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Farmers' markets or the supermarket? Channel selection in small farming businesses

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Abstract

Purpose – Despite the abundance of small-scale farms in the USA and their importance for both rural economic development and food availability, the extensive research on small business management and entrepreneurship has mostly neglected the agricultural context, leaving many of these farms' business challenges unexplored. The authors focus on informing a specific decision faced by small farm managers: selling directly to consumers (i.e. farmer's markets) versus selling through aggregators. By collecting historical data and a series of interviews with industry experts, the authors employ simulation methodology to offer a framework that advises how small-scale farmers can allocate their product across these two channels to increase revenue in a given season. The results, which are relevant for operations management, small business management and entrepreneurship literature, can help small-scale farmers improve their performance and compete against their larger counterparts.

Design/methodology/approach – The authors rely on historical and interview data from key industry players (an aggregator and a small farm manager) to design a simulation analysis that determines which factors influence season-long farm revenue performance under varying strategies of channel allocation and commodity production.

Findings – The model suggests that farm managers should plan to evenly split their production between the two distribution channels, but if an even split is not possible, they should plan to keep a larger percentage in the nonaggregator (farmers' market/direct) channel. Further, the authors find that farmers can benefit significantly from a strong aggregator channel customer base, which suggests that farmers should promote and advertise the aggregator channel even if they only use it for a limited amount of their product.

Originality/value – The authors integrate small business management and operations management literature to study a widely understudied context and present practical implications for the performance of small-scale farms.

Keywords Small business, SME, Agricultural entrepreneurship, Farming, Simulation

Paper type Research paper

1. Introduction

Our society heavily relies on small-scale farming businesses. In the USA alone, there are approximately 31 million entrepreneurs across all industries (Chmura, 2019). The agricultural sector, with its abundance of family and small-scale farms, accounts for a significant percentage of this number. More specifically, there are over two million farms in the USA, and 98% of them are family farms with 90% classified as small-scale farms (Whitt, 2021). Perhaps more importantly, these family farms account for 88% of all food production nationwide and have played an important role in the nation's trend toward consuming local food, commonly

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purchased at farmers' markets (Johnson, 2012; Whitt, 2021). In fact, in 2012, local food production in the USA equated to a $1.4bn industry –double the amount in 1992 (US Department of Agriculture (USDA) Marketing Services, 2016). An explosive growth in the distribution channels available to farmers has contributed to this increase in local food consumption. In 2016, there were 8,675 farmers' markets, 733 community service agriculture programs, 1,393 on-farm markets, and 170 food hubs voluntarily listed in the United States National Farmers Market Directory (US Department of Agriculture (USDA) Marketing Services, 2016). Since 1994, farmers' markets alone have experienced a growth of 394% (US Department of Agriculture (USDA) Marketing Services, 2016). Farmers are supplying food directly to approximately three million Americans, and, in California alone, they supply consumers with around one percent of all produce (Varner and Otto, 2008).

Despite the large number of small-scale farmers and their importance for food accessibility and local food consumption around the country, small business and entrepreneurship literature have surprisingly neglected this context for decades (Carter and Rosa, 1998; Hunt *et al.*, 2021). To date, limited research has explored farmers' antecedents of entrepreneurial behavior (Khoshmaram *et al.,* 2020; Pindado and Sánchez, 2017) as well as their initiatives on income diversification (Rønning and Kolvereid, 2006; Vik and McElwee, 2011). Further, scattered research on entrepreneurship in agricultural settings has acknowledged the important role of identity (i.e. farmers having a strong identification with the occupation of farming) and family (i.e. the farm as a multigenerational family-owned and family-operated business) for understanding entrepreneurs in the farming context (Fitz-Koch *et al.,* 2018). However, this research has yet to investigate performance antecedents for small-scale farmers, especially in the USA, and why some farming entrepreneurs persevere in their pursuit of new business initiatives while others do not (Fitz-Koch *et al.*, 2018). As recently suggested by Hunt *et al.* (2021), there is an important need to contextualize research in rural settings and apply methodologies that capture the richness of this context. In this paper, we aim to extend this limited research by studying a specific question of practical relevance for farmers and regulators alike: how should farmers allocate their products across different sales channels?

One of the distribution channels we study is that in which small-scale farms directly reach the consumers (i.e. avoiding any intermediaries in the transaction) and hereinafter refer to the non aggregator channel. Despite the large direct-to-consumer growth mentioned above, farmers do not exclusively distribute food directly to consumers. A survey of over 150,000 farmers indicated that direct-to-consumer sales accounted for only 35% of total sales, while the remainder was split between retailers (e.g. supermarkets, restaurants and food co-ops) and institutions and local distributors (e.g. schools, hospitals, wholesalers, distributions and processors) (US Department of Agriculture USDA and National Agricultural Statistics Service NASS, 2015). In fact, small-scale farmers see farmers' markets as a sheer alternative outlet (Guthrie *et al.,* 2006).

The other channel we investigate is that in which the small-scale farm relies on a third-party intermediary to access a wider market (i.e. the farm sells to a large hub that, in turn, consolidates from multiple farms and sells to the end consumer). We henceforth refer to this as the aggregator channel. These food hubs have stepped in and helped enlarge farmers' reach beyond a small local community. Examples include aggregator firms that collect produce from a variety of farms and use large fleets to distribute it across entire regions to varying types of customers, including households, restaurants, and institutions (Schmitt *et al.*, 2013). Examples of such aggregators include firms such as Regional Access in New York and Red Tomato and Farm Fresh in Rhode Island. These aggregators give access to larger markets but often with product markups, membership fees, complicated payment schedules (Schmidt *et al.*, 2012) or varying purchase quantities or pricing schemes (e.g. partially-guaranteed prices, fixed price and commodity price) that complicate farmers' operational performance (Tang *et al.*, 2016). Furthermore, some farms may neglect pricing strategies and focus on yield forecasts (Arabska, 2018; Hazell and Scandizzo, 1977), targeting specialized markets or participating in cooperatives that do not necessarily improve their financial performance (Wollni and Zeller, 2006). Several farmers rely on farmers' markets for nearly half of their revenue; meanwhile, some of these markets are simultaneously exhibiting signs of poor market performance as measured by small product offerings, low administrative revenue and high employee/manager turnover (Stephenson *et al.*, 2008).

One way to improve farmers' performance is to provide better access to information (e.g. agricultural advice, price or demand forecast) as they make strategic decisions in the planning horizon (Tang *et al.*, 2015). Another way is to promote research on incentives for efficient food production (Williams *et al.*, 2021) and the integration of data analytics with agricultural production (Pham and Stack, 2018). We integrate these suggestions from farmers' distribution channel perspective and base our theoretical analysis on the transaction cost approach (Williamson, 1981). Through a transaction cost economics theoretical lens, we can focus on farmers' transactions and better evaluate the decision farmers face in managing their organizations. Specifically, we analyze two contrasting channels available to farmers, which are to sell: (1) indirectly through aggregators or (2) directly through farmers' markets. Farmers face uncertainty in the number of customers expected through each sales channel and the average revenue per customer (dollars per sale). While dealing with these uncertainties, farmers must determine what amounts of product to harvest and how much product to sell through each available channel (i.e. aggregator or direct-to-consumer). Currently, the literature lacks frameworks to aid farmers in determining product allocation to increase farm performance.

In this paper, we develop a simulation model to compare farm revenue performance across a wide set of scenarios to devise a framework for better expected performance. Specifically, we aim to address the following research questions:

- *RQ1.* which supply, demand, revenue, and operational factors influence a farmer's season-long performance?
- *RQ2.* does the percentage of produce allotted to each channel (aggregator and direct-to-consumer sales) have an effect on said influential factors?
- *RQ3.* how do fixed levels of commodity production influence the percentage of total commodity production recommended be sent to the aggregator? and
- *RQ4.* how do fixed percentages of total commodity production sent to the aggregator influence the recommended commodity production level?

Results from this study can help farms, from a negotiation/distribution perspective, to determine the quantities of product they should sell through each channel while having a higher likelihood of increased revenue performance.

The rest of this document is divided as follows. First, we review the literature on small businesses in the farming sector, farmers' markets, and applicable operations and supply chain management. Second, we present our simulation model, including factors of interest and the modeling approach. Third, we present the results and conduct sensitivity analysis. Finally, we elaborate on the theoretical and practical implications of our study and provide suggestions for future research.

2. Literature review

2.1 Entrepreneurship and small business management research in the farming sector

Despite the outstanding growth of small business management and entrepreneurship research, it has become apparent that the farming sector and rural venturing have received very limited attention from scholars (Fitz-Koch *et al.*, 2018; Hunt *et al.*, 2021). A recent literature review on small firm productivity research, for example, only seems to include one study conducted in a rural context (Owalla *et al.*, 2022). More than two decades ago, Carter and Rosa (1998) were already drawing attention to this issue and pointing out how small farms share many characteristics of other widely studied types of small firms: they are commonly owner-operated, they tend to have high family involvement and they have to deal with common business challenges related to sales, growth, profitability, marketing, finance, and strategic management. Conducting a literature review of research in agricultural entrepreneurship, Fitz-Koch *et al.* (2018) found that most scholarly activity on this sector has originated from the fields of agricultural economics and rural sociology, whose links to mainstream entrepreneurship research and its abundant theoretical resources to understand this context remain limited.

To the best of our knowledge, only a few studies have addressed specific research questions about the management of small farms. Conducting a survey of 400 farmers in Iran, Khoshmaram *et al.* (2020) studied the relationship between human capital, social capital, and entrepreneurial behavior. The authors found that both types of capital can increase innovative practices in farms by bringing learning opportunities, information exchange, and knowledge to identify viable opportunities. In a relatively similar vein, Pindado and Sánchez (2017) rely on a large survey of European farmers to compare entrepreneurs in agriculture versus other sectors. They found that although farmers seem to possess fewer resources and social networks compared with entrepreneurs in other industries, they do not seem to have a less entrepreneurial orientation. We also found two studies conducted on Norwegian farm family households that explored income diversification initiatives. Specifically, Rønning and Kolvereid (2006) suggest that due to declining profits in agricultural settings, farmers may resort to expand farm operations or seek external employment to increase their income, and Vik and McElwee (2011) expand on this issue to study the social and economic motivations behind various farm diversification initiatives, such as providing hunting rights, lodging, fishing, touring, among others. Finally, taking a more macroperspective, Yu and Artz (2019) compare entrepreneurship location choices among college-educated individuals to explore earning differences in rural versus urban entrepreneurship, finding that returns on entrepreneurial skills tend to be lower in rural areas.

Taken together, these studies have addressed diverse and interesting research questions, but the point raised by Carter and Rosa (1998) and Fitz-Koch *et al.* (2018) clearly remain relevant and has been reinstated by most of these studies: the farm sector has been largely omitted from small business management and entrepreneurship research. Just like other businesses in rural and urban settings, small-scale farm managers also need to adapt to their environments and rely on technological developments to secure new opportunities and improve their performance, especially since their products are vital to local and regional markets. We join these prior studies by developing a model of key practical relevance for small-scale farmers in the USA: determining product allocation across two commonly available channels in order to maximize revenue. As mentioned before, we do so by specifically focusing on aggregators vs direct-to-consumer, i.e. the farmer's markets. We review the literature about the farmer's markets in the subsequent section.

2.2 Farmers' markets

In the farmers' market literature, studies have looked at whether cooperative structures help improve welfare, reduce poverty and improve market performance. An *et al.* (2015) highlight the benefits of farmers' markets in developing countries, while Schmit and Gómez (2011) discuss the benefits of aggregating demand via community supported agriculture programs or farmers' markets in Vermont. Brown (2003) and Brown and Miller (2008) conducted literature reviews on farmers' markets, with the former emphasizing direct marketing for farmers. While useful in many respects, none of the above studies provide insight as to whether or how farmers markets outperform other distribution channels available to farmers.

Farmers' markets have also been analyzed from an analytical perspective. Tang *et al.* (2016) studied the benefits of partially-guaranteed price contracts (wherein the buyer offers a guaranteed unit price for any fraction of the produce and commodity market price at the time of delivery). Hazell and Scandizzo (1977) show how alternative assumptions about how farmers form their price and yield expectations have important consequences for the ensuing market equilibrium under stochastic production. Tang *et al.* (2015) examined how agricultural advice and market information influence farmer behavior under Cournot competition. Similarly, Chen and Tang (2015) studied the impact of information (public vs private) on farmers' welfare when farmers face uncertain market prices under Cournot competition. Schmitt *et al.* (2013) present a case study on Regional Access LLC, a firm that aggregates and delivers products throughout the state of New York and analyze the impact regional food hubs can have on the population. Despite the importance of the aforementioned studies, scant research has specifically focused on the distribution channel selection or evaluation from the perspective of small-scale farmers.

2.3 Operations and supply chain management

Scholars in operations and supply chain management have studied the importance of face-to-face interactions to develop trust and facilitate information sharing (Sonn and Storper, 2008; Storper and Venables, 2004). Additionally, they have stressed that local distribution has benefits such as improving supply chain coordination and reducing transaction costs (Boschma, 2005; Hansen, 2015). Research has shown that short supply chains (i.e. local sales and distribution –such as through farmers' markets and local aggregators) can help improve performance through the reduction of costs related to the transfer of information (Almeida and Kogut, 1997) as well as shorter lead times and delivery cycles (Salvador *et al.*, 2004). Researchers have also mentioned that having local suppliers (farmers) as well as firm operations in the vicinity of their target markets are paramount to a successful supply chain strategy (Bechtel and Jayaram, 1997; Christopher *et al.*, 2006; Patti, 2006; Tan, 2002). However, these works have yet to focus on the impact that the channel selection has on small-scale farms.

The operations (e.g. Chiang and Monahan, 2005; Li *et al.*, 2015) and marketing (e.g. Cai, 2010; Mols, 2000) literature have extensively studied the dual channel distribution problem in a traditional retail setting. Typically, in this literature, a manufacturer can sell indirectly through a traditional brick-and-mortar retailer or directly to consumers online (Zhang *et al.*, 2017). Xiao and Shi (2016) study this dynamic with a focus on pricing and channel priority strategies with random yields. In their study, the manufacturer can prioritize either the indirect or direct channel. However, this sub-stream of research is not particularly applicable to farmers, since most of the studies above focus on either the aggregator or large manufacturers, leaving a research gap on applications for farm operations whose typical channel choices involve either farmers' markets or local aggregators with unwieldy contractual guidelines.

We seek to advance the theory in the knowledge domains of operations and supply chain management by incorporating the theoretical lens of transaction cost economics to analyze the transactions from a distribution-channel perspective. In our paper, we evaluate the degree to which agents (i.e. farmers) can further align their organization's (i.e. small farms) strategy by using either a direct-sales approach or consolidating markets through an aggregator. This dichotomy resembles that of the make-or-buy decision, so prevalent in supply chain management studies (Fan and Stevenson, 2020; Williamson, 2008), but is thus far understudied within the small farm strategy context. Supply chain management scholars have increased attention to the buyer–supplier relations from a microperspective (Carter *et al.*, 2015), wherein the unit of analysis is the buyer–supplier relationship itself (not the organization). We approach this study with the same lens and identify a traditional direct contracting problem (Williamson, 1994) wherein the agent (i.e. small farm farmer/

entrepreneur) can either adopt a vertically integrated strategy of direct sales whilst maintaining full control over the transaction, or they can acquiesce to the terms and conditions set forth by an aggregator (thereby relinquishing control over subsequent tiers of the supply chain and access to an enhanced knowledge base). The former allows the farmer full control over the transaction and a direct connection to its end-consumer but suffers from the problem of reaching a potentially smaller market. The latter (aggregator) grants the farmer/entrepreneur access to a wider market and an extended tacit and formal knowledge base. However, it also forces resource dependence (Handfield, 1993) to befall upon the farmer/entrepreneur as well as, for example, reduced control over potentially inefficient logistics of aggregator operations (Schmitt *et al.*, 2013). Thus, the aggregator can enable the farmer to reach a much wider market and potentially larger profits (though at a noticeably higher individual transaction cost).

Thus, we not only answer calls for future research using transaction cost economics in supply chain management (Sodhi and Tang, 2014; Ketokivi and Mahoney, 2020) but also enhance our current understanding of buyer-supplier relations within the context of small farm distribution strategy by evaluating the advantages and disadvantages of having various levels of control over the transaction and the value for the actor (i.e. farmer) of maintaining further control over the transaction and subsequent supply chain actors involved. We further enhance our scholarly contribution by determining the efficiency of each alternative within the presented *make-or-buy* decision (i.e. direct sales vs aggregator) and the ways in which each option can best suit small farm business with varying strategies.

In summary, traditional operations and supply chain management literature usually examine the impact of distribution channel choices in large, corporate settings but has overlooked its implications for small-scale farms that also face important distribution challenges. Literature focusing on farmers' markets is limited when examining the product-channel allocation problems faced by many small-scale farmers. Further, small business management research has largely neglected the rural context, particularly small-scale farms, and the business challenges that they need to address. Our study takes a step in addressing these understudied areas and providing relevant insights, through the theoretical lens of transaction cost economics, for the highly important agricultural industry made up primarily of small-scale and family farmers.

3. Modeling approach

Our model considers that small-scale farmers face two key decision points. First, the farmer must determine the total amount of product to be harvested to supply the market for the next time period. Second, the farmer must determine how to allocate that product between their various distribution channels. In this study, we assume that the farmer has two distribution channels available. When making these two key decisions, farmers face uncertainties as to (1) the number of customers arriving at each channel and (2) the revenue generated per customer (dollar amount of each sale).

The first distribution channel is through an aggregator, in which the farmer indirectly supplies the product to the end consumer. In this channel, a variable number of customers arrive daily at the aggregator. In the situation where the farmer does not supply sufficient product, there is potential for lost sales (e.g. the customer buys an alternative product). On the other hand, if the farmer oversupplies the aggregator and the product does not sell prior to perishing, then the excess product is discarded, resulting in no revenue for the farmer. Lastly, the farmer is paid for each product that is sold.

The second distribution channel is direct-to-consumer, which we term as non-aggregator, and is modeled after farmers' market. We assume that the farmers' market runs twice per week (every 3.5 days in the simulation) and that any unsold product is held by the farmer (incurring a holding cost) until the next available market. Similar to the aggregator channel, a varying number of customers arrive at each farmer' market.

To aid small-scale farmers in their decision-making process, we use an experimental design with multiple combinations of factors of interest, further detailed in section 3.2.

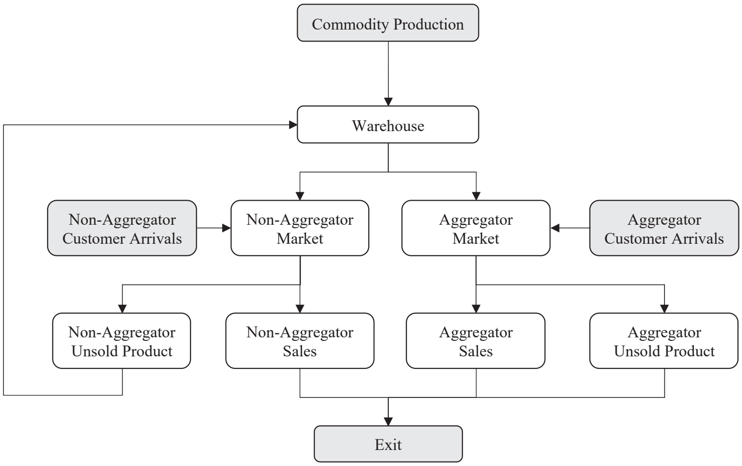
3.1 Simulation background

All researchers desire a closed-form analytical solution when developing their decision-making framework or solution algorithm. Unfortunately, many complex business problems cannot practically be solved using traditional analytical modeling approaches (Ross, 2022). Instead, researchers leverage simulation to compare the outcomes of different decision combinations and build a decision-making framework to handle the multiple levels of uncertainty and multiple decision points (Negahban and Smith, 2014). In this study, there are multiple levels of uncertainty (consumer arrivals and revenue) as well as multiple decision points (commodity production and aggregator split) that create a complex, interconnected system that cannot be practically solved analytically. To compare the outcomes of different decision combinations, we chose to leverage simulation modeling for our analysis.

Simulation modeling has existed in the operations management and operations research literature since the 1950s (Malcolm, 1960). Through simulation, we can represent the underlying theoretical logic that links constructs together when analytical solutions are highly complex (Happach and Tilebein, 2015). Thus, it allows us to balance complexity with flexibility and provides quick and efficient testing of various parameters of the problem (Happach and Tilebein, 2015).

There are two common simulation methods used in management research to model discrete time events: discrete-event simulation (DES) and agent-based simulation (ABS) (Sumari *et al.*, 2013). DES is a process-oriented (or top-down) approach that focuses on modeling the *system*. Meanwhile, ABS is an individual-oriented (or bottom-up) approach that emphasizes modeling the *agents (customers)* and the interactions between them (Siebers *et al.*, 2010). These varying approaches change the way that agents behave in the system. In DES, agents' behavior is "passive", whereas in ABS, their behavior is "active" (Maidstone, 2012). The "active" nature of the agents opens up many simulation modeling opportunities with ABS that could not properly be captured with DES (Siebers *et al.*, 2010). Despite the many benefits of ABS, there are still specific scenarios where DES is the best modeling approach. Specifically, DES is useful when processes can be well, and the emphasis in the approach is to model uncertainties in the *system* through stochastic distributions (Siebers *et al.*, 2010). In our modeling approach, our primary focus is on the larger system (i.e. aggregator vs non-aggregator) and less on the individual agents (customers). Therefore, we chose DES as our simulation modeling approach.

To ensure tractability whilst balancing practical relevance in our simulation, we made a few assumptions. First, the farmer harvests the product to supply to the system every seven days. The supplied product is then split between the aggregator and non-aggregator channels based on a predetermined percentage. In the aggregator channel, customer arrivals occur daily, and the product stays in the channel until it sells or perishes after nine days. In the non-aggregator channel, customer arrivals occur twice a week (one set of customer arrivals for each market, with two markets per week) and unsold product is held until the next market. We further assume a first-in-first-out discipline for producing sales (i.e. leftover items from previous market are sold first). Further, to avoid excessive inventory buildup, we deliberately set production (harvest) to a maximum of 20% above expected market demand. Any customer who arrives in either channel where no product is available is assumed to be a lost sale and leaves the system. Figure 1 outlines the process flow of our simulation.



Source(s): Figure by authors

Figure 1.
Simulation flowchart

3.2 Factors of interest

The focus of this study is to present a framework that can shed light on the effect that aggregator vs non-aggregator contracts can have on a farmer's financial performance and whether small-scale farms should innovate their business model. Based on previous literature (e.g. Schmit and Gómez, 2011) and interviews with industry experts, we identified the key factors to consider in our framework. Specifically, we analyze four sets of exogenous and endogenous factors: supply, demand, revenue, and operational. Each factor has a set of parameters that in turn have vary levels, as detailed in Table 1 and discussed in more detail below.

3.2.1 Supply factors. For supply, we have two factors of interest: commodity production and channel split (both varied across three levels: low, medium, and high). The process starts with commodity production (i.e. producers' harvesting). We use the total expected demand, and we deliberately set an expected 20% production deficit (low), match total expected demand (medium), and induce an expected 20% production surplus (high). This factor will help determine a benchmark performance for a producer operating at an ideal performance level (matching supply and demand as closely as possible) and will shed light on the cost of under (or over) producing in various scenarios.

Producers often face the decision of what percentage of their commodities to make available for the aggregator market and, conversely, which proportion to leave for the nonaggregator market. To study the effects of varying proportions and commodity allocation to each available channel, we vary the proportion of the producer's commodity channel split across three levels: high (75% goes to aggregator), medium (split evenly), and low (25% goes to aggregator). We expect this factor to provide fundamental insight into a primary underlying question of the proposed framework (whether a certain channel split is more conducive to better performance).

3.2.2 Demand factors. The demand factors focus on customer arrivals in both channels. We simulate customer arrivals from two perspectives: customers arriving to purchase in the aggregator and non-aggregator channels. Both factors are varied across two levels (i.e. high and low). First, we follow the findings from Schmit and Gómez (2011) to define arrivals in the non-aggregator market as 63 customer visits per market with low demand.

Factor	Parameter	Value(s)*	Empirical grounds
Supply	Commodity production	High = +20% total expected customer demand Medium = total expected customer demand Low = −20% total expected customer demand	Focus of this study
	Channel split	High = 75% AGG vs 25% NAGG Medium = 50% AGG vs 50% NAGG Low = 25% AGG vs 75% NAGG	Focus of this study
Operational	Inventory holding cost	High = 30% of product value Low = 20% of product value	McCue (2020)
Demand (Sales)	Aggregator customer arrivals (per week)	High ~ Poisson(λ = 127.87) Low ~ Poisson(λ = 76.16)	Interviews with industry professionals; Lai and Ng (2005)
	Non-aggregator Customer arrivals (per week)	High ~ Poisson(λ = 102) Low ~ Poisson(λ = 63)	Schmit and Gómez (2011) and Lai and Ng (2005)
Revenue	Aggregator customer revenue ($/order)	High ~ Normal(μ = 5.32, σ = 4.63) Low ~ Normal(μ = 3.17, σ = 2.76)	Interviews with industry professionals
	Non-aggregator customer revenue ($/order)	High ~ Normal(μ = 6.75, σ = 4.84) Low ~ Normal(μ = 3.93, σ = 2.82)	Schmit and Gómez (2011)

Note(s): *AGG = aggregator and NAGG = non-aggregator
Source(s): Table by authors

Table 1.
Parameters used in the simulation

For non-aggregator markets with high demand, we used 102 customer visits (which is one standard deviation above the mean market visits of 63, following Schmit and Gómez, 2011).

Second, to model the aggregator market, we conducted a series of interviews with two industry professionals: (1) a representative from Farm Fresh Rhode Island, a large aggregator operating in the New England region of the USA and (2) the general manager of Endless Farm, a local producer of organic food in Rhode Island. Using their expert opinions and historical data, we determined that, at the high end of the aggregator market, farmers can expect an average of 127.87 orders per week (equivalent to successful customer visits in our simulation). We obtained this value by dividing the total number of unique Farm Fresh Rhode Island customers in the year 2019, by the estimated number of weeks the aggregator operated in that year. For the low level of this factor, we assume that each customer only places one order every week. Thus, in 2019, an average aggregator can expect 76.16 customer arrivals per week. In the simulation, all customer arrivals are assumed to follow a Poisson distribution (Lai and Ng, 2005) with the means shown in Table 1. Upon discussing with both Farm Fresh and Endless Farm representatives, we confirmed that our simulation parameters are representative of their expected sales patterns.

3.2.3 Revenue factors. Revenue factors focus on revenue per customer in both channels. We incorporate two levels (i.e. high and low) for all factors. In the case of the aggregator market, we use the estimated average size of each producer's weekly drop at Farm Fresh Rhode Island (the average price of the order they delivered each week) and divide that by the customer arrival rate. This results in $5.32 (high) and $3.17 (low) expected revenue per order for each level of this factor. Conversely, for the low level of the non-aggregator market, we use a mean of $3.93 per successful customer order (following Schmit and Gómez, 2011). For the high level of non-aggregator market revenue, we use a mean of $6.75 per customer order (one standard deviation higher while maintaining the coefficient of variation of the probability distribution). In addition, since the moments of the distributions of revenue simulation would theoretically allow negative values of the producer's revenue, we set a lower bound on these distributions equal to 1 standard deviation below the mean. This results in lower bounds for aggregator revenue at \$0.41 (low) and \$0.69 (high). Similarly, for non-aggregate revenue, the lower bounds are \$1.11 (low) and \$1.91 (high). For confidentiality reasons, we were unable to obtain the raw data necessary to determine the appropriate distribution of revenue in the aggregator and non-aggregator markets. With limited prior research into small-scale farmers and their revenue, we assumed that all revenue factors follow a normal distribution (with the truncation described above) in the simulation. In Section 5, we discuss the implications of this assumption and alternative distributions.

3.2.4 Operational factors. The final type of factor in our simulation is operational (i.e. under certain operational conditions, there may not be enough demand for some of the available product). This factor represents the case in which some product is taken to the non-aggregator market and remains unsold. Said product can be stored and reused on the next non-aggregator market, albeit with an inventory holding cost. To model the holding cost, we use 30% of the commodity's selling price for a high level of inventory cost and 20% for a low level (McCue, 2020). Note that, as explained above, we assume commodities in the non-aggregator market are sold using a first-in-first-out discipline, in which leftover items are sold first. In addition, we set a production (harvest) upper bound up to 20% above theoretical demand to avoid excessive inventory buildup.

3.3 Steady state and simulation details

In our simulation, we are interested in observing the season-long performance of a single farm's presence in farmers' market vs selling via an aggregator. Thus, we do not use a warmup period in the simulation in the pursuit of a steady state and instead use a long-run session that represents the entire season (Whitt, 1991). All analysis was performed on an Intel Core i7 computer with 16 GB of memory using ProModel 2018 version 10.1.2. To increase the robustness of our results, we simulate the maximum number of 999 seasons allowed by our version of ProModel for each cell in our experiment's factorial design. This number of replications has been found to achieve stable results (Mundform *et al.*, 2011). Our experiment has seven factors of interest (variables whose levels are detailed above) and a factorial combination of 288 experimental units (3x3x2x2x2x2x2). Thus, the total number of trials was 287,712 independent simulations.

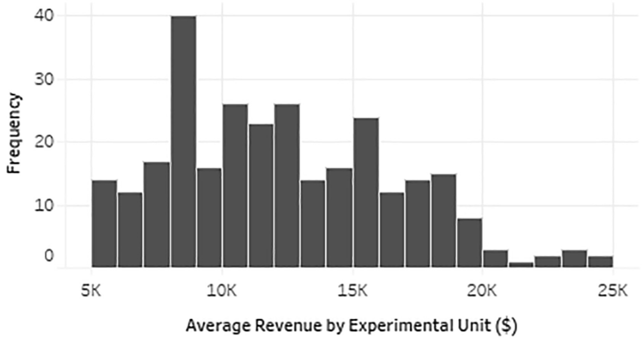
4. Results

Our simulation analysis addresses three main points: (1) which factors are most influential on total season-long revenue? (2) are the influential factors consistent across the three aggregator split levels? and (3) how do fixed levels of commodity production influence the recommended aggregator split and vice versa?

4.1 Overall results

In our simulation, the main variable of interest is season-long revenue. To evaluate each of the 288 experimental units, we analyzed the average revenue across the 999 replications in the simulation. Figure 2 provides the average revenue distribution for each experimental unit.

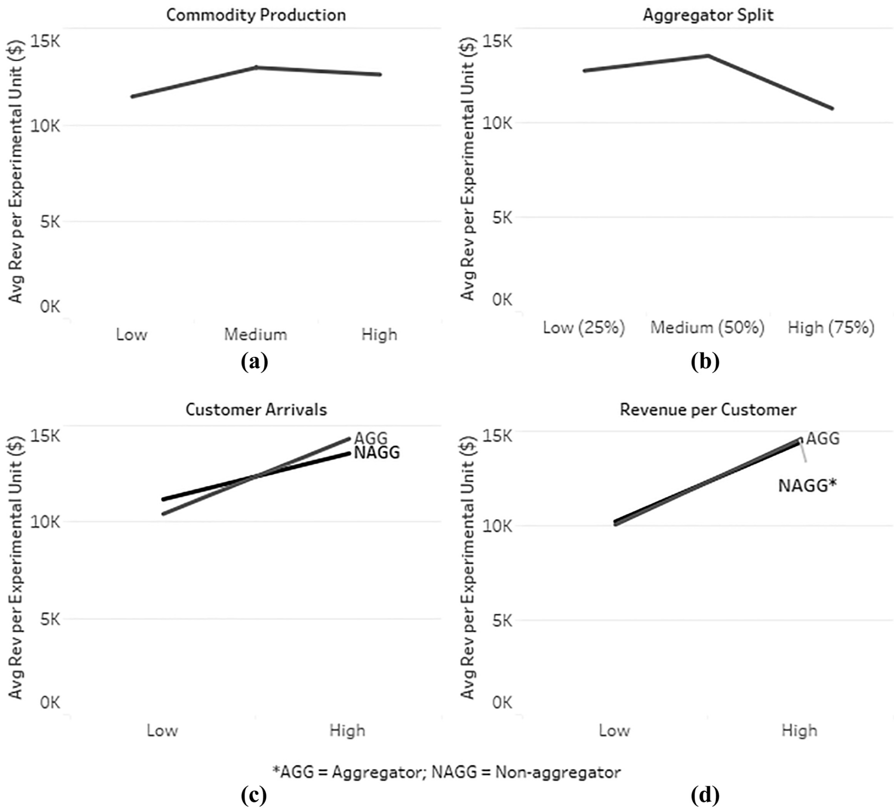
Figure 3 helps to identify the relationship between six of the seven factors and season-long revenue (inventory holding was excluded due to insignificant impacts on season-long revenue). Similar to Figure 2, these results provide the average revenue per experimental unit across the 999 replications. From these results, we can see that farm performance



Note(s): Comprised of 999 simulation trials

Source(s): Figure by authors

Figure 2. Distribution of predicted season-long revenue for each experimental unit



Source(s): Figure by authors

Figure 3. Average revenue per experimental unit across six of the seven key factors: (a) commodity production, (b) aggregator split, (c) customer arrivals at aggregators and non – aggregators, and (d) revenue per customer at aggregators and non-aggregators

(as measured by revenue) increases when (1) commodity production (the total amount of product harvested by the farmer) is at medium (i.e. when the farmer tries to match expected demand) or high (i.e. when the farmer harvests 20% more than expected demand) level; (2) an aggregator split is at medium (even split between aggregator and non-aggregator) or low (25% of production diverted to the aggregator market) level; (3) customer arrivals are at high (for either channel); and (4) revenue per customer is at high (for either channel). The impact of customer arrivals in the aggregator channel is more pronounced when switching from low-level to high-level arrivals in comparison with the non-aggregator channel (see Figure 3c). From a raw customer arrival perspective, the percent change when switching from low to high is similar in the aggregator channel (68% increase in arrivals) and the non-aggregator channel (62%). Furthermore, the percent change in revenue per customer is actually more significant in the non-aggregator channel (81% increase in revenue vs 68% in the aggregator channel). Given these statistics, a more pronounced impact of increasing the aggregator channel customer arrivals is counterintuitive and we will examine that in more detail in Section 4.3.

While these initial results confirm a relationship between season-long revenue and six of the seven factors, they fail to provide a satisfactory level of detail. In the following subsections, we perform additional analyses to help shed more light on the aforementioned relationships.

4.2 Sample splits

Our initial results indicate a relationship between season-long revenue and six of the seven factors. In this section, we focus on the relationship between channel split and season-long revenue by splitting the results into three subsamples, one for each level of aggregator split, each containing 96 experimental units. The goal is to better understand the relationships (and potential interactions) identified in Section 4.1.

First, the overall results shown in Figure 4 highlight the farm performance distribution by aggregator split. These results provide a more holistic view of the impact of each aggregator split level. A *high* aggregator split (75% of production diverted to the aggregator) not only has the lowest average season-long revenue (seen in Figure 3) but also has a limited best-case scenario.

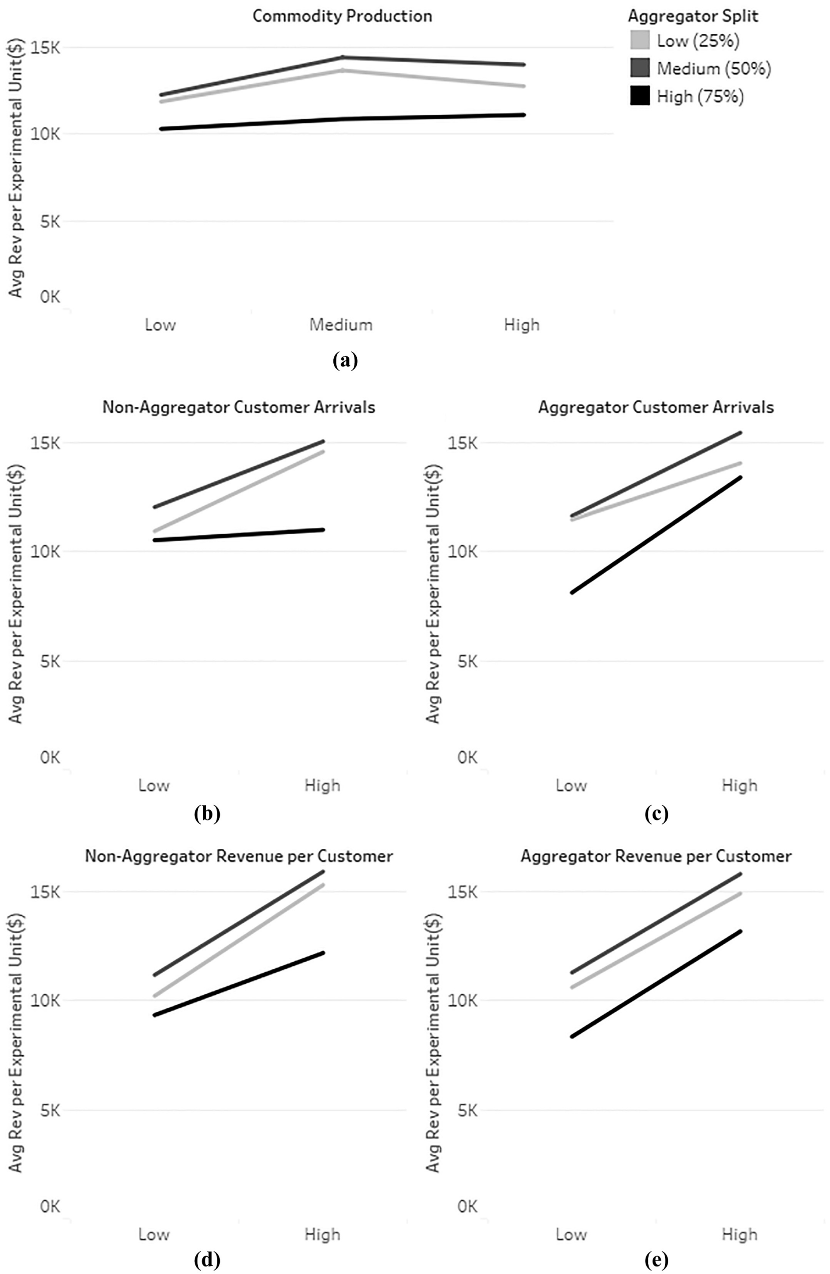
Next, we analyzed the interactions between the aggregator split and the other key factors. Figure 5 visually shows the interactions between the aggregator split and commodity production, customer arrivals (for each channel), and revenue per customer (for each channel). The performance rank of each level of aggregator split remains constant (medium (50%) > low (25%) > high (75%)), but the relative impact of each factor change is often unique.

For commodity production, if the aggregator split is at low or medium, the farmer can maximize their performance by matching their supply (commodity production) with demand.

Note(s): Comprised of 999 simulation trials

Source(s): Figure by authors

Figure 4. Distribution of predicted season-long revenue for each experimental unit split by the level of aggregator split



Source(s): Figure by authors

Figure 5. Average revenue per experimental unit split by the level of aggregator split; examining interaction with (a) commodity production, (b) non-aggregator customer arrivals, (c) aggregator customer arrivals, (d) revenue per customer at aggregators, and (e) revenue per customer at non-aggregators

The expected gain is most pronounced at a low aggregator split (7% improvement), but at a medium aggregator split, the farmer is expected to see a 2% revenue improvement. Meanwhile, if the farmer is locked into a high aggregator split, they are better served to *oversupply* the market with a high level of commodity production.

As expected, if a farmer can achieve higher levels of customer arrivals or revenue per customer, their performance improves. The value-added of these changes does depend on the aggregator split in some situations. Specifically, the benefit of increasing non-aggregator customer arrivals is most pronounced with a low or medium aggregator split (at least a 25% improvement), whereas that performance improvement is only 4.5% in a high aggregator split. Diving deeper into the underlying simulation results, this precipitous drop in performance improvement is highly connected to selling out of the product in the non-aggregator market and accruing lost customers. As a result, the performance benefit is capped by the amount of product available in the non-aggregator market. This is a fairly intuitive result, but the magnitude of the difference in benefit is noteworthy between medium and high aggregator splits. This further supports the broader finding that the farmer should do their best to match their commodity production with demand but with an emphasis on the non-aggregator market. Changes in performance (revenue) associated with changes in aggregator arrivals and revenue per customer are less pronounced, indicating that non-aggregator customer arrivals are a key lever for small-scale farmers to use even if their aggregator split is medium or low.

Additionally, unlike in the overall results, high inventory holding costs *do* decrease season-long expected revenue by just under 4% when a farmer has a low aggregator split (25% to aggregator). With a low split of product going to the aggregator, there is a high potential for oversupply in the non-aggregator market, which can result in significant holding costs.

4.3 Sensitivity analysis

To provide a more granular examination of our main analysis, we examined three avenues of sensitivity analysis. We further analyze the set of factors that provide the maximum season-long average revenue, first, given a production split level (Table 2) and second, given a commodity production level (Table 3). Finally, we examine the impact each parameter has on season-long revenue when switching from a parameter level from low to high.

Table 2. Percentage of simulations with maximum revenue by commodity production for a given level of aggregator split

	Commodity production level with maximum revenue			
Aggregator split	Low	Medium	High	Total
Low	0.00%	100.00%	0.00%	100.00%
Medium	0.00%	75.00%	25.00%	100.00%
High	37.50%	12.50%	50.00%	100.00%

Source(s): Table by authors

Table 3. Percentage of simulations with maximum revenue by aggregator for a given level of commodity production

	Aggregator split levels with maximum revenue			
Commodity production	Low	Medium	High	Total
Low	25.0%	62.5%	12.5%	100.0%
Medium	31.2%	68.8%	0.0%	100.0%
High	75.0%	0.0%	25.0%	100.0%

Source(s): Table by authors

The first sensitivity analysis focuses on the recommended commodity production levels, given a predefined aggregator split. If a farmer must negotiate a contract with an aggregator at the beginning of the season, then these results can provide insights into preferred in-season commodity production levels. Results, presented in Table 2, show that if a low aggregator split is necessary, the best revenue performance is always achieved when production meets expected demand (medium level). Similarly, for a medium aggregator split, farmers should aim to have a commodity production meets or exceeds expected demand (since 75 and 25% of the best-performing cases were achieved under medium and high commodity production levels, respectively). Interestingly, the results change dramatically if a farmer is committed to a high aggregator split. When facing a high aggregator split, 87.5% of the best-performing cases occur when the farmer does not match expected demand (37.5 and 50% of the best performing cases happen under low and high production levels, respectively). Instead, the farmer should reduce (expand) their harvest amount when they expect low (high) average revenue per customer in the non-aggregator channel.

Our second sensitivity analysis emphasizes the best decision for the farmer when he/she must decide the best aggregator split, given the size of the production harvest (relative to the total expected market demand). If a farmer has the flexibility to pick their aggregator split for each market, then these results will assist in the decision-making process after realizing the size of the production harvest. As shown in Table 3, if a farmer has a harvest size such that it is expected to either meet or fall short of market demand, then the best course of action is to provide an even split between the two channels (medium split). This recommendation changes if the farmer has a high yield for a particular harvest (high commodity production). In such a scenario, the farmer should avoid an even split between the two channels. Instead, the general recommendation is to: (1) provide a low percentage to the aggregator (keeping a high percentage in the non-aggregator channel) or (2) send a high percentage to the aggregator, but only if both a high level of aggregator customer arrivals and a low level of non-aggregator customer arrivals are expected.

In Section 4.1, we identified a counterintuitive result where increasing the aggregator channel customer arrivals had a more significant impact on revenue than increasing the non-aggregator channel customer arrivals, despite similar percent increases in both arrival amounts and revenue per customer. To analyze this further, we performed additional sensitivity analysis on each key parameter in the study: customer arrivals, revenue per customer, and inventory holding cost (we vary aggregator split and commodity production in each analysis). These results can be seen in Tables A1–A5.

Focusing on the customer arrivals (Tables A2 and A3), we can immediately see the distinction between customer arrivals in the aggregator and non-aggregator channels. Specifically, in the aggregator channel, the benefits of increased customer arrivals are universal regardless of the aggregator split level or commodity production level, with each cell seeing at least a 20% increase in average revenue. Meanwhile, for the non-aggregator channel, there is a significant benefit of increasing customer arrivals for low and medium levels of aggregator split (when 50% or more of the product stays in the non-aggregator channel), but the benefit drops significantly in situations where a high aggregator split is implemented. This drop occurs because in a high aggregator split, the farmer ends up turning away a large percentage of their non-aggregator customers (they sell out of the product). These results further emphasize the farmer's need to match supply with demand, but with an extra focus on matching *non-aggregator demand*.

5. Discussion

There is an ever-growing need to further our understanding of the agricultural industry and its business challenges, particularly as it pertains to the numerous small-scale farmers and agricultural entrepreneurs who confront the difficulties of any other small business (Carter and Rosa, 1998; Vik and McElwee, 2011) but face unique contextual conditions related to regulations, government support, family involvement, ownership structure, competition, distribution, among others (Fitz-Koch *et al.*, 2018). Our work, grounded on transaction cost economics and using the farmer–buyer relationship as the unit of analysis, contributes to the scant research seeking to advance our understanding of small farm management (e.g. Khoshmaram *et al.*, 2020; Pindado and Sánchez, 2017; Rønning and Kolvereid, 2006). We do so specifically by proposing a practical model that can assist farmers in making critical distribution decisions that impact farm revenue by comparing the outcomes of a wide set of scenarios and subsequently prescribing which decisions tend to provide the most favorable outcomes. Thus, we outline how farmers can better position themselves to compete with larger operations. Further, besides promoting research with strong practical relevance for small business managers, we join important calls to not only contextualize entrepreneurship research (Welter, 2011; Zahra, 2007) but also devote more research attention to small-scale farms and agricultural entrepreneurship settings, which have traditionally escaped the attention of management and entrepreneurship scholars (Fitz-Koch *et al.*, 2018; Hunt *et al.*, 2021).

Our analysis provides important insights for small-scale farmers with regard to the potential effects of different product distribution strategies and expected season-long implications of prioritizing the aggregator or non-aggregator distribution channels. These two fundamentally different strategies have varying transaction costs and widespread implications for firm strategy from the classic supply chain management make-or-buy perspective. For example, by choosing the aggregator, the transaction cost would increase for the farmer since they would have to manage the cognitive proximity (Mattes, 2012; Knoben and Oerlemans, 2006) present in the transaction, seeking to maintain high enough levels to adequately access to any tacit knowledge held by the aggregator, and also to support small farm-aggregator relational cohesiveness to seek better alignment of both agents' objectives (DeWitt, 2006; Tachizawa and Wong, 2014; Tan *et al.*, 2010).

Specifically, our results show expected average season-long revenues of \$17,811, \$22,458, and \$21,690, respectively, for high (75%), medium (50%), and low (25%) aggregator splits. These broad results emphasize that farmers should plan to evenly split their production between the two distribution channels; however, if an even split is not possible, they should plan to keep a larger percentage in the non-aggregator (farmers' market/direct) channel. In terms of commodity production, our broad results emphasize matching their commodity production with expected demand, but erring on the high side. Despite the emphasis on the non-aggregator channel, regardless of the aggregator split, the farmer benefits significantly from a strong aggregator channel customer base. This emphasizes the need for farmers to partner with the aggregator to promote and advertise the aggregator channel, even if they only supply a limited amount of product. At each decision-point for the farmer (e.g. market week), they likely have one of two levers available to maximize farm performance (revenue): (1) the size of the harvest (commodity production) or (2) the aggregator split. Our sensitivity results in Section 4.3 isolate best practices in both scenarios. Specifically, with a low or medium aggregator split, the farmer should always harvest enough product to meet the expected demand; but with a high aggregator split, they should *not* meet the expected demand. Instead, the farmer should under (over) produce if expecting a low (high) non-aggregator customer revenue per order. Additionally, with a low or medium harvest size, the farmer should split evenly between the aggregator and non-aggregator channels. Conversely, with a large harvest size, the farmer should *not* split evenly and, if a high level of aggregator *and* a low level of non-aggregator customer arrivals are expected, send either a high or low percentage to the aggregator.

While the specific performance of our simulation analysis provides important results for both strategic and tactical decision-making, future research can further explore the relationships among the variables of interest. As we explain above, there are important considerations before a small-scale farmer can choose how much of its production should be aimed at the aggregator vs direct-to-consumer sales channel (i.e. production *split*). Furthermore, our study shows that sales volume (i.e. number of orders) and revenue per customer can impact the outcome of season-long performance of a firm (small-scale farm). We further found that inventory holding cost, surprisingly, did not influence the channel allocation decision. Thus, in Figure 6 we present a framework that summarizes the factors our study found to be important in the channel allocation decision as they lead to firm performance and the potential moderating effects that could influence its relationship to small-scale farm production levels. We specifically suggest that although farmers' channel selection (split) has an important relationship with farm performance, this relationship is likely to be moderated not only by how many potential customers are present in each channel (traffic) but also by order size (how much product customers tend to buy in each channel). Future research can aim to explore these relationships empirically to further advance our understanding of the conditions that could most benefit small-scale farms.

Small-scale farms are essential not only for food security around the world but also for employment and productivity in rural areas. We therefore argue that addressing research questions in this area can be a fruitful effort for small business management and entrepreneurship research. We focus on a specific decision regarding channel selection that has key implications for farm revenue, but future research can explore a variety of research questions related to this context. For example, considering that small-scale farms tend to be operated by families and there is a worldwide mobility of labor from rural to urban areas, it would be interesting to explore succession dynamics and how each generation makes the decision to work at the farm or pursue other job opportunities either in rural or urban areas. Globalization and trade dynamics will most certainly play a key moderating role in these phenomena. Other future opportunities include entrepreneurship and management education research. If some small-scale farmers have increased access to higher education opportunities, they may be able to obtain business knowledge to increase overall farm productivity and performance. Natural experiments and qualitative studies could help investigate this possibility and provide results that can be relevant to policy makers at the state and federal levels of government to promote agricultural entrepreneurship. We also encourage entrepreneurship scholars to put emphasis in the practical relevance of their research. Specifically, while we can rely on the agricultural context to advance insightful theories that inform broader entrepreneurship research, particularly as the farming sector has unique contextual conditions that are not as salient in other industries (Fitz-Koch *et al.*, 2018), it can be fruitful to follow Aguinis *et al.*' (2022) suggestions and advance

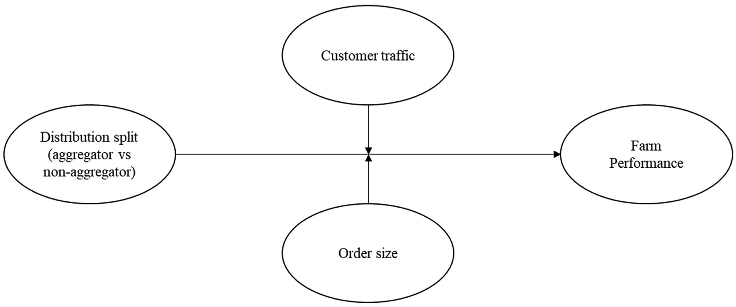


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Figure 6. Proposed framework for future research

entrepreneurship theories while trying to ensure that research questions have significant practical implications for small farm managers or entrepreneurs as well as policy makers.

Our study has important limitations that can provide opportunities for future research. First, as is well known, one of the major potential pitfalls in simulation-based research is the accuracy with which the random variables employed in the simulation model perform in real-world system performance. In our study, we defined the probability distributions of the necessary random variables using parameters either from published research or through historic data provided by real-world practitioners. Some of the studies in said published research were specific to farmers' markets in certain geographical areas (e.g. Midwest region of the USA, New York State, etc.). Thus, future studies may seek alternative sources of information (e.g. archival or empirical data) to better model customer or sales behavior in farmers' markets in the United States or around the world. Additionally, for our revenue-based distributions, we assumed a Normal distribution. Previous literature (e.g. Crawford *et al.*, 2015) found that a skewed distribution (e.g. power-law) may be more applicable to specific industries when analyzing revenue per customer. Therefore, future researchers may collect additional data on small-scale farmers' revenue per customer to better understand the true distribution. Finally, in our study, we leverage a top-down approach by using DES. Future studies can utilize an alternative bottom-up approach—such as ABS—to better understand the behavior of individual agents (customers) in a similar local food dual-channel structure.

Second, our study uses aggregated information about farmers' market performance. Thus, it is difficult to account for specificity in various, more specialized markets, or differences across different types of firms (farms); for example, those operating in highly specialized markets (high levels of asset specificity, which might benefit their operating conditions) vs large-farming conglomerates (which mostly sell large quantities of a limited number of commodities). Future studies may focus on corroboration of the results presented herein via means of archival data or empirical studies with producers (farmers) in an effort to account for varying conditions within specialized markets or farms.

Third, future studies could help further extend this study by incorporating additional variables that exist within the transaction between the small farmer and their clients. Specifically, the simulation was adjusted to take advantage of farmers' absorptive capacity and any tacit knowledge they may develop throughout the season to (1) improve each channel' demand forecasting accuracy and (2) reduce inventory costs over the farming season.

Fourth, more generalized information as to the contractual (both formal and verbal) obligations farmers tend to enter into with aggregators is required. Currently, there are little standards governing these relationships and most of the transactional power seems to lie around the aggregator, potentially due to firm size. However, through interviews with representatives of various aggregators and farm owners, we have realized that aggregators' terms tend to vary significantly. Thus, more generalizable results might emerge by establishing a more holistic set of contractual conditions (e.g. aggregator markup, number of commodity "drops" per week, storage capacity, various fees, accepted forms of payment, etc.) to fine-tune the simulation and provide farmers with more robust results. Further studies could delve deeper into the buyer–supplier relationship and potential power imbalances in the underlying transaction.

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Appendix

As part of our sensitivity analysis in Section 4.3, we isolated the impact of each parameter in the simulation. Specifically, we calculated the average percent change in season-long average revenue as a result of changing the parameter from *low* to *high*. In each of the tables below (one for each parameter), you will see this percent change broken down by each level of a small-scale farmer's two levers examined in this study (commodity production quantity and aggregator split).

Table A1. Percentage change in average revenue as a result of changing the inventory holding cost from low to high

	Commodity production		
Aggregator split	Low	Medium	High
Low	−2.2%	−3.5%	−5.4%
Medium	−0.2%	−0.5%	−1.0%
High	0.0%	0.0%	−0.1%

Source(s): Table by authors

Table A2. Percentage change in average revenue as a result of changing the customer arrivals in the aggregator channel from low to high

	Commodity production		
Aggregator split	Low	Medium	High
Low	20.7%	22.8%	24.3%
Medium	32.6%	36.1%	29.5%
High	60.5%	67.8%	66.5%

Source(s): Table by authors

Table A3. Percentage change in average revenue as a result of changing the customer arrivals in the non-aggregator channel from low to high

	Commodity production		
Aggregator split	Low	Medium	High
Low	34.7%	33.4%	31.8%
Medium	25.2%	22.7%	27.3%
High	8.5%	2.3%	3.2%

Source(s): Table by authors

Table A4. Percentage change in average revenue as a result of changing the revenue per customer in the aggregator channel from low to high

	Commodity production		
Aggregator split	Low	Medium	High
Low	30.8%	42.0%	48.7%
Medium	36.2%	40.5%	43.0%
High	59.3%	57.8%	56.4%

Source(s): Table by authors

Table A5. Percentage change in average revenue as a result of changing the revenue per customer in the non-aggregator channel from low to high

	Commodity production		
Aggregator split	Low	Medium	High
Low	54.3%	45.8%	49.9%
Medium	43.0%	40.3%	43.9%
High	24.9%	30.1%	36.3%

Source(s): Table by authors