

The Hidden Cost of Grocery Delivery Platforms

To accommodate consumers' growing demand for online grocery shopping while avoiding the high costs of in-house fulfillment, brick-and-mortar retailers increasingly partner with third-party grocery delivery platforms. These platforms differ in how they shape consumers' shopping incentives and the competitive environment faced by retailers on the platform. We study how membership-based versus pay-per-order platforms affect retailer profitability by jointly influencing demand expansion and within-platform demand reallocation. We develop a stylized model that decomposes the value of platform partnerships into market expansion and leakage-driven market contraction, and show how this tradeoff is moderated by product characteristics including consumption rate, in-store price, and price dispersion across competing retailers. We test these predictions using a quasi-experimental setting based on the rollout of online delivery partnerships by regional grocery chains operating more than 700 stores across seven U.S. states. Empirically, partnering with a membership-based platform increases product-level gross profit by 2.2% on average, whereas partnering with a pay-per-order platform reduces gross profit by 2.9%, with heterogeneous effects consistent with the model's predictions. Counterfactual simulations further show that selectively offering products on each platform can substantially improve partnership value. Together, our results highlight that platform partnership choice should be guided not only by access to online demand, but also by how platform design interacts with product attributes and the competitive environment it creates.

Key words: Online grocery, platform partnerships, theoretical model, difference-in-differences, market dynamics

History: February 7, 2026

1. Introduction

Consumers increasingly rely on online channels for grocery shopping, with over 90% of U.S. shoppers engaging in both in-store and digital formats and digitally enabled grocery spending projected to reach \$388 billion by 2027 [NielsenIQ \(2025\)](#). To remain competitive, many grocery retailers have expanded into in-house online delivery, but high fulfillment costs—driven by labor-intensive picking, packing, and last-mile delivery—strain already thin margins ([Ghai 2024](#)). Consequently, several retailers partner with third-party grocery delivery platforms that manage product display, in-store picking, and home delivery while pooling orders across multiple retailers to exploit economies of scale and reduce per-order fulfillment costs ([Oberlo 2024](#)). This rapidly growing market—projected to reach \$1.12 trillion globally by 2028—includes both established grocery platforms such as Instacart and Shipt and multi-service delivery platforms such as DoorDash, Postmates, and Uber Eats ([Meisenzahl 2024](#), [Nasdaq 2024](#), [YahooFinance 2024](#)). [LW: During our sample period, Shipt operated exclusively under a membership-based model, offering free delivery above

a minimum order threshold. In contrast, although Instacart offers a membership option, members are still subject to a mandatory 5% service fee which is similar to pay-per order fees.¹ In more recent examples, platforms typically maintain a dominant pricing model but increasingly operate both membership and pay-per-order options, at least in selected markets. For instance, Amazon Fresh UK opened access to non-members in June 2024, while Baemin and foodpanda introduced membership options in 2024 and 2023, respectively. Some local platforms remain pay-per-order only, such as Demae-can, HungryPanda (only in certain locations), Didi Food, and SF Intra-city; however, the grocery partners on these platforms are generally not mainstream household brands.] As this market continues to expand, an important, yet understudied, feature of retailer-platform partnerships is how platforms monetize delivery services. Grocery delivery platforms differ fundamentally in their payment mechanisms. For example, retailers such as Morrisons, Carrefour, and Iceland partner with Amazon Fresh UK that employs a *membership-based model*, in which customers pay a fixed monthly or annual fee and can place unlimited orders without per-order delivery charges.² In contrast, retailers such as Kroger, Albertsons, and Walmart partner with Deliveroo, Postmates, or DoorDash. These platforms primarily use a *pay-per-order model*, in which consumers pay no membership fee but incur a delivery fee for each order. These payment models likely induce distinct customer demand patterns. Membership-based platforms may stimulate customers to order more frequently to amortize the fixed subscription fee over more transactions. Conversely, pay-per-order platforms may reduce customer adoption frictions associated with upfront membership fees and expand the retailer's online market reach. Overall, it is unclear how retailers should choose between these two payment models when forming partnerships. To this end, we address the following research questions: (i) *What is the value of platform partnerships under membership-based versus pay-per-order payment models?* and (ii) *How should retailers choose between platform payment models?*

To answer our research questions, we collaborate with a grocery retailer operating 570 brick-and-mortar (BM) stores under four banners across seven U.S. states. In 2018, the retailer partnered with Shipt, then primarily offering a membership-based model, for one banner and with Instacart, then primarily using a pay-per-order platform, for another banner. The retailer announced these partnerships only after launching platform-facilitated online delivery services, rendering the partnerships plausibly exogenous to customers' purchasing behavior and representing a unique opportunity for a quasi-experimental study. Leveraging this setting, we adopt a multimethod research approach. First, we develop a stylized model that captures the key features of retail–platform partnerships

¹ <https://www.grocerydive.com/news/instacart-slashes-membership-and-delivery-fees/543180/>

² Amazon Fresh UK allows for non member to access with higher fee and restrictive delivery slots.³

and consumer purchase behavior and derive theoretical insights. Second, using 39 weeks of product-level sales data before and after the partnerships, we implement a difference-in-differences design to empirically test and support our theoretical predictions.

Drawing on our analyses, we make several contributions. First, our theoretical model highlights a fundamental trade-off underlying retailer–platform partnerships that operates through two opposing mechanisms. Partnering with delivery platforms such as Shipt (membership-based) and Instacart (pay-per-service) expands a retailer’s effective market reach by granting access to consumers who live beyond the retailer’s physical catchment area and would otherwise be infeasible to serve. Irrespective of their payment models, both platforms also lower consumers’ hassle costs by enabling convenient home delivery and, crucially, by allowing customers to aggregate groceries from multiple retailers into a single order. This aggregation feature, however, generates an offsetting force. Prior to platform adoption, consumers located within a retailer’s reach typically sourced the entirety of their grocery basket from that focal retailer. After joining a platform, even these nearby consumers can reallocate portions of their basket across competing retailers while still enjoying the benefits of a single consolidated delivery. We refer to the first mechanism as the *market expansion effect*, which enlarges the retailer’s customer base, and the second as *market contraction due to aggregation*, which reduces the share of a customer’s total grocery expenditure captured by the focal retailer. The net profitability impact of platform participation depends on the balance between these two effects. Our empirical results show that, the market expansion effect dominates the contraction effect on average for Shipt, whereas the opposite holds for Instacart. Consequently, partnering with Shipt increases retailer profits by 2.2% on average, while partnering with Instacart decreases profits by 2.9%, providing a clear example of how delivery platforms can bring substantial benefits for some platforms but costly setbacks for others.

Second, our theoretical model characterizes how the balance between market expansion and market contraction effects varies with three key parameters: consumer consumption rate, product price level and price dispersion on the platform. When the consumption rate increases, average cart values would naturally rise. Even though partnering with a platform may reduce the proportion of a consumer’s cart allocated to the focal retailer, the market expansion due to increase in cart value dominates this contraction effect. As a result, higher consumption rates strengthen the net value obtained from partnering with a delivery platform irrespective of whether the platform operates under a membership or pay-per-service payment model. However, price levels and dispersion affect the expansion–contraction trade-off differently across payment models. Specifically, as both price levels and price dispersion increase, consumers have stronger incentives to reallocate portions of their carts toward the competing retailers hosted on the platform, which intensifies the negative market contraction effect for both fixed-fee and pay-per-service platforms. Here comes a relative

advantage for fixed-fee membership platforms. Namely, under a fixed-fee model, consumers can place additional orders at basically no incremental cost, whereas a pay-per-service model limits the number of orders placed by consumers. Therefore, the strengthened contraction effect arising from higher prices or greater price dispersion is offset by increasing market expansion effect under a fixed-fee model, whereas it is not under a pay-per-service model. Accordingly, our theoretical analyses predict that higher price levels and dispersion increase the value of partnering with a membership-based platform but decrease the value of partnering with a pay-per-service platform. To test these findings empirically, we use in-store product price along with two proxy variables. We operationalize the consumption rate of a product as the average number of units purchased per week across all customers buying that product. To measure platform price dispersion, we obtained detailed pricing data from Numerator, covering all products offered by any retailer on Instacart and Shipt. For each product, we calculate the standard deviation of prices for comparable products on a given platform. Consistent with our theoretical predictions, our empirical analyses show that the effect of partnering with Shipt on profits is positively moderated by in-store price, consumer consumption rate, and platform price dispersion. In contrast, the effect of partnering with Instacart on profits is positively moderated by consumer consumption rate, but negatively moderated by in-store price and platform price dispersion.

Third, our sensitivity analyses above provide clear guidance on how retailers should choose between membership-based and pay-per-service platforms. First of all, the comparative statistics above immediately imply that as product prices or dispersion increase, membership-platforms become relatively more attractive for the retailers. However, increases in consumption rates raise the value of both payment models, therefore, the comparison between them becomes less straightforward. Our theoretical comparison of values under the two models reveals that the relative attractiveness of membership versus pay-per-service depends on the range of consumption level. Specifically, when serving consumer bases with relatively low consumption rates, the value of partnering with a pay-per-service platform increases more rapidly than that of a membership platform, whereas the opposite holds when the consumption rates are relatively high. This non-monotonicity suggests an important managerial implications: retailers operating in dense downtown areas with a higher prevalence of single-person households are better suited to pay-per-service platforms, while retailers serving residential areas with larger households benefit more from membership-based partnerships.

Finally, our theoretical analyses imply that the value of a platform partnership can be further improved through product selection that aligns with the underlying payment model. Namely, our earlier results suggest that designing assortments that emphasize higher-priced or more price-dispersed products are especially well suited for membership platforms, while designing

assortments on pay-per-service platforms that emphasize lower-priced, less price-dispersed products can weaken market contraction effects and even reverse the overall value of the partnership. Indeed, we empirically quantify the gains from such selective assortment decisions by using a counterfactual analysis. The results show that restricting platform offerings to products identified by our theoretical criteria increases the impact of partnering with Shipt on total gross profit from 2.2% to 8%, and transforms the effect of partnering with Instacart from a negative 2.9% to a positive 1.4%. These findings yield clear managerial insights: retailers partnering with pay-per-service platforms should prioritize commodity items with relatively stable prices on prominent platform placements, whereas retailers partnering with membership-based platforms benefit more from featuring niche or higher-priced products with greater price dispersion, particularly on the platform's front page.

To summarize, our findings have implications for grocery retailers deciding whether and how to partner with membership-based or pay-per-order platforms. In particular, the value of a partnership depends on product, consumer, and platform characteristics, and can vary across different product offerings. Overall, managers should carefully evaluate which platform partnership best aligns with these attributes and selectively determine which products to display through the platform to ensure alignment with their operational priorities and profitability goals.

2. Literature Review

Our study is related to three literature streams: third-party food delivery platforms, membership versus pay-per-order delivery services, and omnichannel retailing.

2.1. Third-Party Food Delivery Platforms

Much of the existing research in this stream has focused on the restaurant sector, documenting both the benefits and drawbacks of platform adoptions. For instance, [Raj et al. \(2020\)](#) highlight the critical role of food delivery platforms in sustaining small restaurant resilience when in-person dining was halted during the COVID-19 outbreak. Similarly, [Li and Wang \(2025\)](#) find that restaurants generally benefit from these platforms, with increases in both takeout and dine-in sales. However, prior research also documents important challenges. [Karamshetty et al. \(2020\)](#) show that heavy reliance on food delivery platforms hamper restaurants' demand forecasting accuracy and increases food waste. Leveraging an episode of these platforms' aggressive restaurant onboarding without permission, [Mayya and Li \(2021\)](#) find that platforms can lead to a net demand loss for independent restaurants, as declines in dine-in traffic outweigh gains in takeout orders. Addressing operational frictions between delivery and dine-in channels, [Feldman et al. \(2023\)](#) propose a coordinating contract to mitigate negative channel interactions. Finally, using a queuing model that distinguishes between traditional and tech-savvy customers, [Chen et al. \(2022\)](#) demonstrate that

for restaurants with a large base of traditional customers, platform adoption may not be profitable, as platforms add delivery costs without sufficiently increasing demand.

Research on the adoption of food delivery platforms in the grocery sector remains relatively scarce. Unlike the restaurant industry, grocery retail is highly concentrated, with most platform-partnering retailers operating at national or regional scale. Consequently, grocery retailers may face distinct strategic and operational challenges when partnering with third-part delivery platforms. Using an analytical model, [Delasay et al. \(2021\)](#) examine the impact of the COVID-19 pandemic on grocery retail operations and show that platform adoption can increase store traffic, but may reduce retailer profits. [Rabello de Castro \(2020\)](#) study the timing of entry for a grocery delivery platform and highlight a first-mover advantage in building a loyal customer base, while [Rabello de Castro \(2019\)](#) analyze platform entry decisions in the presence of switching costs and show that switching costs significantly shape consumer platform choice.

Despite this emerging literature, we are not aware of any study that examines third-party grocery delivery platform partnerships through the lens of platform payment structures. We contribute to this stream by (i) theoretically and empirically investigating the value of platform partnerships under membership-based versus pay-per-order models and (ii) analyzing how retailers should choose between these payment structures when forming platform partnerships.

2.2. Delivery Fee Structures in Online Retail

The literature on online delivery fee policies examines how different shipping fee structures affect consumer behavior and retailer profitability. Early work by [Lewis \(2006\)](#) and [Lewis et al. \(2006\)](#) shows that shipping fees significantly influence customer acquisition, retention, and purchase quantities. [Gümüş et al. \(2013\)](#) compare partitioned pricing—where shipping fees are charged separately—with non-partitioned pricing, in which delivery costs are included in the product price. Another stream of research studies contingent free shipping, where customers receive free delivery when their orders exceed a specified threshold. For example, [Leng and Becerril-Arreola \(2010\)](#) study joint pricing and contingent free shipping decisions in monopoly and duopoly settings; [Hemmati et al. \(2021\)](#) examine the interaction between contingent free shipping and return policies, and [Li et al. \(2023\)](#) investigate optimal thresholds for online grocery retailing, finding that consumer top-up behavior plays a key role in policy design.

More recently, research has focused on membership-based versus pay-per-use delivery. [Balakrishnan et al. \(2024\)](#) find that membership-based delivery increases profits by encouraging purchase frequency, while [Belavina et al. \(2017\)](#) show that memberships lead to more frequent but smaller grocery orders compared to per-order pricing. Empirical work by [Guo and Liu \(2023\)](#) documents that membership-based delivery builds lock-in effects that increase purchase frequency

and order size over time, and Fang et al. (2021) show that membership delivery enables better market segmentation, allowing retailers to charge higher product prices.

A key feature of prior research is its focus on retailer-controlled delivery fee policies. In contrast, platform-mediated delivery fee policies are determined by third-part platforms, requiring retailers to operate within platform-driven constraints. We contribute to this literature by examining how two types of platform-mediated delivery fee policies affect retailer profitability.

2.3. Omnichannel Retailing

Partnering with a third-party delivery platform constitutes a form of platform-enabled omnichannel retailing, whereby a brick-and-mortar retailer extends its physical operations into a digitally mediated ordering and delivery channel. A related stream of research has examined omnichannel partnerships that expand a retailer's service offerings in various settings. For example, Nageswaran et al. (2024) theoretically study a return partnership in which a pure online retailer collaborates with an offline retailer that serves as an in-store return location. Hwang et al. (2022) empirically demonstrate that return partnerships can generate incremental sales for the offline partner. Dan et al. (2022) analytically investigate showrooming partnership, focusing on how an online retailer selects between competing and non-competing offline partners. More recently, Jalali et al. (2026) examine a pickup partnership model in which an online retailer collaborates with an offline partner to provide in-store pickup for online orders. Despite these advances, this literature has thus far remained silent on partnerships involving third-party delivery platforms. Even within the broader omnichannel retailing literature, although prior studies have explored the integration of physical and digital channels through buy-online-pickup-in-store (Gallino and Moreno 2014, Gao and Su 2017), showrooming (Bell et al. 2018, Gao et al. 2022), and ship-to-store (Gallino et al. 2017, Ertekin et al. 2022), no study examines how offline and online channels interact when customers pay for online delivery under a membership-based model versus a pay-per-order model. We contribute to this stream by analyzing how delivery membership fees versus per-order delivery fees shape the dynamics between offline and online channels, when the online channel is operated by a third-party delivery platform.

3. Theoretical Model

In this section, we develop a stylized model to examine how platform partnerships affect retail profitability under the membership-based and pay-per-order payment mechanisms, and to identify conditions guiding retailers' choice between the two. We first introduce the motivating business context, then present the modeling framework. We conclude by analyzing the model and deriving theoretical predictions that we empirically test in Section 7.

3.1. Business Context

The focal grocery retailer operates its stores under four distinct banners, each of which targets different customer segments and geographic markets. As a result, operational decisions such as inventory assortment, product pricing, and payroll management are decentralized and made at the individual banner level. This structure allows each banner to tailor its offerings, pricing strategies, and promotional activities to local market conditions and customer preferences. In contrast, broader strategic decisions are centralized at the corporate level to ensure consistency and alignment with the retailer's long-term objectives. These corporate decisions include initiatives such as whether to introduce a grocery delivery service, which third-party platform to partner with, and how to phase the rollout of such partnerships across stores and banners.

NE: Who makes the operational decisions, i.e., inventory, pricing, and payroll etc., is the decision making centralized at the headquarters or delegated to store managers? For instance, do we see fixed prices across stores for the same product? Prior to May 2018, all banners operated exclusively through brick-and-mortar (BM) stores. In May 2018, the retailer launched online delivery services at two banners, partnering with Shipt for one banner and Instacart for another banner.

NE: We need the provide the following information that can help motivate some model assumptions.

- Some information about consumer consumption rates with supporting statistics from the data. E.g., majority of customers are repeat customers with 65% purchase from the retailer every week. This will be helpful to justify Assumption 1. Or, even if the statistics is not available, some institutional knowledge about this would be great.

- Some statistics about basket size, in particular the average quantity of a purchased item in a single transaction. For instance, if a customer purchased 2 of the same ice cream and 5 of the same chocolate bar, I would like to report the mean (i.e., 3.5) and the range (2 to 5). Along with the repeated customers, this can be helpful to motivate the customer EOQ model and the associated holding cost etc.

- Any information about consumer the market share of the retailer in different regions? This can help us motivate the outside option.

When regional retailers partnered with a delivery platform, customers gained access to same-day grocery delivery from their local stores. Through the platform's mobile app or website, customers could browse the store's full product assortment, add items to a virtual cart, choose a delivery window, and receive their orders at home, fulfilled by a personal shopper of the platform operating out of the local store. The platform managed the entire transaction, including the user interface, payment processing, fulfillment logistics, and customer service.

Shipt operated under a strictly membership-based model: customers were required to purchase an annual \$99 membership to use the service at all, which provided unlimited free delivery on orders over \$35. Without a membership, Shipt was inaccessible. In contrast, Instacart primarily followed a pay-per-order model, charging delivery fees depending on location and timing. Although Instacart also offered an optional Express membership, even members were subject to a mandatory 5% service fee per order.

- What changed for customers with the launch of these services with respect to their purchase options? Explain how customers utilize these services.

- Detail the membership for Shipt and pay-per-order for Instacart. If we can provide some pictures about how membership vs. pay-per-order look like on these platforms, that would be great. For instance, a snapshot of the unlimited delivery for the membership would be nice. Both platforms control the prices of products listed on their marketplaces, charging a premium over retailers' in-store prices. Shipt generally applies a lower price premium than Instacart.⁴ Retailers receive revenue as if customers were shopping in person, since items are picked directly from store shelves by the platforms' in-store shoppers and processed through the standard in-store checkout system.⁵

Both platforms set the prices of products offered on their marketplaces, charging a premium over retailers' in-store prices. Shipt generally applies a lower price premium than Instacart.⁶ Retailers receive revenue as if customers were shopping in person, as items are picked directly from store shelves by the platforms' in-store shoppers and processed through the standard in-store checkout system. Instacart has followed an aggressive, cumulative retail expansion strategy, resulting in a substantially larger retail partner network over time. By 2023, Instacart worked with more than 1,400 retailers,⁷ whereas Shipt partnered with approximately 130 retailers as of 2024.⁸

- Some statistics or institutional knowledge about the fact that one platform charges more than the other for the same product. This will help with the differing prices between the two. Also information on the fact that platforms charge more than the retailer.

- What were the fees charged on each platform? Was there any difference in assortment displayed on the platform between the two? Any difference between the two with respect to the delivery performance?

⁴ <https://savingslifestyle.com/shipt-instacart-grocery-delivery-service/>

⁵ <https://wgme.com/news/i-team/price-check-new-report-reveals-big-price-gaps-between-instacart-and-in-store-shopping-maine-inflation-convenience>

⁶ <https://savingslifestyle.com/shipt-instacart-grocery-delivery-service/>

⁷ <https://research.contrary.com/company/instacart1>

⁸ <https://www.supermarketnews.com/grocery-trends-data/shipt-completes-major-expansion>

- How did the competitive landscape look on each platform? What was the number of retailers available on each platform at that time. Perhaps, we can get this info from the two platforms if they report this publicly
- Additional information regarding the details of the contract between the retailer and these platforms. This can be used to justify that the retailer continues to earn the in-store price from the platform-mediated transactions even though the plarform charges more.
- A summary of key changes—among those discussed above—for customers with the launch of these services

3.2. Model Framework

Consider a grocery retailer with a brick-and-mortar (BM) store facing a decision on whether to partner with an online delivery platform. In line with real-life practices, we examine two types of online delivery models. The first model is membership-based, where consumers pay an annual membership fee for unlimited free deliveries. In this paper, we refer to it as the Online Membership platform, denoted by OM. Shipt, an American delivery service owned by Target Corporation, operates on this membership-fee model. The second model involves online delivery platforms that charge a delivery fee per order. Hereafter, we refer to it as the Online Per-order platform, denoted by OP. This approach is widely used by Instacart, an American delivery company offering grocery delivery and pick-up services in the United States and Canada.

We consider consumers who consume a product at a constant known rate r , incur inventory holding cost h per unit of grocery per unit time, and make purchases when their inventory is depleted. The consumer's purchase quantity, whether from the brick-and-mortar store or the online platform (in the case of an online partnership), is influenced by the hassle costs associated with each channel. To enhance readability, a list of notation is provided in Table 1. The following sections describe the shopping behavior for each model.

3.3. Benchmark: No Partnership Model

We begin by examining the benchmark scenario, denoted as BM, where the grocery store operates solely from its BM location and does not collaborate with any online delivery service. In this scenario, customers make only planned visits to the store (Ho et al. 1998). We assume that customers face a fixed travel cost, v , which represents the imputed cost of travel time. Considering that consumers may be uniformly distributed (Belavina et al. 2017), we assume that travel cost v is heterogeneous among consumers, such that $v \sim U[0, 1]$. Upon arriving the store, observing the price p_b in the BM store, the customer determines the quantity Q_{BM} to purchase. In deciding how much to buy, consumers take into account fixed travel costs, inventory costs, and purchasing

Table 1 List of notations

Parameter	Definition
$i \in \{\text{BM}, \text{OM}, \text{OP}, \text{OO}\}$	Index for the BM store ($i = \text{BM}$), Online Membership ($i = \text{OM}$), Online per-Order ($i = \text{OP}$), and Outside Option ($i = \text{OO}$) Channels
$v \sim U[0, 1]$	Cost of visiting the BM store; consumers are heterogeneous w.r.t. v
r	Consumer consumption rate
p_b	Product price in BM store
p_o^i	Product price in online platform $i \in \{\text{OM}, \text{OP}\}$
p_R	Consumer reference price
σ_p	Price dispersion in online platform
$U(p_R - \sigma_p, p_R + \sigma_p)$	Price p distribution in an online platform with C.D.F $F(p)$
K	Annual cost of purchasing from outside option (e.g. local convenience store)
ϕ	Annual membership fee collected by the online platform $i = \text{OM}$
λ	Delivery cost per order from per-Order online platform $i = \text{OP}$
c	Cost of sourcing grocery for retailer
h	Consumer holding cost per unit per time

costs. The aim of the consumer is to choose the purchase quantity Q_{BM} that minimizes the overall inventory cost:

$$\min_{Q_{\text{BM}}} C_{\text{BM}} = p_b r + v \left(\frac{r}{Q_{\text{BM}}} \right) + h \left(\frac{Q_{\text{BM}}}{2} \right) \quad (1)$$

Analogous to the economic order quantity (EOQ) model, it can be shown that the order quantity $Q_{\text{BM}}^* = \sqrt{\frac{2vr}{h}}$ minimizes Eq. (1). Thus, at optimality, the total inventory cost for visiting the BM store becomes $C_{\text{BM}} = p_b r + \sqrt{2hvr}$.

To reflect real-world behavior, we model no-purchase scenarios where a consumer opts not to buy from the BM store and instead chooses an outside option, denoted as OO (e.g., a local convenience store). Let K represent the long-term cost of purchasing from an outside option. This implies that consumers with zero visit cost ($v = 0$) will choose the outside option when $K \leq p_b r$. To ensure meaningful analysis and avoid trivial cases, we assume $p_b r \leq K$. The following lemma characterizes the optimal shopping behavior in the absence of partnerships, where the grocery retailer operates solely through the BM store.

LEMMA 1. Suppose the retailer operates solely through the BM store. The consumer chooses to purchase from BM store if $v \in [0, v^{\text{BM} \rightarrow \text{OO}}]$, and outside option if $v \in [v^{\text{BM} \rightarrow \text{OO}}, 1]$, where $v^{\text{BM} \rightarrow \text{OO}} = \frac{(K - p_b r)^2}{2hr}$.

According to Lemma 1, the proportion of consumers inclined to buy from the BM store grows with $v^{\text{BM} \rightarrow \text{OO}}$. This quantity rises with the outside option cost, K , but diminishes concerning the consumer's holding cost, h , product price in BM store, p_b , and the consumption rate, r .

4. Partnership with Online Platforms

A grocery store considering a partnership with an online delivery platform faces two strategic options. The first is to collaborate with an *online membership-based* platform, denoted by OM; the second is to work with an *online per-order* platform, denoted by OP. Before analyzing these two

partnership models, we develop a parsimonious framework for a consumer's purchasing behavior when shopping through an online delivery platform.

We focus on grocery categories with sufficiently high purchase and consumption velocity. Let \bar{r}^{OM} and \bar{r}^{OP} denote the platform-specific consumption thresholds that arise endogenously in our analysis (formally characterized later). We assume:

ASSUMPTION 1. *The products offered in online delivery platform are fast-moving consumer goods:*

$$r \geq \bar{r} \triangleq \max \left\{ \bar{r}^{\text{OM}}, \bar{r}^{\text{OP}} \right\}. \quad (2)$$

Assumption 1 aligns with the empirical setting of grocery delivery platforms: groceries and other fast-moving consumer goods are replenished frequently and exhibit high purchase and consumption velocity. For example, Canadian household shoppers report an average of 1.8 grocery baskets per week and 86% shop at least weekly ([Flipp Market Research 2025](#)). Accordingly, Assumption 1 is particularly appropriate for fast-moving categories, which are characterized by limited shelf space, noticeable shelf rotation, and regular replenishment from distribution centers (often at least weekly) ([Hübner and Kuhn 2024](#)). In such environments, joint decisions on assortment, shelf-space assignment, and replenishment are central ([Reiner et al. 2013](#), [Bianchi-Aguiar et al. 2021](#)). Imposing Assumption 1 therefore improves tractability and sharpens the exposition by allowing us to abstract from slow-moving categories that are peripheral to our grocery application and would otherwise introduce additional cases that are theoretically possible but empirically less salient.

Next, consider a consumer who purchases through an online delivery platform. When the retailer joins platform $i \in \{\text{OM}, \text{OP}\}$, the product's listed online price may differ from the BM-store price p_b . Let p_o^i denote the retailer's posted price on platform i . In line with industry practice, the retailer continues to receive p_b from the platform even though the consumer pays p_o^i , where $p_o^i > p_b$. Because platforms list similar products from multiple retailers, the consumer's choice of retailer is inherently probabilistic and depends on perceived relative prices and preferences. We capture this feature by assuming that the distribution of competing retailers' posted prices on the platform, denoted by p_p , is uniform: $p_p \sim U(p_R - \sigma_p, p_R + \sigma_p)$, with cumulative distribution function $F(\cdot)$. Here, p_R is the consumer's reference price—the internal benchmark against which posted prices are evaluated ([Fibich et al. 2003](#), [Amaldoss and He 2018](#), [Thaler 2008](#))—and σ_p measures the extent of price dispersion across retailers for similar products on the platform.

Given the retailer's posted price p_o^i , the probability that the consumer perceives this retailer as the lowest-priced option (and thus purchases from it) is $\Pr(p_o^i \leq p_p) = 1 - F(p_o^i) = \frac{p_R + \sigma_p - p_o^i}{2\sigma_p}$. Conversely, with probability $\Pr(p_p \leq p_o^i) = F(p_o^i) = \frac{p_o^i - p_R + \sigma_p}{2\sigma_p}$, the consumer finds a lower posted price elsewhere and purchases from another retailer. In that event, we assume the consumer pays

the average of the lower-priced alternatives, which under the uniform distribution is $\frac{p_o^i + p_R - \sigma_p}{2}$. Therefore, the expected price paid by the consumer when shopping on platform i is

$$(1 - F(p_o^i)) p_o^i + F(p_o^i) \left(\frac{p_o^i + p_R - \sigma_p}{2} \right),$$

which simplifies to

$$\bar{P}_o^i = p_o^i - F(p_o^i) \left(\frac{p_o^i - p_R + \sigma_p}{2} \right), \quad i \in \{\text{OM, OP}\}. \quad (3)$$

In the next sections, we characterize the consumer's purchasing decision under the two partnership models and compare these outcomes with the benchmark (Lemma 1) to quantify the value of partnering with an online delivery platform for the grocery store.

4.1. Partnership with Online Membership Platform

In this section, we develop and examine a partnership model where the grocery store, in addition to its BM store, collaborates with an online platform delivery company that works under membership-fee model (similar to the Shipt). Therefore, in the partnership model, the consumer has three choices: (i) shop from an outside option at an average cost of K , (ii) shop from the BM store, incurring a cost v for every time visiting the store and purchasing at a price p_b , and (iii) pay membership fee ϕ , purchase at a price p_o^{OM} and benefit from unlimited free delivery⁹. The first two options have been discussed earlier in §3.3. Below, we elaborate on the last option.

Suppose the consumer opts to purchase from the online platform. The consumers chooses the purchase quantity Q_{OM} to minimize the total cost, including membership fee, the expected cost of purchase, and inventory cost:

$$C_{\text{OM}} = \phi + \bar{P}_o^{\text{OM}} r + h \left(\frac{Q_{\text{OM}}}{2} \right) \quad (4)$$

where \bar{P}_o^{OM} is defined in Equation (3). From Eq. (4), the consumer, who benefits from unlimited free delivery, can reduce the inventory holding cost (i.e., $h(\frac{Q_{\text{OM}}}{2})$) to zero by placing very small orders only when the product is needed. In other words, at optimality, the consumer orders based on a *order-for-use* policy, which theoretically means $Q_{\text{OM}} \rightarrow 0$. The total cost if consumer opts for online membership option is therefore $C_{\text{OM}} = \phi + \bar{P}_o^{\text{OM}} r$. By comparing the total costs for consumers under three different options—shopping outside, at the BM store, and through online orders—one can characterize the optimal shopping behavior in the partnership model with an online membership platform:

LEMMA 2. Let $\phi^{\text{OM}} = \frac{(\sigma_p^2 - 2(p_R + p_o^{\text{OM}})\sigma_p + (p_R - p_o^{\text{OM}})^2)r + 4K\sigma_p}{4\sigma_p}$. When partnering with OM-based platform, the consumer's optimal purchasing decision is as follows

⁹We recognize that unlimited delivery in the annual membership model, like Shipt, may require a minimum purchase amount. However, for simplicity and without loss of generality, we normalize this threshold to zero.

- If $\phi \leq \phi^{\text{OM}}$: the consumer chooses to purchase from BM store if $v \in [0, v^{\text{BM} \rightarrow \text{OM}}]$, and online with membership option if $v \in [v^{\text{BM} \rightarrow \text{OM}}, 1]$, where $v^{\text{BM} \rightarrow \text{OM}} = \frac{(\phi + r(\bar{P}_o^{\text{OM}} - p_b))^2}{2hr}$.
- If $\phi > \phi^{\text{OM}}$: the consumer chooses to purchase from BM store if $v \in [0, v^{\text{BM} \rightarrow \text{OO}}]$, and outside option if $v \in [v^{\text{BM} \rightarrow \text{OO}}, 1]$, where $v^{\text{BM} \rightarrow \text{OO}} = \frac{(K - p_b r)^2}{2hr}$.

From lemma 2, it can be verified that a partnership has no effect on consumers' purchasing behavior when the membership cost is relatively high ($\phi > \phi^{\text{OM}}$). Under this condition, the consumer considers purchasing from the BM store or an outside option. Thus, the analysis is similar to that in Lemma 1. However, when the cost of online delivery membership is sufficiently low ($\phi \leq \phi^{\text{OM}}$), the consumer may choose to pay for membership fee and shop online only when the cost of visiting a BM store exceeds a certain threshold, $v \geq v^{\text{BM} \rightarrow \text{OM}}$.

4.2. Partnership with Online Per-order Platform

Consider a scenario where the grocery store partners with an online pre-order platform, denoted as OP. As in the previous section, the consumer faces three options: (i) shop at an outside option with an annual cost of K , (ii) shop at the BM store, incurring a visiting cost v and paying a price of p_b , or (iii) shop using the online pre-order platform, paying a price of p_o^{OP} and a delivery fee of λ per order. The first two options were discussed earlier in §3.3. Below, we elaborate on the last option.

Suppose the consumer chooses to purchase from an online platform. In determining the optimal purchase quantity from the online per-order platform, the consumer considers the purchasing cost, delivery cost, and inventory holding cost. The goal is to select the purchase quantity Q_{OP} that minimizes the total cost:

$$\min_{Q_{\text{OP}}} C_{\text{OP}} = \bar{P}_o^{\text{OP}} r + \lambda \left(\frac{r}{Q_{\text{OP}}} \right) + h \left(\frac{Q_{\text{OP}}}{2} \right) \quad (5)$$

where \bar{P}_o^{OP} is defined in Equation (3). Solving the first-order condition for Q_{OP} yields the optimal order quantity $Q_{\text{OP}}^* = \sqrt{\frac{2\lambda r}{h}}$. Substituting this optimal order quantity into Eq. (5) provides the overall cost of purchasing from the online per-order platform. Finally, by comparing the total costs incurred under three different options—shopping outside, at the BM store, and via online orders—we can characterize the optimal shopping behavior within the partnership model featuring an online per-order platform:

LEMMA 3. Let $\lambda^{\text{OP}} = \frac{((\sigma_p^2 - 2(p_R + p_o^{\text{OP}})\sigma_p + (p_R - p_o^{\text{OP}})^2)r + 4K\sigma_p)^2}{32hr\sigma_p^2}$. The consumer's optimal purchasing decision is as follows

- If $\lambda \leq \lambda^{\text{OP}}$: the consumer chooses to purchase from the BM store if $v \in [0, v^{\text{BM} \rightarrow \text{OP}}]$, and online from per-order platform if $v \in [v^{\text{BM} \rightarrow \text{OP}}, 1]$, where $v^{\text{BM} \rightarrow \text{OP}} = \frac{(\sqrt{2h\lambda r} + r(\bar{P}_o^{\text{OP}} - p_b))^2}{2hr}$.
- If $\lambda > \lambda^{\text{OP}}$: the consumer chooses to purchase from the BM store if $v \in [0, v^{\text{BM} \rightarrow \text{OO}}]$, and outside option if $v \in [v^{\text{BM} \rightarrow \text{OO}}, 1]$, where $v^{\text{BM} \rightarrow \text{OO}} = \frac{(K - p_b r)^2}{2hr}$.

Similar to our discussion in §4.1, partnering with an online delivery platform influences consumers' purchasing decision under the following conditions: (i) the delivery cost per order from the online platform is sufficiently low, i.e., $\lambda \leq \lambda^{\text{OP}}$, and (ii) the cost of visiting the BM store is relatively high, i.e., $v > v^{\text{BM} \rightarrow \text{OP}}$. The former condition is based on the comparison between purchasing from the online platform and outside option, while the latter one ensures that online purchasing dominates visiting the BM store.

5. Value of Partnership with Online Platforms

In §3.2 and §4, we characterize the consumer's optimal purchasing decision without and with an online delivery partnership, respectively. By comparing the results in Lemmas 2 and 3 to those in Lemma 1, we can define the *value of partnership* with an online delivery platform, defined as VOP^i , $i \in \{\text{OM}, \text{OP}\}$:

PROPOSITION 1. *If the grocery store partners with the online delivery platform, then:*

- *The partnership with the online membership platform has no value (i.e., $VOP^{\text{OM}} = 0$) when $\phi > \phi^{\text{OM}}$,*
- *The partnership with the online per-order platform has no value (i.e., $VOP^{\text{OP}} = 0$) when $\lambda > \lambda^{\text{OP}}$,*
- *When $\phi \leq \phi^{\text{OM}}$ for the online membership platform partnership, and $\lambda \leq \lambda^{\text{OP}}$ for the online per-order platform partnership, we have*

$$VOP^i = \underbrace{(1 - v^{\text{BM} \rightarrow \text{OO}}) \cdot (1 - F(p_o^i))}_{\text{Expected market expansion}} - \underbrace{(v^{\text{BM} \rightarrow \text{OO}} - v^{\text{BM} \rightarrow i}) \cdot F(p_o^i)}, \quad i \in \{\text{OM}, \text{OP}\} \quad (6)$$

Note that a partnership with an online delivery platform is only valuable if it influences consumers' purchasing behavior. If an outside option is more attractive than buying online, consumers will opt not to purchase online, and the grocery store gains no benefit from the partnership. For an online membership platform, this occurs when the membership fee is high (i.e., $\phi > \phi^{\text{OM}}$). For an online per-order platform, it happens when the delivery cost is relatively high (i.e., $\lambda > \lambda^{\text{OP}}$).

Conversely, when the membership fee is low (in the case of partnering with an online membership platform), or delivery cost is low (in the case of partnering with an online per-order platform), then online purchasing becomes more attractive than the outside option. Under this condition, as discussed in lemmas 2 and 3, consumers choose between shopping at the BM store or online. This creates three distinct segments: (i) When $v \in [0, v^{\text{BM} \rightarrow i}]$, $i \in \{\text{OM}, \text{OP}\}$, consumers who would choose the BM store without a partnership continue to do so, meaning the partnership has no impact. (ii) When $v \in [v^{\text{BM} \rightarrow i}, v^{\text{BM} \rightarrow \text{OO}}]$, $i \in \{\text{OM}, \text{OP}\}$, consumers who would have originally chosen the BM store without a partnership now opt for the online delivery platform. This results in *market contraction* because consumers may end up buying a similar product from a competitor in the online channel, which occurs with probability $F(p_o^i)$. (iii) When $v \in [v^{\text{BM} \rightarrow \text{OO}}, 1]$, $i \in \{\text{OM}, \text{OP}\}$, consumers who would have chosen the outside option without a partnership now purchase from the

online delivery platform. This leads to *market expansion*, occurring with probability $1 - F(p_o^i)$. The following corollary formalizes the condition under which the market expansion effect outweighs the market contraction effect:

COROLLARY 1. *The value of partnership with online delivery platform $i \in \{\text{OM}, \text{OP}\}$ is positive, i.e., $\text{VOP}^i \geq 0$, when*

$$p_o^i \leq F^{-1} \left(\frac{\overbrace{1 - v^{\text{BM} \rightarrow \text{OO}} }^{\text{Market expansion}}}{\underbrace{(1 - v^{\text{BM} \rightarrow \text{OO}})}_{\text{Market expansion}} + \underbrace{(v^{\text{BM} \rightarrow \text{OO}} - v^{\text{BM} \rightarrow i})}_{\text{Market contraction}}} \right), \quad i \in \{\text{OM}, \text{OP}\}. \quad (7)$$

Corollary 1 indicates that the grocery store benefits from a partnership only if the price offered on the online delivery platform, p_o^i , is sufficiently low. Interestingly, the condition on the reverse C.D.F. resembles the *critical fractile* in the newsvendor problem. In our context, market expansion represents the *cost of not partnering*—analogous to the cost of *under-stocking* in the newsvendor problem—because forgoing a partnership means missing the opportunity to expand the market. Conversely, market contraction represents the *cost of partnering*, capturing the loss incurred when the market shifts from the BM store to the online platform, where consumers may opt for a competitive brand. This is equivalent to the cost of *over-stocking* in the newsvendor problem.

We now examine how key system parameters shape the *value of partnership* (VOP). Recall from Proposition 1 that VOP reflects the net effect of (i) *market expansion* (consumers who would otherwise take the outside option but now purchase through the partnered online channel) and (ii) *market contraction* (consumers diverted from the in-store channel to the online marketplace, where they may end up purchasing a competing product). The signs of comparative statics therefore depend on how parameters shift (a) the size of the switching segments and (b) the likelihood of leakage to competing products conditional on shopping online.

PROPOSITION 2. *There exist platform-specific price cutoffs \bar{p}_b^{OM} and \bar{p}_b^{OP} such that, if the BM-store price satisfies $\bar{p}_b^{\text{OM}} \leq p_b \leq \bar{p}_b^{\text{OP}}$, then VOP^{OM} is increasing in r , p_b , and σ_p , whereas VOP^{OP} is increasing in r but decreasing in p_b and σ_p , where*

$$\bar{p}_b^i \equiv p_o^i - \frac{(\sigma_p - (p_R - p_o^i))^2}{4\sigma_p}, \quad i \in \{\text{OM}, \text{OP}\}.$$

Proposition 2 has three economic implications.

First, Proposition 2 provides additional justification for the high-consumption focus in Assumption 1. In particular, for both platform types, a higher consumption rate increases VOP once r is sufficiently large. This is because frequent purchasing raises the benefit of using delivery to manage consumption and inventory/holding costs, making the partnered online option more

salient in the consumer's channel choice. In the OM model, a larger r effectively amortizes the fixed membership fee over more purchases; in the OP model, a larger r increases the value of flexibility (where consumer compares the online option to the outside option and to in-store shopping) even though each order incurs the per-order fee. In both cases, higher r expands the set of consumers for whom the partnership induces an online purchase, strengthening the expected market expansion component in Equation (6).

Second, to understand the role of in-store price p_b , we need to revisit the VOP in Equation (6). Given p_o^i is fixed, changing p_b affects VOP only through the switching thresholds (the leakage probability $F(p_o^i)$ is unchanged). The VOP can be rewritten as

$$\text{VOP}^i = (1 - F(p_o^i)) - v^{\text{BM} \rightarrow \text{OO}} + F(p_o^i) v^{\text{BM} \rightarrow i}, \quad i \in \{\text{OM}, \text{OP}\}.$$

Therefore,

$$\frac{\partial \text{VOP}^i}{\partial p_b} = \underbrace{-\frac{\partial v^{\text{BM} \rightarrow \text{OO}}}{\partial p_b}}_{\text{Outside-option expansion}} + \underbrace{F(p_o^i) \frac{\partial v^{\text{BM} \rightarrow i}}{\partial p_b}}_{\text{In-store diversion \& leakage}}, \quad i \in \{\text{OM}, \text{OP}\}. \quad (8)$$

Since $v^{\text{BM} \rightarrow \text{OO}} = \frac{(K - p_b r)^2}{2hr}$, we have $\frac{\partial v^{\text{BM} \rightarrow \text{OO}}}{\partial p_b} = \frac{p_b r - K}{h} \leq 0$. But, by assumption (refer to section 3.3), we have $K \geq p_b r$ hence $-\frac{\partial v^{\text{BM} \rightarrow \text{OO}}}{\partial p_b} = \frac{K - p_b r}{h} \geq 0$. Therefore, a higher p_b expands the mass of consumers who prefer the online shopping over the outside option. At the same time, the same increase in p_b also lowers the in-store-to-online threshold $v^{\text{BM} \rightarrow i}$ and therefore raises the weight on potential leakage in the online marketplace. From Lemmas 2–3,

$$\frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial p_b} = -\frac{\phi + r(\bar{P}_o^{\text{OM}} - p_b)}{h}, \quad \frac{\partial v^{\text{BM} \rightarrow \text{OP}}}{\partial p_b} = -\frac{\sqrt{2h\lambda r} + r(\bar{P}_o^{\text{OP}} - p_b)}{h}.$$

Substituting them into Equation (8) shows that the sign of $\partial \text{VOP}^i / \partial p_b$ is governed by the balance between a *positive* outside-option expansion term $\frac{K - p_b r}{h}$ and a *negative* leakage-related term scaled by $F(p_o^i)$. The two platforms differ precisely in this leakage-related term: the OP threshold contains the additional component $\sqrt{2h\lambda r}$ (stemming from the per-order fee), whereas the OM threshold contains the fixed membership fee ϕ . Consequently, for sufficiently high consumption r (consistent with Assumption 1), the OP channel becomes more sensitive to increases in p_b via $v^{\text{BM} \rightarrow \text{OP}}$, so the leakage-related effect is amplified under OP relative to OM. This yields the opposite comparative statics summarized in Proposition 2: $\partial \text{VOP}^{\text{OM}} / \partial p_b > 0$ but $\partial \text{VOP}^{\text{OP}} / \partial p_b < 0$.¹⁰

Finally, price dispersion σ_p affects VOP through marketplace competition: it changes the likelihood that, conditional on shopping online, the consumer buys the focal store's product rather than a competing one (captured by $F(p_o^i)$ in Equation (6)). When the focal store's online offer is

¹⁰ Formally, the extra term $\sqrt{2h\lambda r}$ grows in \sqrt{r} , while ϕ is constant; hence for large enough r the magnitude of $\partial v^{\text{BM} \rightarrow \text{OP}} / \partial p_b$ exceeds that of $\partial v^{\text{BM} \rightarrow \text{OM}} / \partial p_b$, which strengthens the negative (leakage-related) component in (8) under OP.

relatively competitive—as in the OM case with a lower p_o^{OM} —greater dispersion increases the chance that competitors are priced above the focal offer, mitigating expected leakage and raising VOP. When the focal offer is relatively less competitive—as in the OP case with a higher p_o^{OP} —greater dispersion increases exposure to attractive low-priced competitors, exacerbating expected leakage and reducing VOP.

6. Which Delivery Platform to Work with?

In Section 5, we show that partnering with an online delivery platform can create value for the retailer only when the partnership changes consumers' purchasing behavior and the resulting *market expansion* outweighs the expected *market contraction* (leakage to competing products on the online marketplace). The remaining strategic question is therefore comparative: when both partnerships are viable, which model creates more value—a membership-based platform (OM) or a per-order platform (OP)? To answer this question, we compare the VOP under the two partnerships and define

$$\Delta_{\text{VOP}}^{\text{OP-OM}} \equiv \text{VOP}^{\text{OP}} - \text{VOP}^{\text{OM}}, \quad (9)$$

which measures how much more (or less) value the retailer derives from partnering with OP rather than OM.

The platform choice is governed by a simple but powerful tradeoff. The first force is *fee burden*, which determines whether consumers will use the online channel repeatedly. Under OM, consumers pay a fixed membership fee ϕ and then face zero marginal delivery cost, so the value of delivery scales with purchase frequency. Under OP, consumers pay a per-order fee λ , so delivery convenience is evaluated on a transaction-by-transaction basis; it is easier to adopt occasionally, but expensive to use repeatedly.

The second force is *online price competitiveness*, which determines how much of the online demand the retailer can actually retain. Once consumers shop on the platform, they may purchase a competing product with probability $F(p_o^i)$. When online prices differ across platform types—captured by $p_o^{\text{OP}} \geq p_o^{\text{OM}}$ —the per-order model faces systematically higher leakage risk through $F(p_o^{\text{OP}})$ relative to $F(p_o^{\text{OM}})$. In other words, one platform may induce more switching to online, but the other may be better at keeping that demand from drifting to competitors.

PROPOSITION 3. *Let $r_{\phi,\lambda} = \phi^2 / (2h\lambda)$. Then:*

- For $r \leq r_{\phi,\lambda}$, $\Delta_{\text{VOP}}^{\text{OP-OM}}$ is increasing in both p_b and σ_p , whereas for $r > r_{\phi,\lambda}$ it is decreasing in both p_b and σ_p .
- $\Delta_{\text{VOP}}^{\text{OP-OM}}$ is non-monotone in r : it increases for sufficiently small r and decreases for sufficiently large r .
- A larger online-price gap $p_o^{\text{OP}} - p_o^{\text{OM}}$ reduces $\Delta_{\text{VOP}}^{\text{OP-OM}}$, tilting the choice toward OM.

Proposition 3 can be read as a practical *compass* with one primary question: *are we serving a low-frequency or high-frequency replenishment environment?* The benchmark $r_{\phi,\lambda}$ separates these regimes. Below this threshold, the membership fee is difficult for consumers to justify, so the per-order platform tends to be relatively more attractive: it can generate incremental online usage without requiring consumers to commit. Above the threshold, the logic reverses. Frequent purchasing makes the membership fee easier to amortize, while the per-order fee becomes a recurring friction that compounds over time.

The second question is: *how competitive is our online offer on each platform?* This is where platform-specific online prices matter. Even if OP can attract occasional online orders, a higher online price on OP raises the probability that consumers substitute toward competing products once they are on the marketplace. That leakage channel is precisely what turns *switching* into *contraction* in the VOP decomposition. Consequently, a retailer *should not* interpret platform choice as which platform brings more traffic, but rather as *which platform converts traffic into retained demand*.

Finally, Proposition 3 explains why pricing and marketplace conditions can flip the platform preference depending on the consumption environment. Changes in p_b or σ_p do not simply make online more or less attractive—they reshape the balance between expansion and contraction, and that balance interacts with whether consumers are likely to use delivery repeatedly. The same pricing move can therefore strengthen the per-order model in low-frequency settings but strengthen the membership model in high-frequency settings.

6.1. Operational Levers for Platform Fit

The retailer is not a passive taker of platform economics. A central message of the model is that *platform fit can be engineered* by shaping purchase frequency, basket structure, and competitive exposure. Below, we elaborate on different operational levers.

MN: I generated the following section mainly with the help of AI. I'm not sure how much it aligns with the empirical part or adds value overall.

[LW: Perhaps we should avoid calling out specific categories, since our sample also includes dairy and pantry staples, which are similarly characterized by high consumption rates.] First, the retailers need to work on *assortment* and *replenishment* cadence. Holding costs h and perishability drive how often consumers prefer to restock. Fresh categories—dairy, ready-to-eat—implicitly create high holding costs and frequent purchases, naturally aligning with membership economics because the fixed fee can be amortized over many small orders. In contrast, pantry staples and household items can be stocked in bulk and bought infrequently, which aligns with per-order economics because consumers can pay for delivery only when needed. This suggests an actionable approach: retailers can decide not only which platform to partner with, but also which categories

to feature prominently on each platform so that the platform's fee structure matches the category's natural cadence.

Second, retailers should consider how to manage the retailer's online price competitiveness. Because leakage is driven by $F(p_o^i)$, a platform that forces or induces a higher online price mechanically increases expected contraction conditional on online shopping. This makes platform-specific online pricing rules (commissions, service fees, markup conventions, promotion constraints) strategically important. If a retailer cannot maintain a competitive online offer on OP, then even strong traffic can translate into weak VOP because the marketplace becomes a comparison engine that redirects demand to cheaper alternatives. Conversely, if the retailer can sustain a relatively competitive p_o^{OM} , the membership partnership can magnify value through repeated usage while limiting leakage.

[LW: Price dispersion is primarily a platform design variable and is largely outside the direct control of individual retailers. As a result, retailers' strategic choice is not dispersion itself, but rather which platform's dispersion regime best aligns with their in-store pricing strategy. For lower-priced products, partnering with platforms that encourage comparison shopping can be advantageous, whereas for higher-priced products, platforms that promote store loyalty and reduce within-platform shopping-around are more attractive.] Finally, price dispersion σ_p should be treated as a design variable, not background noise. Dispersion can be influenced through targeted promotions, personalized offers, bundling, and the way the platform surfaces products (search ranking, filters, recommendations). The key is to use dispersion differently under each platform model. Under membership, the goal is to reinforce repeated engagement—consistent, credible member value that sustains cadence and keeps loyal demand from drifting. Under per-order, the goal is to win episodic shopping missions—basket-level incentives, threshold offers, or time-window promotions that offset the salience of λ and reduce the temptation to shop around within the marketplace.

Taken together, the platform choice is best viewed as a joint decision: pick the fee structure that matches the category's purchase cadence, and pick (or negotiate) the platform where your online offer remains competitively positioned. The first determines how strongly the partnership can expand demand; the second determines how much of that expanded online demand the retailer can retain rather than losing to competitors.

6.2. Robustness Check: Hybrid Platforms and Membership-Dependent Leakage

Many delivery platforms offer *both* a pay-per-order option and an optional membership plan. Membership programs commonly include member-only promotions or exclusive deals/special items, which changes the consumer's effective online offer set and may reduce comparison shopping within the marketplace ([Uber Eats Help 2026](#), [Shipt 2026](#), [Instacart 2026](#)). More broadly,

evidence from subscription programs suggests that membership can reduce switching and price comparison beyond the offered economic benefits (Iyengar et al. 2020). Motivated by these observations, we conduct a parsimonious robustness check that stays close to our baseline model while allowing (i) hybrid plan availability and (ii) membership-dependent leakage.

We keep the inventory-based channel costs unchanged, but introduce heterogeneity in consumption rates: $r \sim G(\cdot)$ on the compact support $[\underline{r}, \bar{r}]$, where \underline{r} and \bar{r} denote the minimum and maximum consumption rates in the population (independent of $v \sim U[0, 1]$). This single extra dimension ensures that both online plans can be selected in equilibrium. We model membership-dependent leakage using plan-specific dispersions: under plan $s \in \{M, N\}$ (member vs. non-member), competing online prices follow the uniform benchmark $p \sim U(p_R - \sigma_s, p_R + \sigma_s)$ with CDF $F_s(\cdot)$. We assume

$$\sigma_M \leq \sigma_N \iff F_M(p) \leq F_N(p) \text{ for all relevant } p, \quad (10)$$

capturing that members face weakly less marketplace shopping-around than non-members.

Under this benchmark, the expected online purchase price under plan s is

$$\bar{P}_o^s = p_o^s - \frac{(p_o^s - p_R + \sigma_s)^2}{4\sigma_s}, \quad s \in \{M, N\},$$

where $(p_o^M, p_o^N) = (p_o^{\text{OM}}, p_o^{\text{OP}})$. Online plan choice is endogenous: a consumer prefers OM to OP iff $C_{\text{OM}}(r) \leq C_{\text{OP}}(r)$, i.e., $\phi + \bar{P}_o^M r \leq \bar{P}_o^N r + \sqrt{2h\lambda r}$. Let $\Delta\bar{P} \equiv \bar{P}_o^N - \bar{P}_o^M$ and define the cutoff consumption rate $r^{M \leftarrow N}$ by

$$r^{M \leftarrow N} = \begin{cases} \left(\frac{-\sqrt{2h\lambda} + \sqrt{2h\lambda + 4\Delta\bar{P}\phi}}{2\Delta\bar{P}} \right)^2, & \Delta\bar{P} > 0, \\ \frac{\phi^2}{2h\lambda}, & \Delta\bar{P} = 0. \end{cases} \quad (11)$$

Thus, consumers with $r \geq r^{M \leftarrow N}$ choose membership and those with $r < r^{M \leftarrow N}$ choose pay-per-order. Conditional on plan choice, the BM-online visit-cost cutoffs remain threshold-based as in the main model:

$$v^{\text{BM} \rightarrow \text{OM}}(r) = \frac{(\phi + r(\bar{P}_o^M - p_b))^2}{2hr}, \quad v^{\text{BM} \rightarrow \text{OP}}(r) = \frac{(\sqrt{2h\lambda r} + r(\bar{P}_o^N - p_b))^2}{2hr},$$

with $v^{\text{BM} \rightarrow \text{OO}}(r) = \frac{(K - p_b r)^2}{2hr}$ as before. For a given r , let $s(r) \in \{M, N\}$ denote the endogenously chosen plan. When the corresponding online option is active, the VOP conditional on plan s preserves the expansion-minus-contraction form:

$$\text{VOP}^s(r) = (1 - v^{\text{BM} \rightarrow \text{OO}}(r))(1 - F_s(p_o^s)) - (v^{\text{BM} \rightarrow \text{OO}}(r) - v^{\text{BM} \rightarrow i(s)}(r))F_s(p_o^s), \quad s \in \{M, N\}, \quad (12)$$

where $i(M) = \text{OM}$ and $i(N) = \text{OP}$. The retailer's overall value under a hybrid platform is the expected value of the corresponding plan-specific VOP over the population distribution of consumption rates:

$$\text{VOP}^{\text{HYB}} = \int_{\underline{r}}^{\bar{r}} \left(\mathbf{1}_{\{r \geq r^{M \leftarrow N}\}} \text{VOP}^M(r) + \mathbf{1}_{\{r < r^{M \leftarrow N}\}} \text{VOP}^N(r) \right) dG(r),$$

with $\text{VOP}^s(r) = 0$ whenever the corresponding online option is inactive (e.g., dominated by the outside option).

A key takeaway is that our baseline analysis is *conservative* for membership-type offerings in hybrid platforms. To see this, note from (12) that plan-specific leakage affects VOP only through the contraction term, which enters with a negative sign. Under (10) we have $F_M(\cdot) \leq F_N(\cdot)$, so allowing membership-dependent leakage weakly reduces expected contraction under OM and therefore weakly increases $\text{VOP}^M(r)$ for every r for which the membership plan is active. Integrating over r implies that whenever a positive measure of consumers selects membership (i.e., $\Pr(r \geq r^{M \leftarrow N}) > 0$), the overall hybrid-platform value VOP^{HYB} is weakly higher than what would be predicted by the baseline model with common leakage. Hence, the qualitative mechanisms emphasized in the main analysis remain intact (expansion vs. leakage-driven contraction), while the membership partnership becomes more attractive when membership reduces marketplace shopping-around.

In the next section, we provide empirical support for our theoretical model. To complement our analysis regarding the effect of platform partnership on sales, we empirically test the theoretical predictions listed in Table 2.

7. Empirical Application

In this section, we use retail data to empirically evaluate the predictions derived from our theoretical model. We begin by describing the empirical setting and data, followed by our identification strategy and the estimation results.

7.1. Empirical Setting and Data

We collaborate with a grocery retailer that operates 570 stores under four banners across seven southern U.S. states: Alabama, Florida, Georgia, Louisiana, Mississippi, North Carolina, and South Carolina. Prior to May 2018, all banners operated exclusively through brick-and-mortar (BM) stores. In May 2018, the retailer introduced online delivery for two banners, partnering with Shipt for one banner (46 stores) and Instacart for another banner (245 stores). Online delivery was launched simultaneously for all these stores on May 7, 2018. The remaining 279 stores under the other two banners remained BM-only throughout the study period. Partnership decisions were made at the corporate headquarters, and platform assignments were dictated by exclusive

Table 2 Theoretical Predictions Derived from the Analytical Model

Hypothesis	Prediction	Analytical support
$H_{1a/1b}$	OM platform partnership increases/decreases profit.	Corollary 1
$H_{2a/2b}$	OP platform partnership increases/decreases profit.	Corollary 1
H_3	The effect of OM platform partnership on profit is positively moderated by (a) in-store price, (b) consumer consumption rate, and (c) platform price dispersion.	Proposition 2
H_4	The effect of OP platform partnership on profit is (a) negatively moderated by in-store price, (b) positively moderated by consumer consumption rate, and (c) negatively moderated by platform price dispersion.	Proposition 2
H_5	The difference in the profit effect of OP partnership relative to OM partnership is negatively moderated by (a) in-store price, (b) consumer consumption rate, and (c) platform price dispersion.	Proposition 3

regional availability—each banner’s operating region was served by only one platform. NE: Were stores involved with making this decision or informed only after it was made? Was there any announcement for consumers? We need some institutional information here to justify that the launch of these services was an exogenous shock to stores and customers.

NE: Let’s add some info about how popular the two platforms were at that point. We can provide some statistics indicating the percentage of platform-mediated transactions in the data. If needed, we can also justify here that the majority of Instacart customers were using pay-per-order with only very small percentage of customers utilizing the membership option on this platform. In this paragraph, you can also discuss how these platforms have evolved into offering different payment options.

Also, we need to say something about the geographical separation of the two treatment groups and the control group. One may say that customers of the control group stores can also shift to ordering from platforms if the treatment and control groups are in close proximity, violating the SUTVA assumption. Therefore, we need to establish here that the launch of these services did not affect the customers of the control group.

We obtain item-level transaction data spanning 39 weeks, from XX to YY NE: Add the time frame., including 19 weeks before and 20 weeks after the launch of platform partnerships period, covering 570 stores across all four banners. Transaction records include detailed information on price, quantity, product description, product category, time of purchase, and store location, with each product identified by a unique stock keeping unit (SKU). You had the following footnote: We also observe transaction IDs, which allow us to reconstruct customer baskets, and loyalty card IDs, where available. Do you use loyalty card information anywhere in the analysis? If not, let’s remove this information.

Consistent with our theoretical model, we analyze outcomes at SKU level and define the primary main unit of analysis as a SKU-store-week triplet (indexed by i , s , and t , respectively). We aggregate

transactions at this level to construct weekly sales for each product in each store. Our main sample consists of 1,392 SKUs that were continuously available in all 570 stores over the study period. These SKUs span seven categories: dairy, dry grocery, frozen goods, general merchandise, non-food grocery, packaged meat, and beverages.

7.2. Mapping the Theoretical Model to the Data

Our theoretical model features three key parameters—in-store price (p_b), consumer consumption rate (r), and platform price dispersion (σ_p)—which jointly determine the impact of partnership on retailer profit. Below, we describe how we operationalize these constructs in the data and then introduce the additional control variables used in the analysis.

Profit: We operationalize profit ($Profit_{ist}$) as the natural logarithm of the difference between net sales and wholesale cost for product i in store s during week t . Net sales are defined as weekly sales net of returns, while wholesale costs **NE: Is wholesale price a part of the transaction data? If so, let's add this to the paragraph above where we provide information about what transaction records include** correspond to the procurement prices paid by the retailer to suppliers.

In-store price: Because the retailer frequently adjusts prices, we define the in-store price ($Price_{is}$) as the natural logarithm of the average retail price of product i in store s during the pre-platform partnership period.

Consumer consumption rate: To construct this variable, for product i in store s , we first identify all unique customers who purchased the product in that store. For each customer, we identify the weeks of their first and last purchases during the pre-platform partnership period and treat this interval as the period during which the customer was active for product i in store s . We then compute the customer’s purchase rate as the total number of units purchased divided by the number of active weeks. Finally, we operationalize consumer consumption rate for product i in store s ($Consumption_{is}$) as the natural logarithm of the average of these individual purchase rates across all customers.

Platform price dispersion: Recall that this construct captures the price dispersion of similar products on a platform, information not available in the retailer’s own transaction data. To construct this variable, we obtain pricing data from Numerator—a market research firm that collects multichannel transaction records from a representative panel of U.S. consumers—for all products listed on Shipt and Instacart between XX and YY **Add the time of the data.** For each product, the dataset includes unit price, quantity purchased, purchase date, retailer name, delivery platform (Instacart or Shipt), and product category and subcategory **What is “department”? Do you use it anywhere? If not, no need to mention.**

NE: I will review the rest of this subsection after you rewrite how to operationalize the platform price dispersion.

Instacart and Shipt employ different product identification systems, which also differ from the retailer's own labeling. Accordingly, for each product i in the retail's transaction data, we identify similar products on both platforms in the Numerator dataset using a text mining procedure (Larose and Larose 2014).¹¹ We begin by preprocessing product descriptions and subcategory labels by tokenizing them into individual words. We then apply stemming to reduce words to their root forms and remove stop words, ensuring consistency in word representation (Dew et al. 2022). This transformation allows us to represent product descriptions in a structured format suitable for vectorization. To improve the relevance of matches, we restrict comparisons to products within the same category.

Next, we convert the textual data of each focal product and its category-matched candidates from Instacart and Shipt into numerical vectors and compute cosine similarity to identify the most similar items (Hwang et al. 2010). For each product in the main dataset, we generate a list of matched products from both platforms. Finally, we measure the price dispersion of product i as the standard deviation of the prices of its matched counterparts across retailers. This procedure yields in two product-level dispersion measures for the Shipt and Instacart platforms, denoted as $PriceDisp_i^{Shipt}$ and $PriceDisp_i^{Instacart}$, respectively.

Descriptive statistics are provided in Table 3. NE: Can we add sample size in Table 3? I assume these statistics are before the matching.

Table 3 Descriptive Statistics

Variables	Partnership with Shipt		Partnership with Instacart		No Partnership	
	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev
<i>Profit</i>	1.677	1.023	1.793	1.069	1.791	1.079
<i>Price</i>	0.865	0.602	0.899	0.618	0.897	0.610
<i>Consumption</i>	-0.432	0.501	-0.318	0.452	-0.323	0.450
$PriceDisp_i^{Shipt}$	1.046	0.294	—	—	—	—
$PriceDisp_i^{Instacart}$	—	—	1.129	0.312	—	—

7.3. Identification Strategy

Our goal is to estimate the causal effect of launching online delivery through a partnership with a third-party platform on retailer profitability. We implement a difference-in-differences (DiD)

¹¹ For example, Target and Superfresh assign their own retailer-specific item numbers.

approach that compares the post-platform partnership change in per-product profit for items made available for online delivery via Shipt or Instacart after May 2018 (i.e., *treatment group*) with that for products that were never offered online during the study period (i.e., *control group*). This strategy provides two key identification advantages while accounting for baseline differences between groups. First, by examining within-group changes over time, it differences out any time-invariant unobserved heterogeneity that could otherwise bias estimates (Angrist and Pischke 2009). Second, by comparing these changes across groups, it adjusts for common time trends in profit, isolating the effect attributable to the introduction of online delivery services.

Given the longitudinal structure of our data and Hausman test results rejecting the random-effects specification **NE: Have you conducted this test to justify the fixed-effects model?**, we estimate the DiD model using a fixed-effects panel regression framework, specified as follows:

$$Profit_{ist} = \beta_0 + \beta_1 Treatment_s \times After_t + \mathbf{X}'_{is} \beta_c + \mu_{is} + \tau_t + \epsilon_{ist}, \quad (13)$$

where (i) $Treatment_s$ is an indicator equal to one if store s belongs to the treatment group and zero otherwise; (ii) $After_t$ equals one for observations after May 7, 2018 and zero otherwise; (iii) \mathbf{X}_{is} is a vector of time-invariant controls, including $Price_{is}$, $Consumption_{is}$, and $Dispersion_i$; (iv) (μ_{is} denotes SKU-store fixed effects; (v) τ_t denotes week fixed effects; and (vi) ϵ_{ist} is the random error term. Because of the fixed-effects specification, the SKU-store fixed effects absorb the coefficients on time-invariant variables in \mathbf{X}_{is} . The DiD coefficient β_1 captures the effect of launching online delivery via a third-party platform on retailer profitability for treatment stores, corresponding to the value of platform partnerships in the theoretical model, and is used to test Hypotheses 1 and 2. We report robust standard errors clustered at the product–store level.

To assess how the effect of launching online delivery via a third-party platform on retailer profitability is moderated by in-store price, consumer consumption rate, and platofrm price dispersion (i.e., Hypothesis 3), we specify the following fixed-effects triple-differences model:

$$\begin{aligned} Profit_{ist} = & \beta_0 + \beta_1 Treatment_s \times After_t + \beta_2 Price_{is} \times Treatment_s \times After_t \\ & + \beta_3 Price_{is} \times After_t + \beta_4 Consumption_{is} \times Treatment_s \times After_t \\ & + \beta_5 Consumption_{is} \times After_t + \beta_6 Dispersion_i \times Treatment_s \times After_t \\ & + \beta_7 Dispersion_i \times After_t + \mathbf{X}'_{is} \beta_c + \mu_{is} + \tau_t + \epsilon_{ist}, \end{aligned} \quad (14)$$

The coefficients of interest to test Hypotheses 3 and 4 are β_2 , β_4 , and β_6 for in-store price, consumer consumption rate, and platform price dispersion, respectively.

Because the retailer made partnership decision at the banner level based on platform availability in each banner's operating region, treatment and control stores may differ systematically in observable characteristics, potentially weakening the credibility of counterfactuals in the DiD design. To improve comparability, we implement propensity score matching using store-level covariates measured in the pre-platform partnership period. These covariates include (i) the number of SKUs per store, capturing assortment breadth and store size; (ii) the average number of checkout registers, capturing labor and sales floor capacity (Friebel et al. 2022); (iii) the number of households and the average household income in the store's ZIP code, capturing local market conditions; and (iv) the average product price in the store's assortment, capturing pricing strategy that may influence its decision to adopt an online platform.

NE: This last one is a little problematic. It implies that the pricing is determined by each store manager. It also implies that the partnership decision is made by store managers. Is it a writing issue such that those decisions are not made by store managers, but rather by the headquarters? I am fine with keeping this variable in matching. Just, we need to be more careful in writing. To me, this variable can simply capture the quality of the assortment in each store. The matching procedure, described in Online Appendix A, yields 168 control stores successfully matched to 42 treatment stores offering online delivery via Shipt and 226 treatment stores offering online delivery via Instacart. The resulting matched sample comprises 7,716,667 observations.

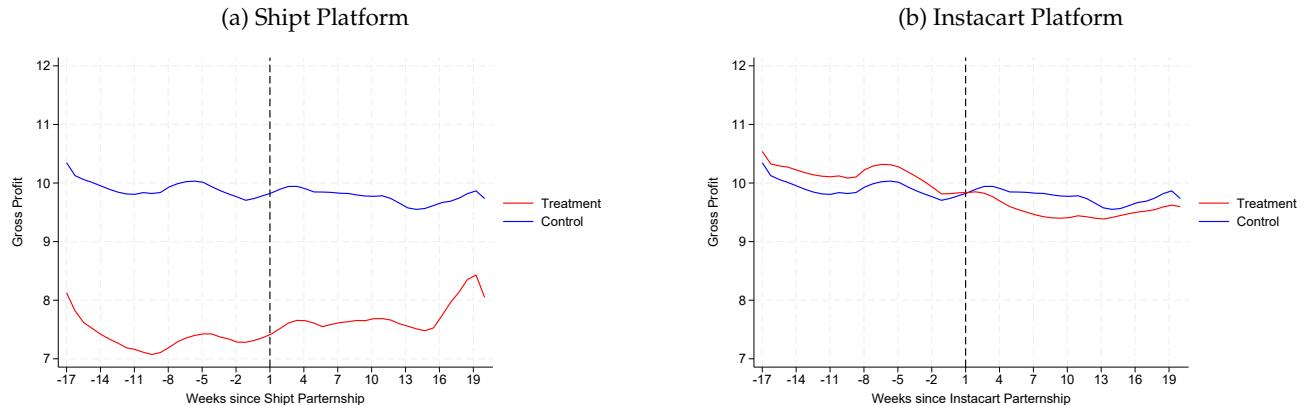
The DiD model relies on the parallel trends assumption, which implies that in the absence of partnership, the trend in profit should be the same between treatment and control groups. Using the matched data, we assess the parallel trends assumption in two ways. First, we plot the average weekly SKU profit for control groups and treatment groups in Figure 1. The vertical line marks the launch of online delivery via third-party delivery platforms. Consistent with the parallel trends assumption, we observe that prior to the launch, profit trends appear similar across all three groups of stores. Following the launch, compared to the control group stores, treatment stores that partnered with Shipt show a slight increase in profits, while treatment stores that partnered with Instacart exhibit a decline in profits.

NE: Lina, can we combine these two plots in Figure 1 into one? The blue line represents the control group in both plots. No need to have two figures

Second, to formally examine these patterns during the pre-platform partnership period, we estimate the following regression using only pre-platform partnership observations:

$$Profit_{ist} = \beta_0 + \beta_1 Treatment_s \times Trend_t + \mathbf{X}'_{is} \beta_c + \mu_{is} + \epsilon_{ist} \quad (15)$$

where $Trend_t$ denotes the number of weeks since the beginning of the data for observation. The coefficient β_1 captures the difference in profit trends between treatment and control groups, with a

Figure 1 Impact of partnership on average weekly gross profit

Note: The lines represent the fitted trend of treatment and control stores using first order polynomials.

statistically significant β_1 indicating a violation of the parallel trends assumption. Since we have two treatment groups, we estimate Equation 15 separately for each group, using the same control group in both cases. Table 4 presents the results. Column (1) reports results for treatment stores that partnered with Shipt and control stores, and Column (2) for treatment stores that partnered with Instacart and control stores. In both cases, β_1 is not statistically significant, providing evidence in support of the parallel trends assumption during the pre-platform partnership period. NE: In table 4, are the betas and std. errors all zero? If the fourth digits after the period is different from zero, let's show that.

Overall, the parallel trends analysis, together with propensity score matching, validates the DiD identification strategy, and we next present results from the DiD model estimations.

Table 4 Parallel Trends Assumption Test

Variables	(1) Partnership with Shipt	(2) Partnership with Instacart
Treatment \times Trend	-0.000 (0.000)	0.000 (0.000)
SKU-Store FE	Yes	Yes
Week FE	Yes	Yes
Observations	3,396,821	6,373,783
R-squared	0.687	0.688

Note: (1) Clustered robust standard errors are reported in parentheses,
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

7.4. Results

In Section 7.4, we interpret the empirical results of hypothesis tests related to the Shipt partnership. First, columns (1) of Table 6 report the estimation results of the effect of the Shipt platform. The effect of partnering with Shipt is positive and statistically significant ($\beta_1 = 0.022$), indicating that, on average, Shipt partnership increases a product's gross profit by approximately 2.2%. This finding supports Hypothesis 1A. Column (2) reports the results including the log Price triple interaction term, Column (3) reports the results adding log Consumption triple interaction term, and Column (4) reports the results adding log $PriceDisp^{Shipt}$ triple interaction. We find that the triple difference estimators across Columns (2)-(4) ($\beta_2 = 0.033$, $\beta_4 = 0.016$, and $\beta_6 = 0.016$) are positive and statistically significant. These findings suggest that the Shipt partnership is particularly beneficial for products with higher retail prices, higher consumption rates, and greater price dispersion on the Shipt platform. This result is consistent with the predictions for the OM platform in Proposition 2, which suggest that when platform price dispersion is below its threshold and consumption rate exceeds its threshold, the value of the partnership increases with higher retail prices, higher consumption rates, and greater price dispersion. Hence, Hypotheses 3A-3C are supported.

Table 5 Estimation results for the value of Shipt partnership

Variables	(1)	(2)	(3)	(4)
Shipt×After	0.022*** (0.002)	-0.006* (0.003)	-0.005 (0.003)	-0.021*** (0.007)
Shipt×After×log Price		0.031*** (0.004)	0.034*** (0.004)	0.033*** (0.004)
After×log Price		-0.031*** (0.001)	-0.037*** (0.002)	-0.037*** (0.002)
Shipt×After×log Consumption			0.017*** (0.004)	0.016*** (0.004)
After×log Consumption			-0.027*** (0.002)	-0.027*** (0.002)
Shipt×After× log PriceDisp ^{Shipt}				0.016*** (0.006)
After×log PriceDisp ^{Shipt}				0.007*** (0.003)
Observations	7,176,667	7,176,667	7,176,667	7,176,667
R-squared	0.667	0.667	0.667	0.667
SKU-Store FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes

Note: (1) Clustered robust standard errors are reported in parentheses,
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

7.5. The Impact of Instacart Partnership on Profit

In Section 7.5, we interpret the empirical results of the proposition tests related to the Instacart partnership. Columns (1) of Table 6 report the estimation results for the effect of the Instacart platform. The estimated coefficient for the effect of Instacart is negative and statistically significant ($\beta_1 = -0.029$), indicating that, on average, Instacart partnership decreases a product's gross profit by approximately 2.9%. This finding supports Hypothesis 2B. Column (2) reports the results including the log Price triple interaction term, Column (3) reports the results adding log Consumption triple interaction term, and Column (4) reports the results adding log $PriceDisp^{Instacart}$ triple interaction. We focus our interpretation on the results of Column (4). The results show the triple difference estimators for log Price and log $PriceDisp^{Instacart}$ ($\beta_2 = -0.019$, $\beta_6 = -0.019$) are consistently negative and statistically significant, while the triple difference estimator of log Consumption is positive and significant. These findings suggest that higher in-store product prices and greater price dispersion of similar products on the Instacart platform amplify the negative effect of the partnership on gross profit. In contrast, products with higher consumption rates help mitigate this negative impact, indicating that demand intensity can offset some of the profitability loss. The moderating effects are consistent with the predictions for the OP delivery platform in Proposition 2 and hence, Hypotheses 4A–4C are supported.

Table 6 Estimation results for the value of Instacart partnership

Variables	(1)	(2)	(3)	(4)
Instacart \times After	-0.029*** (0.001)	-0.008*** (0.002)	-0.007*** (0.002)	0.013*** (0.004)
Instacart \times After \times log Price		-0.023*** (0.002)	-0.021*** (0.002)	-0.019*** (0.002)
After \times log Price		-0.031*** (0.001)	-0.037*** (0.002)	-0.039*** (0.002)
Instacart \times After \times log Consumption			0.008*** (0.002)	0.009*** (0.002)
After \times log Consumption				-0.027*** (0.002)
Instacart \times After \times log $PriceDisp^{Instacart}$				-0.019*** (0.003)
After \times log $PriceDisp^{Instacart}$				0.020*** (0.003)
Observations	13,452,754	13,452,754	13,452,754	13,452,754
R-squared	0.663	0.663	0.663	0.663
SKU-Store FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes

Note: (1) Clustered robust standard errors are reported in parentheses,
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

8. Implications of Heterogeneous Partnership Effects

The empirical results above address our first two research questions by quantifying the value of partnering with an online grocery platform and identifying how product-, consumer-, and market-level characteristics shape this value. The analysis reveals that the Shipt (OM) partnership, on average, increases product-level gross profit, whereas the Instacart (OP) partnership reduces it. Moreover, the moderating effects show substantial heterogeneity across products: while consumption benefits both platform partnership, higher prices and greater price dispersion amplify the benefits of partnering with Shipt but exacerbate the losses under Instacart.

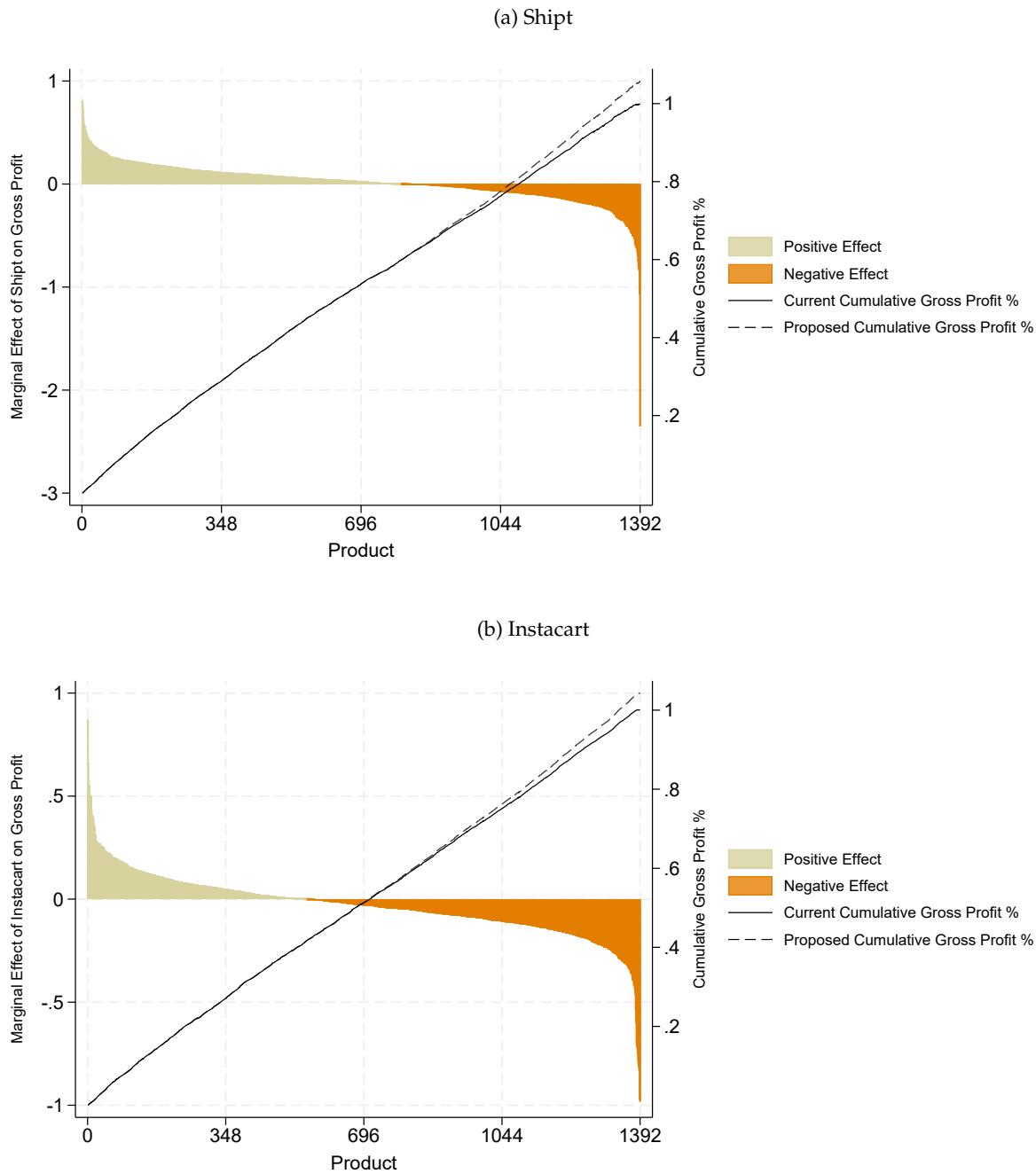
These findings suggest that a uniform partnership strategy, where all products are made available on each platform may be suboptimal. Not all products benefit equally, and some may even experience profitability declines when sold through online platforms. To evaluate the potential gains from a more selective strategy, we conduct a counterfactual analysis that restricts platform offerings to products predicted to generate positive partnership value.

To enable this analysis, we first extend our empirical framework to quantify the impact of Shipt and Instacart partnerships on product-level gross profit. We then implement a counterfactual scenario in which products with a negative estimated profit impact are excluded from the platform, while those with a positive impact are retained. The detailed procedures for this analysis are provided in Online Appendix B.

We present the results of this analysis in Figures 2(a) and 2(b), separately for the Shipt and Instacart partnerships. Each figure displays a bar plot of the natural logarithm of the estimated respective partnership effect on individual products. In these plots, the sand-colored and orange-shaded areas represent products with positive and negative estimated effects, respectively.

For the Shipt partnership, we estimate that 42.74% of products (595 in total, located in the orange-shaded area) would contribute additional gross profit if those with negative impacts were excluded from the partnership. For the Instacart partnership, this proportion rises to 64.15% (893 products). These findings suggest that retailers could improve gross profitability by limiting partnership offerings to products with a positive profit effect.

To quantify the potential gain, we compute each product's gross profit contribution as a share of total gross profits and plot the cumulative contribution in Figures 2(a) and 2(b). The dotted black line represents cumulative gross profit under the current partnership strategy, while the dashed black line reflects the counterfactual strategy. We find that excluding products with negative partnership effects—offering them only in-store—could increase total gross profit by 5.8% for the Shipt partnership and 4.32% for the Instacart partnership.

Figure 2 Changes in gross margin profit

9. Comparing Partnership Value between OM and OP Platforms

To guide retailer decision-making on platform partnerships, it is essential to understand not only whether partnering with an online delivery platform adds value, but also which platform configuration provides greater value given specific product characteristics. This section empirically compares the relative profitability of the Shipt (OM) and Instacart (OP) partnerships to determine

which platform type generates higher returns across different product-, consumer-, and market-level conditions.

We estimate a pooled triple DiD model that includes both Shipt and Instacart interaction terms within a single specification, with results reported in Table 7. To formally assess whether the moderating effects differ across platforms, we perform Wald tests on the corresponding three-way interaction terms. The results show that the moderating effect of in-store price differs significantly between platforms ($p < 0.001$), with Shipt's profitability increasing more strongly in higher-priced categories. Similarly, the moderating effect of platform price dispersion varies sharply across platforms ($p < 0.001$), as Shipt's profitability is more positively affected by greater price dispersion than Instacart's. Finally, the difference in the consumption-rate interaction, while smaller, remains statistically significant ($p < 0.05$), indicating that Shipt's profitability benefits more from high-consumption categories than Instacart's. Collectively, these results support Hypotheses 5A–5C.

Table 7 Estimation results for the value of partnership between Instacart and Shipt platforms

Variables	(1)	(2)	(3)	(4)
Shipt×After	0.022*** (0.002)	-0.006* (0.003)	-0.005 (0.003)	-0.012*** (0.004)
Shipt×After×log Price		0.031*** (0.004)	0.034*** (0.004)	0.033*** (0.002)
Instacart×After	-0.029*** (0.001)	-0.008*** (0.002)	-0.007*** (0.002)	0.016*** (0.002)
Instacart×After×log Price		-0.023*** (0.002)	-0.021*** (0.002)	-0.019*** (0.001)
After×log Price		-0.031*** (0.001)	-0.037*** (0.002)	-0.039*** (0.001)
Instacart×After×log Consumption			0.008*** (0.002)	0.009*** (0.002)
After×log Consumption			-0.027*** (0.002)	-0.028*** (0.001)
Shipt×After×log Consumption			0.017*** (0.004)	0.015*** (0.003)
Instacart×After× log PriceDisp ^{Instacart}				-0.022*** (0.002)
After× log PriceDisp ^{Instacart}				0.030*** (0.002)
Shipt×After× log PriceDisp ^{Shipt}				0.006* (0.003)
After× log PriceDisp ^{Shipt}				-0.008*** (0.002)
Observations	14,869,323	14,869,323	14,869,323	14,869,323
R-squared	0.661	0.661	0.661	0.661
SKU-Store FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes

Note: (1) Clustered robust standard errors are reported in parentheses,

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

10. Conclusion

Our analysis yields several important managerial implications for grocery retailers evaluating platform partnerships. First, platform choice should be guided not by the volume of traffic a platform generates, but by whether that traffic is converted into retained demand. Second, retailers should view platform partnerships as a joint decision over purchase cadence and competitive exposure. Even substantial demand expansion can translate into weak partnership value when online prices are uncompetitive or price dispersion is high, as consumers are more likely to be diverted to rival retailers once they enter the platform marketplace. Maintaining a competitive online offer is therefore critical, particularly on per-order platforms where comparison shopping is salient and leakage is amplified. At the same time, sustaining online price competitiveness is often challenging for retailers because online platforms typically exert significant control over pricing. This tension highlights the importance of platform selection: retailers benefit from partnering with platforms that either allow greater control over online pricing decisions or provide a competitive environment in which the retailer's online offer can remain attractive.

Beyond payment structure, retailers also differ in which products they choose to display on platforms. Some retailers mirror their in-store assortment on the platform, effectively offering the full catalog online (e.g., Kroger, Target, Safeway), whereas others offer only a curated subset of in-store products (e.g., The Fresh Market, Wegmans, Sprouts Farmers Market). Offering the full assortment may enhance customer convenience and basket size but increases picking complexity and fulfillment costs, whereas offering a curated subset simplifies operations but may reduce demand and customer satisfaction.

Research in operations management has long examined assortment planning and revenue management in brick-and-mortar retail environments (Kök and Fisher 2007). With the rise of e-commerce and the diffusion of omnichannel retailing, this literature has expanded to examine how assortments are designed and coordinated across multiple channels. For example, Brynjolfsson et al. (2009) show that offering mainstream products in physical stores while allocating niche products to online channels can mitigate cannibalization. Dzyabura and Jagabathula (2018) demonstrate that in-store assortments can be optimized to maximize joint online and offline profitability. Ertekin et al. (2022) further show that aligning online-only versus dual-channel products with channel characteristics can enhance ship-to-store effectiveness. The growth of third-party online marketplaces has also spurred research on assortment planning from the platform perspective. For instance, Ferreira et al. (2022) develop an online learning algorithm to optimize product ranking and improve consumer search and purchase outcomes, and Gallino et al. (2025) study an algorithmic tool used to curate and present product listings to marketplace customers. A common

feature of these studies is that (i) a retailer makes assortment decisions within their own channels, (ii) the online channel primarily consists of the retailer's own products, (iii) the retailer retains full control over operational decisions, and (iv) the in-store assortment represents a subset of a broader online assortment. In contrast, we study offline grocery retailers' online assortment decision when partnering with a third-party delivery platform, where (i) the online channel is managed by a platform, (ii) the platform includes both the focal retailer's and competing retailers' products, directly exposing the retailer to platform-mediated competition, (iii) online pricing is controlled by the platform, and (iv) the online assortment is often a subset of the in-store assortment. We contribute to this literature by examining how customizing the assortment displayed on a third-party delivery platform influences the effectiveness of grocery retailer-platform partnerships.

Despite their potential, partnerships with grocery delivery platforms pose significant operational and strategic risks that can result in costly setbacks for retailers. Walmart, for instance, discontinued delivery partnerships with Deliv, Uber, and Lyft after limited scalability and operational frictions constrained performance ([Wells 2018](#), [Thakker 2019](#)); Ohio-based specialty grocer Heinen's Fine Foods ended its multi-year partnership with Instacart in 2023, bringing delivery and curbside fulfillment in-house after the third-party arrangement no longer fit its operational model ([Crowe 2023](#)). Similarly, ALDI pulled its UK stores from Deliveroo following a trial, citing the partnership's misalignment with its operational priorities and profitability requirements ([Nazir 2022](#)). Collectively, these cases underscore that choosing the right platform partnership is a critical strategic decision—misalignment between partners can erode returns and trigger major financial losses.

References

- Amaldoss W, He C (2018) Reference-dependent utility, product variety, and price competition. *Management Science* 64(9):4302–4316.
- Angrist JD, Pischke JS (2009) *Mostly harmless econometrics: An empiricist's companion* (Princeton university press).
- Balakrishnan A, Sundaresan S, Mohapatra C (2024) Subscription pricing for free delivery services. *Production and Operations Management* 33(4):943–961.
- Belavina E, Girotra K, Kabra A (2017) Online grocery retail: Revenue models and environmental impact. *Management Science* 63(6):1781–1799.
- Bell DR, Gallino S, Moreno A (2018) Offline showrooms in omnichannel retail: Demand and operational benefits. *Management Science* 64(4):1629–1651.
- Bianchi-Aguiar T, Hübner A, Carraville MA, Oliveira JF (2021) Retail shelf space planning problems: A comprehensive review and classification framework. *European Journal of Operational Research* 289(1):1–16.
- Brynjolfsson E, Hu Y, Rahman MS (2009) Battle of the retail channels: How product selection and geography drive cross-channel competition. *Management Science* 55(11):1755–1765.
- Chen M, Hu M, Wang J (2022) Food delivery service and restaurant: Friend or foe? *Management Science*.
- Crowe E (2023) *Heinen's ends partnership with Instacart*. URL https://progressivegrocer.com/heinens-ends-partnership-instacart?utm_source=chatgpt.com (accessed Jan 27, 2026).
- Dan B, Zhang H, Zhang X, Guan Z, Zhang S (2022) Should an online manufacturer partner with a competing or noncompeting retailer for physical showrooms? *International Transactions in Operations Research* 28(5):2691–2714.
- Delasay M, Jain A, Kumar S (2021) Impacts of the covid-19 pandemic on grocery retail operations: An analytical model. Available at SSRN 3979109 .
- Dew R, Ansari A, Toubia O (2022) Letting logos speak: Leveraging multiview representation learning for data-driven branding and logo design. *Marketing science* 41(2):401–425.
- Dzyabura D, Jagabathula S (2018) Offline assortment optimization in the presence of an online channel. *Management Science* 64(6):2767–2786.
- Ertekin N, Ding Y, Donohue K (2024) Strategic visual merchandising of new and open-box products: Evidence from experiment and retail data. *Management Science* 70(4):2047–2065.
- Ertekin N, Gümuş M, Nikoofal ME (2022) Online-exclusive or hybrid? channel merchandising strategies for ship-to-store implementation. *Management Science* 68(8):5828–5846.
- Fang Z, Ho YC, Tan X, Tan Y (2021) Show me the money: The economic impact of membership-based free shipping programs on e-tailers. *Information Systems Research* 32(4):1115–1127.

- Feldman P, Frazelle AE, Swinney R (2023) Managing relationships between restaurants and food delivery platforms: Conflict, contracts, and coordination. *Management Science* 69(2):812–823.
- Ferreira KJ, Parthasarathy S, Sekar S (2022) Learning to rank an assortment of products. *Management Science* 68(3):1828–1848.
- Fibich G, Gavious A, Lowengart O (2003) Explicit solutions of optimization models and differential games with nonsmooth (asymmetric) reference-price effects. *Operations Research* 51(5):721–734.
- Flipp Market Research (2025) The state of grocery report: Canada 2025. Technical report, Flipp, accessed 2026-01-08.
- Friebel G, Heinz M, Zubanov N (2022) Middle managers, personnel turnover, and performance: A long-term field experiment in a retail chain. *Management Science* 68(1):211–229.
- Gallino S, Karacaoglu N, Moreno A (2025) Algorithmic assortment curation: An empirical study of buybox in online marketplaces. *Manufacturing & Service Operations Management* 27(3):917–934.
- Gallino S, Moreno A (2014) Integration of online and offline channels in retail: The impact of sharing reliable inventory availability information. *Management Science* 60(6):1434–1451.
- Gallino S, Moreno A, Stamatopoulos I (2017) Channel integration, sales dispersion, and inventory management. *Management Science* 63(9):2813–2831.
- Gao F, Agrawal VV, Cui S (2022) The effect of multichannel and omnichannel retailing on physical stores. *Management Science* 68(2):809–826.
- Gao F, Su X (2017) Omnichannel retail operations with buy-online-and-pick-up-in-store. *Management Science* 63(8):2478–2492.
- Ghai N (2024) How to profit in online grocery shopping: Overcome these 4 key challenges. URL <https://www.grocerydoppio.com/articles/how-to-profit-in-online-grocery-shopping-overcome-these-5-key-challenges>, accessed: 2025-06-01.
- Gümüş M, Li S, Oh W, Ray S (2013) Shipping fees or shipping free? a tale of two price partitioning strategies in online retailing. *Production and Operations Management* 22(4):758–776.
- Guo F, Liu Y (2023) The effectiveness of membership-based free shipping: An empirical investigation of consumers' purchase behaviors and revenue contribution. *Journal of Marketing* 87(6):869–888.
- Hemmati S, Elmaghraby WJ, Kabra A, Jain N (2021) Contingent free shipping: Drivers of bubble purchases. *Working Paper, Robert H. Smith School of Business, University of Maryland*.
- Ho TH, Tang CS, Bell DR (1998) Rational shopping behavior and the option value of variable pricing. *Management science* 44(12-part-2):S145–S160.
- Hübner A, Kuhn H (2024) Decision support for managing assortments, shelf space, and replenishment in retail. *Flexible Services and Manufacturing Journal* 36:1–35, URL <http://dx.doi.org/10.1007/s10696-023-09492-z>.

- Hwang EH, Nageswaran L, Cho SH (2022) Value of online-off-line return partnership to off-line retailers. *Manufacturing & Service Operations Management* 24(3):1630–1649.
- Hwang M, Bronnenberg BJ, Thomadsen R (2010) An empirical analysis of assortment similarities across us supermarkets. *Marketing Science* 29(5):858–879.
- Instacart (2026) Instacart+ (membership program and benefits). <https://www.instacart.ca/instacart-plus>, accessed: 2026-01-09.
- Iyengar R, Jedidi K, Kohli R, et al. (2020) The impact of subscription programs on customer purchases. Technical report, SSRN, accessed: 2026-01-09.
- Jalali Z, Cohen MC, Ertekin N, Gumus M (2026) Offline-online retail collaboration via pickup partnership. *Service Science* forthcoming.
- Karamshetty V, Freeman M, Hasija S (2020) An unintended consequence of platform dependence: empirical evidence from food-delivery platforms .
- Kök AG, Fisher ML (2007) Demand estimation and assortment optimization under substitution: Methodology and application. *Operations research* 55(6):1001–1021.
- Larose DT, Larose CD (2014) *Discovering knowledge in data: an introduction to data mining* (John Wiley & Sons).
- Leng M, Becerril-Arreola R (2010) Joint pricing and contingent free-shipping decisions in b2c transactions. *Production and Operations Management* 19(4):390–405.
- Lewis M (2006) The effect of shipping fees on customer acquisition, customer retention, and purchase quantities. *Journal of Retailing* 82(1):13–23.
- Lewis M, Singh V, Fay S (2006) An empirical study of the impact of nonlinear shipping and handling fees on purchase incidence and expenditure decisions. *Marketing Science* 25(1):51–64.
- Li G, Sheng L, Zhan D (2023) Designing shipping policies with top-up options to qualify for free delivery. *Production and Operations Management* 32(9):2704–2722.
- Li Z, Wang G (2025) On-demand delivery platforms and restaurant sales. *Management Science* 71(7):5788–5804.
- Mayya R, Li Z (2021) Growing platforms by adding complementors without consent: evidence from on-demand food delivery platforms. Available at SSRN 3945088 .
- Meisenzahl M (2024) Retailers partner with doordash, instacart, uber eats for last-mile delivery. URL <https://www.digitalcommerce360.com/2024/05/09/retailers-partner-with-doordash-instacart-last-mile-delivery/>, accessed: 2025-06-01.
- Nageswaran L, Hwang EH, Cho SH (2024) Offline returns for online retailers via partnership. *Management Science* 71(1):279–297.
- Nasdaq (2024) Online grocery delivery continues expansion. URL <https://www.nasdaq.com/articles/online-grocery-delivery-continues-expansion>, accessed: 2025-06-01.

- Nazir S (2022) Aldi ends Deliveroo partnership to focus on click-and-collect. URL <https://www.retailgazette.co.uk/blog/2022/01/aldi-ends-deliveroo-partnership-to-focus-on-click-and-collect/> (accessed Jan 27, 2026).
- NielsenIQ (2025) New fmi & nielseniq report explores grocery shopping in the digital age. URL <https://www.fmi.org/newsroom/news-archive/view/2025/02/03/new-fmi---nielseniq-report-explores-grocery-shopping-in-the-digital-age>, accessed: 2025-06-01.
- Oberlo (2024) Online grocery market share by company (2024) [may '24 update]. URL <https://www.oberlo.com/statistics/online-grocery-market-share-by-company>, accessed: 2025-06-01.
- Rabe-Hesketh S, Skrondal A (2008) *Multilevel and longitudinal modeling using Stata* (STATA press).
- Rabello de Castro V (2019) The value of grocery delivery and the role of offline complements. *The Value of Grocery Delivery and the Role of Offline Complements* (January 27, 2019) .
- Rabello de Castro V (2020) Entry timing in the face of switching costs and its welfare effects: Evidence from same-day grocery delivery platforms. *Entry Timing in the Face of Switching Costs and its Welfare Effects: Evidence from Same-Day Grocery Delivery Platforms* (November 4, 2020) .
- Raj M, Sundararajan A, You C (2020) Covid-19 and digital resilience: Evidence from uber eats. *arXiv preprint arXiv:2006.07204* .
- Reiner G, Teller C, Kotzab H (2013) Analyzing the efficient execution of in-store logistics processes in grocery retailing—the case of dairy products. *Production and Operations Management* 22(4):924–939.
- Shipt (2026) Pricing (membership benefits and exclusive deals). <https://www.shipt.com/pricing>, accessed: 2026-01-09.
- Thakker K (2019) *Reuters: Walmart and Deliv terminate grocery delivery partnership*. URL https://www.retaildive.com/news/reuters-walmart-and-deliv-terminate-grocery-delivery-partnership/548261/?utm_source=chatgpt.com (accessed Jan 27, 2026) .
- Thaler RH (2008) Mental accounting and consumer choice. *Marketing science* 27(1):15–25.
- Uber Eats Help (2026) What benefits does uber one offer? <https://help.uber.com/en/ubereats/restaurants/article/what-benefits-does-uber-one-offer?nodeId=5a12c3b1-5d81-45c8-8cda-1608761131b8>, accessed: 2026-01-09.
- Wells J (2018) *Walmart's Uber and Lyft partnerships end*. URL https://www.retaildive.com/news/walmarts-uber-and-lyft-partnerships-end/523172/?utm_source=chatgpt.com (accessed Jan 27, 2026) .
- YahooFinance (2024) Online grocery delivery services market to see major growth by 2028. URL <https://finance.yahoo.com/news/online-grocery-delivery-services-market-212500514.html>, accessed: 2024-09-18.

Online Supplement: The Hidden Cost of Grocery Delivery Platforms

APPENDIX A: Proofs

Proof of Lemma 1. Without a partnership, the grocery store sells only through the BM store. Consumers choose between two purchasing options: (i) purchasing from an outside option at a total cost of K , or (ii) visiting the BM store, incurring a cost of $v \sim U[0, 1]$, and purchasing $Q_{\text{BM}}^* = \sqrt{\frac{2vr}{h}}$, resulting in the total cost of $C_{\text{BM}} = p_b r + \sqrt{2hvr}$. By comparing the total cost under both scenarios, one can verify that the shopper chooses to purchase from the BM store if $v \in [0, v^{\text{BM} \rightarrow \text{OO}}]$, and outside option if $v \in [v^{\text{BM} \rightarrow \text{OO}}, 1]$, where $v^{\text{BM} \rightarrow \text{OO}} = \frac{(K - p_b r)^2}{2hr}$. ■

Proof of Lemma 2. To find the consumer's optimal purchasing decision, we need to compare its overall cost from three different options. As discussed earlier, the overall cost of shopping from an outside option (i.e., local convenience store) is K . The overall cost by shopping from the BM store is $C_{\text{BM}} = p_b r + \sqrt{2hvr}$. Finally, if the consumer chooses to purchase from online membership platform, their total cost, including membership fee and inventory cost, would be $C_{\text{OM}} = \phi + \bar{P}_o^{\text{OM}} r$, where $\bar{P}_o^{\text{OM}} = p_o^{\text{OM}} - F(p_o^{\text{OM}}) \cdot \left(\frac{p_o^{\text{OM}} - p_R + \sigma_p}{2} \right)$ from Eq. (3).

By comparing cost of shopping from online platform C_{OM} to K , one can verify that the consumer prefers order from online delivery platform to purchase from outside option when $\phi \leq \phi^{\text{OM}}$ where $\phi^{\text{OM}} = \frac{(\sigma_p^2 - 2(p_R + p_o^{\text{OM}})\sigma_p + (p_R - p_o^{\text{OM}})^2)r + 4K\sigma_p}{4\sigma_p}$. Therefore, when $\phi > \phi^{\text{OM}}$, the consumer compares the outside option to purchasing from the brick-and-mortar (BM) store, resulting in the same outcome as in lemma 1. However, when $\phi \leq \phi^{\text{OM}}$, the consumer compares the total cost of visiting the BM store with total cost of purchasing from online membership platform. Considering the cost of visiting BM store $v \sim U[0, 1]$, the consumer chooses purchasing from the BM store when $v \leq v^{\text{BM} \rightarrow \text{OM}}$, where $v^{\text{BM} \rightarrow \text{OM}} = \frac{((\sigma_p^2 - 2(p_R - 2p_b + p_o^{\text{OM}})\sigma_p + (p_R - p_o^{\text{OM}})^2)r - 4\phi\sigma_p)^2}{32hr\sigma_p^2} \equiv \frac{(\phi + r(\bar{P}_o^{\text{OM}} - p_b))^2}{2hr}$. ■

Proof of Lemma 3. Similar to proof of lemma 2, we need to compare consumer's overall cost from three different options: First, the overall cost of shopping from an outside option (i.e., local convenience store) is K . Second, the overall cost by shopping from the BM store is $C_{\text{BM}} = p_b r + \sqrt{2hvr}$. Finally, if consumer opts to purchase from online per-order platform, then the optimal order quantity is $Q_{\text{OP}} = \sqrt{\frac{2\lambda r}{h}}$. By plugging the optimal order quantity into Eq. (5), one can verify that the overall cost of purchasing from online per-order platform is as follows:

$$C_{\text{OP}} = p_o^{\text{OP}} r - \frac{(p_o^{\text{OP}} - p_R + \sigma_p)^2}{4\sigma_p} r + \sqrt{2h\lambda r}, \quad i \in \{\text{OM}, \text{OP}\} \quad (\text{A.1})$$

By comparing cost of shopping from online platform in Eq. (A.1) to K , one can verify that the consumer prefers online order to outside option when $\lambda \leq \lambda^{\text{OP}}$ where $\lambda^{\text{OP}} =$

$\frac{((c_p^2 - 2(p_R + p_o^{OP})\sigma_p + (p_R - p_o^{OP})^2)r + 4K\sigma_p)^2}{32hr\sigma_p^2}$. Therefore, when $\lambda > \lambda^{OP}$, the consumer compares the outside option to purchasing from the BM store, resulting in the same outcome as in lemma 1. However, when $\lambda \leq \lambda^{OP}$, the consumer compares the total cost of visiting the BM store with total cost of purchasing from online per-order platform (i.e., Eq. (A.1)). Considering the cost of visiting BM store $v \sim U[0, 1]$, the consumer chooses purchasing from the BM store when $v \leq v^{BM \rightarrow OP}$, where

$$v^{BM \rightarrow OP} = \frac{(\sigma_p^2 - 2(p_R - 2p_b + p_o^{OP})\sigma_p + (p_R - p_o^{OP})^2)^2 r - 8\sigma_p (\sigma_p^2 - 2(p_R - 2p_b + p_o^{OP})\sigma_p + (p_R - p_o^{OP})^2) \sqrt{2h\lambda r} + 32h\lambda\sigma_p^2}{32hr\sigma_p^2} \quad (A.2)$$

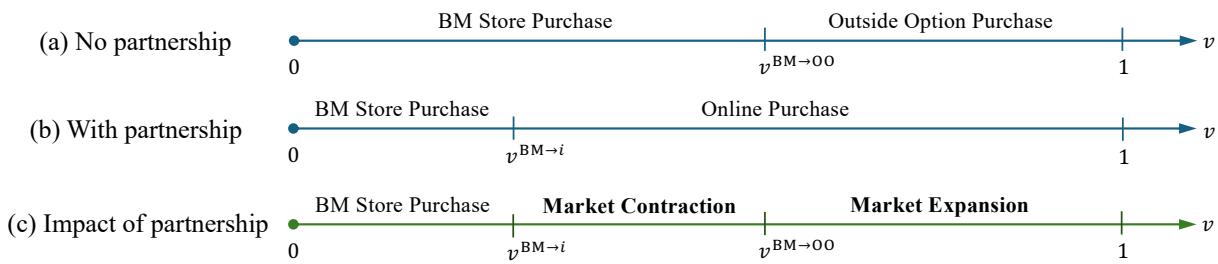
Finally, one can verify that the above equation is equivalent to $v^{BM \rightarrow OP} = \frac{(\sqrt{2h\lambda r} + r(\bar{p}_o^{OP} - p_b))^2}{2hr}$. ■

Proof of Proposition 1. The value of partnership can be characterized by comparing the grocery store demand without (lemma 1) and with partnership (lemmas 2 and 3). In what follows, we elaborate on each case separately.

Recall from lemma 1 that, without partnership, the consumer chooses to purchase from BM store if $v \in [0, v^{BM \rightarrow OO}]$, and outside option if $v \in [v^{BM \rightarrow OO}, 1]$, where $v^{BM \rightarrow OO} = \frac{(K - p_b r)^2}{2hr}$. Figure (.1-a) presents demand characterization without partnership.

With partnership, the consumer has three choices: (i) shop from an outside option, (ii) shop from the BM store, and (iii) shop from online delivery platform (either membership or per-order platform). Clearly, when shopping from outside option is more attractive than online purchases, consumers will not choose to buy online. In such cases, partnering with an online delivery platform brings no value to the grocery store. For an online membership platform, this situation arises when the membership fee is high (i.e., $\phi > \phi^{OM}$). For an online per-order platform, it occurs when the delivery cost is relatively high (i.e., $\lambda > \lambda^{OP}$). However, when the membership fee is low (i.e., $\phi \leq \phi^{OM}$ in the case of partnering with an online membership platform), or delivery cost is low (i.e., $\lambda \leq \lambda^{OP}$ in the case of partnering with an online per-order platform), then online purchasing becomes more attractive than the outside option. Under this condition, as discussed in lemmas 2 and 3, consumers choose between shopping at the BM store or online as shown in Figure (.1-b).

Figure .1 Impact of Partnership on Demand Characterization



By comparing Figures (.1-a) and (.1-b) one can characterize the impact of partnership with platform $i \in \{OM, OP\}$ on demand characterization, as shown in Figure (.1-c). Three distinct segments would appear: (i) When $v \in [0, v^{BM \rightarrow i}]$, $i \in \{OM, OP\}$, consumers who would choose the BM

store without a partnership continue to do so, meaning the partnership has no impact. (ii) When $v \in [v^{\text{BM} \rightarrow i}, v^{\text{BM} \rightarrow \text{OO}}]$, $i \in \{\text{OM}, \text{OP}\}$, consumers who would choose the BM store without a partnership decide to purchase from the online delivery platform. This results in *market contraction* because consumers may end up buying a similar product from a competitor in the online channel, which occurs with probability $F(p_o)$. (iii) When $v \in [v^{\text{BM} \rightarrow \text{OO}}, 1]$, consumers who would choose the outside option without a partnership now pay the membership fee (in the case of membership platform) or pay for delivery (in the case of per-order platform) and purchase from the online delivery platform. This leads to a *market expansion* with probability $1 - F(p_o)$. The value of partnership in Eq. (6) is the total expected value of market expansion and market contraction. ■

Proof of Corollary 1. From value of partnership in Eq. (1) one can verify that $\text{VOP}^i \geq 0$ if

$$F(p_o^i) \leq \frac{1 - v^{\text{BM} \rightarrow \text{OO}}}{(1 - v^{\text{BM} \rightarrow \text{OO}}) + (v^{\text{BM} \rightarrow \text{OO}} - v^{\text{BM} \rightarrow i})}, \quad i \in \{\text{OM}, \text{OP}\}$$

This readily results in Eq. (7). ■

Proof of Proposition 2. Note from Corollary 1, the VOP increases when the right-hand side of Eq. (7) increases. But, the right-hand side of Eq. (7) can be further rewritten as $\frac{1 - v^{\text{BM} \rightarrow \text{OO}}}{1 - v^{\text{BM} \rightarrow i}}$, $i \in \{\text{OM}, \text{OP}\}$. Moreover, the term $v^{\text{BM} \rightarrow \text{OO}}$ in the numerator originates from a fixed segment of consumers who previously purchased from the outside option compared to BM store, independent of the partnership. Therefore, to study how VOP may change w.r.t different parameters related to online delivery platforms, we need to focus on the term $v^{\text{BM} \rightarrow i}$ in the denominator. Specifically, the VOP increases when $v^{\text{BM} \rightarrow i}$ increases, which is equivalent to reduction in market contraction effect. We are therefore interested in finding $\frac{\partial v^{\text{BM} \rightarrow i}}{\partial r}$, $\frac{\partial v^{\text{BM} \rightarrow i}}{\partial p_b}$, and $\frac{\partial v^{\text{BM} \rightarrow i}}{\partial \sigma_p}$.

Consequently, we can define the following equations for membership platform $i = \text{OM}$:

$$\frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial r} = \frac{(\sigma_p^2 - 2(p_R - 2p_b + p_o^{\text{OM}})\sigma_p + (p_R - p_o^{\text{OM}})^2)^2 r^2 - 16\phi^2\sigma_p^2}{32hr\sigma_p^2} \quad (\text{A.3})$$

$$\frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial p_b} = \frac{(\sigma_p^2 - 2(p_R - 2p_b + p_o^{\text{OM}})\sigma_p + (p_R - p_o^{\text{OM}})^2) r - 4\phi\sigma_p}{4h\sigma_p} \quad (\text{A.4})$$

$$\frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial \sigma_p} = \frac{((p_R - p_o^{\text{OM}})^2 - \sigma_p^2)(4\phi\sigma_p - (\sigma_p^2 - 2(p_R - 2p_b + p_o^{\text{OM}})\sigma_p + (p_R - p_o^{\text{OM}})^2)r)}{16h\sigma_p^3} \quad (\text{A.5})$$

Similarly, we can define the followings for per-order platform $i = \text{OP}$:

$$\frac{\partial v^{\text{BM} \rightarrow \text{OP}}}{\partial r} = \frac{-4(\sigma_p^2 - 2(p_R - 2p_b + p_o^{\text{OP}})\sigma_p + (p_R - p_o^{\text{OP}})^2)\sqrt{2}\sigma_p h \lambda}{\sqrt{h}\lambda r} + \frac{(\sigma_p^2 - 2(p_R - 2p_b + p_o^{\text{OP}})\sigma_p + (p_R - p_o^{\text{OP}})^2)^2}{32h\sigma_p^2} \quad (\text{A.6})$$

$$\frac{\partial v^{\text{BM} \rightarrow \text{OP}}}{\partial p_b} = \frac{-4\sqrt{2h\lambda r}\sigma_p + (\sigma_p^2 - 2(p_R - 2p_b + p_o^{\text{OP}})\sigma_p + (p_R - p_o^{\text{OP}})^2)r}{4h\sigma_p} \quad (\text{A.7})$$

$$\frac{\partial v^{\text{BM} \rightarrow \text{OP}}}{\partial \sigma_p} = \frac{(-4\sqrt{2h\lambda r}\sigma_p + (\sigma_p^2 - 2(p_R - 2p_b + p_o^{\text{OP}})\sigma_p + (p_R - p_o^{\text{OP}})^2)r)(\sigma_p^2 - (p_R - p_o^{\text{OP}})^2)}{16h\sigma_p^3} \quad (\text{A.8})$$

To characterize the signs of the above expressions, we introduce the following notation for $i \in \{\text{OP}, \text{OM}\}$:

$$\Delta_i \equiv p_o^i - p_b, \quad B_i \equiv p_R - p_o^i, \quad A_i \equiv (\sigma_p - B)^2 - 4\sigma_p \Delta^i = \sigma_p^2 - 2(p_R - 2p_b + p_o^i)\sigma_p + (p_R - p_o^i)^2.$$

We can now rewrite the equivalents for the above equations. Specifically, the equations (A.3-A.5) for membership platform $i = \text{OM}$ can be rewritten as follows:

$$\frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial r} = \frac{A^2 r^2 - 16\phi^2 \sigma_p^2}{32h r \sigma_p^2}, \quad \frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial p_b} = \frac{Ar - 4\phi \sigma_p}{4h \sigma_p}, \quad \frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial \sigma_p} = \frac{(B^2 - \sigma_p^2)(4\phi \sigma_p - Ar)}{16h \sigma_p^3}.$$

Furthermore, let $\Delta_{\max}^{\text{OM}} \equiv \frac{(\sigma_p - B_{\text{OM}})^2}{4\sigma_p}$. We can then investigate two scenarios:

- $A_{\text{OM}} > 0$ or $\Delta_{\text{OM}} < \Delta_{\max}^{\text{OM}}$: Let $\bar{r}^{\text{OM}} = \frac{4\phi \sigma_p}{A_{\text{OM}}}$. If $r \geq \bar{r}^{\text{OM}}$, then $\frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial r} \geq 0$ and $\frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial p_b} \geq 0$. Moreover, because $B_{\text{OM}}^2 - \sigma_p^2 \leq 0$, then $\frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial \sigma_p} \geq 0$ whenever $4\phi \sigma_p - A_{\text{OM}} r \leq 0$, or $r \geq \bar{r}^{\text{OM}}$. However, when $r < \bar{r}^{\text{OM}}$ we have $\frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial r} < 0$, $\frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial p_b} < 0$, and $\frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial \sigma_p} < 0$.
- $A_{\text{OM}} \leq 0$ or $\Delta_{\text{OM}} \geq \Delta_{\max}^{\text{OM}}$: First, $\frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial r} \geq 0$ if $A_{\text{OM}}^2 r^2 - 16\phi^2 \sigma_p^2 \geq 0$, or equivalently, $r \geq \bar{r}^{\text{OM}}$. However, for $A_{\text{OM}} \leq 0$, we have $A_{\text{OM}} r - 4\phi \sigma_p \leq 0$, hence $\frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial p_b} < 0$. Finally, because $B_{\text{OM}}^2 - \sigma_p^2 \leq 0$, then for $A_{\text{OM}} \leq 0$ we have $4\phi \sigma_p - A_{\text{OM}} r \leq 0$, hence $\frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial \sigma_p} < 0$. If $r < \bar{r}^{\text{OM}}$ we have $\frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial r} < 0$, $\frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial p_b} < 0$, and $\frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial \sigma_p} < 0$.

Similarly, the equations (A.6-A.8) for per-order platform $i = \text{OP}$ can be rewritten as follows:

$$\begin{aligned} \frac{\partial v^{\text{BM} \rightarrow \text{OP}}}{\partial r} &= \frac{A^2 - 4\sqrt{2} A \sigma_p \sqrt{h \lambda} r^{-1/2}}{32h \sigma_p^2}, & \frac{\partial v^{\text{BM} \rightarrow \text{OP}}}{\partial p_b} &= \frac{Ar - 4\sigma_p \sqrt{2h \lambda r}}{4h \sigma_p}, \\ \frac{\partial v^{\text{BM} \rightarrow \text{OP}}}{\partial \sigma_p} &= \frac{(Ar - 4\sigma_p \sqrt{2h \lambda r})(\sigma_p^2 - B^2)}{16h \sigma_p^3}. \end{aligned}$$

With $\Delta_{\max}^{\text{OP}} \equiv \frac{(\sigma_p - B_{\text{OP}})^2}{4\sigma_p}$, we can then investigate two scenarios:

- $A_{\text{OP}} > 0$ or $\Delta < \Delta_{\max}$: Let $\bar{r}^{\text{OP}} = \frac{32\sigma_p^2 h \lambda}{A_{\text{OP}}^2}$. If $r \geq \bar{r}^{\text{OP}}$, then one can verify that $\frac{\partial v^{\text{BM} \rightarrow \text{OP}}}{\partial r} \geq 0$ and $\frac{\partial v^{\text{BM} \rightarrow \text{OP}}}{\partial p_b} \geq 0$. Moreover, because $\sigma_p^2 - B_{\text{OP}}^2 \geq 0$, then $\frac{\partial v^{\text{BM} \rightarrow \text{OP}}}{\partial \sigma_p} \geq 0$ whenever $A_{\text{OP}} r - 4\sigma_p \sqrt{2h \lambda r} \geq 0$, or $r \geq \bar{r}^{\text{OP}}$. If $r < \bar{r}^{\text{OP}}$ we have $\frac{\partial v^{\text{BM} \rightarrow \text{OP}}}{\partial r} < 0$, $\frac{\partial v^{\text{BM} \rightarrow \text{OP}}}{\partial p_b} < 0$, and $\frac{\partial v^{\text{BM} \rightarrow \text{OP}}}{\partial \sigma_p} < 0$.
- $A_{\text{OP}} \leq 0$ or $\Delta \geq \Delta_{\max}$: First, $\frac{\partial v^{\text{BM} \rightarrow \text{OP}}}{\partial r} \geq 0$ if $A_{\text{OP}}^2 - 4\sqrt{2} A_{\text{OP}} \sigma_p \sqrt{h \lambda} r^{-1/2} \geq 0$, which is met for any $r \geq 0$. However, for $A_{\text{OP}} \leq 0$, we have $A_{\text{OP}} r - 4\sigma_p \sqrt{2h \lambda r} \leq 0$, hence $\frac{\partial v^{\text{BM} \rightarrow \text{OP}}}{\partial p_b} < 0$. Finally, because $\sigma_p^2 - B_{\text{OP}}^2 \geq 0$, then for $A_{\text{OP}} \leq 0$ we have $A_{\text{OP}} r - 4\sigma_p \sqrt{2h \lambda r} \leq 0$, hence $\frac{\partial v^{\text{BM} \rightarrow \text{OP}}}{\partial \sigma_p} < 0$.

Using $\Delta_{\max}^i \equiv \frac{(\sigma_p - B)^2}{4\sigma_p}$ for $i \in \{\text{OP}, \text{OM}\}$, we can summarize the key insights:

- If $\Delta_i < \Delta_{\max}^i$, or equivalently, $p_b \geq p_o^i - \frac{(\sigma_p - (p_R - p_o^i))^2}{4\sigma_p} \equiv \bar{p}_b^i$, then for each model $i \in \{\text{OM}, \text{OP}\}$ there exists a demand threshold \bar{r}^i such that for all $r \geq \bar{r}^i$:

$$\frac{\partial \text{VOP}^i}{\partial r} \geq 0, \quad \frac{\partial \text{VOP}^i}{\partial p_b} \geq 0, \quad \frac{\partial \text{VOP}^i}{\partial \sigma_p} \geq 0, i \in \{\text{OM}, \text{OP}\}$$

- If $\Delta_i \geq \Delta_{\max}^i$, or equivalently, $p_b < p_o^i - \frac{(\sigma_p - (p_R - p_o^i))^2}{4\sigma_p} \equiv \bar{p}_b^i$, then

—For all $r > \bar{r}^i$:

$$\frac{\partial \text{VOP}^i}{\partial r} \geq 0, \quad \frac{\partial \text{VOP}^i}{\partial p_b} < 0, \quad \frac{\partial \text{VOP}^i}{\partial \sigma_p} < 0, i \in \{\text{OM}, \text{OP}\}$$

—For all $r \leq \bar{r}^i$:

$$\begin{aligned} \frac{\partial \text{VOP}^{\text{OM}}}{\partial r} &< 0, & \frac{\partial \text{VOP}^{\text{OM}}}{\partial p_b} &< 0, & \frac{\partial \text{VOP}^{\text{OM}}}{\partial \sigma_p} &< 0, \\ \frac{\partial \text{VOP}^{\text{OP}}}{\partial r} &\geq 0, & \frac{\partial \text{VOP}^{\text{OP}}}{\partial p_b} &< 0, & \frac{\partial \text{VOP}^{\text{OP}}}{\partial \sigma_p} &< 0, \end{aligned}$$

where

$$\bar{r}^{\text{OM}} = \left[\frac{4\sigma_p}{(\sigma_p - B)^2 - 4\sigma_p \Delta} \right] \phi, \quad \bar{r}^{\text{OP}} = \left[\frac{32\sigma_p^2}{((\sigma_p - B)^2 - 4\sigma_p \Delta)^2} \right] \lambda.$$

Let $\bar{r} = \max\{\bar{r}^{\text{OM}}, \bar{r}^{\text{OP}}\}$. This is the condition provided in assumption 1. Furthermore, in the above analysis,

$$\frac{\partial \bar{p}_b^i}{\partial p_o} = \frac{\sigma_p + (p_R - p_o)}{2\sigma_p} > 0.$$

Hence, because $p_o^{\text{OP}} \geq p_o^{\text{OM}}$, it follows that $\bar{p}_b^{\text{OP}} \geq \bar{p}_b^{\text{OM}}$. Figure .2 and Table .1 summarize these results. Finally, for Region A_2 , the comparative-statics statements in Proposition 2 follow directly from the analysis above.

■

Proof of Proposition 3. Suppose VOP is positive for both partnership models. From Proposition 1, one can verify that the VOP increases with $v^{\text{BM} \rightarrow i}$, $i \in \{\text{OM}, \text{OP}\}$. Therefore, the difference function $\Delta_{\text{VOP}}^{\text{OP} - \text{OM}}$, which shows $\text{VOP}^{\text{OP}} - \text{VOP}^{\text{OM}}$, increases when the function Δ_v increases, where $\Delta_v \equiv v^{\text{BM} \rightarrow \text{OP}} - v^{\text{BM} \rightarrow \text{OM}}$. In other

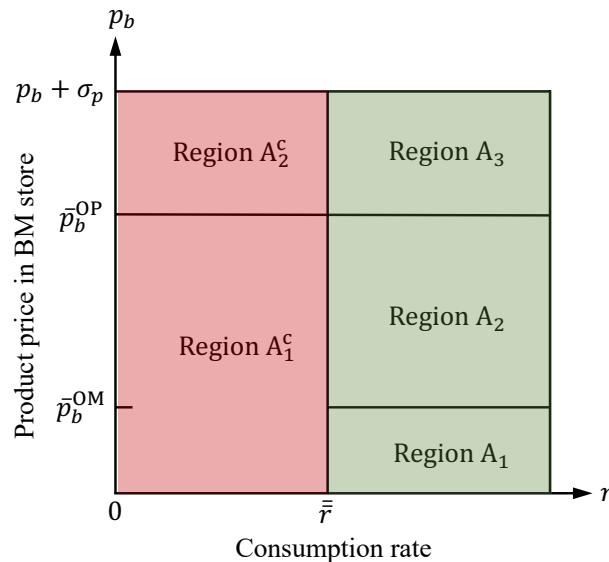


Figure .2 Classification of the regions to study the VOP

Table .1 Impact of price p_b , consumption rate r , and price dispersion σ_p on the VOP.

Region	Platform	$\frac{\partial \text{VOP}^i}{\partial r}$	$\frac{\partial \text{VOP}^i}{\partial p_b}$	$\frac{\partial \text{VOP}^i}{\partial \sigma_p}$
Regions satisfying Assumption 1				
\mathcal{A}_1	OM	> 0	< 0	< 0
	OP	> 0	< 0	< 0
\mathcal{A}_2	OM	> 0	> 0	> 0
	OP	> 0	< 0	< 0
\mathcal{A}_3	OM	> 0	> 0	> 0
	OP	> 0	> 0	> 0
Regions violating Assumption 1				
\mathcal{A}_1^c	OM	< 0	< 0	< 0
	OP	> 0	< 0	< 0
\mathcal{A}_2^c	OM	< 0	< 0	< 0
	OP	< 0	< 0	< 0

words, to understand which partnership delivers more value—and how that preference shifts with key parameters—it suffices to study the slope of Δ_v with respect to the in-store price p_b , the consumption rate r , and the online dispersion σ_p .

For the simplicity in exposition, one can write $v^{\text{BM} \rightarrow i}$, $i \in \{\text{OM}, \text{OP}\}$ in the perfect-square forms:

$$v^{\text{BM} \rightarrow \text{OP}} = \frac{(A\sqrt{r} - 4\sigma_p\sqrt{2h\lambda})^2}{32hr\sigma_p^2}, \quad v^{\text{BM} \rightarrow \text{OM}} = \frac{(Ar - 4\phi\sigma_p)^2}{32hr\sigma_p^2},$$

with $B \equiv p_R - p_o$, $\Delta \equiv p_o - p_b$ and $A \equiv (\sigma_p - B)^2 - 4\sigma_p\Delta$. Since $\sigma_p^2 > B^2$, the comparative statics of Δ_v become particularly transparent, as we discuss below.

We first begin with the in-store price p_b . Differentiating and simplifying shows that the sensitivity of the difference to p_b is $\partial\Delta_v/\partial p_b = (\phi - \sqrt{2h\lambda}, r)/h$. This expression does not depend on A and hinges only on a single threshold on consumption rate; $r_{\phi,\lambda} \equiv \phi^2/(2h\lambda)$. When consumption rate is below this threshold, the membership fee is *heavy* relative to the delivery fee per-order, so increasing p_b pushes the difference in favor of the per-order model: Δ_v rises with p_b . Exactly at $r = r_{\phi,\lambda}$, the two effects balance and Δ_v is locally flat in p_b . Once consumption rate exceeds the threshold, the delivery fee per-order burden dominates, so higher p_b tilts the comparison toward the membership model and Δ_v falls with p_b . Managerially, this means increase in BM price, which reduces the online premium, benefits the per-order model when demand is modest, but the same moves benefit the membership model once demand is relatively high.

Next we study the impact of online price dispersion σ_p . Using term derivatives and subtracting, one can obtain $\frac{\partial\Delta_v}{\partial\sigma_p} = \frac{\sigma_p^2 - B^2}{4h\sigma_p^2}(\phi - \sqrt{2h\lambda}, r)$. Since $\sigma_p^2 \geq B^2$, the prefactor is strictly positive, so price dispersion affects Δ_v through the same consumption rate threshold. When $r < r_{\phi,\lambda}$, then increasing σ_p raises Δ_v (i.e., per-order becomes relatively more attractive); when $r > r_{\phi,\lambda}$, then increasing σ_p lowers Δ_v (i.e., membership becomes relatively more attractive); and when $r = r_{\phi,\lambda}$, then Δ_v is locally flat in σ_p . Intuitively, online price dispersion creates bargain draws; at low consumption rate those draws help the per-order model compete against a

hefty membership fee, while at high consumption rate the same draws amplify the membership model's scale advantage.

Finally, consider consumption rate itself. Differentiating Δ_v with respect to r while holding A and σ_p fixed yields a rational expression with three terms:

$$\frac{\partial \Delta_v}{\partial r} = \frac{1}{32h\sigma_p^2} \left[A^2(1-r) - \frac{4A\sigma_p\sqrt{2h\lambda}}{\sqrt{r}} + \frac{16\phi^2\sigma_p^2}{r} \right].$$

Clearly, a negative term linear in r coming from the membership numerator $(Ar - 4\phi\sigma_p)^2$; a negative term proportional to $1/\sqrt{r}$ arising from per-order frictions $\sqrt{h\lambda r}$; and a positive term proportional to $1/r$ reflecting the fixed membership fee. The balance of these terms delivers a simple shape: for sufficiently small r , the $1/r$ term dominates and $\frac{\partial \Delta_v}{\partial r} > 0$; for sufficiently large r , the linear $-A^2r$ term dominates and $\frac{\partial \Delta_v}{\partial r} < 0$. By continuity, $\Delta_v(r)$ therefore increases at low consumption rate, reaches at least one interior maximum, and decreases at high demand. Economically, the per-order model can outperform at very low purchase frequency (low consumption rate) because there is no fixed fee to amortize, but as consumption rate scales the membership model's value grows faster and ultimately dominates.

Taken together, the single benchmark $r_{\phi,\lambda} = \phi^2/(2h\lambda)$ governs how both BM store price and online price dispersion tilt the comparison, while the inherent curvature in r explains why the per-order model can be preferred at low consumption rate and the membership model at high consumption rate.

We now prove that increasing the online-price gap (e.g., by raising p_o^{OP} while holding p_o^{OM} fixed) weakly decreases $\Delta_{\text{VOP}}^{\text{OP}-\text{OM}} = \text{VOP}^{\text{OP}} - \text{VOP}^{\text{OM}}$. Recall that under platform $i \in \{\text{OM}, \text{OP}\}$ the expected online price is

$$\bar{P}_o^i = p_o^i - \frac{(p_o^i - p_R + \sigma_p)^2}{4\sigma_p}, \quad F(p_o^i) = \frac{p_o^i - p_R + \sigma_p}{2\sigma_p}.$$

Moreover, from Lemmas 2–3, we have the visit-cost thresholds as

$$v^{\text{BM} \rightarrow \text{OM}} = \frac{(\phi + r(\bar{P}_o^{\text{OM}} - p_b))^2}{2hr}, \quad v^{\text{BM} \rightarrow \text{OP}} = \frac{(\sqrt{2h\lambda r} + r(\bar{P}_o^{\text{OP}} - p_b))^2}{2hr}.$$

Step 1: Monotonicity in the platform-specific online price. Differentiating \bar{P}_o^i yields

$$\frac{\partial \bar{P}_o^i}{\partial p_o^i} = \frac{\sigma_p + (p_R - p_o^i)}{2\sigma_p} = \frac{p_R + \sigma_p - p_o^i}{2\sigma_p} = 1 - F(p_o^i) > 0,$$

for $p_o^i \in (p_R - \sigma_p, p_R + \sigma_p)$. Hence, both thresholds are increasing in the corresponding platform price:

$$\begin{aligned} \frac{\partial v^{\text{BM} \rightarrow \text{OM}}}{\partial p_o^{\text{OM}}} &= \frac{\phi + r(\bar{P}_o^{\text{OM}} - p_b)}{h} \cdot (1 - F(p_o^{\text{OM}})) > 0, \\ \frac{\partial v^{\text{BM} \rightarrow \text{OP}}}{\partial p_o^{\text{OP}}} &= \frac{\sqrt{2h\lambda r} + r(\bar{P}_o^{\text{OP}} - p_b)}{h} \cdot (1 - F(p_o^{\text{OP}})) > 0. \end{aligned}$$

Moreover, $F(p_o^i)$ is increasing in p_o^i with density $f(p) = 1/(2\sigma_p)$.

Step 2: Implication for $\Delta_{\text{VOP}}^{\text{OP}-\text{OM}}$. Holding $(p_b, r, \sigma_p, \phi, \lambda)$ fixed, increasing p_o^{OP} (and thus increasing the gap $p_o^{\text{OP}} - p_o^{\text{OM}}$) makes the OP offer (i) less attractive to the marginal consumer (since $v^{\text{BM} \rightarrow \text{OP}}$ rises) and (ii) more prone to leakage to competing products on the marketplace (since $F(p_o^{\text{OP}})$ rises). Both effects reduce the retailer's expected retained demand under the OP partnership relative to the OM partnership, for which p_o^{OM} is held fixed. Therefore, $\Delta_{\text{VOP}}^{\text{OP}-\text{OM}}$ weakly decreases as the online-price gap $p_o^{\text{OP}} - p_o^{\text{OM}}$ increases, implying that a larger gap tilts the platform choice toward OM. ■

A. Propensity Score Matching

We implement a two-step matching process. In the first step, we pair stores that begin using Shipt with those that do not adopt any platform. In the second step, we repeat this process for stores adopting Instacart. This approach enables us to isolate stores adopting Shipt or Instacart while ensuring comparability to non-adopting stores. For matching, we use store-level variables from our treatment assignment model and estimate propensity scores using logistic regression, following the methodology of [Ertekin et al. \(2024\)](#). We apply k-th nearest neighbor matching and adhere to a common support restriction, maintaining a tight caliper range of 0.01. Moreover, to mitigate potential spillover effects of treatment stores on control stores, we exclude control stores that are located in the same ZIPCode of the treatment stores. This methodology yields 168 matched stores without any platform during our sample period, 226 launched Instacart, and 42 launched Shipt. We define the 19-week period prior to the treatment week (the week of May 7th, 2018) as the prior-treatment period and the 20-week period post the treatment week along with the treatment week as the post-treatment period. In Table A.1, we present the balance diagnostics across covariates to assess the quality of matching between Shipt, Instacart, and non-platform stores.

Table A.1 Propensity Score Matching between No Partnership and Shipt and Instacart Partnerships

	Unmatched Matched	Shipt	Matching between No platforms and Shipt					Matching between No platforms and Instacart				
			Mean	Bias	% Reduction	t-test	Instacart	Mean	Bias	% Reduction	t-test	
			No platforms	%	Bias	t	p> t	No platforms	%	Bias	t	p> t
Number of UPCs	U	9.5	9.418	47.4		2.65	0.008	9.568	9.419	-91.3		10.2 0
Average number of registers	M	9.497	9.495	1.2	97.4	0.06	0.953	9.522	9.513	-5.7	93.7	0.64 0.52
	U	2.399	2.206	67.7		4.21	0	2.218	2.209	-3.7		0.42 0.675
Number of household	M	2.38	2.351	10	85.3	0.48	0.634	2.296	2.27	-10.2	-171.6	0.93 0.355
	U	9.527	8.916	117		6.3	0	9.277	8.937	-62.7		7.04 0
Mean income	M	9.482	9.404	15	87.2	0.86	0.393	9.088	9.086	-0.4	99.4	0.04 0.97
	U	11.283	11.032	98.6		6.16	0	11.206	11.035	-63.9		7.23 0
Average price	M	11.246	11.22	10.2	89.6	0.49	0.626	11.113	11.098	-5.4	91.6	0.52 0.607
	U	1.395	1.353	58		3.01	0.003	1.415	1.353	-85.6		9.55 0
	M	1.391	1.39	1.3	97.7	0.06	0.952	1.399	1.39	-12.9	84.9	1.44 0.152

B. Additional Analyses

B1. Counterfactual Analysis

To quantify counterfactual changes in gross profit at the SKU level, we estimate separate triple-difference models for the Shipt and Instacart partnerships within a random-slope multilevel modeling framework (Rabe-Hesketh and Skrondal 2008). These specifications allow the effect of platform partnerships to vary across products.

$$\begin{aligned}\log GP_{ist} = & \beta_0 + \beta_1 Shipt_{is} \times After_t + \beta_2 Shipt_{is} + \beta_3 After_t + \beta_4 \log Price_{is} + \beta_5 \log Consumption_{is} \\ & + \beta_6 \log PriceDisp_i^{Shipt} + \xi_{0i} + \xi_{1i} Shipt_{is} \times After_t + \tau_t + \varepsilon_{ist},\end{aligned}$$

$$\begin{aligned}\log GP_{ist} = & \beta_0 + \beta_1 Instacart_{is} \times After_t + \beta_2 Instacart_{is} + \beta_3 After_t + \beta_4 \log Price_{is} + \beta_5 \log Consumption_{is} \\ & + \beta_6 \log PriceDisp_i^{Instacart} + \xi_{0i} + \xi_{1i} Instacart_{is} \times After_t + \tau_t + \varepsilon_{ist}.\end{aligned}$$

In both models, the coefficient on the platform-after-implementation interaction term (i.e., $Shipt_{is} \times After_t$ and $Instacart_{is} \times After_t$) is specified with a random slope at the SKU level. Here, ξ_{0i} represents the deviation of SKU i 's intercept from the overall intercept β_0 , while ξ_{1i} captures SKU-specific deviations from the average partnership effect β_1 . Thus, for each product, the estimated gross profit change from the partnership is given by $\beta_1 + \xi_{1i}$. Week fixed effects τ_t are also included to control for time-specific shocks.

Estimation results are reported in Tables B.1 and B.2. For each specification, we perform a likelihood-ratio test comparing the random-slope model to a corresponding ordinary linear regression. The test results support the inclusion of random slopes, indicating that the effects of both partnerships vary significantly across products. Finally, the estimated average partnership effects (β_1) are consistent with those reported in Tables 5 and 6, where Shipt and Instacart effects are estimated separately. This consistency lends further credibility to the multilevel model specification.

In each specification, for each SKU we obtain predicted gross profit. This step results in gross profits (i.e., $e^{GP_{ist}^{O1}}$) that the partnership is expected to generate under the current practice. We then remove from the platform the SKUs with negative impact of partnership by setting the variables of platform-after-implementation interaction term (i.e., $Shipt_{is} \times After_t$ and $Instacart_{is} \times After_t$) to 0. We then estimate the predicted gross profit for SKU (i.e., $e^{GP_{ist}^{O2}}$). Thus, the counterfactual impact of the proposed strategy on a given SKU can be estimated as $e^{GP_{ist}^{O2}} - e^{GP_{ist}^{O1}}$. We then calculate average difference the difference as

$$\left(\frac{1}{S \cdot T} \sum_{s=1}^S \sum_{t=1}^T e^{GP_{ist}^{O2}} \right) - \left(\frac{1}{S \cdot T} \sum_{s=1}^S \sum_{t=1}^T e^{GP_{ist}^{O1}} \right)$$

Table B.1 Multilevel model estimation results-Shipt

VARIABLES	Estimate	Std. Err.
Shipt × After	0.016***	(0.006)
Shipt	-0.005***	(0.0006)
After	-0.090***	(0.002)
ln Price	2.049***	(0.006)
ln Consumption	0.069***	(0.001)
ln PriceDisp ^{Shipt}	-0.778***	(0.100)
Week FE	Yes	
Deviation _{Shipt × After}	0.039***	(0.002)
Deviation _{con}	1.305***	(0.050)
Observations	7,176,667	7,176,667

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table B.2 Multilevel model estimation results-Instacart

VARIABLES	Estimate	Std. Err.
Instacart × After	-0.031***	(0.004)
Instacart	-0.0002	(0.0006)
After	-0.045***	(0.002)
ln Price	1.847***	(0.005)
ln Consumption	0.073***	(0.0006)
ln PriceDisp ^{Instacart}	-1.736***	(0.130)
Week FE	Yes	
Deviation _{Instacart × After}	0.024***	(0.0009)
Deviation _{con}	1.014***	(0.039)
Observations	13,452,754	13,452,754

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

B2. Analysis for Comparing Shipt and Instacart Partnerships

We estimate a triple-difference model that jointly includes both partnerships within a random-slope multilevel framework. This estimation model allows the effect of platform partnerships to vary across products.

$$\begin{aligned} \log GP_{ist} = & \beta_0 + \beta_1 Shipt_{is} \times After_t + \beta_2 Shipt_{is} + \beta_3 After_t \\ & \beta_4 Instacart_{is} \times After_t + \beta_5 Instacart_{is} + \beta_6 \log Price_{is} + \beta_7 \log Consumption_{is} \\ & + \beta_8 \log AvgPriceDisp_i + \xi_{0i} + \xi_{1i} Instacart_{is} \times After_t + \xi_{2i} Shipt_{is} \times After_t + \tau_t + \varepsilon_{ist}. \end{aligned}$$

In this specification, the interaction terms between platform exposure and post-implementation period ($Shipt_{is} \times After_t$ and $Instacart_{is} \times After_t$) are modeled with random slopes at the SKU level. Specifically, ξ_{0i} represents the deviation of SKU i 's intercept from the overall intercept β_0 , while ξ_{1i} and ξ_{2i} capture SKU-specific deviations from the average treatment effects of the Shipt and Instacart partnerships, β_1 and β_4 , respectively. As a result, the estimated change in gross profit for SKU i under the Shipt partnership is given by $\beta_1 + \xi_{1i}$, and under the Instacart partnership by $\beta_4 + \xi_{2i}$. To capture differences in price variability across platforms, we compute the average of price dispersion between Shipt and Instacart for each SKU and apply a logarithmic transformation, denoted as $\log AvgPriceDisp_i$. Finally, we include week fixed effects τ_t to account for time-specific shocks that may influence all SKUs simultaneously. We report the results in Table B.3.

Table B.3 Multilevel model estimation results-both platforms

VARIABLES	Estimate	Std. Err.
Shipt × After	0.014***	(0.006)
Shipt	-0.073***	(0.001)
After	-0.058***	(0.002)
Instacart × After	-0.032***	(0.004)
Instacart	-0.001	(0.001)
ln Price	1.962***	(0.005)
ln Consumption	0.071***	(0.001)
ln AvgPriceDisp	-2.214***	(0.168)
Week FE	Yes	
Deviation _{Shipt × After}	0.051***	(0.002)
Deviation _{Instacart × After}	0.026***	(0.001)
<i>Deviation_{con}</i>	1.126***	(0.043)
Observations	14,869,323	14,869,323

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1