ONLINE GROCERY RETAIL: REVENUE MODELS AND ENVIRONMENTAL IMPACT

1. Estimation of the Emissions from Food Wasted

Wilson (2013) estimates the carbon intensity of a dollar of food consumed as $e_f = 1.0$ kg CO_2 per dollar. Heller and Keoleian (2014) estimates the greenhouse gas emitted per dollar of food consumed as a function of various USDA food plans; the values range from $e_f = 0.45$ kg CO_2 per dollar for a "liberal" diet to $e_f = 0.7$ kg CO_2 per dollar for a "thrifty" diet. These estimates of Wilson and of Heller and Keoleian likely underestimate e_f because they consider emissions associated with food *consumed*, which are typically less than the emissions from food *wasted* (since food disposed in landfills has a higher carbon impact than digested food).

This problem does not affect the estimates of Venkat (2011), who directly considers food wasted (and not merely food consumed). According to Venkat: "Avoidable food waste in the US produces life-cycle greenhouse gas emissions of at least 113 million metric tonnes of CO_2 annually, and costs \$198 billion." We can use these figures to calculate that $e_f \geq 113/198 = 0.57$ kg CO_2 per dollar. Even though Venkat considers food wasted, we seek the value for food wasted at the consumption stage. In fact, even Venkat probably underestimates e_f in that the value he proposes is based on a weighted average of the food wasted at different stages: production, transportation, retail, and consumption. Food wasted at consumption stage is the most carbon-intensive (since more energy has been invested in it).

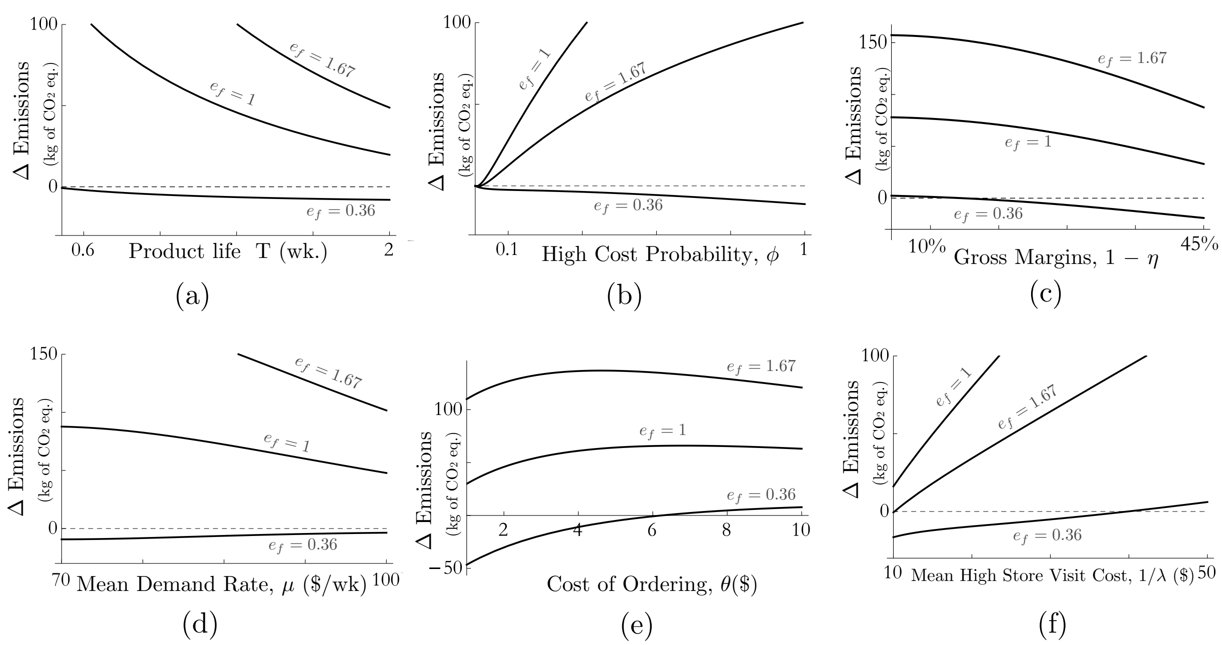
In their study of how US households can reduce their carbon emissions, Jones and Kammen (2011) provide the estimate closest to the parameter relevant for our analysis. Although food waste does not generate the most emissions, Jones and Kammen find that reducing food waste is how people can make the greatest and most cost-effective savings. These authors calculate that a reduction of a metric ton (i.e., 1,000 kg) of CO_2 emissions would save a household \$600 to \$700 in food purchases; this implies an estimate between $e_f = 1,000/600 = 1.67$ kg CO_2 per dollar and $e_f = 1,000/700 = 1.43$ kg CO_2 per dollar.

Although the four studies just cited provide direct estimates of the carbon emissions associated with food waste, one can also impute this parameter from an indirect source. On average a person's annual food waste accounts for 900 kg of CO_2 equivalents, 40% of which occurs at the consumption level (Food and Agriculture Organization, 2013, http://bit.ly/FAO-Waste). In monetary terms this food waste corresponds to \$340–\$570 per year (Gunders, 2012), or a range from $e_f = [(0.4 \cdot 900)$ kg $CO_2]/\$570 = 0.65$ kg CO_2 per dollar and $e_f = [(0.4 \cdot 900)$ kg $CO_2]/\$340 = 1.05$ kg CO_2 per dollar.

Taken together, the estimates range from $e_f = 0.45$ kg CO_2 per dollar (for the estimate of food *consumed* with a liberal diet) to $e_f = 1.67$ kgCO_2 per dollar (for the estimate of food *wasted* by the average consumer). To obtain a conservative estimate of our low range, we go even further and deflate our lowest estimate (of 0.45) in order to account only for the emissions from food *production* (thus excluding energy consumed in cooking, transportation, storage, and so forth).[1] This gives us $e_f \in [0.36, 1.67]$ for a plausible range of values.

The most conservative estimate of the food emissions coefficient, $e_f = 0.36$, implies that \$4.64 ($= 1.683/0.36$) of food wasted is equivalent to 1 mile of driving by a delivery truck and that \$1.16 ($= 0.417/0.36$) of food wasted is equivalent to 1 mile of driving by a passenger vehicle.

2. Emissions Advantage of Subscription Pricing in Los Angeles



Notes: Unless stated otherwise, $\rho = 2,836$ hh/sq. mi, $A = 500$ sq. mi, $\varphi = 1.5$ \$/mi, $\eta = 0.75$, $\zeta = 0.8$, $K = 15$, $1/\lambda = 30\$$, $\theta = 5\$$, $T = 1$ wk, $\mu = 90$ \$/wk, $\varrho = 1\%$, $\phi = 0.42$, $\sigma = 0.5$, and $\delta = 365$. The warehouse is assumed to be centrally located.

Figure 2.1. Annual Per-Household Reduction in Emissions under Subscription Pricing for the City of Los Angeles

[1]Wilson (2013) shows that the vast majority (some 80%) of emissions occur during food production.

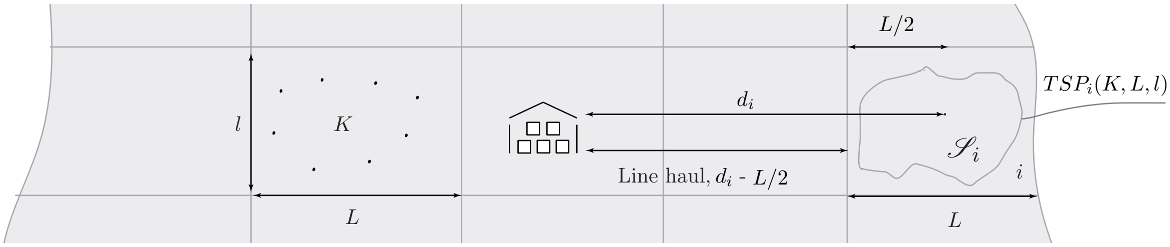


FIGURE 3.1. Distance Traveled to Deliver an Order in Sector i

Figure 2.1 provides the emissions advantage of subscription pricing in the atypical city of Los Angeles (See Section 8.2 of the main paper for a full description of the analysis and the equivalent estimates for more typical cities: Paris, Manhattan and Beijing).

3. Adaptation of Distance Traveled to Deliver an Order

This section adapts and extends the analysis of Daganzo (1984a,b) and Cachon (2014) to determine the distance traveled to deliver an order.

Based on the specific orders to be delivered in a period, the retailer devises the following distribution plan. First, it optimally partitions area $\mathscr{A}$ into sectors $\mathscr{S}_i$, $i \in \{1, \ldots, I\}$, so that each sector has K customers. Each sector is then assigned a vehicle that visits K customers while following an optimal route.

The distance traveled to deliver K orders in sector $\mathscr{S}_i$ has two components: the distance between the warehouse and the boundary of the sector, or the "line haul" distance; and the optimal traveling salesman tour (TSP) within the sector (see Figure 3.1). Minor variations in the shape of the sectors do not greatly affect either the line-haul distance or the length of any traveling salesman tour. We therefore consider dividing area $\mathscr{A}$ into equal rectangular sectors of length L and height l, $L > l$, and define the *slenderness factor* $\beta = l/L$ (Daganzo, 1984a). The distance traveled per order delivered in sector $\mathscr{S}_i$ can then be expressed as

$$D_i \approx \frac{2}{K}\left(d_i - \frac{L}{2}\right) + TSP^*(K, L, l), \tag{3.1}$$

here d_i is the distance traveled in getting to sector $\mathscr{S}_i$'s center of gravity, and $L/2$ is the approximate distance from the sector's center of gravity to the edge of the sector where the traveling salesman tour starts. Together these two components constitute the line-haul distance, which must be covered twice (to get to the sector and back) and is distributed over the K deliveries. We use $TSP^*(K, L, l)$ to denote the per-order average length of the optimal traveling salesman tour within the sector. The average distance traveled per order, obtained by averaging over all sectors $\mathscr{S}_i$, $i \in \{1, ..., I\}$, is $\bar{D}(\bar{\rho}, N, A, K) =$

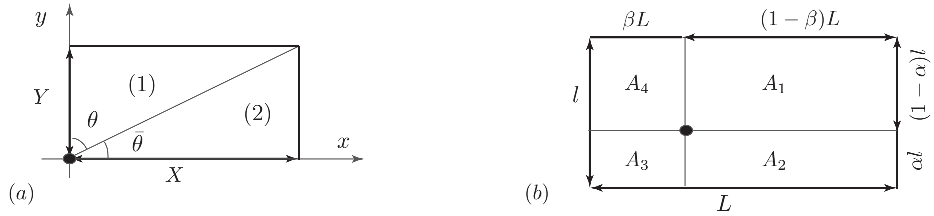


FIGURE 3.2. Partitioning of a Rectangle

$\frac{1}{I}\sum_{i=1}^{I} D_i$. Of D_i's three components, L and TSP^* depend on the area's partition into sectors whereas d_i does not. We start by analyzing d_i.

Average Distance from the Warehouse to the Center of Gravity of Sectors $\bar{d}$. Daganzo (1984a) shows that $\bar{d} = \frac{1}{I}\sum d_i$ can be interpreted as the average distance from the warehouse to a point in the market area.

Lemma 1. *The average distance from the warehouse to a point in the market area is given by $\bar{d}_{\square} = \sqrt{A}\zeta_{\square}$ for a rectangle with length-to-height ratio of $\gamma = \frac{L}{l} \geq 1$ and a centrally located warehouse, by $\bar{d}^{\text{nc}}_{\square} = \sqrt{A}\zeta^{\text{nc}}_{\square}$ for a warehouse at location $(\alpha l, \beta L)$, and by $\bar{d}_{\Diamond} = \sqrt{A}\zeta_{\Diamond}$ for a regular m-gon with a centrally located warehouse. Here*

$$\zeta_{\square} = \frac{1}{3}\cdot\varpi(\gamma)\cdot\sqrt{\frac{1}{\gamma}},\ \varpi(z) = \sqrt{z^2+1} + \frac{1}{2}\left(z^2\ln\left(\frac{\sqrt{z^2+1}+1}{z}\right) + \frac{\ln\left(\sqrt{z^2+1}+z\right)}{z}\right),$$

$$\zeta^{nc}_{\square} = \frac{2}{3}\sqrt{\frac{1}{\gamma}}\left((1-\beta)^2\cdot(\varpi(\gamma\frac{1-\alpha}{1-\beta})(1-\alpha)+\varpi(\gamma\frac{\alpha}{1-\beta})\alpha)+\beta^2\cdot(\varpi(\gamma\frac{1-\alpha}{\beta})(1-\alpha)+\varpi(\gamma\frac{\alpha}{\beta})\alpha)\right),$$

$$\zeta_{\Diamond} = \frac{2}{3}\sqrt{\frac{1}{m\cdot\tan\Phi}}\left(\sqrt{1+\tan^2\Phi} + \ln(\tan\Phi + \sqrt{1+\tan^2\Phi})\cdot\tan^{-1}\Phi\right),\ \Phi = \pi m^{-1}.$$

Proof. Cachon (2014) gives an expression for $\bar{d}_{\Diamond}$ (replicated above). We can derive an expression for a circle and a square by using the one for $\bar{d}_{\Diamond}$ and then setting (respectively) $m = \infty$ and $m = 4$, we obtain $\zeta_{\bigcirc} \approx 0.36$ and $\zeta_{\square} \approx 0.76$. For a rectangle with length X and height Y, the average round-trip distance from the warehouse located at origin to a point in market area 1 (see panel (a) in Figure 3.2), $\bar{d}_1$, and a point in area 2, $\bar{d}_2$, can be calculated as follows:

$$\bar{d}_1 = 2\cdot\frac{\int_0^Y\int_0^{y\tan\theta}\sqrt{x^2+y^2}dxdy}{\frac{1}{2}(Y)^2\tan\theta} \quad\text{and}\quad \bar{d}_2 = 2\cdot\frac{\int_0^X\int_0^{x\tan\bar{\theta}}\sqrt{x^2+y^2}dydx}{\frac{1}{2}(X)^2\tan\bar{\theta}}.$$

We have $\tan\theta = \frac{X}{Y} = \tilde{\gamma}$ and $\tan\bar{\theta} = \frac{Y}{X} = \frac{1}{\tilde{\gamma}}$; moreover, $Y = \sqrt{\frac{XY}{\tilde{\gamma}}}$. Hence $\bar{d}_1 = \frac{2}{3}\sqrt{\frac{XY}{\tilde{\gamma}}}(\sqrt{1+\tilde{\gamma}^2} + \frac{1}{\tilde{\gamma}}\ln[\tilde{\gamma}+\sqrt{1+\tilde{\gamma}^2}])$ and $\bar{d}_2 = \frac{2}{3}\sqrt{\tilde{\gamma}XY}(\frac{\sqrt{1+\tilde{\gamma}^2}}{\tilde{\gamma}} + \gamma\ln[\frac{1}{\tilde{\gamma}} + \frac{\sqrt{1+\tilde{\gamma}^2}}{\tilde{\gamma}}])$. Finally, areas 1 and 2 contain an equal number of square miles. This means that $\bar{d}_{XY} = \frac{1}{2}(\bar{d}_1+\bar{d}_2) = \frac{2}{3}\sqrt{\frac{XY}{\tilde{\gamma}}}\varpi(\tilde{\gamma})$. If the warehouse is centrally located, then $X = \frac{L}{2}$, $Y = \frac{l}{2}$, $\frac{X}{Y} = \tilde{\gamma} = \frac{L}{l}$, and $XY = \frac{1}{4}A$; hence the expression for $\bar{d}_{\square}$ follows. For a noncentrally located warehouse (see panel (b) in Figure 3.2), $\bar{d} = \frac{1}{A}(\bar{d}_{A_1}A_1 + \bar{d}_{A_2}A_2 + \bar{d}_{A_3}A_3 + \bar{d}_{A_4}A_4)$ and so the expression for $\bar{d}^{\mathrm{nc}}_{\square}$ follows. Finally, if the warehouse is located in the corner of the delivery area ($\alpha = \beta = 0$) then $\bar{\zeta}^{\mathrm{nc}}_{\square} = \frac{2}{3}\varpi(\gamma)\sqrt{\frac{1}{\gamma}} = 2\zeta_{\square}$. $\square$

Partitioning a Market into Sectors. The area of individual sectors is predetermined by the per-delivery period order volume ρ_d; thus, $L \cdot l = K\rho_d^{-1}$. Although the area is fixed, we can still choose the shape of its sectors—that is, the slenderness factor β. As we elongate the rectangle toward the warehouse, the distance from the center of the sector to the start of the tour increases (L is increasing). This elongation reduces the distance traveled, $d_i - L/2$, but increases the length of the traveling salesman tour.

Average Distance Traveled to Deliver an Order. We seek $\bar{D}(\bar{\rho}, N, \mathscr{A}, K) = \frac{1}{I}\sum_{i=1}^{I} D_i = \frac{2}{K}\frac{1}{I}\sum_{i=1}^{I} d_i - \frac{L}{K} + \mathrm{TSP}^*(K, L, l)$ (since all sectors are partitioned in the same fashion and contain K points). Daganzo (1984b) offers the following approximation of the traveling salesman tour:

$$\mathrm{TSP}^*(K, L, l) = \frac{\phi(\beta K)}{\sqrt{\rho_d}}, \text{ where } \phi(x) = \begin{cases} 0.9, & x \geq 12; \\ \frac{\sqrt{x}}{6} + \frac{2}{\sqrt{x}}\frac{2}{(x/4)^2}[(1+\frac{x}{4})\log(1+\frac{x}{4}) - \frac{x}{4}], & x < 12. \end{cases} \tag{3.2}$$

Using Lemma 1 and Equation 3.2 yields $\bar{D}(\bar{\rho}, N, \mathscr{A}, K) = \frac{2}{K}\bar{d} - \frac{L}{K} + \frac{\phi(\beta K)}{\sqrt{\rho_d}}$; furthermore, $L \cdot l = K\rho_d^{-1}$ and $\beta = \frac{l}{L}$, which means that $L = \sqrt{\frac{K}{\beta\rho_d}}$ and so $\bar{D}(\bar{\rho}, N, \mathscr{A}, K) = \frac{2}{K}\bar{d} - \rho_d^{-\frac{1}{2}}((\beta K)^{-\frac{1}{2}} + \phi(\beta K))$. Optimizing with respect to β, we obtain the *optimal* "slenderness factor" (see Daganzo (1984b) for additional nuances of this derivation):

$$\beta^* = \begin{cases} 1, & K \in [1, 7]; \\ \frac{6.7}{K}, & K \geq 7. \end{cases} \tag{3.3}$$

Finally, for $K \leq 4$ the approximation displayed as Equation 3.1 is not very accurate; Daganzo (1984a) provides the more accurate expression $\bar{D}(\bar{\rho}, N, \mathscr{A}, K) = \frac{2}{K}\bar{d} - \rho_d^{-\frac{1}{2}}(\frac{(K-2)^+}{K+1}(\beta K)^{-\frac{1}{2}} + \frac{K-1}{K}\phi(\beta K))$. Combining this equality with the results from Lemma 1 and Equation 3.3 establishes the congruence displayed as Equation 5.1 in the main paper, where the factor $\Lambda(K)$ is given as

$$\Lambda(K) = \begin{cases} \frac{(K-2)^+}{K+1}\frac{1}{\sqrt{\beta^* K}} + \frac{K-1}{K}\phi(\beta^* K), & K \le 4; \\ \phi(\beta^* K) - \frac{1}{\sqrt{\beta^* K}}, & K > 4. \end{cases} \tag{3.4}$$

4. Extensions

4.1. **Number of Orders per Delivery Vehicle As a Function of Basket Size.** Our original analysis assumed that delivery trucks carry the same number of orders irrespective of the basket size. This assumption is likely to hold when delivery batch sizes—as determined by delivery window promises—are such that the physical capacity of the truck is not binding. However, if the batches are large then it is possible that the truck's size does become binding. Our analysis can be modified to incorporate this possibility.

Consider a setup where the number of orders delivered per truck is $K = \min\{k, \bar{K}/Q\}$, where the batch size k is determined by delivery window promises (as before) and where $\bar{K}$ is the truck size and Q is the order size (including nonperishables and perishable groceries). The preceding analysis considered the case where capacity is not binding, $\min\{k, \bar{K}/Q\} = k$; now we consider the case where it is, $\min\{k, \bar{K}/Q\} = \bar{K}/Q$. The retailer's optimization problem can still be formulated as before (i.e., as in Equations 7.1 and 7.2) provided we modify the third and fourth terms of the per-customer costs:

$$h_s(x) = \eta Q_s N_s + (\theta + c_p) N_s + \varphi \cdot \frac{2\zeta\sqrt{A}}{\bar{K}}(Q_s N_s + \sigma\mu) + \varphi \cdot \Lambda(\frac{\bar{K}}{Q_s + \frac{\sigma\mu}{N_s}})\sqrt{\frac{\delta}{\hat{\rho}\bar{G}(x)\phi}}\sqrt{N_s};$$

$$h_o(x) = \eta Q_x N_x + (\theta + c_p) N_x + \varphi \cdot \frac{2\zeta\sqrt{A}}{\bar{K}}(Q_x N_x + \sigma\mu) + \varphi \cdot \Lambda(\frac{\bar{K}}{Q_x + \frac{\sigma\mu}{N_x}})\sqrt{\frac{\delta}{\hat{\rho}\bar{G}(x)\phi}}\sqrt{N_x}.$$

The grocery sourcing costs that drive the food waste disadvantage are not modified, but the order frequency advantage of the per-order model is now reduced. The order frequency advantage ($N_x < N_s$) stems from the combined effects of the delivery cost, which comprises the second, third, and fourth components of the per-customer costs. The second component remains as before. Also, the fourth component changes little: the term $\Lambda(x)$ is constant for $x \ge 12$ and the expected order quantity $Q_x + \sigma\mu/N_x$ is typically such that $\bar{K}/(Q_x + \sigma\mu/N_x) \ge 12$, even in the per-order model; hence $\Lambda(\bar{K}/(Q_s + \sigma\mu/N_s)) \approx \Lambda(\bar{K}/(Q_x + \sigma\mu/N_x))$ and so this change will have at most a small effect on the fourth term. However, the third component—the per-customer annual line-haul delivery cost—is now actually lower in the subscription model ($Q_s N_s < Q_x N_x$) because the line-haul distance is "amortized" over a higher number of orders.

The resulting lower order quantity in the subscription model now leads to more orders delivered per truck, which increases the retailer's profit and also reduces the model's environmental impact. The subscription model will be preferred financially for a larger range of values while becoming even greener (and thus dominating) from the environmental standpoint—reinforcing our main numerical result.

4.2. **Limited Storage Space for Customers.** It could be that the basket size of some urban customers is determined not only by the perishability of groceries but also by the limited storage space in city apartments. The size of the customer's order (perishables + nonperishables) is higher for adopting customers in the per-order model than in the subscription model. So depending on the extent to which storage space is constraining, three cases may arise.

First, the customer's storage capacity could be greater than the online order size in the per-order model. Our numerical analysis suggests that this is, in fact, the predominant case.[2] Here, our original analysis continues to hold without any modifications.

The second scenario is when the storage space is less than the per-order model's order size but more than the subscription model's order size. In this case, the two models yield results that are more similar. The revenue disadvantage is unaffected, while the order frequency advantage and the food waste disadvantage are diminished. Thus there will now be less difference between the two models' environmental and financial effects.

In the final scenario, the storage space is insufficient to accommodate the order size in either model. In this case, the two models will lead to identical basket sizes and order frequencies. The order frequency advantage and food waste disadvantage will disappear, while the revenue disadvantage will diminish. Overall, the subscription model will dominate—both financially and environmentally—owing to a higher adoption rate for eco-friendly online shopping.

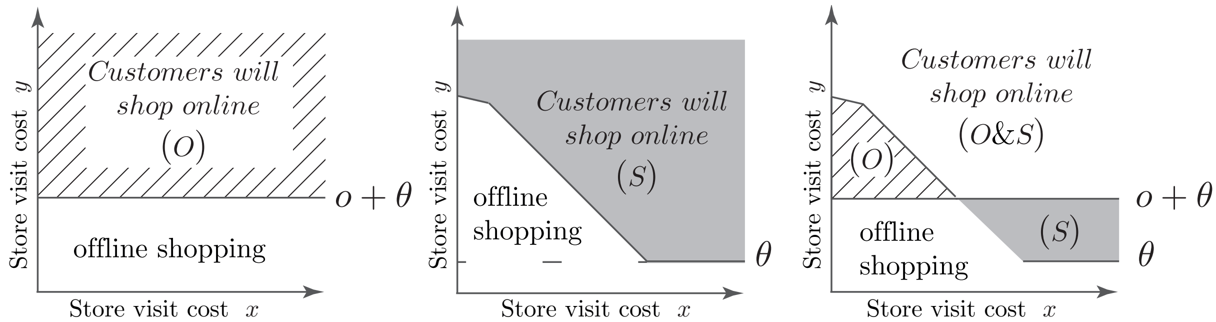
4.3. **Distribution of Store Visit Costs Depends on Location.** Our analysis has assumed independence from other factors related to the distribution of store visit costs in the population. However, those costs might depend on the customer's location; that is, customers located closer to the offline store should have lower store visit cost.

[2]Even in the worst-case scenarios (a large and sparsely populated city, high per-order delivery fees, etc.), the maximum grocery inventory—including perishables and nonperishables both—of online customers is modest: less than $100 worth of groceries per household.

If that presumption holds, then the nonadopting (always offline) customers will be clustered around the offline stores—that is, rather than being distributed uniformly throughout the area. Yet even in that case, under mild symmetry conditions, all our results continue to hold because the formula for distance traveled (Lemma 2) remains unchanged. The distance traveled to deliver an order consists of two components: the line-haul distance and the traveling salesman tour. The latter is not much affected by minor variations in sector shape (Daganzo, 1984a) and will therefore not change. More interestingly, neither does the line-haul distance change. Recall that the line-haul distance is the average distance from the warehouse to a point in the market area $\mathscr{A}$. This is equivalent to finding the center of gravity of the sub sector of the market area with the warehouse as the origin. Cutting out a circular hole around the center of gravity of this sector or any number of symmetric shapes centered at the center of gravity of the sector does not change the sector's center of gravity. With uniformly distributed offline stores, this is exactly what happens in terms of customer adoption and so the line-haul distance remains unaffected.

4.4. **Three-Level Variation in Store Visit Costs.** In our main model we considered the cost of going to the store, α, which can take two extreme values: a high value x (determined by the customer type) or a low value 0. In this section we extend this cost structure to include an additional, intermediate, outcome. So now $\alpha \in \{x, y, 0\}$ with respective probabilities ϕ_x, ϕ_y, and $1 - \phi_x - \phi_y$. Hence the customer type becomes two-dimensional: $\{x, y\}$. The three-level of costs can be interpreted as three potential scenarios that could arise on any given shopping day: First, it might be one of the days where the shopper would anyways pass by the grocery store and he or she has plenty of free time, this corresponds to the costs-less scenario where $\alpha = 0$. Second, is the scenario where the costs of offline shopping are very high on account of bad weather busy schedule, etc., this corresponds to $\alpha = x$. Finally, there might be an intermediate case, where the costs are neither zero nor too high, essentially a moderately busy day, this corresponds to $\alpha = y$.

As before, the customer will shop offline if the cost of doing so is zero ($\alpha = 0$). With the per-order model, the customer will shop online as long as her cost of shopping offline, x or y, is higher than the online cost, $o + \theta$. Figure 4.1 illustrates the store choice when the store visit cost is $\alpha = y$. Panel (a) graphs this choice under the per-order model; panel (b) graphs this choice under the subscription model, the more complicated case. In the latter model, customers will shop online if the store visit cost y (similarly, x) is greater than the cost θ of ordering online. It remains to determine which customers will subscribe. Customers make this decision based on their expectations of what the store



(a) Per-order (b) Subscription (c) Per-order & Subscription

FIGURE 4.1. Customer Shopping Channel Choice with Store visit Cost Realization $\alpha = y$.

visit cost α will be. In particular: a customer will adopt the online subscription model only if her expected store visit cost $\phi_x x + \phi_y y$ exceeds the threshold $\bar{\alpha}$ (determined by the subscription fee s).

Panel (c) of the figure shows the difference in the two models' adoption rates. All customers will participate equally in the subscription and per-order model *except* for those whose type is in the hatched region or the shaded region. The per-order (resp., subscription) model will be adopted by customers with type in the hatched region O (resp., the shaded region S). So as compared with our base model, there is now an additional difference in adoption between the two models: the per-order model captures more customers whose expected store visit cost is low, $\phi_x x + \phi_y y < \bar{\alpha}$, but cost of store visit y is high $y > o + \theta$. While the subscription model captures more low-y customers, $y \in [\theta, o+\theta]$, whose expected store visit cost is high enough to induce subscription, $\phi_x x + \phi_y y > \bar{\alpha}$. If the customer concentration in the shaded region is higher than in the hatched region, then the subscription model will be preferred even more. We call this the *market segmentation effect*, which tilts the scales both financially and environmentally.

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