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Making the Wait Worthwhile: Experiments on the Effect of Queueing on Consumption

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1. Introduction

Customers spend a significant amount of time waiting in lines. For instance, the average wait before being seated at a restaurant in the United States is 23 minutes (FSR 2013), extending to more than an hour at popular eateries (Grose 2011). According to some estimates, the time spent in lines adds up to 37 billion hours per year in the United States alone (Stone 2012). Extant literature has identified two important effects of long lines on a firm’s sales. First, queues have a recognized negative effect on sales as a result of lost customers (Pazgal and Radas 2008, Allon et al. 2011, Lu et al. 2013). Second, queues can signal quality and thus help a firm attract more customers (Raz and Ert 2008, Veeraraghavan and Debo 2009, Giebelhausen et al. 2011, Debo et al. 2012, Kremer and Debo 2016).

Whereas past literature provides insights about how queues might influence the number of customers served (i.e., whether customers join and remain in line), it is typically assumed that queues do not affect individual customers’ consumption decisions. This may be a valid assumption in contexts where the customer commits to a purchase/consumption decision prior to waiting in line—for instance, grocery shopping at Costco. However, when the consumption decision is made after having spent time waiting in a line (e.g., at a restaurant or a bakery), the mere act of waiting might influence subsequent decisions. Specifically, it is possible that a long wait could lead to increased spending, as customers try to amortize the cost of waiting over larger quantities or more expensive purchases (Thaler 1985). It is also plausible that after enduring a long wait, individuals end up spending less as they may become dissatisfied and frustrated (Maister 1984, Larson 1987) and therefore be unwilling to reward the firm with a large purchase.

In this paper, we conduct a series of experimental studies in the laboratory and in the field to investigate how the amount of time a customer spends waiting influences subsequent consumption decisions. Our work contributes to the literature in several ways. First, our findings suggest that the amount of time customers spend waiting in line results in increased consumption, provided they do not leave the line. This means that the two archetypal stages of service processes, waiting and service, which are assumed to be independent, are in fact interdependent. Second, we study the underlying mechanism and show that this behavior is consistent with mental accounting for sunk costs—that is, customers amortizing the fixed (and sunk) cost of waiting in a queue by increasing consumption. Third, we explore the effect of common managerial practices that aim to improve customers’ waiting experience. Despite the intuitive benefits of improving the queueing experience, we show that such practices have a paradoxical side effect in that they can actually reduce spending. Specifically, when customers are distracted while they wait in line, we observe that their satisfaction with the waiting experience goes up, but their actual spending
goes down. Finally, our work provides evidence for the sunk-cost fallacy in the time domain, which has been more elusive than that in the domain of monetary investments.

2. Literature Review

Queueing literature suggests that the act of waiting leads to economic costs for customers as a result of lost time (Baker et al. 2002), as well as psychological costs such as boredom, frustration, and anxiety (Maister 1984, Larson 1987); it results in unpleasant negative emotions and cognitions (Maister 1984, Larson 1987, Taylor 1994, Carmon and Kahneman 1995, Hui and Tse 1996, Brady and Cronin 2001, Dabholkar and Bagozzi 2002). As a result, the process of waiting can adversely affect product evaluations, service evaluations, and purchase satisfaction (Hui and Tse 1996, Houston et al. 1998). Decreased affect has specifically been found to reduce impulse purchase intentions (Beatty and Ferrell 1998, Mohan et al. 2013). Furthermore, wait times can lead some customers to abandon the queue without making a purchase (Pazgal and Radas 2008, Allon et al. 2011, Lu et al. 2013).

Nevertheless, in some cases, queues may be of use, both for service firms and for their customers. Research in marketing and operations management suggests that customers can infer quality information from long lines (Raz and Ert 2008, Veeraraghavan and Debo 2009, Giebelhausen et al. 2011, Debo et al. 2012); if quality were low, it would not be worth the wait, and there would not be a long line. Experimental work has demonstrated that long lines can increase the likelihood that customers join a line (Raz and Ert 2008) and can signal quality to the customers (Giebelhausen et al. 2011, Kremer and Debo 2016). Related work finds that customers infer that products are more valuable when others are behind them (Koo and Fishbach 2010). Hence, a service provider may sometimes prefer to slow down the service rate to signal high quality via long lines, even if some customers might be lost as a result of longer waiting times (Debo et al. 2012).

The literature has studied how queue length influences whether people join a line based on quality signaling (e.g., Lu et al. 2013, Kremer and Debo 2016) or waiting time certainty (e.g., Leclerc et al. 1995, Aşın et al. 2017), and whether they continue to stay or abandon a physical or virtual queue (e.g., Zhou and Soman 2003, Webb et al. 2017). It has also explored how queue length and speed influences experienced utility, in real time and in retrospect (e.g., Carmon and Kahneman 1995, Houston et al. 1998, Koo and Fishbach, 2010). However, it has not addressed how the time spent in a queue itself impacts customers’ subsequent consumption decisions. Our work takes an important first step toward understanding of this perspective.

Our findings contribute to the emerging behavioral queueing literature (see Allon and Kremer 2018 for an exceptional review in this area). Some representative experimental and empirical works in this area include Buell and Norton (2011) and Buell et. al (2017), who find that customers’ perceived value of the service may increase if the server’s work is observable; Song et al. (2015), Wang and Zhou (2018), and Shunko et al. (2018), who find that agents may slow down when working with pooled as opposed to dedicated queues; and Buell (2017), who suggests that customers in the last spot are more likely to switch queues or renege as a result of “last place aversion.” Modeling papers that study behavioral queueing include Plambeck and Wang (2013), Dong et al. (2015), and Armony et al. (2017), to name a few. Our work provides evidence for a positive relationship between waiting time and consumption, suggesting a new perspective for why queues might sometimes be beneficial for firms. To our knowledge, this is the first observation and explicit exploration of temporal investments in a queue leading to increased spending/consumption.

Our findings also add to the empirical evidence on customers’ bounded rationality in service systems. For example, Conte et al. (2016) report that participants in experiments seem to use a rule of thumb that ignores server-speed information and choose to join shorter queues. Similarly, upon studying queueing data from the deli counter at a supermarket, Lu et al. (2013) conclude that customers ignore the number of servers and rely primarily on queue-length information to make their purchasing decisions. The evidence of decision biases offered in this paper comes from the customers’ tendency to consider sunk time investments in their decision making. For a review of the recent developments in modeling bounded rationality in queues (e.g., Huang et al. 2013, Li et al. 2016, Tong and Feiler 2017), we refer readers to Ren and Huang (2018).

Finally, our paper contributes to the literature on sunk-cost fallacy by providing evidence for the sunk-cost effect when the investments are in the time domain, which has previously found mixed support (Heath 1995, Soman 2001, Long et al. 2016). We show that consumption increases with the time spent in line and that the effect is stronger for individuals who are more susceptible to the sunk-cost fallacy. Furthermore, we show that one way to “debias” the decisions is to distract or engage people as they wait in line, thereby weakening the sunk-cost effect. These findings are in line with arguments made for the different ways in which people account for time and money (Leclerc et al. 1995, Okada and Hoch 2004): whereas money is concrete and fungible, people have a hard
time making trade-offs involving time as its value is subjective, hard to assess, and context dependent (Soman 2001).

3. Hypotheses Development
The extant queueing literature assumes that consumption decisions are made independently of the wait experienced by rational economic players whose decisions are based on future marginal costs and benefits, with no concern for the irreversible fixed (sunk) costs of queueing (see Hassin and Haviv 2003). If the waiting time, \( W \), is longer than an individual’s maximum willingness to wait, \( W_{\text{max}} \) then the customer balks (e.g., Naor 1969, Allon et al. 2011, Lu et al. 2013); if the waiting time is less than the individual’s maximum willingness to wait, the customer makes a purchase that is unaffected by the queue.

However, a long stream of behavioral literature suggests that real people’s decisions are influenced by sunk costs as they mentally account for irreversible costs. Thaler (1980) observes that people who had paid for tickets for a basketball game in advance chose to drive despite a snowstorm, whereas those who got the tickets for free preferred to stay home. Arkes and Blumer (1985) find that season ticket holders who were randomly offered price discounts attended fewer plays relative to those who paid full price. Gourville and Soman (1998) observe that attendance at a sports club reached its peak right after the dues were paid and declined over time until the next payment. Navarro and Fantino (2009) show that people persist in projects in which they have invested effort. Similarly, Webb et al. (2017) find that customers were less likely to abandon virtual queues at a bank’s call center when they had spent more time waiting.

According to Thaler (1980, 1985, 1990, 1999), people engage in such behavior because of mental accounting; they mentally track costs and benefits associated with their decisions. When a cost is incurred, rather than being immediately recognized as a loss, the cost is recorded in a mental account; the “negative balance” is carried forward until the account is closed. In making subsequent decisions, people act to avoid closing the account “in the red”; as a result, past (sunk) costs have an influence on future decisions. In other words, the desire to avoid closing the mental account in the red creates a coupling between the sunk cost and subsequent decisions.

Mental accounting explains consumption decisions through the prism of a utility model that decomposes consumer utility into acquisition utility (the value of the good/service obtained relative to its price) and transaction utility (the perceived value of the “deal”). It suggests that an otherwise inferior (superior) transaction might occur because consumers try to get (avoid) a good (bad) deal. One manifestation of this is the sunk-cost fallacy driving increased consumption; after having spent money, time, or effort, an individual consumes more, trying to offset the sunk costs incurred, even after the object of marginal consumption becomes less desirable. For instance, people who paid a higher price at an all-you-can-eat restaurant ate more, because more food for the same fixed price resulted in higher transaction utility (i.e., a better deal), even though they enjoyed the food less (Just and Wansink 2011). Similarly, car owners that paid a higher purchase price, taxes, and fees used their cars more to avoid the psychological costs of an expensive asset that did not get enough use (Ho et al. 2018). We expect to see a similar effect in the queueing context, where the sunk cost recorded in the mental account is the waiting time. A small purchase, which may be optimal (a “good deal”) for a customer in the absence of a wait, would represent a “bad deal” after a long wait; the perceived value of the deal (transaction utility) can be improved by adjusting the purchase quantity upward.

To see this formally, consider the following model that builds on Thaler (1999) and Ho et al. (2018); a more detailed version is relegated to Appendix A. We assume that the acquisition utility of purchasing quantity \( Q \) (at unit price \( P \)) after waiting in line for amount of time \( W \) (at unit cost \( c \)) is represented by \( f(Q) - P \cdot Q - c \cdot W \). The gross value from consumption, \( f \), is nonnegative, bounded from above, and concave increasing in \( Q \) (\( 0 \leq f'(Q) < \infty, f''(Q) > 0, f'''(Q) < 0 \)); \( f''(Q)^{a} \) is monotonic. Furthermore, similar to Ho et al. (2018), we assume that transaction utility is lower if consumption (purchase quantity) is not commensurate with the sunk cost (amount of time spent in the queue). Finally, define parameter \( \lambda \geq 0 \) to represent the degree to which sunk costs play a role in the decisions. One can write the resulting net utility for the individual as follows:

\[
U(Q) = f(Q) - P \cdot Q - c \cdot W + \lambda \cdot W \cdot Q. \tag{1}
\]

Assume that the waiting time is smaller than a customer’s willingness to wait (i.e., \( W < W_{\text{max}} \)). Then, the customer would stay in line to complete the transaction and choose optimal purchase quantity \( Q^{*} \) to equate \( f'(Q^{*}) = P - \lambda \cdot W \). Furthermore, it can be shown that \( \frac{\partial Q^{*}}{\partial W} > 0 \) (see Appendix A). Correspondingly, we have the following hypothesis.

**Hypothesis 1.** Assume that the waiting time is less than \( W_{\text{max}} \). Consumption increases with the waiting time.

There might be alternative explanations for the hypothesized positive correlation between waiting time and consumption (e.g., self-selection, quality inference from queue length, ego depletion). As will be described in detail in the next section, the studies were designed
to isolate the effect of mental accounting from these confounding factors. To explicitly attribute the effect of queueing on consumption decisions to the sunk-cost fallacy, we demonstrate that the effect is moderated by customers’ individual susceptibility to the sunk-cost fallacy. Past work has found that there are individual differences in decision-making competence and, specifically, in susceptibility to sunk costs (Parker and Fischhoff 2005). Accordingly, one should anticipate that greater susceptibility to the sunk-cost fallacy, a proxy measure for engagement in mental accounting, increases the positive effect of queueing on purchase decisions.

The consumer utility model in (1) embeds rational decision makers ($\lambda = 0$); such individuals would choose the same quantity regardless of how much they wait. By contrast, for customers that are susceptible to the sunk-cost fallacy ($\lambda > 0$), our model predicts that consumption increases with the waiting time and that this effect becomes stronger as $\lambda$ becomes more positive (see the proof in the appendix). We put this in other words as follows.

**Hypothesis 2.** The effect of waiting time on consumption is stronger for customers who are more susceptible to the sunk-cost fallacy.

On the other hand, mental accounting for sunk costs may have a stronger influence in some contexts and weaker in others. One such contextual factor is the cost of consumption. When customers feel compelled to increase consumption as a result of mental accounting for sunk costs, it may be easily done when the per-unit price paid to increase consumption is low, but not so when the price points are high. This is because the utility achieved from spreading the waiting cost over larger purchases competes against the disutility of paying extra money out of pocket. Therefore, we hypothesize that the effect of the sunk-cost fallacy will be diminished at high price points (see the proof in Appendix A).

**Hypothesis 3.** The effect of waiting time on consumption is weaker for a more expensive product.

Finally, we consider the moderating impact of operational levers that influence the waiting experience on the focal relationship. In the context of queueing, the investment is time, which differs from monetary investments in important ways. The value of time is ambiguous, malleable (Heath 1995, Okada and Hoch 2004), and context dependent (Leclerc et al. 1995). As a result, decisions are more dependent on heuristics than those made in situations involving money (Saini and Monga 2008). In Soman’s (2001) words, “The same quantity of time investment may have a different sunk cost impact in different settings, i.e., when the quality of the experience was different” (p. 183).

Maister (1984) suggests that although queues might be unavoidable, people’s experiences in queues can be improved and the wait can be made less unpleasant through various practices. Such practices include reducing the unoccupied wait (for instance, distracting them by placing reading materials, setting up TV screens, or playing music in waiting areas) and engaging them in the process earlier (for instance, a restaurant providing customers with a menu to view while they wait). These practices aim to reduce the perceived economic and psychological costs associated with waiting (Maister 1984, Oxoby and Bischak 2005). For instance, it was shown that distractions in queueing settings reduce perceived waiting time (Hui et al. 1997, Borges et al. 2015) and increase satisfaction (Katz et al. 1991). At the same time, because they lower the perceived cost of waiting (Maister 1984, Katz et al. 1991, Hui et al. 1997), we expect such approaches to diminish the sunk costs in the mental accounts associated with the transaction and, as a result, decrease the urge to spread it over a larger consumption quantity. Accordingly, we propose that such practices will moderate the relationship between waiting and consumption. We put this formally as follows.

**Hypothesis 4.** Initiatives that improve the queueing experience diminish the effect of waiting on consumption.

### 4. Studies

We test the hypotheses developed above over six studies including experiments, a field study, and transaction data. These studies collectively provide consistent support for the hypotheses and provide evidence against alternative explanations such as self-selection bias, ego depletion, increasing hunger, and quality inference (see Table 1).

Study 1 provides evidence of a positive relationship between waiting time and increased consumption in a real context. This study finds that purchase intentions at a local cupcake store were increasing with both self-reported and externally recorded proxies for waiting time. Importantly, to rule out quality signaling as the driving mechanism, this study controlled for quality perceptions and whether the participants were repeat customers. One weakness of this study is the potential confounding effect of self-selection. The study limits this effect (the lines were persistently long when the study was run); however, it cannot fully rule it out.

Study 2 circumvents self-selection with a controlled experiment design that randomly assigned participants to simulated queues that varied in length and as to whether a menu was presented during the wait. It also provides evidence against ego depletion, diminishing willpower, increasing hunger, quality signaling, and cognitive dissonance as
alternative explanations. Furthermore, Study 2 utilizes sunk-cost susceptibility scores (collected two months after the original study) to provide more direct evidence for the sunk-cost fallacy as the driving mechanism.

Study 3 isolates the sunk costs associated with waiting as the driving mechanism for increased purchase intentions and sheds light on operational levers by considering different versions of long lines that only differed in the waiting experience. This study also shows that measures that reduce unoccupied time and engage the customers early indeed improve customer experience as previously suggested (Maister 1984, Larson 1987, Borges et al. 2015); however, they also lead to lower consumption for individual customers.

Study 4 investigates the effect of price; it shows that purchase quantities are more sensitive to waiting times under low prices and that the effect dissipates under higher prices. Therefore, the sunk-cost effect has a more meaningful economic impact in some settings than others.

Study 5 shows that the findings hold in an incentive-compatible experiment where participants are asked to bid their own money for an Amazon gift card; the bids increased with the amount of time spent waiting. This study also finds a significant interaction effect between waiting time and participants’ susceptibility to sunk costs.

Finally, Study 6 involves the analysis of a data set containing transaction data over the course of one year from a fast-casual salad shop. We find that dollar transaction amounts per customer were higher at times when the salad shop was more congested, controlling for day of the week and time of day, confirming our hypotheses and providing additional external validity.

### 4.1. Queues at a Cupcake Store

#### Methods.

For Study 1, 164 participants completed questionnaires while waiting in line at a well-known cupcake shop in a commercial district on a busy Saturday afternoon. The percentage of customers that declined to participate was less than 5%.

Two research assistants, blind to the hypotheses, asked customers waiting in line to complete the questionnaires; a researcher provided supplies and monitored the queue length during data collection.

#### Table 1. The Road Map for the Studies

<table>
<thead>
<tr>
<th>Study</th>
<th>Methods</th>
<th>What the study does</th>
<th>Main findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Cupcake store</td>
<td>Customers waiting in line at a cupcake store filled questionnaires while research assistants recorded their positions in the queue.</td>
<td>—Establishes the main effect (Hypothesis 1) on the field.</td>
<td>—Purchase intentions are higher when the wait is long Hypothesis 1.</td>
</tr>
<tr>
<td>2. Simulated queue</td>
<td>Students reported purchase intentions for cupcakes after waiting in a simulated queue. Varied queue length and whether the participants saw a menu during the wait.</td>
<td>—Replicates the main effect (Hypothesis 1) in the laboratory.</td>
<td>—Purchase intentions are higher when the wait is long (Hypothesis 1).</td>
</tr>
<tr>
<td>3. Operational levers</td>
<td>MTurk recruits report purchase intentions for cupcakes after waiting in a simulated queue. Varied queue length and whether the participants saw a menu or video during the wait.</td>
<td>—Provides evidence for Hypothesis 4.</td>
<td>—The effect is diminished when the menu or video was present (Hypothesis 4).</td>
</tr>
<tr>
<td>4. Effect of price</td>
<td>MTurk recruits reported purchase intentions for T-shirts after waiting in a simulated line. Varied queue length and price.</td>
<td>—Provides evidence for Hypothesis 3.</td>
<td>—Purchase intentions are higher when the price is high (Hypothesis 3).</td>
</tr>
<tr>
<td>5. Auction</td>
<td>Students bid for an Amazon gift card after waiting in a simulated queue. Varied bidding positions.</td>
<td>—Provides evidence for Hypothesis 1 and Hypothesis 2 with an incentive-compatible design.</td>
<td>—Bids are higher when the wait is long (Hypothesis 1).</td>
</tr>
<tr>
<td>6. Salad restaurant</td>
<td>Analysis of year-long transaction data from a salad restaurant.</td>
<td>—Provides evidence for the main effect (Hypothesis 1) based on real transaction data.</td>
<td>—Transaction amounts are larger when the wait is long (Hypothesis 1).</td>
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</table>
The research assistants began by requesting participation from customers at the back of the line and moved forward; upon reaching the entrance to the store, they returned to the back of the line, which had been refreshed with a new set of participants. Customers completed the survey outside the store, where they did not have a clear view into the store and the display case. The assistants cycled through the line nine times over a span of three hours. The researcher noted that the line length varied only slightly during the three hours in which data collection proceeded; it remained at about 53 people, and less than 3% of the people left the line over the course of data collection.

Participants were provided a clipboard with which to complete the questionnaire. The respondents first answered a question regarding their anticipated purchase quantity. They then responded to a few follow-up questions (see Appendix B) that aimed to capture information on anticipated total wait times (WaitEst) and interrespondent heterogeneity (familiarity with the store, the number of people they were buying for, how much they like cupcakes, their maximum willingness to wait in line). The research assistants recorded the approximate number of people ahead (Ahead) and behind (Behind) the participant while he or she answered the questionnaire. These counts captured the position of the participant with respect to the store entrance and served as proxies for the amount of time the participants had spent waiting. Recall that all participants joined a long line during peak business hours; Little’s law suggests that a customer with a large number of customers waiting behind him or her when completing the survey had waited for a longer time. By contrast, a large number of customers ahead indicates that the customer is likely to have joined the line more recently relative to a customer who is about to enter the store.

Results. We ran three regressions for the number of cupcakes that customers intended to purchase (Quantity) as a function of their expected total wait (WaitEst), the number of people in front of them (Ahead), and the number behind them (Behind), controlling for party size (PartySize), whether the customers were familiar with the cupcake establishment (Repeat), and how much they liked cupcakes (LikeCupcakes). Poisson regressions were used because the dependent variable was based on count data.

The number of cupcakes people planned to purchase increased with the participants’ self-reported estimates for the total time they would spend in line (WaitEst). Similar results were obtained when the analysis was conducted with the two externally observed proxies that tracked the participants’ progress in the queue, Ahead and Behind: the intended purchase quantity was higher for participants who were closer to the store entrance when they responded to the questions (i.e., fewer people Ahead and more people Behind). The effect sizes were economically significant:5 the coefficient estimates for the Poisson regression in Table 2 suggest that Quantity was 16.2% (35%) larger for a person with an estimated wait (WaitEst) of 20 (40) minutes compared with a person who did not experience any wait. The magnitude of the effect was similar when Ahead and Behind (proxies for experienced wait) were used instead of WaitEst.

Discussion. Study 1 has demonstrated a positive relationship between time spent waiting in a real line and purchase intentions, providing support for Hypothesis 1. Given that the time spent in the queue prior to the purchase decision is a sunk cost, this is a systematic deviation from rationality. One would expect queue length to play a role in customers’ decisions as to whether join a line, but the subsequent purchase decisions should not be affected by the time spent in the line. This suggests that, up to a point, firms may potentially benefit from customers waiting in line; even if some customers decide to leave, the increased purchase quantities for those who remain behind can result in higher profits. Of course, if the wait is excessive, a larger fraction of the customers would be

<table>
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<th>Table 2. Cupcake Store Field Study Results</th>
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<tr>
<td>Quantity</td>
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<td></td>
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<tr>
<td>WaitEst</td>
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<tr>
<td>Ahead</td>
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<td>Behind</td>
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<td>LikeCupcakes</td>
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<td>PartySize</td>
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<td>Repeat</td>
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<td>N</td>
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<td>Log likelihood</td>
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<td>AIC</td>
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Notes. Ahead (Behind) denotes the number of people ahead of (behind) the participant when the questionnaire was administered. WaitEst denotes the participants’ estimate of the total wait time. LikeCupcakes denotes the scale response of participants’ general cupcake liking. PartySize denotes the number of people the participant is buying for. Repeat denotes whether the participant is a new or repeat customer, coded as 0 for new and 1 for repeat. AIC, Akaike information criterion. Standard errors are reported in parentheses.

*p < 0.1; **p < 0.05; ***p < 0.01.
lost, and hence the net effect of waiting on revenues may turn negative.

There might be several alternative explanations for the positive effect of queueing on purchase intentions. First, in line with past research, long lines may have influenced customer decisions by signaling high quality to uninformed customers, thereby increasing purchase intentions (e.g., Kremer and Debo 2016). However, in this experiment, all participants had chosen to join a long line; hence they did not see different quality signals. Furthermore, even when only the repeat customers who were familiar with the product quality were included in the analysis, the same effect was observed. Hence, quality signaling did not seem to be the primary driving mechanism for the positive effect of waiting time on consumption decisions. Second, the correlation between waiting times and purchase intentions may be due to screening—that is, the customer mix changing as a function of queue length. Study 1 partially circumvents this potential confound because all participants had joined a similarly long line during peak business hours; however, it cannot fully eliminate it. Finally, Study 1 does not account for the possibility that customers may have experienced increased hunger and ego depletion when they waited longer, which may have resulted in increased purchase intentions.

In Study 2, we avoid selection effects by experimentally manipulating the queue length and control for hunger and ego depletion; we demonstrate that the relationship between waiting time and consumption is indeed driven by the sunk-cost fallacy. This study also examines how providing menus to those waiting in the line impacts purchase decisions.

4.2. Laboratory Experiments with Simulated Queues

Methods. Students (529) in a business school research pool participated in Study 2 in exchange for course credit. The students were 47% female, and the average age was 20.2. Participation occurred in a behavioral research laboratory, and the study was run using Qualtrics software. The study employed a 2 (line long versus short) × 2 (menu absent versus present) design; participants were randomly assigned to one of the four experimental conditions.

Participants were told that they would be completing a simulated shopping trip to a well-known local cupcake shop. The waiting experience was simulated by an animated line of stick figures, one of which was highlighted as the participant’s own stick figure. In the short-line (long-line) condition, there were 2 (16) people in line, including the participant. Participants had to wait for 15 seconds at each position before they could advance by clicking on a progress button. As a result, participants in the short line had to wait for 30 seconds before ordering; those in the long line had to wait for 240 seconds. Each time a participant advanced in line, his or her stick figure would move forward in line while the line length remained constant.

In the menu-present condition, the menu was displayed on the right side of the screen during the simulated wait. In the menu-absent condition, participants were shown the menu only when they reached the head of the line. In all conditions, once the participants were at the head of the line, they were asked how many cupcakes they wanted to order, priced at $3 each. The waiting task was hypothetical; no money was exchanged, and participants did not receive any cupcakes. The task was followed up by a series of questions to capture differences among the participants such as, for instance, whether they were familiar with the store and how much they like cupcakes (see Appendix C for details).

Two months after the simulated waiting experience, additional data were collected from the same group of participants to measure their susceptibility to the sunk-cost fallacy. Of the 529 original participants, 468 completed the measures. Participants were presented with four questions that were adapted from Soman (2001) and Navarro and Fantino (2009) in a randomized order (see Appendix D for details). They were asked to choose between two options: one option was comparatively more attractive, whereas the other option allowed them to persist in a course in which they had already invested some time. Participants’ binary responses to the questions were aggregated to develop a measure of the extent each individual was influenced by sunk-time investments, $S_{Time}$, providing a score of 0–4. Higher scores represent greater sunk-cost susceptibility, as they reflect the number of scenarios in which participants persisted in an action in which they had previously invested time.

Results. To test the relationship between waiting time and consumption (Hypothesis 1), a Poisson regression was run for simulated purchase quantity as a function of queueing time and the presence of a menu (Model 1 in Table 3). As predicted, the main effect of the wait condition was statistically and economically significant; the number of cupcakes was larger in the long-line condition ($M_{ShortNoMenu} = 2.56$, $M_{LongNoMenu} = 3.58$, $M_{ShortMenu} = 2.40$, $M_{LongMenu} = 2.67$). This is consistent with the notion that the time spent waiting in line is perceived as a negative entry in customers’ mental account, and to offset this cost, a greater quantity is purchased. There was also a significant interaction effect of menu presence and queue condition. When participants were shown the menu while they waited in line, the positive effect of queueing time on purchase quantity was diminished. This is consistent with the prediction that when people are occupied, the cost.
of waiting in line is lessened, and as a result, they feel less of a need to spread this cost and purchase fewer cupcakes.

We find that both the main effect of waiting time and its interaction with menu presence are robust to the inclusion of variables that may vary by individuals, such as the perceived quality of cupcakes, whether people have tried cupcakes in this store previously, or whether they like cupcakes (Model 2). When the analysis was repeated considering only the respondents with a nonzero purchase quantity, the same pattern of results is observed (Model 3). We then ran a regression including only the participants who had tried this particular store’s cupcakes before (78% of the participants) and hence did not face any uncertainty regarding product quality (Model 4). The results remain unchanged, which suggests that the observed behavior is not driven by quality signaling. Finally, neither the duration in line nor the presentation of the menu during wait had any significant influence on product appeal.

The sunk-cost scores collected from a large subset (88.5%) of the participants allow us to provide evidence for the role of sunk-cost susceptibility. Recall that higher scores represent greater sunk-cost susceptibility; we expect the relationship between the wait and the purchase quantity to be stronger (weaker) for respondents that are (not) susceptible to sunk cost. When we include the sunk-cost susceptibility scores ($S_{\text{Time}}$) for the participants in the regressions (Table 4), we find that this is indeed the case. As hypothesized, the results depict an interaction between waiting time and susceptibility to sunk-cost mentality: there was a stronger relationship between queue length and consumption for participants who were more susceptible to the sunk-cost fallacy than those who were less susceptible (Hypothesis 2). A median split of the data confirms this relationship: there was a weaker relationship between queue length and consumption for those with a sunk-cost susceptibility score of 0 or 1 ($\beta = 0.22, p = 0.02$) relative to those with a sunk-cost score of 2 or greater ($\beta = 0.45, p < 0.001$).

**Discussion.** Building on the results from the field study presented previously, Study 2 provides additional evidence for the positive relationship between the wait and the purchase quantity. The controlled

---

**Table 3. Laboratory Experiments with Simulated Queues**

<table>
<thead>
<tr>
<th></th>
<th>Quantity</th>
<th>HowAppealing</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
</tr>
<tr>
<td>Wait</td>
<td>0.333***</td>
<td>0.332***</td>
</tr>
<tr>
<td></td>
<td>(0.071)</td>
<td>(0.071)</td>
</tr>
<tr>
<td>Menu</td>
<td>-0.065</td>
<td>-0.065</td>
</tr>
<tr>
<td></td>
<td>(0.078)</td>
<td>(0.078)</td>
</tr>
<tr>
<td>PastExperience</td>
<td>0.085</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
<td></td>
</tr>
<tr>
<td>Quality</td>
<td>0.073***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td></td>
</tr>
<tr>
<td>PerSitting</td>
<td>0.155***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
<td>0.024</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td></td>
</tr>
<tr>
<td>LikeCupcakes</td>
<td>-0.035*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td></td>
</tr>
<tr>
<td>HowAppealing</td>
<td>0.077***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td></td>
</tr>
<tr>
<td>Wait × Menu</td>
<td>-0.228**</td>
<td>-0.242**</td>
</tr>
<tr>
<td></td>
<td>(0.105)</td>
<td>(0.106)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.943***</td>
<td>0.045</td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td>(0.115)</td>
</tr>
<tr>
<td>N</td>
<td>529</td>
<td>529</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-1,131.1</td>
<td>-1,063.7</td>
</tr>
<tr>
<td>AIC</td>
<td>2,270.2</td>
<td>2,147.4</td>
</tr>
</tbody>
</table>

**Notes.** *Wait* denotes the queue condition, coded as 0 for a short wait and 1 for a long wait. *Menu* denotes whether a menu was presented throughout the wait or not. *PastExperience* denotes whether the participants tried the cupcakes before or not. *Quality* denotes the participants’ quality perception of the establishment in the scenario. *PerSitting* denotes how many cupcakes the participant eats per sitting. *LikeCupcakes* denotes the seven-point scale rating for how much the participant likes cupcakes. *Frequency* denotes how often the participant eats cupcakes. *HowAppealing* is the seven-point scale rating for the appeal of a cupcake at that point. AIC, Akaike information criterion. Standard errors are reported in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. 

---
Table 4. Susceptibility to Sunk Costs

<table>
<thead>
<tr>
<th>Quantity</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Wait</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.303***</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.11)</td>
</tr>
<tr>
<td></td>
<td>$S_{\text{Time}}$</td>
<td>$-0.075^*$</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Menu</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$-0.044$</td>
<td>$-0.045$</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.08)</td>
</tr>
<tr>
<td></td>
<td>Wait $\times$ $S_{\text{Time}}$</td>
<td>0.200***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.06)</td>
</tr>
<tr>
<td></td>
<td>Wait $\times$ Menu</td>
<td>$-0.294^*$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.11)</td>
</tr>
<tr>
<td></td>
<td>Constant</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.952***</td>
<td>1.044***</td>
</tr>
<tr>
<td></td>
<td>(0.056)</td>
<td>(0.078)</td>
</tr>
<tr>
<td></td>
<td>$N$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>468</td>
<td>468</td>
</tr>
<tr>
<td></td>
<td>Log likelihood</td>
<td>$-993.7$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$-986.9$</td>
</tr>
<tr>
<td></td>
<td>AIC</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1,995.3</td>
<td>1,985.8</td>
</tr>
</tbody>
</table>

Notes. **Wait** denotes the queue condition, coded as 0 (1) for a short (long) wait. $S_{\text{Time}}$ denotes the participants’ susceptibility to sunk-cost fallacy. **Menu** denotes the presence of a menu, coded as 0 for a menu being absent and 1 for a menu being present. AIC, Akaike information criterion. Standard errors are reported in parentheses.

*p < 0.1; **p < 0.05; ***p < 0.01.

...
condition (Long), only a picture depicting the wait in line was displayed. In the long-wait, menu-present condition (Menu), participants were told that they could see the menu from where they were standing, which was simulated by displaying the menu on the right side of the screen. Finally, in the long-wait distraction condition (Video), participants were told that they decided to take out their cell phone and watch a video while waiting. This experience was simulated by playing an animal video on the right side of the screen.

After the wait, a progress button appeared on the screen which brought participants to a screen that displayed the menu, and asked, “How many cupcakes would you buy given they are $2 each?” Responses were provided in a text box. Participants then answered follow-up questions regarding their decision, consumption habits, demographics, and experience in the simulated queue (see Appendix F).

**Results.** We ran three Poisson regressions for the number of cupcakes as a function of the experimental condition dummies (Short, Menu, and Video) (Table 5). In essence, this analysis provides a comparison with respect to the long-wait baseline condition. First, we find a positive relationship between queue length and simulated purchase quantity (Model 1, excluding seven respondents that reported a purchase quantity of zero). Customers ordered more cupcakes in the base long-wait condition ($M_{Long} = 4.30$) than in the short-wait condition ($M_{Short} = 3.44$)—that is, a 25% increase relative to the short-wait condition. Next, we find that the presence of both a menu ($M_{Menu} = 3.55$) and a distracting video ($M_{Video} = 3.71$) decreased simulated purchase quantity relative to the base long-line condition ($M_{Long} = 4.30$). All of these effects persisted when we controlled for quality (Model 2) and when we included the respondents that reported a purchase intent of zero (Model 3). Finally, as a manipulation check, we investigate how customer experience was influenced by the queue length, the presence of the menu, and a distracting video; we find that customers found the waiting experience to be less unpleasant in the short-wait ($M_{Short} = 2.11$) relative to the base long-wait ($M_{Long} = 5.17$) scenario. Similarly, the distraction ($M_{Video} = 3.59$) and the menu ($M_{Menu} = 4.53$) also improved the customer experience in the queue (Model 4).

**Discussion.** In Study 3, we once again find that queue length increases purchase quantity. In this study, we also explored how managerial levers that improve customer experience influence subsequent consumption decisions. We show that two such levers (distracting

<table>
<thead>
<tr>
<th>Table 5. The Moderating Role of Operational Levers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quantity</td>
</tr>
<tr>
<td>Model 1</td>
</tr>
<tr>
<td><strong>Short</strong></td>
</tr>
<tr>
<td>−0.224***</td>
</tr>
<tr>
<td>(0.08)</td>
</tr>
<tr>
<td>−0.207***</td>
</tr>
<tr>
<td>(0.08)</td>
</tr>
<tr>
<td>−0.199***</td>
</tr>
<tr>
<td>(0.08)</td>
</tr>
<tr>
<td>−3.088***</td>
</tr>
<tr>
<td>(0.24)</td>
</tr>
</tbody>
</table>

Notes. Short denotes the queue condition, coded as 1 (0) for a short (long) wait. Menu denotes the presence of a menu, coded as 0 (1) for a menu being absent (present). Video denotes the presence of a video, coded as 0 (1) for a video being absent (present). Quality denotes the participants’ quality perceptions. PerSitting denotes the self-reported number of cupcakes participants would eat in a sitting. Frequency denotes the scale response for how frequently participants eat cupcakes. LikeCupcakes denotes the scale response for how much participants like cupcakes. AIC, Akaike information criterion. Standard errors are reported in parentheses.

*p < 0.1; **p < 0.05; ***p < 0.01.
the customers with a video and engaging them with a menu) moderate the positive effect of waiting on consumption quantity. That is, whereas prior literature shows that occupied time feels shorter (Maister 1984) and that distractions such as TV screens reduce the perceived wait (Borges et al. 2015), we show that such distractions can decrease purchase relative to a long-wait baseline condition. This is consistent with our theory, which predicts that efforts that reduce the perceived economic and psychological costs associated with waiting should diminish the positive effect of waiting on consumption that is driven by the perception of greater sunk costs. In other words, firms’ efforts to improve customer service by reducing actual or perceived time in queues may negatively impact sales. Notably, the effect of the menu condition of Study 3 mirrors what we observed in Study 2. Ex ante, one might expect that when the menu is presented during a long wait, the participants might experience ego depletion, or get hungrier, and as a result make a larger purchase (Vohs and Faber 2007, Baumeister et al. 2008). Instead, we find the opposite: the intended purchase quantity is, in fact, lower in the menu condition. This can be understood in light of Maister’s (1984) propositions: by presenting the menu up front, people are engaged in the service early on and the unoccupied wait is eliminated. This finding also helps explain away ego depletion as the driver for an increase in the purchase quantity during the wait, as one would expect the presentation of the menu to make this stronger, rather than eliminate it.

In Studies 2 and 3, we have discussed operational levers that moderate the relationship between waiting time and consumption. It is possible that certain contextual factors may also strengthen or weaken the observed effect. In the next study, we examine how price plays a role in moderating this relationship.

### 4.4. The Moderating Effect of Price

**Methods.** For Study 4, 200 participants were recruited from Amazon Mechanical Turk (52% male, and the average age was 33.5) and were compensated $0.25 to respond to a short survey. After reading a brief scenario that manipulated the waiting time (2 versus 60 minutes) and price of T-shirts being offered ($5 versus $30) during Black Friday at a clothing store, participants were asked the number of T-shirts they would purchase (see Appendix G). Participants also reported the perceived quality of the T-shirts using a seven-point scale, anchored by far below average and far above average, and then provided demographic information.

**Results.** We ran two regressions to assess the effect of waiting time on the purchase intents and to rule out quality perceptions as a driver of the effect (Table 6).

<table>
<thead>
<tr>
<th>Table 6. The Moderating Effect of Price</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>---</td>
</tr>
<tr>
<td>Wait</td>
</tr>
<tr>
<td>(0.095)</td>
</tr>
<tr>
<td>Price</td>
</tr>
<tr>
<td>(0.11)</td>
</tr>
<tr>
<td>Quality</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Wait × Price</td>
</tr>
<tr>
<td>(0.154)</td>
</tr>
<tr>
<td>Constant</td>
</tr>
<tr>
<td>(0.071)</td>
</tr>
<tr>
<td>N</td>
</tr>
<tr>
<td>Log likelihood</td>
</tr>
<tr>
<td>AIC</td>
</tr>
</tbody>
</table>

Notes. Wait denotes the long-wait (short-wait) condition, coded as 1 (0). Price denotes the low-price (low-price) condition, coded as 1 (0) for the high-price (low-price) condition. Quality denotes the participants’ quality perception of the T-shirts. AIC, Akaike information criterion. Standard errors are reported in parentheses. **p < 0.01.

The results revealed a significant interaction of waiting time and price (Model 1) on the quantity ($M_{2\text{min}$5 = 3.92, $M_{60\text{min}$5 = 5.31, $M_{2\text{min}$30 = 2.94, $M_{60\text{min}$30 = 2.44}), which persisted when controlling for quality perceptions (Model 2). Although there was a significant relationship between simulated purchase quantity and waiting time under the low-price condition, the relationship was not significant under the high-price condition.

**Discussion.** In the prior studies, we established that when people need to wait before making a consumption decision, the time spent in line influences their decisions because of the sunk-cost fallacy. One would expect this effect to be stronger in certain contexts and weaker in others. Study 4 considers one such factor that might moderate the relationship: price. We find that increased queue time resulted in a higher purchase quantity only in the low-price condition. This makes intuitive sense: even if people feel compelled to increase consumption after a long wait, this might not be feasible at a high price. This finding suggests that at low price points, it is important that firms take the sunk costs associated with waiting into account; at higher price points, this may be less important.

The laboratory and field studies so far have collectively provided evidence for increasing consumption in a variety of settings in response to longer waiting times resulting from the sunk-cost fallacy. In the remaining two studies, we seek to further affirm these findings by examining the effect of waiting time on spending in an incentive-compatible design where participants bid for a gift card after waiting in a virtual
queue (Study 5) and using transaction data from a salad restaurant (Study 6).

### 4.5. The Influence of Waiting in an Auction

**Methods.** Students (475) participated in Study 5 in exchange for course credit. The students were 47% female, and the average age was 20.1. Participation occurred in a behavioral research laboratory; participants completed a variety of tasks, which took place over a full hour (unless the participant chose to stop participating for any reason).

Participants were told that they would be completing a real auction, bidding against the participants that were in the laboratory at the same time (they could see how many other participants were present). They were informed that if they chose to bid (and subsequently won), their bid would be subtracted from their student account and that they would receive the auction item, a $10 Amazon gift card. Apart from one instance in which there was only one participant in the laboratory (who was excluded from the analysis), the total number of participants varied between 2 and 15. The students were told they would have only one chance to bid and that they would not see the other participants’ bids. They were instructed to bid 0 if they did not want to participate. After reading through the instructions (which emphasized that any winning bid would be subtracted from their student accounts), participants were randomly assigned to a bidding position, ranging from 1 to 15. Upon receiving a bid position, participants pressed “next” to enter the auction. Until it was the participant’s turn to bid, the screen refreshed and stated that nth participant was bidding, lasting 14 seconds each time. If the participant was selected to bid first, they proceeded directly to bidding without seeing any waiting screens. After a waiting period of 0–196 seconds, participants were asked to input their bid. On a subsequent screen, participants were asked a series of questions to assess how much they wanted to win the auction and how long they perceived the wait to be on seven-point scales (see Appendix H). After participating in this study, participants were directed to another study and thus had no incentive to not bid as a way to save time. The winning participants were awarded the difference between the $10 value of the Amazon gift card and their bid amount.

**Results.** A series of regressions were run to investigate how the participants’ bids were influenced by their randomly assigned positions and their susceptibility to sunk cost in the time domain (Table 7). In Models 1–3, only participants that bid between $0.01 and 9.99 were included. In Model 4, the participants that bid $0 and $10 were included in the analysis as well. To isolate the effect of queue length on bidding,

### Table 7. The Influence of Waiting in an Auction

<table>
<thead>
<tr>
<th>Bid</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
<th>Model 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spot</td>
<td>0.085* (0.05)</td>
<td>−0.033 (0.09)</td>
<td>−0.068 (0.08)</td>
<td>−0.058 (0.07)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WaitEst</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.294*** (0.08)</td>
<td>0.098 (0.14)</td>
<td>0.027 (0.13)</td>
<td>−0.05 (0.11)</td>
</tr>
<tr>
<td>STime</td>
<td>−0.294 (0.34)</td>
<td>−0.498 (0.33)</td>
<td>−0.39 (0.25)</td>
<td>−0.431 (0.42)</td>
<td>−0.618 (0.40)</td>
<td>−0.446 (0.30)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Participants</td>
<td>0.004 (0.06)</td>
<td>0.013 (0.05)</td>
<td></td>
<td></td>
<td>0.006 (0.06)</td>
<td>0.014 (0.05)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>WinAuction</td>
<td>0.632*** (0.10)</td>
<td>1.045*** (0.07)</td>
<td>0.605*** (0.10)</td>
<td>1.033*** (0.07)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spot × STime</td>
<td>0.092* (0.05)</td>
<td>0.119** (0.05)</td>
<td>0.079** (0.04)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WaitEst × STime</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.148* (0.09)</td>
<td>0.179** (0.08)</td>
<td>0.124* (0.07)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>3.813*** (0.32)</td>
<td>4.175*** (0.52)</td>
<td>1.858** (0.78)</td>
<td>−0.385 (0.60)</td>
<td>3.053*** (0.39)</td>
<td>3.633*** (0.65)</td>
<td>1.525* (0.84)</td>
<td>−0.46 (0.67)</td>
</tr>
<tr>
<td>N</td>
<td>306</td>
<td>305</td>
<td>305</td>
<td>474</td>
<td>306</td>
<td>305</td>
<td>305</td>
<td>474</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>−759</td>
<td>−754.2</td>
<td>−735.5</td>
<td>−1,144.9</td>
<td>−754.5</td>
<td>−749.9</td>
<td>−732.4</td>
<td>−1,144.3</td>
</tr>
<tr>
<td>AIC</td>
<td>1,522.1</td>
<td>1,516.4</td>
<td>1,483</td>
<td>2,301.8</td>
<td>1,513.1</td>
<td>1,507.9</td>
<td>1,476.8</td>
<td>2,300.6</td>
</tr>
</tbody>
</table>

**Notes.** Spot denotes the participants’ bidding position. WaitEst denotes the participants’ estimated duration of wait before bidding. STime denotes the participants’ susceptibility to the sunk cost of time. Participants denotes the number of participants in the given auction. WinAuction denotes the scale response of how much participants wanted to win the auction. AIC, Akaike information criterion. Standard errors are reported in parentheses.

*p < 0.1; **p < 0.05; ***p < 0.01.
the number of participants competing for the prize in the auction and the extent to which each participant wanted to win the auction were controlled for in Models 3 and 4. The results depict an interaction between waiting time and susceptibility to sunk-cost mentality in all models: for participants who were susceptible to the sunk-cost fallacy, there was a positive relationship between queue position and bid amount; the relationship was insignificant for the others.8 Similar results were obtained when regressions were run using the participants’ self-reported perceived wait durations instead of their assigned positions (Models 5–8).

Discussion. We find that the longer participants waited to bid in an auction, the more they bid, regardless of whether wait was measured by the participants’ bidding order or their estimated wait. Given that we controlled for the number of participants in each auction and no information was provided regarding others’ bids, this effect can be attributed to the time spent waiting. The effect persisted when we controlled for participants’ desire to win. The replication of the positive effect of waiting time on consumption in this context adds to the generalizability of the effect of queue length on consumption. Furthermore, the incentive-compatible nature of this study assures us that the observed effects are robust.

In our final study, we analyze sales data from a casual salad restaurant to complement the experimental findings with real transaction data.

4.6. Transaction Data—Purchase Decisions at a Salad Restaurant

Methods. To examine the effect of waiting on transaction amounts in a real context, we used a data set of 73,108 transactions that occurred at a salad restaurant between June 5, 2016, and June 1, 2017. The data set contained the dollar amount, date, and time for each transaction, as well as some other information such as the mode of payment, discounts, and tips for each transaction.

Similar to the previous studies, the purchase decisions at the restaurant occurred after the customers waited their turn in line, after which they placed their order, choosing from a selection of salads that varied in price or customizing their own from the available ingredients. After the preparation of the salad, they moved to the cashier to complete their order, with some customers adding drinks, snacks, and desserts, and then they made their payment.

No information was available regarding the waiting time experienced by the individuals prior to making their purchase. Hence, a proxy measure was constructed based on traffic intensity, assuming that the line was longer during more congested periods when there were more customers back-to-back compared with times when the transaction density was sparse, in line with queueing theory. To this end, the variable LineT was defined to capture the total number of transactions in the T minutes prior to the focal transaction. Observations by the research team corroborated the use of transaction data as a proxy for line length; weekday lunches, the time of week, and day with the longest line (per observation) had significantly greater transaction density than did weekday late afternoons or weekends, during which time there typically is not a line. Transactions made outside of operation hours 10:00 a.m.–11:59 p.m., transactions that were discounted to $0, and bulk purchases above $50 were excluded from the analysis. Furthermore, dummy variables were created as controls for days of the week, weekends, lunch time (11:30 a.m.–2:30 p.m.),

Table 8. Purchase Decisions at a Salad Restaurant

<table>
<thead>
<tr>
<th>Transaction Amount</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
<th>Model 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Line5</td>
<td>0.069***</td>
<td>0.061***</td>
<td>0.067***</td>
<td>0.054***</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.009)</td>
<td>(0.017)</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Line10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.078***</td>
<td>0.076***</td>
<td>0.077***</td>
<td>0.054***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.010)</td>
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<td></td>
<td>(0.065)</td>
<td>(0.161)</td>
<td>(0.068)</td>
<td>(0.103)</td>
<td>(0.065)</td>
<td>(0.161)</td>
<td>(0.073)</td>
<td>(0.105)</td>
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<td>1 hour</td>
<td>1 hour</td>
<td>1 hour</td>
<td>15 min</td>
<td>1 hour</td>
<td>1 hour</td>
</tr>
<tr>
<td></td>
<td>68,342</td>
<td>68,342</td>
<td>28,671</td>
<td>13,319</td>
<td>68,342</td>
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<tr>
<td>R²</td>
<td>0.043</td>
<td>0.049</td>
<td>0.011</td>
<td>0.005</td>
<td>0.047</td>
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<td>0.007</td>
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<td>Adjusted R²</td>
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<td>0.048</td>
<td>0.011</td>
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<td>0.051</td>
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<tr>
<td>F-statistic</td>
<td>147.33***</td>
<td>52.03***</td>
<td>47.38***</td>
<td>10.80***</td>
<td>160.76***</td>
<td>55.91***</td>
<td>70.573***</td>
<td>13.13***</td>
</tr>
</tbody>
</table>

Notes. Line5 (Line10) denotes the total number of transactions in the 5 minutes (10 minutes) prior to the focal transaction. Time dummy indicates whether the model includes controls for hour-long or fifteen-minute intervals. Standard errors are reported in parentheses.

**p < 0.01.
dinner time (5:30 p.m.–8:30 p.m.), 15-minute intervals, and hour-long intervals.

**Results.** Below, we present the analysis with window sizes $T = 5$ and $T = 10$ minutes. The mean transaction amount was $8.00 (median = $8.00). The mean and median for Line5 (Line10) were 3.89 and 4.00 (7.75 and 7.00), respectively. In line with our hypothesis, our analysis of the transaction data points to a positive relationship between transaction intensity (which is a proxy for line length prior to the transaction) and transaction amounts (see Table 8). This relationship holds when controlling for the day of the week and hour of the day, using hourly (Model 1) or 15-minute (Model 2) intervals. It also holds when the analysis is confined to transactions during lunch (Model 3) or dinner (Model 4). In all models, we find that the transaction amount increased with the preceding transaction intensity, Line5 and Line10.  

**Discussion.** Examination of the data reveals that for each person in line ahead of a given customer, on average, there was an about 7-cent increase in the order size. Using the reported 7-cent increase observed per prior transaction when analyzing the data, we can extrapolate that a customer who waited in a line where 10 others made purchases in the five minutes before him or her would spend an extra 70 cents—or, in other words, nearly an extra 10% on their overall transaction. These findings provide additional support for the notion that waiting in a queue can increase consumption amounts considerably, not only in experimental contexts but also in real ones.

One should note that it is possible that some customers may have balked or reneged when the lines were long, but the available data set does not allow us to track these customers. This means that some of the observed effect can be due to self-selection (i.e., customers who made higher ticket purchases staying in line, whereas those would have made smaller purchases avoiding it); hence it is not possible to infer overall revenue impact.

**4.7. Alternative Mechanisms**

Although it is plausible that queues might influence consumption through several other mechanisms, we have isolated mental accounting for sunk costs from these confounding effects through experimental design, control variables, and a measurement of sunk-cost susceptibility. In what follows, we discuss how our studies help isolate the sunk-cost effect among other alternative explanations.

**Self-Selection.** The correlation between waiting time and purchase quantities can be due to self-selection (Allon et al. 2011, Lu et al. 2013), with the customer mix choosing to stay in line changing as a function of queue length: when the line is long, the purchase quantities might be large because only the customers who like the product the most stay in the line; when the line is short, the purchase quantities can be low because all customers stay. Whereas the sunk-cost effect would imply a shift in the willingness to pay with the length of the wait, self-selection would imply a filtering of customers based on their willingness to wait. Study 1 partially isolates the findings from selection, because it was conducted during peak business hours when the line was always long; with low-valuation customers selected out, the data collected represent high-valuation customers. The laboratory experiments (Studies 2, 3, 4, and 5) completely avoid self-selection by randomly assigning participants to conditions.

**Quality Inference.** It is possible that long lines result in increased purchase quantities because participants might infer quality information from lines (Koo and Fishbach 2010, Giebelhausen et al. 2011, Kremer and Debo 2016). To isolate the sunk-cost effect, we show that the results in Studies 1 and 2 hold when the analysis is confined to participants who were well informed about quality (i.e., repeat customers). Furthermore, we again found an effect of wait time in a study that limited quality inferences from the number of people in the queue by varying the pace of progress rather than queue length (see Appendix F). Similarly, when participants waiting in equally long lines were distracted (via menu or video) in Studies 2 and 3, the effect of waiting was diminished, providing further evidence that the driver was not quality inferences. Finally, in Study 5, bidding was for a standard product, an Amazon gift card, which makes the quality inference explanation implausible.

**Ego Depletion and Increasing Hunger.** A long wait might increase consumption by depleting the limited willpower reserves from which self-control draws on to inhibit compulsive purchases (Baumeister et al. 2008). Alternatively, waiting might increase appetite (Vohs and Faber 2007), causing consumers to order more after a long wait. Ego depletion and hunger would be expected to become stronger in the presence of the menu, which would make the cupcakes more salient. However, in Studies 2 and 3, we find that the positive effect of wait time on consumption quantity, in fact, dissipates when the menu is presented during the wait; we also did not find an increase in product appeal, further suggesting ego depletion and hunger were not at play. In Studies 4 and 5, where waiting would not lead to increased appetite (Amazon gift card and T-shirt), we continue...
to observe a positive relationship between queue length and consumption decisions. Finally, Studies 2 and 5 provide more direct evidence for the sunk-cost fallacy as the driver for the focal relationship: there was a stronger relationship between queue length and consumption for participants who were more susceptible to the sunk-cost fallacy than those who were less susceptible (which is not related to hunger or ego depletion).

**Cognitive Dissonance.** Finally, the observed behavior can be driven by cognitive dissonance. According to Festinger (1957), people experience mental discomfort when they hold contradictory beliefs, ideas, or values. Hence, they make changes, either in their cognitions or in their actions, to resolve the dissonance. In contrast with the rest of the mechanisms discussed in this section, at its core, cognitive dissonance is about consistency with one’s prior decisions, and hence, it is closely related to the sunk-cost fallacy. Rather than an alternative explanation, some authors argue that cognitive dissonance presents a deeper psychological process explanation for the sunk-cost fallacy observed herein (Staw 1976, Brockner 1992, Soman 2001). Notably, though, any behavioral change predicted by cognitive dissonance requires a change in attitudes first; otherwise, there would still be a dissonance as a result of the mismatch between attitudes and behavior. If cognitive dissonance were the driver for increased consumption, this would be preceded by an attitude change and would be reflected in increased product appeal. Studies 2 and 3 provide evidence against this: whereas purchase intentions increase with queue length, there was no accompanying attitudinal change; the participants who spent a longer time waiting in line did not find the product more appealing. Although this null result does not allow us to completely rule out cognitive dissonance, we believe the results are consistent with mental accounting. Most important, regardless of the mechanism, the managerial implications would remain the same.

5. **Concluding Remarks**

In their review article, Allon and Kremer (2018) point to the importance of understanding human behavior in queueing systems for improving operational performance. They argue that this would not only help assess the effectiveness of managerial levers but also provide new levers. In this vein, over the six studies reported, we examine how waiting in queues influences individuals’ consumption decisions. In doing so, we provide novel insights into the implications and psychology of queues. Our hope is that this improved understanding of individual-level behavior in queues will help make better decisions in regard to the design of service systems.

First, we hypothesize and find that customers have the tendency to adjust their consumption upward after a long wait, provided that they do not leave. This is consistent with the customers trying to make large temporal investments worthwhile by amortizing the cost of waiting over a larger purchase. Because the “waiting cost” is already sunk when the consumption decision is made, this is a deviation from what would be considered rational economic behavior; once a person has joined a line, the purchase quantity should be independent of how long he or she has waited.

Second, we show that the relationship between queueing time and spending depends on customer perceptions of the queueing experience. The irreversible sunk cost in the queueing context is one that regards time, which is qualitatively different from monetary investments, because people find it difficult to measure and account for time (Soman 2001, Okada and Hoch 2004). We show that by reducing unoccupied waiting and introducing distractions (Maister 1984), the positive relationship between waiting time and purchase quantity can be weakened. Hence, from a managerial point of view, such practices might have unintended consequences.

Our experimental results provide new insights for both researchers and managers; it also points to interesting research questions that can be addressed using empirical analysis as well as analytical models. In what follows, we discuss a number of managerial implications and highlight limitations and future research directions.

5.1. **Managerial Implications**

Queues may exist as a result of natural ebbs and flows in demand, operational inefficiencies, or firms’ unwillingness to invest in additional capacity in response to growing demand. They are typically bad for business, leading to dissatisfied customers and to lost revenues. Our findings point to an effect of queues, which has previously gone unnoticed: firms with long lines may be (sometimes unwittingly) experiencing higher revenues because of the sunk-cost effect, with consumers adjusting their consumption quantities upward to justify the long wait. Nevertheless, increased consumption does not always translate into higher profits. For instance, consider a cupcake store and an all-you-can-eat restaurant with persistently long waiting times. One would expect a positive profit impact at the cupcake store (as long as the waiting time does not exceed customers’ willingness to wait), because an individual customer’s purchase quantity does not impact the service rate (selling three versus six cupcakes takes about the same time). By contrast, customers’ response to long waiting times at the restaurant can lead to lower profits: the total number
of people served might be reduced as patrons linger longer at the table, and the cost of goods sold can increase as a result of increased food consumption. \footnote{11}

One implication of the above is that the same managerial lever could result in opposite outcomes in different contexts. For instance, capacity expansion can result in decreased profits at the cupcake store, because the company would incur a higher operational cost but sell fewer cupcakes to each customer. On the other hand, adding capacity at the all-you-can-eat restaurant can disproportionately increase the profits: when the waiting times are reduced, the throughput rate can be increased as customers do not feel compelled to linger longer and feel obliged to eat more (paying the same fixed price). In other words, price and capacity decisions that ignore the sunk-cost effect could be misguided, resulting in either too much or too little capacity investment. \footnote{12}

Because queues are often unavoidable, firms implement operational practices that can improve customer experience as they wait in line (Chebat and Filiatrault 1993, Liang 2016). This includes placing reading materials, setting up TV screens, or playing music in waiting areas and providing customers with a menu to view while they wait. These practices aim to distract the customer and avoid idle waiting, as this results in the wait being perceived as less costly (Maister 1984, Oxoby and Bischak 2005). Our results suggest that such practices might have an unintended consequence; by reducing the perceived cost of waiting, these efforts may decrease the purchase quantity. Although such practices might be more effective in certain contexts (e.g., the buffet restaurant mentioned above), they can be less effective or counterproductive in others (e.g., the cupcake store).

We should finally note that the positive link identified herein between waiting time and increased revenues is contingent on the customers staying in line and completing the transaction. However, it is well established that long lines increase the likelihood of reneging and balking; if the wait is too long, revenue from some customers can be higher, but more customers can balk or abandon, resulting in lost sales. The firm may also suffer long-term loss of business from customers who experience a long wait, and this can be exacerbated as a result of negative word of mouth and bad reviews on social media. Therefore, we caution managers against concluding that throttling the pace of the line, for example, by reducing the number of servers, would lead to higher sales; the proper course of action for a manager will require consideration of competing forces in the context. And for consumers who would like to avoid the decision bias identified herein (and making decisions that they might later regret), our research suggests that one way to make better decisions can be to distract their attention away from the time they spend in line.

5.2. Limitations and Directions for Future Research
The goal of this paper has been to study an empirical regularity exhibited by consumers waiting in lines (consumption increases with wait), delineate the underlying mechanism (mental accounting for sunk costs), and demonstrate that some interventions can diminish this effect (videos and menus). With our focus on the individual consumer, our research does not address the net effect of a longer queue on firm profitability or the trade-off between increased purchases as a result of the sunk-cost fallacy and decreased purchases as a result of balking, reneging, and long-term reputational effects. The modeling of this trade-off, contrasting positive effects from sunk costs and quality inferences relative to negative effects from balking and reneging on firm performance, would be an excellent area for further study. Given the many competing effects of queueing, it would be worthwhile to develop models to answer questions regarding how firms should modify their operational policies in light of the sunk-cost effect in queues. For example, how should firms adapt their approach capacity and pricing decisions? Given that long lines and discounts have similar effects on purchase quantities, should a firm provide quantity discounts when the customers need to wait in line for a long time for a product?

Our experiments have mainly focused on quantity decisions after waiting in line. However, consumers make other important decisions that may be influenced by the waiting time in different ways. For instance, would a customer want to stretch out the service time at a restaurant (alternatively, a department of motor vehicles, call center, or a doctor’s office) after a long wait to make the wait worthwhile, or would he or she speed up the service? Would a customer who waited in line for a long time be more likely to purchase a substitute product if the original product is out of stock? From an experimental point of view, it would also be interesting to explore the effects of various interventions, such as the provision of a menu or distraction through a video while waiting in line, as the effects can be context dependent.

Finally, it would be fruitful to study other mechanisms through which queues influence purchases. For instance, whereas consumers’ likelihood of making impulse purchases (Dholakia 2000, Baumeister 2002) as a function of a number of variables including individual propensity (Rook and Fisher 1995), ego depletion (Vohs and Faber 2007), and product type (Rook 1987) have been studied, to our knowledge, there has been little work studying the relationship between queues and impulse purchases (Han et al. 2018). One plausible mechanism is a long line driving impulse purchases.
through increased exposure to the product on display (which is distinct from the effect of mental accounting for sunk costs, which does not necessitate such an exposure): the longer the wait, the more likely the customer is to see the product and make the purchase. Future research directions abound.

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Appendix A. Models

A.1. Formal Model

Recall that the net utility of the individual is \( U(Q) = f(Q) - P \cdot Q - c \cdot W + \lambda \cdot W \cdot Q \), where \( \lambda \geq 0 \). Before joining the queue (and suffering from the sunk-cost fallacy), a customer’s rational utility function can be modeled as \( U(Q) \) with \( \lambda = 0 \); that is, \( U(Q) = f(Q) - P \cdot Q - c \cdot W \). It follows that the optimal purchase quantity \( Q^*_m \) solves the first-order condition \( f'(Q^*_m) = P \). There exists a unique \( Q^*_m \) because \( f' \) is decreasing in \( Q \). Moreover, \( U(Q^*_m) > 0 \) if and only if \( W < f(Q^*_m) - PQ^*_m \)/\( c = W_{\text{max}} \). So a customer would decide to join the queue if the expected waiting time is less than \( W_{\text{max}} \) and balks otherwise. Once the customer has joined the queue, their expected waiting time is less than \( W_{\text{max}} \) and balks otherwise. Once the customer has joined the queue, the customer’s optimal purchase quantity as \( Q^*_m \) for any actual wait \( W \) as well as the following proposition, which corresponds to our Hypotheses 1–3 in Section 3.

Proposition. (i) \( \frac{dQ}{dW} > 0 \) (Hypothesis 1); (ii) \( \frac{d^2Q}{dWd\lambda} > 0 \) (Hypothesis 2); and (iii) \( \frac{d^2Q}{dWdP} < 0 \) (Hypothesis 3).

Proof. Note that \( Q^* \) must satisfy the first-order conditions of (1); that is,

\[
\frac{d}{d\lambda} f(Q^*) = P - \lambda \cdot W. \tag{A.1}
\]

It is easy to verify that the second-order condition is \( U''(Q^*) = f''(Q^*) < 0 \). Because \( f'(Q^*) = P - \lambda \cdot W < P = f'(Q^*_m) \) when \( \lambda > 0 \) and \( f'(Q) \) is decreasing in \( Q \), we know that \( Q^* < Q^*_m \).

(i) By taking the partial derivative of (A.1) with respect to \( W \), we have

\[
\frac{d}{dW} f''(Q) \frac{dQ}{dW} = -\lambda \Rightarrow \frac{dQ}{dW} = -\frac{\lambda}{f''(Q)} > 0 \tag{A.2}
\]

because \( \lambda > 0 \) and \( f'' < 0 \).

(ii) Our assumption on \( f \) in the paper (i.e., \( 0 \leq f(Q) < \infty \), \( f'(Q) > 0, f''(Q) < 0, f'''(Q) \) is monotonic) implies that \( f'''(Q) > 0 \).

Taking the partial derivative of (A.1) with respect to \( \lambda \), we have

\[
f''(Q) \frac{dQ}{d\lambda} = -W \Rightarrow \frac{dQ}{d\lambda} = -\frac{W}{f''(Q)} \tag{A.3}
\]

Together with (A.1) and (A.3), we have

\[
\frac{d^2Q}{dWd\lambda} = \frac{d}{d\lambda} \frac{dQ}{dW} = -\frac{d}{d\lambda} \left[ f''(Q) \right] = -\frac{f''(Q) + \lambda f'''(Q)}{f''(Q)^2} \frac{W}{f''(Q)^2} > 0
\]

because \( \lambda > 0, f'' < 0 \) and \( f''' > 0 \).

(iii) By taking the partial derivative of (A.1) with respect to \( P \), we have

\[
f''(Q) \frac{dQ}{dP} = 1 \Rightarrow \frac{dQ}{dP} = \frac{1}{f''(Q)} \tag{A.4}
\]

Together with (A.2) and (A.4), we have

\[
\frac{d^2Q}{dWdP} = \frac{d}{dP} \frac{dQ}{dW} = \frac{\lambda f''(Q)}{f''(Q)^2} \frac{W}{f''(Q)^2} = \frac{f''(Q)}{f''(Q)^2} \frac{1}{f''(Q)} > 0
\]

because \( \lambda > 0, f'' < 0, \) and \( f''' > 0 \). Q.E.D.

A.2. Loss Aversion Model

We also provide more details for the loss aversion model mentioned in Endnote 4. Let \( f(\cdot) \) be the S-shaped utility function for loss aversion (e.g., see Maggi 2004) with the following properties: (a) \( f(0) = 0 \), (b) \( f''(x) > 0 \), (c) \( f \) is convex \( f''(x) > 0 \) for \( x < 0 \) and concave \( f''(x) < 0 \) for \( x > 0 \), and (d) \( f(x) = f(-x) \) for all \( x \geq 0 \). The customer chooses \( Q^* \) to maximize \( f(g(Q)) + f\left(-P \cdot Q - c \cdot W\right) \), where \( g \) is the value of each unit of the product. Assume \( f(g) + f(-P) > 0 \); that is, a customer will purchase at least one unit of the product when there is no waiting. The optimal purchase quantity \( Q^*_m \) must satisfy the first and second-order conditions (i.e., FOC = 0 and SOC < 0):

\[
g \cdot f'(g(Q)) + f'(-P \cdot Q - c \cdot W) = 0 \text{ and } g^2 f''(g(Q)) + P^2 f''(-P \cdot Q - c \cdot W) < 0.
\]

By taking the derivative of FOC with respect to \( W \), we have

\[
g^2 \cdot f''(g(Q)) \cdot \frac{dQ}{dW} - P \cdot f''(-P \cdot Q - c \cdot W) \left(-P \cdot \frac{dQ}{dW} - c\right) = 0
\]

\[
\Rightarrow g^2 \cdot f''(g(Q)) + P^2 \cdot f''(-P \cdot Q - c \cdot W) \frac{dQ}{dW} = -P \cdot c \cdot f''(-P \cdot Q - c \cdot W).
\]

Because \( g^2 \cdot f''(g(Q)) + P^2 \cdot f''(-P \cdot Q - c \cdot W) < 0 \) as a result of the SOC and \( f''(-P \cdot Q - c \cdot W) > 0 \) as a result of (c), we can conclude that \( \frac{dQ}{dW} > 0 \).
Appendix B. Study 1 Measures Completed on a Half-Page Paper-and-Pencil Survey

How many cupcakes are you going to purchase? __________
How good do you think Georgetown Cupcake's cupcakes are? (Circle one) Average = 1 2 3 4 5 6 7 8 9 10 – The best ever
How many times have you been to Georgetown Cupcakes? 0 1 2 3 4 5 6 7 8 9 10+
How far away do you live (in miles)? < 1 1-5 6-10 11-20 21-50 > 50
How many people are you buying for? __________
How much do you like cupcakes? Not at all 1 2 3 4 5 6 7 Like a lot
How long will the wait be from the time you entered the line until the time you order your cupcakes? (in minutes) __________
Shorter than expected 1 2 3 4 5 6 7 Longer than expected
What is the longest time you'd wait for cupcakes? __________
RESEARCHER ONLY BELOW THIS LINE
#A #B

Appendix C. Study 2 Measures

—How many cupcakes would you buy given they are $3 each? (Numeric text entry)
—How appealing does a cupcake seem right now? (Seven-point scale, where 1 = “not appealing” and 7 = “very appealing”)
—How good do you think the cupcakes are? (Seven-point scale, where 1 = “average” and 7 = “far above average”)
—How many cupcakes would you usually eat in a single sitting? (Seven-point scale, where 1 = “0” and 7 = “6+”)
—How often do you eat cupcakes? (Five-point scale, where 1 = “never” and 5 = “all the time”)
—How much do you generally like cupcakes? (Seven-point scale, where 1 = “not at all” and 7 = “like very much”)
—Have you been to Georgetown Cupcakes before? (Yes/No)

Appendix D. Measures for Susceptibility to the Sunk-Cost Fallacy

Question 1 (Adapted from Soman 2001)
Imagine that you recently saw an advertisement on the bulletin board. A literature professor was looking for a research assistant to work for about 15 hours. The payment was in the form of a front row seat to a professional theater performance. On the same bulletin board, a music professor was also looking for a research assistant to work for about 5 hours and this assistant would be paid with a ticket (in a good section) to a rock concert by a band that you like. You had recently seen posters for both the theater performance and the rock concert. You think you will like to see both these events, although you expect to like the rock concert more. You work for both the professors (15 hours for literature and 5 hours for music) and get paid with the two tickets (theater and rock concert, respectively).

As you are putting the tickets away in your wallet, you notice that both events are scheduled for the same evening and are both at good locations on campus. The tickets are non-transferable, nor can they be exchanged. You can use only one of the tickets and not the other. Which ticket will you use? (theater) (rock concert)

Question 2 (Adapted from Soman 2001)
You are planning to submit an entry to the “new invention” competition organized by the students’ club. You have spent 30 hours preparing a design for an innovative rocket engine and estimate that it will take you an additional 10 hours to finish it. You just learn that the winner of the previous year’s competition was also working on a rocket engine design similar to yours. You had also thought about working on a (equally innovative and good) design for a solar powered pump that would take about 10 hours to complete. You can submit only one entry, and since the deadline is very close, you must choose now. The question is: Should you spend 10 hours trying to finish your rocket engine design or would you rather work on the solar-powered pump?

Question 3 (Adapted from Soman 2001)
Imagine that you are a member of a store loyalty program where you get points for making purchases. Because you had a lot of points, the store selected you to receive a free gift—two tickets to a one-day cruise on the Chesapeake on a luxury ship. In order to receive your free gift, however, you had to participate in a marketing research program for the store. Specifically, you needed to attend four focus group interviews about grocery shopping, and also fill out a lengthy survey. In all, these activities took a total of 24 hours of your time and were spread over three weeks. The tickets had arrived in the mail last week, and you were all set to go on the cruise with a friend tomorrow.

However, you went to class today and received some bad news. An exam had been rescheduled and it will now be held tomorrow, the same day as your cruise. The instructor will not allow you to take a make-up examination, so if you miss the exam your grade will come down from A− (which you had been expecting and working hard for) to a B+ (which would still keep your GPA high but would leave feeling a little disappointed). On the other hand, if you attend the exam, you would be not able to go to the cruise that you had been so eagerly anticipating. The question is: Will you go on the cruise or will you attend the exam?

Question 4 (Adapted from Navarro and Fantino 2009)
Imagine that you are the leader of a copper-mining group. Your group’s job is to dig the ground in search of copper. Currently, your group is digging at a local spot known as “Shady Creek.” So far, your group has been digging at Shady Creek for the past 60 days. The ground so far has been hard. The time spent digging has been very difficult and has involved a lot of effort from you and your group. This morning, you and your group found a vein of copper.
However, there is a thick wall of quartz, which is easy to dig through, covering most of the copper. Some special equipment you have (which is 100% accurate) indicates that it will take 10 more days to dig through the quartz and collect all the copper. Unfortunately, your equipment also indicates that the amount of copper is small—about 10 pounds. Typical mines contain upwards of 500 pounds. You now face two options: What is your choice?

**Appendix E. Manipulating Line Speed**

**Methods.** A total of 239 participants were recruited on Amazon Mechanical Turk. The participants were 53% female, and the average age was 28.3. Participants were compensated $0.50 for completing a short survey. Participants were told they were completing a simulated shopping trip to a donut shop. As in Studies 2 and 3, to move forward, participants had to use the next button. Different from prior studies, the number of people ahead of the participant was the same in both conditions (15 people), but the speed of progress varied. In the fast-wait condition, participants were able to move forward every 2 seconds (i.e., 30-second wait); in the slow-wait condition, they were able to move forward every 12 seconds (i.e., 180-second wait). After the wait, a progress button appeared on the screen that brought participants to a screen that displayed the menu, stated how much the donuts were, and asked, “How many donuts would you like to order?” Responses were provided in a text box. Participants then answered a few follow-up questions regarding their decision, their consumption habits, demographics, and their experience in the simulated queue.

**Results.** We ran two Poisson regressions for the number of donuts as a function of the experimental condition dummy (Slow) (see Table E.1). First, we find a positive relationship between the quantity consumed and the perceived speed of the line (Model 1, excluding respondents that reported a purchase quantity of zero). Customers ordered more donuts in the slow-wait condition (M_{Slow} = 3.52) than in the fast-wait condition (M_{Fast} = 3.04); this effect persisted when we controlled for quality (Model 2) and when we include the respondents that reported a purchase quantity of zero (Model 3). Finally, we investigate how the waiting experience was influenced by the rate of progress and find that customers found the waiting experience to be less unpleasant in the fast-moving scenario (M_{Fast} = 5.29) relative to the slow-moving line (M_{Slow} = 5.29) scenario (Model 4).

**Discussion.** We again find that purchase quantity increases with queue time. Importantly, we also demonstrate that this effect persisted when queue time was operationalized through the speed of the line, rather than through the length of the line. This rules out the possibility that the results were produced as a result of participants perceiving higher product quality from a longer line or through the implication that those willing to wait in the long-wait condition simply liked the donuts more.

**Appendix F. Study 3 Measures and Screenshots for Virtual Queues at a Cupcake Store**

— How many cupcakes would you buy given they are $2 each? (Numeric text entry)
— How appealing does a cupcake seem right now? (Seven-point scale, where 1 = “not appealing” and 7 = “very appealing”)
— How good do you think the cupcakes are? (Seven-point scale, where 1 = “average” and 7 = “far above average”)
— How many cupcakes would you usually eat in a single sitting? (Seven-point scale, where 1 = “0” and 7 = “6+”)
— How often do you eat cupcakes? (Five-point scale, where 1 = “never” and 5 = “all the time”)
— How much do you generally like cupcakes? (Seven-point scale, where 1 = “strongly disagree” and 7 = “strongly agree”)

**Appendix G. Study 4 Measures**

— How many T-shirts would you purchase? (Numeric text entry)
— How good do you think the T-shirts are? (Seven-point scale, where 1 = “far below average” and 7 = “far above average”)

**Appendix H. Study 5 Measures**

— It is your turn to bid. If you wish to abstain from bidding, please respond with 0. Remember, this is a REAL auction. The winner will be charged the amount they bid and will receive a $10 Amazon Gift card. This is your only opportunity to bid. (Numeric text entry)
— I really wanted to win the auction. (Seven-point scale, where 1 = “strongly disagree” and 7 = “strongly agree”)
— How long did you perceive the wait to be? (Five-point scale, where 1 = “not very long” and 5 = “a long time”)
1 “Consumption” is used as an umbrella term that captures the various types of quantity decisions made in different settings: how many rounds of a game to play, how many items to purchase, how much time to spend at a restaurant, etc.

2 Various psychological processes have been proposed to explain the sunk-cost fallacy, such as cognitive dissonance (Staw 1976, Brockner 1992), waste aversion (Arkes and Blumer 1985), and loss aversion (Garland and Newport 1991). Soman (2001) observes that these explanations require the individual to track the resulting costs and benefits; hence it can be related to the mental accounting framework (Thaler 1980, 1985, 1990, 1999). According to Soman and Ahn (2011), mental accounting is a paramorphic model of human behavior (i.e., people behave as if they mentally account) for which the underlying psychological processes are not well understood. An early model of mental accounting in operations management was presented by Chen et al. (2013) to study how payment schemes affect inventory decisions.
This parsimonious specification captures the essence of the problem and embeds the utility of the rational decision maker with a single parameter (i.e., when $\lambda = 0$). It also approximates consumer decisions with a loss-averse utility function (see p. 49 of Thaler 1980). Let $f(\cdot)$ be the S-shaped utility function for loss aversion (Tversky and Kahneman 1991). The customer chooses $Q^*$ to maximize $(g - Q) + (-P - Q - c - W)$, where $g$ is the value each unit of the product. Assume that $g + (-P) > 0$ (i.e., a customer will purchase at least one unit of the product when there is no waiting). When $W = 0$, the customer chooses the quantity that maximizes $(g - Q) + (-P - Q)$. When $W > 0$, the second term of the utility function, which represents the losses as a result of the costs incurred, becomes flatter with respect to $Q$, whereas the shape of the first term representing the gains remains unchanged. It is easy to verify that $\partial Q^*/\partial W > 0$ (see Appendix A).

Ideally, one would want to know how the purchase quantity increases for each person over time. However, this is not straightforward. First, if one were to ask a participant at the beginning of the line, it is possible that she would want to remain consistent with her answer later on; hence, the mere fact of asking this question might change the behavior of the participants. Second, it would also require each participant to answer the same question twice, which would negatively affect the response rate. Instead, we try to capture this by administering the survey at different points in the line and using location information to infer the changes that occur while they wait in line.

Because the dependent variable is a count variable, the analysis was based on a Poisson regression. We inserted the parameter estimates in Table 2 into the following formula: $\text{Quantity} = \exp(\text{Constant} + \beta_1 \times \text{WaitEst} + \beta_2 \times \text{PartySize} + \beta_3 \times \text{Repeat})$.

Note that 20% of the participants did not exhibit the sunk-cost fallacy in any of the scenarios, whereas 41% displayed it in one, 27% in two, 11% in three, and 1% in all four scenarios.

A median split of the data confirms this relationship: for those with a sunk-cost susceptibility score of 0 or 1, there was no effect of queue position on consumption ($p = 0.75$), but for those with a sunk-cost score of 2 or greater, there was a positive effect of queue position on consumption ($p = 0.03$).

Although the analysis is conducted for $T = 5$ and $T = 10$, the results are robust to the choice of time window. Similar results were obtained when the time window was set to values ranging from 3 to 10 minutes, with the exception of the analysis confined to the dinner time with $T = 3$, for which the small window size results in little variation in the independent variable.

More specifically, Soman (2001) suggests that cognitive dissonance is subsumed by mental accounting, which in turn would explain the sunk-cost fallacy.

In such contexts one can also observe positive feedback loops, as people tend to increase dining time in response to a long wait, hence leading to an even longer wait for the incoming cohort of patrons.

Here, we assume that waiting time is not excessive, resulting in a large number of customers balking. Another way to compare the profit effect of capacity additions in the two contexts is as follows: capacity additions can reduce the average waiting times in both settings; however, the second-order effect is different in the two settings—negative in the cupcakes example (because of the lower purchase quantities for each individual customer) and positive in the all-you-can-eat restaurant (because people do not stay longer, and they consume more).


