Information Sharing Effects of High Stock Delivery Windows on Online Platforms

In this paper, we analyze a novel information-sharing policy that can be used to reduce the number of stockouts on online grocery retail platforms and thereby improve platform performance. This policy involves leveraging the digital interface of the online platform to disseminate information about delivery windows when retailer stock levels are at their peak. Notably, it is not clear ex-ante if such a policy would actually positively influence customers’ purchasing patterns, particularly in terms of its impact on platforms’ fundamentals. We conducted a large-scale field experiment on over 1M users on the Instacart platform. In this experiment, customers in the treatment group were prompted “Higher stock at this time” under delivery windows corresponding to peak supermarket stock levels. Interestingly, we found that this completely cost-free information-sharing policy significantly increased the propensity of customers to pick high-stock delivery windows as well as increase the conversion rate. We also observe that this policy reduces the refund and replacement rates by 2.2% and 2.7%, respectively, as well as increases the platform’s revenue by 6% and the number of orders placed by 3%. Finally, treated users are more likely to explore different stores and order novel items. Our findings suggest simple information sharing policies can increase customer orders, enhance their willingness to explore new products and retail partners, and potentially lead to a more significant positive long-term impact on platform fundamentals.

Key words: delivery window information sharing; high stock information disclosure; food delivery; stockouts; large-scale field experiment; online platforms

1. Introduction

Online platforms and brick-and-mortar stores engage in a competitive landscape that has evolved significantly in recent years. Rapid digital transformation has given online platforms a scale advantage, allow them to offer a long tail of goods while simultaneously collecting data on millions of customers’ purchasing behavior. Better targeting has increased user satisfaction as well as advertisement revenue, leading to elevated customer expectations. Such advantages seem difficult for any single offline retailer to match. On the other hand, brick-and-mortar stores offer customers immediate gratification through in-store shopping, as well as examine products prior to making the purchase decision. Indeed, despite the convenience of online shopping, the majority of customers still favor the overall in-store shopping experience (see Figure 1).

In particular, food and grocery delivery platforms, the focus of this paper, face added challenges vis-a-vis brick-and-mortar stores because of stockouts: online platforms generally lack control over retailers’ inventory management and when/whether items are in stock. As per a recent survey
conducted in 2022 by Locidworks\(^1\), 58% of customers often encounter instances where their preferred grocery item is out of stock during their visits. This situation is exacerbated by the fact that nearly half of the participants (i.e., 47%) indicated that they would switch to a different grocery retailer if they could not find their desired products on their preferred app or website. Moreover, nearly 90% of shoppers mention that they would not consider a substitute for at least one product, considering factors like ingredients, preparation, and brand. All of this suggests that grocery delivery platforms face more than just the risk of losing a single sale when the right item is not available at the moment a customer desires it. In the present omnichannel grocery environment, customers are swift to discover alternative products or explore new grocery providers if their initial selection is unavailable. This not only translates to lost sales but also results in frustrated and lost customers, and perhaps most critically, a compromised brand reputation. Although the survey reveals a similar prevalence of stockout issues in both the online and in-store channels, it is crucial to recognize that brick-and-mortar stores and online platforms significantly differ in their abilities to tackle stockout events.

Online grocery platforms have adopted information sharing policies in which they share inventory information with customers, but the competitive nature of such policies is not well understood. A large literature in operations management has shown that sharing information about inventories can increase demand via reductions in uncertainty and more flexible options for substitutes (e.g., Cui, Zhang, and Bassamboo, 2019; Peinkofer et al., 2016; Gallino and Moreno, 2014; Boada-Collado and Martínez-de Albeniz, 2010). Such increases in demand and customer loyalty would be beneficial for the delivery platform. However, information sharing can also intensify competition in the presence of multihoming (e.g., Li and Zhu, 2021) or price competition (e.g., Hagiu and Halaburda, 2014; Choe, Cong and Wang, 2023), potentially hurting the platform’s performance. The existing literature has been largely theoretical, and no empirical studies to our knowledge have looked at inventory information as a key determinant of platform performance.

\(^1\) Source:[https://www.supermarketnews.com/online-retail/online-consumers-want-assistance-grocery-out-stocks]
In this paper, we study how sharing information about inventory affects customer behaviors as well as platform performance. We collaborate with a large online grocery delivery platform to run a randomized control trial on 1+ million users. In this experiment, treated users are given information about delivery windows in which their items are more likely to be in stock, while control users’ experiences do not change. Importantly, in addition to documenting the changes in users’ behavior, we observe the information sharing policy’s effect on the 70+ thousand retailers’ online sales, as well as the platform’s performance. Our paper provides a unique opportunity to bridge the operations management and information systems literature to provide a comprehensive analysis of inventory sharing policies and platform performance.

1.1. Summary of Results

The results of our study can be outlined as follows.

- Consumers strategically adjust their decisions for delivery time slots on the platform when presented with information regarding high stock delivery windows. We observe that the disclosure of high-stock delivery windows results in a 4.4% percentage point increase in customers’ propensity to opt for these high-stock windows (a 9% increase from baseline). The magnitude of the effect is stronger for larger orders and for previously ordered items.

- Consumers visit the checkout screen more often and place more orders. We observe a 4.9% increase in daily checkout visits and a 2.9% increase in daily orders placed.

- This information-sharing policy can significantly boost the platform’s revenue. Our analyses suggest that this high stock information sharing policy results in a 6% revenue boost by both making customers place more orders as well as increasing customer spending per order.

- Disclosure of high-stock delivery windows leads to a higher found rate on the platform. We observe that the treatment leads to a 2.7% decrease in the proportion of items replaced and a 2.2% decrease in the proportion of items refunded which positively affects the customers’ found rate.

- The information sharing policy also leads to a more exploratory behavior of customers. Our results show that orders from users who received treatment are approximately 0.7% more likely to include new items, and the likelihood of placing orders from new stores rises by 1.6%. Treated users tend to switch their orders to retailers with fewer physical stores, those that are more popular, and those that offer lower prices.

- Disclosing information regarding high stock delivery slots can lead to a significant positive effect on the retail partners’ revenue. Our findings reveal that each order placed with a high stock message leads to a 1% increase in the daily revenue of the platform’s retail partners over one month following the launch of the experiment. Additionally, while all stores on the platform experienced benefits, it is the smaller stores, high-priced stores, and stores with significant fluctuations in stock availability that benefited the most.
1.2. Structure of the Paper
In Section 2, we discuss the relevant literature. In Section 3, we describe the underlying field experiment and provide an overview of the underlying data. Section 4 presents our main results from running the field experiment, including quantifying the impact of revealing high stock delivery windows on customer delivery window preferences, conversion rates, order outcomes, and platform revenue. In Section 5, we estimate the effect of this information disclosure policy on the retailers. Finally, we conclude in Section 6 by summarizing our findings and exploring future research directions.

2. Related Literature
First, our study is related to the numerous literature in operations management that studies the effect of inventory information sharing in the context of online retail. The study by Peinkofer et al. (2016) provides a detailed analysis of how sharing information about inventory availability impacts consumer behavior in retail. It highlights that consumer competition is not merely a response to inventory levels, but also a key factor affecting how inventory availability relates to consumer satisfaction. This indicates that consumers view purchasing not just as a simple transaction, but as a competitive act. In situations where inventory is low or unavailable, not being able to obtain a product is perceived as a competitive loss, intensifying dissatisfaction more than the mere inconvenience of a stockout. Relatedly, Gallino and Moreno (2014) highlight the profound influence of accurate inventory availability information on consumer behavior, especially within the buy online and pick-up in store (BOPS) framework. Reliable inventory data encourages research online and purchase offline behavior, where customers verify product availability online but choose to buy in a physical store. Implementing BOPS positively impacts the perceived accuracy of online inventory, boosting customers’ trust in the alignment of online data with in-store availability. This trust translates into a channel-shift effect, where, despite online sales remaining constant, there is a noticeable increase in in-store sales and foot traffic as customers visit to collect their items, often leading to additional in-store purchases.

Therefore, the strategic disclosure of inventory information can significantly influence consumer behavior. For example, disclosing that an item has a limited availability can generate a sense of urgency and increase sales, yet it might also result in dissatisfaction among consumers who find themselves unable to buy the product. The study by Calvo et al. (2023) suggests that in the online retail sector, especially during flash sales, disclosing limited product availability proves to be a successful tactic for boosting sales and profits. The impact of signaling scarcity increases with frequent announcements, substantial discounts, a wide range of products, and as the sales campaigns approach their conclusion. On the other hand, the effectiveness of these signals wanes when they
are made infrequently, linked to modest discounts, available in a narrow product selection, and when there is still a considerable duration left in the campaign. In a similar spirit, Park et al. (2020) examines the effect of displaying scarcity messages on the daily sales of durable goods by an online retailer. The research reveals that showing messages about limited stock results in an average decline of 17.60% in daily sales volumes. This adverse outcome is more significant for products with higher daily sales. Nonetheless, the study also discovers that offering price discounts can mitigate this detrimental effect. Contrary to earlier research which presumes precise inventory data, the study by Knight and Mitrofanov (2022) explores a situation where inventory information is probabilistic and imprecise, indicating a potential for stockouts even when an item appears available on the platform. This uncertainty regarding stock availability could result in unique consumer behaviors due to their dislike of stockouts. The findings suggest that sharing inventory information under these conditions could notably enhance the platform’s revenue, substantially decrease the number of stockouts, and make customers place more orders on the platform in the long run. Our study aligns closely with this line of research, with the primary distinction being that, rather than focusing on the sharing of product availability information, we examine the effectiveness of sharing high-stock delivery window information for online platforms.

Our research, focusing on disclosing inventory-related information about delivery windows, intersects with studies on service systems that highlight the strategic importance of sharing delay information for enhancing customer satisfaction and operational efficiency (Whitt, 1999; Singh et al., 2023). Ibrahim (2018) investigates how customers respond to wait times in service settings, noting that uncertainty around waiting can negatively affect customer satisfaction. Providing information about delays can offer psychological relief by giving customers a feeling of control, potentially making the waiting period seem shorter and more acceptable, and providing a sense of progress. Expanding on this concept, Yu et al. (2022) examines the impact of wait time information on customer decisions in the context of ride-sharing services. This study provides empirical evidence that an initial longer wait time estimate, followed by regular, minor reductions, can enhance the customer experience by minimizing unnecessary wait times without increasing service abandonment rates. In our research, rather than offering delay information for various delivery windows, we share details on product availability across different delivery windows. This approach can influence customer decisions by decreasing their uncertainty regarding stockout rates.

Our research is also connected to the existing literature on information sharing in supply chains (Cachon and Fisher, 2000; Swaminathan and Tayur, 2003; Chen, 2003; Li and Zhang, 2008). Li (2002) discusses that information sharing not only affects interactions between directly involved firms but also impacts competitors’ strategies. The essential takeaway is that the influence of information sharing extends beyond immediate participants in a supply chain. Then, the research by
Buell et al. (2017) demonstrates that introducing transparency into service processes can substantially enhance both service quality and efficiency. This is supported by a field experiment that records a 22.2% increase in quality as perceived by customers and a 19.2% decrease in throughput times. The authors determine that voluntary self-disclosure fosters increased trust and brand appeal. Similarly, Mohan et al. (2020) find that revealing the costs involved in producing goods and services enhances trust and results in better consumer engagement and higher sales. In addition, Zhou and Zhu (2010) finds that transparency about a competitor’s costs can be advantageous in competitive online environments. Our study is related to this stream of work, as it involves sharing information about high-stock delivery windows, embodying the concept of platform transparency regarding the risk of stockouts for specific delivery windows.

Given, that one of the main goals of our field experiment is to reduce the stockout rate on the platform, our paper is also related to the stream of work studying the impact of stockouts on the customers and platforms’ operations (Li et al., 2023). The study by Anderson et al. (2006) reveals that stockouts not only significantly reduce the revenue associated with an order due to likely cancellations, but also increase the chance of customers abandoning other items in their order, contributing to considerable opportunity costs. Additionally, the authors highlight that customers facing stockouts tend to reduce future orders and spending. Craig et al. (2016) carry out an empirical analysis and discover that a rise in the historical fill rate correlates with a notable increase in demand. Similarly, Heim and Sinha (2001) demonstrate that stockouts can adversely affect customer loyalty.

A large literature in information systems considers the effect of information sharing on platform performance. In particular, Hagiu and Halaburda (2014) study how sharing information about prices can affect platform profits. They model a two-sided platform that links developers and users (e.g., app stores) and whether the platform owner should share pricing information with the users. They find that monopolist platform owners prefer sharing information because users become more responsive to price cuts and the platform owner is able to fully capture those changes in demand. In contrast, platform owners with less market power prefer not to share information. Recent work also considers which parties platforms should share information with (Zha, Li, Huang, and Yu, 2023), and suggests platforms may even share information with competitors to allow for price discrimination (Choe, Cong, and Wang, 2023).

Fewer studies empirically analyze the relationship between information sharing and platform performance. Closest to our work is Li and Zhu (2021) who study the impact of information transparency on platform competition. Specifically, the authors study how Groupon’s reduction of information transparency impacted LivingSocial, a close competitor. They find that reduced information transparency led LivingSocial to increase efforts to attract merchants, resulting in more diverse deals, but potentially diminishing the long-term profitability.
3. Randomized Field Experiment Description and Data

In this section, we describe our field experiment and give background information about our industry partner, Instacart. Following this, we present evidence to verify that customers allocated to both the treatment and control groups are similar in key characteristics. The major goal of this experiment is to examine the effects of disclosing high-stock delivery window information on both customers and the platform. Note that this experiment provides a unique opportunity to study customer behavior and platform efficiency in the context of sharing item inventory information, specifically by disclosing information about delivery windows with high stock availability. Using rich data on user behavior and order outcomes, we assess the effects of disclosing inventory information on order dynamics, highlighting the heterogeneity among different groups of users, stores, and products. Furthermore, the comprehensive nature of our field experiment data enables us not only allows us to determine the causal impact of this information-sharing policy but also to document interesting patterns in the purchasing behavior of customers.

3.1. Field Setting Description

In April of 2022, we conducted a one-month-long randomized control trial in collaboration with Maplebear Inc., owner and operator of Instacart. Instacart is a large food logistics and technology firm operating across the United States and Canada. Instacart mainly acts as an online grocery delivery platform, serving as an intermediary between online grocery shoppers and offline retailers. Once customers place grocery orders through Instacart, personal shoppers purchase the ordered items, then delivers the goods to the customer’s home. When placing orders, customers can specify “delivery windows” in which their items arrive. If some items in an order are not found, customers have the option to specify replacements, or communicate with their personal shopper to discuss options.

Instacart is an ideal setting to study the competitive interaction between online and offline retailers for two reasons. First, it is economically important as one of the largest online grocery delivery platforms in the U.S., with 7.7 million monthly active users and over 900 million orders since 2011. Instacart accounts for up to 32.1% of the e-Commerce market share, and is projected to reach $40.54 billion in revenue in 2024. Second, the Instacart platform provides access to a diverse set of retailers and is appropriate to study how information policies shape the competitive dynamics between online and offline retailers.

Our experiment exposes users to information about retailers’ inventory levels via the checkout screen. Specifically, when placing orders on the web or mobile web version of the platform, some

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Figure 2  High stock delivery window prompts. Sample checkout screen for users. Eligible checkout visits by treatment group users will display “High stock” messages in the default checkout screen (panel a) or in the extended checkout screen (panels b and c).

customers are shown messages displaying “Higher stock in stores at this time” for delivery windows that fall between 10am and 3pm (see Figure 2). If the default delivery window falls between 10am and 3pm, this message is shown on the checkout screen (Panel a). Alternatively, if the default window falls outside this range, the user may select “See more delivery options” to see which windows have “Higher stock in store at this time.” The 10am to 3pm window was chosen because Instacart experiences its highest fulfillment success rate for orders delivered within this time frame. Figure 3 displays the average found rate of the fulfilled orders associated with delivery windows beginning at specific hourly intervals. The found rate peaks in the interval of time from 11 am to noon and declines afterward, suggesting the 10am to 3pm window is an appropriate information treatment.

Treatment was randomized at the user-date level. Each day, half of the visitors were assigned to the “Treatment” group (N = 509,363) while the other half were assigned to the “Control” group (N = 509,703). Importantly, once a customer is allocated to either the treatment or control group, their assignment remains unchanged for future orders, throughout the experiment. This consistency
is maintained by the platform’s policy requiring users to log in before adding items in their cart and finalizing their purchases. Finally, it is important to emphasize that the delivery window options for both treatment and control groups are identical, with the sole distinction being that customers in the treatment group received “High Stock” prompts as stated above. The criteria for which delivery windows was not changed. Thus, we attribute the difference in experiences between treatment and control customers on the Instacart website solely to the policy of sharing information about high stock delivery windows.

To check randomization, we collect data on users’ characteristics pre-experiment based on their activities and orders from March 1, 2022, to March 31, 2022. Table 1 confirm that the assignment is random over several key user attributes: (1) the proportion of ordered items that were replaced or refunded; (2) the average item’s quantity and price; (3) number of monthly orders; and (4) customers experience measured by the total number of orders placed on the platform. The actual numbers are unreported to protect confidentiality.

Additionally, we display the distributions of key outcome variables for both control and treatment customers during the pretreatment period. Figure 4 specifically focuses on the order frequency, customer spending per order, and item counts per order. The plots in Figure 4 are designed to showcase how these variables are distributed among customers and also validate the randomization of the treatment and control groups visually. We see that the distribution of our key variables for the treatment and control groups are virtually identical, confirming our balance table results.
Table 1  Pre-period covariate balance for treatment and control

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Diff</th>
<th>se</th>
</tr>
</thead>
<tbody>
<tr>
<td>Replaced (fraction)</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Replaced (count)</td>
<td>-0.001</td>
<td>0.007</td>
</tr>
<tr>
<td>Refunded (fraction)</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Refunded (count)</td>
<td>-0.004</td>
<td>0.006</td>
</tr>
<tr>
<td>Item quantity</td>
<td>-0.001</td>
<td>0.003</td>
</tr>
<tr>
<td>Item price</td>
<td>-0.021</td>
<td>0.016</td>
</tr>
<tr>
<td>Orders in pre-period</td>
<td>-0.004</td>
<td>0.005</td>
</tr>
<tr>
<td>Orders placed to date</td>
<td>-0.096</td>
<td>0.176</td>
</tr>
</tbody>
</table>

The Diff column is the coefficient of a simple regression of treatment status on the variable, with cluster robust standard errors, clustered at the user ID level. Stars indicate whether this difference is significant.

*  p < 0.05, **  p < 0.01, ***  p < 0.001.

4. Main Results
4.1. Model free evidence

First, we evaluate if there is a shift in users’ propensity to select a delivery window between 10 am to 3 pm. The left plot in Figure 5 illustrates the difference between treatment and control groups in the likelihood of selecting a delivery window in that time interval. Therein, the y-axis represents the difference in the probabilities of choosing the 10-3 delivery window between the treated and control groups, while the x-axis indicates the days elapsed since the treatment began. Consequently, the chart shows how the treatment influences the choice of a 10-3 delivery window over time. The impact of the “high stock delivery window” prompt is both positive and lasting. From the treatment day onwards, the treated group shows a higher propensity towards selecting the 10-3 window. This effect begins to diminish towards the end of the experiment, which could be attributed to the boundary effect given that customers tend to place orders in advance and thus might not be exposed to the same number of prompts on the last days of the experiment.

In the right panel in Figure 5, we depict the distribution of orders placed during the post-period across different delivery windows, with each point representing the percentage of orders with a specific start time of a delivery window. It follows from this panel that the treated group exhibits a higher likelihood of selecting delivery windows having the start time in the interval from 10 am
to 2 pm. The treatment effect makes the distribution of delivery window choices more “pointy” and concentrated.

![Figure 5](image.png)  
**Figure 5** The impact of the treatment on delivery window selection.

We also present some model-free evidence of the heterogeneous effect of the treatment on the choice of delivery windows. In the left panel in Figure 6, we see that users tend to opt for the high-stock delivery windows more frequently if they have previously ordered the item and it was unavailable. More specifically, the figure illustrates the variance in the probability of selecting the high stock delivery window between the treated and control groups for ordered items. It appears that the greater the users’ knowledge about the product, the higher their likelihood of embracing the treatment. The relationship between the users’ experience and their propensity to alter their window selection is not linear. Users with either limited or extensive experience seem to modify their delivery window choices to a lesser degree.

![Figure 6](image.png)  
**Figure 6** Users with prior stockout experience and larger orders are more likely to respond to treatment
The right panel in Figure 6 shows a significant positive correlation between the size of users’ orders and their propensity to change delivery windows, consistent with the notion that users exhibit greater risk aversion with larger orders.

4.2. Intent-to-Treat Estimates

Does our intervention affect the likelihood of users placing orders on the platform? To address this question, we aggregate the order-related data to the user-date level and estimate a difference-in-differences model with user and date fixed effects.

$$\log(Y_{it} + 1) = \beta_{Treated_i} \times Post_{it} + \lambda_t + \phi_i + \varepsilon_{it},$$

where $Y_{it}$ is the value of the outcome variable of a customer $i$ on a day $t$, $Treated_i$ is a binary variable and it is equal to 1 if user $i$ is in the treatment group, $Post_{it}$ is equal to 1 if $t$ is greater than the treatment assignment date for user $i$. Finally, $\lambda_t$ and $\phi_i$ denote date and user-level fixed effects, respectively.

4.2.1. Customers’ Delivery Window Choice.

We begin this subsection by analyzing the impact of disclosing information on high-stock delivery windows on a customer’s delivery window choices. Specifically, we want to know if customers in the treatment group are more likely to choose high-stock delivery windows when presented with information on time slots that are more likely to be high in stock. In Table 6, we present the outcomes of estimating the regression equation (2), where the dependent variable $Y_{ijt}$ indicates whether customer $i$, when ordering $j$ at time $t$, selects a high stock delivery window. In Table 6, the first column indicates that messages about high stock levels lead to a 4.42 percentage point increase in the likelihood of customers choosing a high stock delivery window for their orders. This constitutes a 9.8% enhancement in selecting our specified delivery window, given a base probability of 45.11%. This result validates the model-free evidence presented above and provides a precise estimate of the LATE of high stock delivery window formation sharing on the customers’ delivery window choice. After confirming that this policy does influence the purchasing behavior of customers, it is also reasonable to anticipate that this information-sharing policy might also affect the platform’s metrics.

Customers’ Delivery Window Choice: Heterogeneous Treatment Effects.

Displaying information about high-stock delivery windows might affect the online platform only if it is factored into customers’ purchasing choices. Moreover, it is unrealistic to expect uniform reactions from all customers upon encountering high delivery window prompts. Hence, to determine if the influence of revealing this information varies with customer characteristics, we analyze how the treatment’s effect interacts with individual attributes of customers. We pinpoint two key factors influencing the probability of responding to the treatment: the perceived risk of stock shortages and the user’s
flexibility (or the presence of alternative options). We anticipate a more significant effect of the treatment on users who perceive a high risk of stockouts. Similarly, we expect a more pronounced effect on users who have a higher flexibility. The rationale is that for users with lower flexibility (such as consistently shopping at the same time or purchasing from physical stores), knowledge about the high-stock delivery windows might not significantly alter their final choice. This is because less flexible users might already be limited in what windows they are able to choose. Therefore, for less flexible customers, the high-stock delivery window information may not be as novel or impactful.

In what follows below, we proceed to evaluate these theories.

The flexibility (or the presence of alternative options) may be driven either by the nature of the order or the characteristics of the user. For example, the impact of the treatment is likely to be diminished for products accessible via offline brick-and-mortar stores, as enhancements in stock availability rates will scarcely influence user choices for such items. Regarding user attributes, the treatment’s influence is anticipated to be less pronounced for users with flexible delivery window preferences.

Then, it is observed in Table 2 that users who make purchases at specific times or on particular days are more susceptible to the treatment’s effects. In contrast, users who make purchases at various times are less susceptible. Next, we also quantify the heterogeneity of the treatment effect on the delivery window selection by means of the regression analyses. Columns (2) and (3) in Table 2 indicate that the treatment effect is greater for orders that contain items that the user has purchased in the past. Users are 2.4 percentage points more likely to select the high stock delivery window for orders containing only new items but are 4.8 percentage points more likely to do so for orders with items they have ordered before. Similarly, Columns (4) and (5) in Table 2 show that the effect of the treatment is greater for larger orders. Orders with below median GMV increase target window selection by 3.1 percentage points, as opposed to orders with above median GMV, which increase by 5.3 percentage points.
4.2.2. Customers’ Purchasing Behavior. In this subsection, we analyze the impact of the treatment assignment on a customer’s purchasing behavior, looking at factors such as the frequency of visits to the checkout page, the number of orders made, the average number of items per order, and the time duration spent during checkout. We estimate Equation 1 and present the results in Table ??.

Table 3  ITT estimates at checkout level: User engagement increases

<table>
<thead>
<tr>
<th></th>
<th>(1) Converted</th>
<th>(2) Duration (minutes)</th>
<th>(3) Unique Items</th>
<th>(4) Order GMV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treated x Post</td>
<td>0.0507***</td>
<td>0.5404***</td>
<td>0.0283***</td>
<td>0.0384***</td>
</tr>
<tr>
<td></td>
<td>(0.0012)</td>
<td>(0.0043)</td>
<td>(0.0025)</td>
<td>(0.0025)</td>
</tr>
<tr>
<td>Control Mean</td>
<td>0.77</td>
<td>183.07</td>
<td>13.99</td>
<td>95.67</td>
</tr>
</tbody>
</table>

User FE: Yes Date FE: Yes

N: 3180039 3180039 1580457 1579043
R-squared: 0.48 0.46 0.58 0.58

Note: Coefficients measure changes in the log outcome variables from information sharing. Observations at the checkout level. All dependent variables except Converted are log-transformed. Treated is an indicator for treatment group user observations. Post is an indicator for treatment period dates. Standard errors in parentheses, clustered at the User-ID level. * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 3 shows the intent to treat estimates at the checkout level. We see that when treated users visit the checkout screen, they are around 5% more likely to place orders than the treatment group, suggesting that the conversion rate increases with the treatment. Column (2) shows that treated users also spend more time on the checkout screen, with treated users spending 71.7% more time on the checkout screen than control group customers. Columns (3) and (4) show that treated users order 2.8% more items than control group users, and increase their order amount by 3.9%.

Table 4  ITT estimates at order level: Order fulfillment improves

<table>
<thead>
<tr>
<th></th>
<th>(1) Found Rate</th>
<th>(2) Refund Rate</th>
<th>(3) Replacement Rate</th>
<th>(4) Is Priority Order</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treated x Post</td>
<td>0.2230***</td>
<td>-0.0753*</td>
<td>-0.1477***</td>
<td>-0.0075***</td>
</tr>
<tr>
<td></td>
<td>(0.0552)</td>
<td>(0.0377)</td>
<td>(0.0427)</td>
<td>(0.0015)</td>
</tr>
<tr>
<td>Control Mean</td>
<td>86.41</td>
<td>5.29</td>
<td>8.30</td>
<td>0.28</td>
</tr>
</tbody>
</table>

User FE: Yes Date FE: Yes

N: 2334541 2334541 2334541 2334541
R-Squared: 0.29 0.32 0.27 0.51

Note: Coefficients measure changes in outcome variables from information sharing. Observations at the checkout level. All outcome variables are percentages except Is Priority Order, which is binary. Treated is an indicator for treatment group user observations. Post is an indicator for treatment period dates. Standard errors in parentheses, clustered at the User-ID level. * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 4 shows the intent to treat estimates at the checkout level. We see that when treated users visit the checkout screen, they are around 5% more likely to place orders than the treatment group,
suggesting that the conversion rate increases with the treatment. Column (2) shows that treated users also spend more time on the checkout screen, with treated users spending 71.7% more time on the checkout screen than control group customers. Columns (3) and (4) show that treated users order 2.8% more items than control group users, and increase their order amount by 3.9%.

4.2.3. Aggregate effect on platform

Above, we estimated the effect of treatment conditional on the checkout visit. However, it does not show whether users visit the checkout screen more often; it is possible that treated customers reduce the number of visits to the app, and thus the net effect of the treatment is negligible. To test this, we aggregate the data to the user-date level and repeat our intent to treat estimations.

Table 5

<table>
<thead>
<tr>
<th>ITT estimates at user-date level: Platform fundamentals improve</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Treated x Post</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Control Mean</td>
</tr>
<tr>
<td>User FE</td>
</tr>
<tr>
<td>Date FE</td>
</tr>
<tr>
<td>Day of Week FE</td>
</tr>
<tr>
<td>N</td>
</tr>
<tr>
<td>R-squared</td>
</tr>
</tbody>
</table>

Note: Coefficients measure changes in log transformed outcomes from information sharing. Observations aggregated to the user-date level. Treated is an indicator for treatment group user observations. Post is an indicator for treatment period dates. Standard errors in parentheses, clustered at the User-ID level. * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 5 estimates the intent to treat effect at the customer date level. We restrict dates to just those in which users visited the checkout screen or placed orders, dropping days on which users did not interact with the app. The final dataset consists of about 5.5 million user-date observations and 1.26 million unique users. In column (1), we see that treated users are 0.73% more likely to place orders, compared to the control group. This is consistent with treated users being more engaged with the platform when the platform shares inventory information improving their decision making process when it comes to choosing the best delivery window. Similarly, Column (4) shows that treated users spend 16% more minutes per day on the platform, again consistent with increased user engagement. Additionally, column (2) shows that treated users increase their order amount by 0.46%, and column (3) shows that treated users increase the number of unique items ordered by about 3%. Note that we display the findings using log-transformed outcome variables. Our results are robust to applying Poisson models with fixed effects.

This observation aligns with expectations, considering that treated customers receive extra information. Typically, processing new information requires additional time, but this is particularly
true when customers encounter the high stock delivery window prompt for the first time. They may need more time to understand this new information and figure out the best way to integrate it into their decision-making process for purchases. Note that we display the findings using log-transformed outcome variables; however, our results remain consistent when applying Poisson models with fixed effects and without log-transformation.

4.3. Local Average Treatment Effect Estimates

The intent-to-treat analysis conducted in the previous section overlooks non-compliance. Users in the treatment group do not necessarily encounter high-stock delivery window notifications. Certain orders might not be eligible for high stock messages (for instance, if a user accesses the platform at a particular time), and some individuals might bypass the delivery window choice, thereby not seeing the high stock alerts despite their assignment to the treatment group. Figure 7 plots the fraction of orders placed by treated users that see the high stock message. This figure indicates that most of the customers who were assigned to the treatment group did not experience it with every order they placed. Therefore, of more interest is the estimation of the effect of this policy when the users in the treatment group actually see high stock prompts when selecting delivery windows. To assess the causal effect of high stock delivery window information sharing policy in this context, we use a standard instrumental-variable technique, with treatment exposure serving as an instrument for receiving the high stock message. This method specifically estimates a local average treatment effect (LATE), capturing the causal impact of high stock messages on orders where users are presented with a high stock prompt as a result of randomized treatment. Our LATE estimate assumes that the exposure to treatment affects the outcomes under study exclusively.
through the high stock messages. To estimate the LATE of high stock messages, we estimate the following regression specification using two-stage least squares (2SLS):

$$\log(Y_{ijt} + 1) = \pi_0 HighStockMessage_{ijt} + \phi_i + \lambda_t + \varepsilon_{ijt},$$ \hspace{1cm} (2)

where $HighStockMessage_{ijt}$ is an indicator for orders where the user observed the high stock message. In the first-stage regression, we estimate the effect of the treatment exposure on observing a high stock message:

$$HighStockMessage_{ijt} = \delta_0 + \delta_1 \text{Treated} \times Post_{ijt} + \phi_i + \lambda_t + \varepsilon_{ijt}.$$ \hspace{1cm} (3)

We interpret the coefficient on $HighStockMessage_{ij}$ from the instrumental variable estimation of equation (2) as the local average treatment effect of showing high stock messages. As stated above, the underlying assumption for identification is that treatment exposure influences found rates only via the high stock delivery window prompts, a reasonable assumption given the randomness of the treatment assignment.

<table>
<thead>
<tr>
<th>Table 6</th>
<th>LATE: Heterogeneous effects of window selection</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Previously Ordered</td>
</tr>
<tr>
<td></td>
<td>All</td>
</tr>
<tr>
<td>High stock message</td>
<td>0.0442***</td>
</tr>
<tr>
<td>(0.0028)</td>
<td>(0.0071)</td>
</tr>
<tr>
<td>User FE</td>
<td>Yes</td>
</tr>
<tr>
<td>Date FE</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>2334541</td>
</tr>
</tbody>
</table>

Note: Standard errors in parentheses, clustered at the User-ID level. Observations at the user-date level. Treated is an indicator for treatment group user observations. Post is an indicator for treatment period dates.

4.3.1. Impact of the Information Policy on Delivery Choice Table 6 presents the results from estimating equation 2 on the probability of choosing the 10-3 window. We see the results are consistent with our ITT estimates. Overall, a high stock message increases the likelihood of placing an order under the high stock window by 4.4 percentage points. This number is larger compared to the ITT results in Table 2, which was a 2.9 percentage point increase. Since not all treated customers see the high stock message, we expect the LATE estimates to be greater than the ITT estimates. Compared to the 0.45 baseline probability of placing an order between 10-3pm, high stock messages shift users’ window selection by about 9.7 percent. We also see again that users are more likely to switch delivery windows for items they have previously ordered (Columns 2 and 3), for more expensive orders (Columns 4 and 5), and if the users have flexible ordering schedules (Columns 6 and 7).
4.3.2. Impact of the Information Policy on Platform Fundamentals In this section, we quantify the local average treatment effects on outcomes related to orders. Specifically, we are interested in whether high stock delivery window messages can improve found rates and increase the orders’ GMV (i.e., customer spending per order). To this end, we estimate the regression specification 2 and present the results below.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Found Rate</td>
<td>0.3415***</td>
<td>-0.1153*</td>
<td>-0.2262***</td>
<td>-0.0115***</td>
<td>0.0547***</td>
</tr>
<tr>
<td>Refund Rate</td>
<td>(0.0846)</td>
<td>(0.0578)</td>
<td>(0.0655)</td>
<td>(0.0022)</td>
<td>(0.0033)</td>
</tr>
<tr>
<td>Replacement Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Is Priority Order</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>lod_gmv_final</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 7  Effect of high stock windows on order outcomes

Control Mean 86.41 5.29 8.30 0.28 95.67

User FE Yes Yes Yes Yes Yes
Date FE Yes Yes Yes Yes Yes
N 2334541 2334541 2334541 2334541 2334541

Note: Standard errors in parentheses, clustered at the User-ID level. Observations are at the order level. High Stock Message is an indicator for orders placed during a high stock window. We include user and date fixed effects. * p < 0.10, ** p < 0.05, *** p < 0.01.

First, it follows from the first column in Table 7 that orders influenced by the high stock delivery window prompts are more likely to be successfully fulfilled, with the found rates significantly increasing by about 0.39% (β = 0.3430, p < 0.001). In addition, it follows from the second and third columns in the table that the likelihood of refunds and replacements decreases by 2.19% (β = −0.1157, p < 0.05) and 2.74% (β = −0.2273, p < 0.001), respectively. These findings suggest that under the influence of this information-sharing policy, customers are indeed selecting high-stock delivery windows for their orders, thereby experiencing enhanced service reliability on the platform.

Then, we also see from the fourth column in Table 7 that the presence of high-stock messages reduces the customers’ propensity to choose a priority delivery window by 4.1% (β = −0.0115, p < 0.001). One interpretation could be that service responsiveness is not the sole factor influencing customer decisions in the treatment group. The fact that the priority delivery window may not have high stock levels could lead customers to opt for other (i.e., non-priority) delivery windows with higher stock availability. Moreover, the last column in the table indicates that the average value of an order, referred to as the Order Gross Merchandise Value (Order GMV), experiences an increase of 6.08% under the influence of the actual treatment, underlining a very significant economic impact given this cost-free intervention. There could be multiple mechanisms of how a customer might increase her order GMV: (a) increase the average price of an item in order if the treatment leads to the items’ substitution or store substitution; (b) increase in the number of unique items included in the order; or (c) increase in the quantities of the items purchase on the platform.
In the next section, our goal is to find a specific mechanism that leads to an increase in order GMV. In addition, note that it was previously mentioned that users show greater responsiveness to the treatment when placing larger orders (i.e., orders with more items and higher GMV). This might be attributed to treated users making larger orders, contributing to an increase in revenue. Hence, in the next section, it is worth investigating if the high stock delivery window information indeed motivates users to expand the size of their baskets.

<table>
<thead>
<tr>
<th>Table 8</th>
<th>Logged Users increase order bundle and spend more after seeing high stock message</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Unique Items</td>
</tr>
<tr>
<td>High stock message</td>
<td>0.0415***</td>
</tr>
<tr>
<td></td>
<td>(0.0033)</td>
</tr>
<tr>
<td>User FE</td>
<td>Yes</td>
</tr>
<tr>
<td>Date FE</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>2334541</td>
</tr>
</tbody>
</table>

Note: Standard errors in parentheses, clustered at the User-ID level. Observations at the order level. All dependent variables are log-transformed. All specifications include user and order date fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.4. Mechanism and Discussion

Overall, we have shown how sharing high-availability delivery window information has a range of effects on customer behavior, and by extension, the platform’s fundamentals. First of all, it increases customer spend per order and encourages customers to place more orders on the platform. We have found that the treatment tends to lead to better outcomes for both the platform and customers via several pathways: (1) it increases the probability of customers placing the orders during high stock delivery windows, (2) it reduces the number of refunds and replacements by improving found rate, and (3) it makes customers visit checkout page more often and place more orders. In addition, we also found that this high stock information-sharing policy makes customers place less number of priority orders and also increases the order duration time. As yet, the primary mechanism identified in the paper for short-term customer spend increase has been the decrease in refund rates, which directly boosts the company’s revenue by increasing the actual spending per order. In this section, our goal is to introduce additional factors that are likely to contribute to the short-term revenue increase. Table 8 illustrates that high stock delivery window prompts result in bigger bundle sizes. Orders made under the influence of treatment have 4.17% more items (see Column 1 in Table 8), and the quantity of each item increases by 0.73% (see Column 2 in Table 8). Even though the average price per item stays relatively stable (see Column 3 in Table 8), the average value of each item experiences a 0.89% increase due to the higher quantities (see Column 4 in Table 8).
4.4.1. Decoupling stock information from user experience

We first study whether the positive effects come from changes in the users’ behaviors, or from the actual increases in found rates due to changing the window choice. Towards this, we split the treatment group into two groups: users who chose the high stock windows and placed orders but 1) encountered a decrease in found rates, or 2) encountered an increase in found rates. We estimate Equation 1 again, but interact Treated x Post with a dummy variable for users with decreased found rates.

Intuitively, if the improvements come solely from changes in users’ ordering behavior, we would see no difference between for treated users, regardless of their experience with high stock orders. This would be the case if the triple interaction term is statistically insignificant. On the other hand, a negative triple interaction term would suggest that actually experiencing increases in found rates is important for information policies to have a positive effect.

<table>
<thead>
<tr>
<th>Table 9</th>
<th>Customers switch which stores they order from when high stock messages are shown</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>HS Window</td>
<td>Is Priority</td>
</tr>
<tr>
<td>Treated x Post</td>
<td>0.252***</td>
</tr>
<tr>
<td>Treated x Post x Low Found</td>
<td>-0.107***</td>
</tr>
<tr>
<td>N</td>
<td>718478</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.25</td>
</tr>
</tbody>
</table>

Note: Standard errors in parentheses, clustered at the User-ID level. Observations are at the order level. Low Found is an indicator for treatment group users whose high stock orders had lower found rates than their pre-period found rates. All specifications include user and date fixed effects. * p < 0.10, ** p < 0.05, *** p < 0.01.

We see that users that suffer decreased found rates via the experiment are less likely to order using the high stock window (Column 1). Compared to treated users whose found rates increase, they are 10.7 percentage points less likely to order during the 10-3pm window. However, they are still more likely than the control group to place during this time period, suggesting that customers are able to learn the general availability of items is higher during this period. We also see that users that suffer reduced found rates are more likely to place priority orders (Column 2) but are not likely to order more items (Column 3). This perhaps suggests that users with decreased found rates strategically adjust their ordering strategy. Columns 5-7 suggest more evidence that customers are changing the bundle of goods being purchased.

4.4.2. Customer exploration and substitution

Next, we examine patterns of customer substitution. Our focus is on determining if users persist in purchasing the same items from the same retailers as during the pre-treatment period, or if they are exploring new items or stores. Table 10 presents our results.
First, this table indicates that users are less likely to reorder from stores where they have previously shopped. Column 1 in Table 10 indicates a 0.39 percentage point rise in the likelihood of users choosing new items. Additionally, according to Columns 2 and 3 in Table 10, there is a 0.93 percentage point higher chance of users making purchases from new stores, and a 0.56 percentage point increased probability of them placing orders with new retailers. We also see in this table that users tend to order less from retailers that have a large number of locations, aligning with the effect of the treatment (see Column 4 in Table 10). Yet, users show a higher likelihood of purchasing from more popular retailers, determined by the number of users ordering from these retailers (see Column 5 in Table 10). Then, it is presented in this table that users have a greater tendency to buy from retailers offering lower prices (see Column 6 in Table 10).

### 5. High Stock Information Sharing and Retailers’ Performance

To assess the experiment’s effect on the retailers’ performance, we begin by compiling data at the store-day level. For every store location, we sum over the orders, users, items, and the total order GMV. Importantly, we count the number of orders made by treatment or control users, by users exposed to the treatment, the number of orders influenced by treatment, and the number of orders that elected the high stock window.

We identify the effect of displaying high stock alerts on outcomes at the firm level using a 2SLS approach described above.

\[
\log(GMV_{it} + 1) = \beta HighStockMessages_{it} + X_{it} + \epsilon_{it}
\]

The main dependent variable is the order GMV for store \(i\) on date \(t\). \(HighStockMessages_{it}\) represents the count of orders that received high stock alerts, for each store \(i\) on day \(t\). The key coefficient, \(\beta\), measures the variation in GMV in response to high stock alerts being displayed: for each unit rise in the displayed messages, GMV increases by \(\beta\) percent. In the first stage, we
use the quantity of orders exposed to the treatment as an instrument for the count of orders that encountered high stock alerts.

\[ HighStockMessages_{it} = \gamma Treated_{it} + \varepsilon_{it} \]  

(5) 

Table 11  Firms benefit from high stock windows

<table>
<thead>
<tr>
<th>Users</th>
<th>Orders</th>
<th>Price</th>
<th>Variance (days)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>All</td>
<td>0.9727***</td>
<td>0.8594***</td>
<td>11.9484***</td>
</tr>
<tr>
<td>High</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Store Location FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Store Location FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N                | 5687517 | 3387759 | 2255962 | 3358730 | 2284991 | 2787325 | 2856396 | 2462543 | 2825948 |

Note: Standard errors in parentheses, clustered at the store location ID level. Observations are at the store location ID-date level. Influenced is the number of orders placed that were shown the high stock prompt at the store location ID. All specifications include Store location ID and date fixed effects. * \( p < 0.10 \), ** \( p < 0.05 \), *** \( p < 0.01 \).

The findings in Table 11 indicate that each high stock prompts leads to a roughly 0.97% rise in order GMV for retailers (Column 1). The subsequent columns reveal a significant heterogeneity in the impact of high stock prompts. According to Columns 2-3, while high stock prompts are advantageous for stores that were popular in the pretreatment period, the gains are notably greater for less popular stores. Specifically, for stores with user numbers below the median before the experiment, each high stock prompt contributes to a revenue increase of approximately 12%. Likewise, Columns 4-5 demonstrate that stores with a smaller number of orders in the pretreatment period see greater benefits. Column 6 indicates that stores with prices above the median before the experiment see a 1.5% increase in GMV per high stock message, compared to a 0.8% increase for stores with prices below the median. Furthermore, stores experiencing high variability in found rates gain more than those with stable/consistent found rates, with Column 8 showing a 11.6% GMV increase for stores above the median variability in found rates, in contrast to a mere 0.7% for those with less variability.

6. Conclusion, Limitations, and Future Work

This paper addresses a timely and increasingly important challenge: stockout management. This issue has gained particular significance with the growing scale and number of online platforms. Acting as intermediaries in the supply chain between traditional retailers and consumers, these platforms encounter the distinct challenge of lacking direct control over stock levels on their platforms. Considering this, rather than trying to make proactive changes on the platform to improve inventory management, one could employ information sharing. By specifically disclosing high stock
delivery window details to customers, it might be possible to decrease stockout incidents, boost
customer satisfaction, and enhance the company’s operational efficiency. In fact, this paper demon-
strates that implementing such a policy has several effects. First, it indeed makes customers choose
delivery windows that are characterized by high stock availability. In turn, it leads to a reduc-
tion in refunds and replacements, thereby enhancing the rate of successfully fulfilled orders on the
platform. Secondly, it results in a 6% revenue boost by making customers place more orders and
also increasing the customer spending per order. Finally, our research indicates that the treatment
enhances customers’ propensity to discover new products and retail partners on the platform which
might have a positive implication for the long-term platform revenue.

6.1. Limitations
A possible shortcoming of our experimental setup is the risk of interference effects, which could
breach the stable unit treatment values assumption (SUTVA). This scenario occurs when the
treatment applied to one consumer affects the outcomes for consumers in the control group within
the same household (or among housemates), undermining the SUTVA and potentially skewing our
findings with confounding variables. Under this violation of SUTVA condition, our results in this
paper present the lower bound estimates of the true treatment effect sizes. However, we believe
this interference effect is insignificant in our context since individuals living in the same household
or among closely connected housemates tend to merge their delivery orders into one account.
This consolidation is motivated by the fixed delivery fees per order and the shared benefits of an
Instacart+ delivery subscription.

Another potential violation of the SUTVA condition in our RCT analysis could arise from the
risk of confounding, where the treatment given to one customer might affect the outcomes for
others. Specifically, it is possible that customers who have access to high-stock delivery windows
could influence the inventory levels of stores, potentially impacting other customers (for example,
those in the control group). Theoretically, this interference could lead to an underestimation of the
treatment effect size in our analysis. Nonetheless, we believe this effect is minimal in our scenario
for the following reason: retailers on Instacart primarily obtain their revenue from conventional
walk-in customers who shop for themselves, not from the online platform.

6.2. Future Work
In conclusion, this study opens the door for further research into how online marketplace facili-
tators or online retailers, who cannot directly manage inventory levels, can optimize operational
decisions through information sharing policies to enhance the platform’s found rate. One future
research direction could involve revising the setup of the field experiment. Currently, our exper-
iment simplifies the allocation of delivery windows to high-stock periods based solely on them
occurring between 10 am and 3 pm. However, in practice, this interval may vary among retailers and could also depend on the specific items in a cart/order. Thus, it would be intriguing to explore whether tailoring the assignment of high-stock delivery windows more precisely in the experiment could amplify the treatment’s impact and by how much. Another avenue for research could delve into the inventory management strategies of retail stores, specifically how their stock levels are adjusted based on the degree to which an online platform discloses product availability to consumers. The question arises: how would the inventory strategies of retail partners, who offer their products on the online platform, change in response to the platform sharing stock information with shoppers? How does this high stock delivery window information-sharing policy change the competition on the platform? In addition, one could also analyze how this information-sharing policy would impact the supply side of the platform, i.e., gig workers fulfilling orders. Is it going to be easier to match supply and demand under this novel information-sharing policy? Or is there any other information-sharing policy that could more effectively balance supply and demand on the platform?

References
Knight B, Mitrofanov D (2022) Disclosing low product availability: An online retailer’s strategy for mitigating stockout risk. Available at SSRN 4137758.


