POMS

Impacts of the COVID-19 pandemic on grocery retail operations: An analytical model

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Abstract

The COVID-19 pandemic has had profound effects on grocery retailers, forcing them to make many operational changes in response to public health concerns and the shift in customers' shopping behavior. Grocery retailers need to understand the impact of pandemic conditions on their operations, but the literature has not modeled and analyzed this issue. We bridge this gap through economic models that consider the documented changes in the customers' shopping behavior during the COVID-19 pandemic, including less frequent in-store shopping and bulk-shopping tendency. We capture the impact of occupancy limitation guidelines on grocery retailers' service capacity, customers' shopping behavior, and, consequently, on the retailers' store traffic and profit. We find that though store occupancy limitations reduce the in-store foot traffic (which helps with curbing the disease spread), interestingly, they do not necessarily result in a profit decline. Under occupancy limitations and when the retailer offers the delivery or curbside pickup service, our analyses highlight the externality impact of online customers on the shopping behavior of in-store customers. When the retailer adds the delivery service, such externalities may increase the store traffic (higher infection risk inside the grocery store) and reduce the retailer's profit. When the retailer adds the curbside pickup instead, it has more control over the impact of externalities, which helps in lowering the store traffic and increasing the profit. Our results offer valuable insights into how retailers should regard occupancy limitations and health safety measures. Our results also highlight conditions under which various operating modes may help retailers reduce infection risk and achieve higher profit.

KEYWORDS
COVID-19, occupancy limitations, omnichannel grocery retailing, shopping behavior, social/physical distancing

1 | INTRODUCTION

Grocery retailers play an essential role in American communities. They are the primary source for people to purchase food, and they serve other community functions, such as supporting local commerce and providing employment. The grocery retail industry, comprising around 38,000 stores, accounted for $682.86 billion of sales and employed more than 2.5 million people in 2019 (Statista, 2020a). Visiting grocery stores is a familiar and comforting ritual for many Americans, with 40% visiting a store at least once a week and many visiting more than four times a week. It is

not surprising that COVID-19 has affected grocery retailing profoundly.

On the one hand, grocery retailers have to adapt to a massive shift in consumer behavior, including reducing shopping frequencies and a higher tendency to shop in bulk (Wang et al., 2020). On the other hand, grocery retailers face severe constraints due to safe operating guidelines imposed by local governments to prevent stores from becoming potential hotspots for disease transmission (Szymkowiak et al., 2020). In other words, grocery retailers have to step up to serve community needs while curbing the possibility of infection among their customers and staff.

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In response, many retailers invested heavily in measures to assure customers about the health safety of their shopping to boost how comfortable shoppers feel about in-store shopping (Moran, 2021). Many retailers went beyond and forayed into online shopping by scaling their delivery operations in partnership with third-party delivery services or retrofitting their internal capability to provide curbside pickup service to their customers (Redman, 2020b). While there is a general skepticism about the profitability of online retailing (Kang, 2020), the existing research does not offer any guidance on how pandemic conditions impact grocery retailers' operations and how a retailer should adopt in response. Given the likely long-lasting impacts of the ongoing pandemic (Mandavilli, 2021), these are critical issues that we aim to address in this paper.

1.1 | Motivation

During a pandemic, the risk of disease transmission inside grocery stores impacts customers' shopping behavior. First, as reported in various surveys, customers reduce their visit frequency to grocery stores (Renner et al., 2020), accompanied by their increased tendency toward bulk shopping, that is, stockpiling or buying more than needed (Redman, 2020e). Second, many customers open up to alternative shopping modes, including delivery or curbside pickup, which the Centers for Disease Control and Prevention (CDC) recommended in their guideline about safe grocery shopping during the COVID-19 pandemic (CDC, 2020). A survey of customers during the early days of the COVID-19 pandemic found that near 80% of responders shifted to ordering groceries online (Redman, 2020a). As a result of these changes, the anemic 3% share of online grocery shopping from pre-COVID-19 surged to 12.5% (Statista, 2020b).

Grocery retailers react to these changes in several ways. At the basic level, they can provide additional health measures to assuage customers' concerns about the infection risk while shopping (Pacheco, 2020). Examples of measures adopted during COVID-19 are reading customers' vitals before entry, protective shields around high-contact stations, contactless checkout terminals, increasing frequency of cleaning/sanitation, and provisioning for sanitizer/wipes throughout stores (Bove & Benoit, 2020). While these measures help reduce the infection risk and make customers less stressed about visiting grocery stores, they increase the cost of serving customers.

Another major change grocery retailers can implement under pandemic conditions is limiting *store occupancy*, that is, the maximum number of customers allowed inside the store. In the COVID-19 pandemic, local governments required grocery retailers to alter their occupancy levels to 20%–50% of their maximum to meet social/physical distancing guidelines (Redman, 2020d). While effective in their primary purpose, store occupancy limitations lower the capacity of stores to serve grocery shoppers. Not surprisingly, lines of customers waiting to enter grocery stores became a common sight during the COVID-19 pandemic (Yang, 2020). A cascading impact of such service capacity limitations is a further reduction in shopping frequency, as customers find waiting in queues one of the least satisfying aspects of the in-store shopping experience (Browne, 2018).

Finally, grocery retailers may turn toward alternative operating modes in response to customers' shopping behavior changes, such as providing *delivery* and *curbside pickup* services—the two commonly employed omnichannel strategies during the COVID-19 pandemic (Redman, 2020b). With the delivery service, online orders are delivered at customers' doorsteps, whereas with the curbside pickup service, customers travel to the store to pick up their prepacked orders. Given that scaling up last-mile delivery capabilities requires significant investment and time, many retailers partner with third-party delivery platforms (e.g., Instacart and DoorDash) for their foray into delivery service (Jia et al., 2021). These platforms use gig-economy workers to offer doorstep delivery by charging customers some delivery fee and charging retailers a commission as a fraction of each order (Kang, 2020). On the other hand, curbside pickup is relatively easier to deploy, and retailers require minimal external support to implement it (Dumont, 2019).

1.2 | Research questions

One of the main concerns of grocery retailers under pandemic conditions is staying profitable while facing many restrictions on their operations to ensure a safe environment for customers and employees. In particular, there are concerns that occupancy limitations (to comply with the social/physical distancing guidelines) and the accompanying loss of service capacity may reduce the number of served customers and hence profitability (Antonucci, 2020). Thus, our first research question is: How do occupancy limitations impact grocery retailers' store traffic and profit?

While online shopping appears attractive due to its lower health concerns, carrying out fulfillment profitably remains a significant challenge (Repko, 2020). Further, under the pandemic conditions, the two common choices—delivery by partnering with third-party delivery firms and curbside pickup using internal resources—impose externalities on in-store customers (Redman, 2020b; Sugar, 2020). Thus, we ask the following: What are the impacts of adding the delivery service or curbside pickup service on the store traffic and retailer's profit under occupancy limitations? Furthermore, given grocery stores' role in supplying food for communities and their potential to become a hotspot for disease spread (Szymkowiak et al., 2020), what are the implications of these operational changes on customers' access to grocery and the risk of disease spread inside grocery stores?

To address these, we model the operations of a grocery retailer under occupancy limitations and various operating modes by capturing the changes in customers'

shopping behavior during a pandemic (like those documented during COVID-19). Our economic models allow customers to reduce their shopping frequency (due to the fear of infection and inconvenience of waiting) and practice bulk shopping (spending more per shopping session). We consider the single-channel in-store mode as the base operating mode. For their prevalence during the COVID-19 pandemic, we consider two omnichannel operating modes: (i) the *delivery* mode, in which the retailer facilitates the service through a partnership with a third-party delivery service provider, and (ii) the *curbside pickup* mode, in which the retailer facilitates the service by mainly using its internal resources.

Our analyses suggest that though occupancy limitations reduce in-store foot traffic (which helps curb the disease spread), they do not necessarily result in a profit decline. The impact of such occupancy limitations depends on the interaction of the customers' bulk-shopping behavior, the retailer's health safety efforts, and the strictness of the occupancy limitations. One intention of adding the delivery and curbside pickup services is to reduce the infection risk in the stores. However, these services could result in higher store traffic, imposing higher risk on in-store customers and limiting their access to groceries. In both the delivery and curbside pickup operating modes, the presence of online customers creates an externality on the in-store customers when stores face occupancy limitations. Appropriate price premium and required minimum shopping amount mitigate such negative externalities. Overall our economic modeling analyses highlight vital aspects of the operations of grocery retailers under pandemic conditions. We consider additional modeling extensions and analyze them numerically in Section 5.

2 | LITERATURE REVIEW

We mainly contribute to two streams: (1) managing service facilities during a pandemic and (2) omnichannel retailing and services. We review these streams and highlight our contributions.

2.1 | Management of service facilities during a pandemic

We contribute to the growing analytic research on various issues related to the management of service facilities during COVID-19, including interventions to curb the infection risk inside such facilities. Shumsky et al. (2021) measure the efficiency of facilitating the one-way movement of customers inside grocery stores in lowering the risk of infection. Perlman and Yechiali (2020, 2021) propose metrics for the customers' infection risk in a grocery store where occupancy limitations cause customers to line up in front of the store and use the metrics to optimize staffing levels and store configuration. Kang et al. (2022) use queueing-theoretic metrics to measure infectious disease transmissibility inside congestion-

prone service facilities to explore the efficacy of various interventions, such as limiting the occupancy of service facilities and prioritizing high-risk customers.

The intervention that we focus on is the social/physical distancing store occupancy limitations, mainly because it was imposed on the retail stores in most states in the United States and has an immediate impact on the service capacity. Perlman and Yechiali (2020, 2021) also consider the impact of occupancy limitations by focusing on the waiting time experience of customers when they shop in-store. We model multiple shopping modes and consider broader performance metrics such as store traffic and profitability. Thus, our approach allows us to capture operational features of omnichannel settings (as many retailers launched an online channel during COVID-19) and compare the retail stores' performance under various operating modes in the presence of occupancy limitations. Furthermore, using our analysis, we can also provide high-level public health implications of the social/physical distancing intervention by tracking how the grocery stores traffic varies depending on the strictness of occupancy limitations and the different operating modes.

2.2 | Omnichannel retailing and services

We also contribute to the literature on the emerging issues related to omnichannel retailing (Kumar et al., 2018). Belavina et al. (2017) show that the best revenue structure for a grocery retailer operating its delivery service depends on the hassle of store visits, customers' baskets size, and delivery costs. Gao and Su (2017) show that by facilitating more convenient shopping and providing real-time information about product availability, the buy-online-pickup-in-store (BOPS) service could increase retailers' demand when the hassle of visiting the store is high. Gao et al. (2022) show that omnichannel retailers' decisions on the number and size of their physical stores depend on the return rate of online purchases and online shopping convenience degree. Hu et al. (2021) investigate BOPS' impact from an inventory perspective and show that it may benefit or hurt profitability depending on the cost associated with store visits and waiting time for online orders.

Our models include factors that affect customers' decisions, including the abovementioned hassle of visiting the store, delivery service cost, and waiting inconvenience. A distinguishing feature of our models is that they also incorporate factors specific to the customers' shopping behavior change during a pandemic. For example, the perception of the infection risk from visiting a store affects shopping frequency for in-store customers. Furthermore, as customers adjust their shopping frequency, their basket size (or expenditure) also changes accordingly; specifically, bulk shopping has been documented extensively during previous pandemics and the COVID-19 pandemic (Wang et al., 2020). To the best of our knowledge, previous studies on economic models of single-channel or omnichannel retailing did not explicitly model these features.

Another distinctive feature is that online customers in our models impose an externality on in-store customers as the two groups of customers share the service capacity under store occupancy limitations. In that respect, our models are also related to the literature on omnichannel services in which the demand from one channel affects other channels. Gao and Su (2018) show that omnichannel services, such as coffee shops with self-ordering technologies, may reduce wait time while attracting more demand. On the other hand, Wang et al. (2018), Kang et al. (2020), and Roet-Green and Yuan (2020) highlight that due to the *externalities* that online customers impose, adding an online channel could increase wait times. In this paper, we distinguish between two types of such externalities (i.e., *congestion* externality and *capacity* externality), which emerge when the retailer adds *delivery* and *curbside pickup* services, and we explain their impacts.

3 | MODEL

We model the operations of a grocery retailer under various single- and omnichannel operating modes by capturing customers' shopping behavior during a pandemic (such as COVID-19). Grocery customers adopt less frequent physical store visits due to the fear of infection, which increases their tendency to shop more items in each shopping visit (Wang et al., 2020). To assure customers about the safety of their shopping, grocery retailers undertake various initiatives, such as facilitating social/physical distancing by limiting the number of customers in the store (e.g., through a one-in, one-out admission policy) (Bove & Benoit, 2020). This practice, however, limits the service capacity of grocery retailers and leads to the waiting inconvenience for in-store shoppers—as evident by long lines outside grocery stores during the COVID-19 pandemic (Yang, 2020).

Accordingly, we consider models where the retailer faces social/physical distancing occupancy limitations. The resulting waiting inconvenience and infection risk associated with in-store shopping affect customers' in-store shopping behavior. While some retailers continued to allow for only in-store shopping, some retailers responded to these limitations by expanding their presence in the online shopping market by offering delivery or curbside pickup services (Redman, 2020b). Accordingly, we consider the following three operating modes for the retailer:

- *In-store mode*, in which the retailer does not offer delivery or curbside pickup services. Thus, customers can shop only by visiting the store.
- *Delivery mode*, in which the retailer offers delivery service. Thus, customers can either shop by visiting the store or shop online for their orders to be delivered.
- *Curbside pickup mode*, in which the retailer offers curbside pickup service. Thus, customers can either shop by visiting the store or shop online for curbside pickup of their orders.

In line with the observed trends (Unnikrishnan & Figliozzi, 2020), we consider that the retailer offers delivery service by partnering with a third-party delivery firm (e.g., Instacart). Also, as the curbside pickup service is easier to implement (Dumont, 2019), the retailer provides this service using its resources. We elaborate our modeling choices for the customers' behavior in Section 3.1 and the retailers' operations in Section 3.2.

3.1 | Customers' shopping behavior

Based on the conceptual framework of household grocery shopping behavior proposed in Bawa and Ghosh (1999), the two main factors that characterize the shopping behavior of grocery customers are their (1) *shopping rate* and (2) *expenditure*. The shopping rate is the average number of "shopping sessions"[1] per unit time. The expenditure is the average amount a grocery customer spends in one shopping session. Customers' decisions about these two factors are primarily determined based on their consumption needs and costs. Next, we elaborate on these modeling choices inxbrk detail.

3.1.1 | Modeling customers' expenditure

We model customers' average expenditure in a shopping session as a function of their shopping rate λ. As customers shop less frequently, they purchase more in each shopping session, on average (Bawa & Ghosh, 1999). In a rational purchasing decision model, a reduction in the shopping rate would result in a proportional increase in expenditure, ensuring constant overall consumption. However, customers exhibit stockpiling and panic buying during pandemics due to inherent uncertainty about future shopping trips and product availability (Hall et al., 2020).

We capture this *bulk-shopping* behavior by allowing a proportional increase in expenditure. Hence, the retailer's average *gross profit* $R(\lambda)$ (i.e., revenue minus cost of goods sold) per shopping session is to be more than the reduction in the shopping rate. Motivated by the empirical specifications of customers' expenditure in Bawa and Ghosh (1999), one such functional form is $R(\lambda) = R_0 e^{\nu(\alpha_0 - \lambda)}$, where α_0 and R_0 are the *base shopping rate* and the corresponding *base average gross profit* per shopping session in the absence of any additional frictions that may reduce customers' shopping rate. The customers' *bulk-shopping tendency factor*, $\nu > 0$, regulates the sensitivity of the expenditure, hence gross profit, to the shopping rate λ. We note that our analyses and results do not depend on a specific functional form for $R(\lambda)$ as long as $\lambda \times R(\lambda)$ is unimodal in λ. For the above functional form, we show that this property holds and discuss its implication on customers' bulk-shopping behavior in Lemma 1 and accompanying discussion.

3.1.2 | Modeling customers' shopping rate

Since various shopping modes impose different costs on customers, their shopping rates depend on their shopping channel choice (Chintagunta et al., 2012). We distinguish among the shopping rates of in-store, delivery, and curbside pickup customers, and we denote them by λ_s, λ_d, and λ_c, respectively. Due to various factors specific to each shopping mode, which we discuss next, these shopping rates may be lower than the base shopping rate, that is, $\lambda_s < \alpha_0$, $\lambda_d < \alpha_0$, and $\lambda_c < \alpha_0$. Next, we elaborate on how the shopping rates λ_s, λ_d, and λ_c are determined.

In-store customers' shopping rate
We consider that three key factors could influence λ_s during a pandemic: (1) the perceived risk of infection associated with physically visiting the store (Renner et al., 2020), (2) the inconvenience of waiting (Chen et al., 2021; Gao & Su, 2018; Yang, 2020), and (3) the hassle cost associated with traveling to the store (Gao & Su, 2017). We elaborate on modeling each of these factors below.

During a pandemic, customers are less willing to physically visit stores due to the risk of being infected after coming close to other people (Renner et al., 2020). Retailers can reduce this risk perception by undertaking measures such as reading customers' vitals before entry, increasing sanitization, providing contactless checkout, and curtailing shopping hours (Bove & Benoit, 2020). Accordingly, we consider the in-store customers' *adjusted-shopping rate* (during the pandemic) to be a function $\alpha(\psi)$ that depends on the retailer's health safety efforts level ψ. In our numerical analyses, we use the concave increasing function $\alpha(\psi) = \alpha_0 - (\alpha_0 - \alpha_{\min})e^{-\psi/\eta}$, where $\alpha_{\min} < \alpha_0$ is then shopping rate when the store exerts the minimum health safety effort (i.e., $\psi = 0$), and $\eta > 0$ captures the pandemic severity (or, equivalently, the customers' risk aversion factor). In this function, $\alpha(\psi)$ plateaus at α_0 as the health safety effort ψ increases; as customers are more risk averse (higher η), it requires higher levels of health safety efforts to achieve a specific adjusted-shopping rate $\alpha(\psi)$.

In addition to the health safety concerns, in-store customers also experience disutility due to waiting associated with in-store shopping and reduce their shopping rate in response (Yang, 2020). In line with the existing models on the impact of waiting times on the customers' shopping rate (e.g., Gao & Su, 2018; Yuan et al., 2021), we consider that the waiting time decreases the in-store customers' shopping rate λ_s linearly. Furthermore, following Gao and Su (2017), we let the customers' hassle h of physically visiting the store reduce the in-store customers' shopping rate λ_s linearly. Accordingly, we express the in-store customers' shopping rate as follows:

$$\lambda_s = \left(\alpha(\psi) - h - \beta_w w_s\right)^+, \qquad (1)$$

where $\beta_w > 0$ is the customers' sensitivity to waiting time, and w_s is the average wait a customer experiences during a store visit (which we will explain in Section 3.2).

Delivery customers' shopping rate
Since delivery customers do not visit the store physically, they do not experience the associated hassle cost, the infection risk, or the inconvenience of the store waiting. However, on average, they experience a *service waiting time w_d*, the time lag between when they place their order and when they have their groceries delivered. This service waiting time depends on the supply and demand matching mechanisms used by the third-party delivery platforms, and retailers do not have any control over it. Customers can often schedule a delivery window within a few hours of their order placement. When customers set a delivery time window, the third-party delivery firm facilitates the delivery before the end of the scheduled time window. Thus, there is negligible stochasticity in the waiting times after scheduling a delivery. For this, and the fact that the delivery service times are beyond the control of grocery retailers, we model the delivery service waiting time w_d as exogenous to the retailer's decisions.

In addition to the waiting time, delivery customers need to pay a premium p_d. For example, Instacart charges \$3.99 on each delivery (Nickle, 2018), and customers are expected to pay (and most indeed pay) a tip to the gig-economy shoppers who deliver groceries (Smith, 2020). We model that the price premium p_d, like the delivery service waiting time w_d, linearly reduces the delivery customers' base shopping rate α_0. Another factor impacting the shopping rate of delivery customers is the required minimum shopping amount imposed by the third-party delivery firms. Let $\underline{R}_d$ denote the average gross profit per shopping session corresponding to the minimum delivery shopping amount; $\underline{R}_d$ constrains the delivery customers' viable minimum shopping rate. Accordingly, we express the shopping rate for delivery customers as:

$$\lambda_d = \min\{(\alpha_0 - \beta_p p_d - \beta_w' w_d)^+, R^{-1}(\underline{R}_d)\}, \qquad (2)$$

where $\beta_w' < \beta_w{}^2$ and β_p denote the delivery customers' sensitivities to the delivery service waiting time and delivery premium, respectively. For simplicity of exposition, we refer to $\underline{R}_d$ as the *minimum delivery shopping amount* in the remainder of the paper.

Curbside pickup customers' shopping rate
Unlike delivery customers, curbside pickup customers need to travel to the store and incur the associated hassle h (like in-store customers). However, unlike in-store customers, curbside pickup customers do not enter the store and are not exposed to the infection risk. Like delivery customers, curbside pickup customers also experience a service waiting time w_c, on average, which is the time lag between when they place their order and when the order is ready for curbside pickup. Motivated by several examples from various grocery retailers, including Kroger, Safeway, and Walmart (Masur, 2020), we consider that the grocery retailer

implements the curbside pickup service using its resources (rather than through a partnership). Therefore, we treat the curbside pickup service waiting time as an endogenous variable that depends on the retailer's capacity allocation; we elaborate more on the curbside pickup service waiting time in Section 3.2.[3]

There are various ways that retailers implement the curbside pickup service. In most cases, they charge a service premium p_c, usually less than the delivery service premium p_d (McGrath, 2019), or impose a minimum shopping amount. Like how we operationalized the minimum delivery shopping amount, let $\underline{R}_c$ denote the average gross profit per shopping session corresponding to the minimum curbside pickup shopping amount. Then, we express the shopping rate for curbside pickup customers as in Equation (3). In the remainder of the paper, we refer to $\underline{R}_c$ as the *minimum curbside pickup shopping amount* for simplicity of exposition.

$$\lambda_c = \min\{\left(\alpha_0 - h - \beta_p p_c - \beta_w' w_c\right)^+, R^{-1}(\underline{R}_c)\}. \quad (3)$$

3.1.3 | Modeling customers' shopping channel choice

Customers' choices for the shopping channel depend on the retailer's operating mode. Under the *in-store mode*, the only available shopping option for customers is physically visiting the store. Under the *delivery mode*, customers can either visit the store or buy online for delivery. Customers can shop under the *curbside pickup mode* by visiting the store or using the curbside pickup service.

The focus in our primary model is on the retailer's operations during a widespread pandemic, like COVID-19, in which exogenous factors, such as age and other risk factors based on prior diseases, are the main drivers for customers to choose between in-store and online shopping (for delivery or curbside pickup). Therefore, in the case that the grocery retailer provides the delivery or curbside pickup services, we consider that a fraction θ_d of customers under the delivery mode (resp., θ_c under the curbside pickup mode) shop online, and the remaining fraction $\bar{\theta}_d = 1 - \theta_d$ (resp., $\bar{\theta}_c = 1 - \theta_c$) continue shopping in-store. We allow for the possibility of the retailer losing a fraction θ_s of its customer base if such online services are not made available during the pandemic. In other words, adding the delivery and (or) curbside pickup services expand retailers' customer base from $\bar{\theta}_s = 1 - \theta_s$ to 1. To include the possibility that some in-store customers may opt to buy online after such services are available, we allow $\theta_d \geq \theta_s$ and $\theta_c \geq \theta_s$.

We note that our choice of modeling the total demand through endogenizing the shopping rates (as we explained in Section 3.1.2), but keeping θ_s, θ_d, and θ_c exogenous, is consistent with the other papers that like our work model the impact of congestion in omnichannel retailing (e.g., in Gao & Su, 2018). Another alternative practice in some other papers, which focus on different aspects of omnichannel retailing rather than the impact of congestion, is to endogenize the

fraction of customers switching to online shopping but keeping the shopping rate exogenous (e.g., in Gao & Su, 2017). Note that both approaches endogenize the total demand. In our numerical analysis in Section 5.1, we explore the sensitivity of our results to varying values of θ_s, θ_d, and θ_c.

3.2 | Retail store operations

We model the social/physical distancing guidelines to simultaneously restrict the number of customers allowed in the store (denoted by n). Since the occupancy limitations cause customers to wait at various stages of the shopping process (before entering the store, accessing products in aisles, and checking out), we model the waiting time experienced by in-store customers (w_s in Equation (1)) as the average sojourn time of an $M/M/1$ queue with service rate n/τ, where τ represents the average time a customer spends in the store in a shopping session. This modeling choice is consistent with the extant literature on the economic modeling of service operations (e.g., Anand et al., 2011; Yuan et al., 2021).

To distinguish between the parameters and variables under the three operating modes (whenever necessary), we use superscript "I" to represent the **i**n-store only shopping mode, superscript "D" to represent the **d**elivery mode, and superscript "C" to represent the **c**urbside pickup mode. Thus, after normalizing the market size to one, w_s in Equation (1) for the in-store and delivery modes follow:

$$w_s^I = \frac{1}{n/\tau - \bar{\theta}_s \lambda_s^I}, \quad (4)$$

$$w_s^D = \frac{1}{n/\tau - \left(\bar{\theta}_d \lambda_s^D + \theta_d \lambda_d\right)}. \quad (5)$$

It is implicit in Equations (4) and (5) that the average shopping time τ does not change with the customers' shopping rates and remains the same across in-store and delivery customers. In practice, most activities in shopping do not change with the basket size. For example, time for checking out is much less sensitive to the number of items in the cart (Wang & Zhou, 2018); similarly, shopping for online customers is carried out by gig-economy workers who may not be more efficient shoppers compared to in-store customers. We consider a model extension to allow the average shopping time to vary with the customer type and average expenditure per shopping session (and hence, the shopping rate) in Section 5.

In contrast to the delivery service provided through third-party firms, when the retailer provides the curbside pickup service by deploying its internal capabilities—as implemented by various retailers, including Kroger, Safeway, and Walmart (Masur, 2020)—it might be necessary to divert some of the resources from serving in-store customers to carrying out the tasks of picking up and packing grocery for curbside pickup customers. This reduces the available staff to help the in-store customers with activities such as

searching and finding grocery items and checking out. We operationalize this capacity loss by allowing the average time τ_c that the in-store customers spend in the store under the curbside pickup mode to be longer than the average time τ they spend under the other two operating modes. Specifically, we let $\tau_c = (1 + f(x))\tau$, where the general function f increases in the fraction x of the internal capacity used to fulfill the curbside pickup orders. Thus, under the curbside pickup mode, the average waiting time for in-store customers is as follows:

$$w_s^C = \frac{1}{n/\tau_c - \bar{\theta}_c \lambda_s^C}. \tag{6}$$

As noted, grocery retailers can adopt various measures to ensure customers' health safety during a pandemic (Bove & Benoit, 2020). Most of these measures are costly, and the cost increases with the number of store visits. For example, a larger store with higher daily traffic requires more frequent cleaning and sanitization of the shopping carts and surfaces and more disinfecting wipes and masks to hand out to shoppers. We aggregate all safety-related costs and model it as cost $C(\psi)$ incurred on each store visit, where $C(\psi)$ is increasing in the health safety efforts ψ. Thus, we can obtain the retailer's *profit rate* (i.e., the average long-run profit per unit time)[4] by multiplying the in-store customers' shopping rate $\bar{\theta}_s \lambda_s^I$ with the net profit $R(\lambda_s^I) - C(\psi)$ per shopping session as in Equation (7), where the equilibrium shopping rate λ_s^I is determined by solving Equations (1) and (4) (note that we normalize the market size by setting it to one).

$$\Pi^I = \left(R(\lambda_s^I) - C(\psi)\right)\bar{\theta}_s \lambda_s^I. \tag{7}$$

Under the delivery mode, the retailer does not collect all the revenue from online customers as the third-party delivery firm retains a significant cut (Kang, 2020). Let γ denote the fraction of the gross profit collected by the retailer. Therefore, we express the retailer's profit rate under the delivery mode as in Equation (8), where the respective equilibrium shopping rates λ_s^D and λ_d of the in-store and delivery customers are determined by solving Equations (1), (2), and (5).

$$\Pi^D = \left(R(\lambda_s^D) - C(\psi)\right)\bar{\theta}_d \lambda_s^D + \left(\gamma R(\lambda_d) - C(\psi)\right)\theta_d \lambda_d. \tag{8}$$

As mentioned earlier, most grocery retailers handle the curbside pickup service using their resources. Therefore, they can retain all the revenue from the online sales stream (unlike the delivery mode). However, they may need to hire additional staff for fulfilling curbside pickup orders. We use the systems' *volume-based capacity* concept—introduced in Allon and Federgruen (2007) and used in Yuan et al. (2021)—to determine the total capacity μ_c required for fulfilling the curbside pickup orders as follows:

$$\mu_c = \theta_c \lambda_c + \frac{1}{w_c}, \tag{9}$$

where the shopping rate λ_c for curbside pickup customers follows Equation (3); therefore, μ_c depends on the curbside pickup service premium p_c, minimum shopping amount $\underline{R}_c$, and expected pickup service waiting time w_c. Equation (9) ensures that the capacity μ_c meets the desired expected pickup service waiting time w_c set by the retailer—for example, to match it with the service waiting time of the third-party delivery platforms.

Suppose the retailer fulfills fraction x of required capacity μ_c by deploying its current resources and fulfills the remainder fraction $1 - x$ by hiring additional capacity at marginal cost g. In that case, we can express the retailer's profit rate under the curbside pickup mode as Equation (10), where the respective equilibrium shopping rates λ_s^C and λ_c of the in-store and curbside pickup customers are determined by solving Equations (1), (3), and (6).

$$\Pi^C = \left(R(\lambda_s^C) - C(\psi)\right)\bar{\theta}_c \lambda_s^C + (R(\lambda_c) + p_c)\theta_c \lambda_c$$
$$- (1 - x)g\mu_c. \tag{10}$$

In the remainder of the paper, we suppress dependencies of the notations to the parameters unless ambiguous; specifically, we denote $\alpha := \alpha(\psi) - h$ and $C := C(\psi)$ for the ease of the exposition of expressions. We provide the list of notations used in this paper in Table EC.1.

4 | MODELS ANALYSES AND RESULTS

This section presents our main findings on how the social/physical distancing occupancy limitations impact the retailer's store traffic and profit under the three operating modes. As the retailer's profit depends critically on the store traffic (Perdikaki et al., 2017), we begin our analyses by exploring the relationship between the customers' shopping rate λ and function $\lambda(R(\lambda) - C)$, the common building block of the profit functions (7), (8), and (10) under the three operating modes.

As customers shop less frequently (i.e., lower λ), the overall risk of virus transmission inside the store reduces. However, the potential downside is that it could hurt the grocery retailer's profit. On the other hand, less frequent shopping invokes bulk-shopping behavior causing customers to spend more per shopping session (i.e., higher average gross profit $R(\lambda)$ per session). In Lemma 1, we characterize the net effect of these two opposing forces on the function $\lambda(R(\lambda) - C)$, using it to derive some of our later results. We relegate all the proofs and technical details to the e-companion.

Lemma 1. *For $R(\lambda) = R_0 e^{\nu(\alpha_0 - \lambda)}$, the function $\lambda(R(\lambda) - C)$ is unimodal in λ. Let the threshold value $\lambda^* = \arg\max_\lambda\{\lambda(R(\lambda) - C)\}$, then $\lambda(R(\lambda) - C)$ is increasing for $\lambda < \lambda^*$ and decreasing for $\lambda > \lambda^*$.*

We can explain the unimodal structure, outlined in Lemma 1, in terms of how the customers' expenditure and

retailer's profit change as the shopping rate λ decreases. Due to the bulk-shopping behavior, as customers shop less frequently (i.e., lower shopping rate λ), they purchase larger baskets in each shopping session (which implies larger $R(\lambda)$). The joint influence of these two opposing factors on the function $\lambda(R(\lambda) - C)$ depends on whether the increase in the average expenditure (hence, gross profit $R(\lambda)$) per shopping session is higher or lower in proportion to the change in the shopping rate λ.

When customers frequently shop (i.e., the shopping rate λ is large), they purchase smaller baskets in each shopping session. In this case, as they start shopping less frequently (i.e., as λ decreases), for example, due to the fear of infection risk, their average expenditure per session (hence, $R(\lambda)$) increases more than proportionally because the bulk-shopping behavior becomes more evident. Consequently, the impact of bulk shopping dominates (which we refer to through the rest of the paper as *bulk shopping being significant*), and the function $\lambda(R(\lambda) - C)$ increases as λ decreases from its high levels.

However, when customers do not frequently shop (small values of the shopping rate λ), the impact of the bulk-shopping behavior on the average expenditure per session (hence, $R(\lambda)$) is already strong. In this case, a further decrease in the shopping rate λ is accompanied by a proportionally smaller increase in $R(\lambda)$. This can be attributed to the fact that the further rise in the already-large shopping baskets is limited by the customers' budget/space constraints. Consequently, the impact of the shopping rate dominates, and the function $\lambda(R(\lambda) - C)$ decreases as λ decreases.

4.1 | Impact of social/physical distancing store occupancy limitations

The occupancy limitations in response to social/physical distancing guidelines have several implications for retailers and the community. First, from a public-health perspective, limiting the store occupancy effectively reduces the pandemic spread in retail and grocery stores (NYS Department of Health, 2020). On the other hand, such limitations and the consequent loss of store traffic could impact the retailers' profit. In Sections 4.1.1 and 4.1.2, we focus on the impact of social/physical distancing on the grocery retailer's store traffic and profit, respectively.

4.1.1 | Impact of store occupancy limitations on store traffic

Occupancy limitations influence the shopping rate of in-store customers. Such occupancy limitations create waiting inconvenience for in-store customers causing them to adjust their shopping rates accordingly—a widespread phenomenon reported during COVID-19 (Kasprzak, 2020). Since in-store customers are the common component of the store traffic under the three operating modes, their equilibrium shopping rates under occupancy limitations, as we obtain in Lemma 2,

determine the store traffic and its implications on the infection risk and profit.

Lemma 2. *The equilibrium shopping rates of in-store customers follow Equations* (11)–(13) *under the in-store, delivery, and curbside pickup modes. The equilibrium in-store and overall shopping rates decrease as occupancy limitations become stricter* (*smaller values of n*).

$$\lambda_s^I = \frac{1}{2\bar{\theta}_s}\left(\bar{\theta}_s\alpha + \frac{n}{\tau} - \sqrt{\left(\bar{\theta}_s\alpha - \frac{n}{\tau}\right)^2 + 4\beta_w\bar{\theta}_s}\right), \quad (11)$$

$$\lambda_s^D = \frac{1}{2\bar{\theta}_d}\left(\bar{\theta}_d\alpha - \theta_d\lambda_d + \frac{n}{\tau} - \sqrt{\left(\bar{\theta}_d\alpha + \theta_d\lambda_d - \frac{n}{\tau}\right)^2 + 4\beta_w\bar{\theta}_d}\right), \quad (12)$$

$$\lambda_s^C = \frac{1}{2\bar{\theta}_c}\left(\bar{\theta}_c\alpha + \frac{n}{\tau_c} - \sqrt{\left(\bar{\theta}_c\alpha - \frac{n}{\tau_c}\right)^2 + 4\beta_w\bar{\theta}_c}\right). \quad (13)$$

Lemma 2 confirms the expected dynamics of our models: Stricter occupancy limitations result in lower store traffic in all operating modes. However, the store traffic reduction is not proportional to the decline in the store occupancy limit n. From Equations (11)–(13), it can be shown that the shopping rates of in-store customers λ_s^I, λ_s^D, and λ_s^C are concave increasing in the store occupancy limit n (i.e., $d^2\lambda_s^i/dn^2 < 0, i \in \{I, D, C\}$); that is, by a decrease in the store occupancy limitation, the store traffic decreases less proportionally, and more meaningful reductions in the store traffic can only be achieved when the store limits are severe. This shows that occupancy limitations need to be strict for the social/physical distancing protocols to efficiently control store traffic and the spread of contagion in grocery stores. This could explain why some local government protocols target limiting grocery stores occupancy to 20%–30% of their maximum capacity (Redman, 2020d).

The shopping rates of in-store customers (Equations (11)–(13)) and, hence, the store traffic under all operating modes are concave increasing in the grocery retailer's health safety efforts (i.e., $d\lambda_s^i/d\psi > 0$ and $d^2\lambda_s^i/d\psi^2 < 0, i \in \{I, D, C\}$). Therefore, if grocery retailers are concerned by their loss of foot traffic due to occupancy limitations, a remedy is to practice safe shopping measures and signal them to their customers. Such measures increase foot traffic from in-store customers (Moran, 2021) and generate more revenue for the retailer. At the same time, they control the contagion spread to some extent. The downside is that the cost of such safety measures could be high (Pacheco, 2020).

It is also worth noting that the in-store traffic and the mix of customers forming that traffic depend on the retailer's operating mode. Rearranging Equations (11)–(13) results in respective Equations (14)–(16), which imply that shopping rates of in-store customers are adjusted such that the *in-store service capacity* (n/τ under the in-store and delivery modes and n/τ_c under the curbside pickup mode) matches the traffic from those who enter the store augmented by some

safety capacity:

$$\frac{n}{\tau} = \bar{\theta}_s \lambda_s^I + \frac{\beta_w}{\alpha - \lambda_s^I}, \tag{14}$$

$$\frac{n}{\tau} = \left(\bar{\theta}_d \lambda_s^D + \theta_d \lambda_d \right) + \frac{\beta_w}{\alpha - \lambda_s^D}, \tag{15}$$

$$\frac{n}{\tau_c} = \bar{\theta}_c \lambda_s^C + \frac{\beta_w}{\alpha - \lambda_s^C}. \tag{16}$$

Under the in-store and curbside pickup modes, only in-store customers enter the store (explaining $\bar{\theta}_s \lambda_s^I$ and $\bar{\theta}_c \lambda_s^C$ in the right-hand sides of Equations (14) and (16)), whereas, under the delivery mode, delivery customers also add to the traffic entering the store as their orders are fulfilled by gig-economy workers who shop on their behalf (explaining $\bar{\theta}_d \lambda_s^D + \theta_d \lambda_d$ in the right-hand side of Equation (15)). Under the delivery mode, in-store and online customers share the service capacity n/τ. Therefore, delivery customers impose an externality on the in-store customers. If they shop more frequently, in-store customers will shop less frequently. We refer to this as the *congestion externality* and elaborate on its consequence in Section 4.2. Under the curbside pickup mode, pickup customers do not enter the store; however, they limit the capacity available to in-store customers ($n/\tau_c < n/\tau$ in Equations (14) and (16) as $\tau_c > \tau$). This imposes another type of externality on in-store customers, which we refer to as *capacity externality*, and we elaborate on its consequences in Section 4.3.

4.1.2 | Impact of store occupancy limitations on retailer's profit

By reducing the store foot traffic, occupancy limitations help control the contagion spread inside grocery stores, but they negatively impact shopping rates, as confirmed by Lemma 2. This reduction in traffic raises an immediate concern about the retailers' profitability (Antonucci, 2020). Hence, in Proposition 1, we show how the occupancy limitations affect the retailer's profit.

Proposition 1. *Under stricter occupancy limitations (i.e., a smaller n), the profit under each operating mode may sometimes increase ($d\Pi^i/dn < 0, i \in \{I, D, C\}$), even though the store traffic always decreases. Specifically, this happens when the adjusted base shopping rate is above a threshold (i.e., $\alpha > \lambda^*$) and the store occupancy limit n is above a threshold characterized by $\lambda_s^i = \lambda^*$.*

As a consequence of the imposition of social/physical distancing under COVID-19, it has been speculated that the store traffic reduction will result in lower profits for retailers (Antonucci, 2020). However, Proposition 1 lays out a situation in which occupancy limitations control the disease by reducing store foot traffic and resulting in higher profit for grocery retailers.

This counterintuitive result can be explained by considering customers' bulk-shopping behavior. As follows from Lemma 2, the equilibrium in-store customers' shopping rates λ_s^I, λ_s^D, and λ_s^C indeed decrease as the store occupancy limit n decreases (i.e., $d\lambda_s^i/dn > 0, i \in \{I, D, C\}$). However, the effect of this shopping rate change on the retailer's profit depends on whether the shopping rate is below or above the threshold value λ^* (Lemma 1). When the adjusted base shopping rate α and store occupancy limit n are higher than their thresholds (as specified in Proposition 1), in-store shopping rates are high. In this case, a reduction in the shopping rate due to stricter occupancy limitations is compensated by a proportionally higher increase in the customers' expenditure per shopping session (i.e., more significant bulk shopping), which increases the retailer's profit.

In light of this explanation, it is natural to ask whether customers exhibit the bulk-shopping behavior and whether it sustains during a pandemic. As the empirical findings in Bawa and Ghosh (1999) suggest, customers indeed increase their expenditure more than proportionally as they reduce their shopping rate. Also, recent anecdotal and empirical evidence points to the increased bulk-shopping behavior during COVID-19: For example, a survey shows that 42%–64% of customers buy goods in bulk in response to pandemic conditions (PWC, 2020). Another study shows that Americans' average weekly grocery spending increased by 17% during the COVID-19 pandemic, compared to the prepandemic period, despite making fewer shopping trips (CISION, 2020a).

Our findings in Proposition 1 mitigate the grocery retailers' concern about the negative impact of occupancy limitations on their profit (Antonucci, 2020). However, this assurance does not apply when the adjusted base shopping rate α is small (bulk-shopping behavior is not significant, i.e., $\alpha < \lambda^*$), or the occupancy limit n is very strict. Under these conditions, a reduction in the shopping rate is not adequately compensated by an increase in the expenditure per shopping session. As a result, the retailer's profit decreases as occupancy limitations become stricter.

It is also worth noting that the observation from Proposition 1 that the retailer may experience lower traffic and higher profit simultaneously is in contrast to the positive association between traffic and sales explored in the past literature (Chuang et al., 2016; Lam et al., 1998). This can be attributed to the fact that these papers focus on nongrocery retailing, in which bulk shopping may not be a factor. In line with our model, Perdikaki et al. (2017) allow sales to decrease with store traffic at high store traffic levels. Consequently, they find it is not optimal to increase the advertising budget (which boosts store traffic) when advertising is more effective.

The store occupancy limit n is, to a great extent, an exogenous operational factor imposed on grocery retailers. As mentioned earlier, grocery retailers were required to reduce their occupancy by 20%–50% of their maximum capacity during the COVID-19 pandemic (NYS Department of Health, 2020; Redman, 2020d). Therefore, retailers do not

control parameter n that captures store occupancy. However, their strategic position could determine whether or not they will fall in the category that will observe profit increase after imposing occupancy limitations. In Corollary 1, we link two characteristics of a grocery retailer, namely, customers' bulk-shopping tendency (parameter ν in the functional form $R(\lambda) = R_0 e^{\nu(\alpha_0 - \lambda)}$) and health safety effort level (parameter ψ), to how the occupancy limitations may impact its profit.

Corollary 1. *Grocery retailers are more likely to observe a profit increase after the imposition of occupancy limitations when: (i) they have customers with a higher bulk-shopping tendency (i.e., higher ν), or (ii) they practice more health safety efforts (i.e., higher ψ).*

Given the role of the bulk-shopping behavior in explaining Proposition 1, the effect of bulk-shopping tendency ν on whether the retailer's profit increases with the occupancy limitations (as specified in Proposition 1) is along the expected direction. Specifically, the threshold value λ^*, which determines whether the retailer's profit increases after occupancy limitations, decreases as ν increases (i.e., $d\lambda^*/d\nu < 0$). In other words, the significance of the bulk-shopping behavior (i.e., the more than proportional increase in customers' expenditure with reduced shopping rate) prevails for a broader range of adjusted base shopping rates.

The effect of higher health safety efforts on whether the retailer's profit increases with occupancy limitations is less obvious. We can explain this by noting two changes that accompany an increase in the retailer's health safety effort level ψ: First, as the cost C is increasing in ψ, a higher health safety effort increases the marginal cost of serving each customer, which results in the threshold value λ^* to decrease. Second, due to the lower risk of infection resulting from higher safety efforts, the adjusted base shopping rate α increases as customers have more confidence in the safety of their shopping. As a result of these changes, the significance of the bulk-shopping behavior, which occurs when $\alpha > \lambda^*$, prevails for a broader range of adjusted base shopping rates.

Proposition 1 suggests that in the case of more severe pandemics, a retailer should not be wary of embracing measures to ensure social/physical distancing inside the store (limiting the store occupancy) since these conditions are likely to result in an increased bulk-shopping behavior among customers. Retailers may also devise other strategies that intensify bulk shopping, for example, by adopting assortment decisions that favor larger product packages. Proposition 1 also suggests that an efficient strategy to mitigate the risk of losing profit under occupancy limitations is to practice high levels of health safety efforts, explaining significant investments in such measures by many grocery retailers during the COVID-19 pandemic (Pacheco, 2020).

4.2 | Impact of offering delivery service

In the face of customers' fear of becoming infected while shopping in stores and the stores' social/physical distancing occupancy limitations, many retailers sought to provide delivery service during the COVID-19 pandemic as a safer shopping option, especially for more susceptible customers (Kim, 2020). While in-store shopping remained the most common form of grocery shopping, the use of delivery services surged substantially during COVID-19. According to a survey, 62% of grocery shoppers continued shopping in-store, while 12% relied on delivery services during the COVID-19 pandemic (CISION, 2020b).

Most retailers cannot carry out delivery operations themselves, and the general approach is to partner with third-party delivery services, like Instacart (Jia et al., 2021). While this strategy allows retailers to scale their presence in delivery and boost sales under normal circumstances (Redman, 2020c), the study of the impact of such a strategy on the store traffic and retailers' profit in the presence of occupancy limitations deserves attention, which we examine in Sections 4.2.1 and 4.2.2.

4.2.1 | Impact of delivery service on store traffic

According to Lemma 2, the occupancy limitations reduce the shopping rates and store traffic under the in-store mode. Providing the delivery service brings another dimension affecting the store traffic. The adoption of delivery services by grocery retailers surged after the COVID-19 pandemic in response to the high interest in this service. Nearly 80% of the American grocery shoppers used the delivery (or pickup) service after the COVID-19 pandemic, and more than half of the users of such services increased their online shopping frequency after the pandemic (Redman, 2020a).

Though the delivery service provides safe shopping for customers who are willing to pay the delivery premium, the impact on the store traffic in the presence of occupancy limitations is not clear. Not only the store traffic could impact the in-store customers' (those who are not willing to pay the delivery premium) shopping satisfaction, but it also has implications on their access to groceries and the disease spread inside retail stores (Sugar, 2020). In Proposition 2, we show whether offering the delivery service reduces the store traffic.

Proposition 2. *Under occupancy limitations, adding the delivery service may sometimes increase store traffic (i.e., $\bar{\theta}_d \lambda_s^D + \theta_d \lambda_d > \bar{\theta}_s \lambda_s^I$) despite reducing in-store customers' shopping rates (i.e., $\lambda_s^D < \lambda_s^I$) and their contribution to the store traffic (i.e., $\bar{\theta}_d \lambda_s^D < \bar{\theta}_s \lambda_s^I$). Specifically, this occurs if the delivery premium and the minimum shopping amount are not sufficiently high (i.e., $p_d < (\alpha_0 - \lambda_s^I \bar{\theta}_s / \theta_d - \beta_w' w_d)/\beta_p$ and $\underline{R}_d < R(\lambda_s^I \bar{\theta}_s / \theta_d)$).*

Though adding online channels in nongrocery retail settings has been shown to reduce store traffic (Hernant & Rosengren, 2017), this might not be the case in a grocery retail setting under occupancy limitations, as noted in Proposition 2. The proposition follows from the fact that the demand from delivery customers directly contributes to the store congestion, as their orders still need to be fulfilled by the gig-economy workers who enter the stores to shop on their behalf. Under normal conditions, when retailers do not have occupancy limitations (beyond their nominal capacity), demand from delivery customers imposes minimal effect on in-store customers. However, under occupancy limitations, delivery customers impose a congestion externality on in-store customers because in-store and delivery customers have to share the limited available capacity.

Suppose delivery premium and the minimum requires shopping rate are not sufficiently high (i.e., $p_d < (\alpha_0 - \lambda_s^I \bar{\theta}_s / \theta_d - \beta_w' w_d)/\beta_p$ and $\underline{R}_d < R(\lambda_s^I \bar{\theta}_s / \theta_d)$). Then, their convenience-driven frequent shopping of delivery customers will increase the overall store traffic (with those conditions, we will have $\theta_d \lambda_d > \bar{\theta}_s \lambda_s^I$) and force in-store customers to decrease their shopping rates due to higher wait times and infection risk. The impact of congestion externality on in-store customers could be severe because delivery customers face neither the inconvenience of waiting nor the infection risk themselves. This congestion effect is evident in the growing frustration of in-store customers about stores overcrowding due to the abundance of gig-economy shoppers picking products on behalf of delivery customers (Haddon & Kang, 2019). Due to their apparent advantages, the increased popularity of delivery services exacerbated this effect during the COVID-19 pandemic (Sugar, 2020).

From a public health perspective, Proposition 2 implies that the popularity of delivery services could lead to higher stores traffic (if the delivery premium and the minimum required shopping amount are not properly set), resulting in a higher rate of disease spread inside grocery stores and eventually in communities. Though delivery service is a safe shopping option for those customers who use it, the overall impact on public health could be damaging. Furthermore, there have been concerns about the higher infection risk for delivery workers due to the nature of their work, as they cannot always ensure social/physical distancing in stores (Rani & Dhir, 2020).

Thus, when retailers make partnership decisions with third-party firms, two levers to control the impact of delivery demand surge on the store traffic under occupancy limitations are the delivery premium and the minimum required shopping amount. Both must be sufficiently high, so they do not cause the negative implications of congestion externality, such as limiting the in-store customers' access to groceries, inferior in-store customer satisfaction due to overcrowding and long wait times, and a higher risk of infection. Of course, the delivery premium and the minimum required shopping amount also impact the retailers' profit. The best-case scenario is that the retailer hinders all negative implications of congestion externality and can obtain higher profit under occupancy

limitations. Next, we explore the impact of offering delivery service on the retailers' profit in the presence of occupancy limitations.

4.2.2 | Impact of delivery service on retailer's profit

Proposition 2 highlights the challenge retailers face when introducing the delivery service in the presence of occupancy limitations. Retailers hope to give an alternative shopping channel for some of their customers. This may boost the overall demand but could adversely impact the shopping rate of in-store customers. As the shopping rates of customers who continue shopping in-store and those who switch to online shopping change under the delivery mode (compared to the shopping rates under the in-store mode), their expenditure per shopping session also changes. We show in Proposition 3 that the net effect of these changes could lower the retailer's profit under the delivery mode in the presence of occupancy limitations.

Proposition 3. *Under occupancy limitations, adding the delivery service may reduce the retailer's profit, even when it increases the profit in the absence of occupancy limitations if θ_s is below a threshold (i.e., $\theta_s \leq \bar{\theta}_d (1 - \frac{(R(\lambda_s^D) - C)\lambda_s^D}{(R(\lambda^*) - C)\lambda^*})$). Specifically, this happens when the adjusted base shopping rate is above the threshold value (i.e., $\alpha > \lambda^*$), the delivery premium p_d is within a range (i.e., $p_d \in ((\alpha_0 - \alpha - \beta_w' w_d)/\beta_p, (\alpha_0 - \underline{\alpha} - \beta_w' w_d)/\beta_p)$), and the minimum shopping amount is not adequately high (i.e., $\underline{R}_d < R(\underline{\alpha})$), where $\underline{\alpha} < \alpha$ satisfies $(R(\underline{\alpha}) - C)\underline{\alpha} = (R(\alpha) - C)\alpha$.*

The widespread adoption of delivery services by grocery retailers during the COVID-19 pandemic might give the impression that this strategy always helps retailers overcome the possible demand and profit reduction due to customers' fear of contagion with in-store shopping (Sugar, 2020). However, Proposition 3 shows that this is not always the case under occupancy limitations. We can explain this finding as follows. In the absence of occupancy limitations, adding the delivery service may result in higher profit when customers' bulk-shopping behavior is significant (i.e., $\alpha > \lambda^*$). Specifically, this occurs if the delivery premium and the minimum required shopping amount are such that customers who switch to the delivery service shop at a rate that amplifies their bulk-shopping behavior, resulting in an increased profit accrued from them.

However, in the presence of occupancy limitations, offering the delivery service creates a congestion externality causing in-store customers to lower their shopping rates, as we showed in Proposition 2. When $\alpha > \lambda^*$ (the bulk-shopping behavior is already significant), though in-store customers' lower shopping rate could marginally signify the bulk-shopping effect more, it cannot compensate for the effect of lower shopping rates. On the other hand, those

customers who begin using the delivery service could generate lower profit than when shopping in-store, as they might start shopping more frequently if the delivery premium or the required minimum shopping amount is not properly set. Therefore, the severe congestion externality on one side and the attenuation of the delivery customers' bulk shopping from the other side could lower the retailer's profit after adding the delivery service in the presence of occupancy limitations. Of course, if a significant fraction of customers stop shopping in the absence of delivery service (i.e., θ_s is too large), adding the delivery service will result in higher profit for the retailer.

The potential downsides of adding the delivery service on the retailers' profit in the presence of occupancy limitations could be even more pronounced for two reasons: First, in Proposition 3, we consider that the retailer retains all the profit from the online sales through the delivery service (i.e., $\gamma = 1$). However, the third-party firms that provide delivery services usually retain a significant portion of the retailers' profit (i.e., $\gamma < 1$). For example, Instacart charges a commission of more than 10% on each order (Kang, 2020). Second, as the pool of customers under the delivery mode changes to a mix of in-store and online customers, the cross-selling opportunity to in-store customers reduces, further lowering the retailer's profit (Eley & McMorrow, 2020).

In summary, adding the delivery service under occupancy limitations reduces the shopping rate of in-store customers but increases the shopping rate of online customers and may increase the overall shopping rate. The combined effect of the delivery premium, the minimum required shopping amount, and occupancy limitations on the shopping rates may result in the retailer losing the opportunity to benefit from in-store customers' bulk-shopping behavior and earning lower profit. In the absence of the retailer's control on the delivery premium or the minimum delivery shopping amount, partnering with third-party delivery services may not be a reasonable strategic decision.

The growing literature on omnichannel retailing has primarily assumed that retailers' foray into delivery is profitable due to market expansion, that is, selling products online allows the retailer to attract new customers (Brynjolfsson et al., 2009). In the grocery retailing context during a pandemic, the interest in delivery services is instead driven by the customers' preference shift from in-store shopping to the safer delivery option (Wang et al., 2020). Under these conditions, our results shed light on how delivery services could affect the shopping behavior of in-store customers. In Section 5.1, we investigate the impact of market expansion after adding the delivery service in our model.

4.3 | Impact of offering curbside pickup service

Curbside pickup service is another strategy adopted by retailers during the COVID-19 pandemic to mitigate the potential negative consequences on demand and profit. Curbside pickup is similar to the popular BOPS service employed by many large non-grocery retailers (Gallino & Moreno, 2014; Song et al., 2020). Curbside pickup became more popular than BOPS during the pandemic as it provided a high level of protection for customers and staff by minimizing person-to-person contact. Compared to the delivery service, curbside pickup is a more straightforward strategy for retailers as it does not always require a high amount of new infrastructure investment (Meyer, 2020). Furthermore, partnerships needed for executing curbside pickup are much less demanding; for example, online shopping platforms like Shopify allow retailers to take curbside pickup orders for a modest monthly fee (Hensel, 2020). We analyze the effect of adding this service on the store traffic and the retailer's profit under occupancy limitations in Sections 4.3.1 and 4.3.2, respectively.

4.3.1 | Impact of curbside pickup service on store traffic

The curbside pickup service possesses fundamentally different characteristics than the delivery service that its addition warrants separate investigation. Unlike the delivery mode, online customers under the curbside pickup mode do not directly create extra store congestion (as they do not enter the store). Nevertheless, they contribute *indirectly* to the store congestion by occupying some of the staff capacity who now need to perform fulfillment activities, such as picking and assembling curbside pickup orders. As a result, less staff help is available for the in-store customers (Lesavage & Maak, 2021), extending the average time τ_c they spend in the store if the retailer satisfies fraction x of the required capacity for curbside pickup using its current resources (as mentioned in Section 3.2, we can use an increasing function in x, like $\tau_c = (1 + f(x))\tau$, to connect τ_c, τ, and x). The average time τ_c should not be overextended, as the resulted capacity loss will be too severe that customers are not willing to shop in-store due to its inconvenience. We address the impact of curbside pickup service on the in-store traffic under occupancy limitations in Proposition 4.

Proposition 4. *In the presence of occupancy limitations, adding the curbside pickup service may result in a decline in the shopping rate of in-store customers (i.e., $\lambda_s^C < \lambda_s^I$), which in turn reduces the store traffic (i.e., $\bar{\theta}_c \lambda_s^C < \bar{\theta}_s \lambda_s^I$). Specifically, this occurs if the resulted service capacity loss is beyond a threshold (i.e., $n/\tau - n/\tau_c > (\bar{\theta}_s - \bar{\theta}_c)\lambda_s^C$).*

Past research on BOPS has highlighted increasing store traffic (Gallino & Moreno, 2014). However, we show in Proposition 4 that the curbside pickup service could reduce the store traffic under occupancy limitations. In this case, the demand from curbside pickup customers imposes an externality on in-store customers who experience wait during their shopping. As opposed to the delivery mode, this *capacity* externality manifests itself through the loss of service capacity if the capacity required for curbside pickup is

primarily allocated using the current resources. The service capacity loss could be so severe (specifically, $n/\tau - n/\tau_c > (\bar{\theta}_s - \bar{\theta}_c)\lambda_s^C$) that it creates inconvenience of longer waits for in-store customers under occupancy limitations, reducing their shopping rate and potentially limiting their access to grocery shopping.

As we mentioned earlier, the externalities imposed on in-store customers under the delivery mode could be associated with their dissatisfaction with stores overcrowding during the COVID-19 pandemic (Sugar, 2020). Similarly, though offering the curbside pickup service provides convenient and safe shopping for those customers who adopt it, it could negatively impact the in-store customers' shopping rate if the capacity is not allocated properly between the two channels. Adding capacity by hiring more staff can mitigate the capacity externality under the curbside pickup mode. However, such a strategy has cost implications for the retailer, depending on the required service capacity μ_c and the fraction x of the required capacity filled by the current resources (we elaborate on this issue in Section 4.3.2).

In our earlier discussion about the delivery mode (in Section 4.2.1), we noted that the higher in-store traffic could attribute to a higher risk of disease spread (compared to the in-store mode). However, it is not reasonable to connect the in-store traffic and the risk of infection (to compare the curbside pickup and in-store modes) because the risk of disease spread in confined-space service facilities depends both on the store traffic and how long customers spend in a store, among other factors (Stadnytskyi et al., 2020; Tupper et al., 2020). In comparing the in-store and delivery modes, the duration of time customers spend in the store is the same (on average, τ units of time). However, the curbside pickup service impacts the store traffic (as shown in Proposition 4) and results in a longer in-store duration (on average, $\tau_c > \tau$). In Section 5.1, we numerically explore the implication of the interaction of the store foot traffic and the time that customers spend in the store on the infection risk of in-store customers.

4.3.2 | Impact of curbside pickup service on retailer's profit

Like the delivery service, adding the curbside pickup service under occupancy limitations could have opposing impacts on the operations of the grocery retailer. Though the curbside pickup service may boost the overall demand, it may also reduce the shopping rate of in-store customers if it results in a substantial capacity externality (Proposition 4). We show in Proposition 5 that by properly setting the curbside pickup premium and minimum shopping amount requirement, the curbside pickup could overcome its potential disadvantages and result in a higher profit than the other two operating modes.

Proposition 5. *Under the curbside pickup mode and occupancy limitations, the retailer can achieve a higher profit compared to the other two operating modes by choosing*

an appropriate pair $(p_c, \underline{R}_c)$ for the curbside service premium and minimum shopping amount as long as the health safety efforts level ψ is above a threshold; specifically, $\psi > C^{-1}(\frac{(1-x)g\mu_c}{\theta_c \lambda_s^C})$ for $\Pi^C > \Pi^I$, and $\psi > C^{-1}(\frac{(1-x)g\mu_c}{\theta \lambda_d})$ for $\Pi^C > \Pi^D$ when $\theta_c = \theta_d = \theta$.

Proposition 5 highlights that curbside pickup mode can earn the retailer higher profit than the in-store and delivery modes at sufficiently high health safety efforts. To explain this, note that all customers contribute to the health safety costs under both in-store and delivery modes.[5] When the health safety efforts level ψ is high, the associated cost reduces the profit under the in-store and delivery modes. However, under the curbside pickup mode, those customers who use the service do not contribute to the store traffic as they do not enter the store. Therefore, health safety initiatives need to be provided only for in-store customers. Thus, retailers save on health safety expenses. However, this saving may not directly translate to higher profit due to the capacity externality and its impact on the shopping rates, as discussed in Section 4.3.1. The curbside premium p_c and minimum shopping amount $\underline{R}_c$ can be set to control the impact of capacity externality such that the corresponding shopping rate λ_c induces bulk shopping. This, when combined with the cost-saving from the health safety efforts, results in higher profit under the curbside pickup mode.

Past research has attributed the increase in retailers' profit after the BOPS implementation to cross-selling, that is, BOPS customers shop more during their pickup visits (Gallino & Moreno, 2014). Proposition 5 shows that this could occur even under curbside pickup where such cross-selling opportunities are not available as curbside pickup customers do not enter the stores.

We note that when the curbside pickup service does not result in a significant service capacity loss, the store traffic may increase (i.e., $\bar{\theta}_c \lambda_s^C > \bar{\theta}_s \lambda_s^I$). This result echoes the empirical findings in Gallino and Moreno (2014) in the context of BOPS implementation in non-grocery retailing. Like Gallino and Moreno (2014), existing studies on BOPS have primarily focused on non-grocery retail settings and have found that BOPS is beneficial to the retailer based on the type of product (Gao & Su, 2017) and the potential for pooling inventory (Hu et al., 2021). In grocery retail, specifically under the pandemic-induced service capacity limitations, other factors such as waiting times and customers' bulk-shopping behavior are the main drivers of benefits of the curbside pickup service.

5 | MANAGERIAL IMPLICATIONS AND MODEL EXTENSIONS

This section discusses managerial insights from our main model and considers additional model extensions to illustrate their robustness to various modeling choices.
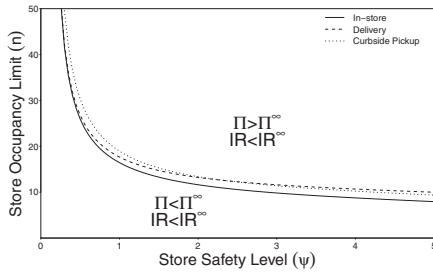
FIGURE 1 Win-win scenarios (curbing the infection risk and gaining a higher profit)

5.1 | Managerial implications

5.1.1 | Insights about store occupancy limitations

The insights from our models reveal that though occupancy limitations reduce stores traffic, they are not always accompanied by a reduction in retailers' profit. To some extent, this mitigates the concerns that some grocery retail managers might have about the negative implications of social/physical distancing guidelines on their profitability. When customers practice bulk shopping and occupancy limitations are not too severe, the increase in customers' basket sizes could offset the reduction in the store traffic and even increase the retailers' profit. In such cases, occupancy limitations lead to a "win-win" scenario where retailers can help to curb the infection risk inside their stores (and eventually, in communities) and can do so without hurting their profitability.

Figure 1 illustrates that the aforementioned win-win scenario is achievable under the three operating modes.[6] The infection risk depends on the store traffic and the time customers spend inside the store (Stadnytskyi et al., 2020; Tupper et al., 2020). Accordingly, in Figure 1, we measure the infection risk (denoted by IR) under the in-store, delivery, and curbside pickup modes as $IR^I = \bar{\theta}_s \lambda_s^I \tau$, $IR^D = (\bar{\theta}_d \lambda_s^D + \theta_d \lambda_d^D)\tau$, and $IR^C = \bar{\theta}_c \lambda_s^C \tau_c$, respectively. Letting Π^∞ and IR^∞ denote the profit and infection risk when there is no occupancy limitation, the win-win scenario can be defined as conditions $\Pi > \Pi^\infty$ and $IR < IR^\infty$ (i.e., an increase in the retailer's profit and a reduction in the infection risk under occupancy limitations). The figure specifies such scenarios based on different values for the health safety efforts ψ and store occupancy limits n (the two interventions to reduce the risk of infection inside the stores).

As Figure 1 shows, the win-win scenario is achievable when occupancy limitations are not too restrictive (i.e., n is not too small). Though a strict n reduces the infection risk, the consequent decline in the store traffic results in profit loss. When occupancy limitations are moderate, higher investment in health safety efforts (i.e., higher ψ) could turn the profit loss under a specific store occupancy to profit gain. In other words, despite being costly, investment in health measures allows retailers to weather the potential negative impact of occupancy limitations better.

It is plausible that the store occupancy limit beyond which the win-win scenario is achieved (for a specific health safety effort level ψ) is smaller under the in-store mode than the delivery and curbside pickup modes (as shown in Figure 1). We can explain this as follows: One of the factors that helps the retailer gain higher profit after the imposition of occupancy limitations is the increase in the bulk-shopping behavior. Under both the delivery and curbside pickup modes, online customers' shopping rate (and consequently, their bulk-shopping tendency) is not affected by the occupancy limitations. Thus, the retailer's profit is more susceptible to decline with occupancy limitations under the delivery and curbside pickup modes.

5.1.2 | Insights about offering the delivery service

Our delivery model highlights that while adding the delivery service may effectively reduce store traffic and improve retailers' profit when the store occupancy limitation is not restrictive, it could underperform as occupancy limitations become restrictive. Our results show the adverse impact of store congestion caused by delivery customers; as they neither face the infection risk nor experience the waiting inconvenience from store congestion, their shopping behavior does not adjust to the prevailing conditions. Additionally, their shopping activity negatively impacts the in-store customers' shopping rate. A combination of these factors can ultimately reduce retailers' profit compared to the in-store mode.

Figure 2a–c depicts this insight by comparing Π^I and Π^D. Here, we observe that when the occupancy limitations are not very restrictive (i.e., n is not too low), adding the delivery service increases the profit (the top regions where $\Pi^I < \Pi^D$). However, as the occupancy limit n becomes sufficiently (but not extremely) small, adding the delivery service hurts the profit (i.e., the regions where $\Pi^I > \Pi^D$). When the store occupancy limit n becomes extremely restrictive, we observe small regions where $\Pi^I < \Pi^D$ again; in such regions, the store occupancy is so limited that the shopping rate of in-store customers approaches zero, due to severe waiting inconvenience (though that region is theoretically possible, in practice, limitations are not restrictive in that magnitude).

Figure 2a–c also shows that the abovementioned observations continue to hold as we change the fraction θ_d of delivery customers, their shopping rate λ_d (determined by delivery premium p_d, minimum shopping amount $\underline{R}_d$, and service waiting time w_d), and the fraction $\theta_s = 1 - \bar{\theta}_s$ of in-store customers who turn away if delivery service is not available. These observations continue to hold as we experiment with different values of the fraction γ of the profit the retailer collects from delivery customers (in Figure 2, $\gamma = 0.95$). This shows the robustness of our general insights from the delivery model to these parameter values. As a side note, in line with Proposition 3, Figure 2c highlights that as more customers stop shopping from the retailer in the absence of the
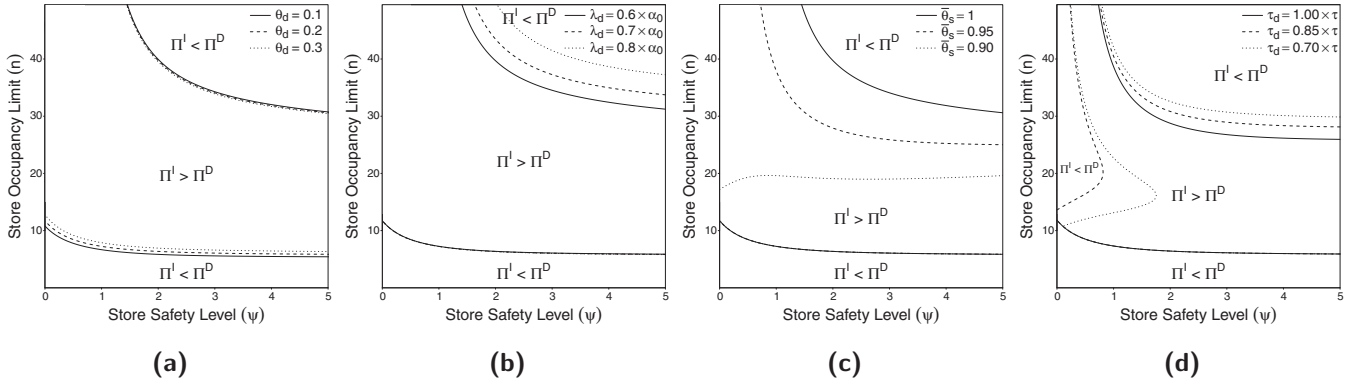
FIGURE 2 Comparing the in-store and delivery modes

delivery service (larger θ_s), the delivery mode outperforms the in-store mode more often.

A modeling extension to the delivery model is to consider that gig-economy workers shopping on behalf of delivery customers shop more efficiently than the in-store customers. This could be because they could shop for multiple delivery customers simultaneously. To allow for this higher efficiency, in Figure 2d, we consider the shopping time τ_d for delivery customers to be shorter than the shopping time τ of in-store customers. Figure 2d shows this extension does not significantly impact the main insights from how delivery mode compares with the in-store mode when the health safety efforts ψ is sufficiently large ($\psi > 2$ in Figure 2d). However, for smaller values of ψ, the delivery mode results in a higher profit than the in-store mode for a broader range of store occupancy limits n. Overall, this suggests that the higher efficiency of gig-economy shoppers does not always translate into better performance for the delivery mode relative to the in-store mode.

5.1.3 | Insights about offering the curbside pickup service

Finally, our analysis suggests that implementing the curbside pickup service (using the retailer's resources) may be more effective than the delivery service in ensuring profitability and curbing the disease spread inside grocery stores. The key to achieving this is properly setting the curbside pickup premium and minimum shopping amount and sufficient health safety efforts. These measures allow for better control of the capacity externality that curbside pickup customers impose, sufficient profit from curbside pickup customers, and sufficient frequent shopping trips by the in-store customers.

Figure 3 illustrates the aforementioned insights and highlights the robustness of these insights to the parameter values. Similar to the plot for the delivery mode (Figure 2), we observe in Figure 3 that when the occupancy limitations are not very restrictive, adding the curbside pickup service increases the profit in case the curbside pickup premium and minimum shopping amount are set properly. As the store

occupancy becomes sufficiently (but not extremely) limited, adding the curbside pickup service hurts the profit (i.e., the region where $\Pi^I > \Pi^C$). As in Figure 2, we observe $\Pi^I < \Pi^C$ when the store occupancy limit becomes extremely small, as the occupancy is impractically so limited that the in-store customers' shopping rate approaches zero.

We also observe that as the health safety efforts ψ increases, the curbside pickup generates higher profit than the in-store mode (i.e., $\Pi^I < \Pi^C$) at more restrictive store occupancy limits n. This further highlights the importance of health safety efforts in improving the efficacy of the curbside pick service under occupancy limitations. The four panels in Figure 3 suggest that the aforementioned insights are robust to different parameters, including the change in the fraction θ_c of curbside pickup customers, shopping rate λ_c of curbside pickup customers (where λ_c is determined by the curbside pickup premium p_c, minimum required shopping amount $\underline{R}_c$, and service waiting time w_c), the degree of the store capacity loss τ_c / τ after adding the curbside pickup service, and the fraction $\theta_s = 1 - \bar{\theta}_s$ of customers who turn away if curbside pickup service is not available.

5.2 | Model extensions

We consider two modeling extensions in Sections 5.2.1 and 5.2.2.

5.2.1 | Offering delivery and curbside pickup services (Combined Mode)

This section considers a model extension in which the retailer employs both delivery and curbside pickup services. We continue considering that the delivery service is provided in partnership with a third-party delivery firm, whereas the curbside pickup service is offered using the retailer's resources. Let θ'_d and θ'_c denote the fractions of delivery and curbside pickup customers under the combined model; then $1 - \theta'_d - \theta'_c$ represents the fraction of in-store customers. We present the detailed formulation of the combined model in Section EC.4 of the Supporting Information.
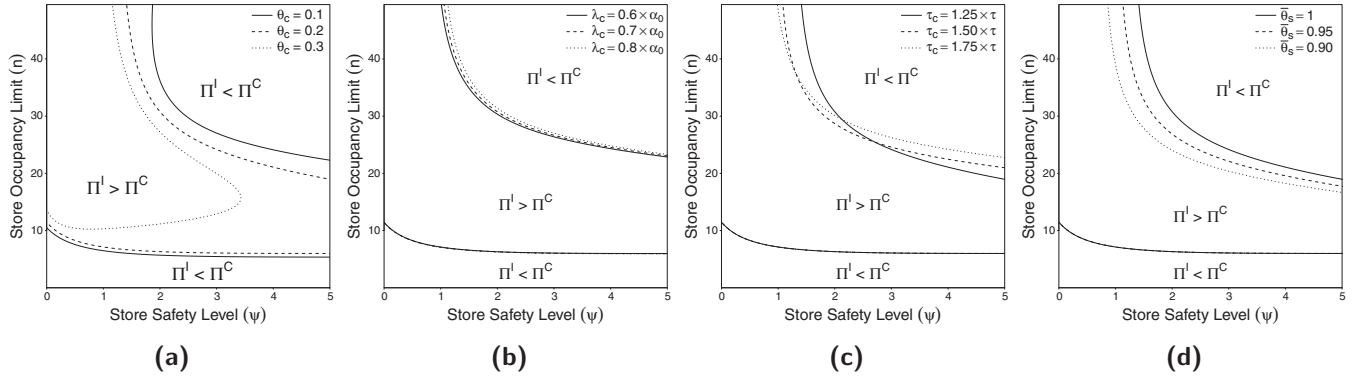
FIGURE 3   Comparing the retailer's profit under the in-store and curbside pickup modes
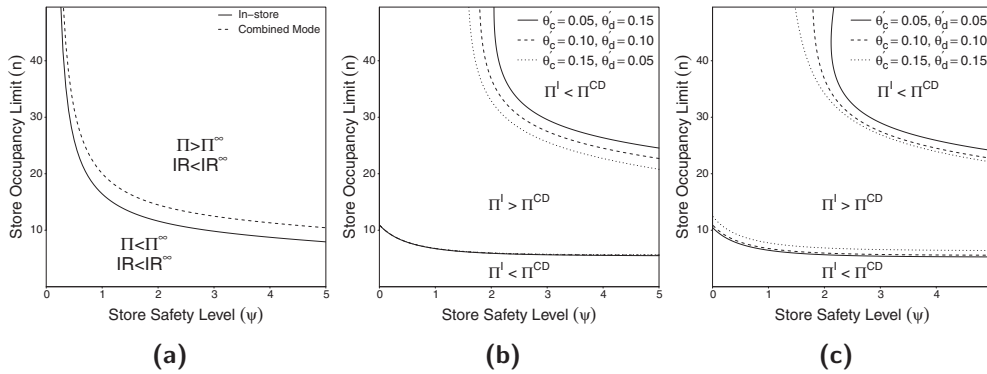

FIGURE 4   Combined delivery and cubside pickup services

Figure 4a shows that the win-win scenario is again achievable under the combined mode when the occupancy limitations are not too restrictive. Like the other modes, higher safety efforts help the retailer achieve higher profit and curb the infection risk. Figure 4b (in which we vary θ'_d and θ'_c while fixing $\theta'_d + \theta'_c$) shows that as the fraction θ'_c of curbside pickup customers becomes more dominant in the mix of online customers, the performance of the combined mode improves compared to the in-store mode. Finally, Figure 4c (in which we change $\theta'_d + \theta'_c$ while fixing the ratio $\theta'_d/\theta'_c = 1$) shows that similar to the delivery and curbside pickup modes, the combined mode performs better for a more extensive range of n and ψ combinations, relative to the in-store model, as the total fraction $\theta'_d + \theta'_c$ of online customers increases. Finally, a comparison of Figure 4 with Figures 1–3 suggests that the combined model's overall insights align with the delivery and curbside pickup modes.

5.2.2 | Dependence of shopping time on expenditure

In this section, we consider an extension of our primary model in which in-store customers' shopping time varies with the customers' expenditure, and hence with their shopping rate, to capture that customers purchasing a larger basket spend longer time in the store. In this extension, we allow
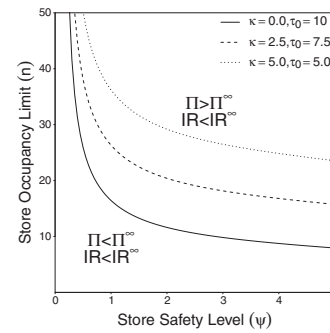

FIGURE 5   Shopping time and expenditure

for the shopping time to depend on the shopping rate λ_s using the function $\mathcal{T}(\lambda_s) = \tau_0 + \kappa \times e^{\gamma'(\alpha_0 - \lambda_s)}$, where τ_0 is the fixed portion of shopping time, and κ is the value of the variable part of the shopping time when shopping rate $\lambda_s = \alpha_0$. When $\kappa = 0$, this function converges to our main model with the shopping time being a constant.

Given the functional form $\mathcal{T}(\lambda_s)$, Equations (1) and (4) can be solved numerically to determine the equilibrium shopping rate λ_s. However, we can show analytically that, similar to our main model, λ_s decreases with stricter occupancy limitations (i.e., n becomes smaller). Thus, in this model extension, stricter occupancy limitations have a similar effect on customers' bulk-shopping behavior and hence the retailer's

profit. We capture this in Figure 5, where we display the win-win scenario for different values of variable shopping time κ. Based on this similarity with observations from our main model, we expect insights from our model to be robust to this extension.

6 | CONCLUDING REMARKS AND FUTURE DIRECTIONS

This paper mainly focuses on how a pandemic affects grocery retailers and how retailers can effectively respond by balancing between profitability and curbing the infection risk inside stores. The central premise of our analytical models is that occupancy limitations transform grocery stores into capacity-constrained systems, which need to make difficult trade-offs. We find that though store occupancy limitations reduce the in-store foot traffic (which helps curb the disease spread), they do not necessarily result in a profit decline. Such win-win scenarios occur when occupancy limitations are not too restrictive. Our analyses further highlight the externality impact of online customers on in-store customers' shopping behavior. Under the delivery mode, such externalities may increase the store traffic and reduce the retailer's profit. Whereas, under the curbside pickup mode, the retailer can better control the impact of externalities, which helps reduce the store traffic and increase profit. Finally, when the occupancy limitations are not very restrictive, adding the delivery or curbside pickup service could increase the profit if the corresponding premiums and minimum shopping amounts under the two modes are appropriately set.

Future work can explore several directions. First, given the insufficient empirical understanding of online purchasing behavior, we considered the gross profit function $R(\lambda)$ the same across in-store and online customers. Given the rise of online grocery shopping, future research can empirically explore how $R(\lambda)$ could be different for online customers and take that into account in the analytical models. Second, future research can consider the detailed interaction of third-party delivery platforms with the grocery retailer. Future research can also explore the impact of pandemic conditions and the consequent changes in customers' shopping behavior in other settings of omnichannel retailing, including the existence of both delivery and curbside pickup services; another example includes BOPS with cross-selling opportunities. Finally, our model's gross profit function $R(\lambda)$ only accounts for costs-of-goods-sold and not inventory-related costs (i.e., ordering and holding). As discussed in Section EC.5 of the Supporting Information, including these costs will not qualitatively affect our results in most cases. However, in cases where bulk shopping results in a steep increase in inventory costs, these factors must be accounted for in the decision-making process.

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ENDNOTES
[1] A "shopping session" corresponds to a trip to the grocery store in the case of in-store shopping and corresponds to visiting the store's website in the case of online shopping.
[2] We consider $\beta'_w < \beta_w$ as online delivery customers wait at the comfort of their home or while running other tasks.
[3] The curbside pickup service could also involve waiting at the pickup site (the time it takes for the store staff to bring the groceries outside); however, this waiting is negligible compared to the service waiting w_c. For this reason, and to not complicate the model representation, we exclude the waiting time at the curbside pickup site.
[4] For brevity, in the remainder of the paper, we refer to the profit rate as simply "profit," unless ambiguous.
[5] Under the delivery mode, delivery customers contribute to store traffic via the gig-economy workers who shop on their behalf.
[6] The parameter values used for Figure 1 and other plots are provided in Section EC.3 of the Supporting Information.

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