of 74 queues and 444 participants.

3.4.3 Independent measures. To control for the experience of participants at the queue level, average cycle times of each queue were measured. Participants in treatment queues spent an average of 23.26 seconds responding to the survey (SD = 4.88), while participants in control queues spent an average of 23.34 seconds responding (SD = 6.38). As in prior studies, data on participants' gender, age, and education level were also collected, and for the analysis are aggregated at the queue level.

3.4.4 Dependent Measures. The focal dependent measures for this study were the number of participants who chose to renege from each queue, the number of participants who reneged while in last place, and the number of participants who received service. An average of 1.27 participants reneged from each control queue (SD = 0.99), 85.1% of whom were in last place when they reneged. An average of 0.76 participants reneged from the average treatment queue (SD = 0.76), 82.1% of whom were in last place when they reneged. Interestingly, the proportion of participants who departed from the queue who were in last place when they reneged was similar in the treatment and control queues. However, 40.4% fewer participants left in total in the treatment queues, suggesting that the elimination of last place aversion had a substantive effect on the number of participants who received service. Accordingly, an average of 4.73 participants received service in the control queues (SD = 0.99), compared with an average of 5.24 participants in the treatment queues (SD = 0.76).

3.4.5 Empirical approach. Counts of the number of participants who reneged, reneged while they were in last place, and were served, $COUNT_i$, were modelled using a Poisson regression with robust standard errors clustered at the queue pair level, as modelled in Equation 8 below:

$$COUNT_i = f\left(TREAT_i + CYCLE_i + X_i + \epsilon_i\right) \tag{8}$$

In the equation above, $TREAT_i$ is a queue-level indicator variable denoting whether the queue was in the treatment condition. $CYCLE_i$ represents the average cycle time of the queue. X_i represents the proportion of female participants, and the average ages and education levels of the participants waiting in each queue.

	(1)	(2)	(3)	(4)
	Reneged in last place count	Reneged count	Reneged count	Served count
Treatment indicator	-0.641**	-0.572**	0.004	0.118**
	(0.286)	(0.229)	(0.127)	(0.047)
Reneged in last place count			0.830***	
			(0.086)	
Cycle time	0.024	0.021	-0.008	-0.005
	(0.016)	(0.013)	(0.007)	(0.004)
Female percentage	-0.211	-0.107	0.326	0.022
	(0.607)	(0.561)	(0.291)	(0.121)
Average age	-0.041*	-0.033*	-0.002	0.007**
	(0.023)	(0.019)	(0.009)	(0.003)
Average education	-0.150	-0.076	0.124	0.018
	(0.127)	(0.129)	(0.090)	(0.029)
Constant	1.841*	1.428	-1.399**	1.313***
	(1.093)	(0.962)	(0.685)	(0.221)
Model selection	Poisson	Poisson	Poisson	Poisson
Queue-level observations	74	74	74	74

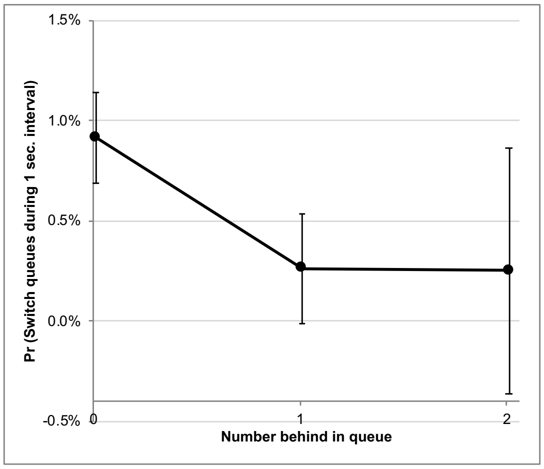
Table 5: Eliminating the effects of last place aversion increases the capacity of queues to serve customers (Study 5). Owing to the count dependent measures, all columns are estimated with Poisson regression with robust standard errors, clustered at the queue-pair level. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively.

3.4.6 Analysis and results. In **Table 5**, Column 1 demonstrates that, controlling for the speed and demographic composition of the queue, 47.3% fewer participants in the treatment queues, who were not made to experience last place aversion, quit the line when they were in last place (β = -0.641, P < 0.05). Column 2 shows that this reduction contributed to a 43.5% reduction in total reneging from treatment queues (β = -0.572, P < 0.05). Column 3 demonstrates that the reduction in total defections is attributable to the reduction in those who departed the queue while in last place ($\beta = 0.830$, $P < 0.01$), with the treatment having an insignificant effect on reducing other defections ($\beta = 0.004$, $P = 0.98$). Finally, Column 4 shows that 12.5% more people received service in the treatment queues, when the effects of last place aversion were nullified ($\beta = 0.118$, $P < 0.05$). Indeed, untabulated analyses show that, although average service rates were statistically indistinguishable among the treatment and control queues ($\beta = 0.21$, $P = 0.87$), the average peak queue length was 9.5% longer ($\beta = 0.360$, $P < 0.05$) and the average wait of the last to arrive was 13.5% longer ($\beta = 13.27$, $P < 0.10$) in the treated queues. Taken together, these results provide support for H4, suggesting that last place aversion can reduce the capacity of queues to serve customers.

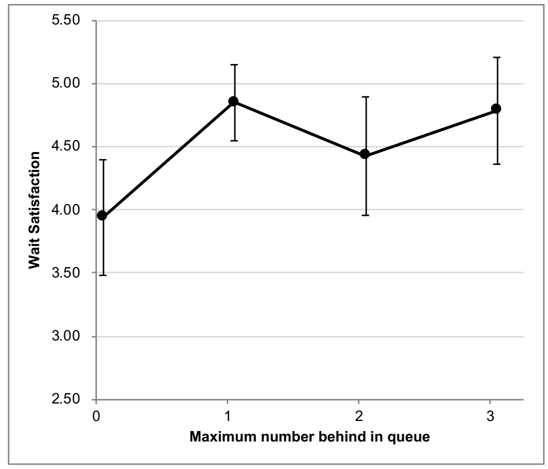
4. General discussion

In five studies, conducted in physical and virtual queuing environments, this paper has demonstrated that last place aversion is a potent driver of the experiences of people waiting in queues, driving maladaptive behaviors that diminish service capacity. As initial evidence, an observational analysis of a grocery store queuing environment reveals that customers waiting for service are more likely to switch queues when they are in last place, controlling for the number of people ahead of them, how long they have been waiting, and how fast the line is moving (Study 1). Subsequent studies provide converging evidence of the effects of last place aversion (**Figure 6**), disentangling it from the linear effect of the number of customers behind in the queue, tracing out its implications for experiences and behaviors, identifying a psychological mechanism underlying the effect, and highlighting a potential managerial approach for reducing its impact in practice.

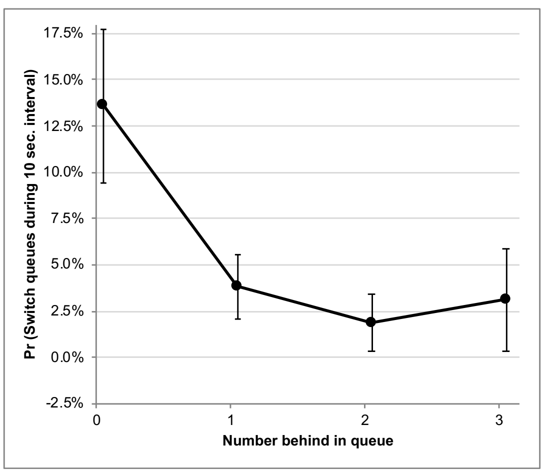
The results demonstrate that waiting in last place diminishes satisfaction, but that people habituate to being in last place over time, suggesting that interventions targeting customers early in their waits might be most promising for nullifying the effects of last place aversion in queues (Study 2). The results further reveal that the negative experiences engendered by being in last place affect peoples' behavior. When people are in last place, they are more likely to switch queues (Study 3) and more likely to abandon queues altogether (Study 4). Subsequent analysis reveals that these behaviors can be maladaptive. People who are driven to switch queues while in last place may do so in the absence of strategic reasons for switching, increasing the overall duration of their wait without improving their own satisfaction (Study 3). Moreover, people in last place may be more likely to quit queuing for services that are more valuable, since the absence of a target for downward social comparison causes them to perceive the wait to be less worthwhile (Study 4). The results provide evidence that actively managing queue transparency, by obscuring from customers when they are in last place, and revealing to customers when they are not in last place, holds promise for reducing abandonment (Study 4), and a system-level analysis shows how nullifying the effects of last place aversion in queues can increase overall service capacity (Study 5).



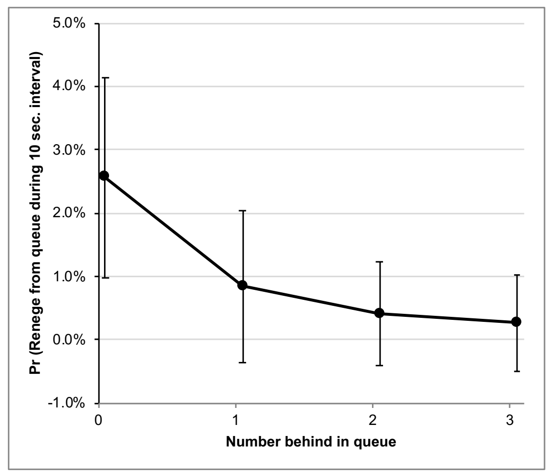
A. **Switching Behavior** (Study 1)



B. **Wait Satisfaction** (Study 2)



C. **Switching Behavior** (Study 3)



D. **Reneging Behavior** (Study 4)

Figure 6: Margin Plots for individual-level behavioral studies (Studies 1-4). Study 1 (Panel A) explored how relative position affected switching behaviors in a grocery store. Study 2 (Panel B) explored how relative queue position affected wait satisfaction in the online environment. Study 3 (Panel C) explored how relative queue position affected switching behavior in the online environment. Study 4 (Panel D) explored how relative queue position affected reneging behavior in the online environment, and displays results for a transparent queue with low compensation for quitting (5 cents). All plots are estimated with robust standard errors, clustered at the individual level. They reveal a discontinuity in perceptions and behaviors when a person is last in a queue. 95% confidence intervals are presented with each estimate.

4.1 Managerial Implications

Although considerable attention is devoted to designing efficient service processes that reduce waiting times and to designing experiences that manage customers' perceptions of what's ahead of them in the queue, this research highlights the counterintuitive and outsized effect of what's taking place behind them – in particular, whether they're in last place. Since the last place customer is readily identifiable in any queue, these dynamics have important practical implications for managers, who can design queuing environments and service practices that account for the powerful effects of last place aversion. This section highlights a handful of important managerial implications that arise from this research.

4.1.1 Last place aversion undermines experiences and drives maladaptive customer behaviors. The present research reveals how a factor that is often ignored by service managers – in particular, whether a queuing customer is in last place – can wield considerable influence over how they perceive and engage in queueing environments. In the present research, controlling for other factors, participants who spent the duration of their wait in last place reported declines in satisfaction that were the same as waiting an additional 70 seconds for service – equivalent to waiting behind two extra people. People queuing in last place were more than twice as likely to switch queues, even without visual information that would have enabled them to do so strategically, which prolonged their wait times and further diminished their satisfaction. Moreover, being in last place more than quintupled the probability of defecting from queues in which it would have been most worthwhile to persist. This pattern of results, wherein last place aversion leads to negative outcomes for customers and service firms alike, casts it as an opportunity for mutually advantageous service innovation.

4.1.2 The negative effects of last place aversion may not be easily detected and may be misattributed to other factors. To the extent that the effects of last place aversion may be most pronounced among customers who value the service more, those who abandon due to last place aversion may be more likely to blame the service provider for the queuing experiences that led to their defection. To the extent these customers feel particularly aggrieved, there may be important long-term implications for the service relationship that would not be captured through traditional post-sales customer survey initiatives – especially if they reneged before providing feedback. Even the experiences of customers who choose not to abandon the queue may be jeopardized by last place aversion. In Study 2, we observed that controlling for other factors, participants who spent the duration of their wait in last place reported being 25.8% less satisfied with their waiting experience than participants who waited elsewhere in the queue. Hence, even interactions that result in a near-term sale may erode the long-term service relationship if the dynamics of last place aversion undermine customers' experiences. Furthermore, since a customer's relative position in the queue and their choice to switch queues are data that are rarely tracked in practice, diminished satisfaction with the interaction, if it is captured at all, may be misattributed to other factors, such as the agent who served the customer, rather than to the queuing dynamics themselves.

4.1.3. The effects of last place aversion can be mitigated through thoughtful service design. Study 4 highlights how queue transparency is one lever that can be used to dampen the negative behavioral effects of last place aversion in queues. What's interesting about this intervention is that it highlights both the demotivating and motivating aspects of last place aversion. Controlling for other factors, when participants could see they were in last place in a less discretionary queuing environment (5 cents offered for quitting), they were 1.5 times more likely to renege than when they could not see they were in last place. Making the fact that they were in last place salient had a demotivating effect, increasing the likelihood they would give up on waiting. In contrast, when participants could not see that they were not in last place, they were 3.7 times more likely to renege than when they could see they were not in last place. Making the fact that they were not in last place salient had a motivating effect, decreasing the likelihood they would give up on waiting. This pattern of results suggests that interventions that engage, distract, or obscure one's relative position when they are in last place, and that emphasize one's relative position when they are not, may help motivate individuals to stay the course. Furthermore, Study 2 reveals that wait satisfaction is most compromised by last place aversion early in a customer's wait. Consistently, evidence from Studies 1, 3, and 4 demonstrated that customers become more persistent the longer they remain in queues, exhibiting fewer switching and reneging behaviors. Consequently, interventions targeting last place customers early in their waits may hold the most promise for improving their experiences and forestalling switching and reneging. For example, a diner with a first-come-first-served queue may improve customer experiences and reduce customer defections by providing refreshments to those waiting near the end of the line (Buell 2016).

4.1.4 Addressing last place aversion can increase service capacity. Study 5 demonstrates the potential for service firms that are able to successfully address the negative effects of last place aversion. When experiences were managed such that participants were not able to perceive themselves as being in last place, overall defections fell by 43.5%, and 12.5% more people were served, holding constant the arrival and service rates. These results suggest that when increasing the speed of service may be costly or otherwise difficult, a promising alternative may be to allocate resources to improve the experiences of those at the back of the queue – in particular, the experiences of those who are in last place.

4.2 Limitations and Opportunities for Future Research

An important caveat to these results is that just as last place aversion may be an innate part of human psychology, it may also be a natural process that regulates the length of queues – a means by which those with the least invested in the interaction can censor themselves from the system, thereby preventing the realization of exponential queue growth that occurs when the arrival rate exceeds the service rate. In congested queuing environments, reducing abandonment by actively managing last place aversion may lead to longer lines and broader challenges with the operation, which would be a fruitful area for future research. For example, all of the queues examined in this paper were relatively short – with six or fewer people waiting. Future research could examine how last place aversion manifests in longer queues, and how the dynamics of addressing its effects in longer queues may differ. For example, it may be the case that the feeling of being in "last place" in a longer queue expands beyond the individual at the very end of the line. Moreover, to the extent that mitigating the negative effects of last place aversion makes people persist longer in queues, increasing the average number of people waiting, addressing last place aversion may reduce queue joining behavior, an interesting tradeoff worthy of future analysis.

Nevertheless, the present results suggest that active management of last place aversion may be beneficial in many contexts and that thoughtful consideration of its effects may improve experiences in performance in a wide array of settings. For example, operations could be designed to facilitate social comparisons among customers in ways that help them more deeply engage in their own medical care, save more for their own retirement, or persist in their pursuit of exercise or education. Similarly, these insights hold promise for improving the productivity and performance of employees. These results provide converging evidence with prior research (Kuziemko et al. 2014; Song et al. 2015) that the desires to get out of last place, and to avoid falling into last place, are powerful motivators that can help drive human behavior.

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