Mechanisms for Increasing Sourcing from Capacity-Constrained Local Suppliers∗

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ABSTRACT

The fresh produce supply chain is characterized by large (mainstream) farms that are located far from consumers, and capacity-constrained (local) farms that are located close to the consumer. In this setting, we study: (i) how leadtime and capacity asymmetry between mainstream and local farms affect a retail grocer’s order policy for fresh produce, and (ii) how various operational mechanisms can increase the amount sourced from local farms. We show that this supply chain structure is disadvantageous for local suppliers (farms) because it induces the retailer to treat the local supply as a de facto responsive supply without paying a premium for the responsiveness. This disadvantage is exacerbated when the retailer’s objective is to achieve a high service level. We study three mechanisms that can improve conditions for local farms: working with an intermediary, backhauling, and a retail order policy, purchase guarantee, that explicitly supports local farms. The intermediary and backhauling mechanisms help the local farm by making local supply more attractive to the retailer, inducing her to order more locally sourced produce. The intermediary reduces the retailer’s overstock and stockout costs whereas backhauling increases the average margin. The purchase guarantee order policy helps local farms at the expense of retail profit. However, we show that purchase guarantee and

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backhauling are complementary mechanisms that together can benefit the retailer and local farms. [Submitted: September 18, 2014. Revised: September 3, 2015. Accepted: September 29, 2015.]

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INTRODUCTION

Public interest in bolstering “local economies” has been increasing in recent years and the food industry in particular has been a focus of the local economy movement. A study conducted in the Central Puget Sound area in Washington state showed that if consumers shifted 20% of their food dollars to purchases from local food businesses and suppliers, the annual income in the region would increase by $1 billion (Sonntag, 2008). In some regions of the United States, farming is a significant part of the food industry (e.g., New England, mid-Atlantic region, and west coast). In addition to regional economic benefits, the vibrancy of local farms can contribute to the overall character of the region. For example, New England is known for its iconic landscapes that include lush farms and green orchards—the beauty of the landscape is appreciated by tourists and residents alike. Moreover, local farms can be an integral part of preserving the natural ecology and biodiversity of a region. Independent farmers, typically operating family owned farms, have an incentive to manage the farm for long-term productivity so they can pass on the enterprise to future generations. Many practices that help ensure the farm’s long-term productivity such as soil management to prevent soil loss or water quality management also preserve the natural ecology of the area (Kirschenmann, Stevenson, Buttel, Lyson, & Duffy, 2015). Thus, a significant thrust of the local economy movement has been to ensure the survival and revival of local farms.

In this article, we examine how supply chain dynamics can affect the viability of local farms, in particular, mid-sized local farms in the United States. The term “local farm” often evokes an image of a farmer engaging with consumers at a farmer’s market. Indeed, the number and sales of these types of small local farms have increased dramatically. However, many local farms are mid-sized farms that are too big to sell only through direct channels such as farmer’s markets or community supported agriculture (CSA) programs. Thus, they must sell to the wholesale market (including retail grocers) to remain viable. The challenge in this channel is that mid-sized farms must compete with large mainstream farms. The evidence suggests that mid-sized farms are losing out—the number and sales of mid-sized farms are in decline (Kirschenmann et al., 2015).

Our article analyzes the supply chain dynamics when a large retail grocer sources from mid-sized local farms, and explores how operational mechanisms can increase the amount sourced from these local farms to help them remain economically viable. The geographic structure of the fresh produce industry drives much of the supply chain dynamics. In the United States, fresh produce is primarily grown on large farms located in geographical areas that specialize in certain agricultural products (i.e., mainstream supply). For example, two-thirds of fresh tomatoes sold in the United States are grown in California and Florida (USDA,
Although the mainstream supply is large, these regions are typically far from urban areas where most consumers live, and thus has a long leadtime. Farms that are closer to urban areas (i.e., local supply) have shorter leadtimes, but tend to be smaller in size because of increased competition for land. Because local supply is capacity-constrained, the retailer cannot rely solely on local farms. Peters, Bills, Lembo, Wilkins, and Fick (2009) show that only 34% of the food required by the population of New York state could be supplied by local sources. Therefore, to incorporate local farms into her sourcing policy, a large retail grocer would have to implement a hybrid sourcing policy that includes sourcing from mainstream farms in addition to local farms.

The geographic structure of the fresh produce industry also affects the lead-time of the mainstream and local suppliers. Local suppliers have shorter leadtimes and thus the retailer places the local order closer to the demand realization. This benefits the retailer because she can observe a better demand signal and can adjust her order accordingly, but local farms end up serving as de facto responsive suppliers that are subjected to unpredictable order patterns. This increases the risk of the local farms’ business, makes operating conditions very difficult (e.g., making it hard to staff pick and pack lines), and results in low farm utilization. Moreover, since most fresh produce is sold using “daily sales” transactions where the price is determined by the market on the day of the sale (Calvin et al., 2001), local farms may not be able to charge a premium for being responsive. The perishability of the product puts local farms in an inherently weak position once the crop has been harvested. The well-known industry expression, “sell it or smell it,” colorfully captures the predicament of the farm. Mid-sized local farms facing this kind of order volatility will try to find other channels for their produce, but if they cannot, they will be at risk of becoming economically unviable.

We use our characterization of the fresh produce supply chain dynamics to investigate three mechanisms that could induce the retailer to source more from local suppliers and as a consequence, improve operating conditions for local farms: (i) working through an intermediary, (ii) backhauling, and (iii) a purchase guarantee order policy. We compare the effectiveness of these mechanisms under two retailer objective functions: maximizing profit and achieving high service level (i.e., low stockouts). Although profit maximization is a typical objective function in the operations management literature, for some produce items, the retailer’s objective is to maintain a certain, typically high, service level. For example, retail grocers try to achieve a high service level on staple items such as tomatoes or bananas because consumers expect those items to always be in stock.

An intermediary such as Red Tomato (redtomato.org, Alvarez, Shelman, & Winig, 2010) can help increase local sourcing by aggregating more local farms, which increases local supply and decreases local supply volatility. We show that working with an intermediary results in higher local order quantities, a more stable order pattern, and higher retail profit. Moreover, an intermediary can facilitate information exchange between the retailer and local farms, thus reducing local supply uncertainty. This also helps to increase local order quantities.

In some cases, the retailer may be able to reduce the transportation cost of locally sourced produce by leveraging backhauling. As trucks return empty from the retail store to the distribution center (DC), they can be diverted to local farms to pick
up fresh produce. Our analysis shows that the backhauling mechanism has a very
different effect than using an intermediary. Backhauling decreases the retailer’s cost
of ordering local produce. Therefore, as the fraction of local produce increases,
the retailer’s average margin increases because the higher margin local produce
accounts for more of the sales. With backhauling, the retailer may actually incur
higher stockout or overstock cost by incorporating more uncertain local supply,
but the increased mismatch cost is more than offset by the higher average margin.
Backhauling thus increases the quantity ordered from the local supplier, decreases
local order volatility, increases local farm utilization, and increases retail profit.

We investigate an order policy, which we call purchase guarantee, where the
retailer guarantees to order at least a minimum quantity, or in an extreme case,
everything the local farm produces. This clearly benefits the local farm, but makes
the retailer worse off. Under this order policy, the retailer’s demand visibility ad-

tage from the local farm’s short lead time is curtailed. Moreover, the retailer
must incorporate local supply uncertainty into her safety stock when she orders
from the mainstream supplier. Thus, retail profit decreases under purchase guaran-
tee. However, we show that by combining purchase guarantee and backhauling, if
the cost of locally sourced produce with backhauling is sufficiently low, the retailer
can increase profit by sourcing locally and guarantee orders to the local farm. This
is, in fact, the combination used by Walmart in its Heritage Agriculture Program.

We find that if the retailer’s objective is to achieve high service level rather
than to maximize profit, the local farm’s proportion of the total retail order de-
creases and the effectiveness of the intermediary and backhauling mechanisms are
less effective for increasing local sourcing. The local farm’s capacity constraint
and supply uncertainty are more costly to the retailer when she is trying to achieve
a high service level. Therefore, the retailer shifts more of her order to the higher
capacity, more reliable mainstream supplier.

In this article, we focus on operational mechanisms for increasing local
sourcing. Another mechanism that can be used to increase local sourcing is dif-
ferentiation of the product. Some consumers may pay a premium for “local food”
(vs. simply food sourced from a local supplier), and this could incentivize the
retailer to order more from the local farm. To understand how this demand-side
mechanism affects supply chain dynamics would require characterizing consumer
preferences in a manner that is outside the scope of this analysis. We focus instead
on operational mechanisms because they are highly relevant for mid-sized farms
selling to a retail grocer. There are also examples of grocers such as Walmart who
source from local farms and may even advertise local sourcing at a company level,
but do not differentiate or price locally sourced produce differently at the item
level (Swanson, 2013).

**Literature Review**

Our article uses an operational lens to examine the viability of sourcing locally
produced food, a question that is very topical in the food policy and agricultural
economics literature. This literature falls broadly into two categories. One stream
of work examines the demand-side of localizing food supply, that is, consumers’
willingness to pay for a differentiated local food product (cf. Darby, Batte, Ernst,
This article contributes to another stream of research that examines the supply-side of food system localization. The focus of this research has primarily been on food miles, the distance from the farm to the consumer, and the implications for the supply chain when food miles are reduced. A number of studies present metrics for assessing the “localness” of the food system. For example, Pirog and Benjamin (2005) use a weighted average source distance metric to calculate the food miles of a multi-ingredient food production. Hein, Ilbery, and Kneafsey (2006) use an Index of Food Relocalization to measure and compare the local food activity in regions of the United Kingdom. Other supply-side studies have examined the effect of localization on supply chain metrics. For example, Coley, Howard, and Winter (2009) compare the carbon emissions of two local food distribution systems. Nicholson, Gomez, and Gao (2011) and Atallah, Gomez, and Bjorkman (2014) use optimization models to determine the lowest cost supply chain configurations for localizing dairy products and broccoli, respectively.

Whereas the supply-side studies in the agricultural economics literature focus on the distance-traveled effects of localization on supply chain economic and environmental performance, our article focuses on the leadtime effects of localization—in particular, the effect of leadtime asymmetry on inventory management. We draw and build on the inventory management literature (cf. Tayur, Ganeshan, & Magazine 1999; Zipkin 2000; Porteus 2002) to characterize the order policy of the retailer, given the geographic structure of the fresh produce industry, and the subsequent implications for the mainstream and local farms. Thus, we contribute to the local food sourcing literature by incorporating inventory management in the analysis of localizing food supply chains.

Our work also relates to the stream of inventory management literature that incorporates forecast updating into inventory control decisions, because the retailer can update her demand forecast between her orders from the mainstream and local farms. One important trade-off studied in this literature is between the improved demand forecast and the increased cost of ordering as one waits to acquire more information. Wang, Atasu, and Kurtulus (2012) studies this trade-off and provides an overview of this literature; also see Ozer, Uncu, and Wei (2007). This trade-off need not exists in our setting, because the cost of local produce may be higher or lower than mainstream produce. The key tension in our model is between improving the retailer’s demand forecast and ensuring adequate supply, an issue that arises because the local supply is capacitated.

Last, our work relates to the literature on dual sourcing. In the dual sourcing literature, there is a low-cost, long-leadtime supplier and a high-cost, short-leadtime (responsive) supplier. The first periodic review dual sourcing study was done by Barankin (1961) who derived the optimal order policy for a single-period inventory model with a regular supplier with a fixed leadtime and an emergency response supplier with zero leadtime. Subsequent work in this area extended the analysis to n periods (cf. Fukuda 1964), suppliers with leadtimes shorter than the review cycle (cf. Chiang & Gutierrez 1996, Tagaras & Vlachos 2001), and stochastic leadtimes (cf. Kouvelis & Li 2008, Zhou, Leung, & Pierskalla 2011). In the dual sourcing literature, the buyer’s trade-off is typically between low cost and high responsiveness. The key notion is to source the base demand from the

& Roe, 2008; Hardesty, 2008).
low-cost, long-leadtime supplier, and source the surge demand from the expensive yet responsive supplier.

By comparison, in our setting, the local (responsive) supplier may be the same or even lower cost than the mainstream supplier. Fresh produce wholesale prices are set by the market on the day of the order, therefore, the local (responsive) supplier cannot charge a premium for responsiveness. In fact, if the buyer could, she would buy only from the local supplier because she pays the market price and benefits from the short leadtime. The constraint on the local order quantity is the limited capacity of the local supplier. In our setting, the mainstream (long-leadtime) supplier is needed only because the local supplier does not have sufficient capacity, whereas in the dual sourcing literature, the long-leadtime supplier could be preferred because it is lower cost. Abginehchi, Larsen, and Thorstenson (2015) also consider a capacity-constrained responsive supply, but this supply source is a fixed quantity reserve inventory that is more expensive than the normal supplier. The decision studied is also different from our setting in that the buyer either uses the entire reserve inventory or none of it. More generally, there is a stream of literature that studies multiple sourcing with capacity constraints, however, unlike our model, all the suppliers have the same leadtime. The focus is on ensuring adequate supply quantity when there is yield uncertainty (cf. Anupindi & Akella 1993, Tomlin 2006, Dada, Petruzzi, & Schwartz 2007), whereas our focus is on the order quantity when there is leadtime asymmetry.

The article is organized as follows. We present the model in the second section and then derive the retailer’s order policy under profit maximization and target service level in the following section. In the fourth section, we study several mechanisms that affect the order policy and the operating conditions for the local farm. We conclude in the final section.

MODEL

We use a stylized model to capture how the geographic structure of the fresh produce supply chain affects supply chain dynamics. Our model incorporates a buyer that represents a large retail grocer in an urban area who can choose to source from local farms in addition to a large mainstream farm, to fill demand for a single fresh produce item. The mainstream farm represents a supply source from a specialized agricultural region such as Florida, which produces more than two-thirds of the tomatoes in the United States. Thus, we assume that the mainstream supplier is arbitrarily large and has enough capacity to satisfy any order from the retailer. However, the mainstream farm is located far from the retail store and therefore requires a long leadtime to transport the produce from the farm to the retail store.

Local farms that are close to urban areas are typically constrained by arable land availability (due to land development). Therefore, we assume the local farms are capacity constrained, i.e., even combined, they cannot fill the entire demand (cf. Peters et al. 2009). We focus on mid-sized farms that are much smaller than the mainstream farm, but too big to sell all their produce through direct channels such as farmers’ markets and CSA programs (Agriculture of the Middle, 2012). We assume that the retailer can source from $n$ symmetric local farms.
The leadtime from a local farm to the retail store is significantly less than the leadtime for the mainstream farm. For example, it may take 5–10 days to ship produce from a mainstream farm in California to a retail store in Massachusetts, whereas the leadtime to pick, pack, ship, and deliver from a New England farm to the same store can be done in 48 hours.\(^1\) To represent the difference in leadtimes, we assume the leadtime of the mainstream supplier is two periods and the leadtime of the local supplier is one period, respectively. It is important to note that farms make a commitment and plant crops months before the retail order is placed. At the time of planting, the farms do not know how much the retailer will order (if at all from the local farm).

The retailer’s wholesale costs of sourcing from the mainstream and local suppliers are, respectively, \(w_m\) and \(w_l\). These costs include the cost of the produce (i.e., payment to the supplier) and the cost of transporting the produce from the farm to the retail store. Note that \(w_l\) could be equal to, higher than, or lower than \(w_m\). We assume that the fresh produce from the two types of farms is not differentiated and the retail price for the produce item is \(r\). Although locally sourced produce is sometimes treated as a vertically or horizontally differentiated item with a separate stock keeping unit, we focus on the case where the locally sourced produce is not differentiated by price. For example, although Walmart advertises that it sources from local farms in general, they do not differentiate or price differently at the item level (Swanson, 2013). We consider the retailer’s order policy within a given season, for example, the summer season, thus we are not considering seasonality in demand.

Adopting the terminology of Zipkin (2000), the timing of events is as follows. Define time \(t\) as the start of period \(t\). To satisfy the demand in period 2, the retailer orders \(y_m\) from the mainstream farm at time 1 (to accommodate the two-period leadtime). When the retailer orders from the mainstream farm, local supply and demand are uncertain. Local supply in each period is uncertain because the retailer lacks visibility on local supply (i.e., how much the farms have planted, and how much they will harvest). We model the supply of a given local farm as \(\mu_l + \epsilon_i\), where \(\mu_l\) is the mean supply and \(\epsilon_i\) is a Normal, mean-zero random variable with variance \(\sigma_i^2\). We assume the supplies of local farms are independent and identically distributed, and the retailer treats the \(n\) local farms as a combined local supply. Thus, from the perspective of the retailer, the local supply capacity is \(\mu + \epsilon_s\), where \(\mu = n\mu_l\) and \(\epsilon_s\) is a Normal, mean-zero random variable with variance \(n\sigma_i^2\). Note that in our derivations, we restrict \(\mu + \epsilon_s\) to be nonnegative.

Because the leadtime for ordering from the mainstream farm is longer than that from the local supply, the retailer faces higher demand uncertainty at the point she orders from the mainstream farm. We model demand uncertainty as follows. When ordering from the mainstream farm, the retailer’s demand forecast is \(\lambda + \epsilon_1 + \epsilon_2\), where \(\lambda\) is the mean demand, and \(\epsilon_1\) and \(\epsilon_2\) are Normal, mean-zero random variables with variances given by \(\sigma_1^2\) and \(\sigma_2^2\), respectively.

At time 2, the retailer orders \(y_l\) from the local supply. We assume the local order is split among the \(n\) local farms according to their respective realized supply

\(^1\)These estimates are from personal conversations with industry managers.
Figure 1: Timing of events.

**Period 1**
- At time 1:
  - Uncertain demand: \( \lambda + \epsilon_1 + \epsilon_2, \epsilon_1 \sim N(0, \sigma^2_1), \epsilon_2 \sim N(0, \sigma^2_2) \)
  - Uncertain local supply: \( \mu + \epsilon_s, \epsilon_s \sim N(0, \sigma^2_s) \)
  - Retailer orders \( y_m \) from mainstream farm for arrival in period 2

**Period 2**
- At time 2:
  - Some demand uncertainty resolved: \( \lambda + \tilde{\epsilon}_1 + \epsilon_2, \epsilon_2 \sim N(0, \sigma^2_2) \)
  - Local supply is realized: \( \mu + \tilde{\epsilon}_s \)
  - Retailer orders \( y_l \) from local farm for arrival in period 2

The retailer has more information about demand when placing the local order than when placing the mainstream order. This additional information can be significant. For example, demand for fresh produce can vary from day to day—a key factor is weather, for example, rain can reduce the demand for salad items considerably.\(^\text{ii}\) Because fresh produce has a short shelf life, these day-to-day fluctuations can significantly affect the retailer’s mismatch cost (i.e., the combined cost of stocking out and overstocking). The ability to order fresh produce a few days later when the weather prediction is more accurate can be very advantageous. To capture the informational advantage the retailer has when ordering from the local supply, the retailer updates her demand forecast as follows: \( \lambda + \tilde{\epsilon}_1 + \epsilon_2 \), where \( \tilde{\epsilon}_1 \) denotes a realization of \( \epsilon_1 \). This is a single-item application of the additive version of the martingale model of forecast evolution for modeling the evolution of demand forecasts (Heath & Jackson, 1994; Gullu, 1996; Toktay & Wein, 2001). Because the local leadtime is short, local supply uncertainty is resolved prior to ordering from the local farm. We use \( \tilde{\epsilon}_s \) to denote a realization of \( \epsilon_s \).

Finally, in period 2, fresh produce from the farms is delivered and sold in the retail store. Fresh produce is perishable, therefore, leftover inventory is discarded at the end of period 2. We assume the salvage value is zero. The resulting sales is the minimum of the demand and the inventory on-hand. Excess demand is lost. The retailer chooses \( y_m \) and \( y_l \). Figure 1 illustrates the timing of events.

An operational lever that can possibly increase local sourcing is to extend the shelf life of locally sourced food. Because locally sourced food spends less time in transport, if handled correctly (i.e., proper and timely refrigeration), the available shelf life of local fresh produce could be longer than mainstream fresh produce.

\(^{\text{ii}}\) Moreover, this also implies that demand in a particular geographic area is likely to be correlated. Therefore, even with multiple retail buyers, the fluctuation would persist.
Currently however, it is not the practice of retailers or local farms to actively try to extend the shelf life of locally sourced food. Thus, extended shelf life is not considered in this model.

THE RETAILER’S ORDER POLICY

In this section, we derive the optimal order policy of the retailer under two objective functions: profit maximization and target service level. Although profit maximization is a standard objective function in operations management, in the retail grocer business, another common objective is to maintain a certain service level (Steven-son, 2015). In particular, for staple produce items such as tomatoes or bananas, it is important for the retailer to maintain high service levels because consumers have come to expect these items to always be in stock. The profit maximization objective would be more applicable for specialty product items (e.g., eggplant, pomegranate). Maintaining a high service level may not be necessary for specialty items and thus the objective of the retailer’s stocking policy would be more closely aligned with profit maximization. For each objective function, we first derive the optimal order policy for the straightforward case where the retailer only orders from one supplier, the mainstream farm (since the local farm does not have enough capacity to be the sole supplier). We call this the mainstream only sourcing policy. We then derive the hybrid sourcing policy, where the retailer sources from both the mainstream and local farms.

Profit Maximization

Under the mainstream only policy, maximizing profit is equivalent to minimizing the expected one period overstock and stockout costs. Thus, the retailer solves the following problem:

\[
\min_{y \geq 0} w_m \mathbb{E}_{\epsilon_1, \epsilon_2} \left[ (y - \lambda - \epsilon_1 - \epsilon_2)^+ \right] + (r - w_m) \mathbb{E}_{\epsilon_1, \epsilon_2} \left[ (\epsilon_1 + \epsilon_2 + \lambda - y)^+ \right].
\]

This problem is a straightforward application of the Newsvendor problem. The retailer’s profit-maximizing order quantity is given by \( y^* = \lambda + \sqrt{\sigma_1^2 + \sigma_2^2 \Phi^{-1}(\frac{r-w_m}{r})} \), where \( \sigma_1^2 + \sigma_2^2 \) is the variance of the demand forecast at time 1, \( \Phi(\cdot) \) denotes the cumulative distribution function of the standard Normal distribution, and \( (r - w_m)/r \) is the critical fractile. We will use \( \phi(\cdot) \) to denote the probability density function of the standard Normal distribution.

If the retailer can choose to also source from the local supply (hybrid sourcing), she can do at least as well as when she sources only from the mainstream farm. We first consider the problem of how much to order from the local farm having ordered \( y_m \) from the mainstream farm. To minimize the expected one period cost of stocking out and overstocking, the retailer solves the following problem at time 2:

\[
\min_{y \geq y_m} (r - w_l) \mathbb{E}_{\epsilon_2} \left[ (\lambda + \epsilon_1 + \epsilon_2 - y)^+ \right] + w_l \mathbb{E}_{\epsilon_2} \left[ (y - \lambda - \epsilon_1 - \epsilon_2)^+ \right].
\] (1)

If we ignore the bound on \( y \), this also is a typical Newsvendor problem. The retailer’s commitment to receive \( y_m \) units in period 2 from the mainstream farm constrains the Newsvendor solution. That is, if the Newsvendor solution is
smaller than \( y_m \) for a particular period, the retailer does not order any produce from the local farm. The following proposition provides the optimal profit-maximizing quantity from the local farm, \( y_l^* \). Note that \( y_l^* \) is the optimal order quantity, but the retailer actually receives \( \min\{y_l^*, \mu + \bar{\epsilon}_s\} \) from the local supply. We use \( q^+ \) to denote \( \max\{q, 0\} \).

**Proposition 1:** The unconstrained objective in Equation (1) is minimized at \( \tilde{y} = \lambda + \bar{\epsilon}_1 + \sigma_2 \Phi^{-1}\left(\frac{r - w_l}{r}\right) \). Thus, the retailer’s profit-maximizing order quantity from the local supply is \( y_l^* = (\tilde{y} - y_m^*)^+ \), where \( y_m^* \) is the optimal order quantity from the mainstream farm.

Next, we find the profit-maximizing order quantity from the mainstream farm, \( y_m^* \). In choosing \( y_m^* \), the retailer includes the capacity limit of the local farm in the optimization problem by constraining \( y \) from above by \( y_m + \mu + \epsilon_s \) and solves the following for optimal \( y_m^* \):

\[
\min_{y_m \geq 0} E_{\epsilon_1, \epsilon_s} \left[ \min_{y_m + \mu + \epsilon_s \leq y \leq y_m} w_l E_{\epsilon_2} \left[ (y - \lambda - \epsilon_1 - \epsilon_2)^+ \right] + (r - w_l) E_{\epsilon_2} \left[ (\lambda + \epsilon_1 + \epsilon_2 - y)^+ \right] + (w_m - w_l)y_m \right]. \tag{2}
\]

The minimization between the square brackets in Equation (2) is the retailer’s cost of overstocking plus cost of stocking out with the expectation taken over \( \epsilon_2 \), the random component left at time 2. The outer expectation is taken over \( \epsilon_s \) and \( \epsilon_1 \), both random at time 1. The last term represents the additional cost of units ordered from the mainstream farm (within the expectation, we use \( w_l \) as the wholesale cost of all units). The following proposition offers a characterization of the optimal mainstream order \( y_m^* \).

**Proposition 2:** The optimal order quantity from the mainstream farm \( y_m^* \) solves the following:

\[
\frac{r - w_l}{r} \int_{-\infty}^{\mu/\sigma_1} \int_{(y_m + \mu + \nu \sigma_3 - \sigma_2 z^* - \lambda)/\sigma_1}^{\infty} \Phi(u) du \phi(v) dv + \int_{-\infty}^{\mu/\sigma_1} \int_{(y_m - \sigma_2 z^* - \lambda)/\sigma_1}^{\infty} \Phi \left( \frac{y_m - \lambda - u \sigma_1}{\sigma_2} \right) \phi(u) du \phi(v) dv
\]

\[
+ \int_{-\infty}^{\mu/\sigma_1} \int_{(y_m + \mu + \nu \sigma_3 - \sigma_2 z^* - \lambda)/\sigma_1}^{\infty} \Phi \left( \frac{y_m + \mu + \nu \sigma_3 - \lambda - u \sigma_1}{\sigma_2} \right) \phi(u) du \phi(v) dv
\]

\[
+ \int_{-\infty}^{\mu/\sigma_1} \int_{(y_m - \sigma_2 z^* - \lambda)/\sigma_1}^{\infty} \Phi \left( \frac{y_m - \lambda - u \sigma_1}{\sigma_2} \right) \phi(u) du \phi(v) dv = \frac{r - w_m}{r}, \tag{3}
\]

where \( z^* = \Phi^{-1}\left(\frac{r - w_m}{r}\right) \).

From Proposition 2, we see that the profit-maximizing mainstream order \( y_m^* \) is determined by the model primitives. Thus, for any given set of parameters, \( y_m^* \) is fixed. However, Proposition 1 shows that the local order \( y_l^* \) depends on the realization of \( \epsilon_1 \). This implies that the retailer’s profit-maximizing order strategy is to use local supply to react to demand volatility. However, because the dual sourcing
policy presented in Propositions 1 and 2 arises from the geographic characteristics of the fresh produce supply chain (which cause the leadtime asymmetry) and prices are set by the market, the local supplier is not paid a premium for responsiveness. The local supply sees a volatile order pattern which makes operating conditions very difficult. We found this result to be consistent with sentiments expressed by local farmers (e.g., Joel Salatin of Polyface Farm and Frank Carlson of Carlson Orchards) who found it undesirable to supply some large retail grocers. Mid-sized local farms facing this kind of order volatility will try to find other channels for their produce, but if they cannot, they will be at risk of becoming economically unviable.

**Target Service Level**

We consider now the problem where the retailer optimizes her profit subject to a service level constraint. We focus on type 1 service level, the probability of being in stock.\(^{iii}\) The desired service level is denoted by \(\rho\). Under the mainstream only sourcing policy, the retailer’s optimal order can be obtained by

\[
\hat{y} = \lambda + \sqrt{\sigma^2 + \sigma^2 \Phi^{-1} \left( \max \left\{ \rho, \frac{r - w_m}{r} \right\} \right)}.
\]

In the hybrid sourcing case, the retailer’s optimal order policy follows from a constrained optimization problem. To state the retailer’s problem, let \(y = (y_m, y_l)\) denote her order policy with the understanding that \(y_m\) and \(y_l\) are chosen sequentially. In particular, the local order quantity \(y_l\) is chosen after observing \(\tilde{\epsilon}_1\) and \(\tilde{\epsilon}_s\). Also denote the retailer’s cost under the order policy \(y\) by \(C(y)\):

\[
C(y) = (w_m - w_l)y_m + w_lE_{\epsilon_1, \epsilon_s, \epsilon_2}\left[(y_m + \min(y_l, (\mu + \epsilon_s)^+) - \lambda - \epsilon_1 - \epsilon_2)^+\right]
+ (r - w_l)E_{\epsilon_1, \epsilon_s, \epsilon_2}\left[\left(\lambda + \epsilon_1 + \epsilon_2 - y_m - \min(y_l, (\mu + \epsilon_s)^+)\right)^+\right].
\]

Similarly, denote the service level under order policy \(y\) by \(S(y)\):

\[
S(y) = \mathbb{P}\left(\lambda + \epsilon_1 + \epsilon_2 \leq y_m + \min(y_l, (\mu + \epsilon_s)^+)\right).
\]

Then the retailer’s problem is to choose \(y\) (with \(y_m, y_l \geq 0\)) so as to

\[
\min C(y) \text{ subject to } S(y) \geq \rho.
\]

To solve this problem, we consider the following relaxed problem in which the constraint is replaced by a penalty term in the objective: For \(q > 0\), choose \(y\) to minimize

\[
\min C(y) - qS(y).
\]

It is straightforward to argue that the objective is strictly convex, and hence, the optimal solution is unique, and that \(y(q)\) is well defined. Letting \(y(q) = \arg\min\{C(y) - qS(y)\}\), the following lemma shows that higher penalties lead to higher service levels.

**Lemma 1:** As \(q\) increases, \(S(y(q))\) increases too.

\(^{iii}\)Type 1 service is the type of service level given by the Newsvendor model, that is, the probability that demand is less than the quantity available.
To facilitate the solution to the retailer’s problem (6), define
\[
\overline{\rho} = S(y(0)) \text{ and } \overline{\rho} = \lim_{q \to \infty} S(y(q)). \tag{8}
\]
It is clear from Lemma 1 that \(S(y(\cdot))\) is invertible and that \(q(\rho)\) is well defined. Then for \(\rho \in (\overline{\rho}, \overline{\rho})\), let \(q(\rho)\) be such that \(S(y(q(\rho))) = \rho\). The following proposition provides a solution to the retailer’s problem (6).

**Proposition 3:** The order policy \(y(q(\rho))\) is an optimal solution for (6) and constitutes an optimal order policy for the retailer.

Next, we characterize the optimal order quantity \(y(q(\rho))\) further. Note that the probability \(S(y)\) of being in stock can be written as follows:
\[
S(y) = \mathbb{E}_{\epsilon_1, \epsilon_2} \left[ \mathbb{P} \left( \lambda + \epsilon_1 + \epsilon_2 \leq y_m + \min(y_1, (\mu + \epsilon_i)^+) \right) \right]
= \mathbb{E}_{\epsilon_1, \epsilon_2} \left[ \Phi \left( \frac{\min(y_1, (\mu + \epsilon_i)^+) + y_m - \lambda - \epsilon_1}{\sigma_2} \right) \right]. \tag{9}
\]
The formulation (7) can be rewritten as follows:
\[
\min_{y_m \geq 0} (w_m - w_l)y_m + \mathbb{E}_{\epsilon_1, \epsilon_2} \left[ \min_{\mu + \epsilon_i \geq y_l \geq 0} w_l \mathbb{E}_{\epsilon_2} \left[ (y_m + y_l - \lambda - \epsilon_1 - \epsilon_2)^+ \right] \right]
+ (r - w_l) \mathbb{E}_{\epsilon_2} \left[ (\lambda + \epsilon_1 + \epsilon_2 - y_m - y_l)^+ \right] - q \Phi \left( \frac{y_l + y_m - \lambda - \epsilon_1}{\sigma_2} \right). \tag{10}
\]
Then we consider the inner optimization (or, the second period) problem given \(y_m, \tilde{\epsilon}_1, \tilde{\epsilon}_2\):
\[
\min_{\mu + \tilde{\epsilon}_2 \geq y_l \geq 0} w_l \mathbb{E}_{\epsilon_2} \left[ (y_m + y_l - \lambda - \tilde{\epsilon}_1 - \epsilon_2)^+ \right]
+ (r - w_l) \mathbb{E}_{\epsilon_2} \left[ (\lambda + \tilde{\epsilon}_1 + \epsilon_2 - y_m - y_l)^+ \right] - q \Phi \left( \frac{y_l + y_m - \lambda - \tilde{\epsilon}_1}{\sigma_2} \right). \tag{11}
\]
Let \(z(q)\) denote the unique solution of the following equation:
\[
\frac{r - w_l}{r} = \Phi(z) - \frac{q}{\sigma_2 r} \phi(z). \tag{12}
\]
Without the second term on the right-hand side of Equation (12), it would be the typical Newsvendor critical fractile. The term is an adjustment to the critical fractile to account for the service-level constraint \(S(y) \geq \rho\). We use this in the following proposition to characterize the optimal solution to (11).

**Proposition 4:** Let \(y = \lambda + \tilde{\epsilon}_1 + \sigma_2 z(q(\rho))\). Then the retailer’s profit maximizing order quantity from the local farm is \(y_l = (y - y_m)^+\).

Note that the unconstrained order quantity \(y = \lambda + \tilde{\epsilon}_1 + \sigma_2 z(q(\rho))\) can be interpreted as the order quantity in a simple Newsvendor setting with the optimal service level \(\hat{\rho}\):
\[
y = \lambda + \tilde{\epsilon}_1 + \sigma_2 \Phi^{-1}(\hat{\rho}), \tag{13}
\]
where $\hat{\rho} = \Phi(z(q(\rho)))$. Therefore, when ordering from the local supply the retailer strives to achieve a service level $\hat{\rho}$, which does not depend on the realizations of $\epsilon_1$ and $\epsilon_s$ (though the quantity delivered from the local supply depends on both). This observation simplifies the numerical solution of the retailer’s problem (6). Namely, it suffices to search over $y_m$ and $\hat{\rho}$. For each such pair, one computes the cost $C(y)$ and the service level $S(y)$. Then restricting attention to those pairs $(y_m, \hat{\rho})$ such that $S(y) = \rho$, the pair with the lowest cost gives the optimal order policy for the retailer.

Last, observe that whenever the service-level constraint binds, that is, $q > 0$, we have that $\hat{\rho} > (r - w)/r$, which follows from (12). This merely means that the retailer seeks to achieve a service level higher than the optimal service level in the simple Newsvendor model. Interestingly, we also observe that $\hat{\rho} > \rho$. Otherwise, if $\hat{\rho} \leq \rho$, because of the capacity constraint and the resulting truncation of local orders, we would have $S(y) < \rho$, violating the service level constraint. In other words, recognizing the local capacity constraint, the retailer seeks a higher service level $\hat{\rho}$ in the second-stage problem than the required service level $\rho$. This enables her to achieve the service level $\rho$ on average.

### INCREASING LOCALLY SOURCED FOOD

We now examine three mechanisms commonly used in local food supply chains: working with an intermediary, backhauling, and a retail store order policy which we will call purchase guarantee. We examine the impact of these mechanisms on retail profit and local farm utilization. We first derive analytical results using the profit maximization objective function. In the following subsection, we use a numerical study to compare the effect of these mechanisms under profit maximization and target service level.

**Intermediary**

The Red Tomato organization (redtomato.org, Alvarez et al., 2010) acts as an intermediary between local farms and retailers. An important function performed by the intermediary is to aggregate the supply from more local farms. When working directly with local farms, the retailer will likely only work with a small number of farms to keep the number of suppliers to a manageable level (Calvin et al., 2001). However, an intermediary that focuses on aggregation will likely work with more local farms. Suppose that by working with an intermediary, the retailer can increase the number of local farms from $n$ to $n + k$, where $k > 0$ (i.e., the retailer gains an additional $k$ local farms by working with the intermediary).

Assuming that the local farms’ supplies are independent and identically distributed, the average combined local supply through the intermediary is $(n + k)\mu_l$ with standard deviation $(\sqrt{n + k})\sigma_l$. The aggregation of multiple local farms makes them appear like a large, reliable, and hence more attractive, supplier to the retailer.

The following proposition shows how increasing the number of local farms affects the local farm and the retailer.

**Proposition 5:** As the number of local farms $n + k$ increases or $k$ increases, the average amount the retailer orders from the local supply increases, the average
amount supplied by the local supply increases, and the retailer’s expected one period cost decreases.

Proposition 5 shows that the Red Tomato model can benefit both the retailer and local farms. Recall that the retailer uses the local supply to react to demand volatility. With a larger, more reliable local supply source, the retailer can delay a bigger portion of her order (i.e., order less from the mainstream supplier). Because local supply is more reliable, the probability that the local supply can fill the order increases. Moreover, our numerical analysis in the following subsection shows that the local farms see a more stable order pattern from the retailer. Increased order stability lowers the overall risk for the local farms and allows the farmers to better manage staffing (pick and pack lines) and transportation.

Another function that the intermediary serves is to facilitate information sharing between the retailer and local farms. The intermediary is in frequent contact with the local farms and is aware of what has been planted, and how the season is going in general. Although there is still uncertainty about the eventual yield, the intermediary can mitigate the uncertainty in local supply because of the constant contact with the local farms. Thus, at time 1 when the retailer places her mainstream order, she has a better idea of what local supply is (i.e., \( \sigma_s \) is lower). Then, similar to the aggregation effect presented in Proposition 5, reducing local supply uncertainty would benefit both the retailer and local suppliers. The local supply becomes a more desirable supply source because it is more likely to be able to deliver the ordered quantity. Therefore, the retailer will place a higher local order, and the average amount supplied by the local supply would increase.

Note that the focus of our intermediary analysis is on the aggregation and informational advantages. There are potential risks to working with an intermediary, notably the possibility that the intermediary may extract a significant portion of the supply chain margin, leaving the farmer with a very small margin. This pricing analysis is out of the scope of our model, but is an important dimension for future study that can shed light on the effectiveness of the intermediary mechanism.

**Backhauling**

An operational lever that could reduce the logistical cost of sourcing from local farms is backhauling. For example, Walmart’s local sourcing program (Heritage Agriculture) leverages its ability to backhaul local produce from farms that are located between its DCs and stores. The retailer regularly sends loaded trucks from her DCs to her stores. On the way back from the stores, the trucks are empty. Using this truck capacity to transport produce from farms to the DC significantly reduces the logistics cost of sourcing from local farms. Clearly, not every local supplier would be able to implement backhauling, however, our analysis shows how the successful implementation of backhauling would affect the retailer’s order policy and we investigate the subsequent effect on the local supplier.

Suppose that the retailer could implement backhauling and reduce the freight (transportation) cost for local produce by \( \delta > 0 \). Then the wholesale cost of sourcing from the local supply reduces to \( w_l - \delta = b \). At time 1, the retailer solves the
following optimization problem to determine the optimal quantity to order from the mainstream farm, \( y_m \):

\[
\min_{y_m \geq 0} \mathbb{E}_{\epsilon_1, \epsilon_2} \left[ \min_{y_m + \mu + \epsilon \geq y_m} b \mathbb{E}_{\epsilon_2} \left[ (y - \lambda - \epsilon_1 - \epsilon_2)^+ \right] + (r - b) \mathbb{E}_{\epsilon_2} \left[ (\lambda + \epsilon_1 + \epsilon_2 - y)^+ \right] + (w_m - b) y_m \right].
\]  

(14)

Equation (14) is analogous to Equation (2), except that the wholesale cost is \( b \) instead of \( w_l \). Thus, the retailer’s profit-maximizing order quantity from the mainstream farm follows the results from Proposition 2, and substituting \( b \) for \( w_l \).

The following proposition shows the effect of backhauling on the local farm.

**Proposition 6:** As the wholesale cost with backhauling \( b \) decreases,

(a) the average amount the retailer orders from the local supply increases,

(b) the profit-maximizing order quantity from the mainstream farm \( y^*_m \) decreases,

(c) the average amount sold by the local supply increases,

(d) the retailer’s optimal expected one period cost decreases.

The backhauling mechanism works differently than the intermediary mechanism to improve conditions for the local farm. Instead of allowing the retailer to better manage mismatch cost, backhauling increases the per unit margin of the retailer. Therefore, the retailer prefers to sell more locally sourced produce. Thus, as shown in Proposition 6, she orders less from mainstream and more from local. However, our numerical analysis in the following subsection shows that the retailer may stock out more because of local supply uncertainty. Therefore, with backhauling, the retailer’s mismatch cost can actually increase, but her average margin on each unit sold increases, allowing her to increase profit.

**Purchase guarantee**

The purchase guarantee mechanism is an order policy that the retailer can choose to adopt in order to support local farmers. A number of grocery chains have local sourcing policies, including Whole Foods, Walmart, Wegmans, and Thrifty Foods. In fact, in the extreme case, Walmart will agree to buy everything a local farm produces. Note, however, that even if the retailer buys everything the local farms produce, she must still order from the mainstream supplier because she knows that there will not be enough local supply to satisfy demand. We consider a purchase guarantee mechanism where the retailer guarantees to buy at least a minimum quantity \( Q \) units from the local supply. However, the retailer will order the optimal local order quantity (given in Proposition 1) if the optimal local order quantity is higher than \( Q \). Taking into account the minimum local order of \( Q \) units at time 2, the optimal mainstream order is given in the following proposition.

**Proposition 7:** If the retailer implements a purchase guarantee where she guarantees to buy at least \( Q \) units (but possibly more) from the local supply, the optimal
order quantity from the mainstream farm $y_m^*$ solves the following:

\[
\frac{r - w_m}{r} = \int_0^\infty \int_{(Q-\mu)/\sigma_s}^{\infty} \phi(v;\mu,v\sigma_s) \left( \frac{m + \mu + v\sigma_s - \lambda - u\sigma_1}{\sigma_2} \right) \phi(u;\mu,u\sigma) dv du
\]

\[
+ \int_{-\infty}^{(Q-\mu)/\sigma_s} \int_{-\mu/\sigma_s}^{(y_m+\mu+\sigma_s\mu+\sigma_2\lambda-z^*\sigma_s)/\sigma_2} \Phi \left( \frac{m + \mu + v\sigma_s - \lambda - u\sigma_1}{\sigma_2} \right) \phi(u;\mu,u\sigma) dv du
\]

\[
+ \int_{-\mu/\sigma_s}^{\infty} \int_{-\infty}^{\infty} \Phi \left( \frac{y_m + \mu + v\sigma_s - \lambda - u\sigma_1}{\sigma_2} \right) \phi(u;\mu,u\sigma) dv du
\]

\[
+ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \Phi \left( \frac{y_m + \mu + v\sigma_s - \lambda - u\sigma_1}{\sigma_2} \right) \phi(u;\mu,u\sigma) dv du = \frac{r - w_m}{r}, \tag{15}
\]

where $z^* = \Phi^{-1} \left( \frac{r - w_m}{r} \right)$.

**Corollary 1:** If the purchase guarantee quantity is for everything the local supplier produces (i.e., $Q \to \infty$), the retailer’s profit maximizing mainstream order is

\[
y_m^* = \lambda - \mu + \sqrt{\sigma_1^2 + \sigma_2^2 + \sigma_3^2} \Phi^{-1} \left( \frac{r - w_m}{r} \right). \tag{16}
\]

By committing to buy at least a minimum quantity of $Q$ units, the retailer’s ability to take advantage of demand visibility at the time of the local order is curtailed—she cannot adjust her order down if demand turns out to be low (but is still able to increase her order if the demand turns out to be high). Moreover, she must account for local supply uncertainty when she orders from the mainstream farm, thus increasing the amount of safety stock she carries. We can see this explicitly as $Q \to \infty$. In the last term in Equation (16), we see that the safety stock increases in supply volatility $\sigma_s$ and is higher than the safety stock required in the mainstream only or hybrid sourcing order policies. Therefore, under the purchase guarantee ($Q \to \infty$), the retailer’s profit decreases compared to the mainstream only or hybrid sourcing order policies.

**Combining purchase guarantee and another mechanism**

The purchase guarantee order policy is an effective mechanism for improving local farm operating conditions, however, it comes at the expense of retail profit. The question is whether combining purchase guarantee with working with an intermediary or backhauling can break this tradeoff?

Clearly, the higher the purchase guarantee minimum quantity $Q$, the worse off the retailer is. In fact, as $Q \to \infty$, the combination of a purchase guarantee with an intermediary will at best increase the retailer’s profit to the same level as sourcing from mainstream only. This is because with a purchase guarantee, the demand visibility advantage is significantly reduced because the retailer has already committed to ordering a minimum amount from the local farm. Aggregation can reduce supply uncertainty, but at best this makes local supply deterministic. This would simply make local supply an extension of the mainstream supply.
However, combining purchase guarantee and backhauling gives better results. In the following proposition, we show the interaction between the purchase guarantee and backhauling mechanisms for an arbitrarily large $Q$ (i.e., as $Q \to \infty$, therefore the retailer buys everything the local supply produces).

**Proposition 8:** Suppose the retailer offers a purchase guarantee (with $Q \to \infty$) and implements backhauling. The retailer’s profit increases as the wholesale cost with backhauling $b$ decreases. There exists $\hat{b} > 0$, such that if $b < \hat{b}$, the retailer’s profit is higher than her profit under mainstream only and under hybrid sourcing. The result holds for both the profit maximization and target service level objective functions.

Implementing a purchase guarantee with backhauling wholesale cost $b < \hat{b}$ makes sourcing locally not only viable, but more profitable than sourcing from mainstream only. Not only do the higher margin backhaul units compensate for the loss in profit from the purchase guarantee policy, backhauling and purchase guarantee are complementary mechanisms. The lower the backhaul wholesale cost, the more units the retailer wants to order from the local farm. This dovetails with the purchase guarantee mechanism, which can increase the local order quantity. Thus, backhauling increases the margin of local units, and purchase guarantee increases the percentage of local units in the retailer’s total order—both effects increase the retailer’s average margin. This is the winning combination used by Walmart in its Heritage Agriculture program. We show an example of this combination in the following numerical example where the higher the purchase guarantee quantity, the more the retailer benefits from backhauling.

**Numerical Example**

We now use our analytical results in a numerical example to show how the hybrid sourcing policy compares to the mainstream only policy, and to illustrate the impact of aggregation (through an intermediary), backhauling, and purchase guarantee on the retailer’s order policy and the subsequent impact on local farm operating conditions. We consider the example of stocking one produce item, that is, tomatoes, at a retail grocery store, using parameter values that are consistent with an average suburban retail store. We assume the average weekly demand for tomatoes is $\lambda = 2,000$ pounds, and the uncertainty around the demand is captured in $\epsilon_1 \sim N(0, 160)$ and $\epsilon_2 \sim N(0, 120)$. We assume that the local supply is approximately 10% of demand, 200 pounds per week, but there is uncertainty that is captured by $\epsilon_s \sim N(0, 100)$ (a sensitivity analysis on $\epsilon_1$, $\epsilon_2$, and $\epsilon_s$ is provided in Appendix C). The retail price of tomatoes is $1.50 per pound and the retailer’s wholesale cost is $0.80 per pound for the mainstream and local supplies. For the base case, we assume the two wholesale costs are equal so that we can compare the effects of leadtime and the local capacity constraint on the retailer’s order policy and the subsequent effects on retailer and supplier outcomes. We find that the qualitative results from the base case hold when we set the local wholesale cost higher ($w_l = $0.90) or lower ($w_l = $0.70) than the mainstream wholesale cost. The numerical results presented below are obtained using our analytical derivations for the retailer’s mainstream and local orders, and Monte Carlo simulations for the outcome variables.
Table 1: Retail performance and local farm operating conditions under mainstream only and hybrid sourcing policies when the retailer’s objective is to maximize profit or target service level of 0.99.

<table>
<thead>
<tr>
<th>Decision variables</th>
<th>Profit Maximization</th>
<th>Target Service Level 0.99</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mainstream Only</td>
<td>Hybrid Sourcing</td>
</tr>
<tr>
<td>y^\text{*}_m</td>
<td>1,983</td>
<td>1,898</td>
</tr>
<tr>
<td>Avg. local order</td>
<td>120</td>
<td>47</td>
</tr>
<tr>
<td>Outcome variables</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg. retail profit ($)</td>
<td>1,281.12</td>
<td>1,307.60</td>
</tr>
<tr>
<td>Avg. retail mismatch cost ($)</td>
<td>118.88</td>
<td>92.40</td>
</tr>
<tr>
<td>Avg. local farm utilization</td>
<td>0.49</td>
<td>0.24</td>
</tr>
<tr>
<td>Coeff. var. local farm util</td>
<td>0.85</td>
<td>1.53</td>
</tr>
</tbody>
</table>

**Mainstream only versus hybrid sourcing**

We first compare the results for the mainstream only and hybrid sourcing policies for the base case using both objective functions (i.e., profit maximization and target service level for high service level 0.99). Looking at the two profit maximization columns in Table 1, we see that by using hybrid sourcing, the retailer increases profit by reducing mismatch cost ($118.88 vs. $92.40). She is able to match demand better (lower mismatch cost) because the reduced leadtime of the local supply enables better demand visibility. Compared to the profit-maximizing objective, under the target service level objective, the retailer increases her profit significantly more by moving to hybrid sourcing ($1,026.80 increases to $1,100.07, an increase of 7%). However, this increase comes almost entirely from reducing overstock cost. Target service level forces the retailer to carry a lot of excess inventory—the marginal units are highly unlikely to be sold. Thus, the retailer can mitigate overstock cost considerably by having a short leadtime supplier that is used very infrequently. Note that the net profit margin for grocery stores is typically less than 3% (CSIMarket, 2015). Therefore, if the gross margin is approximately 40%, an increase of 7% would increase net profit by 2.8%.

However, the impact of target service level on local farm utilization and order volatility is significant. The utilization was only 0.49 (with c.v. 0.85) under profit maximization, but it drops to 0.24 (with c.v. 1.53) under target service level. The average order drops from 120 units to 47 units. Thus, we see that hybrid sourcing helps the retailer more when her objective is to achieve high service level. However, the high service level objective worsens the operating conditions for the local supplier significantly.

Note that the utilization of the local supply is dampened by our assumption that there is one buyer. In practice, there are other buyers that the local farm could sell to, for example, direct channels such as farmers’ markets, or wholesalers. However, as mentioned in the second section, our focus is on mid-sized farms that are too big to sell only through direct channels. The local farm would command
Mechanisms for Increasing Sourcing from Capacity-Constrained Local Suppliers

a lower price selling to a wholesaler who also must make a margin. Moreover, the local farm would encounter similar problems selling to a wholesaler as to a retailer. The times when the retailer would not order from the local supplier is when supply is high relative to demand (e.g., bad weather depresses demand in the region, or an unusually high crop yield year increases supply). During these times, it is in general more difficult to sell the produce. Moreover, as it gets close to harvest time, the leverage of the farmer decreases—he must find a buyer quickly because of the perishability of the product. In fact, if the farmer does not think he will command a high enough price for his produce, he will not pay to harvest it. In practice, for some fraction of the time, the supplier would be able to sell the produce through an alternate (typically less desirable) channel, and this would mitigate the low utilization, but it would not eliminate it because the fundamental order volatility persists due to the leaddtime difference and capacity constraint.

We examine in the following sections how aggregation through an intermediary, backhauling, and purchase guarantee affect the retailer’s profit and the local farms’ operating conditions. Because tomatoes are a staple item (and to streamline the exposition in the article), we focus on the target service level objective when we analyze the effect of the mechanisms below. However, we present the analysis for the profit maximization objective in Appendix D. We find that working through an intermediary helps both the retailer (higher profit) and the local farm (lower order volatility and potentially higher utilization). Backhauling also benefits the retailer and local supplier. The reduction in wholesale cost increases retail profit, and thus the retailer increases the local order quantity and decreases the local order volatility. The purchase guarantee clearly benefits the local farm, but it decreases retail profit. However, we show that the retailer can increase profit by combining the purchase guarantee and backhauling mechanisms if backhauling decreases wholesale cost enough. Moreover, these two mechanisms are complementary—the higher the purchase guarantee quantity, the more the retailer benefits from backhauling. Thus, the retailer can implement a sourcing policy that supports the local farm, and also increase her own profit. Overall, comparing with the results in Appendix D, we find that these mechanisms have qualitatively the same effect if the retailer’s objective is profit maximization. Following are more detailed analysis of the mechanisms.

### Aggregation through an intermediary

In our benchmark setting, the retailer sources from $n = 2$ local farms. We chose $n$ to be a small number because typically retailers prefer to use a small number of vendors to streamline the order process (Calvin et al., 2001). Aggregation through an intermediary can grow the total number of farms considerably. Table 2 shows the results for $k = 0$ (two farms total) to $k = 8$ (10 farms total). The good news is that aggregation makes the retailer and the local suppliers better off. Retail profit increases from $1,100.02$ (2 farms) to $1,174.14$ (10 farms), average local farm utilization increases from 0.24 (2 farms) to 0.32 (10 farms), and the coefficient of variation of local farm utilization decreases from 1.53 (2 farms) to 0.59 (10 farms).

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This policy has been affirmed by personal conversations with several farmers.
Table 2: The impact of aggregating $n + k$ local farms on retail performance and local farm operating conditions when the objective is target service level (0.99), $n = 2$.

<table>
<thead>
<tr>
<th>Target Service Level 0.99</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of farms $(n + k)$</td>
</tr>
<tr>
<td>Local supply capacity $(\mu, \sigma_S)$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Decision variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mainstream order, $y^*_m$</td>
</tr>
<tr>
<td>Avg. local order</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Outcome variables</th>
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<td>Avg. retail profit ($)</td>
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</tr>
<tr>
<td>Coeff. var. local farm util</td>
</tr>
</tbody>
</table>

Local farm utilization will obviously depend on how much supply (i.e., how many farms) is added by the intermediary, relative to demand. In this particular example, local farm utilization remains quite low—the average local order per farm increases slightly from 23.5 ($= 47/2$ for 2 farms) to 29.9 ($= 299/10$ for 10 farms), and may actually decrease if more supply is added (see Appendix D). As local supply capacity increases and local supply uncertainty decreases, the distinction between the local and mainstream supplies boils down to leadtime. The retailer will take advantage of the short local leadtime by using local supply to react to demand volatility. However, each marginal local unit reduces demand uncertainty less than the unit before, whereas the supply uncertainty increases for each additional unit. Therefore, there is a threshold local quantity where the retailer’s benefit from sourcing locally is outweighed by the cost. When the retailer’s objective is to achieve a high service level, this threshold quantity is even lower because the retailer faces the additional constraint that the local supply uncertainty be low enough to achieve the target service level. Thus, aggregation helps to improve the operating conditions for the local farm, but the impact is limited.

**Backhauling**

Backhauling decreases the retailer’s wholesale cost by decreasing transportation cost. We perform a sensitivity analysis as backhauling reduces local wholesale cost to $w_l = b$, where $b \in \{0.70, 0.50, 0.30, 0.10\}$. In Table 3, we see that with backhauling, utilization increases from 0.24 ($w_l = 0.8$) to 0.45 ($b = 0.1$). However, the retailer cannot rely on the local supply as much as it would like because local supply uncertainty and the capacity constraint would prevent the retailer from achieving its target service level, thus local farm utilization remains relatively low. The retailer benefits from backhauling—her profit increases as wholesale cost with backhauling decreases. However, note that the retailer’s mismatch cost can increase if wholesale cost with backhauling decreases enough. The backhaul mechanism works through the retailer’s cost, which affects her mismatch cost and her margin. As the wholesale cost decreases, the retailer’s per unit overstock cost decreases and that has a downward effect on the average
Table 3: The impact of backhauling on retail performance and local farm operating conditions when the objective is target service level (0.99).

<table>
<thead>
<tr>
<th>Wholesale Cost with Backhauling</th>
<th>Decision Variables</th>
<th>Outcome variables</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$w_l = 0.8$</td>
<td>$b = 0.7$</td>
</tr>
<tr>
<td><strong>Target Service Level 0.99</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Wholesale Cost</strong></td>
<td>$2,336$</td>
<td>$2,333$</td>
</tr>
<tr>
<td><strong>Mainstream order, $y^*_m$</strong></td>
<td>Avg. local order</td>
<td>47</td>
</tr>
<tr>
<td><strong>Avg. local order</strong></td>
<td>47</td>
<td>51</td>
</tr>
<tr>
<td>Avg. retail profit ($)</td>
<td>1,100.07</td>
<td>1,104.00</td>
</tr>
<tr>
<td>Avg. retail mismatch cost ($)</td>
<td>299.93</td>
<td>299.62</td>
</tr>
<tr>
<td>Avg. local farm utilization</td>
<td>0.24</td>
<td>0.25</td>
</tr>
<tr>
<td>Coeff. var. local farm util</td>
<td>1.53</td>
<td>1.46</td>
</tr>
</tbody>
</table>

mismatch cost. However, as $b$ decreases, the retailer’s margin increases, inducing her to order more from the local supply. Higher local orders implies that local supply uncertainty will increase average stockout cost. Increased margin also means that the retailer carries more safety stock, thereby increasing overstock cost. Thus, overall mismatch cost increases if $b$ is low enough.

**Purchase guarantee**

The effect of the purchase guarantee policy under target service level 0.99 is illustrated in Figure 2 for $Q \in \{0, 100, 200, 300, \infty\}$. The curve $Q = 0$ represents the case with no purchase guarantee. The curve $Q = \infty$ represents the case where the retailer buys everything produced by the local supply. Focusing on the point where $w_l = w_m = 0.80$ in Figure 2(a), we see that the purchase guarantee for each minimum quantity $Q > 0$ results in lower retail profit than $Q = 0$ (no purchase guarantee). Moreover, as the minimum quantity $Q$ increases, retail profit decreases from $1,099.85$ ($Q = 0$) to $986.16$ ($Q = \infty$). We see in Figure 2(b) that this is because the retailer’s mismatch cost increases as $Q$ increases from $300.15$ ($Q = 0$) to $413.84$ ($Q = \infty$). Guaranteeing a minimum order quantity helps the local farms, however, the retailer loses the flexibility to react to lower than expected demand information thereby increasing her own costs.

**Combining purchase guarantee and backhauling**

By combining purchase guarantee and backhauling, the retailer can potentially help the local farms while simultaneously increasing her own profit. In Figure 2(a), we see that for any given purchase guarantee minimum quantity $Q$, as the backhauling wholesale cost $b$ decreases, retail profit increases. For example, when $Q = 100$, if $b$ decreases below $0.40$, the retailer’s profit with purchase guarantee and backhauling results in higher profit than hybrid sourcing without purchase guarantee or backhauling. We see this in Figure 2(a) where the profit of hybrid sourcing without purchase guarantee or backhauling is represented by the point on the “$Q = 0$” curve at $b = 0.80$, which equals $1,099.85$. The profit curve of $Q = 100$ exceeds $1,099.85$ when $b < 0.40$. The profit is higher despite the fact that the mismatch cost with purchase guarantee of 100 units is always higher than without purchase guarantee.
Figure 2: The impact of backhauling and purchase guarantee combination on retail performance with purchase guarantee minimum quantity $Q \in \{0, 100, 200, 300, \infty\}$ units when the objective is target service level (0.99).

guarantee (see Figure 2b). Under purchase guarantee and backhauling, retail profit increases from the synergy between the two mechanisms. As $b$ decreases, the retailer's margin increases and the cost of overstocking decreases. Therefore, as $Q$ increases, the more benefit the retailer gains from backhauling (i.e., in Figure 2a, the slope of profit increase is steeper for higher $Q$). Thus, these mechanisms are complementary.

CONCLUSION

As local sourcing becomes more important for retailers, how best to incorporate local suppliers within the existing supply chain infrastructure becomes increasingly
salient. In our analysis of supply chain dynamics, we focused on a distinct feature of the fresh produce supply chain that we found to have significant operational implications: the geographical structure. Namely, the location of a farm (local or mainstream) relative to where most consumers live (in urban areas) affects the leadtime and capacity of the farm. By characterizing the retailer’s order policy, we showed that local farms end up being used as de facto responsive suppliers, but may not able to charge a premium for responsiveness because of the daily sales transactions in the fresh produce industry. This makes it difficult for mid-sized local farms to remain economically viable unless they can find alternate channels for their produce.

We studied three mechanisms that are used in practice to incorporate local farms into the retailer’s sourcing policy: working with an intermediary, backhauling, and a purchase guarantee. Working with an intermediary and backhauling benefit both the retailer and the local farm. The intermediary can help increase the effective capacity and decrease the supply uncertainty of local farms, allowing the retailer to respond better to demand volatility. Backhauling increases the retailer’s margin on local produce. Thus, both mechanisms induce the retailer to order more from the local supply. The purchase guarantee is an effective mechanism for improving operating conditions for the local farm, but it comes at the expense of retail profit.

The effectiveness of these mechanisms also depends on the retailer’s objective function. If the retailer’s objective is to maintain a high service level (i.e., consistently in stock), the retailer must rely even more on the mainstream supplier who is large and reliable, and only order from the local supply in the very unlikely event that demand is very high. In this case, the effectiveness of the intermediary is reduced because high service level forces the mismatch cost to be high. Backhauling is very effective when the retailer’s objective is profit maximization because it increases retail margin, but like the intermediary mechanism, the effect is dampened when the retailer’s objective is to achieve a high service level. However, we show that purchase guarantee and backhauling are complementary mechanisms that can be combined to effectively incorporate local suppliers into the retailer’s sourcing strategy, even when she targets a high service level. The combination reduces the local farm’s risk of not selling its produce, and for sufficiently low backhaul cost, can increase the retail profit.

This article is an effort to contribute to the understanding and improvement of a complex food system that sits at the nexus of business, regulation, culture, environment, and human health. There is evidence that establishing a vigorous local food system can contribute to a robust local economy, reduce the environmental impact of food production, and improve human health (O’Hara, 2011, 2013). Moreover, it aligns with the notion of creating shared value for the firm and the community (Porter & Kramer, 2011). Creating a robust local economy where consumers trust food producers to grow healthy, nutritious food using environmentally sustainable practices and fair wages are paid to producers, can enable a thriving symbiosis of commerce and community. However, to enable this value creation (using operational, marketing, or regulatory mechanisms), it is critical for business leaders and regulators to understand the physical operations and decision-making dynamics of the supply chain.
REFERENCES


Mechanisms for Increasing Sourcing from Capacity-Constrained Local Suppliers


**APPENDIX A: AUXILIARY DERIVATIONS**

**Derivations of Equations (1) and (2)**

For period 2 arrivals, the retailer orders at time 1 from the mainstream farm and at time 2 from the local farm. For generality, consider the scenario in which ordering costs from the local farm and the mainstream farm are different, denoted, respectively, by $w_l$ and $w_m$; and sales revenue is $r$ regardless of the source of produce.

First, consider the problem of ordering from the local farm at time 2 having committed to an amount $y_m$ from the mainstream farm. Assuming unmet demand is lost and ignoring the constraint on local capacity the retailer’s problem at time 2 is (cf. Porteus, 2002)

$$\max_{y \geq y_m} \left\{ r \left( \lambda + \bar{\epsilon}_1 - \mathbb{E}_{\epsilon_2} \left[ (\lambda + \bar{\epsilon}_1 + \epsilon_2 - y)^+ \right] \right) - w_l (y - y_m) \right\},$$

(A1)

where the first term represents average revenue if the inventory level at the start of the period is $y$ and the second term is the cost of ordering $y - y_m$ units from the local farm.

Substituting $y = \lambda + \bar{\epsilon}_1 + \mathbb{E}_{\epsilon_2} [(y - \lambda - \bar{\epsilon}_1 - \epsilon_2)^+] - \mathbb{E}_{\epsilon_2} [(\lambda + \bar{\epsilon}_1 + \epsilon_2 - y)^+]$ into (A1) yields

$$\max_{y \geq y_m} (r - w_l) \left( \lambda + \bar{\epsilon}_1 - \mathbb{E}_{\epsilon_2} \left[ (\lambda + \bar{\epsilon}_1 + \epsilon_2 - y)^+ \right] \right)$$

$$- w_l \mathbb{E}_{\epsilon_2} \left[ (y - \lambda - \bar{\epsilon}_1 - \epsilon_2)^+ \right] + w_l y_m.$$

An equivalent problem to this is given by (1).

At time 1, the retailer finds optimal order quantity $y_m$ from mainstream farms for period 2 arrival. Incorporating the capacity limit in the local ordering problem
at time 2 and considering the uncertainties in local supply and in demand at time 1, retailer’s problem is given by Equation (2).

**Alternative Representations of Equations (1) and (2)**

For the analysis in the Appendix, we use an alternative representation of the retailer’s problem at time 2 rather than the one in (1). That is, the retailer solves \( \min_{y \geq y_m} w_l y + r \mathbb{E}_{\epsilon_2} \left[ (\lambda + \epsilon_1 + \epsilon_2 - y)^+ \right] \). Note that, this follows directly from Equation (A1). Similarly, the retailer’s problem at time 1 can be represented by

\[
\min_{y_m \geq 0} (w_m - w_l) y_m + \mathbb{E}_{\epsilon_1, \epsilon_2} \left[ \min_{y_m + \mu + \nu \geq y \geq y_m} w_l y + r \mathbb{E}_{\epsilon_2} \left[ (\lambda + \epsilon_1 + \epsilon_2 - y)^+ \right] \right]. \tag{A2}
\]

**Auxiliary Derivations Used in Proofs of Propositions 2 and 5**

Recall that \( \epsilon_1, \epsilon_2, \) and \( \epsilon_s \) are mean-zero normally distributed random variables with standard deviations of \( \sigma_1, \sigma_2, \) and \( \sigma_s, \) respectively. Define \( U, V, \) and \( Z \) as standard normal random variables such that \( \epsilon_1 = U \sigma_1, \epsilon_s = V \sigma_s, \) and \( \epsilon_2 = Z \sigma_2; \) and \( u, v, \) and \( z \) are realizations, respectively. Define \( v(y_m) \) as the objective of the retailer’s problem at time 1 given by Equation (A2). Through the change of variables introduced above this can be written as

\[
v(y_m) = (w_m - w_l) y_m + \mathbb{E}_{U, V} \left[ \min_{y_m + U \sigma_1 + V \sigma_s \geq y \geq y_m} w_l y + r \mathbb{E}_Z \left[ (\lambda + U \sigma_1 + Z \sigma_s - y)^+ \right] \right]. \tag{A3}
\]

Optimal \( y \) of the inner optimization problem is \( \max \{ y_m, \min \{ y_m + \mu + \nu \sigma_s, \tilde{y} \} \} \) where \( \tilde{y} \) is the optimal solution to the unconstrained problem and can be written in the new notation as \( \tilde{y} = \lambda + u \sigma_1 + \sigma_2 \Phi^{-1}(\frac{r - w_l}{r}). \)

Define \( z^* = \Phi^{-1}(\frac{r - w_l}{r}) \) and write \( v(y_m) \) under the following four parameter regimes.

(i) For \( \tilde{y} < y_m \) and \( \mu + \nu \sigma_s > 0. \) That is, \( u < (y_m - \sigma_2 z^* - \lambda)/\sigma_1 \) and \( v > -\mu/\sigma_s. \)

\[
v(y_m) = w_m y_m + r \int_{-\mu/\sigma_s}^{\infty} \int_{-\infty}^{(y_m - \sigma_2 z^* - \lambda)/\sigma_1} \int_{-\infty}^{(y_m - u \sigma_1 - \lambda)/\sigma_2} \left( \lambda + u \sigma_1 + z \sigma_2 - y_m \right) \phi(z) \phi(u) du \phi(v) dv
\]

(ii) For \( \tilde{y} \in [y_m, y_m + \mu + \nu \sigma_s] \) and \( \mu + \nu \sigma_s > 0. \) That is, \( (y_m - \sigma_2 z^* - \lambda)/\sigma_1 < u < (y_m + \mu + \nu \sigma_s - \sigma_2 z^* - \lambda)/\sigma_1 \) and \( v > -\mu/\sigma_s. \)

\[
v(y_m) = w_m y_m + u_l \int_{-\mu/\sigma_s}^{\infty} \int_{(y_m - \sigma_2 z^* - \lambda)/\sigma_1}^{(y_m + \mu + \nu \sigma_s - z^* \sigma_2 - \lambda)/\sigma_1} \left( \lambda + u \sigma_1 + z \sigma_2 - y_m \right) \phi(u) du \phi(v) dv + r \int_{-\mu/\sigma_s}^{\infty} \int_{(y_m - \sigma_2 z^* - \lambda)/\sigma_1}^{(y_m + \mu + \nu \sigma_s - z^* \sigma_2 - \lambda)/\sigma_1} \int_{z^*}^{\infty} \phi(z) \phi(u) du \phi(v) dv
\]
(iii) For \( \tilde{y} > y_m + \mu + v\sigma_s \) and \( \mu + v\sigma_s > 0 \),
That is, \( (y_m + \mu + v\sigma_s - \sigma_2 z^* - \lambda)/\sigma_1 < u \) and \( v > -\mu/\sigma_s \).

\[
v(y_m) = w_m y_m + w_t \int_{-\mu/\sigma_s}^{\infty} \int_{-\infty}^{(y_m + \mu + v\sigma_s - \sigma_2 z^* - \lambda)/\sigma_1} (\mu + v\sigma_s)\phi(u)du\phi(v)dv
\]

\[
+ r \int_{-\mu/\sigma_s}^{\infty} \int_{(y_m + \mu + v\sigma_s - \sigma_2 z^* - \lambda)/\sigma_1}^{\infty} \int_{(y_m + \mu + v\sigma_s - \sigma_1 u - \lambda)/\sigma_2}^{\infty} (\lambda + u\sigma_1 + z\sigma_2 - y_m - \mu - v\sigma_s)\phi(z)dz\phi(u)du\phi(v)dv
\]

(iv) For \( \mu + v\sigma_s < 0 \). That is, \( v < -\mu/\sigma_s \).

\[
v(y_m) = w_m y_m + r \int_{-\infty}^{\mu/\sigma_s} \int_{-\infty}^{\infty} \int_{(y_m - \mu - \lambda)/\sigma_2}^{\infty} (\mu + v\sigma_s)\phi(u)du\phi(v)dv
\]

\[
+ \int_{-\mu/\sigma_s}^{\infty} \int_{(y_m - \sigma_2 z^* - \lambda)/\sigma_1}^{\infty} (\lambda + u\sigma_1 + z\sigma_2 - y_m)\phi(u)du\phi(v)dv
\]

Then, combining the statements for \( v(y_m) \), which covers four parameter
regimes, and collecting similar cost terms together we can write (A3) as

\[
v(y_m) = w_m y_m + w_t \int_{-\mu/\sigma_s}^{\infty} \int_{(y_m + \mu + v\sigma_s - \sigma_2 z^* - \lambda)/\sigma_1} \frac{(\mu + v\sigma_s)\phi(u)}{\sigma_1} du\phi(v)dv
\]

\[
+ r \int_{-\mu/\sigma_s}^{\infty} \int_{(y_m - \sigma_2 z^* - \lambda)/\sigma_1}^{\infty} \int_{(y_m - \mu - \lambda)/\sigma_2}^{\infty} (\lambda + u\sigma_1 + z\sigma_2 - y_m - \mu - v\sigma_s)\phi(z)dz\phi(u)du\phi(v)dv
\]

Taking the derivative of this with respect to \( y_m \) and after several tedious but
straightforward steps, which are omitted for brevity, we arrive at the following

\[
\frac{dv(y_m)}{dy_m} = w_m - w_t \int_{-\mu/\sigma_s}^{\infty} \int_{(y_m + \mu + v\sigma_s - \sigma_2 z^* - \lambda)/\sigma_1} \phi(u)du\phi(v)dv
\]

\[
- r \int_{-\mu/\sigma_s}^{\infty} \int_{-\infty}^{(y_m - \sigma_2 z^* - \lambda)/\sigma_1} \left[ 1 - \Phi \left( \frac{y_m - \lambda - u\sigma_1}{\sigma_2} \right) \right] \phi(u)du\phi(v)dv
\]
is straightforward to show that

\[ -r \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[ 1 - \Phi \left( \frac{y_m + \mu + v \sigma_s - \lambda - u \sigma_1}{\sigma_2} \right) \right] \phi(u) du \phi(v) dv. \]

This expression is equivalent to the following:

\[
\frac{dv(y_m)}{dy_m} = (w_m - r) + (r - w_l) \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[ 1 - \Phi \left( \frac{y_m - \lambda - u \sigma_1}{\sigma_2} \right) \right] \phi(u) du \phi(v) dv
\]

Using the derivative of \((A6)\) with respect to \(y_m\), using the fact that \(\Phi(z^*) = (r - w_l)/r\) and deleting the terms that cancel each other out, we arrive at the following:

\[
\frac{\partial^2 v(y_m)}{\partial y_m^2} = \frac{r}{\sigma_2} \left\{ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \phi \left( \frac{y_m - \lambda - u \sigma_1}{\sigma_2} \right) \phi(u) du \phi(v) dv
\]

In this statement, all terms are positive. Thus, \(\partial^2 v(y_m)/\partial y_m^2 > 0\) and \(v(y_m)\) is convex.

**Auxiliary Derivations Used in Proofs of Propositions 5 and 6**

Again, for generality, we consider the scenario in which ordering costs from local farms and mainstream farms are different, denoted, respectively, by \(w_l\) and \(w_m\). Define \(z^* = \Phi^{-1}(\frac{r - w_l}{r})\). Then from Proposition 1, the optimal order quantity is \(y^*_l = (\lambda + \epsilon_1 + \sigma_2 z^* - y_m)^+\).

Assume that (i) \(\lambda + \epsilon_1 + \sigma_2 z^* - y_m \geq 0\) almost surely and (ii) \(\mu + \epsilon_s \geq 0\) almost surely. Then the amount received from the local farm can be written as \(\min(\lambda + \epsilon_1 + \sigma_2 z^* - y_m, \mu + \epsilon_s)\). The objective function in (1) is given by

\[ L(z) = \sigma_2[w_l z + r I(z)], \]

where \(z = \min(z^*, (y_m - \lambda + \mu + \epsilon_s - \epsilon_1)/\sigma_2)\) and \(I(z) = \phi(z) - z(1 - \Phi(z))\). It is straightforward to show that \(I(\cdot)\) is convex decreasing.

Then the objective function in (2) can be written as

\[ v(y_m) = (w_m - w_l)y_m + E_{\epsilon_1, \epsilon_s}[L(\min(z^*, (y_m - \lambda + \mu + \epsilon_s - \epsilon_1)/\sigma_2))]. \]
Define another random variable $X = \epsilon_s - \epsilon_1$ which is a mean-zero normally distributed random variable with variance $\sigma_x^2 = \sigma_1^2 + \sigma_2^2$. Then, defining $Z = X/\sigma_x$ as a standard normal variable (A9) becomes
\[
v(y_m) = (w_m - w_l)y_m + \mathbb{E}_Z \left[ L \left( \min \left( z^* , \frac{y_m - \lambda + \mu + Z\sigma_z}{\sigma_2} \right) \right) \right], \tag{A10}
\]
and the derivative of $v(y_m)$ with respect to $y_m$ is
\[
\frac{\partial v(y_m)}{\partial y_m} = (w_m - w_l) + \mathbb{E}_Z \left[ L' \left( \frac{y_m - \lambda + \mu + Z\sigma_z}{\sigma_2} \right) \frac{1}{\sigma_2} ; y_m - \lambda + \mu + Z\sigma_z \leq z^* \right],
\]
\[
= (w_m - w_l) + \int_{-\infty}^{(\lambda - y_m - \mu + z^*\sigma_z)/\sigma_z} L' \left( \frac{y_m - \lambda + \mu + z\sigma_z}{\sigma_2} \right) \frac{1}{\sigma_2} \phi(z)dz. \tag{A11}
\]
From (A8),
\[
L'(z) = \sigma_2[w_l + rI'(z)] = \sigma_2[w_l + r(-z\phi(z) - (1 - \Phi(z)) + z\phi(z)] = \sigma_2[w_l + r(-1 + \Phi(z))]. \tag{A12}
\]
From (A11) and (A12), the second derivative of $v(y_m)$ with respect to $y_m$ can be derived as follows:
\[
\frac{\partial^2 v(y_m)}{\partial y_m^2} = \frac{\partial}{\partial y_m} \int_{-\infty}^{(\lambda - y_m - \mu + z^*\sigma_z)/\sigma_z} \left[ w_l + r \left( -1 + \Phi \left( \frac{y_m - \lambda + \mu + z\sigma_z}{\sigma_2} \right) \right) \right] \phi(z)dz.
\]
Then, using Leibniz Rule gives
\[
\frac{\partial^2 v(y_m)}{\partial y_m^2} = -(w_l - r + r\Phi(z^*))\phi \left( \frac{\lambda - y_m - \mu + z^*\sigma_z}{\sigma_z} \right)
\]
\[
+ \int_{-\infty}^{(\lambda - y_m - \mu + z^*\sigma_z)/\sigma_z} \frac{r}{\sigma_2} \phi \left( \frac{y_m - \lambda + \mu + z\sigma_z}{\sigma_2} \right) \phi(z)dz.
\]
The first term is zero by the definition of $z^*$ and the second term is always positive. Hence,
\[
\frac{\partial^2 v(y_m)}{\partial y_m^2} > 0. \tag{A13}
\]

**APPENDIX B: PROOFS**

**Proof of Proposition 1:** The demand forecast at time 2, $\lambda + \tilde{\epsilon}_1 + \epsilon_2$, is a normal random variable with mean $\lambda + \tilde{\epsilon}_1$ and standard deviation $\sigma_2$. Then the unconstrained problem in Equation (1) is a straightforward application of the newsvendor problem with optimal solution at $\tilde{y} = \tilde{\epsilon}_1 + \lambda + \sigma_2^{-1}(\frac{r - w_l}{r})$, where $(r - w_l)/r$ is the critical fractile of the newsvendor model and $\Phi(\cdot)$ denotes the cumulative distribution function of the standard normal distribution.

Amount ordered from the local farm is simply the difference between the optimal inventory level $\tilde{y}$ and the optimal amount already ordered from the main-
stream farm. If the amount already ordered exceeds the optimal inventory level, then the retailer does not order from the local farm.

**Proof of Proposition 2:** Denoting the objective function of the retailer’s problem at time 1 by \( v(y_m) \) and optimal order quantity from the mainstream farm by \( y_m^* \)

\[
\frac{dv(y_m)}{dy_m} \bigg|_{y_m^*} = 0
\]  

(B1)
yields first-order condition (FOC). In Appendix A, we derive \( dv(y_m)/dy_m \) from \( v(y_m) \) given by Equation (2). Substituting (A6) in (B1) and dividing both sides of the equation by \( r \) and reorganizing yields Equation (3).

**Proof of Lemma 1:** Consider the formulation (7), and let \( 0 < q_1 < q_2 \). Also let \( y_i = y(q_i) \) for \( i = 1, 2 \). By the optimality of \( y_1 \) for \( q_1 \) (and the feasibility of \( y_2 \)) we write\(^v\)

\[
C(y_1) - q_1S(y_1) < C(y_2) - q_1S(y_2).
\]  

(B2)

Similarly, by the optimality of \( y_2 \) for \( q_2 \) (and the feasibility of \( y_1 \)), we write \( C(y_1) - q_2S(y_1) > C(y_2) - q_2S(y_2) \), which is equivalent to

\[
q_2S(y_1) - C(y_1) < q_2S(y_2) - C(y_2).
\]  

(B3)

Adding (B2) and (B3) gives \( S(y_1) < S(y_2) \).

**Proof of Proposition 3:** Note that \( S(y(q(\rho))) = \rho \). Therefore, it suffices to show that \( C(y(q(\rho))) \leq C(y) \) for all \( y \) with \( S(y) \geq \rho \). Since \( y(q(\rho)) \) is optimal for the formulation (7) with penalty \( q(\rho) \) we conclude that \( C(y(q(\rho))) - q(\rho)S(y(q(\rho))) \leq C(y) - q(\rho)S(y) \) for all \( y \). Then by definition of \( q(\rho) \), we write \( C(y(q(\rho))) - q(\rho)\rho \leq C(y) - q(\rho)S(y) \), which implies \( C(y(q(\rho))) \leq C(y) - q(\rho)(S(y) - \rho) \).

Note that \( S(y) - \rho \geq 0 \) for all \( y \) with \( S(y) \geq \rho \) (feasible \( y \) for (6)). Therefore, we conclude that for all \( y \) with \( S(y) \geq \rho \), \( C(y(q(\rho))) \leq C(y) \). Thus, the order policy \( y(q(\rho)) \) is optimal for the retailer’s problem (6).

**Proof of Proposition 4:** The objective function in (11) can be written equivalently as follows:

\[
w_l \int_{-\infty}^{y_m+y_l-\hat{\epsilon}_1} (y_m + y_l - \lambda - \hat{\epsilon}_1 - \epsilon_2)f(\epsilon_2)d\epsilon_2
\]

\[+(r - w_l) \int_{y_m+y_l-\hat{\epsilon}_1}^{\infty} (\lambda + \hat{\epsilon}_1 + \epsilon_2 - y_m - y_l)f(\epsilon_2)d\epsilon_2
\]

\[-q \Phi \left( \frac{y_l + y_m - \lambda - \hat{\epsilon}_1}{\sigma_2} \right),
\]

where \( f \) is the probability density function of \( \epsilon_2 \). The FOC gives the following:

\[
w_l - r \left[ 1 - \Phi \left( \frac{y_l + y_m - \lambda - \hat{\epsilon}_1}{\sigma_2} \right) \right] - \frac{q}{\sigma_2} \Phi \left( \frac{y_l + y_m - \lambda - \hat{\epsilon}_1}{\sigma_2} \right) = 0.
\]

\(^v\)The strict inequality follows from strict convexity and the uniqueness of the optimal solution.
Rearranging terms give
\[ r - w_l = \Phi \left( \frac{y_l + y_m - \lambda - \tilde{\epsilon}_1}{\sigma_2} \right) - \frac{q}{\sigma_2 r} \phi \left( \frac{y_l + y_m - \lambda - \tilde{\epsilon}_1}{\sigma_2} \right). \]

Note that the right-hand side is strictly increasing in \( y_l \), from which the result follows after truncating \( y_l \) to ensure \( 0 \leq y_l \leq \mu + \tilde{\epsilon}_s \).

**Proof of Proposition 5:**

**Part 1. As \( k \) increases, average amount ordered from the local supply increases.** It suffices to show that optimal order quantity from the main-stream farm \( y_m^* \) decreases as \( k \) increases, since average amount ordered from the local supply increases as \( y_m^* \) decreases.

We want to show that \( dy_m^*/dk < 0 \). Using the implicit function theorem, we can write
\[
\frac{\partial y_m^*}{\partial k} = -\frac{\partial^2 v(y_m)}{\partial y_m \partial \mu} \frac{1}{\partial^2 v(y_m)}
\]
where \( v(y_m) \) is the objective function of the retailer’s problem at time 1 given by Equation (2). From (A7), we know that \( \partial^2 v(y_m)/\partial y_m^2 > 0 \). It suffices to show that \( \partial^2 v(y_m)/\partial y_m^2 k > 0 \).

The statement for \( \partial v(y_m)/\partial y_m \) is given by equation (A6). In this setting, \( \mu = (n + k)\mu, \) and \( \sigma_s = \sqrt{n + k\sigma_1}. \) Thus, \( \partial \mu/\partial k = \mu, \) and \( \partial \sigma_s/\partial k = \frac{1}{\sqrt{n+k}} \sigma_1. \)

Taking the derivative of \( \partial v(y_m)/\partial y_m \) in (A6) with respect to \( k \) yields
\[
\frac{\partial^2 v(y_m)}{\partial y_m \partial k} = \frac{(r - w_l)}{\sigma_1} \left( \mu + v \sigma_1 \right) \int_{-\infty}^\infty \phi \left( \frac{y_m + \mu + v z^* - \sigma_2 z^* - \lambda}{\sigma_1} \right) \phi(u)du
\]
\[
+ r \frac{\mu_1}{\sqrt{n+k} \sigma_1} \phi \left( \frac{-\mu}{\sigma_1} \right) \left( \int_{-\infty}^\infty \Phi \left( \frac{y_m + \lambda - u \sigma_1}{\sigma_2} \right) \phi(u)du \right)
\]
\[
+ r \frac{\mu_1}{\sigma_2} \left( \mu + v \sigma_1 \right) \int_{-\infty}^\infty \int_{y_m + v \sigma_1 - \sigma_2 z^* - \lambda/\sigma_1}^\infty \phi \left( \frac{y_m + \mu + v \sigma_1 - \lambda}{\sigma_2} \right) \phi(u)dudv
\]
\[
- \frac{r}{\sigma_1} \Phi(z^*) \left( \mu + v \sigma_1 \right) \int_{-\infty}^\infty \phi \left( \frac{y_m + \mu + v \sigma_1 - \sigma_2 z^* - \lambda}{\sigma_1} \right) \phi(u)du
\]
\[
+ r \frac{\mu_1}{\sqrt{n+k} \sigma_1} \phi \left( \frac{-\mu}{\sigma_1} \right) \left( \int_{-\infty}^\infty \Phi \left( \frac{y_m + \lambda - u \sigma_1}{\sigma_2} \right) \phi(u)du \right)
\]
\[
- \frac{r}{\sqrt{n+k} \sigma_1} \phi \left( \frac{-\mu}{\sigma_1} \right) \int_{-\infty}^\infty \Phi \left( \frac{y_m + \lambda - u \sigma_1}{\sigma_2} \right) \phi(u)du.
\]

The first and fourth terms in (B4) cancel each other and sum of second, fifth, and sixth terms are zero. Since the only remaining term (third term) is always positive, \( \partial^2 v(y_m)/\partial y_m^2 k > 0 \), which completes the proof of part (i).

**Part 2.** Average amount supplied by the local supply, call \( S \), is the minimum of the retailer’s order \( y_l^* \) and the available supply. That is,
$S = \min(y_i^*, ((n + k)\mu_i + \nu \sqrt{n + k}\sigma_i)^+)$. Clearly, $S$ increases in $k$ since both terms in the minimum operator increases in $k$. The fact that $y_i^*$ increases in $k$ is shown in part (i) of this proposition.

**Part 3.** Increasing the local supply, while keeping mainstream orders at $y_m^*$, can reduce the retailer’s cost as this is a relaxation on local supply constraint. At the minimum, the retailer can preserve her original optimal ordering policy, hence realizing the same expected one period cost as before. □

**Proof of Proposition 6:**

**Part 1.** Clearly, as $b$ decreases the order-up-to-level $\tilde{y} = \lambda + \tilde{e}_1 + \sigma_2 \Phi^{-1}(\frac{b}{r})$ increases. Also, as will be shown in part 2, the optimal order quantity from the mainstream farm $y_m$ decreases as $b$ decreases. Hence, the optimal order quantity from the local farm increases as $b$ decreases.

**Part 2.** It suffices to show that $\partial y_m / \partial b > 0$. Using the implicit function theorem, we can write

$$\frac{\partial y_m}{\partial b} = -\frac{\frac{\partial v(y_m)}{\partial y_m}}{\frac{\partial^2 v(y_m)}{\partial y_m^2}}.$$  

We showed in (A13) that $\frac{\partial^2 v(y_m)}{\partial y_m^2}$ is positive. In the remainder of this proof we will show that $\frac{\partial v(y_m)}{\partial y_m}$ is negative. Setting $w_i = b$ in the objective function as stated in (A10) yields

$$v(y_m) = (w_m - b)y_m + \mathbb{E}_\mathcal{Z}\left[L\left(\min\left(y_m - \frac{\lambda - \mu + Z\sigma_X}{\sigma_2}\right)\right)\right],$$

and the derivative of $v(y_m)$ with respect to $y_m$ is

$$\frac{\partial v(y_m)}{\partial y_m} = w_m - b + \mathbb{E}_\mathcal{Z}\left[L'\left(\frac{y_m - \lambda + \mu + Z\sigma_X}{\sigma_2}\right)\frac{1}{\sigma_2} y_m - \frac{\lambda - \mu + Z\sigma_X}{\sigma_2} \leq z^*\right],$$

$$= w_m - b + \mathbb{E}_\mathcal{Z}\left[L'\left(\frac{y_m - \lambda + \mu + Z\sigma_X}{\sigma_2}\right)\frac{1}{\sigma_2} Z \leq \frac{\lambda - y_m - \mu + z^*\sigma_2}{\sigma_2}\right]$$

$$= w_m - b + \frac{1}{\sigma_2} \int_{-\infty}^{z^*} L'\left(\frac{y_m - \lambda + \mu + Z\sigma_X}{\sigma_2}\right) \phi(z)dz.$$

(B5)

Consider the following change of variable $\psi = \frac{y_m - \lambda + \mu + Z\sigma_X}{\sigma_2}$. Then rewrite (B5) as

$$\frac{\partial v(y_m)}{\partial y_m} = w_m - b + \frac{1}{\sigma_2} \int_{-\infty}^{z^*} L'(\psi) f_\psi(\psi) d\psi.$$

Then

$$\frac{\partial^2 v(y_m)}{\partial y_m \partial b} = -1 + \frac{1}{\sigma_2} \int_{-\infty}^{z^*} \frac{\partial}{\partial b} L'(\psi) f_\psi(\psi) d\psi.$$  

(B6)

From (A12), $L'(\psi) = \sigma_2 [b + r(-1 + \Phi(\psi))]$ and $\frac{\partial}{\partial b} L'(\psi) = \sigma_2$. Then, Equation (B6) simplifies to

$$\frac{\partial^2 v(y_m)}{\partial y_m \partial b} = -1 + \int_{-\infty}^{z^*} f_\psi(\psi) d\psi.$$
which is negative since the second term is a cumulative distribution function and is always less than 1.

**Part 3.** This result is implied by part 1 since there is no change in the local farm’s ability to supply the retailer as $b$ changes.

**Part 4.** Clearly, when the ordering cost from the local farm $w_l$ dropped to $b < w_l$, the retailer achieves a lower cost, using the policy that is optimal for when the ordering cost from the local farm is $w_l$. Using the optimal policy with backhauling would further reduce the expected one period cost.

**Proof of Proposition 7:** Define $v(y_m)$ as the objective of the retailer’s problem at time $t - 1$ given by Equation (A2). Through the change of variables $\epsilon_1 = U\sigma_1$, $\epsilon_s = V\sigma_s$ and $\epsilon_2 = Z\sigma_2$, $v(y_m)$ can be written in this setting as

$$v(y_m) = (w_m - w_l)y_m + \mathbb{E}_U, V \min_{y_m + \mu + V\sigma_s \geq y \geq y_m + \min(Q, \mu + V\sigma_s)} w_l y$$

$$+ r\mathbb{E}_Z [(\lambda + U\sigma_1 + Z\sigma_2 - y)^+] \tag{B7}$$

Optimal $y$ of the inner optimization problem, $\tilde{y}^*$, is $\max[y_m + \min(Q, \mu + V\sigma_s), \min(y_m + \mu + V\sigma_s, \tilde{y})]$ where $\tilde{y}$ is the optimal solution to the unconstrained problem and can be written in the new notation as $\tilde{y} = \lambda + u\sigma_1 + \sigma_2\Phi^{-1}(\frac{\lambda - u\sigma_1}{\sigma_2})$.

Define $z^* = \Phi^{-1}(\frac{\lambda - u\sigma_1}{\sigma_2})$ and write $v(y_m)$ under the following five parameter regimes:

**(i)** For $Q < \mu + v\sigma_s$ and $\tilde{y} < y_m + Q$, $\tilde{y}^* = y_m + Q$.

$$v(y_m) = (w_m - w_l)y_m + w_l(Q + y_m) \int_{(Q - \mu)/\sigma_1}^{\infty} \int_{(Q - \mu)/\sigma_1}^{(y_m + Q - z\sigma_2 - \lambda)/\sigma_1} \phi(u) du \phi(v) dv + r \int_{(Q - \mu)/\sigma_1}^{\infty} \int_{(Q - \mu)/\sigma_1}^{(y_m + Q - z\sigma_2 - \lambda)/\sigma_1} (\lambda - y_m - Q + u\sigma_1 + z\sigma_2) \phi(z) dz \phi(u) du \phi(v) dv$$

**(ii)** For $Q < \mu + v\sigma_s$ and $\tilde{y} \in [y_m + Q, y_m + \mu + v\sigma_s]$, $\tilde{y}^* = \tilde{y}$.

$$v(y_m) = (w_m - w_l)y_m + w_l \int_{(Q - \mu)/\sigma_1}^{\infty} \int_{(y_m + \mu + v\sigma_s - z\sigma_2 - \lambda)/\sigma_1}^{(y_m + \mu + v\sigma_s - z\sigma_2 - \lambda)/\sigma_1} (\lambda + z\sigma_2 + u\sigma_1) \phi(u) du \phi(v) dv + r \int_{(Q - \mu)/\sigma_1}^{\infty} \int_{(y_m + \mu + v\sigma_s - z\sigma_2 - \lambda)/\sigma_1}^{(y_m + \mu + v\sigma_s - z\sigma_2 - \lambda)/\sigma_1} (\lambda + z\sigma_2 + u\sigma_1) \phi(u) du \phi(v) dv$$

$$+ \int_{z^*}^{\infty} (z - z^*) \sigma_2 \phi(z) dz \phi(u) du \phi(v) dv$$
(iii) For $Q < \mu + v\sigma_s$ and $\tilde{y} > y_m + \mu + v\sigma_s$, $\tilde{y}^* = y_m + \mu + v\sigma_s$.

$$v(y_m) = (w_m - w_l)y_m + \int_{(Q-\mu)/\sigma_s}^{\infty} (y_m + \mu + v\sigma_s)\phi(u)d\nu(u)d\phi(v)dv$$

$$+ r\int_{(Q-\mu)/\sigma_s}^{\infty} \int_{(y_m + \mu + v\sigma_s - 2\sigma^* - \lambda)/\sigma_1}^{\infty} \int_{(y_m + \mu + v\sigma_s - 1\mu - \lambda)/\sigma_2}^{\infty} (\lambda - y_m - u\sigma_1 + z\sigma_2 - v\sigma_s)\phi(z)d\nu(z)d\phi(u)d\phi(v)dv$$

(iv) For $0 < \mu + v\sigma_s < Q$, $\tilde{y}^* = y_m + \mu + v\sigma_s$.

$$v(y_m) = (w_m - w_l)y_m + \int_{-\mu/\sigma_s}^{(Q-\mu)/\sigma_s} (y_m + \mu + v\sigma_s)\phi(v)dv$$

$$+ r\int_{-\mu/\sigma_s}^{(Q-\mu)/\sigma_s} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{(y_m - u\sigma_1 - \lambda)/\sigma_2}^{\infty} (\lambda - y_m - u\sigma_1 + z\sigma_2 - v\sigma_s)\phi(z)d\nu(z)d\phi(u)d\phi(v)dv$$

(v) For $\mu + v\sigma_s < 0$, $\tilde{y}^* = y_m$.

$$v(y_m) = (w_m - w_l)y_m + \int_{-\mu/\sigma_s}^{\infty} \phi(v)dv + r\int_{-\mu/\sigma_s}^{\infty} \int_{-\infty}^{\infty} \int_{(y_m - u\sigma_1 - \lambda)/\sigma_2}^{\infty} (\lambda - y_m - u\sigma_1 + z\sigma_2 - v\sigma_s)\phi(z)d\nu(z)d\phi(u)d\phi(v)dv$$

Then, combining the statements for $v(y_m)$, which covers five parameter regimes, and collecting similar cost terms together we can write (A3) as

$$v(y_m) = w_my_m + w_l\left\{ \int_{(Q-\mu)/\sigma_s}^{\infty} \int_{(y_m + Q - \sigma^*_z - \lambda)/\sigma_1}^{\infty} Q\phi(u)d\nu(u)d\phi(v)dv \right. $$

$$ + \int_{(Q-\mu)/\sigma_s}^{\infty} \int_{(y_m + Q - \sigma^*_z - \lambda)/\sigma_1}^{\infty} (\lambda + u\sigma_1 + z\sigma_2 - y_m) \phi(u)d\nu(u)d\phi(v)dv $$

$$ + \int_{(Q-\mu)/\sigma_s}^{\infty} \int_{(y_m + Q - \sigma^*_z - \lambda)/\sigma_1}^{\infty} (\mu + v\sigma_s)\phi(u)d\nu(u)d\phi(v)dv $$

$$ + \int_{(Q-\mu)/\sigma_s}^{\infty} \int_{(y_m + Q - \sigma^*_z - \lambda)/\sigma_1}^{\infty} (\lambda - y_m - Q + u\sigma_1 + z\sigma_2)\phi(z)d\nu(z)d\phi(u)d\phi(v)dv $$

$$ + \int_{(Q-\mu)/\sigma_s}^{\infty} \int_{(y_m + Q - \sigma^*_z - \lambda)/\sigma_1}^{\infty} (z - z^*)\sigma_2\phi(z)d\nu(z)d\phi(u)d\phi(v)dv $$

$$ + \int_{(y_m + Q - \sigma^*_z - \lambda)/\sigma_1}^{\infty} \int_{(y_m + Q - \sigma^*_z - \lambda)/\sigma_1}^{\infty} (\lambda - y_m - Q + u\sigma_1 + z\sigma_2)\phi(z)d\nu(z)d\phi(u)d\phi(v)dv $$

$$ + \int_{(y_m + Q - \sigma^*_z - \lambda)/\sigma_1}^{\infty} (z - z^*)\sigma_2\phi(z)d\nu(z)d\phi(u)d\phi(v)dv $$
\[
+ \int_{(Q-\mu)/\sigma_1}^{\infty} \int_{(y_m+\mu+\sigma_1, -\sigma_2 z^* - \lambda)/\sigma_1}^{\infty} \Phi \left( \frac{y_m + Q - \lambda - u \sigma_1}{\sigma_2} \right) \phi(z) dz \phi(u) du dv \\
+ \int_{-\mu/\sigma_1}^{\infty} \int_{-\infty}^{\infty} \Phi \left( \frac{y_m + \mu + \sigma_1, -\sigma_2 z^* - \lambda - \lambda - \mu}{\sigma_1} \right) \phi(z) dz \phi(u) du dv
\]

Taking the derivative of this with respect to \( y_m \) and after several tedious but straightforward steps, which are omitted for brevity, we arrive at the following:

\[
\frac{dv(y_m)}{dy_m} = (w_m - r) + (r - w_1) \int_{(Q-\mu)/\sigma_1}^{\infty} \int_{(y_m+\mu+\sigma_1, -\sigma_2 z^* - \lambda)/\sigma_1}^{\infty} \phi(z) dz \phi(u) du dv \\
+ r \int_{(Q-\mu)/\sigma_1}^{\infty} \int_{-\infty}^{\infty} \Phi \left( \frac{y_m + Q - \lambda - \mu}{\sigma_2} \right) \phi(u) du dv \\
+ r \int_{(Q-\mu)/\sigma_1}^{\infty} \int_{(y_m+\mu+\sigma_1, -\sigma_2 z^* - \lambda)/\sigma_1}^{\infty} \phi(u) du dv + r \int_{-\mu/\sigma_1}^{\infty} \Phi \left( \frac{y_m - \lambda - u \sigma_1}{\sigma_2} \right) \phi(u) du dv.
\]

Taking the derivative of (B9) with respect to \( y_m \), using the fact that \( \Phi(z^*) = (r - w_1)/r \) and deleting the terms that cancel each other out, we arrive at the following:

\[
\frac{\partial^2 v(y_m)}{\partial y_m^2} = \frac{r}{\sigma_2} \left\{ \int_{(Q-\mu)/\sigma_1}^{\infty} \int_{-\infty}^{\infty} \Phi \left( \frac{y_m + Q - \lambda - u \sigma_1}{\sigma_2} \right) \phi(u) du dv \\
+ \int_{(Q-\mu)/\sigma_1}^{\infty} \int_{(y_m+\mu+\sigma_1, -\sigma_2 z^* - \lambda)/\sigma_1}^{\infty} \phi(u) du dv + \int_{-\mu/\sigma_1}^{\infty} \Phi \left( \frac{y_m - \lambda - u \sigma_1}{\sigma_2} \right) \phi(u) du dv \right\}.
\]

In this statement, all terms are positive. Thus, \( \frac{\partial^2 v(y_m)}{\partial y_m^2} > 0 \) and \( v(y_m) \) is convex.
FOC is given by
\[
\frac{dv}{(y_m)} \bigg|_{y_m^*} \frac{dy_m}{y_m} = 0. \tag{B11}
\]

Substituting (B9) in (B11), dividing both sides of the equation by \(r\) and reorganizing yields Equation (15).

**Proof of Corollary 1:** Assume that \(\mu + \bar{\varepsilon}_s \geq 0\) almost surely. Optimal \(y\) of the inner optimization problem in Equation (B7), \(\bar{y}^*\) is \(y_m + \mu + v\sigma_s\). Then
\[
v(y_m) = (w_m - w_l) y_m + w_l(y_m + \mu) + r \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (\lambda - y_m - \mu + u \sigma_1 + z \sigma_2 - v\sigma_3) \phi(z) dz \phi(u) du \phi(v) dv.
\]

Define \(X\) as standard normal random variable such that \(X = (U\sigma_1 + Z\sigma_2 - V\sigma_3)/\sigma_X\) where \(\sigma_X = \sqrt{\sigma_1^2 + \sigma_2^2 + \sigma_3^2}\). Then, through the change of variables the above statement can be written as
\[
v(y_m) = (w_m - w_l) y_m + w_l(y_m + \mu) + r \int_{(y_m + \mu - \lambda)/\sigma_X}^{\infty} (\lambda - y_m - \mu + x\sigma_X) \phi(x) dx.
\]

Taking the derivative of this with respect to \(y_m\) and setting this equal to 0, we arrive at the following:
\[
\frac{dv(y_m)}{dy_m} = w_m - r \int_{(y_m + \mu - \lambda)/\sigma_X}^{\infty} \phi(x) dx = 0. \tag{B12}
\]
Rearranging terms yields the result in Equation (16).

**Proof of Proposition 8:** Given the order quantity from the mainstream farm \(y_m\), the retailer’s profit under manager’s discretion (\(y^*_m = \mu + \epsilon_s\)) with backhauling is given by
\[
\Pi_{PGB}(y_m, b) = (r - b) \lambda - (w_m - b) y_m - b \mathbb{E}\left[ (y_m + \mu - \lambda + \epsilon)^+ \right] - (r - b) \mathbb{E}\left[ (\lambda - \mu - y_m - \epsilon)^+ \right], \tag{B13}
\]

where \(\epsilon = \epsilon_1 + \epsilon_2 - \epsilon_s\).

It is straightforward to see that \(\Pi_{PGB}(\cdot)\) is strictly decreasing and continuous in \(b\). Note that optimal \(y_m\) is given by (16) and does not depend on \(b\).

Let \(\Pi_{PGB}(b)\) denote the retailer’s optimal profit under discretion with backhauling. Similarly, let \(\Pi_H\) and \(\Pi_{HB}(b)\) denote the retailer’s optimal profit under hybrid sourcing and hybrid sourcing with backhauling policies, respectively.

First, note that
\[
\Pi_{HB}(b) > \Pi_H \text{ for all } b \in (0, w_m). \tag{B14}
\]
This follows because backhauling lowers the order cost from the local farm and helps the retailer. Next, we argue that
\[
\Pi_{PGB}(0) \geq \Pi_{HB}(0) > \Pi_{HB}(b) \text{ for all } b \in (0, w_m). \tag{B15}
\]

The second inequality follows because lowering the unit ordering cost \(b\) from the local farmer increases the retailer’s profit. To see why the first inequality follows,
let \( y^*_m, y^*_l(\epsilon_1, \epsilon_2) \) denote the optimal policy achieving \( \Pi_{HB}(0) \). Then consider the purchase guarantee policy with the same \( y_m \), which orders \( \mu + \epsilon_2 - y_l(\epsilon_1, \epsilon_2) \) more from the local farmer but incurs no additional costs since \( b = 0 \). Since the optimal purchase guarantee policy corresponding to \( \Pi_{PGB}(0) \) does at least as well as any feasible policy we conclude that \( \Pi_{PGB}(0) \geq \Pi_{HB}(0) \).

Combining (B14) and (B15) gives \( \Pi_{PGB}(0) > \Pi_H \). Since \( \Pi_{PGB}(\cdot) \) is continuous, there exists \( \hat{b} > 0 \) such that \( \Pi_{PGB}(b) > \Pi_H \) for all \( b \in (0, \hat{b}) \). This proves that for sufficiently low \( b \), the retailer’s profit is higher than her profit under hybrid sourcing, and hence also than that under mainstream only ordering policy.

Then the retailer’s optimal profit under purchase guarantee with backhauling subject to the service level, denoted by \( \Pi_{SPGB}(b) \), can be derived from (5) and (B13) and same arguments can be used to complete the proof.

**APPENDIX C: SENSITIVITY ANALYSIS**

Table C1 shows the effect of varying \( \sigma_1, \sigma_2, \) and \( \sigma_s \) on the retailer’s order policy under profit maximization. The analysis indicates that as \( \sigma_1 \) increases, the average local order increases. Since \( \sigma_1 \) is resolved by the time the local order is placed, the retailer benefits by delaying more of her order. In contrast, increasing \( \sigma_2 \) or \( \sigma_s \) decreases the average local order because the local order’s uncertainty increases. However, as any type of uncertainty increases (i.e., \( \sigma_1, \sigma_2, \) or \( \sigma_s \)), retail profit decreases. We see the same general effects in Table C2 when the retailer’s objective is to achieve target service level 0.99.

**Table C1:** The effect of varying \( \sigma_1, \sigma_2, \) and \( \sigma_s \) on the retailer’s order policy under profit maximization.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>( \sigma_1 )</th>
<th>( \sigma_2 )</th>
<th>( \sigma_s )</th>
<th>Mainstream Order</th>
<th>Avg. Local Order</th>
<th>Avg. Retail Profit ($)</th>
<th>Avg. Retail Mismatch Cost ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base Case</td>
<td>160</td>
<td>120</td>
<td>100</td>
<td>1,898</td>
<td>120</td>
<td>1,308</td>
<td>92</td>
</tr>
<tr>
<td>( \sigma_1 ) Low</td>
<td>80</td>
<td>120</td>
<td>100</td>
<td>1,920</td>
<td>78</td>
<td>1,325</td>
<td>75</td>
</tr>
<tr>
<td>( \sigma_1 ) High</td>
<td>240</td>
<td>120</td>
<td>100</td>
<td>1,887</td>
<td>156</td>
<td>1,279</td>
<td>121</td>
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<tr>
<td>( \sigma_2 ) Low</td>
<td>160</td>
<td>60</td>
<td>100</td>
<td>1,899</td>
<td>123</td>
<td>1,335</td>
<td>65</td>
</tr>
<tr>
<td>( \sigma_2 ) High</td>
<td>160</td>
<td>180</td>
<td>100</td>
<td>1,895</td>
<td>118</td>
<td>1,277</td>
<td>123</td>
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<tr>
<td>( \sigma_s ) Low</td>
<td>160</td>
<td>120</td>
<td>50</td>
<td>1,889</td>
<td>126</td>
<td>1,311</td>
<td>89</td>
</tr>
<tr>
<td>( \sigma_s ) High</td>
<td>160</td>
<td>120</td>
<td>150</td>
<td>1,906</td>
<td>114</td>
<td>1,305</td>
<td>95</td>
</tr>
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</table>
Table C2: The effect of varying $\sigma_1$, $\sigma_2$, and $\sigma_s$ on the retailer’s order policy under target service level 0.99.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>$\sigma_1$</th>
<th>$\sigma_2$</th>
<th>$\sigma_s$</th>
<th>Mainstream Order</th>
<th>Avg. Local Order</th>
<th>Avg. Retail Profit ($)</th>
<th>Avg. Retail Mismatch Cost ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base case</td>
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<td>120</td>
<td>100</td>
<td>2,336</td>
<td>47</td>
<td>1,100</td>
<td>300</td>
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<td>80</td>
<td>120</td>
<td>100</td>
<td>2,251</td>
<td>51</td>
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<tr>
<td>$\sigma_1$ High</td>
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<td>120</td>
<td>100</td>
<td>2,472</td>
<td>37</td>
<td>999</td>
<td>401</td>
</tr>
<tr>
<td>$\sigma_2$ Low</td>
<td>160</td>
<td>60</td>
<td>100</td>
<td>2,261</td>
<td>26</td>
<td>1,173</td>
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<td>160</td>
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<td>100</td>
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<td>120</td>
<td>50</td>
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<td>1,114</td>
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<tr>
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<td>38</td>
<td>1,087</td>
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</tr>
</tbody>
</table>

APPENDIX D: NUMERICAL EXAMPLE: PROFIT MAXIMIZATION OBJECTIVE

Aggregation through an intermediary

Table D1 shows the effect of the intermediary under the profit maximization objective. Similar to the target service level objective, the local order quantity increases in the number of farms. However, the utilization decreases as the number of farms increases. This is because under profit maximization, the service level is lower than under target service level, and thus retail demand is lower. Whereas more supply (farms) is added, demand stays constant, therefore, even though the absolute total local quantity increases, local farm utilization decreases. However, local orders become less volatile and retail profit increases as the number of farms increases (similar to target service level). Thus, the local farms benefit from more stable orders (but not necessarily higher quantity orders), and the retailer increases profit.

Table D1: The impact of aggregating $n + k$ local farms on retail performance and local farm operating conditions when the objective is profit maximization, $n = 2$.

<table>
<thead>
<tr>
<th>Profit Maximization</th>
<th>Number of farms ($n + k$)</th>
<th>2 farms</th>
<th>4 farms</th>
<th>6 farms</th>
<th>8 farms</th>
<th>10 farms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Local supply capacity ($\mu, \sigma_s$)</td>
<td>(200,100)</td>
<td>(400,141)</td>
<td>(600,173)</td>
<td>(800,200)</td>
<td>(1,000,224)</td>
</tr>
<tr>
<td>Decision variables</td>
<td>Mainstream order, $y_m^*$</td>
<td>1,898</td>
<td>1,824</td>
<td>1,755</td>
<td>1,692</td>
<td>1,633</td>
</tr>
<tr>
<td></td>
<td>Avg. local order</td>
<td>121</td>
<td>179</td>
<td>240</td>
<td>300</td>
<td>358</td>
</tr>
<tr>
<td>Outcome variables</td>
<td>Avg. retail profit ($)</td>
<td>1,308.04</td>
<td>1,319.78</td>
<td>1,325.07</td>
<td>1,327.20</td>
<td>1,327.92</td>
</tr>
<tr>
<td></td>
<td>Avg. local farm utilization</td>
<td>0.49</td>
<td>0.45</td>
<td>0.42</td>
<td>0.40</td>
<td>0.38</td>
</tr>
<tr>
<td></td>
<td>Coeff. var. local farm util</td>
<td>0.85</td>
<td>0.76</td>
<td>0.67</td>
<td>0.58</td>
<td>0.51</td>
</tr>
</tbody>
</table>
Table D2: The impact of backhauling on retail performance and local farm operating conditions when the objective is profit maximization.

<table>
<thead>
<tr>
<th>Profit Maximization</th>
<th>Wholesale Cost with Backhauling</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decision variables</td>
<td></td>
</tr>
<tr>
<td>Mainstream order, $y_m^*$</td>
<td>1,898 1,875 1,832 1,802 1,785</td>
</tr>
<tr>
<td>Avg. local order</td>
<td>120 153 226 301 395</td>
</tr>
<tr>
<td>Outcome variables</td>
<td></td>
</tr>
<tr>
<td>Avg. retail profit</td>
<td>1,307.72 1,317.34 1,342.17 1,373.25 1,408.60</td>
</tr>
<tr>
<td>Avg. retail mismatch cost</td>
<td>92.28 93.52 100.85 111.08 122.20</td>
</tr>
<tr>
<td>Avg. local farm utilization</td>
<td>0.49 0.59 0.75 0.87 0.95</td>
</tr>
<tr>
<td>Coeff. var. local farm util</td>
<td>0.85 0.70 0.47 0.31 0.17</td>
</tr>
</tbody>
</table>

**Backhauling**

Table D2 shows the effect of backhauling under the profit maximization objective. The directional effect is qualitatively similar to the target service level objective (see Table 3), however, the mechanism is more effective. As wholesale cost with backhauling decreases, local farm utilization increases considerably (from 0.49 to 0.95, 94% increase compared to 88% increase under target service level) and the coefficient of variation decreases considerably (from 0.85 to 0.17, 80% decrease compared to 40% decrease under target service level). Retail profit also increases from $1,307.72 to $1,408.60 (7.7% increase compared to 3.4% increase for target service level).

**Purchase guarantee**

The effect of the purchase guarantee policy under profit maximization is illustrated in Figure D1 for $Q \in \{0, 100, 200, 300, \infty\}$. The curve $Q = 0$ represents the case with no purchase guarantee. The curve $Q = \infty$ represents the case where the retailer buys everything produced by the local supply. Similar to Figure 2(a), we see that in Figure D1(a), at the point where $w_l = w_m = $0.80, the purchase guarantee for each minimum quantity $Q > 0$ results in lower retail profit than $Q = 0$ (no purchase guarantee). Also, we see in Figure D1(b) that the mismatch cost increases as $Q$ increases.

**Combining purchase guarantee and backhauling**

Figure D1 qualitatively shows the same effect as Figure 2—that is, by combining purchase guarantee and backhauling, the retailer can potentially help the local farms while simultaneously increasing her own profit. For example, when $Q = 100$, if p decreases below $0.70, the retailer’s profit with purchase guarantee and backhauling results in higher profit than hybrid sourcing without purchase guarantee or backhauling ($1,307.60), even though the mismatch cost is higher (Figure D1 b). Moreover, we see in Figure D1(a) that purchase guarantee and
Figure D1: The impact of backhauling and purchase guarantee combination on retail performance with purchase guarantee minimum quantity $Q \in \{0, 100, 200, 300, \infty\}$ units when the objective is profit maximization.

Backhauling are complementary because the slope of profit increase is steeper for higher $Q$—the higher $Q$ is, the more benefit the retailer gains from backhauling.

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