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Online Grocery Retail: Revenue Models and Environmental Impact

Elena Belavina
Booth School of Business, University of Chicago, Chicago, Illinois 60637, elena@belavina.com

Karan Girotra, Ashish Kabra
Technology and Operations Management, INSEAD, 77305 Fontainebleau Cedex, France
{karan@girotra.com, ashish.kabra@insead.edu}

This paper compares the financial and environmental performance of two revenue models for the online retailing of groceries: the per-order model, where customers pay for each delivery, and the subscription model, where customers pay a set fee and receive free deliveries. We build a stylized model that incorporates (i) customers with ongoing uncertain grocery needs and who choose between shopping offline or online and (ii) an online retailer that makes deliveries through a proprietary distribution network. We find that subscription incentivizes smaller and more frequent grocery orders, which reduces food waste and creates more value for the customer; the result is higher retailer revenues, lower grocery costs, and potentially higher adoption rates. These advantages are countered by greater delivery-related travel and expenses, which are moderated by area geography and routing-related scale economies. Subscription also leads to lower food waste–related emissions but to higher delivery-related emissions. Ceteris paribus, the *per-order* model is preferable for higher-margin retailers with higher-consumption product assortments that are sold in sparsely populated markets spread over large, irregular areas with high delivery costs. Geographic and demographic data indicate that the *subscription* model is almost always environmentally preferable because lower food waste emissions dominate higher delivery emissions.

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1. Introduction

More than a decade has passed since the spectacular failure of Webvan, the heavily funded online grocery retailer. Today, retail-savvy tech companies, ambitious start-ups, and deep-pocketed investors (Instacart, Amazon Fresh, etc.) are again betting on the online grocery opportunity (Wohlsen 2014, Mitchell 2014).

How customers buy groceries is closely tied to two major causes of greenhouse gas emissions. First, driving to buy groceries is—after driving to work—the most common reason for using passenger vehicles; online grocery shopping has the potential to reduce some of that driving by replacing individual trips to grocery stores with a more efficient delivery truck route. Second, the mode of buying fresh groceries also affects the amount of food wasted by consumers, which is a less well-known but arguably more important contributor to emissions. In the United Kingdom, eliminating food scraps from landfills would be equivalent to taking a fifth of all cars off the roads (Gunders 2012); U.S. consumption and dietary habits make food waste an even more significant climate pollutant (Food and Agriculture Organization of the United Nations 2013). By making grocery shopping more convenient, online grocery retail could change customer buying patterns and thereby reduce food waste and its environmental consequences.

Despite the financial and environmental promise of online grocery retailing, most early attempts were unsuccessful. Since the failure of Webvan in 2001, customers have become more accustomed to online shopping, and contemporary retailers are more cautious in designing their expansion strategies. Yet nearly 15 years later, there is still only a limited understanding of appropriate revenue models and their operational consequences. The current generation of online grocery retailers is experimenting with different revenue models. Amazon charges a \$7.99 per-order delivery fee in the Seattle area; a subscription model (Amazon Prime Fresh) is offered in the Los Angeles and San Francisco areas, for which customers pay \$299/year for the privilege of unlimited free deliveries (McCarthy 2014).

This study is the first to present a (stylized) model that compares the two revenue approaches most commonly used by online fresh grocery retailers: the *per-order* model, where customers pay for each delivery, and the *subscription* model, where customers pay once each year and subsequently receive unlimited free deliveries. On the customer side, our analysis includes stochastic processes that model a customer's ongoing grocery needs; the evolution of her perishable grocery inventory; and her choice of offline/online store, basket size, and order frequency in response to the retailer's delivery pricing. For the retailer, we develop a detailed delivery cost model, identifying the cost-minimizing delivery routing and relating customer order streams to driving costs, delivery area geography, and demographics.

The subscription model's lower ordering costs incentivize more frequent orders. It is worth noting that, in the context of perishable groceries, this greater frequency results not only in *lower* grocery sales but also in *higher* supplemental customer value vis-à-vis offline shopping. When deciding how many groceries to buy in one order (the so-called basket size), customers trade off the risk of having to place additional orders against the risk of buying more groceries than can be consumed within their shelf life. The former risk is more consequential in the per-order model, leading to larger basket sizes and greater total grocery sales. Thus, an online grocery retailer that offers subscription pricing creates extra value for customers by allowing them to reduce their "safety stock" and their waste of perishable groceries. From a financial standpoint, the retailer can extract this extra value by setting a sufficiently high subscription price and thus earning higher total revenues (grocery + subscription). We refer to this as the *revenue disadvantage* of the per-order model.

It is interesting that the extra revenues in the subscription model are earned while selling fewer perishable groceries—in particular, fewer wasted groceries. Financially and environmentally, this means that the per-order model also has a *food waste disadvantage.* Yet the per-order model has the advantage that its less frequent orders have the effect of reducing delivery costs. The delivery area's specific geography and demographics moderate the extent to which these economies play out. Overall, the subscription model leads to more frequent orders and to higher delivery costs and emissions, although the difference (in comparison with the per-order model) is diminishing in the adoption rate and certain delivery area characteristics. Thus, the per-order model has a financial and environmental *order frequency advantage* over the subscription model. Finally, these advantages and disadvantages result in different per-customer marginal costs and revenues, which implies that the retailer's profit-maximizing prices lead to different rates of adoption.

This analysis allows us to characterize the financially and environmentally preferred revenue model given the retailer's product assortment (i.e., the products' average margins and rates of consumption), the delivery area's characteristics (size, shape, and per-mile driving costs), the delivery area's population demographics (population density, distribution of store visit costs, and comfort with ordering online), and the economics of a retailer's delivery operations (per-mile driving costs and number of orders a delivery vehicle can carry). We find that, all else being equal, online retailers should prefer the per-order model (over the subscription model) for products with higher margins and in markets that are spread over a large and less regularly shaped area, are associated with higher per-mile delivery costs, are sparsely populated, or are served with faster delivery promises (which require that vehicles carry fewer deliveries at a time).

Finally, we calibrate the models with real demographic and geographic data from major cities around the world. We find that, for reasonable estimates of input parameters and for a wide range of cities and product categories, the *financial* consequences of the food waste disadvantage and the order frequency advantage are comparable in magnitude and that the trade-off at the heart of our analysis is of practical relevance. Moreover, which model yields greater revenues depends strongly on product margins and city characteristics. For a city such as Los Angeles and a retailer selling fresh product assortments with average gross margins below approximately 12%, the subscription model is preferred; the per-order model is preferred for higher margins. The critical gross margin is higher from about 25% to 35% for denser delivery regions (e.g., Manhattan) and for cities with lower per-mile delivery costs (e.g., Beijing).

As for the *environmental* consequences, the results of our calibrated estimates are even more interesting. The setup we employ predicts a trade-off between the two models, yet the actual estimates suggest that—for almost all realistic delivery geographies, product assortments, and customer characteristics—the subscription model is environmentally preferable even though it entails more driving. Environmental costs associated with the per-order model's food waste are much greater than the environmental costs of extra driving, so the financially relevant trade-off is of no practical concern when the environment is considered. Although the subscription model's additional driving makes it less ecofriendly for durable products, the food waste effect reverses that prescription when the delivered product is fresh groceries.

This paper makes three contributions. First, our analysis provides important insights and prescriptions regarding the design of viable revenue models for the online retailing of fresh groceries, which is arguably the most lucrative and exciting open opportunity in online retail. Second, our analysis and calibrated numerical study of the grocery value chain's environmental impact show that food waste—an often overlooked contributor to emissions—is more important than the emissions associated with transportation, which is the main focus of past work (e.g., Cachon 2014). The implication is that future work on the environmental impact of grocery supply chains should specifically incorporate a consumer inventory model that accurately accounts for consumer food waste. Third, our model combines different economic and operational components that have heretofore been studied independently (i.e., optimal delivery routing, perishable inventories, and choice of revenue model); hence our predictions are more precise—and sometimes contradict—those derived from piecemeal models. Thus the approach described here provides a template for a more holistic analysis of business models.

2. Related Literature

Our paper is related to previous research on subscription versus usage-based pricing models, inventory planning for perishables, and delivery networks. We also contribute to the active literature on the environmental impact of operational choices.

Subscription vs. Per-Order Revenue Models. Past work has considered the choice between the two revenue models in the context of consumer services such as cellphones, DVD rentals, etc. (see Cachon and Feldman 2011 and the references therein). Our paper extends this literature by examining the choice of revenue model in the rich new context of grocery delivery. We compare the models not only from a financial but also from an environmental standpoint. The subsequent analysis will show that our model exhibits positive externalities (scale economies) rather than the congestion effects found in existing work.

Inventory Management of Perishable Products. Our model of consumer grocery ordering decisions builds directly on the vast literature addressing firm-level inventory models. In contrast to our setting, most inventory management theory focuses either on single-period decision making or on *nonperishable* products. The literature analyzing perishable products is less extensive (for an up-to-date review, see Nahmias 2011).

Delivery Networks. Our model includes the retailer's optimal choice of delivery routing, combining the well-known traveling salesman problem (see, e.g., Bramel and Simchi-Levi 1997) and an optimal division of the delivery area into sectors (Daganzo 1984a, b). We draw extensively on this literature.

Environmental Impact of Operational Decisions. A recent high-impact body of literature has studied the environmental effects of operational decisions. Among other authors, Agrawal et al. (2012) compare the revenue models of leasing and selling. Akkas et al. (2014) use data from a large grocery retailer to identify the drivers of *in-store* product expiration. Cachon (2014) compares the environmental performance of different supply chains in *offline* retailing. That paper is probably the closest to ours, although we consider *online grocery* retail (while incorporating the role of consumer food waste) as well as the retailer's choice of revenue model.

3. Model Setup

3.1. The Grocery Customer

Consider an online grocery retailer that serves a market $\mathcal{A}$ of size A (see Figure 1). Potential customers are distributed with uniform density ρ in this area. The grocery consumption of customers is random as a result of unpredictable demand shocks (e.g., unexpected guests, last-minute plans to dine out) and consists of both perishable and nonperishable items. Formally, each customer's grocery consumption is generated according to a Poisson process whereby instances of consumption occur at a rate of μ per year. Each consumption instance corresponds to a consumption of 1 (normalized) monetary unit's worth of perishables and σ monetary units' worth of nonperishables.

Customers choose when to buy groceries and also choose their preferred channel: visiting an offline store, ordering at an online store that offers home delivery, or a combination of these channels. In addition, for each purchase of groceries, they choose what amount to buy (i.e., the basket size).

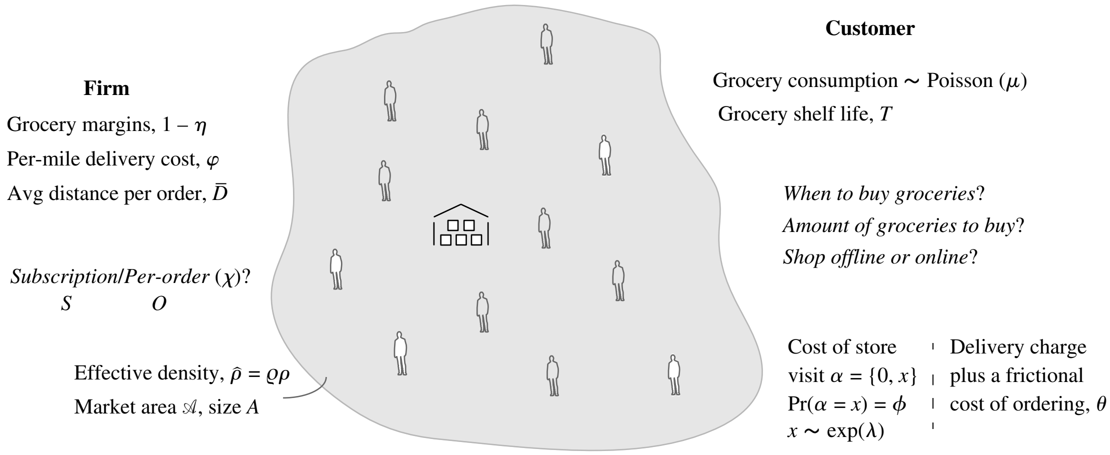
A customer who buys groceries *offline* incurs an idiosyncratic and time-varying cost for each store visit. Customers differ in terms of the inconvenience they associate with visiting the offline store owing to different opportunity costs of time, distances from the grocery store, fondness for shopping, and so forth. Furthermore, a given customer may value this inconvenience differently at different times because of unpredictable changes—for instance, on some days she might pass by a grocery store, whereas a store visit might be less convenient on other days.

We model these store visit costs with a random variable α. At the time of each store visit, α takes either the value x with probability ϕ or the value 0 with probability $1-\phi$;[1] the latter represents convenient store visits. The inconvenient (high) store visit cost x itself differs for each customer; this captures the time-invariant heterogeneity among customers. We assume that x is distributed exponentially in the customer population: $x \sim \exp(\lambda)$.[2] We use $G(x)$ to denote the

[1] Section 4.4 of the electronic companion (available as supplemental material at http://dx.doi.org/10.1287/mnsc.2016.2430) provides a three-level model for the intertemporal variation in store visit costs.

[2] Brown and Borisova (2007) provide empirical support for this assumption; they find that the major component of the store visit cost is time. The value of time can be approximated by income, whose distribution is known to be roughly exponential (*Wikipedia, The Free Encyclopedia*, s.v. "Household income in the United States," http://bit.ly/HHIIncome, accessed May 9, 2016).

Figure 1 **The Grocery Delivery Business Model**



cumulative distribution function of x; $g(x)$ is the density function, and $\bar{G}(x)\equiv 1-G(x)$ is the survival function.

A customer who instead orders from the *online* retailer incurs—in addition to the delivery charges—an ordering cost θ. This term captures the inconvenience of going to the website, selecting groceries, placing the order, and receiving the delivery. We assume that groceries ordered online are delivered almost instantly (same-day delivery is typically offered by prominent online grocery retailers). Finally, the perishable groceries purchased by the customer have a limited shelf life; a representative basket expires T days after purchase.

3.2. The Online Grocery Retailer

The online retailer of fresh groceries builds a web-based storefront and a proprietary distribution network to make deliveries.[3] This network consists of a warehouse along with a fleet of vehicles, each of which can make as many as K deliveries per run.[4] Product diffusion, market penetration, and Internet access constraints limit the online retailer to serving only a fraction ϱ of the population, so the effective density of potential customers for that retailer is $\hat{\rho}=\varrho\rho$.

Revenues. The retailer generates revenue from the grocery sales and also charges for delivery. It can choose between two revenue models for its delivery service: the subscription model (S) or the per-order model (O). In the former, customers pay a subscription fee s each year and enjoy free delivery for all orders placed during that year; in the latter, the customer pays a delivery fee o for each order.

[3] Using third-party logistics providers is seldom viable in this context because of the short delivery times, special transit requirements, and perishable nature of the products.

[4] The number of deliveries (K) is determined by the delivery offer. In particular, K is smaller for a faster delivery offer, for tighter delivery time windows, for a longer time required to reach customers, and for smaller delivery vehicles.

Costs. The retailer has two main variable costs: the cost of sourcing groceries and the cost of delivering them. It sources groceries at a cost of η times the sale price, where $\eta<1$ and $1-\eta$ captures the gross margin. For every order *delivered*, the retailer incurs an average direct delivery cost of $\varphi\bar{D}$; here, φ is the per-mile delivery cost (which subsumes the costs of fuel, labor, truck purchase, licensing, depreciation, etc.), and $\bar{D}$ is the average distance traveled to deliver an order. It is determined by the lowest-cost feasible routing scheme that can fulfill all delivery commitments (we derive the expression for this distance in Section 5.1).

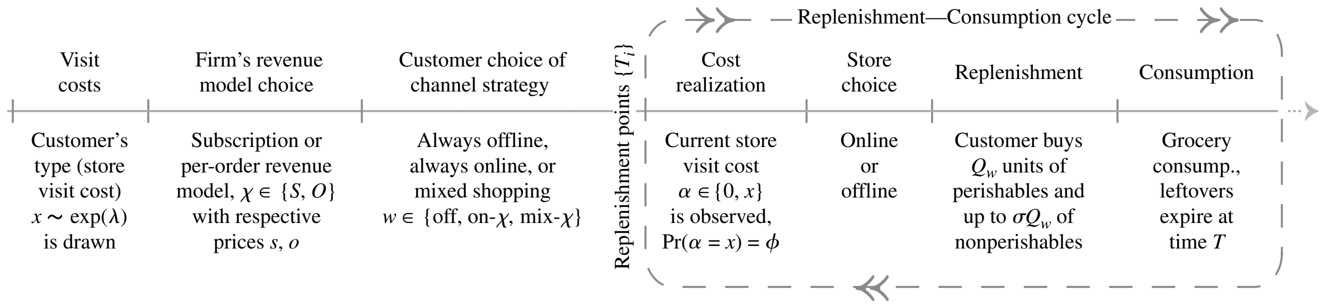
An online retailer also incurs "picking" costs as well as the costs of building a warehouse, buying vehicles, training employees, and so forth. These costs have three potential components: one that depends on the amount of groceries sold, one that depends on the number of orders serviced by the online warehouse, and finally some fixed costs. The first component is subsumed by the sourcing cost (η), and the second is captured by a picking cost c_p that the retailer incurs for each order. The third component (fixed costs) does not change under the two revenue models in question, so it has been excluded from all model comparisons.

3.3. Sequence of Events

The sequence of events is illustrated in Figure 2. First, nature draws each customer's type x, which captures the inconvenient store visit costs. This cost is known only to the customer, although its distribution is common knowledge. Then the retailer chooses a subscription (S) or per-order (O) revenue model, $\chi\in\{S,O\}$, and the relevant prices: the yearly subscription fee s or the per-order fee o.

Next, the customer decides on her channel strategy $w\in\{\text{off},\text{on-}\chi,\text{mix-}\chi\}$. The customer may plan to (i) always shop offline (off), (ii) always shop online (on-χ), or (iii) choose between online and offline shopping as a function of the store visit costs when a purchase is contemplated (mix).

Figure 2 **Sequence of Events**



Finally, the customer reviews her grocery inventory and, based on the realized consumption and spoilage of groceries, decides when to replenish them. At each replenishment time, the customer realizes her current store visit cost, visits the chosen store (following her channel strategy and the cost realization), and decides on her basket size—that is, how many perishable and nonperishable groceries to buy in anticipation of future consumption, spoilage, and store visit costs. This replenishment–consumption cycle continues indefinitely.

4. Customer Behavior

A customer's decisions include choosing a channel strategy $w \in \{\text{off}, \text{on-}\chi, \text{mix-}\chi\}$, the timing $\{T_i\}$ of ith replenishment, and—at each replenishment time—the basket size. We start by describing the timing and basket size choices for any given channel strategy.

4.1. Order Timing

The customer continuously reviews her inventory level and decides whether or not to place a new order while bearing in mind the costs of replenishment, grocery spoilage, and the constraint that her grocery demand must be met. Our analysis reveals that the replenishment timing choice is driven by perishable grocery: it is optimal to make the purchase of durable goods coincide with the purchase of perishables (see Lemma 5 in the appendix).

The customer's perishable grocery replenishment process can be viewed as a continuous-review inventory management problem with state-dependent replenishment costs. The optimal replenishment policy in such settings is likely to be state dependent: the reorder point might depend on the time remaining before inventory expiration and the current realization of store visit costs. Berk and Gurler (2008) show that policies with stationary reorder points are very close to the state-dependent policies. Thus, we develop our analysis using a stationary reorder point. Groceries are perishable, there is a cost of replenishment, and there is no lead time. Therefore the customer will replenish groceries only when she runs out (through depletion or expiration)—that is, replenish as seldom as possible and no sooner than necessary.

4.2. Basket Size

The optimal perishable grocery replenishment quantity must be such that it appropriately trades off the customer's costs of replenishing groceries against food waste. On the one hand, if the customer buys too many groceries, then some of them will be wasted and thus lead to unnecessary grocery expenses. On the other hand, if she buys too few groceries, then all items will be consumed before expiration; that would lead to an extra order/store trip and hence to extra *future* replenishment costs. These depend on the channel strategy but not on the *current* realization of store visit costs, and so, for any given channel strategy, the consequences of buying too few groceries are the same at every replenishment time. Thus, at each replenishment, the system returns to the same state. Consequently, the basket sizes are the same at each replenishment, $Q_{w_{T_i}} = Q_w$, and are a function of the expected replenishment costs.

Since the customer buys the same quantity of perishables each time, successive cycles are independent and identical. The length of the ith cycle, CT_i, depends on the basket size Q. The expected cycle length is $E[CT_i(Q)] = \mu^{-1}(Q - \sum_{j=0}^{Q}(Q-j) \cdot p_j(\mu T))$, $p_j(\mu T) = e^{-\mu T}(\mu T)^j/j!$ (Lemma 5). The term in large parentheses is the expected consumption of perishable groceries per cycle, and μ is the average consumption rate of perishables. Of Q units ordered, it is expected that $\sum_{j=0}^{Q}(Q-j) \cdot p_j(\mu T)$ will be wasted; p_j is the probability that consumption during the shelf life T is equal to j. Furthermore, the expected number of orders in a year induced by ordering Q units at a time (Lemma 5): $N(Q) = 1\ \text{year}/(E[CT_i(Q)]) = \mu(Q - \sum_{j=0}^{Q}(Q-j) \cdot p_j(\mu T))^{-1}$. We consider all costs on an annual basis, so that annual subscription costs can be incorporated accurately.

For nonperishable items, the replenishment policy is simply an order-up-to policy. At each replenishment point, the customer buys enough nonperishables to bring her inventory level up to σ times the perishable inventory Q_w—that is, up to level σQ_w (Lemma 5).

Now, for a size Q basket of perishable groceries and replenishment costs a, we can write the customer's expected yearly cost as $aN(Q)+QN(Q)+\sigma\mu$. Here, $\sigma\mu$ captures the expected nonperishable purchases and $QN(Q)$ the expected cost of perishable groceries—namely, the direct costs of purchasing groceries, Q, multiplied by the number of ordering cycles in a year, $N(Q)$. Finally, $aN(Q)$ captures the total replenishment costs. The optimal basket size is given by $Q^*(a) \equiv \arg\min_Q (aN(Q)+QN(Q)+\sigma\mu)$. Lemma 5 provides the implicit definition of the function $Q^*(a)$.

Lemma 1. *Higher replenishment costs a lead to larger perishable grocery basket sizes,* $\partial_a Q^* > 0$; *fewer annual orders,* $\partial_a N(Q^*) < 0$; *a higher annual volume of perishable groceries purchased,* $\partial_a (N(Q^*)\cdot Q^*) > 0$; *and higher customer's optimal grocery cost,* $\partial_a (aN(Q^*)+Q^*N(Q^*)+\sigma\mu) > 0$.

Proofs for all results are given in the appendix. The optimal basket size for perishables trades off the risk of buying too many groceries (which would lead to waste) against the risk of buying too few (which would trigger additional replenishments and increase replenishment costs). Thus, a higher replenishment cost a induces customers to buy larger baskets, but less frequently. Larger baskets increase the likelihood that some of the groceries expire before they are consumed, thus increasing the average waste. Given that annual grocery consumption is independent of replenishment costs, higher waste implies that the customer purchases a higher annual quantity $N(Q^*)Q^*$ of groceries. Finally, the "larger basket size" effect dominates the "less frequent replenishment" effect and so the customer's grocery costs are increasing in a.

4.3. Channel Strategy

The customer's channel strategy $w \in \{\text{off}, \text{on-}\chi, \text{mix-}\chi\}$ determines her replenishment costs a. If the strategy is to always choose the offline store, $w=\text{off}$, then the replenishment costs are simply the expected store visit costs: $a_{\text{off}} = E[\alpha] = \phi x$. If the strategy is to always choose the online store, $w = \text{on-}\chi$, then the replenishment costs are the online ordering costs θ plus the per-order delivery fee (when the per-order model is used).

Finally, suppose the customer chooses the contingent combination strategy, $w=\text{mix-}\chi$. Of the various possible combinations, the best one is to shop online when the store visit cost is high ($\alpha = x$) and to shop offline whenever that cost is low ($\alpha = 0$). Then the ordering cost is $a_{mix-O} = \phi(\theta+o)$ under the per-order revenue model and $a_{mix-S} = \phi\theta$ under the subscription revenue model.

The contingent combination strategy dominates the always *online* strategy, but preference for the always *offline* strategy versus the combination strategy depends on the customer's type and the retailer's specific offer. The customer's optimal annual costs under the always offline strategy are

$$C_{\text{off}} \equiv (\phi x + Q^*(\phi x)) \cdot N(Q^*(\phi x)) + \sigma\mu, \tag{1}$$

while the costs with combination strategy are as follows:

$$C_{\text{mix-}\chi} = \begin{cases} (\phi o + \phi\theta + Q^*(\phi o + \phi\theta)) \\ \quad \cdot N(Q^*(\phi o + \phi\theta)) + \sigma\mu \quad \text{if } \chi = O, \\ s + (\phi\theta + Q^*(\phi\theta)) \cdot N(Q^*(\phi\theta)) + \sigma\mu \\ \qquad\qquad \text{if } \chi = S. \end{cases} \tag{2}$$

The customer's choice between the always offline strategy and the combination strategy simply boils down to minimizing the yearly cost: $w^* = \arg\min_{w\in\{\text{off},\,\text{mix-}\chi\}} C_w$.

We simplify the notation for the optimal order size by denoting $Q_{\text{off}} \equiv Q_x \equiv Q^*(\phi x)$ as the optimal perishable basket size under the always offline strategy for a type x customer, $Q_o \equiv Q^*(\phi o + \phi\theta)$ as the optimal basket size when using the combination strategy and the per-order revenue model, and $Q_s \equiv Q^*(\phi\theta)$ as the optimal basket size when using the combination strategy and the subscription revenue model. Similarly, for the number of orders per year, we set (respectively) $N_{\text{off}} \equiv N_x \equiv N(Q_x)$, $N_o \equiv N(Q_o)$, and $N_s \equiv N(Q_s)$.

5. Retailer Decisions

The online grocery retailer builds a distribution network to deliver groceries, chooses either the subscription or the per-order model, and determines the relevant price. We start by analyzing the design of the distribution network that meets the delivery requirements at the lowest cost.

5.1. The Proprietary Distribution Network

The retailer's distribution network consists of a warehouse located in area $\mathcal{A}$ and a fleet of delivery vehicles. We assume that the number of orders delivered by one vehicle in one delivery period K is significantly smaller than the number to be delivered in the entire market at the same time, $K \ll A\rho_d$. We have $\rho_d = \bar{\rho}N\delta^{-1}$; here, $\bar{\rho}$ is the density of the population that adopts the online service (in Section 5.2 we define this term explicitly), N is the annual number of orders per customer, and δ is a coefficient that converts the annual number of orders into the number of orders per delivery period. For example, if the retailer delivers once a day, then $\delta = 365$. On the basis of the specific orders to be delivered in a period, the retailer devises the following distribution plan. First, it optimally partitions area $\mathcal{A}$ into sectors $\mathcal{S}_i$, $i \in \{1, \dots, I\}$, so that each sector has K customers. Each sector is then assigned a vehicle that, following an optimal route, visits each of the K customers. A detailed version of this analysis is provided in Section 3 of the electronic companion; the key results follow.

LEMMA 2. (i) *When K orders are delivered by one vehicle, the average distance traveled to deliver an order in a region of size A, of uniform customer population density $\bar{\rho}$, and with customer yearly order frequency N is*

$$\bar{D}(\bar{\rho}, N, A, K) \cong \frac{2\zeta\sqrt{A}}{K} + \Lambda(K)\sqrt{\frac{\delta}{\bar{\rho}N}}, \quad \text{with } \partial_K \Lambda(K) < 0. \qquad (3)$$

(ii) *The per-order average distance is decreasing in the number of orders ($\partial_N \bar{D} < 0$) and in the adopting density ($\partial_{\bar{\rho}} \bar{D} < 0$), but it is increasing in the order costs ($\partial_a \bar{D} > 0$). The total annual distance traveled per customer, $N\bar{D}$, is increasing in the number of orders ($\partial_N N\bar{D} > 0$) but is decreasing in the order costs ($\partial_a N\bar{D} < 0$).*

The first component of Equation (3), $\zeta\sqrt{A}$, constitutes the average "line-haul" distance that has to be traveled to reach a delivery sector, which must be covered twice (to get to the sector and back) and is distributed over the K deliveries. The coefficient ζ is determined by the region's shape and the warehouse's location. Shape parameter ζ is greater when markets are more irregular: it is smallest for the circular regions, followed by square and rectangular regions ($\zeta_{\text{ci}} < \zeta_{\text{sq}} \le \zeta_{\text{re}}$). Increasing the rectangle's length-to-height ratio γ (a higher γ corresponds to the more elongated rectangle) also increases the shape parameter $\partial_\gamma \zeta_{\text{re}} > 0$ and so does a noncentral warehouse location ($\zeta_{\text{re}} \le \zeta_{\text{re}}^{\text{nc}}$). The exact expressions for $\zeta_{\text{ci}}, \zeta_{\text{sq}}, \zeta_{\text{re}}$, and $\zeta_{\text{re}}^{\text{nc}}$ are provided in Section 3 of the electronic companion for the interested reader.

The second component of Equation (3) is the traveling salesman tour that visits each of K customers within the sector. The proof of Lemma 2 identifies an expression for the coefficient $\Lambda(K)$. It captures the economies of scale in the traveling salesman tour: the per-order average length of the optimal tour decreases as we add more points (orders) to the tour.

Part (ii) shows that there are economies of scale in delivery. If there are more customers (i.e., if $\bar{\rho}$ increases) and/or if customers order more often (N increases), then the per-order delivery distance decreases. Along the same lines, a higher ordering cost a will lead both to fewer orders and to fewer customers and thus to a higher average distance traveled. Finally, with respect to total annual distance traveled per customer, the order frequency effect dominates the average delivery distance effect; hence a higher frequency leads to more annual travel.

5.2. Choice of Revenue Model

Suppose the retailer chooses the *per-order* pricing model. Then customers whose type x is above a certain threshold will choose the combination channel strategy, whereas those of the type lower than this threshold will choose to always shop offline (Lemma 6).

The retailer's profits (at the profit-maximizing per-order price) can then be written as

$$\begin{aligned}\pi_O = \max_o \big(&\sigma\mu(1-\eta) + (o + Q_o)N_o \\ &- \{\varphi \cdot \bar{D}(\hat{\rho}\bar{G}(\tilde{x}), \phi N_o, A, K) + \eta Q_o + c_p\} \cdot N_o\big) \\ &\cdot A\hat{\rho}\phi\bar{G}(\tilde{x}_o),\end{aligned} \qquad (4)$$

where $\tilde{x}_o = \min\{x \text{ s.t. } C_{\text{off}} \ge C_{\text{mix-O}}\}$. The first term in this formulation is the per-customer profit from the sale of nonperishable items, and the second term is the per-customer delivery and perishable grocery revenues. The third term includes the variable cost components, the per customer-order costs of delivery, and the costs of sourcing perishable groceries (and picking) multiplied by the number of customer orders per year. Finally, the multiplicative term represents the number of customers buying from the online grocery retailer; that is, $\phi\bar{G}(\tilde{x}_o)$ captures the fraction of potential customers who buy from the online retailer on any given day.

If instead the retailer chooses the *subscription* model, then again, the customer's choice of channel strategy is a threshold choice in the customer's type x. So the maximum expected profit under subscription pricing (at the profit-maximizing subscription price) is, analogously,

$$\begin{aligned}\pi_S = \max_s \Big(&\phi\sigma\mu(1-\eta) + \{s + Q_s\phi N_s\} \\ &- \{\varphi \cdot \bar{D}(\hat{\rho}\bar{G}(\tilde{x}_s),\ \phi N_s, A, K) + \eta Q_s + c_p\} \\ &\cdot \phi N_s\Big) \cdot A\hat{\rho}\bar{G}(\tilde{x}_s),\end{aligned} \qquad (5)$$

where $\tilde{x}_s = \min\{x \text{ s.t. } C_{\text{off}} \ge C_{\text{mix-S}}\}$. As before, the first term is the nonperishable grocery profit, the second is the per-customer subscription and perishable grocery revenues, the next terms include the delivery and sourcing costs, and the multiplicative term captures the fraction of customers who buy online. Finally, the retailer will choose the pricing scheme that maximizes its profit: $\chi = \arg\max_{\chi \in \{O, S\}} \pi_\chi$.

6. Equilibrium Outcomes

6.1. Per-Order Revenue Model

LEMMA 3 (EQUILIBRIUM OUTCOME UNDER THE PER-ORDER REVENUE MODEL). (i) *The online retailer charges a delivery fee $o = x_o^* - \theta$, where the optimal market coverage x_o^* is the unique solution to $(N_x + (1-\phi)x\partial_x N_x - \partial_x h_o(x))\bar{G}(x) = (C_x - h_o(x))g(x)$. Here, $h_o(x) \equiv \{\varphi \cdot \bar{D}(\hat{\rho}\bar{G}(x), \phi N_x, A, K) + \eta Q^*(\phi x) + \theta + c_p\}N_x - \sigma(1-\eta)\mu$; $C_x \equiv (x + Q_x)N_x$.*

(ii) *Customers of type $x > x_o^*$ choose the contingent combination channel strategy: shop online when store visit costs are high ($\alpha = x$) and shop offline when store visit costs are low ($\alpha = 0$). These customers all purchase the same basket size $Q^*(\phi x_o^*)$. Customers of type $x < x_o^*$ always shop offline, and each such customer's idiosyncratic basket size is $Q^*(\phi x)$.*

The equilibrium is best understood by examining the effect of a price change on each term in the retailer's profits (Equation (4)) while keeping in mind customer response to this price (i.e., her ordering costs; see Lemma 1), delivery costs (Lemma 2), and the adoption rate.

Recall that an increase in ordering costs increases the customer's basket size, reduces the annual number of orders per customer, and increases the amount of perishable groceries purchased by each customer (and hence the amount of food waste); see parts (ii) and (iii) of Lemma 1. Thus an increase in the per-order price increases the direct perishable grocery profits $(1-\eta)Q_o N_o$ but also increases a customer's cost of using the online channel—both directly (owing to higher annual delivery costs oN_o) and indirectly (owing to higher perishable grocery expenses $Q_o N_o$). As a result, customer adoption $\bar{G}(\tilde{x}_o)$ declines and so does the amount $\sigma\mu\bar{G}(\tilde{x}_o)$ of nonperishable groceries sold. With regard to delivery, an increase in the per-order price increases *per-order* delivery costs $\varphi\bar{D}$ because of a lower order frequency and lower adoption rate; however, the annual *per-customer* delivery costs $\bar{D}N_o$ actually decrease because the order frequency effect dominates (Lemma 2(ii)). Hence the delivery profits $(o-\varphi\bar{D})N_o$ are increasing in o. Overall, the delivery costs and perishable grocery profits increase when the retailer sets higher per-order prices—although doing so reduces adoption by customers. A per-order delivery price of $o=x_o^*-\theta$ (with x_o^* defined as before) optimally trades off the per-customer profit effect against the adoption effect or the market size effect. Given an optimal delivery fee, customers of type $x \geq x_o^*$ employ the combination channel strategy while all other customers always use the offline channel. The resulting yearly per-customer delivery and grocery purchase cost is captured by $h_o(x_o^*)$.

6.2. Subscription Pricing

Lemma 4 (Equilibrium Outcome Under the Subscription Pricing Model). (i) *The online retailer charges a yearly subscription fee* $s^*=(\phi x_s^*+Q^*(\phi x_s^*))N(Q^*(\phi x_s^*))-(\phi\theta+Q_s)N_s$, *where the optimal market coverage* x_s^* *is a unique solution to* $(N_x-\partial_x h_s(x))\bar{G}(x)=g(x)(C_x+\Gamma_x-h_s(x))$; *here,* $h_s(x)\equiv\{\theta+\varphi\cdot\bar{D}(\hat{\rho}\bar{G}(x),\phi N_s,A,K)+\eta Q_s+c_p\}\cdot N_s-\sigma(1-\eta)\mu$ *and* $\Gamma_x\equiv((1-\phi)/\phi)[Q_x N_x-Q_s N_s]$.

(ii) *Customers of type* $x \geq x_s^*$ *choose the contingent combination channel strategy*: *shop online when store visit costs are high* $(\alpha=x)$ *and shop offline when store visit costs are low* $(\alpha=0)$. *These customers all order the same basket size* Q_s *on an ongoing basis. Customers of type* $x<x_s^*$ *always shop offline*; *each such customer's idiosyncratic basket size is* $Q^*(\phi x)$.

Subscription price affects the direct delivery revenues and market adoption (which in turn affect delivery costs) but has no effect on either the amount of groceries purchased or the order frequency. Thus the trade-off driving the choice of subscription price is simpler than that for the choice of per-order price: higher subscription prices increase the retailer's revenue but also reduce adoption rates. Lower levels of adoption entail higher delivery costs because in that case there are fewer economies of scale. As before, our marginal customer is the one with high store visit cost x_s^*. The resulting yearly per-customer delivery and grocery purchase cost for online customers is captured by $h_s(x_s^*)$.

7. Comparing Revenue Models: Subscription vs. Per Order

7.1. Comparing Equilibrium Customer Behavior

Irrespective of the revenue model employed, there are two kinds of customers: *adopting* customers—those who follow the contingent combination strategy of sometimes buying offline and sometimes online—and customers who always buy offline. Not surprisingly, the latter group's behavior is not affected by the revenue model employed, whereas the former group's behavior is. Even when adopting customers buy offline, they consider the expected costs of future grocery orders because such future purchases include the possibility of online purchases whose costs depend on the online retailer's revenue model. This section examines the equilibrium behavior of adopting customers, which has important ramifications for the retailer's choice of revenue model and for the environmental impact of that choice.

Theorem 1. *Adopting customers order larger grocery basket sizes and order less frequently in the per-order model than in the subscription model. Overall, the total offline and online purchases of perishable groceries is higher in the per-order model* (*i.e., larger basket size dominates the lower frequency*), *and greater delivery distances are traveled in the subscription model to serve an adopting customer. Offline or online, adopting customers purchase the same amount of nonperishable groceries in the two revenue models.*

Corollary. *Adopting customers' expected food waste—that is, the amount of perishable groceries that expire before being used—is higher in the per-order model than in the subscription model.*

At equilibrium subscription and per-order prices, for adopting customers, the expected ordering costs are higher in the per-order model. By Lemma 1, it follows that the per-order model is characterized by larger perishable grocery basket sizes, fewer orders, and more perishable groceries purchased annually. Expected perishable grocery consumption is simply the mean demand rate, which is the same for the two models. Since more perishable groceries are purchased in the per-order model, waste is higher.

A higher annual grocery volume with fewer orders suggests that the per-order retailer sells more per customer while spending less delivering the groceries and hence that the per-order model should dominate. This analysis is incomplete, however, because of another factor distinguishing the two models. Since they lead to different customer behavior and grocery waste, the two models also create different supplemental value (over offline shopping) for customers. This factor affects the prices (subscription or per order, as applies) that can be set and thus how much of that value can be extracted by the retailer. Furthermore, if different revenue models create different levels of supplemental value, then the implication is that the two models will exhibit different adoption rates and hence different economies of scale in delivery. Together these effects lead to a drastic departure from the naïve analysis.

7.2. Comparing Equilibrium Outcomes

The equilibrium profits can be rewritten as maximization problems in which the retailer—rather than choosing the delivery price, which determines the rate of market adoption—directly chooses an optimal adoption level via the critical store visit costs x^*:

$$\begin{aligned}\pi_s &= \max_x \pi_s(x)\\ &\equiv \max_x \phi(\sigma(1-\eta)\mu + C_x + \Gamma_x - h_s(x))A\hat{\rho}\bar{G}(x); \quad (6)\\ \pi_o &= \max_x \pi_o(x)\\ &\equiv \max_x \phi(\sigma(1-\eta)\mu + C_x - h_o(x))A\hat{\rho}\bar{G}(x). \quad (7)\end{aligned}$$

Here, $\Gamma_x \equiv ((1-\phi)/\phi)[Q_xN_x - Q_sN_s]$. This formulation subsumes customer behavior and allows for an intuitive decomposition of model differences into (a) per-customer revenues, (b) per-customer costs, and (c) market adoption rates. Note that, regardless of the adoption rate, the *nonperishable* grocery *profits* (i.e., $\phi\sigma(1-\eta)$) are the same in the two revenue models; hence we can exclude them when comparing per-customer revenues and costs. The comparison of revenues and costs for per-customer delivery and perishable grocery is more involved. We start with the revenues.

From Theorem 1, it follows that the retailer's per-customer perishable grocery revenues are higher in the per-order case because the customer buys more (she builds higher safety stock) in anticipation of higher ordering costs. However, this extra grocery, in expectation, ends up as waste and so does not create additional value for the customer. That a given customer type (as signified by x) spends less on groceries in the subscription model has important consequences for how the retailer sets its subscription fee s. It can set s to extract additional value created by lower grocery purchases, in which case the grocery revenue losses of the subscription model are compensated by the increased subscription fee; hence the term C_x is the same in both models.

It is noteworthy that, under the subscription model, offline purchases are also reduced because expected replenishment costs are lower (since costs are expected to be lower when shopping online). This allows the retailer to increase the subscription fee still more, an advantage that is captured by the term Γ_x. In essence, with a subscription fee the retailer can recover any grocery revenue losses and can also extract the customers' gains as a result of their savings compared with the offline shopping, as they stock and waste fewer perishable groceries. We call this the *revenue disadvantage* of the per-order model (see Figure 3(a)).

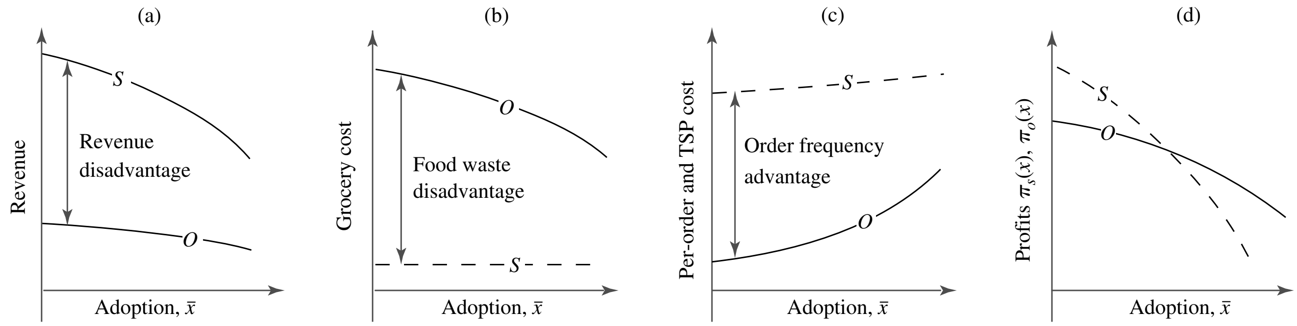
Next we compare per-customer costs, which are captured by the following two equations:

$$\begin{aligned}h_s(x) &= \eta Q_sN_s + (\theta + c_p)N_s + \varphi\cdot\frac{2\zeta\sqrt{A}}{K}N_s\\ &\quad + \varphi\cdot\Lambda(K)\sqrt{\frac{\delta}{\hat{\rho}\bar{G}(x)\phi}}\sqrt{N_s};\\ h_o(x) &= \eta Q_xN_x + (\theta + c_p)N_x + \varphi\cdot\frac{2\zeta\sqrt{A}}{K}N_x\\ &\quad + \varphi\cdot\Lambda(K)\sqrt{\frac{\delta}{\hat{\rho}\bar{G}(x)\phi}}\sqrt{N_x}.\end{aligned}$$

In both models, these costs have four components. The first is the per-customer grocery sourcing cost, $\mathcal{G}_{\cdot} = \eta Q_{\cdot}N_{\cdot}$, which is always higher for the per-order model. As discussed previously, the per-order model sells more groceries (see Theorem 1); so all else equal, the subscription model surprisingly outperforms from the standpoint of grocery cost. This is the second fundamental difference between the two revenue models: the per-order model has a *food waste disadvantage* (see Figure 3(b)).

The second component combines the retailer's per-order cost $c_pN_{\cdot}$ and the customer's ordering costs $\theta N_{\cdot}$ (in both models, the firm compensates the consumer for her ordering inconvenience θ by lowering prices). The third component is the per-customer annual line-haul delivery costs $\varphi((2\zeta\sqrt{A})/K)N_{\cdot}$. Both of these cost components are increasing in the order frequency and are therefore higher under the subscription model, $N_s > N_x$. The fourth and final component is the per-customer annual traveling salesman tour cost: the average per-order traveling salesman tour costs $\varphi\cdot\Lambda(K)\sqrt{\delta/(\hat{\rho}\bar{G}(x)\phi N_{\cdot})}$ multiplied by the order frequency $N_{\cdot}$; thus, $\varphi\cdot\Lambda(K)\sqrt{\delta/(\hat{\rho}\bar{G}(x)\phi)}\sqrt{N_{\cdot}}$. Note that this cost is also increasing in the order frequency but at a slower than linear rate, since there are two kinds of scale economies: the order frequency itself ($\sqrt{N_{\cdot}}$) and the

Figure 3 Per-Order vs. Subscription Revenue Model: Comparison of Per-Customer Revenue, Grocery, and Delivery Costs and of Overall Profits



Note. TSP, traveling salesman problem.

adoption level $\bar{G}^{-1/2}(x)$. For the same level of adoption, the traveling salesman tour costs will be higher in the subscription model. Although different equilibrium adoption rates might change this, they are usually higher in the subscription model. We refer to the combined effect of these delivery costs (sum of the second, third, and fourth components) as the per-order model's *order frequency advantage* (see Figure 3(c)).

In sum, the per-order model enjoys the order frequency advantage but suffers from the food waste and revenue disadvantages. All three effects are on a per-customer basis, and the fourth and final effect concerns optimal adoption levels. Because adoption influences the magnitude of the first three advantages by scaling them upward, it determines which of them dominates. It turns out that all three differences are decreasing in the adoption level, as evidenced in panels (a), (b), and (c) of Figure 3. Figure 3(d) depicts the retailer's profit curves (as a function of the adoption level $\bar{x}$, where all customers of type $x \geq \bar{x}$ will adopt) under the two models. We can show that if in both models the adoption levels are above (respectively, below) the intersection point of the two profit curves, then the financial impact of the order frequency advantage dominates (respectively, is dominated by) the impact of the food waste and revenue disadvantages. We refer to the role of adoption as the *adoption effect*.

7.3. Which Revenue Model Yields Higher Profits?

The financial and environmental comparison between the two revenue models is driven by a nonlinear interaction involving the revenues (the revenue disadvantage), the grocery costs (the food waste disadvantage), the delivery costs (the order frequency advantage), and the adoption effect. However, further analysis shows that an overall comparison of the two revenue models can be expressed using a single metric—one that allows us to identify the preferred revenue model as a function of the market area's spatial and demographic properties, the product's characteristics, and the economics of delivery. Analyzing the constituent marginals allows us to demonstrate a single-crossing property in the shape parameter.[5]

Theorem 2. *If*

$$\partial^2_{x_o^*} h_o(x_o^*) \geq \frac{1}{4}\varphi\Lambda(K)\lambda^2\sqrt{\frac{\delta}{\phi\hat{\rho}}\frac{N_{x_o^*}}{\bar{G}(x_o^*)}},$$

then the subscription model is preferred when the shape parameter of the delivery region is below a threshold level, $\zeta < \bar{\zeta}$; otherwise, the per-order model is preferred.[6]

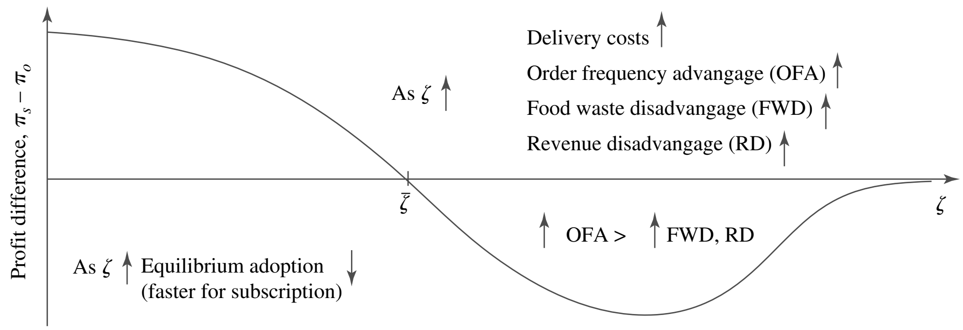
The profit difference takes the form shown in Figure 4. As the shape parameter ζ increases (i.e., as the delivery region becomes more irregular/elongated), there are two associated changes: delivery costs increase (because of longer line-haul distances) and the adoption rate declines (in response to higher prices—recall that higher costs make higher prices optimal from the retailer's perspective).

The increase in delivery costs increases the relative value of the order frequency advantage, since each trip becomes more costly; this is the main effect that progressively favors the per-order model. Higher delivery costs mean that the optimal adoption rate decreases in both models; yet despite the higher per-customer revenues, in the subscription model this decline is more rapid because there are more deliveries to make than in the per-order model. Hence we observe second-order effects: lower adoption rates for the subscription model imply a scaling down of its advantages. This dynamic also favors the per-order model. However, reduced adoption also implies an increase in the order frequency advantage and in both the food waste and

[5] The single-crossing property that drives Theorem 2 holds also for the market size A, population density ρ, per-mile delivery cost φ, and number K of deliveries per truck. The intuition is the same as that for the shape parameter (explained next), and both Theorem 2 and the financially preferred model could be equivalently characterized using any of these parameters.

[6] Condition $\partial^2_{x_o^*} h_o(x_o^*) \geq \frac{1}{4}\varphi\Lambda(K)\lambda^2\sqrt{(\delta/(\phi\hat{\rho}))(N_{x_o^*}/\bar{G}(x_o^*))}$ is technical; based on our extensive numerical experimentation, the threshold result holds for all reasonable parameters.

Figure 4 **Retailer Profit: Subscription Model vs. Per-Order Model**



revenue disadvantages. This increase in order frequency advantage—when combined with the direct first-order effect through an increase in ζ—outpaces the increase in the food waste and revenue disadvantages (second-order effects), favoring once again the per-order model. Eventually, in both models the adoption level becomes low enough to reduce not only absolute profits but also the difference *between* the models' respective profits. Hence the profit lines cross only once, which allows us to characterize the preferred revenue model in terms of the threshold shape parameter alone.

The main advantage of an intuitive statement of Theorem 2 is that it allows one to characterize the area, product, and operational characteristics that are best suited for each model.

Theorem 3. *Ceteris paribus, the per-order model is preferred over the subscription model if the population is sparse, the delivery area is either large or irregular/elongated, and/or retailer delivery commitments require that delivery vehicles carry fewer orders. Formally, the threshold shape parameter $\bar{\zeta}$ is decreasing in the delivery area A and in the per-mile delivery costs φ, but it is increasing in ρ, the population density, and K, the number of deliveries per truck.*

Theorem 3 follows from our previous discussion about the effect of increasing per-mile distances. A sparsely populated area (lower ρ), a large delivery area (greater A), and high delivery costs (higher φ) lead to the same first- and second-order effects as an increase in the shape parameter—namely, an increase in the order frequency advantage; a lower optimal adoption rate; and a consequent increase in the food waste, revenue, and order frequency effects. The only difference is that the order frequency–related phenomena in the main and second-order effect appear through the traveling salesman component of the delivery distance for population density (and not through the line-haul component, as in the case of the shape parameter); for the per-mile cost φ, they appear through both components. Finally, less batching of deliveries (reduced K) results in the same operating phenomena and, like the per-mile delivery cost, operates through both the line-haul and traveling salesman distances. Lower K implies that more trips are needed to the sectors and that the tours within a sector are longer on a per-order basis, which increases the order frequency advantage and lowers the adoption rate.

7.4. Environmental Impact of Revenue Models

We compare the population's driving and food waste–related carbon emissions from the two revenue models. To understand this comparison, it is useful to start by simply comparing adopting and nonadopting customers. Regardless of the revenue model, customers that adopt the online channel do so in order to reduce their grocery ordering costs; for these customers, then, the online channel is associated with less food waste and its related emissions. Moreover, orders are now pooled in delivery and so the per-order travel is also reduced. But online customers will shop more frequently and thus induce more trips (especially in the subscription model), which could cancel out the benefits from their lower food waste and per-order travel.

The total emissions for the delivery area's population of potential customers in the subscription model are written as $E_s = A\hat{\rho}(E^{mix-S}(Q_s, N_s, x_s^*) + E^{\text{off}}(x_s^*))$ and those in the per-order model as $E_o = A\hat{\rho}\{E^{mix-O}(Q_{x_o^*}, N_{x_o^*}, x_o^*) + E^{\text{off}}(x_o^*))$. The first part of each expression $E^{\text{mix-}\chi}$ captures the emissions resulting from adopting customers who use a combination of the two modes:

$$
\begin{aligned}
&E^{\text{mix-}\chi}(Q, N, \hat{x}) \\
&\quad = e_f(QN - \mu) \cdot \bar{G}(\hat{x}) + e_d \cdot \phi N \bar{D}(\hat{\rho}\bar{G}(\hat{x}),\ \phi N,\ \mathcal{A},\ K) \\
&\qquad \cdot \bar{G}(\hat{x}) + e_p(1-\phi)N \int_{\hat{x}}^{\infty} d_x^0 g(x)\, dx.
\end{aligned}
$$

Here, e_d and e_p are the CO_2-equivalent per-mile emissions for a delivery truck and a passenger vehicle, respectively, and e_f signifies the CO_2-equivalent emissions for every dollar's worth of food wasted. The first component is food waste emissions, which are calculated as the carbon load of all food purchased ($e_f QN$) *minus* the carbon load of the food consumed ($e_f \mu$). The second component is emissions from driving, which are generated by driving of the delivery truck (when the consumer is shopping online) or by the consumer's own driving (when shopping offline); d_x denotes the distance traveled by consumers of type x when shopping offline has a high cost, and d_x^0 is the corresponding distance when store visits happen to be cheap. The second part E^{off} is emissions resulting from customers who employ the always offline channel strategy:

$$E^{\text{off}}(\hat{x}) = \int_0^{\hat{x}} (e_f(N_x Q_x - \mu) + e_p(\phi d_x + (1-\phi) d_x^0) N_x) g(x)\, dx.$$

Comparing the two models in terms of their environmental impact is analogous to comparing them in terms of profits. On the one hand, the per-order model leads to more food waste and so has a higher environmental cost; hence the per-order model suffers from a food waste disadvantage. On the other hand, that model requires fewer deliveries, which translates into less driving and fewer carbon emissions. Finally, adoption rates, which reflect the number of customers who actually use the online channel, differ across the two models, and thus there is also an adoption effect. Although the preferred model is determined by a nonlinear interaction of these effects, it can be more easily characterized by using a single metric: a threshold level of food waste emissions.

Theorem 4. *If $x_s^* - x_o^* < \bar{\bar{x}}^*$, the per-order model is more ecofriendly than the subscription model when the emissions e_f for every dollar's worth of food wasted are less than a threshold level $\bar{e}_f$.*

This threshold result is easier to establish than is the threshold result for our profit comparisons. An increase in emissions from a dollar of wasted food increases the relative environmental consequences of the food waste disadvantage while leaving the other effects unchanged. Increased unit emissions from food waste render the per-order model progressively less "green," so at some point the subscription model becomes greener despite involving more travel.[7] The result now follows. This analysis suggests that one revenue model's being greener than the other depends on the parameters. However, in the next section we calibrate our model using realistic parameters and find that the subscription revenue model almost always dominates.

8. Managerial Implications: Cities, Product Categories, and Revenue Models

The foregoing analysis can be used by an online grocery provider to choose the revenue model that yields the highest profits and the best chance of financial viability. We now illustrate this choice by calibrating our model using realistic values of the input parameters.

8.1. Financial Effects

We proceed by analyzing four different delivery areas: Manhattan, Los Angeles, Paris, and Beijing (old city). Table 1 lists our parameter estimates for these cities,[8] which vary widely in terms of geography. Paris, Beijing, and Manhattan are relatively small in area; Los Angeles is about 10 times their size. Paris and Beijing are roughly circular/oval cities, whereas Los Angeles and Manhattan are rectangular. Note that Manhattan is extremely elongated and so its shape parameter is much higher. The cities also vary widely with respect to household density, ranging from fewer than 3,000 households per square mile in Los Angeles to about eight times that density in Manhattan. Finally, the cities have different labor markets. The per-mile delivery costs in China are estimated to be less than a third of those in Western cities. We estimate other relevant parameters using census data and industry sources (see Table 2). In addition to the estimates in Tables 1 and 2, we compared the two revenue models for many other cities and even more parameter values; the full ranges examined are reported in the bottom row of Table 1 and the rightmost column of Table 2.

Figure 5 shows the prescribed revenue model strategy for the different cities. The horizontal axes of each panel are the product gross margins. Gross margins $(1-\eta)$ vary considerably among different fresh grocery categories and between premium and basic products. Products in the bulk section generally earn higher margins (around 40%); by contrast, margins in the bread aisle are only about 20%.[9] The vertical axes represent the weekly consumption of groceries by consumers. The average U.S. household consumption of groceries is \$86/week,[10] but the exact value depends

[7] Condition $x_s^* - x_o^* < \bar{\bar{x}}^*$ ensures that more food is wasted under the per-order model, i.e., its food waste disadvantage (see the proof of Theorem 4 for details; $\bar{\bar{x}}^*$ is defined therein). Based on our extensive numerical experimentation, condition $x_s^* - x_o^* < \bar{\bar{x}}^*$ holds for all reasonable parameters.

[8] Each city's area is obtained from its *Wikipedia* entry. Density is obtained by dividing the population density by an average household size of 2.9 (*Consumer Expenditure Survey* of the Bureau of Labor Statistics, Table 1500: Composition of consumer units, 2012Q3–2013Q2 (http://www.bls.gov/cex/, accessed May 9, 2016)). Shape parameter ζ is computed based on the following assumptions: Manhattan can be represented by a rectangle whose sides are proportioned as 1:5; Los Angeles, by a rectangle of proportion 2:3; Paris, by approximately a circle; and Beijing, by an oval whose minor and major axes are proportioned as 5:6. Delivery cost φ is computed as the cost of operating a truck, including labor and delivery costs. For Western cities, the operating cost is \$1.38 per mile ("The Real Cost of Trucking," http://bit.ly/1ojPJaF, accessed May 9, 2016) plus about \$0.12 per mile for other items; for Beijing, costs are estimated to be about 27% of Western costs (Foley 2014).

[9] According to Reinvestment Fund (2011).

[10] *Consumer Expenditure Survey* of the Bureau of Labor Statistics, Table 1500: Composition of consumer units, 2012Q3–2013Q2 (http://www.bls.gov/cex/, accessed May 9, 2016).

Table 1 City Characteristics

	Area, A (sq. mi)	Density, ρ (households per sq. mi)	Shape parameter, ζ	Delivery cost, φ ($/mi)
Manhattan	23	24,137	1.16	1.5
Los Angeles	500	2,836	0.8	1.5
Paris	40	18,930	0.4	1.5
Beijing	33.63	22,168	0.61	0.413
Range examined	$A \in [10, 600]$	$\rho \in [2, 20{,}000]$	$\zeta \in [0.4, 3]$	$\varphi \in [0.5, 2.5]$

on the market segment. Large households and high-net worth households naturally consume more, as do households that purchase premium, imported, organic, and/or luxury items.

Note that in each of the cities, retailers that sell higher-margin product assortments are better off taking the per-order approach to pricing. In fact, for all realistic parameter values, the per-order model is preferred as long as the margin is roughly above a certain threshold (about 30% for Beijing, Paris, and Manhattan and about 12% for Los Angeles).

The differences between cities are more interesting. Manhattan, Paris, and Beijing (panel (a) in Figure 5) are small and densely populated delivery areas. Of the three, Beijing and Manhattan are the most densely populated; however, Beijing has two advantages vis-à-vis Manhattan. First, in contrast to Manhattan's highly skewed rectangle, Beijing has an oval shape; this difference in shape reduces travel distances. Second, because of Beijing's lower labor costs, its per-mile delivery costs are only about 30% of those in Manhattan. Hence Beijing is the city in which deliveries are the easiest to make, so the subscription model—with its frequent deliveries and low levels of wasted food—is preferred for the most margins and consumption rates. Comparing Paris and Manhattan, we see that Manhattan's density is higher but that Paris has a more favorable shape. The shape effect is more significant, so the subscription model should be preferred more in Paris than in Manhattan.

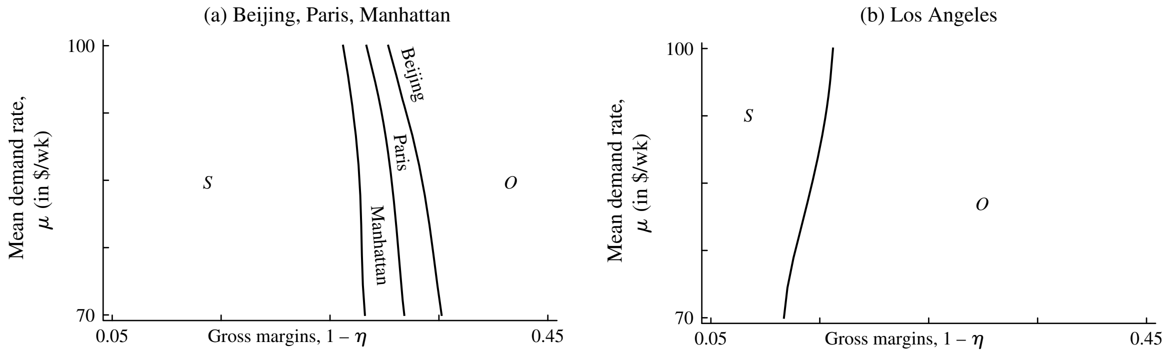
Finally, Los Angeles (panel (b) of Figure 5) has a much lower density of population and a much larger area. Here, the subscription model's higher-order frequency constitutes more of a disadvantage than does the per-order model's food waste; as a result, the per-order model is preferred more there.

These comparisons illustrate that the trade-offs on which we focus are not only theoretically but also practically relevant, leading to different choices in various realistic contexts. Prospective online retailers should employ the type of formal analysis described in this paper in order to give themselves the best chance of succeeding in the online grocery market.

Table 2 Retailer and Product Parameters

Parameter	Value	Sources and comments
Cost of ordering	$\theta = 5$\$/order	Hann and Terwiesch (2003) estimate the mean cost of online ordering to be approximately $5. Range examined: $\theta \in [0, 10]$ $/order.
Perishable/nonperish. mix	$\sigma = 0.5$	*Consumer Expenditure Survey* of the Bureau of Labor Statistics, Table 1500: Composition of consumer units, 2012Q3–2013Q2. Range examined: $\sigma \in [0, 2]$.
High store visit cost	$x \sim \exp(\lambda)$ $E[x] = 30$\$ per round-trip	The cost of a store visit is estimated as the value of time spent shopping for groceries. Brown and Borisova (2007) report that the average consumer spends about 140 minutes each week shopping for groceries, including travel time. If we value the customer's time at $13/hour, then the mean store visit costs $30 per round-trip. Range examined: $E[x] \in [10, 50]$\$.
Probability of high cost	$\phi = 0.42$	Estimates in Chintagunta et al. (2012). Range examined: $\phi \in [0, 1]$.
Product life	$T = 1$ week	Author estimates; we examine product lives between 3.5 days and 2 weeks, $T \in [0.5, 2]$.
Number of deliveries	$K = 15$/truck	Peapod routing data (Peapod corporate fact sheet, http://bit.ly/peepod (accessed May 9, 2016)). Range examined: $K \in [5, 50]$ (per truck).
Days in operation	$\delta = 365$	Customers can usually place orders seven days a week (Peapod corporate fact sheet, http://bit.ly/peepod (accessed May 9, 2016)).
Picking costs	$c_p = \$2$	Author estimates. Range examined: $c_p \in [0, 5]$.
Market penetration	$\varrho = 1\%$	Author estimates. We examine penetration between 0.1% and 81%. In the United States, 81% of the population uses the Internet but only about a third have fixed-line broadband ((*Wikipedia, The Free Encyclopedia,* s.v. "Internet in the United States," http://bit.ly/HHIIncome, accessed May 9, 2016). Effective penetration is capped by Internet access and varies as a function of, inter alia, marketing efforts; $\varrho \in [0.1, 81]$ (percent).

Figure 5 **Product Characteristics and Preferred Revenue Models by City**



Notes. The per-order revenue model is preferred to the right of the indifference curve (regions marked *O*); the subscription model is preferred to the left of the indifference curve (regions marked *S*). The warehouse is assumed to be centrally located.

8.2. Environmental Effects

We also calibrate our results on the environmental impact of different revenue models. This analysis requires estimates for the carbon emissions of travel for passenger vehicles e_p and delivery vehicles e_d. We use estimates from Cachon (2014): $e_p = 0.417$ kg of CO_2 equivalents per mile and $e_d = 1.683$ kg of CO_2 equivalents per mile. We also require estimates of the food waste emissions coefficient e_f. There are a variety of different sources with estimates that differ as a reflection of the composition of consumers' diet, consideration of food consumed or food wasted (wasted food is more carbon polluting than consumed food), and the inclusion or exclusion of different stages of production, transport, storage, and consumption (since we are examining food wasted by the consumer, we need to include the carbon load of all stages). We provide a summary of the most relevant sources as well as their estimation techniques and potential biases in Section 1 of the electronic companion. For purposes of numerical analysis, we verify the results by considering the widest plausible range of estimates—$e_f \in [0.36, 1.67]$ kg of CO_2 equivalents per dollar of food wasted—built by considering the most conservative lower bound (i.e., only production-related emissions and low-carbon diets). All results are presented for three representative values from that range. For the distance traveled by offline consumers when their cost is high d_x, we use an indicative average round-trip distance to the nearest grocery store, $d_x = 1$ miles. Likewise, for distance traveled when store visits happen to be cheap (consumer is passing by the store), we use $d_x^0 = 0.5$ miles.

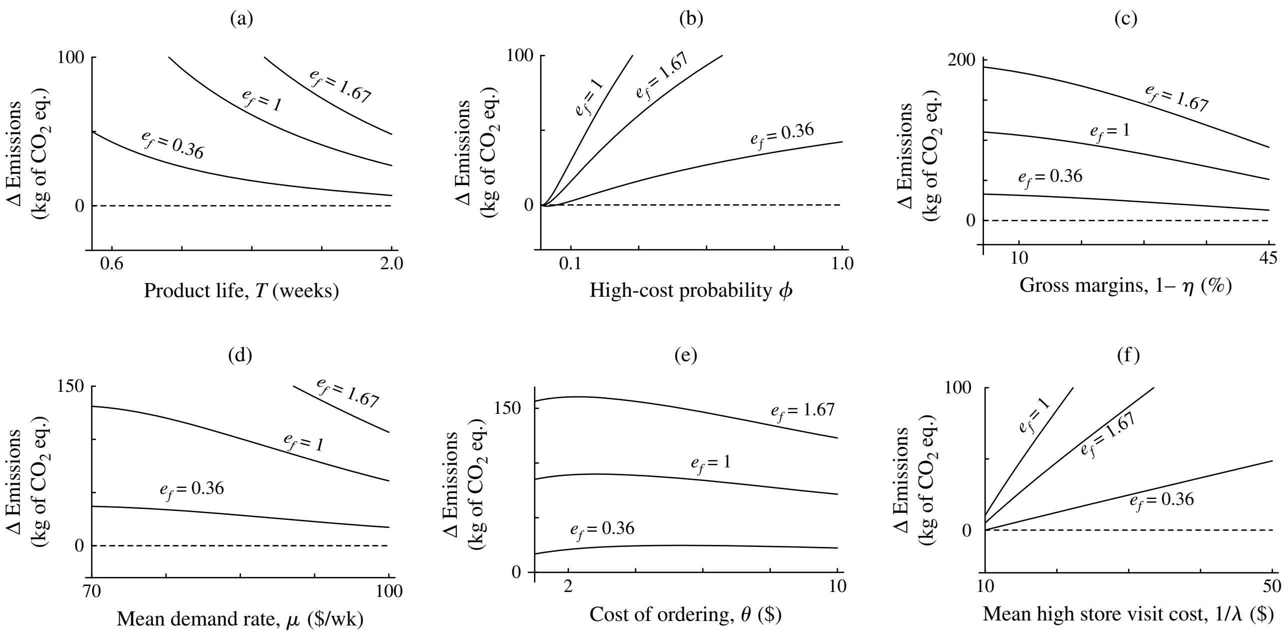
The results of our analysis for environmental impact are more stark than those for financial impact; see Figure 6. We find that, for all reasonable parameter values, emissions under the subscription model are *lower* than those under the per-order model. The carbon impact of extra food waste turns out to be much higher than that of extra driving. In other words, the negative effects of wasted groceries (in the per-order model) far outweigh the negative effects of extra miles driven when delivering the groceries (in the subscription model). This result holds for all plausible ranges of parameters for the cities of Paris, Beijing, and Manhattan.

In practical terms, the subscription model's emissions advantage over the per-order model amounts to between 5% and 10% of the food waste emissions created by an average citizen of the Western world. This means that *the combination of subscription pricing and online grocery retailing can significantly reduce emissions from the food supply chain*. Finally, our findings indicate that food waste plays a much more important role in the emissions impact of grocery retail than do the travel-related emissions upon which previous studies have focused (e.g., Cachon 2014). Most previous analysis fails to account for emissions from food waste and so would wrongly condemn the subscription model by focusing only on its driving-related downsides. Although this conclusion may well apply to nonperishable products, the prescription should be reversed for perishable grocery items.

Our results are a bit moderated for the somewhat atypical city of Los Angeles—which has a slightly elongated shape and (compared with the other two cities) a much larger area and much lower population density—we find that, for the lower bound on the food emissions coefficient (i.e., $e_f = 0.36$) and for a warehouse located far from the delivery area's center, the subscription and the per-order model become comparable environmentally; furthermore, for some parameter values, the per-order model (marginally) dominates. For example, our finding has potential to be reversed for a vegan grocery store selling high-margin, fast-to-expire products, delivered from a suburban warehouse in a vast urban area such as Los Angeles. Section 2 of the electronic companion provides detailed estimates for such extreme cases.

Figure 6 illustrates how the environmental advantage of the subscription model depends on select parameters. For all cities considered, the advantage of the

Figure 6 Annual Per-Household Reduction in Emissions Under Subscription Pricing for Paris



Notes. Unless stated otherwise, the city parameters used are those given in Table 1 for Paris and other parameters are from the second column of Table 2. The warehouse is assumed to be centrally located. Estimates are very similar for Beijing and Manhattan.

subscription model is higher (i) in small cities, where the driving disadvantage is small; (ii) for low margins, high delivery costs, and high store visit costs (all of which increase waste because of lower adoption rates); and (iii) for low mean demand and product life, which increase waste in the per-order model. The advantage is higher for moderate costs of ordering (in the subscription model, waste is increasing in θ; eventually, this increase approaches and exceeds the relatively modest effect of θ under the per-order model). Finally (as expected), more frequent customer use of the online channel in comparison with offline shopping—as captured by higher ϕ—enhances the subscription model's advantage.

9. Discussion

In our base model, it is never optimal for the retailer to offer customers a choice between subscription and per-order pricing. The reason is that there is only one dimension of customer heterogeneity and so one of the two models will yield higher retailer profits; offering two options will lead to one revenue model cannibalizing the other revenue model's profits. That being said, it could be optimal for the retailer to offer two pricing schemes if there were two (or more) dimensions of customer heterogeneity—for instance, if offline shopping costs had three levels instead of two. In this case, the per-order model and the subscription model would be able to capture different market segments, and offering both models might allow the retailer to screen customers in different segments and thereby improve its profits. This possibility is an intriguing prospect for future study.

Our analysis assumed that delivery trucks carry the same number of orders irrespective of the basket size. However, it is possible that if delivery batch sizes—as determined by delivery window promises—are large, then the truck's size does become binding and the number of orders carried in a truck is a function of the basket size. Analysis of this scenario (provided in Section 4.1 of the electronic companion) shows that this eventuality increases both the financial and environmental advantages of the subscription model, reinforcing our finding.

We did not consider any customer storage space constraints. Incorporating such constraints (discussed in Section 4.2 of the electronic companion) does not have any practical effect on our results (the constraints are not binding for any reasonable settings). Another interesting facet is the dependence of store visit costs on the physical location of the customer. Interestingly, the geometric properties of the area serviced and adopting customer locations ensure that incorporating this dependence also does not change any of the expressions provided and requires minor adjustments in the parameter values used (see Section 4.3 of the electronic companion).

The costs of online or offline shopping may vary seasonally (in addition to the random variations already considered); in effect, such variation shifts grocery purchase volume to days characterized by lower inconvenience costs. For our model, that would be equivalent to reducing the effective replenishment costs (θ and α)—in which case our original analysis still applies. We have also assumed the inconvenience cost of online shopping to be the same throughout the population, yet customers might be heterogeneous in that respect. Principally, only the *difference* between online and offline costs matters; since the store visit cost is already heterogeneous, this second degree of customer heterogeneity yields few (if any) new conceptual insights but makes all the mathematical expressions far more cumbersome.

In our model, there is no lead time between placing and receiving an order. Positive lead times will result in more waste. A random shelf life of the grocery basket and the fact that it consists of multiple items that have different perishability also increase food waste, increasing the food waste disadvantage of the per-order model and, thus, making the subscription model more desirable.

Although our analysis assumed that the market area is exogenously specified, it could instead be chosen endogenously in concert with the service model. In general, the choice of service area (both its size and shape) is driven by several factors that we did not consider. These factors include population density and the rate of its decay from the center of a city, regulation and licensing, natural geographical factors (bodies of water, etc.), the growth in delivery costs, and the rate of increase in line-haul distances, etc., over and above its dependence on per-customer revenues that depend on the revenue model. Our analysis could be modified to include endogenous area choices, in which case the per-order (respectively, subscription) model would likely correspond to larger (respectively, smaller) service areas.

We did not explicitly consider the retailer's management of inventory and fleet size. The pricing model may influence day-to-day variability in orders to be delivered, which in turn would affect costs related to inventory management. Note also that reduced intertemporal variability at the warehouse would require fewer vehicles to provide the same service level for on-time order deliveries. We also assumed that the fixed costs of building and servicing the per-order and subscription models are the same—that is, costs that depend neither on the volume of groceries sold nor on the number of orders serviced are the same in each model. Incorporating such costs would be but a minor extension.

Behavioral phenomena can also alter customer preferences for different pricing schemes. Empirical analysis by Danaher (2002) shows that customers vary in their sensitivity to subscription and per-order fees. There might be other behavioral effects—for example, the ability to select appropriate groceries, impulse buying, the physical exercise benefits of shopping offline, and the effect on consumer behavior of marketing and pricing strategies. Many of these factors could be easily incorporated into our model via adjustment of the store visit costs.

We also assumed that the per-unit prices of groceries are the same in both revenue models and in the offline store. Obviously, that may not be the case. Lower prices can increase adoption, enhancing the relevant model's effects. It is also worth mentioning that customers may have different grocery demand rates. Yet because the retailer cannot discriminate ex ante among different customers—and must therefore offer different market segments the same pricing scheme—our analysis provides a close first-order approximation. If, indeed, there are widely different customer segments, then offering a menu of contracts (and/or two-part tariffs) might help the retailer select which segments to serve and help it steer different segments toward different revenue models.

Finally, we considered an online retailer that competes with offline stores. This is a fair description of almost all major markets, but an extended model might consider the competition between different online retailers. Our model captures competitive aspects through the customer's outside option cost of buying offline. Under online competition, this cost could be substituted by the customer's outside *online* option. Further analysis of these issues remains an open question and a promising avenue for future work.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mnsc.2016.2430.

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Appendix. Proofs

All statements are given in their order of appearance in the main text.

Lemma 5. (i) *An optimal order-up-to policy is one where, at each perishable grocery replenishment point, the customer buys enough nonperishables to bring the nonperishable inventory to σ times the perishable inventory basket size—that is, up to level σQ_w.* (ii) $E[CT_i(Q)] = \mu^{-1}(Q - \sum_{j=0}^{Q}(Q-j)\cdot p_j(\mu T))$, $N(Q) = 1$ *year*$/(E[CT_i(Q)])$ *and* $Q^*(a)$ *is a solution to* $Q - \sum_{j=0}^{Q}(Q-j)p_j(\mu T) \approx (a+Q)(1-P_j(Q,\mu T))$, $P_j(Q,\mu T) = \sum_{j=0}^{Q} p_j(\mu T)$.

Proof. (i) For nonperishable items, the customer has full control over when and how much to buy (because these items do not expire). Since there is no holding cost and since items do not perish, the customer's cost of shopping does not change provided no additional orders or shopping trips are triggered in addition to the those required to restock perishable items. By ordering up to level σQ_w, the customer can ensure that no additional orders are triggered owing to her consumption of nonperishables.

(ii) Adopting the analysis of Weiss (1980) to our setting, we obtain expressions for $E[CT_i(Q)]$ and $N(Q)$ and that the customer's expected average long-run cost, $(a+Q)(Q-\sum_{j=0}^{Q}(Q-j)p_j(\mu T))^{-1}$, is first decreasing and then increasing in Q. Hence the optimal quantity is either the highest Q such that

$$\wp \equiv \frac{a+Q+1}{Q+1-\sum_{j=0}^{Q+1}(Q+1-j)p_j(\mu T)}-\frac{a+Q}{Q-\sum_{j=0}^{Q}(Q-j)p_j(\mu T)} \le 0$$

or the lowest Q such that $\wp \ge 0$. □

Proof of Lemma 1
For high enough μT ($\mu T>10$), Poisson(μT) random variable may be considered approximately normal. We can therefore rewrite the expected waste during a cycle $\sum_{j=0}^{Q}(Q-j)p_j(\mu T)\approx \int_{-\infty}^{Q}(Q-x)f(x)\,dx$, $f(x)\equiv(1/\sigma)(1/\sqrt{2\pi})e^{-(1/2)(x-\mu T)^2/\sigma^2}$, and $\sigma=\sqrt{\mu T}$. Thus, from Lemma 5, after a few simplifications, Q^* is given as a solution to $\int_{-\infty}^{Q}xf(x)\,dx=a\bar{F}(Q)$, where $\bar{F}(Q)\equiv 1-\int_{-\infty}^{Q}f(x)\,dx$; $\partial_a Q=\bar{F}(Q)/(f(Q)(Q+a))>0$. Similarly, $N(Q)=\mu(Q-\sum_{n=0}^{Q}(Q-n)p_n(\mu T))^{-1}\approx\mu[Q-\int_{-\infty}^{Q}(Q-x)f(x)\,dx]^{-1}$ and $\partial_Q N(Q)=-(1/\mu)N(Q)^2\bar{F}(Q)<0$ and so $\partial_a N(Q)=\partial_Q N(Q)\partial_a Q<0$. Finally, $\partial_a(N(Q^*)Q^*)=(1/\mu)[N(Q)]^2 a\bar{F}(Q)\partial_a Q>0$. Also, $\partial_a(a+Q^*)N(Q^*)=N(Q^*)+\partial_a Q^*\partial_Q((a+Q)N(Q))=N(Q^*)>0$ because, at Q^*, we have $\partial_Q((a+Q)N(Q))=0$. Now, note that $\partial_a(aN_a)=N_a+a\partial_a N^*=N_a(1-a\bar{F}(Q)/(f(Q)(Q+a)^2))$ and that Q is implicitly defined by $\int_{-\infty}^{Q}xf(x)\,dx=a\bar{F}(Q)$; therefore, $a\bar{F}(Q)/(f(Q)(Q+a)^2)\approx\int_{-\infty}^{Q}x(f(x)/f(Q))\,dx/(Q+a)^2$. For μT sufficiently high, $\int_{-\infty}^{Q}xf(x)\,dx\approx\int_0^Q xf(x)\,dx$ (this must be true for the approximation of Poisson to be reasonable). Now, if $Q<\mu T$, then $\int_{-\infty}^{Q}x(f(x)/f(Q))\,dx\approx\int_0^Q x(f(x)/f(Q))\,dx\le\int_0^Q x\,dx=\frac{1}{2}Q^2$; thus we obtain

$$\frac{a\bar{F}(Q)}{f(Q)(Q+a)^2}\le\frac{(1/2)Q^2}{(Q+a)^2}<1.$$

Furthermore, if $Q>\mu T$, then it follows (from the "increasing failure rate" property of a normal distribution) that

$$\frac{f(Q)}{\bar{F}(Q)}>\frac{f(\mu T)}{\bar{F}(\mu T)}=\frac{2}{\sqrt{2\pi\mu T}}.$$

That is, we need to show that

$$\frac{1}{\sqrt{(\pi/2)\mu T}}>\frac{a}{Q+a}\frac{1}{Q+a}\quad\text{or}\quad 1>\frac{a}{Q+a}\frac{\sqrt{(\pi/2)\mu T}}{Q+a}.$$

These inequalities hold if $\pi/2<\mu T$, which holds per our assumption $\mu T>10$.

Proof of Lemma 2
(i) This result follows from adapting the analysis of Daganzo (1984a, b) to our setting (see Section 3 of the electronic companion for details). The factor $\Lambda(K)$ is given as $\Lambda(K)=((K-2)^+/(K+1))1/\sqrt{\beta^*K}+(K-1/K)\phi(\beta^*K)$ for $K\le 4$ and $\Lambda(K)=\phi(\beta^*K)-1/\sqrt{\beta^*K}$ for $K>4$; $\beta^*=1$ for $K\in[1,7]$ and $\beta^*=6.7/K$ for $K\ge 7$. (ii) We have $\partial_N\bar{D}=-\Lambda(K)(1/(2N))\sqrt{\delta/(\bar{\rho}N)}<0$ and $\partial_{\bar{\rho}}\bar{D}=-\Lambda(K)(1/(2\bar{\rho}))\sqrt{\delta/(\bar{\rho}N)}<0$. Now $\partial_a\bar{D}=(\partial_N\bar{D})\partial_a N>0$, since $\partial_a N<0$ (by Lemma 1); therefore, $\partial_N N\bar{D}=2\zeta\sqrt{A}/K+\Lambda(K)(1/2)\sqrt{\delta/(\bar{\rho}N)}>0$ and $\partial_a N\bar{D}=(\partial_N N\bar{D})\partial_a N<0$.

Lemma 6. *If and only if the customer with store visit cost $\tilde{x}$ chooses the online retailer, then customers with store visit costs $x\ge\tilde{x}$ will also choose to shop online.*

Proof. Since C_{off} is an increasing function of x, it follows that (a) all customers for whom $x\ge\tilde{x}$ will purchase online and (b) all other customers will purchase offline. □

Proof of Lemma 3
The firm seeks to maximize its profit: $\pi_O=\max_o(\sigma\mu(1-\eta)+(o+Q_o)N_o-\{\varphi\bar{D}(\hat{\rho}\bar{G}(\tilde{x}),\phi N_o,A,K)+\eta Q_o+c_p\}N_o)A\hat{\rho}\phi\bar{G}(\tilde{x}_o)$, where $\tilde{x}_o=\min\{x \text{ s.t. } C_{\text{off}}\ge C_{\text{mix-O}}\}$; $C_{\text{off}}\ge C_{\text{mix-O}}$ is equivalent to $(\phi x+Q^*(\phi x))N(Q^*(\phi x))\ge(\phi o+\phi\theta)+Q^*(\phi o+\phi\theta))N(Q^*(\phi o+\phi\theta))$. The constraint $C_{\text{off}}\ge C_{\text{mix-O}}$ is always binding, and the firm will charge $o+\theta=\tilde{x}_o$; hence we can reformulate the problem as

$$\max_{0\le x\le\infty}(C_x+\sigma(1-\eta)\mu-h_o(x))\phi A\hat{\rho}\bar{G}(x),\qquad C_x\equiv(x+Q^*(\phi x))N(Q^*(\phi x)).\tag{8}$$

Since C_{off} is an increasing function of x, it follows that all customers for whom $x\ge x_o^*$ will purchase online and that all other customers will purchase offline. The equation for determining the optimal solution follows from taking the derivative of (8), and that solution's uniqueness follows from the concavity of (8). We have $\partial_x C_x=N(Q^*(\phi x))+(1-\phi)\cdot x\partial_x N(Q^*(\phi x))$, as $N(Q^*(\phi x))+(\phi x+Q^*(\phi x))\partial_Q N(Q^*(\phi x))=0$, since $Q^*(\phi x)$ is determined from $\partial_Q(\phi x+Q)N(Q)=N(Q)+(\phi x+Q)\partial_Q N(Q)=0$.

Proof of Lemma 4
The firm seeks to maximize its profit: $\pi_S=\max_s(\phi\sigma\mu(1-\eta)+\{s+Q_s\phi N_s\}-\{\varphi\bar{D}(\hat{\rho}\bar{G}(\tilde{x}_s),\phi N_s,A,K)+\eta Q_s+c_p\}\phi N_s)A\hat{\rho}\bar{G}(\tilde{x}_s)$, where $\tilde{x}_s=\min\{x \text{ s.t. } C_{\text{off}}\ge C_{\text{mix-S}}\}$; $C_{\text{off}}\ge C_{\text{mix-S}}$ is expressed as $(\phi x+Q^*(\phi x))N(Q^*(\phi x))\ge s+(\phi\theta+Q^*(\phi\theta))N(Q^*(\phi\theta))$. At $\tilde{x}_s$, then, $(\phi\tilde{x}_s+Q^*(\phi\tilde{x}_s))N(Q^*(\phi\tilde{x}_s))=s+(\phi\theta+Q^*(\phi\theta))N(Q^*(\phi\theta))$, and thus $s=(\phi\tilde{x}_s+Q^*(\phi\tilde{x}_s))N(Q^*(\phi\tilde{x}_s))-(\phi\theta+Q^*(\phi\theta))N(Q^*(\phi\theta))=(\phi\tilde{x}_s+Q^*(\phi\tilde{x}_s))N(Q^*(\phi\tilde{x}_s))-(\phi\theta+Q_s)N_s$. Hence, $\pi_S=\max_x(C_x+\sigma(1-\eta)\mu+\Gamma_x-h_s(x))\phi\cdot A\hat{\rho}\bar{G}(x)$. Now $\partial_x(C_x+\Gamma_x)=N_x$, as $Q^*(\phi x)$ is determined by $\partial_Q(\phi x+Q)N(Q)=N(Q)+(\phi x+Q)\partial_Q N(Q)=0$.

Proof of Theorem 1
The theorem's statements follow from Lemmas 1, 3, and 4 combined with the higher cost of ordering under the per-order model: $\theta\le x_o^*=o+\theta$ since $o\ge 0$; that is, $Q^*(\phi x_o^*)>Q_s$, $N(Q^*(\phi x_o^*))<N_s$, and $Q^*(\phi x_o^*)N(Q^*(\phi x_o^*))\ge Q_sN_s$.

Proof of Corollary to Theorem 1
The yearly expected amount of groceries that is spoiled and hence becomes food waste can be written as $(Q_\cdot)N_\cdot - \mu$. Theorem 1 establishes that $(Q_\cdot)N_\cdot$ is higher in the per-order model, so the annual amount of wasted groceries is higher in that model.

Lemma 7. *Optimal x_s^* is increasing in ζ; i.e., $\partial_\zeta x_s^* > 0$.*

Proof. We first establish that x_s^* is increasing in ζ; that is, $\partial_\zeta x_s^* > 0$. To find the optimal x_s^*, the firm solves $\max_x (C_x + \sigma(1-\eta)\mu + \Gamma_x - h_s(x))\bar{G}(x)$. Since the firm can guarantee a zero profit by choosing $x = \infty$, it follows for any $x_s^* < \infty$ that $C_{x_s^*} + \sigma(1-\eta)\mu + \Gamma_{x_s^*} - h_s(x_s^*) > 0$ (A.2). By Lemma 4, x_s^* is implicitly defined by (using $g(x)/\bar{G}(x) = \lambda > 0$) $N_{x_s^*} - \partial_{x_s^*} h_s(x_s^*) = \lambda(C_{x_s^*} + \sigma(1-\eta)\mu + \Gamma_{x_s^*} - h_s(x_s^*))$. The next step is determining the behavior of x_s^* with regard to ζ. For this, we can use the implicit function theorem and our optimality condition to obtain

$$\partial_\zeta x_s^* = \frac{\lambda\varphi(\sqrt{A}/K)N_s}{\lambda^2(C_{x_s^*} + \sigma(1-\eta)\mu + \Gamma_{x_s^*} - h_s(x_s^*)) - \partial_{x_s^*} N_{x_s^*} + \partial^2_{x_s^*} h_s(x_s^*)}.$$

The numerator is positive, so it remains only to establish that the denominator is also positive. In the proof of Lemma 1 we showed that $\partial N_a/\partial a < 0$, from which it follows that $\partial N_x/\partial x < 0$; furthermore, the first summand is positive because $C_{x_s^*} + \sigma(1-\eta)\mu + \Gamma_{x_s^*} - h_s(x_s^*) > 0$ (see A.2). Finally, the last summand is positive because

$$\partial_x(\partial_x h_s)\,|_{x_s^*} = \partial_x\left(\frac{1}{2}\lambda z\sqrt{\frac{N_s}{\bar{G}(x)}}\bigg|_{x_s^*}\right) = \frac{1}{4}\lambda^2 z\sqrt{\frac{N_s}{\bar{G}(x)}}\bigg|_{x_s^*} > 0,$$
$$z = \varphi\Lambda(K)\sqrt{\delta/(\phi\hat{\rho})}.$$

Similarly, x_o^* is $\partial_\zeta x_o^* = (\lambda\varphi(\sqrt{A}/K)N_{x_o^*})/(\lambda^2(C_{x_o^*} + \sigma(1-\eta)\mu - h_o(x_o^*)) - (2-\phi)\partial_x N_x - (1-\phi)x\partial_x^2 N_x + \partial^2_{x_o^*} h_o(x_o^*))$. □

Proof of Theorem 2
First, observe that $(\partial/\partial\zeta)(\pi_o^* - \pi_s^*) = \varphi(2\sqrt{A}/K)\{N_s\bar{G}(x_s^*) - N_{x_o^*}\bar{G}(x_o^*)\}$.

Next we show that if $N_s\bar{G}(x_s^*) = N_{x_o^*}\bar{G}(x_o^*)$ for some $\hat{\zeta}$ (which entails that $x_s^* > x_o^*$) and if $\pi_o^* > \pi_s^*$, then $N_s\bar{G}(x_s^*) < N_{x_o^*}\bar{G}(x_o^*)$ for all $\zeta > \hat{\zeta}$. To establish these conditions, we need only show that $\partial_\zeta x_s^* > \partial_\zeta x_o^*$ for $\zeta > \hat{\zeta}$. In Lemma 7 we established that $\partial_\zeta x_s^* > 0$; now if $\partial_\zeta x_o^* < 0$, we directly obtain desired $\partial_\zeta x_s^* > \partial_\zeta x_o^*$. Thus, in what follows we consider $\partial_\zeta x_o^* > 0$. We can rewrite the expression for $\partial_\zeta x_o^*$ (derived in Lemma 7) to obtain $\partial_\zeta x_o^* = (\lambda(1/2)\varphi(2\sqrt{A}/K)N_s)/((N_s/N_{x_o^*})(\lambda^2(C_{x_o^*} - h_o(x_o^*)) - (2-\phi)\partial_x N_x - (1-\phi)x\partial_x^2 N_x + \partial^2_{x_o^*} h_o(x_o^*)))$. The numerators of $\partial_\zeta x_s^*$ and $\partial_\zeta x_o^*$ are now equal, and we use den_s and den_o to denote the respective denominators. Next we show that $\text{den}_o > \text{den}_s$ for $\zeta > \hat{\zeta}$:

$$\begin{aligned}\text{den}_o - \text{den}_s = {} & \lambda^2\{(N_s/N_{x_o^*})C_{x_o^*} - (N_s/N_{x_o^*})h_o(x_o^*) \\ & \quad - (C_{x_s^*} + \Gamma_{x_s^*} - h_s(x_s^*))\} \\ & + \{\partial_{x_s^*} N_{x_s^*} - (N_s/N_{x_o^*})\partial_{x_o^*} N_{x_o^*} \\ & \quad - (1-\phi)(N_s/N_{x_o^*})(x_o^*\partial^2_{x_o^*} N_{x_o^*} + \partial_{x_o^*} N_{x_o^*})\} \\ & + \{(N_s/N_{x_o^*})\partial^2_{x_o^*} h_o(x_o^*) - \partial^2_{x_s^*} h_s(x_s^*)\}.\end{aligned}$$

We start by establishing that the second summand is positive. We have already proved that $\partial_a N_a = -N_a(1/(a+Q_a)^2)\cdot(\bar{F}(Q_a)/f(Q_a))$, so

$$\begin{aligned}&\partial_{x_s^*} N_{x_s^*} - \frac{N_s}{N_{x_o^*}}\partial_{x_o^*} N_{x_o^*} \\ &\quad = \frac{N_s}{(x_o^* + Q_{x_o^*})^2}\frac{\bar{F}(Q_{x_o^*})}{f(Q_{x_o^*})} - \frac{N_{x_s^*}}{(x_s^* + Q_{x_s^*})^2}\frac{\bar{F}(Q_{x_s^*})}{f(Q_{x_s^*})} > 0.\end{aligned}$$

The third summand is also positive; $\partial^2_{x_o^*} h_o(x_o^*) - (N_{x_o^*}/N_s)\cdot\partial^2_{x_s^*} h_s(x_s^*) > 0$, since

$$\frac{N_{x_o^*}}{N_s}\partial^2_{x_s^*} h_s(x_s^*) = \frac{z}{4}\lambda^2 N_{x_o^*}\sqrt{\frac{1}{N_s\bar{G}(x_s^*)}},$$

and when $\partial^2_{x_o^*} h_o(x_o^*) \ge (z/4)\lambda^2\sqrt{N_{x_o^*}/\bar{G}(x_o^*)}$, we have

$$\begin{aligned}&\partial^2_{x_o^*} h_o(x_o^*) - (N_{x_o^*}/N_s)\partial^2_{x_s^*} h_s(x_s^*) \\ &\quad \ge \varphi(z/4)\lambda^2 N_{x_o^*}\left(\sqrt{1/(N_{x_o^*}\bar{G}(x_o^*))} - \sqrt{1/(N_s\bar{G}(x_s^*))}\right) > 0.\end{aligned}$$

Finally, the first summand is positive, $(N_s/N_{x_o^*})(C_{x_o^*} - h_o(x_o^*)) - (C_{x_s^*} + \Gamma_{x_s^*} - h_s(x_s^*)) > 0$, and can be rewritten as follows:

$$\begin{aligned}&(x_o^* + (1-\eta)Q_{x_o^*})N_s - (x_s^* + Q_{x_s^*})N_{x_s^*} + N_s\eta Q_s \\ &\quad + zN_s\left(\sqrt{1/(N_s\bar{G}(x_s^*))} - \sqrt{1/(N_{x_o^*}\bar{G}(x_o^*))}\right).\end{aligned}$$

We can now show that $(x_o^* + (1-\eta)Q_{x_o^*})N_s - (x_s^* + Q_{x_s^*})N_{x_s^*} + N_s\eta Q_s$ is increasing in ζ: $\partial_\zeta(x_o^* + (1-\eta)Q_{x_o^*})N_s - (x_s^* + Q_{x_s^*})N_{x_s^*} = (\partial_\zeta x_o^* + (1-\eta)\partial_\zeta Q_{x_o^*})N_s - \partial_\zeta N_{x_s^*}\partial_\zeta x_s^* > 0$. Furthermore, at $\hat{\zeta}$ we have $(N_s/N_{x_o^*})(C_{x_o^*} - h_o(x_o^*)) - (C_{x_s^*} + \Gamma_{x_s^*} - h_s(x_s^*)) > 0$ if $\pi_o^* > \pi_s^*$; hence $(N_s/N_{x_o^*})(C_{x_o^*} - h_o(x_o^*)) - (C_{x_s^*} + \Gamma_{x_s^*} - h_s(x_s^*)) > 0$ for all $\zeta > \hat{\zeta}$. This means that, for all $\zeta > \hat{\zeta}$, we have $\partial_\zeta x_o^* > \partial_\zeta x_s^*$, and so $x_s^* > x_o^*$. That is, $(\partial/\partial\zeta)(\pi_o^* - \pi_s^*) < 0$ for $\zeta > \hat{\zeta}$.

Proof of Theorem 3
By definition, $\bar{\zeta}$ is such that $\pi_s^* = \pi_o^*$. That is,

$$\begin{aligned}&(\sigma(1-\eta)\mu + C_{x_s^*} + \Gamma_{x_s^*} - \tilde{h}_s(x_s^*))\bar{G}(x_s^*) - z\sqrt{N_s}\sqrt{\bar{G}(x_s^*)} \\ &\quad = (\sigma(1-\eta)\mu + C_{x_o^*} - \tilde{h}_o(x_o^*))\bar{G}(x_o^*) - z\sqrt{N_{x_o^*}}\sqrt{\bar{G}(x_o^*)};\end{aligned}$$

here $\tilde{h}_s(x) = (\theta + c_p)N_s + \bar{\zeta}yN_s + \eta Q_s N_s$; $\tilde{h}_o(x) = (\theta + c_p)N_x + \bar{\zeta}yN_x + \eta Q_x N_x$, $z \equiv \varphi\Lambda(K)\sqrt{\delta/\hat{\rho}}$ and $y \equiv (2\varphi\sqrt{A})/K$. Now using the implicit function theorem yields

$$\frac{\partial\bar{\zeta}}{\partial A} = -\bar{\zeta}\,\frac{\partial y}{\partial A}\,\frac{(\bar{G}(x_s^*)N_{x_o^*} - N_s\bar{G}(x_s^*))}{y(\bar{G}(x_o^*)N_{x_o^*} - \bar{G}(x_s^*)N_s)} < 0$$

because $\partial y/\partial A > 0$; also,

$$\begin{aligned}\frac{\partial\bar{\zeta}}{\partial\varphi} &= -(\bar{\zeta}(\partial y/\partial\varphi)(\bar{G}(x_o^*)N_{x_o^*} - \bar{G}(x_s^*)N_s) \\ &\quad + \frac{\partial z}{\partial\varphi}\,\frac{\sqrt{N_{x_o^*}\bar{G}(x_o^*)} - \sqrt{N_s\bar{G}(x_s^*)}}{y(\bar{G}(x_o^*)N_{x_o^*} - \bar{G}(x_s^*)N_s)} < 0\end{aligned}$$

since $\partial y/\partial\zeta, \partial z/\partial\varphi > 0$ and since $(\bar{G}(x_o^*)N_{x_o^*} - N_s\bar{G}(x_s^*))$ and $(\sqrt{N_{x_o^*}\bar{G}(x_o^*)} - \sqrt{N_s\bar{G}(x_s^*)})$ always have the same sign. Moreover,

$$\frac{\partial\bar{\zeta}}{\partial\rho} = -\bar{\zeta}\,\frac{\partial z}{\partial\rho}\,\frac{\sqrt{N_{x_o^*}\bar{G}(x_o^*)} - \sqrt{N_s\bar{G}(x_s^*)}}{y(\bar{G}(x_o^*)N_{x_o^*} - \bar{G}(x_s^*)N_s)} > 0$$

because $\partial z/\partial\rho < 0$.

Finally, $\partial\bar{\zeta}/\partial K = -((\partial z/\partial K)(\sqrt{N_{x_o^*}\bar{G}(x_o^*)} - \sqrt{N_s\bar{G}(x_s^*)}) + \bar{\zeta}\cdot(\partial y/\partial K)(\bar{G}(x_o^*)N_{x_o^*} - N_s\bar{G}(x_s^*)))/(y(\bar{G}(x_o^*)N_{x_o^*} - \bar{G}(x_s^*)N_s)) > 0$ since $\partial z/\partial K, \partial y/\partial K < 0$.

Proof of Theorem 4

We can express the emission difference as follows: ($z \equiv \varphi\Lambda(K)\sqrt{\delta/\rho}$, $y \equiv (2\varphi\sqrt{A})/K$ and $e \equiv e_p/e_d$): $(1/(A\hat{\rho}))(E_s - E_o) = e_d(\dagger) + e_f(*)$, where $(\dagger) \equiv \phi\{\bar{G}(x_s^*)yN_s + z\sqrt{\bar{G}(x_s^*)N_s} - \bar{G}(x_o^*)yN_{x_o^*} - z\sqrt{\bar{G}(x_o^*)N_{x_o^*}}\} + e(1-\phi)\{N_s\int_{x_s^*}^{\infty} d_x^0 g(x)\,dx - N_o\cdot\int_{x_o^*}^{\infty} d_x^0 g(x)\,dx + \int_{x_o^*}^{x_s^*}(\phi d_x + (1-\phi)d_x^0)N_x g(x)\,dx\}$ and $(*) \equiv \bar{G}(x_s^*)Q_sN_s - \bar{G}(x_o^*)Q_{x_o^*}N_{x_o^*} + \int_{x_o^*}^{x_s^*} N_xQ_xg(x)\,dx$. Both $(\dagger)$ and $(*)$ are independent of e_f and e_d. There are three possible combinations: (i) $(*), (\dagger) < 0$, in which case $\bar{e}_f = 0$; (ii) $(*) < 0, (\dagger) > 0$, in which case $\bar{e}_f = -e_d((\dagger)/(*))$; and (iii) $(*) > 0$. We next show that case (iii) is ruled out by condition $x_s^* - x_o^* < \bar{\bar{x}}^*$, where $\bar{\bar{x}}^* \equiv \max\{0, \bar{x}^*\}$ and $\bar{x}^*$ is such that $\bar{G}(x_o^* + \bar{x}^*)Q_sN_s + \int_{x_o^*}^{x_o^*+\bar{x}^*} N_xQ_xg(x)dx = \bar{G}(x_o^*)Q_{x_o^*}N_{x_o^*}$.

We first consider $x_s^* - x_o^* \le 0$, which implies $\bar{G}(x_s^*) \ge \bar{G}(x_o^*)$. We have $\bar{G}(x_o^*)(Q_sN_s - Q_{x_o^*}N_{x_o^*}) \le 0$ because $Q_sN_s < Q_{x_o^*}N_{x_o^*}$ (by Theorem 1). Thus, we need only show that $(**) \equiv (\bar{G}(x_s^*) - \bar{G}(x_o^*))Q_sN_s - \int_{x_s^*}^{x_o^*} N_xQ_xg(x)\,dx < 0$. Since $\int_{x_s^*}^{x_o^*} N_xQ_xg(x)\,dx > N_{x_s^*}Q_{x_s^*}\int_{x_s^*}^{x_o^*} g(x)\,dx = N_{x_s^*}Q_{x_s^*}(G(x_o^*) - G(x_s^*))$, it follows that $(**) < (\bar{G}(x_s^*) - \bar{G}(x_o^*))(Q_sN_s - N_{x_s^*}Q_{x_s^*}) < 0$. This inequality allows us to obtain the desired result, $(*) < 0$, which rules out case (iii).

Next consider $x_s^* - x_o^* > 0$, which implies $\bar{G}(x_o^*) \ge \bar{G}(x_s^*)$. This means that, under the subscription revenue model, the retailer's market coverage will be smaller, and so customers with $x \in (x_o^*, x_s^*]$ would waste more under the subscription model (as they do not adopt) then under the per-order model (where such customers adopt online shopping). Condition $x_s^* - x_o^* < \bar{\bar{x}}^*$ ensures that additional waste stemming from nonadopters does not overcome the reduction in waste of the adopting customers, i.e., $(*) < 0$, which rules out case (iii). This completes the proof. □

References

Agrawal VV, Ferguson M, Toktay LB, Thomas VM (2012) Is leasing greener than selling? *Management Sci.* 58(3):523–533.

Akkas A, Gaur V, Simchi-Levi D (2014) Drivers of product expiration in retail supply chains. Working paper, Cornell University, Ithaca, NY.

Berk E, Gurler U (2008) Analysis of the (q, r) inventory model for perishables with positive lead times and lost sales. *Oper. Res.* 56(5):1238–1246.

Bramel J, Simchi-Levi D (1997) *The Logic of Logistics: Theory, Algorithms, and Applications for Logistics Management*, Series in Operations Research and Financial Engineering (Springer, New York).

Brown C, Borisova T (2007) Understanding commuting and grocery shopping using the American Time Use Survey. Presentation, International Association of Time Use Research XXIX, http://bit.ly/23DpWj5.

Cachon GP (2014) Retail store density and the cost of greenhouse gas emissions. *Management Sci.* 60(8):1907–1925.

Cachon GP, Feldman P (2011) Pricing services subject to congestion: Charge per-use fees or sell subscriptions? *Manufacturing Service Oper. Management* 13(2):244–260.

Chintagunta PK, Chu J, Cebollada J (2012) Quantifying transaction costs in online/off-line grocery channel choice. *Marketing Sci.* 31(1):96–114.

Daganzo CF (1984a) The distance traveled to visit *n* points with a maximum of c stops per vehicle: An analytic model and an application. *Transportation Sci.* 18(4):331–350.

Daganzo CF (1984b) The length of tours in zones of different shapes. *Transportation Res. Part B: Methodol.* 18(2):135–145.

Danaher PJ (2002) Optimal pricing of new subscription services: Analysis of a market experiment. *Marketing Sci.* 21(2): 119–138.

Foley J (2014) China's e-commerce secret weapon: The delivery guy. *Breakingviews* (blog) (August 11), http://bit.ly/reutersdelguy.

Food and Agriculture Organization of the United Nations (2013) Food wastage footprint: Impacts on natural resources. Summary report, FAO, Rome. http://bit.ly/FAOWaste.

Gunders D (2012) Wasted: How America is losing up to 40 percent of its food from farm to fork to landfill. NRDC Issue Paper IP:12-06-B, the Natural Resources Defense Council, New York.

Hann I-H, Terwiesch C (2003) Measuring the frictional costs of online transactions: The case of a name-your-own-price channel. *Management Sci.* 49(11):1563–1579.

McCarthy K (2014) Amazon Fresh: Big radish or bad kiwi? *ChannelAdvisor Blog* (blog) (May 8), http://bit.ly/AmazonPricing.

Mitchell D (2014) Next up for disruption: The grocery business. *Fortune* (April 4), http://bit.ly/GroceryDisruption.

Nahmias S (2011) *Perishable Inventory Systems*, International Series in Operations Research and Management Science, Vol. 160 (Springer, New York).

Reinvestment Fund (2011) Understanding the grocery store. Brief, Reinvestment Fund, Philadelphia. http://bit.ly/GroceryIndustry.

Weiss HJ (1980) Optimal ordering policies for continuous review perishable inventory models. *Oper. Res.* 28(2):365–374.

Wohlsen HJ (2014) The next big thing you missed: Online grocery shopping is back, and this time it'll work. *Wired* (February 4), http://bit.ly/wiredOnlineBack.