Learning from Inventory Availability Information: Evidence from Field Experiments on Amazon

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Many online retailers provide real-time inventory availability information. Customers can learn from the inventory level and update their beliefs about the product. Thus, consumer purchasing behavior may be impacted by the availability information. Based on a unique setting from Amazon lightning deals, which displays the percentage of inventory consumed in real time, we explore whether and how consumers learn from inventory availability information. Identifying the effect of learning on consumer decisions has been a notoriously difficult empirical question due to endogeneity concerns. We address this issue by running two randomized field experiments on Amazon in which we create exogenous shocks on the inventory availability information for a random subset of Amazon lightning deals. In addition, we track the dynamic purchasing behavior and inventory information for 23,665 lightning deals offered by Amazon and use their panel structure to further explore the relative effect of learning. We find evidence of consumers learning from inventory information: a decrease in product availability causally attracts more sales in the future; in particular, a 10 percent increase in past claims leads to a 2.08 percent increase in cart add-ins in the next hour. Moreover, we show that buyers use observable product characteristics to moderate their inferences when learning from others; a deep discount weakens the learning momentum whereas a good product rating amplifies the learning momentum.

Key words: Learning, inventory availability, field experiment, panel data, fixed effect, consumer behavior, Amazon, retail operations.

1. Introduction

Flash deal websites, such as Amazon’s deals, Groupon or LivingSocial, have emerged as a popular means of selling products online. Using these platforms, sellers can advertise their products by offering them at a deep discount. New deals are announced on a daily basis and are only available over a short period of time, ranging from a few hours to a few days. In the United States alone, consumers spent approximately $9 million per day and more than $3.6 billion per year on flash
deals by 2012, and this number exceeded $5.5 billion per year by 2016. Amazon, the largest U.S. online retailer, offers hundreds of limited-time deals every day, known as lightning deals. On July 15, 2015, Amazon promoted a 24-hour sale event with lightning deals called Prime Day, in which the number of orders surpassed that of Black Friday in 2014. Prime Day sales rose more than 26 percent to $525 million in 2016. The popularity of flash deals has grown in many countries across the world, as well. In China, Alibaba’s Singles’ Day sales surged 60 percent to $14.3 billion on November 11, 2015, and reached $20 billion on November 11, 2016.

Many flash deal websites provide inventory information in real time. Thus, it is important to understand whether this piece of real-time information affects consumer purchasing behavior during flash sales and, if so, how. When making purchasing decisions, customers use various information presented online to learn about the deal. They infer the quality of the deal—i.e., whether it is worthwhile to purchase it. Inventory information signals previous customers’ preferences and opinions. By observing past purchasing decisions from inventory information, customers can draw inferences and update their beliefs about deal quality, especially when their prior knowledge about the deal is imperfect. A product’s low inventory level can also create an out-of-stock pressure among customers, prompting a resulting urgency to buy that product immediately. Thus, when deals advertise a product’s brisk prior sales or limited availability, learning may cause an acceleration in subsequent sales. Consumers not only learn from inventory availability but also moderate their learning using various observable deal characteristics such as discount depth and product rating.

In this paper, we explore whether consumers’ purchasing behavior is impacted by inventory availability information and, if so, the types of information inventory availability conveys to customers.

By showing a product’s sold inventory as a real-time percentage, Amazon’s lightning deals are an ideal research context in which to investigate whether consumers react to inventory availability. Lightning deals differ from traditional online sales in two distinctive ways. First, lightning deal sellers allocate a fixed amount of inventory to a lightning deal sale, and the deal page prominently displays in real time the percentage of products claimed, which reveals product availability. By allowing customers to observe how much inventory has been consumed, this practice enables customers to reevaluate their desire for a product and could drive more sales for popular items. Second, unlike traditional online sales, lightning deals are sold at a discounted price for a limited time—e.g., four hours for most deals—and the remaining time is displayed as a countdown. Having

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3. [http://www.cnbc.com/2016/07/13/amazon-prime-day-is-biggest-day-for-online-retailer-ever.html](http://www.cnbc.com/2016/07/13/amazon-prime-day-is-biggest-day-for-online-retailer-ever.html)
to make decisions in a limited time under the pressure of missing the deal, customers need to rely on as much information as possible about the product. These features make inventory availability an important factor in their assessment. For example, the *New York Observer* made the following observation:

“The countdown underneath each limited-time item on Amazon.com is both stressful and exciting. Better yet, seeing that 83 percent of the inventory has already been purchased is much more appealing.”


We collect a proprietary and rich data set from Amazon.com by downloading lightning deals’ information every 30 seconds. Besides the standard product information displayed on Amazon, such as customer reviews, prices and promotional discounts, we also collect the dynamic inventory information from a status bar under each deal indicating the percentage of that item currently in customers’ carts or purchased in real time. When a customer clicks the “Add to Cart” button, a claim is triggered, and the claimed status bar increases the relative percentage over the total predetermined inventory. As a result, we can create reliable metrics to measure cart-adding behavior given our fine downloading-time resolution. We define the outcome variable as the potential sales that we measure using the number of cart add-ins within a certain period.\(^6\) Inventory availability information is measured by the percentage of deals claimed.

Our paper aims to estimate the causal relationship between product availability information and consumers’ purchasing behavior. We refer to consumers’ response to the inventory information as “consumer learning” and the magnitude of such response as “learning momentum.” Identifying the effect of learning on consumer decisions has been recognized as a notoriously difficult empirical question due to endogeneity concerns (Manski 1993 and Manski 2000). For instance, the observation that well-sold products attract more future sales may simply be due to the fact that products are heterogeneous and products with a high (low) quality are sold faster (slower). The main challenge is to distinguish learning from the unobserved effects, such as heterogeneity across deals.

To address this issue, we design and conduct a randomized field experiment on Amazon.com over two weeks in September 2016. In the experiment, we create an exogenous and instant shock in the inventory availability information for a random subset of Amazon lightning deals by adding deals to carts from multiple accounts. We then adopt a difference-in-difference approach to quantify the incremental cart add-ins across nontreatment and treatment periods of the treated and controlled deals. Using our randomized treatments, we find that a decrease in product availability, i.e., an

\(^6\) We also construct a proxy for sales by taking the difference between the hour-end number of claims and the hour-beginning number of claims. We find our results hold qualitatively across the sales measure. However, this measure is less accurate than cart add-ins and therefore is not included as the main outcome variable.
increase in past sales, causally attracts more sales in the future. In particular, a 10 percent increase in past claims\(^7\) leads to a 2.08 percent increase in potential sales in the next hour. This result indicates that consumer learning has a significant and substantial impact on purchasing behavior. To demonstrate robustness, we conduct a second field experiment in April 2017 with the same setup, and we show that the estimated results are consistent in both direction and magnitude.

We further investigate how inventory information and deal characteristics interact with each other in affecting learning. To study the moderating effects, we exploit the data set collected from Amazon.com in August 2016, which contains 23,665 lightning deals launched by Amazon in that month. We take advantage of the panel structure of our data and employ the fixed-effect model to capture any time-invariant, unobserved heterogeneity among different products. We find that buyers use observable deal characteristics to moderate their inferences: they attribute herding to observable characteristics rather than solely to intrinsic quality. Two key observable characteristics determine a deal’s quality: discount depth (i.e., deal value) and product rating (i.e., product quality). Interestingly, our findings suggest that inventory availability and deal value convey similar information to customers. A deep discount rate weakens the learning momentum because customers partially attribute herding to a good deal and might ignore the inference drawn from the inventory information. In other words, the discount rate is a substitute for learning when it serves as a signal to update customers’ beliefs. However, a good customer review amplifies learning, which indicates that reviews attract customers by a different mechanism that complements learning. Further, we find that customers’ learning momentum increases when they face lower inventory availability (higher past sales)—i.e., deals with low availability sell faster. This result is consistent with the scarcity effect: advertising a product’s low inventory level can create an out-of-stock pressure among customers and thus prompt a resulting urgency to buy that product immediately.

Our study indicates that in the online flash sales context, inventory availability is an important source of information that dictates consumer purchasing behavior. Past literature has documented how sales ranking or the absolute past sales volume affects future sales (Cai et al. 2009, Chen et al. 2011, and Li and Wu 2014). To the best of our knowledge, we are the first to establish the causal relationship between inventory information and consumer learning by running a field experiment in a retail context. Moreover, we complement the literature by shedding light on the underlying behavioral mechanisms behind consumer learning and pinpointing the specific aspects of a deal that a customer learns about from inventory information. More broadly, our results contribute to the literature on consumer learning and customers’ strategic reaction to inventory information, which we summarize next.

\(^7\) Past claims include past sales and items currently in customers’ carts.
2. Literature Review

Past studies have explored the impact of inventory information on consumer demand and how to use inventory information as a strategic lever to reshape demand. A key theoretical assumption within this literature is that consumers react strategically to inventory information. Our paper supports and contributes to the literature by providing the first causal evidence of consumer learning on one of the biggest retail platforms in the world.

By studying consumer learning, our paper is related to the stream of literature on observational learning or herding. The theoretical work shows that herding behavior—an individual may draw inferences from accumulative decisions by previous decision makers and follow their actions—can arise as an equilibrium (Banerjee 1992 and Bikhchandani et al. 1992). Stock and Balachander (2005) and Debo and Van Ryzin (2009) show that companies could adopt the “scarcity strategy” and “asymmetric inventory allocation strategy” respectively to signal product quality and drive profits. In the service context, uninformed customers could learn about product quality from waiting time (Kremer and Debo 2015), and herding is shown to arise as a queue-joining equilibrium (Veeraraghavan and Debo 2011).

Our paper follows the recent interest in empirically quantifying herding in various contexts. In microloan markets, Herzenstein et al. (2011) and Zhang and Liu (2012) find evidence of herding among lenders; that is, well-funded borrower listings tend to attract more funding. In the context of restaurant dining, Cai et al. (2009) design a field experiment to distinguish the observational learning effect from the saliency effect. Chen et al. (2011) and Li and Wu (2014) study the interaction between herding and social media word-of-mouth using Amazon and Groupon’s observational data respectively. Our identification strategies are inspired by the above literature. To our knowledge, however, our paper is the first to (1) introduce a field experiment technique to causally identify learning on Amazon, (2) provide empirical evidence that availability information shapes consumers’ behavior, and (3) investigate how this effect is contingent on deal value and perceived product quality.

Our work is also related to the stream of literature on scarcity. Scarcity can be a deliberate strategy for making a product more desirable. A low inventory level indicates that the product may not be available in the future, which can induce a “buying frenzy” behavior among customers (DeGraba 1995). Brock (1968), Lynn (1991) and Tereyagoglu and Veeraraghavan (2012) also point out that customers may prefer a product that is more exclusive, and thus scarcity is associated with a stronger preference. Recent research has proposed various strategies in response to consumers’ strategic reactions to scarcity. Gallino et al. (2013) empirically explore the scarcity effect in the

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8 We use observational learning and herding interchangeably throughout the paper.
automotive industry. The authors show evidence of the scarcity effect when the added inventory does not increase the variety of models, but this effect vanishes as the variety increases. Liu and Van Ryzin (2008) show that sellers can create rationing risk by deliberately understocking products, and that the resulting threat of shortages induces customers to purchase earlier at higher prices. Cui and Shin (2016) show that sellers can adopt an aggregate inventory-information-sharing strategy to reduce the shortage penalty cost by creating a stockout pressure among customers.

Further, our paper studies how consumers react to product availability information. In this sense, our study is closely related to the literature that studies consumers’ strategic reactions to product availability. The literature explores mechanisms behind decision-making: customers learn from the past stockout experience and anticipate a higher probability of a stockout on future orders; the variety in inventory augments consumer choice options, which may confuse customers or enable a better preference match among heterogeneous customers.

In the face of a stockout, Netessine and Rudi (2003) consider a demand substitution behavior between competing sellers in a single-period model, and Netessine et al. (2006) analyze a back-order behavior in a multi-period game. Hall and Porteus (2000) and Gaur and Park (2007) study the change in retailers’ optimal inventory policy in response to strategic consumer learning when customers react to the last stockout or remember the entire service history. Musalem et al. (2010) develop a structural demand model that estimates the effect of stockouts on consumer demand. Anderson et al. (2006) conduct a field experiment in a mail-order catalog to show that stockouts adversely impact both current demand and future demand. Craig et al. (2016) use a field experiment to show that an increased fill rate drives a significant increase in next-year sales. Tomlin (2009) investigates a retailer’s inventory and sourcing strategy when it learns about changes in the supplier’s service level. Kabra et al. (2015) study a bike-sharing context and empirically show that customers trade off bike availability and accessibility. Inventory variety has also been shown to be an important factor in dictating consumer buying decisions. Ryzin and Mahajan (1999), Gaur and Honhon (2006), and Cachon and Kök (2007) use consumer choice models to study the optimal assortment strategies, i.e., selecting a subset of variants to stock. Gallino et al. (2013) provide empirical evidence that product variety drives more sales for car dealers because customers are more likely to find an item that matches their preferences. On the other hand, Iyengar and Lepper (1999) and Iyengar and Lepper (2000) point out that high variety may create confusion in the decision-making process and thus lead to lower sales.

These papers offer innovative operations strategies in response to consumers’ past negative encounters or strategic decision-making, whereas we focus on the consumer behavior aspect and provide causal empirical evidence of consumer learning in a retail context. Our paper shows that customers not only learn from real-time availability information, but also rationally use observable
product attributes to moderate their inferences. This finding supports the fundamental assumption of consumers’ strategic and rational reaction to inventory information in the literature.

3. Research Background and Hypotheses

In this section, we demonstrate our research setting and develop hypotheses for customers’ response to inventory information and how observable product characteristics moderate consumer learning.

3.1. Research Background

Online flash sales provide a unique context to study how product availability influences consumers’ purchasing behavior. We choose the Amazon lightning deal platform, one of the largest daily deal sites, as our research setting.

Amazon launched “lightning deals” in 2009 — a marketing tool to raise awareness for a product or a brand. Amazon offers hundreds of lightning deals daily. These deals are deeply discounted (an average of 40 percent) and limited in time (lasting for 4 to 24 hours). A unique feature of lightning deals is that a seller allocates a fixed, limited amount of inventory to a lightning deal sale, and the page provides a real-time status bar indicating the percentage of available units that have already been claimed by customers, which reveals product availability. A timer appears below each lightning deal, indicating how much time remains for the deal in real time. Like regular Amazon product pages, lightning deal pages also display standard product characteristics, such as price and reviews.

On Amazon’s main page, customers can find lightning deals by first clicking the “Today’s Deals” button and selecting “Lightning Deals” as the deal type. Figure 2 in the Appendix shows how Amazon presents lightning deals on Amazon’s webpage.
3.2. Hypothesis Development

3.2.1. Consumer Response to Inventory Information. We refer to consumers’ overall responses to inventory information as consumer learning. When making purchasing decisions, customers use various information presented online to learn about the product. They aim to infer the quality of the deal, i.e., whether it is worthwhile to purchase the deal, and the availability of the deal, i.e., the likelihood of obtaining the deal before it runs out of stock. The deal’s quality depends on observable and unobservable characteristics. The depth of the promotional discount and product reviews are examples of observables characteristics. How often the deal is on sale and how good the discount is relative to other sources are examples of unobservables characteristics. The percentage claim information reveals how much inventory has been consumed and is left. Inventory information provides customers a source of information that signals deal quality and product availability. These two types of signals cause herding behavior and the scarcity effect respectively.

The mechanism to explain the effect of inventory information when it signals deal quality is herding (Bikhchandani et al. 1992). The premise of herding is as follows. A market participant makes decisions based on two sources of information. One is her private knowledge of the product. This information is often imperfect, and thus she is uncertain about the deal value. The other is the information derived from the behavior of other market participants. When a subsequent decision maker observes predecessors’ decisions, she uses this information to update her belief about the product’s value. If the decision maker has limited private information, she may disregard her own information and simply follow others’ behavior. If the decision maker is very knowledgeable about the product, the reliance on others’ actions diminishes. Such behavior—using information acquired by watching others—is referred to as herding or observational learning.

While past herding literature focuses on the situation when all prior actions are observable, herding can also happen if only aggregated information is shared. For example, Guarino et al. (2011) show that when agents only observe the total number of customers who have purchased a product, herding on the aggregate observable choices can sustain as an equilibrium. In our research context, herding occurs when deals with higher prior aggregated sales tend to attract more sales in the future. Intuitively, consider two deals with the same characteristics: the deal with higher prior sales sends a strong signal to subsequent customers, and an uninformed customer can draw an inference of the deal value and would expect the more popular deal to be more valuable than the alternative, even though their observables are the same.

The two key drivers of herding are the uncertainty in buyers’ own information and their ability to learn from prior customers’ purchasing decisions. Amazon’s lightning deal platform satisfies both these requirements. First, more than 80 percent of deal buyers are new customers who are likely
to be uninformed about the product and thus tend to herd when prior sales are high (Dholakia 2011). Second, by explicitly highlighting the percentage of products sold in real time, lightning deals provide a useful signal to customers that allows them to learn about the deal's quality. Moreover, lightning deals run for only a limited number of hours. Having to make the buying decisions in limited time under the pressure of missing the deal, customers tend to rely on as much information about the product as possible. These features make other customers’ decisions an important information resource to infer a deal’s quality.

The mechanism to explain the effect of inventory information when it signals low inventory availability is the scarcity effect. DeGraba (1995) suggests that scarcity creates a buying frenzy among customers. Because low inventory availability indicates that the deal with the current discount level may not be available in the future, consumers may rush to purchase it under the out-of-stock pressure.

To summarize, consumer learning refers to overall customer response to inventory information. The response could be driven by herding and scarcity. When product availability is relatively high, i.e., the percentage claimed is low, the inventory is far from stockout and it is unlikely that customers face an out-of-stock pressure. Thus, consumer learning—i.e., higher past sales drive more future sales—is likely to be driven by herding. When product availability is relatively low, i.e., the percentage claimed is high, the scarcity effect begins to kick in and consumer learning is likely to be driven by both herding and scarcity.10

In short, our paper seeks to quantify the learning momentum on the Amazon flash-sale platform. We expect that consumer learning from inventory availability information significantly affects future sales.

**Hypothesis 1.** *When inventory availability information is shown to customers, higher prior percentage claim information will attract more sales in the future.*

**3.2.2. Inventory Information and Moderating Effects.** Based on the herding mechanism, we expect customers will respond to inventory availability by updating their beliefs and altering purchasing decisions. However, the effect may be affected by the product’s observable characteristics. We next study how the two key characteristics of a deal—discount rate and product review rate—moderate learning.11

10 Note that in this research, we cannot completely disentangle the herding effect from the scarcity effect as it is not well understood when the scarcity effect begins to kick in (e.g., the availability level below which customers start to care about scarcity). We will provide side evidence that is consistent with the scarcity effect in Section 7.2.3. We expect that in the presence of scarcity, the average learning momentum increases as customers respond to an increasing average percentage of claimed products.

11 The moderating effect is built upon the herding theory. Because in our empirical context herding and the scarcity effect cannot be separately identified, we will use learning momentum instead of herding momentum throughout the paper.
The learning literature has shown evidence that observational learners care about not only the presence of herding, but also the various reasons that give rise to the herd (Zhang and Liu 2012). For example, an observational learner learns about product quality based on inventory information and other public product information. When the public information sends similar signals, the customer will herd less because she has less to learn from inventory information. In other words, consumers attribute herding to observable merits rather than solely to intrinsic quality by using observable deal characteristics to moderate their inferences. Duan et al. (2009), Zhang and Liu (2012), and Li and Wu (2014) identify user rating, credit score, and social media as sources of external efforts that can moderate the learning momentum among software downloaders, lenders, and deal buyers respectively.

**Inventory Information and Deal Value.** We measure a deal’s value by the promotional depth. We investigate whether learning is accentuated or mitigated by the deal value. Because Amazon computes the discount based on the manufacturer’s suggested retail price, the listed discount rate (around 40 percent) is usually higher than the actual discount percentage (around 20 percent). If customers are rational and strategic, they will not respond to the listed discount, and thus the listed discount will not affect consumer learning from inventory information. The actual discount, however, not only directly influences consumer buying decision but also changes how consumers react to inventory availability.

We have two opposing hypotheses. One hypothesis suggests that inventory availability and deal value convey similar information to customers. When seeing that a deeply discounted deal has low inventory availability, customers will partially attribute the high sales to the deal’s value (Zhang and Liu 2012). Intuitively, consider two equally well-sold deals with identical observable characteristics except that deal 1 has a larger discount than deal 2. A buyer would think that previous customers must possess positive private information if they chose deal 2 over deal 1. For example, previous customers might be experienced lightning deal buyers and know that deal 2 is more valuable because the product is rarely on sale. Therefore, a subsequent buyer would partially attribute deal 1’s sales to its deep discount and draw a more positive incremental quality inference about deal 2. As a result, a deep discount weakens the learning momentum.

Another hypothesis suggests that inventory availability and deal value convey dissimilar information to customers. Prior research has shown that different signals on product quality often interact with each other to affect sales (Kirmani and Rao 2000 and Li and Wu 2014). For example, Basuroy et al. (2006) show that sequels and advertising expenditures are complements in generating box office sales. Through Amazon’s sorting and filtering option, a deep discount rate may

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12 Following the empirical evidence of Zhang and Liu (2012), we assume that instead of passively mimicking others’ choices, customers make rational inferences using past decisions or other observables.
attract traffic to a deal. Once customers land on the deal’s page, they are more likely to buy if others have bought it. While inventory availability provides information about others’ opinions, deal value brings awareness and attention to the deal. In this situation, a deep discount amplifies the learning momentum.

We speculate that a deal’s actual discount is unlikely to serve as a different information source to attract customers because Amazon only offers to sort by listed discount, which is often far from the actual discount, and it becomes relatively difficult for customers to obtain the actual discount information. Therefore, we hypothesize that

**Hypothesis 2.** The listed discount will not affect consumer learning. A high actual discount will weaken the learning momentum.

**Inventory Information and Product Quality.** Another important attribute of a deal is the quality of the product for sale. We measure product quality by the average product rating. We investigate whether learning is accelerated or mitigated by the product quality. Following the same logic, one hypothesis suggests that when inventory availability and product quality convey similar information to customers, they partially attribute large sales to a high product rating, and hence a higher customer review weakens a deal’s learning momentum. Another hypothesis suggests that a higher rating can amplify a deal’s learning momentum when reviews and inventory availability provide different information signals. Customer reviews could attract potential buyers to the lightning deal’s page, and inventory information could drive them to make a purchase.

Prior research has shown a positive interaction between sales ranking and number of customer reviews in the digital camera market (Chen et al. 2011). In contrast to actual discounts, Amazon allows customers to filter by the number of stars that products receive. Thus, we speculate that product rating is more likely to serve as a different information source to attract customers.

**Hypothesis 3.** A high product rating will amplify the learning momentum.

4. **Data**

We collect a proprietary data set from Amazon.com by downloading information about lightning deals every 30 seconds in August 2016. In addition, we continue to download the data while we run two field experiments in September 2016 and April 2017. Although Amazon is one of the largest flash-sale sites in the world, our paper is (to our knowledge) the first one to gather and take advantage of this data source. We gather two types of data from Amazon lightning deals: (i) real-time information and (ii) static product characteristics.

**Real-time Inventory Information.** When a customer clicks the “Add to Cart” button, a claim is triggered and the claimed status bar increases the relative percentage over the total predetermined
inventory. If the customer does not complete the purchase within 15 minutes, Amazon will delete the product from the cart and drop the corresponding percentage of units claimed. Since each customer is restricted to purchasing only one unit from each lightning deal, the percentage increase reflects the number of customers who intend to purchase the deal. Figure 3 shows an example of the dynamic change of the percentage claim information over time for a lightning deal.

Our granular download-time resolution (i.e., 30 seconds) allows us to capture the minimum increment (or decrement) of product availability. We use it to calculate the number of customers who add the product to their carts within a period of time. We can also use it to impute the approximate inventory allocated to a deal. In addition, we collect the remaining time from the timer displayed under each lightning deal.

For each deal at any given period, we construct the independent variable Cart add-ins as the total positive increment in the percentage claimed in this specific time period. When a customer adds an item to the cart, she expresses her interest in the product and creates a chance to make a purchase. Cart add-ins, as a result, measure potential customers who have expressed interest in purchasing. We also construct the dependent variable Claim as the percentage claimed of the product at the beginning of a time period. Figure 3 in the Appendix illustrates these variables.

Product Characteristics Data. For each deal, we also gather static product information. Specifically, we collect the final discounted price, the listed original price, the actual original price, the product rating, the number of reviews, and the number of options (in color or size). Lightning deals display the listed original price and a corresponding discount percentage below each deal. However, the listed original price is the manufacturer’s suggested retail price, which is often higher than the non-promotional price on Amazon. Therefore, we also collect the actual original price from Amazon, from which we calculate the actual discount rate. We obtain two measures of the promotional depth: the actual discount and the listed discount. These allow us to investigate whether customers are knowledgeable enough to differentiate them and which discount rates dictate decision-making.

Descriptive Statistics. Table 1 presents the summary statistics for the dynamic variables and the time-invariant product characteristics in August 2016. Our sample includes 23,665 deals that run for an average of 5.2 hours. The average cart add-ins per hour are 4.47 percent. The average final deal price is $24.15 with an actual original price of $31.67 (discount percentage of 22 percent).

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13 We calculate inventory as 100/(the minimum increment). For example, if the minimum increment is 2 percent, the inventory level is 50 units. Please note that the minimum increment takes only integers. Therefore, we approximate the inventory level as 100 for deals with more than 100 units.

14 Given our granular download-time resolution and one-customer-one-deal purchasing restriction, Cart add-ins is an accurate and good measure of potential customer demand.

15 The max cart add-in is 228 percent. It indicates that for this product in a specific hour, many customers have shown interest in purchasing but eventually dropped the item.
and a listed original price of $43.73 (discount percentage of 39 percent). On average, a deal has 130.37 reviews and an average rating of 3.91 out of 5 stars. The sellers allocate more than 35.47 units of inventory to lightning deal sales.

## 5. Identification Strategies

We aim to estimate the causal relationship between product availability and consumers’ future purchasing behavior. Identifying the effect of learning on consumer decisions has been recognized as a notoriously difficult empirical question due to endogeneity concerns (Cai et al. 2009). The main problem is in distinguishing learning from unobserved heterogeneity across deals. A common unobserved heterogeneity is the product quality. Deals with good quality tend to have high past sales and high future sales even without learning, while some other deals are less popular and in the most extreme case may have zero sales across the selling period. In this case, the ordinary least squares (OLS) regression may attribute high future sales to high past sales when it could actually be driven by the unobserved product quality. Therefore, the OLS estimator may overestimate the learning effect and suffer from omitted variable bias.

Following the past empirical literature, we address this issue by using two identification strategies: (i) randomized field experiment and (ii) panel data analysis. The randomized field experiment randomly assigns the treatment to products or individuals; Cai et al. (2009) and Chen et al. (2011) have adopted randomized experiments to estimate the learning effect in other research contexts. The advantage of using randomized experiments is that since the treatment is unconditionally randomly assigned, the estimator represents an unbiased causal effect. In other words, the estimators obtained from randomized control experiments have high internal validity (Levitt and List 2007). However, because field experiments are often conducted under financial and human resource constraints, the number of observations is relatively small, which limits the external validity and the statistical power to investigate moderation effects.
The panel data approach exploits the panel structure of the data and uses individual-level fixed effects to control for time-invariant unobserved heterogeneity; Sorensen (2006), Duan et al. (2009), Zhang and Liu (2012), and Li and Wu (2014) have adopted the fixed-effect specification. The advantage of using this approach is that the panel data set is often large and covers various products or individuals. Thus, the estimators derived from the panel approach have high external validity. Moreover, the large size of the panel data provides us enough power to test different moderating effects. However, because the causal identification obtained by the fixed-effect model requires the assumption that the unobserved heterogeneity is time invariant, the fixed-effect specification often lacks internal validity and needs various robustness checks to prove this assumption.

Our paper employs both identification strategies to establish the internal and external validity of our findings. In particular, we first conduct several randomized field experiments to quantify the causal impact of consumer learning on sales among a set of Amazon deals. We then turn to the panel data set to reestimate the learning effect over a much larger set of deals. By demonstrating that these two estimators are similar in direction and magnitudes, we not only provide a crucial understanding of consumer learning but we also show that our findings are equally descriptive of the world at large.

Randomized Field Experiment. We run several field experiments on Amazon. In our experiments, we generate a shock in the claim information by creating an instance spike in claims, which is our treatment, to a randomly selected group of Amazon deals. This spike lasts for one hour. We started our experiment on average two hours before the deal period ends. This allows us to compare the purchasing behavior across three periods: pre-treatment, treatment, and post-treatment periods. We adopt a difference-in-difference analysis to quantify the incremental cart-adding behavior driven by our treatment.

Panel Data Approach. Our proprietary data set has a panel structure, where for each deal, the percentage claimed varies dynamically over time. The panel structure allows us to use a fixed-effect model to capture any time-invariant unobserved heterogeneity; in this way, we exploit the variation within each deal to obtain an estimate of learning and its interaction with product attributes. Using this fixed-effect approach, we strengthen the external validity given that the panel data covers a much broader spectrum of products. Further, the size of the panel data allows us to interact the availability information with observable product characteristics to explore possible moderating effects.

6. Randomized Field Experiment
In this section, to identify the causal effect of the availability information on purchasing behavior, we design and conduct several randomized field experiments on Amazon’s lightning deal platform.
6.1. Experiment Design and Data Summary

Recall that an increment in claim is triggered by clicking the “Add to Cart” button. We take advantage of this mechanism and create an exogenous shock to the availability information. In particular, we create 10 Amazon accounts and add products to these accounts’ carts in a short period of time (i.e., within three minutes) to spike the claim information. Before the experiment starts, we download all available deals that have a single option (e.g., products with one color or one size) and will last for at least two hours. We randomly assign about 40 percent of these deals to the treatment group that receives a shock in “past sales,” leaving the rest of the deals to the control group. Figure 4 in the Appendix illustrates our field experiment design.

With the help of four research assistants, we are able to add the treated deals to the cart of each of the 10 accounts within three minutes. Figure 5 in the Appendix illustrates how the availability information changes when we spike cart add-ins in the experiment. Because Amazon removes products from carts after 15 minutes if a purchase has not been completed, we re-added the treated deals every 15 minutes. We start the experiment at either 2 p.m. or 3 p.m. (EST) in the afternoon and keep the shocks on each deal for around 60 minutes on one day (the 60 minutes include 45 minutes effective in-cart time and around 15 minutes operating time). We repeat the experiment six times: on Tuesday, Friday, and Saturday of two consecutive weeks.

There are in total 181 deals in the treatment group and 264 deals in the control group. Table 2 summarizes the deal characteristics, inventory information dynamics across the treatment and control groups within a 50-minute window before the experiment, a 60-minute window within the experiment, and a 50-minute window after the experiment. On average, we created an exogenous average increment of 16.48 percent in the percentage claimed for the 181 treated deals at the beginning of the treatment period. Table 2 also demonstrates that the deals in the treatment and control groups have similar characteristics, such as hours to the end, listing discount percentage, actual discount percentage, review ratings, and number of reviews. Table 2 provides initial evidence of consumer learning: in the treatment period, the treated deals receive a higher number of cart add-ins than the control deals.

---

16 We choose products that will run for another two hours because we exert the shock for one hour and the additional hour allows us to observe the purchasing behavior after we stop adding the treatment. We choose the products that have only one option because Amazon displays the mean inventory level across variants of a product on the main page, which might dilute the exogenous shocks and complicate how to measure the treatment size.

17 There are on average 300 active deals during our experiment periods. Among the active deals, around 100 deals satisfy our time requirement and around 70 deals satisfy both time and single-option requirements.

18 The experiment design was thoroughly reviewed and approved by the institutional review board (IRB) of a U.S. university. The data was collected at the aggregate level and cannot be used to identify any individual.

19 An experiment spanning Tuesday, Friday, and Saturday captures the effects on both weekdays and weekends.
Table 2 Field Experiment Summary Statistics

<table>
<thead>
<tr>
<th>Window</th>
<th>Variable</th>
<th>Treatment (N=181)</th>
<th>Control (N=264)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Mean</td>
<td>Std. Dev</td>
</tr>
<tr>
<td>Pre-50-min</td>
<td>Start claim</td>
<td>5.18</td>
<td>8.29</td>
</tr>
<tr>
<td></td>
<td>Cart add-ins</td>
<td>7.13</td>
<td>9.40</td>
</tr>
<tr>
<td></td>
<td>Hour to end</td>
<td>3.44</td>
<td>0.50</td>
</tr>
<tr>
<td></td>
<td>List discount pct</td>
<td>0.62</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td>Actual discount pct</td>
<td>0.23</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>Review rating</td>
<td>4.08</td>
<td>1.35</td>
</tr>
<tr>
<td></td>
<td>No. of reviews</td>
<td>97.88</td>
<td>255.82</td>
</tr>
<tr>
<td>Experiment</td>
<td>Start claim (before shocks)</td>
<td>9.14</td>
<td>13.04</td>
</tr>
<tr>
<td></td>
<td>Start claim (after shocks)</td>
<td>25.62</td>
<td>19.20</td>
</tr>
<tr>
<td></td>
<td>Cart add-ins</td>
<td>10.49</td>
<td>9.88</td>
</tr>
<tr>
<td>Post-50-min</td>
<td>Start claim</td>
<td>19.42</td>
<td>21.09</td>
</tr>
<tr>
<td></td>
<td>Cart add-ins</td>
<td>5.88</td>
<td>7.85</td>
</tr>
</tbody>
</table>

6.2. Experiment Results

We analyze the treatment effect of availability information on consumer cart-adding behavior. We first employ a pre-post comparison specification. Specifically, for each deal, we compare the total cart add-ins within the experiment time window with those within 50 minutes before (or after) the experiment. The validity of this specification relies on the assumption that the potential demand and consumer purchasing behavior are time invariant. To control for potential heterogeneity over time, we then employ a difference-in-difference approach.

6.2.1. Pre-post Treatment Comparison. Let $Treated\ Deal_i$ be a dummy variable to denote whether deal $i$ was assigned in the treatment group; $Treated\ Deal_i = 1$ represents the deals that received the treatment on inventory availability. Let $Treated\ Period_p$ denote the period dummy, where $p \in \{\text{pre-50-min period, experiment period, post-50-min period}\}$; $Treated\ Period_p = 1$ represents treatment period (i.e., the experiment hour). We estimate the treatment effect by the following specification,

$$s_{i,p} = c + \alpha Treated\ Period_p + T_i + Z_i + e_{i,p}, \ \forall i \ s.t. \ Treated\ Deal_i = 1$$  (1)

where $s_{i,p}$ denotes the number of times deal $i$ was added to the cart per minute within period $p$, i.e., cart-adding rate. The term $e_{i,p}$ is the error component. In addition, $T_i$ controls for time characteristics, e.g., day of the week and the hour of the day effects, and $Z_i$ controls for deal characteristics, e.g., review rating, total number of reviews, and discount depth. Please note that in the randomized experiment we do not need to add any control covariates to obtain an unbiased estimate of the treatment effect because treatment is unconditionally randomly assigned; the addition

20 The reason we measure the outcome variable by the cart-adding rate is that we vary the duration of the pre-experiment control period and the post-experiment control period as a robustness test. In order to make an accurate and correct comparison, we adopt the cart add-ins per minute as the dependent variable.
of controls, however, can make the estimates more efficient (Paulsen and Smart 2013). Our main analysis will not include deal characteristics, but our analysis is qualitatively and quantitatively robust after including the deal characteristics in Table 8 in the Appendix.

The learning effect can be measured by the incremental potential sales driven by the treatment, i.e., the coefficient of Treated Period. The validity of this specification resides in the assumption that the incoming potential demand and consumer purchasing behavior do not systematically change over time (conditional on our control variables),

**Assumption 1.** Pre-post comparison assumption: $E(e_{i,p} \mid \text{Treated Period}_p) = 0$.

We let $p = \{\text{pre-50-min period, experiment period}\}$ in specification (1) to compare the treated period with the pre-50-min window. At the end of our experiment period, the fictional add-ins from our treatment are dropped from the carts, and as a result the treatment effect diminishes in the 50-min period after the experiment. To show the robustness of our treatment effect over the period after the experiment, we re-run specification (1), where $p = \{\text{experiment period, post-50-min period}\}$. The estimation results are displayed in columns I and III in Table 3. Column I shows evidence of consumer learning: a product’s brisk prior sales causally drive an acceleration in sales in the future period. The main finding also holds in column III, i.e., the treatment effect is statistically significant on the cart-adding rate over the post-experiment period.

However, this treatment effect may be confounded by temporal heterogeneity in cart-adding behavior. To control for such time heterogeneity, we next employ a difference-in-difference analysis.

### 6.2.2. Difference-in-difference (DiD) Analysis

The difference-in-difference estimator is derived from the following specification,

$$s_{i,p} = c + \text{Treated Deal}_i + \text{Treated Period}_p + \beta \text{Treated Deal}_i \times \text{Treated Period}_p + T_i + Z_i + e_{i,p}, \quad (2)$$

<table>
<thead>
<tr>
<th>specification</th>
<th>dependent variable: cart add-ins per minute</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>pre-50-min comparison</td>
</tr>
<tr>
<td></td>
<td>I. treated</td>
</tr>
<tr>
<td>Treated Period</td>
<td>0.045***</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
</tr>
<tr>
<td>Treated Deal</td>
<td>−0.013</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
</tr>
<tr>
<td>Treated Period × Treated Deal</td>
<td>0.057**</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
</tr>
<tr>
<td>time controls</td>
<td>yes</td>
</tr>
<tr>
<td>observations</td>
<td>362</td>
</tr>
</tbody>
</table>

Note: Column I reports the pre-post comparison relative to the pre-50-min period for the treated deals of Equation (1); column III reports the pre-post comparison relative to the post-50-min period for the treated deals of Equation (1); columns II and IV report the estimation results from the difference-in-difference approach in Equation (2). Time controls include the day of the week and hour of the day. The errors are robust and clustered at the deal level. Significance is at ***p<0.1; **p<0.05; ***p<0.01.
where the learning effect can be measured by the incremental cart-adding behavior driven by the treatment after removing the time effect, i.e., the coefficient of Treated Deal \( i \times \) Treated Period \( p \).

The term \( e_{i,p} \) is the error component. The key identification assumption for any DiD strategy is the parallel trends assumption: the outcome in treatment and control groups would follow the same time trend in the absence of the treatment. In other words, the unobserved characteristics of deals in the treatment and control groups are independent of the treatment, which we summarize below.

Because our treatment is unconditionally randomly assigned (i.e., \( \mathbb{E}(e_{i,p} | Treated Deal_i) = 0 \forall i,p \)), the parallel trend assumption is satisfied by the experiment design.

Assumption 2. DiD assumption: \( \mathbb{E}(e_{i,p} | Treated Period_p \times Treated Deal_i) = 0 \forall i,p \).

In our experiment, the treatment, i.e., the shocks in the percentage claim information, is not very likely to create a cannibalization effect and impact purchasing behavior for the control deals. This is because Amazon offers a wide product variety and the types of products sold around the same time are quite different. This concern is even less severe given that we exclude the “multiple-option” deals, the variants of which have similar characteristics.

Columns II and IV estimate the treatment effect using the difference-in-difference specification in Equation (2) relative to the pre-50-minute time period and the post-50-minutes time period, respectively. After removing the potential time heterogeneity, our DiD estimates remain significant, which suggests that a spike in past sales causally increases future sales. This provides empirical evidence for the existence of consumer learning.

Recall that we created an exogenous increment of 16.48 percent in the inventory claim bar. The result of the difference-in-difference specification in Columns II and IV indicates that such an increment translates into an increase of 3.42 percent cart add-ins in an hour (0.057 percent units per minute \( \times \) 60 minutes). In other words, a 10% increase in the inventory claim bar leads to a 2.08 percent increase in cart add-ins. This supports Hypothesis 1 that customers react to and learn from the inventory information, and the impact is significant and sizable. As a robustness test, we re-run our results using different time windows, i.e., 5 minutes, 10 minutes, and 20 minutes before and after the experiment. The treatment effect is also robust to these time-window specifications.

In Section 7, we compare this estimate with the estimates obtained from the panel data analysis and examine whether estimates based on these two approaches are consistent in magnitude.

6.3. Robustness of Experiment Results

A potential concern of the above study is the timing of the field experiment, which was conducted in the afternoon (2 p.m. to 4 p.m. EST) in September 2016. Morning buyers might behave differently than the afternoon buyers. Are the results robust across different time windows? Another potential concern is whether Amazon responds to our treatment, including ranking, pricing, and inventory
Table 4  Second Round Field Experiment Analysis

<table>
<thead>
<tr>
<th>Specification</th>
<th>Pre-50-min Comparison</th>
<th>Post-50-min Comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>I. Treated</td>
<td>II. DiD</td>
</tr>
<tr>
<td>Treated Period</td>
<td>0.093***</td>
<td>0.013</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Treated Deal</td>
<td>0.007</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Treated Period × Treated Deal</td>
<td>0.083***</td>
<td>0.097***</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.024)</td>
</tr>
<tr>
<td>Time Controls</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>406</td>
<td>1,152</td>
</tr>
</tbody>
</table>

Note: Columns I - IV are similar to those in Table 3. Time controls include the day of the week and hour of the day. All standard errors are robust and clustered at the deal level. Significance at *p < 0.1; **p < 0.05; ***p < 0.01.

strategies, which might confound the estimation. For example, Amazon may rank deals on the lightning deal page based on their past sales. Whereas treated deals may be bumped up in ranking due to the treatment, untreated deals are not, thereby leading us to confound learning with more attention drawn by ranking. Observing “sales spikes” introduced by our treatment, the seller might also adjust the inventory level and price of the complement or substitute products. In this case, a treated item might receive higher sales because the treatment convinces the seller to allocate more resources to these “popular” treated items. We need to rule out these potential confounding factors and assess the robustness of our results.

To circumvent these problems, we conduct another set of field experiments across two weeks in April 2017. We expand the time window of the experiment to cover both morning (10 a.m. to 12 p.m. EST) and afternoon (1 p.m. to 5 p.m. EST). This experiment includes 576 lightning deals, 203 of which are in the treatment group. We created an exogenous average increment of 11.84 percent in the inventory claim bar. Table 4 demonstrates the estimation results following Equations (1) and (2). Columns II and IV present the DiD estimation for the pre-treatment and post-treatment comparison respectively. We find that the treatment has a significant and positive effect on cart add-ins. The estimated effects are consistent with results in Table 3.

In addition, we record the positions of the treated deals (i.e., their rankings and pages) across four time points: 10 minutes before the start of the experiment, 20 minutes and 40 minutes after the start of the experiment, and 10 minutes after we cease adding the treatment. Because Amazon might vary its recommendations across different IPs, we use four IPs addresses to query the ranking information covering eastern, southern, midwestern and western states in the U.S. For each deal, we compute its average ranking across four IP addresses at each time point. We observe that even though a product’s ranking changes over time, (1) the variations are small, as most products are within the same page across those four time points (i.e., each page displays 32 products and most of them stay on the same page during the experiment), and (2) the rankings of the treated deals
before the start of the experiment are not statistically significantly different from those in the other three time points (i.e., the t-test shows that the p-values between the rankings 10 minutes before the start of the experiment and those of 20 minutes, 40 minutes, and 70 minutes after the experiment starts are 0.4041, 0.5899, and 0.2837). Therefore, the variations in assortment are orthogonal to our treatment. This provides strong evidence that our findings are not driven by Amazon’s ranking algorithm.

In the experiment, we also take snapshots of the recommended and top-selling products from the same sellers of the treated products across the four time points. Figure 6 displays an example of the pages we keep track of. A change in the allocated inventory level will cause a sudden drop in the claim information and alter the minimum increment. We find that during our experiments, the price and the total inventory level of the treated and control items, as well as the ranking and price of related products in the recommendation panel do not change, which shows our results are not artifacts of sellers’ strategic reactions.

In summary, we conducted a second set of experiments in a different time window on different products with a potentially different customer population. Despite these differences, the estimates are highly consistent. We also collected a number of products’ dynamic characteristics which confirm that both Amazon and third-party sellers do not systematically respond to our treatments.

7. **Panel Data Analysis**

In this section, we exploit the panel structure of the data to estimate the learning momentum and moderating effect during the purchase of flash-sale products.

7.1. **Fixed-Effect Specification**

In our collected data set, the inventory information for each deal varies dynamically over time, but the product characteristics are time invariant, which provides us with a panel structure of the data. The panel structure allows us to exploit the fixed-effect specification.

We denote $t$ as the hour from the start of the deal, where $t = 1, ..., T$; $T$ is the duration of a deal. We use $C_{i,t}$ to denote the total percentage of inventory claimed for deal $i$ at the beginning of hour $t$, and we use $y_{i,t}$ to denote the total cart add-ins during hour $t$, i.e., potential sales. The total amount of inventory claimed reflects the previous customers’ collective opinions regarding the deal’s worthiness. The learning effect can be measured by the dependency of future sales on current inventory information, i.e., the coefficient of $C_{i,t}$ on $y_{i,t}$.

We first conduct a preliminary OLS analysis by looking at the correlation between future cart add-ins and current inventory information. The analysis tests whether $y_{i,t}$ is positively correlated with the inventory information $C_{i,t}$ after controlling for time-varying attributes $X_t$ and time-invariant attributes $Z_i$,

$$
y_{i,t} = \gamma C_{i,t} + \beta_1 X_t + \beta_2 Z_i + e_{i,t}.
$$

(3)
The time-varying attributes $X_t$ include the hour of the day and day of the week fixed effects. These attributes capture the possibility that sales tend to concentrate in certain hours of a day or on certain days of the week. Time-invariant deal attributes $Z_i$ include No. of Reviews, the number of reviews under a deal during the period when the deal is active; Review Rating, the average star rating of the reviews; Discount, the actual and listed promotional depth of the deal; Variety, a dummy variable equal to one if the product has multiple options, e.g., colors or sizes. The term $e_{i,t}$ is the error component. The coefficient of $C_{i,t}$ tests the correlation between $C_{i,t}$ and $y_{i,t}$.

The available data may not capture all the heterogeneity across the deals. For example, a deal with a detailed product description or professional-looking photos is likely to attract more customers, but our data does not include these variables. Statistically, there may be unobserved heterogeneity in the error term, i.e., $e_{i,t} = u_i + \epsilon_{i,t}$, where $\epsilon_{i,t}$ is orthogonal of all the independent variables and $u_i$ represents the unobserved deal attributes such as the inherent quality of the deal. Since $u_i$ is correlated with other deal-specific features, $C_{i,t}$ and $Z_i$, without controlling for $u_i$, the OLS regression in Equation (3) suffers from the omitted variable bias (Wooldridge 2010). Fortunately, the panel structure of the data allows us to use a fixed-effect specification to capture any time-invariant unobserved deal heterogeneity $u_i$,

$$y_{i,t} = \gamma_{i,t} + \beta_1 X_t + \beta_2 Z_i + u_i + \epsilon_{i,t}.$$  (4)

The key identification assumption for the fixed-effect model is that unobservable deal heterogeneity is time invariant, which we summarize below:

**Assumption 3.** Fixed-effect assumption: $E(\epsilon_{i,t} | C_{i,t}, u_i) = 0 \forall i, t.$

This is plausible in our research context because our study examines the learning effect on sales over the course of a four-to-six-hour deal. It is unlikely that the characteristics of the deal would change during the time period when the deal is active. Therefore, by controlling for the unobserved heterogeneity $u_i$, we identify consumer learning using within-deal variations in $C_{i,t}$, $y_{i,t}$ and $X_t$.

Moreover, consumers rely on observable deal characteristics to moderate their inferences from observing the inventory information. To explore the moderating effects, we examine the cross-sectional variations in the observable listing attributes, allowing us to distinguish the types of information the inventory availability primarily conveys. We augment equation (4) by including the interaction term between the cumulative inventory information and the observable deal characteristics, such as customer reviews and deal discount,

---

$^{21}$ We downloaded Amazon’s data every 30 seconds, which allows us to examine the variation of reviews over the four hours when the deal is active. We find that the review properties do not change much during the lightning deal period. Therefore, the number of reviews and product ratings are time-invariant variables.
\[ y_{i,t} = \gamma C_{i,t} + \beta_1 X_t + \beta_2 Z_i + \beta_3 C_{i,t} \times Z_i + u_i + \epsilon_{i,t}. \] (5)

The deal’s value, i.e., the discount level, impacts customer learning in two opposing ways. When a customer sees that a minimally discounted deal has a low inventory availability, she may think there must be something good about this deal that attracts other customers despite its small discount and make a more positive incremental quality inference about these minimally discounted deals from the inventory information. Therefore, the learning momentum can be accentuated by a low discount rate; i.e., the coefficient of \( C_{i,t} \times \text{Deal discount} \) should be negative. In contrast, the opposite relation would suggest the discount rate and information availability provide different information content since they complement each other to attract sales.

Product quality, i.e., customer reviews, may also drive learning in two opposing ways. When a customer sees that a low-rated deal has a low inventory availability, she will justify the herd with some other positive characteristics of the deal and make a more positive incremental quality inference about it. Therefore, the learning momentum can be enlarged by a low product rating; i.e., the coefficient of \( C_{i,t} \times \text{Review rating} \) should be negative. In contrast, the opposite sign would suggest product quality and information availability provide different information content.

### 7.2. Estimation Results

Table 5 provides the estimated coefficients. Column I displays the results for the OLS model in Equation (3). Column II displays the results for the fixed-effect model in Equation (4). Columns III and IV report the results for the interacted fixed-effect model in equation (5) with respect to customer reviews, deal discount rate, and the option variety. Note that the base effects of moderators are absorbed by the fixed effects for columns II, III, and IV.

The OLS estimator in column I suggests that the effect of inventory information \( (C_{i,t}) \) is positive and significant on sales in the next hour. However, the OLS estimates may suffer from the omitted variable bias and overestimate the learning effect. Below we report the estimates from the fixed-effect model.\(^{22}\)

#### 7.2.1. Consumer Learning.

Column II of Table 5 reports the coefficient of the past inventory information for the fixed-effect model with time controls. As expected, the OLS specification in column I overestimates the effect compared with the fixed-effect specification in column II. After controlling for deal-specific heterogeneity, \textit{Claim} has a significant and positive coefficient, which shows the existence of consumer learning—i.e., the availability information influences following customers’ choices, and a deal with higher past sales attracts more purchases in the future. More

\(^{22}\)In the Appendix, we demonstrate that our results are robust to linear specifications and multicollinearity issues.
Table 5 Fixed-effect Analysis

<table>
<thead>
<tr>
<th>Specification</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Claim</td>
<td>0.452***</td>
<td>0.299***</td>
<td>0.243***</td>
<td>0.215***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.023)</td>
<td>(0.045)</td>
<td>(0.044)</td>
</tr>
<tr>
<td>Claim × No. of Reviews</td>
<td>0.00001</td>
<td>0.00001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00002)</td>
<td>(0.00001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Claim × Review Rating</td>
<td>0.029***</td>
<td>0.032***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.008)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Claim × Variety</td>
<td>−0.114***</td>
<td>−0.111***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.013)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Claim × Actual Discount</td>
<td>−0.002***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0006)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Claim × List Discount</td>
<td>0.0003</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Time Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Deal Fixed Effects</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>123,115</td>
<td>123,115</td>
<td>123,115</td>
<td>123,115</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.369</td>
<td>0.590</td>
<td>0.592</td>
<td>0.592</td>
</tr>
</tbody>
</table>

Note: Standard errors are robust and clustered at the deal level with the hour of the deal controls. Column I reports the correlation results of the OLS regression in Equation (3); column II reports the results of the fixed-effect regression in Equation (4); column III reports the results of the fixed-effect model with actual deal discount and all other moderators; column IV reports the results of the fixed-effect model interacted with listed deal discount and all other moderators; importantly, the magnitude of the causal effect identified by the panel data analysis aligns with the magnitude identified by the randomized field experiment. The panel data analysis suggests that all else equal, a 10 percent increase in the cumulative percentage claimed leads to a 2.99 percent increase in potential sales in the next hour, which supports Hypothesis 1. Recall that the field experiments suggest a 2.08 percent increase in the next hour’s cart add-ins. These two estimates are highly consistent in both direction and magnitude, which helps establish internal validity for the fixed-effect approach by strengthening the causal argument and helps establish external validity for the field experiments by extrapolating our finding over a larger data set.

7.2.2. Moderating Effects. We find that consumer learning depends on the deal attributes, suggesting that consumers not only learn from other customers but also moderate their inferences using various observable deal characteristics that give rise to the herd.

We show that a higher actual discount rate mitigates the learning effect, i.e., the actual discount has a negative interaction with Claim. In other words, the same learning momentum signals a better promotion quality if the deal has a weaker promotional depth. This finding suggests that discount rate and percentage-claimed information convey similar information content, which supports Hypothesis 2.

Interestingly, the listed discount by deal sellers has no significant impact on learning, i.e., the interaction term of Claim × List discount in column IV is insignificant. Recall that the listed discount percentage is almost twice as much as the actual discount percentage. This finding provides
side evidence that customers are rational decision makers; they search for the actual regular price or the price offered by other sellers before making a purchase and they are knowledgeable enough to differentiate the actual discount rate from the listed discount rate.

We also show that a higher product rating amplifies the learning effect, i.e., the rating has a positive interaction with Claim. This suggests that customer ratings and the availability information signal different information content, which supports Hypothesis 3. In addition, the number of reviews has no significant effect on potential sales. This indicates that compared with the sentiment toward the products, the number of reviews does not significantly influence consumers’ choices.

Finally, the interaction term $\text{Claim} \times \text{Variety}$ is negative, which suggests that the signal strength of the availability information diminishes when customers choose from a larger number of options. Amazon’s lightning deal page displays the average inventory information across multiple options of deals. Customers have to click the “choose option” button and select the exact option they want. This costly action may dilute customer attention to the inventory information and thus weaken the signal’s strength.

**Remark.** Note that so far, we study the potential sales—i.e., cart add-ins—as the dependent variable. When a customer purchases a lightning deal item that she has added to her cart, the purchase is counted as an actual sale and the incremental claim percentage that corresponds to her purchase remains in the inventory status bar. If a customer chooses not to check out the product, the item will be dropped from her cart and this dropped item will not translate into an actual sale. Thus, there is a difference between cart add-ins and actual sales. To show the robustness of our finding in actual sales, we also construct an approximate measure of the hourly sales as the difference between the hour-end and hour-beginning percentage claims. Note that this measure is less accurate because it requires an implausible assumption that the exact same number of items is in the cart at the beginning and at the end of any time period that we study. Given that the average approximate sales is 2.4 units per hour, this measure becomes very sensitive to an imbalance between hour-beginning and hour-end in-cart units. Therefore, our main result does not include this measure. We repeat the fixed-effect analysis and the interacted fixed-effect analysis using this approximate measure, and we find that the signs of the parameters align with those for the cart add-ins. Nevertheless, if the conversion rate is constant across deals, our main finding with respect to the cart add-ins shows the ability of the inventory information to catch customers’ attention and translate more of these add-ins, these potential sales, into actual sales.

### 7.2.3. The Impact of Inventory Scarcity.

So far, we have identified customers’ response to inventory availability, which could be driven by the herding or the scarcity effect. We next provide evidence that supports scarcity. We re-run the fixed-effect model across subsets of the panel data
Table 6 Impact of Low Inventory Level

<table>
<thead>
<tr>
<th>Specification</th>
<th>I. All Data</th>
<th>II. ( \text{Claim} &lt; 85% )</th>
<th>III. ( \text{Claim} &lt; 70% )</th>
<th>IV. ( \text{Claim} &lt; 55% )</th>
<th>V. All Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Claim</td>
<td>0.243***</td>
<td>0.225***</td>
<td>0.172***</td>
<td>0.150***</td>
<td>0.102***</td>
</tr>
<tr>
<td>( \text{Claim}^2 )</td>
<td>(0.045)</td>
<td>(0.045)</td>
<td>(0.045)</td>
<td>(0.045)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>Time Control</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Deal Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>123,115</td>
<td>121,981</td>
<td>120,137</td>
<td>117,439</td>
<td>123,115</td>
</tr>
<tr>
<td>Adjusted ( R^2 )</td>
<td>0.590</td>
<td>0.584</td>
<td>0.561</td>
<td>0.517</td>
<td>0.597</td>
</tr>
</tbody>
</table>

Note: This table reports the estimated coefficient values of Equation (5) and standard errors clustered at the deal level with the time and deal characteristic controls over different levels of scarcity. The first four columns report the estimation based on subsets that include deals with the maximum percentage-claim smaller than 100%, 85%, 70% and 55%, respectively. The last column reports the estimation based on a subset that includes deals with the maximum percentage-claim larger than 55%. The errors are corrected for heteroskedasticity. Significance at *\( p < 0.1 \); **\( p < 0.05 \); ***\( p < 0.01 \).

with various levels of scarcity. We measure the level of scarcity of each deal by its final claim. When the final percentage of products claimed is small, there is plenty of leftover inventory during the selling period and thus customers do not face a high out-of-stock risk. In this case, the dominant driver in customer learning is herding. In contrast, when the final claimed percentage is large, customers might rush their purchasing decisions because they might be afraid of stockouts. The scarcity effect suggests that the speed of customer learning increases as the percentage claimed increases. We also include the second order of Claim (i.e., \( \text{Claim}^2 \)). If the scarcity effect exists, we would expect customers’ average response to inventory information increases with claim and thus, cart add-in would be a convex function of claim.

Table 6 presents the estimated results about the scarcity effect. Columns I to IV suggest a significantly increasing trend in the learning coefficient: the intensity of learning increases with the scarcity level. Column V suggests that Cart add-in is a convex function of Claim. This empirical evidence is consistent with the scarcity effect. For deals with low inventory, the learning momentum is intensified by the scarcity effect.

7.3. Robustness of Panel Data Analysis

The independent variables might be correlated. To test for multicollinearity, we follow Zhang and Liu (2012) and compute the variance inflation factors (VIFs) of all moderators (i.e., No. of reviews, product rating, variety, and discounts). All moderators’ VIFs are less than 3. In addition, we include the moderating variables one by one in the fixed-effect model to test whether the coefficients vary across specifications. Columns I through IV in Table 7 show that all the interaction terms retain sign, significance, and magnitude. These results demonstrate that multicollinearity does not bias our findings of learning and moderating effects.
### Table 7 Robustness of Panel Data Results

<table>
<thead>
<tr>
<th>Specification</th>
<th>I. FE Linear</th>
<th>II. FE Linear</th>
<th>III. FE Linear</th>
<th>IV. FE Linear</th>
<th>V. OLS</th>
<th>VI. FE Poisson</th>
</tr>
</thead>
<tbody>
<tr>
<td>Claim</td>
<td>0.296***</td>
<td>0.156***</td>
<td>0.220***</td>
<td>0.243***</td>
<td>0.688***</td>
<td>0.0087***</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.048)</td>
<td>(0.049)</td>
<td>(0.050)</td>
<td>(0.029)</td>
<td>(0.0003)</td>
</tr>
<tr>
<td>Claim × No. of Reviews</td>
<td>0.00002</td>
<td>0.00001</td>
<td>0.00001</td>
<td>0.00001</td>
<td>0.00001</td>
<td>0.00001</td>
</tr>
<tr>
<td></td>
<td>(0.00002)</td>
<td>(0.00002)</td>
<td>(0.00002)</td>
<td>(0.00001)</td>
<td>(0.00001)</td>
<td>(0.00001)</td>
</tr>
<tr>
<td>Claim × Review Rating</td>
<td>0.032***</td>
<td>0.032***</td>
<td>0.029***</td>
<td>0.004</td>
<td>0.0014***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.005)</td>
<td>(0.0004)</td>
<td></td>
</tr>
<tr>
<td>Claim × Variety</td>
<td>-0.111***</td>
<td>-0.114***</td>
<td>-0.027***</td>
<td>-0.0042***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.015)</td>
<td>(0.010)</td>
<td>(0.0006)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Claim × Actual Discount</td>
<td>-0.002**</td>
<td>-0.001**</td>
<td>-0.0001***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.0005)</td>
<td>(0.00003)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Deal Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>123,115</td>
<td>123,115</td>
<td>123,115</td>
<td>123,115</td>
<td>123,115</td>
<td>123,115</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.590</td>
<td>0.590</td>
<td>0.592</td>
<td>0.592</td>
<td>0.375</td>
<td></td>
</tr>
</tbody>
</table>

Note: Columns I - IV report the estimated coefficient values of Equations (5) with different moderators added one-by-one. Column V reports Equations (1) with all moderators. Column VI reports the results for a Fixed Effect Poisson model with all moderators. All standard errors are robust and clustered at the deal level. Significance at *p<0.1; **p<0.05; ***p<0.01.

There might also be multicolinearity between moderators and deal-level fixed effects. Column V of Table 7 presents the interactions estimated by an OLS model, which are qualitatively the same as those in column IV.²³ Moreover, the adjusted R-square of the OLS model is significantly lower than that of the fixed-effect model, which suggests that fixed effects explain a significant amount of heterogeneity among deals and are important to control for. These suggest the findings of learning and moderating effects do not seem to be biased by multicolinearity between deal-level fixed effects and moderators.

Another technical concern with our linear fixed-effect model specification is that the dependent variable can only be integers. To address this issue and demonstrate that our models are robust to the specification, we estimate a fixed-effects Poisson model in column VI of Table 7 (Wooldridge 2010). The Poisson model allows the outcome variable, i.e., card add-ins, to follow a Poisson distribution. Compared with column IV, all variables remain the same sign. This result confirms that our results are not driven by the linear specification.

### 8. Conclusions

The extant literature in operations management has studied how customers’ strategic reactions to inventory information may impact firms’ inventory management, assortment, sourcing, and information-sharing decisions. Our paper provides empirical evidence that confirms the necessity ²³ The significance of Review Rating drops when we do not include fixed effects. This suggests that deal fixed effects might be correlated with deals’ review ratings.
to explore the strategic relations between customers and inventory information. In particular, our results show that consumers strategically learn from inventory information. Because inventory information reflects the collective peer purchasing decisions, subsequent consumers can update their own beliefs about the deal value from such information.

Identifying the learning effect has been recognized as a difficult task due to endogeneity concerns. To tackle this challenging problem, we design and run several randomized field experiments on Amazon by generating exogenous shocks to inventory information, which establishes the internal validity of our findings. We also employ a fixed-effect model analysis on our rich observational data to establish the external validity of our findings. We then explore how moderating factors influence consumer learning. We not only show that consumers learn from the inventory information, but also identify what types of information inventory availability conveys to consumers. In particular, our results show that inventory availability information primarily signals a deal’s value rather than the product’s quality. Moreover, our empirical results are consistent with the scarcity effect as the learning momentum amplifies when availability decreases.

Decreasing inventory availability not only favorably signals deal quality but also may create a stockout pressure among customers. While we demonstrate that both herding and scarcity mechanisms are likely to exist by focusing on projects at different stages, our experiments cannot perfectly disentangle them. Future research should explore the conditions under which the scarcity effect begins to influence consumers and try to estimate herding and scarcity effects separately. In our research context, the retailer reveals inventory availability by showing percentage left in real time. Future research should also explore whether the format of inventory information, e.g., absolute leftover units or percentage, may affect how much and how customers learn from it.

Our results shed light on practical implications. First, we point out that real-time inventory information could serve as an effective lever to signal popularity and attract future customers. Second, we offer retailers several angles to think about how to disclose inventory information. Our findings indicate that consumers moderate their reliance on inventory information based on other observable product characteristics. In particular, we find that consumers learn more from inventory information—i.e., such information is able to drive more sales—for deals without good observable characteristics, such as a deep discount. We recommend retailers evaluate the usefulness of inventory information and the necessity to disclose it for their own products. In addition, the initial allocated inventory level determines the percentage increment per click, i.e., how fast “past sales” grow. A low inventory allocation could trigger more learning but limit total sales, while ample inventory might discourage learning. We point out that the total inventory level could be another strategic lever for retailers to optimize profits.
In an era when the advances in information technology have allowed companies to share their information at a much lower cost, it is important to understand how information impacts consumer behavior and reshapes demand so that it aligns profitably with supply. Information has been used as an important operations lever by companies to balance supply and demand. Prior research has shown that this goal can be achieved, for example, by disclosing obscure pricing or inventory information to customers (Fay and Xie 2008, Jerath et al. 2010), by sharing committed product availability to customers (Su and Zhang 2009), or by enhancing trust in the shared information (Özer et al. 2011, 2016). Our paper demonstrates that disclosing firms’ inventory availability information can also lead to customer learning and cause an acceleration in sales, and we hope that exploring such a relationship may spark future empirical research in the interaction between strategic customer learning and operations decisions.

Further, we are the first to collect data from a new and rich source: the Amazon lightning deal platform, which allows us to study consumer behavior in retail operations. We also make a methodological contribution to the literature by introducing an innovative approach to run field experiments on Amazon’s flash-sale platform. By showcasing this data source and the experimentation technique, we hope that our paper serves as a steppingstone for future research to explore new issues in consumer purchasing behavior.

References


Li, Xitong, Lynn Wu. 2014. Herding and social media word-of-mouth: Evidence from groupon. *Available at SSRN 2264411*.


Appendices

Supplementary Tables and Graphs

Figure 2  How Amazon Presents Lightning Deals on Amazon’s Webpage
Figure 3  An Example of Percentage Claim Information over Time

<table>
<thead>
<tr>
<th>Period 1:</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Claim at the beginning of the period: 24%</td>
<td></td>
</tr>
<tr>
<td>Claim at the end of the period: 34%</td>
<td></td>
</tr>
<tr>
<td>Total number of cart add-ins: 16%</td>
<td></td>
</tr>
</tbody>
</table>

Figure 4  Field Experiment Design Illustration

Note: This figure is an illustration of the field experiment design and does not present the actual data.
Figure 5  Field Experiment Mechanism Illustration

Click the “Add to Cart” button one time from one account; claim increases by 1%

The deal is added to the cart and can be found in the Shopping Cart

Click the “Add to Cart” button from 10 accounts within 2 minutes

Shopping Cart

$15.99
Price: $159.99 (90% off)
53% Claimed	Ends in 2:21:00
Voeons Women's Watches Japan Quartz Movement Analog Lady Fashion Luxury Bracelet Watch KW6036S Gold Blue by VOEONS
In Stock
Eligible for FREE Shipping & FREE Returns
☐ This is a gift Learn more
Delete | Save for later

$15.99
Price: $159.99 (90% off)
54% Claimed	Ends in 2:19:49
Voeons Women's Watches Japan Quartz Movement Analog Lady Fashion Luxury Bracelet Watch KW6036S Gold Blue by VOEONS
In Stock
Eligible for FREE Shipping & FREE Returns
☐ This deal is in your Cart. You have 14:08 left to check out

$15.99
Price: $159.99 (90% off)
63% Claimed	Ends in 2:21:00
Voeons Women's Watches Japan Quartz Movement Analog Lady Fashion Luxury Bracelet Watch KW6036S Gold Blue by VOEONS
In Stock
Eligible for FREE Shipping & FREE Returns
☐ This deal is in your Cart. You have 14:08 left to check out

$15.99
Price: $159.99 (90% off)
54% Claimed	Ends in 2:19:49
Voeons Women's Watches Japan Quartz Movement Analog Lady Fashion Luxury Bracelet Watch KW6036S Gold Blue by VOEONS
In Stock
Eligible for FREE Shipping & FREE Returns
☐ This deal is in your Cart. You have 14:08 left to check out

$15.99
Price: $159.99 (90% off)
53% Claimed	Ends in 2:21:00
Voeons Women's Watches Japan Quartz Movement Analog Lady Fashion Luxury Bracelet Watch KW6036S Gold Blue by VOEONS
In Stock
Eligible for FREE Shipping & FREE Returns
☐ This deal is in your Cart. You have 14:08 left to check out
### Table 8: Robustness of Field Experiment Results

<table>
<thead>
<tr>
<th>Specification</th>
<th>Dependent variable: Cart add-ins per minute</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pre-50-min Comparison</td>
</tr>
<tr>
<td></td>
<td>I. Treated (0.017)</td>
</tr>
<tr>
<td></td>
<td>II. DiD (0.018)</td>
</tr>
<tr>
<td></td>
<td>III. Treated (0.026)</td>
</tr>
<tr>
<td></td>
<td>IV. DiD (0.033)</td>
</tr>
<tr>
<td>Treated Period</td>
<td>0.045***</td>
</tr>
<tr>
<td>Treated Deal</td>
<td>−0.017</td>
</tr>
<tr>
<td>Treated Period × Treated Deal</td>
<td>0.057**</td>
</tr>
<tr>
<td>Saturday</td>
<td>0.004</td>
</tr>
<tr>
<td>Tuesday</td>
<td>0.040</td>
</tr>
<tr>
<td>Hour</td>
<td>−0.019**</td>
</tr>
<tr>
<td>No. of Reviews</td>
<td>0.00003</td>
</tr>
<tr>
<td>Review Rating</td>
<td>0.018**</td>
</tr>
<tr>
<td>List discount</td>
<td>−0.002</td>
</tr>
<tr>
<td>Constant</td>
<td>0.379***</td>
</tr>
</tbody>
</table>

Note: This table reports the estimated coefficient values of equations (1) and (2) with the time controls and deal characteristic controls. Standard errors are robust and clustered at the deal level. Significance at "p<0.1; ""p<0.05; """"p<0.01."