

Development of Horizontal Coordination Mechanisms for Planning

Agricultural Production

by

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## ABSTRACT

Agricultural supply chains are complex systems which pose significant challenges beyond those of traditional supply chains. These challenges include: long lead times, stochastic yields, short shelf lives and a highly distributed supply base. This complexity makes coordination critical to prevent food waste and other inefficiencies. Yet, supply chains of fresh produce suffer from high levels of food waste; moreover, their high fragmentation places a great economic burden on small and medium sized farms.

This research develops planning tools tailored to the production/consolidation level in the supply chain, taking the perspective of an agricultural cooperative—a business model which presents unique coordination challenges. These institutions are prone to internal conflict brought about by strategic behavior, internal competition and the distributed nature of production information, which members keep private.

A mechanism is designed to coordinate agricultural production in a distributed manner with asymmetrically distributed information. Coordination is achieved by varying the prices of goods in an auction like format and allowing participants to choose their supply quantities; the auction terminates when production commitments match desired supply.

In order to prevent participants from misrepresenting their information, strategic bidding is formulated from the farmer's perspective as an optimization problem; thereafter, optimal bidding strategies are formulated to refine the structure of the coordination mechanism in order to minimize the negative impact of strategic bidding. The coordination mechanism is shown to be robust against strategic behavior and to provide solutions with a small optimality gap. Additional information and managerial insights are obtained from

bidding data collected throughout the mechanism. It is shown that, through hierarchical clustering, farmers can be effectively classified according to their cost structures.

Finally, considerations of stochastic yields as they pertain to coordination are addressed. Here, the farmer's decision of how much to plant in order to meet contracted supply is modeled as a newsvendor with stochastic yields; furthermore, options contracts are made available to the farmer as tools for enhancing coordination. It is shown that the use of option contracts reduces the gap between expected harvest quantities and the contracted supply, thus facilitating coordination.

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# 1 PROBLEM DEFINITION

## 1.1 Introduction

The recent increase in consumption of fresh agricultural products has been impressive; nearly 25 percent from 1970 to 1997 (Jones Putnam & Allshouse, 1999) and a further increase of 16 percent between 1998 and 2008 (Stewart, 2010). Fresh produce now accounts for an industry worth over \$122 billion in sales for the US alone (Cook, 2011). Likewise, crop yields improved remarkably throughout the last century. Nonetheless, significant challenges remain in this industry; two of which are: socioeconomic issues arising from the decline of small and medium sized farms, and environmental issues resulting from overconsumption and waste of resources (Hazell & Wood, 2008).

With respect to environmental issues, we cannot solve these simply by increasing agricultural production--especially considering those that could adversely affect food supply in the future (Millennium Ecosystem Assessment, MEA, 2005). The case of fresh produce stands out as a prime example, which requires a “cold supply chain” and for which product loss reaches an astonishing 30% of total production before reaching the consumer (Gustavsson, 2011). This loss of production is the result of several factors, chief among them a lack of coordination in the supply chain.

On the socioeconomic front, food producers suffer from significant economic pressure (Jang & Klein, 2011). Unfavorable supply chain practices, low consolidation, and their position at the bottom of the supply chain, where margins are thin, make it difficult for these enterprises to thrive. These problems are further aggravated for small and medium sized growers of fresh produce, for whom short shelf lives make it harder to store their products and tolerate swings in supply/demand and price (Makeham & Malcolm, 1993). If

an excess of product exists, farmers will generally have no choice but to sell for a lower price, many times at a loss. The immediate result is a high level of food waste, lower profits for the farmer and higher prices to consumers. This issues take a toll on already thin margins in a supply chain where only 20% of the revenue generated goes to producers in the U.S. (Cook, 2011).

It comes as no surprise that farmers in the US are now starting to form tighter relationships and seek to expand their operations vertically through the establishment of cooperatives and consolidation centers (James Matson, Martha Sullins, & Chris Cook, 2010). Thus a tendency of vertical consolidation is in place; this is similar to the case of European farmers, where cooperatives of growers expanded into marketing and retail (Bijman & Hendrikse, 2003). The emergence of these groups of collaboration allow farmers to obtain economies of scale, provide a steady stream of products, and expand their operations downstream while increasing the efficiency of the supply chain (James Barham & Debra Tropp, 2012). This is particularly true for small and mid-sized farmers, since they have the greatest difficulty competing successfully with larger producers (Stevenson, 2008).

To make a collective marketing point successful, it needs to coordinate the production of its members, its customers and outside suppliers. Unfortunately, the production across many farms remains, for the most part, uncoordinated and without sophisticated planning; decisions are not necessarily made with the efficiency of the overall system in mind. Moreover, despite more small and medium sized farmers becoming associated, there is no evidence in the literature of structured planning mechanisms used in these organizations. Unfortunately, conflicting objectives within the cooperative often



limit the success of these joint ventures (Diamond & Berham, 2012). In fact, a lack of cost/production information sharing within partners in the cooperative is prevalent, despite its central role for collaboration (Bahinipati, 2014). The association of small farmers is a trend which will allow them to compete with larger operations; however, for this to become a reality, the necessary tools for coordinated planning must be in place.

*In response to these trends, this document presents a tactical level planning tool to coordinate the supply chain, such that the production decisions of individual members of a cooperative are aligned and planned supply is matched to projected demand. We explore three sequential paths of research necessary to coordinate these organizations: (1) we use auctions as tools for information discovery and transparent assignment of seasonal production plans; (2) we show that auction mechanisms coordinate the supply chain in spite of strategic behavior from farmers; and (3) we explore the impact of stochastic yields to the risk of farmers once production contracts are assigned and the repercussion of yield risk on the extended supply chain.*

The proposed research considers various factors which are relevant to the fresh produce industry, such as resource requirements, labor considerations, price dynamics, perishable inventories and associated costs. Moreover, the proposed research also addresses an important issue, which hampers coordination and which is commonly overlooked in agricultural supply chains: The limited availability of information and the reluctance of participants to share private information. This research is vital for emerging cooperatives as their situation warrants a tool specially tailored for coordinating multiple parties at the same level.

## 1.2 Problem Definition

Agricultural supply chains (ASCs) are the collection of activities, from production to distribution, that bring agricultural products from the farm to the table (Aramyan, Ondersteijn, Kooten, & Oude Lansink, 2006). However, unlike traditional supply chains, planning agricultural production and distribution is hindered by the limited shelf life of products, variable yields, variable market prices (Makeham & Malcolm, 1993) and the long lead times from planting until the time of harvest (Lowe & Preckel, 2004). All of these issues, create a complex and risky planning environment (Fleisher, 1990). Moreover, within ASCs, specialty horticultural products are the most susceptible to disturbances in supply; this is because, in addition to all of the aforementioned issues, these ASCs must also deal with food quality, safety and higher weather related variability (Salin, 1998). Thus, the focus of this dissertation is on ASCs of highly perishable crops, as these are likely to reap the most benefits from increased coordination.

Since the problem at hand is complex, we focus here on a critical element of the modern fresh supply chain--the interface between the farmer and the first marketing echelon of the fresh supply chain, which usually takes the form of a consolidation/packing facility (CF). We assume that this CF is structured as a farming cooperative (co-op) that is in charge of the marketing and distribution of the products and which must assign production contracts to the various farmers. Furthermore, we focus our attention on tactical planning (developing a planting plan for the upcoming season), rather than strategic and operational issues, which are generally less problematic from the cooperation standpoint.

In order to consolidate and coordinate production, considering all aforementioned issues is paramount; however, a new layer of complexity is added if production decisions

must be made without complete visibility of all components of the system. In practice, an enterprise seeking to coordinate production among multiple farmers cannot know with certainty what the comparative advantages (and disadvantages) of the growers it seeks to coordinate are. To overcome this issue and gain efficiencies, centralized supply-chain control is ideal; however, this is neither feasible nor practical in most cases. On the other hand, decentralized coordination becomes a significant challenge due to concerns of fair contract allocation, internal competition and sharing of private information (Karina, Bamber, & Gereffi, 2012).

Table 1.1 – Conflicting Objectives between Farmers and the Consolidation Facility

	<b>Farmer</b>	<b>Consolidation Facility</b>
<b>Operations</b>	<ul style="list-style-type: none"> <li>• Growing a set of crops and selling them to the food hub or open market</li> </ul>	<ul style="list-style-type: none"> <li>• Consolidating crops from farmers and selling products to retailers</li> </ul>
<b>Objective</b>	<ul style="list-style-type: none"> <li>• Making the best planting allocation such that costs and risk are minimized and income is maximized</li> </ul>	<ul style="list-style-type: none"> <li>• Maximizing profit by matching supply and demand with efficient sourcing and marketing</li> </ul>
<b>Decision Variables</b>	<ul style="list-style-type: none"> <li>• <i>Planting, harvesting and resource usage</i></li> </ul>	<ul style="list-style-type: none"> <li>• <i>Purchasing, storing and marketing of crops</i></li> </ul>
<b>Constraints</b>	<ul style="list-style-type: none"> <li>• Land, labor, capital and climate</li> </ul>	<ul style="list-style-type: none"> <li>• Supply, demand and available infrastructure</li> </ul>
<b>Conflicting Objectives</b>	<ul style="list-style-type: none"> <li>• Obtaining best prices for its crops</li> <li>• Planting most profitable sets of crops</li> <li>• Influencing food hub decisions</li> </ul>	<ul style="list-style-type: none"> <li>• Giving fair prices and contracts to growers</li> <li>• Obtaining highest profit from selling crops</li> <li>• Efficient contract allocation</li> </ul>
<b>Risk Exposure</b>	<ul style="list-style-type: none"> <li>• Exposed to high risk from variable yields and market prices</li> </ul>	<ul style="list-style-type: none"> <li>• Can pool risk of yields across suppliers</li> <li>• Can mitigate price risk through storage and higher bargaining power</li> </ul>

If we take the perspective of an enterprise seeking to coordinate multiple farmers, access to information is critical; unfortunately, farmers are unlikely to reveal their complete and true information, as such actions could result in a weakening of their own positions.

Therefore, as part of the research, we must view the coordination problem from its two main perspectives: (1) The perspective of a farmer and (2) the perspective of the CF. We must also recognize that conflictive objectives will exist due to the two perspectives being considered; some of these conflicting are illustrated in Table 1.1 above.

### 1.3 Research Contribution

For over 50 years, decision support tools and optimization models have aided decision making in agriculture (Glen, 1987). Nonetheless, there still exists a lack of research on optimization models for production and supply chain planning of perishable crops (Ahumada & Villalobos, 2009a). Most models for agricultural planning have a limited scope, and fail to capture all relevant features from these complex systems (A. J. Higgins et al., 2009); these missed features include a variety of simultaneous decisions and objectives for all competing and collaborating participants.

The fresh produce planning problem, from the single farmer's perspective with centralized control of production and distribution, has been addressed by Ahumada & Villalobos (2009a, 2009b) and Ahumada, Villalobos, & Mason (2012). Building on previous efforts, this research goes further by developing coordination models that take into consideration the needs and actions of the different actors in the supply chain, without compromising assumptions of independent decision-making; thus, the analytical results are much more relevant and applicable to real world decentralized decision problems.

Our first research contribution is a direct enhancement of planning tools for the coordination of the agricultural supply chains. This mainly includes capturing key interactions between growers and buyers, and as a result, extending the scope of traditional models into various echelons of the supply chain. Moreover, the proposed research

develops more realistic models by better approximating the dynamics of the agricultural supply chain and considering game theoretic aspects of the decision-making process.

Our research also advances the knowledge of the scientific community in various fields. First and foremost, it provides an analytical decision-making framework for the planning and coordination of farmers working as a group. We contribute, additionally, to horizontal coordination research using auction mechanisms when no single party has all relevant production information; this is a problem of great relevance, not only in agriculture, but also other industries. Furthermore, this research increases our understanding of auctions as coordination tools and the design considerations that allow them to work effectively, despite deviation from the ideal information sharing assumptions. Finally, our research analyzes the consequences of production yield-risk on agricultural cooperatives, and the additional challenges it poses for coordination and supply contract fulfillment.

#### 1.4 Benefits of the Research

This research provides better tools for small and medium size farms to collectively market their products. Currently, large farming operations tend to dominate the business because they can better withstand the large swings in market prices, as well as use economies of scale to their advantage. Having access to efficient tools for planning and collaboration will put the individual farmers on a more level playing field. However, the ultimate beneficiary of the proposed research would be the final consumer of fresh produce, since a more efficient participation of the small and medium farmers will result in reduced food waste and more stable, lower prices for the general population.

This research also provides more robust and realistic models which can be implemented in practice. The models developed are grounded in economic theory and designed to be robust against deviations from the ideal behavior of the members of the supply chain. For instance, even if farmers attempt to strategically misrepresent their information, the auction mechanism still allows the greater system to reach coordinated and efficient outcomes. This presents a major advance on current agricultural planning models, which fail to represent the true dynamics of the system.

Finally, to the best of our knowledge, this is the first decentralized coordination mechanism to be implemented at the producer level in an ASC. Moreover, the research is also groundbreaking on the introduction of iterative auction mechanisms as viable coordination tools for ASC's; this advance highlights the importance of broader disciplines such as mechanism design to the coordination of supply chains.

## 1.5 Thesis Overview

The remainder of this doctoral dissertation is structured as follows: In Chapter 2, we present a brief description of the related literature on coordination tools in supply chains and their application to ASCs; we also analyze the literature on mechanism design and bidding problems to create a context for our proposed mechanism. In Chapter 3, we detail the methodology for the research activities and the outcomes of the dissertation. In Chapter 4, we develop the mathematical models for tactical planning under centralized and decentralized supply chain management; we show that the decentralized model can be formulated as an auction and be made to converge to the centralized solution. In Chapter 5 we identify the weaknesses and failure points of the auction used for tactical coordination. We focus on the decision problem of bidders acting strategically and not revealing truthful

information to the consolidation facility, at the expense of system wide profits; thus, changes on the mechanism structure are made to address this problem. As a continuation to the design approach, in Chapter 6 we address the problem of maintaining coordinated outcomes in the presence of stochastic yields. In this chapter, we resume our analysis assuming that production assignments have been made through the auction mechanism and focus on the farmer decision of how much to plant in order to fulfill his/her commitments. In Chapter 7, we provide an extension to our research--exploring the information contained in the bids for production placed by farmers; here we are concerned on the potential inferences that can be made about the various farmers based on their behavior throughout the auction. Finally, in Chapter 8, we provide a brief summary of the dissertation results and discuss opportunities for future research.

## 2 LITERATURE REVIEW

Developing a coordination mechanism for an agricultural cooperative business model is a task with higher complexity than the usual problems recognized in agricultural planning. Addressing this problem requires expanding the scope of the problem beyond production and into the supply chain context. As a result the problem has to be addressed from multiple perspectives simultaneously; mainly from a production perspective, as well as marketing and consolidation. Moreover, if we consider the conflicting objectives between the supply chain integrants, then we must combine the disciplines of supply chain management, agricultural planning, optimization, game theory and the theory behind mechanism design and coordination.

As a result, the current literature review addresses the coordination problem from the perspective of agriculture, as well as supply chain management and mechanism design. Specifically, the review starts by addressing the research that has been done for supply chain optimization models with a focus on agriculture; for that we focus only on agricultural planning problems which involve more than one echelon in the supply chain (Section 2.1). Thereafter, we look exclusively at coordination mechanisms in supply chain management, focusing on horizontal coordination and multilateral information asymmetry (Section 2.2). Additionally, we draw on basic research and relevant findings from the mechanism design field and the general intuition and modeling tools that can be applied to agricultural coordination problems (Section 2.3). Finally, in Section 2.4, we draw conclusions and from our review and identify the gaps in research which we fill throughout this dissertation.



## 2.1 Management of ASCs

Numerous operations research models for agriculture and agricultural supply chains exist in the literature starting with (Glen, 1987; Lowe & Preckel, 2004). These reviews cover decision models for agricultural planning, which date back to 1954, where most of the focus lies on models of a limited scope for small sections of the overall supply chain. Later, a compilation of a broader scope focusing on strategic decisions was compiled by Lucas & Chhajed (2004), who focus on location analysis in agriculture.

A more detailed compilation of optimization models focused primarily on agricultural supply chains was later provided by Ahumada & Villalobos (2009a), who provide the most comprehensive compilation focused in ASC planning. In this publication, ASC models are catalogued according to their scope as strategic, tactical and operational; furthermore, they are also organized further by their focus on perishable or non-perishable items. Thereafter, Zhang & Wilhelm (2009) compiled a review with a more specific focus on optimization models for specialty crops. Both reviews conclude that supply chain management is becoming increasingly important for the fresh produce industry; yet insufficient attention is devoted to this emerging field. Finally, on a more recent review, Manish Shukla & Sanjay Jharkharia (2013) highlight the increased emphasis on fresh produce supply chain management and the difficulties of the industry on matching supply and demand. They emphasize the importance of information and collaborative forecasting across the supply chain; however, they fail to address the game-theoretic aspects of information sharing and seeking coordinated outcomes.

Information sharing is important for achieving coordinated outcomes, and more recent case studies address coordination issues in agricultural supply chains, ranking

information sharing as the number one enabler of collaboration (Bahinipati, 2014). Moreover, optimizing ASCs requires an expanded scope and a significant increase in modeling efforts. For this new challenging context, it is not enough to optimize individual parts of this complex system, but rather we must take the extended supply chain into account (A. J. Higgins et al., 2009). Unfortunately, to do this, information sharing is not sufficient due to the complex, interdependent and competitive nature of supply chain participants. In supply chain management, we usually have conflicting objectives that must be addressed when modeling the interactions among supply chain participants (which we will refer to interchangeably as “agents”). Specifically, we must account for the key factors of competitive behavior and information asymmetry, which compromise the primary assumptions behind information sharing. This is a reality not only for agriculture, but also for any other supply chains (Albrecht, 2010).

Although models for supply chain management in agriculture are well documented (Ahumada & Villalobos, 2009a; Zhang & Wilhelm, 2009), we take a more selective approach and review the more relevant models for supply chain coordination. This implies looking at models that observe more than supply chain echelon and which attempt to reach an optimal solution for the extended system. For this, we separate our findings into three main categories according to their scope: (1) Interactions and coordination policies between partners, (2) centralized optimization of supply chains and (3) extended supply chain modeling with stand-alone models for each participant. We will briefly discuss and give examples of research on each of these categories.

### 2.1.1 Direct Interactions and Coordination Policies

These models have a limited scope and generally seek analytical solutions between only two entities; their value stems from deriving valuable intuition and frameworks in which conflicting interests can be addressed. Formulations are similar to the newsvendor problem for supply chains, but using applications specific to agriculture. Some examples include: Analysis of cost sharing contracts, which have the objective of ensuring proper ripeness of fruits at the retail level, maximizing customer satisfaction and revenues (Schepers & Van Kooten, 2006); and similar problems with the addition of freshness keeping efforts (Cai, Chen, Xiao, & Xu, 2010). Likewise, we find applications such as using of bonus/penalty contracts to reduce costs of returns from spoiled goods (Burer et al. 2008). Similarly, we find the use of vendor managed inventory with stochastic demand of perishable goods to improve financial performance of a retailer and a producer who must plan ahead of the growing season (Lodree Jr. & Uzochukwu, 2008). In another case study, Nadia Lehoux (2014) modeled the decision process for collaborative planning, forecasting and replenishment (CPFR) and its impact on the profitability of the forest industry; in this research an incentive system is devised to share the benefits between partners to ensure collaboration.

Another field to which much attention has been devoted is that of contract farming and its direct impact on risk (for growers and retailers). In this research topic, Huh & Lall (2013) quantify the impact of contract farming on production decisions for a given farmer when he/she must deal with stochastic yields; likewise, Wang & Chen (2013) consider the case coordination with options contracts but with deterministic yields. Finally, Huh et al.

(2012) show that a contract farming policy with possible renegeing by producers may, under some circumstances, increase the profits of the retailer when producers are risk neutral.

### 2.1.2 Centralized Optimization Models

These models analyze optimization problems spanning multiple echelons and time periods. They do not consider interactions among agents or separate the objectives from each echelon, but rather assume centralized control by one single planner. For instance, handling, processing and distribution of perishable goods assuming full control of all operations throughout the supply chain was done by Gigler et. al (2002). Other models such as (Ahumada & Villalobos, 2009b, 2011; Ahumada et al., 2012; Kazaz, 2004; Kazaz & Webster, 2011; Rantala, 2004; Widodo, Nagasawa, Morizawa, & Ota, 2006; Wishon et al., 2015) model similar centralized decisions for more than one echelon, with their contributions varying from perishability modeling, to plant location and production planning. These models are generally tactical in nature, and their inclusion of multiple echelons simultaneously make them of particular relevance to our research.

### 2.1.3 Extended (Multiple Agent) Supply Chain Models

For this category of research, the scope is generally wider than that of the previous two categories, with considerations of large systems spanning several echelons and several stakeholders; in these models, each echelon has its own independent optimization model. These decentralized models, due to their complexity, must resort to metaheuristics to coordinate the actions of the various independent stakeholders. Some examples include the use genetic algorithms to coordinate 8 separate supply chain component models (Dharma & Arkeman, 2010). Other articles, in turn, use methods such as agent based simulation in order to obtain a solution. For instance, Higgins et al. (2004) used agent based simulation

to link stand-alone models for harvesting, transportation and machinery selection in the sugar mill industry. Similar research, where separate models are analyzed simultaneously was done by Frayret et al. (2008). Unfortunately, in these extended models, what is gained from an increased scope is lost in the capability of deriving analytical insights.

Each of the aforementioned modeling approaches has its virtues, either by accounting for private information, conflicting objectives, explicitly analyzing collaboration, or by making comprehensive assessments of sections of the supply chain. However, there are significant opportunities for improvement by combining virtues from these categories. A model that assumes that each supply chain agent will have a private decision model is desirable; but also, such a model must be capable of providing results of analytical value without compromising assumptions of independence and self-interested behavior.

We note that a common theme across all research categories is that of vertical coordination. Here, the objective is generally to coordinate the actions of one echelon with the next (i.e. supplier-retailer). However, little emphasis is placed on horizontal coordination, where the problem is to coordinate the actions of several players that provide similar products/services. In horizontal coordination, the potential for improvement is equally attractive, but the focus is on collaborating competitors. The lack of research in this area creates an opportunity and derive results of significant value for agricultural planning. In particular, research in horizontal coordination may be fruitful to small and medium enterprises, which can benefit the most from collaboration.

## 2.2 Supply Chain Coordination Literature

Although the topic of supply chain management has been researched in ASCs, it still lags behind from research for traditional manufacturing supply chains. In recent years, as

the business environment became more competitive, manufacturing firms were forced to seek improvements outside of their own borders (Christopher, 2005). This ongoing tendency converted supply chain management into a rapidly emerging field. Ultimately, what used to be improvement within a firm has evolved into improvement for the supply chain as a whole, taking competition to the enterprise level (Stadtler, 2008).

Collaboration within a supply chain has been proven to provide competitive advantages to all involved parties both empirically and theoretically; in particular, models of collaboration such as the Efficient Customer Response movement (ECR) or the Collaborative Planning, Forecasting and Replenishment (CFPR) introduced by Wal-Mart have been prominent (Skjoett-Larsen, Thernøe, & Andresen, 2003). As a result, it is worthwhile to analyze how firms are able to collaborate and achieve coordinated outcomes such that similar success stories can be created in agricultural supply chains.

### 2.2.1 Coordination

Because supply chain management deals with multiple firms, one central theme is how to coordinate these various players and overcome difficulties presented by their conflicting objectives. Here, it is central to understand what is meant by coordination. To this end we say that a supply chain is coordinated if, as compared to a baseline performance measure, applying a set of rules results in a tangible positive change (Albrecht, 2010).

Such rules can be simple guidelines such as information sharing, or they can be more involved economic incentives. For instance, sharing information is a simple and intuitive measure, and it has been proven to play a significant role in reducing the bullwhip effect (H. L. Lee, Padmanabhan, & Whang, 1997), as well as other improvements in supply chain efficiency. However, there exist other more sophisticated approaches to coordinate supply

chains including buyback, revenue sharing and options contracts (Simchi-Levi, Kaminsky, & Simchi-Levi, 2003). These more sophisticated approaches use economic decisionmaking and don't necessarily rely on assumptions of reliable information being shared; for instance, buyback contracts operate by reducing the risk for a retailer, thus creating an economic incentive to order additional units (Simchi-Levi et al., 2003).

Among the set of tools which can be utilized to coordinate a supply chain, we focus our attention on a specific type: coordination mechanisms, which we define as:

*“A set of rules which, when enforced, create a game for which the implementation of the optimal strategies by decentralized, self-interested parties may lead to an improved outcome and neither violates individual rationality nor budget balance for the participating parties”* (Albrecht, 2010).

In the context of the previous definition, we find two relevant concepts: **Individual rationality (IR)**, defined as allowing agents to participate without obligation, expecting to gain something from participating in the game (Sandholm, 1999); and **budget balance (BB)**, meaning that the mechanism requires no external subsidies to be implemented (Chu & Shen, 2006).

In other words a mechanism indirectly shapes the behavior of various agents through incentives. Under this framework, the actions of supply chain participants are not explicitly dictated or imposed by the mechanism; but rather, the mechanism provides an environment that shapes the strategies and the decisions made by profit-maximizing agents. Here, we fall within the field of cooperative game theory, where a coordination mechanism is one which implements a Bayesian game for which the Nash Equilibrium coordinates the system; where Nash Equilibrium is a state in which all players act strategically and no player stands to gain by changing their strategy (Cachon & Lariviere, 2005).

### 2.2.2 Difficulties of Horizontal Coordination

As stated earlier, a basic tool for coordination is information sharing, which allows parties throughout the supply chain to improve overall system efficiency. This simple observation highlights the importance of transparent information in a supply chain. Unfortunately, even when information is shared, concerns may arise regarding the veracity of the information. For instance, if supply is uncertain, some players may overstate their demand in order to secure supply later in time; this would create a rationing game where demand forecasts can no longer be trusted (H. L. Lee et al., 1997). This is a clear example that, although information sharing is necessary, it may not be sufficient to achieve a coordinated outcome.

Although the aforementioned problem is in the context of vertical coordination, the problems relating to information sharing are no less relevant for the horizontal coordination problem. However, the main difference when dealing with horizontal coordination is not demand uncertainty, but rather the uncertainty on the comparative advantages and disadvantages of the firms being coordinated. This arises from the fact that, when you seek to coordinate horizontally, you may need to work with your direct competitors. Under this setting, supply chain participants may be reluctant to share their true information as revealing information to their competitors may weaken their own competitive positions. This creates a game theoretic problem; specifically, it is a problem of cooperative game theory with multilateral information asymmetry (Albrecht, 2010; Cachon & Lariviere, 2005; F. Chen, 2003).

We thus observe that a key factor in cooperative games, and in particular for the firm coordination problem, is guaranteeing the veracity of information provided. Unfortunately,



self-interested behavior and strategic thinking may lead participants to misrepresent their true costs; therefore, unless truthful revelation is in the best interest of each individual participant, the mechanism outcome may be a failure. Thus, we introduce two new concepts which will be central to our analysis: **Incentive compatibility (IC)**, which is the property of a mechanism to elicit truthful information by making it a dominant strategy to bid ones true valuation<sup>1</sup> (Myerson, 1981). And we also define **efficiency** as the property of allocating goods to the parties which value them the most such that the overall system utility is maximized.

In the remainder of this section, we analyze some of the coordination mechanisms which are of interest to us. It is worthwhile to note that the set of all possible coordination mechanisms is very broad and varied. For a thorough review of various supply chain coordination mechanisms we refer the reader to (Albrecht, 2010). Hereafter, we focus on a reduced set of all coordination mechanisms; those designed to facilitate the efficient allocation of goods under a multilateral information asymmetry, where each player knows its own valuations but is uncertain on the valuations of all its competitors. These mechanisms are generally structured as simple auctions, or iterative multiunit auctions.

### 2.2.3 Coordination Mechanisms for the Procurement of Goods

When a transaction must be carried out and goods have to be moved along the supply chain, many times it is necessary to assign a value to these items. Generally, we can assume that prices are given by the market and that buyers simply take prices as given. However,

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<sup>1</sup> We treat “valuations” and “goods” as general concepts, where they could be the typical perspective for how much an agent may be willing to pay for a specific item; but it could also be a production contract which some agent may be willing to sign given its own production costs and the expected revenue from the contract.

at times when these prices are unknown, a mechanism is necessary. This problem was addressed by Vickrey (1961), who analyzed the dynamics of various auction formats and whose findings became the centerpiece to modern auction theory.

In supply chain management, it is not uncommon to see the implementation procurement auctions (where suppliers compete against each other on the price of their bids) for maximizing the profit of the buyer, or to better utilize the resources of the supply chain. Auctions are generally emphasized in these problems because they have a rich theoretical backing and their mathematical structure makes them suitable for application in operations research. In particular, implementing auctions generally gives a good basis to make decisions where optimality can be strived for. We will briefly detail some cases where auctions or other mechanisms are used in a supply chain context.

#### 2.2.3.1 Single Product Type

Some of the research on auctions has been done in procurement auctions for a single type of item; for instance (Chen, 2007) proposes an auction mechanism for supply contracts in when suppliers compete with one another and must make newsvendor-like decisions. Likewise, Chen et al. (2005) proposed the use of auctions which include transport costs on suppliers bids; this internalizes the costs and increases the efficiency of procurement. These are straightforward procurement auctions, where the products being auctioned are of a single type.

#### 2.2.3.2 Multiple Product Types

The most interesting research in supply chain coordination occurs with auctions for multiple goods. Here, valuations for one good are no longer independent of the valuation for another good; moreover, one addition that greatly enriches the problem of coordination

is when suppliers have limited capacity, which must be allocated between multiple types of items. This consideration creates interdependence between suppliers and emphasizes the need for coordination. In particular, unlike procurement auctions for a single product, when capacity restrictions are added the auction cannot be efficiently solved in a single round and an iterative approach must be formulated. For instance, Gallien & Wein (2005) use discrete bidding and allocation rounds in order to properly account for the capacity of the bottleneck resource. Likewise, new variants of auctions for multiple products have been implemented by Mishra & Veeramani (2007), who use an auction with strictly increasing prices.

#### 2.2.3.3 Multiple Product Types with Extended Constraints

If in addition to multiple products types and capacity constraints we include more variables (such as a time component, inventories and production schedules), then the coordination problems become increasingly multidimensional and efficiency becomes even elusive. Due to their size and scope, mechanisms for these problems must emphasize on rapid convergence to a good solution. Due to their complexity, decomposition methods are many times utilized to model these detailed problems (Albrecht, 2010).

For the research done in this area, the focus is finding an efficient solution fast and through means of automatic negotiations; therefore, not all methods are structured as auctions. For instance, Arikapuram & Veeramani (2004) use the L-shaped method as a way to quickly link a distributed supply chain, where each integrant solves its sub-problems and communicates its constraints. Similarly, Dudek & Stadtler (2005, 2007) propose a negotiation based mechanism to coordinate a supply chain, contrasting the negotiation approach with simple upstream communication of forecasts.

In this setting, auctions modeled through dual decomposition have the greatest prominence. Some implementations include Ertogral & Wu (2000), who solved a lot sizing problem for multiple facilities using an auction mechanism; likewise, Kutanoglu & Wu (1999) used an auction mechanism for a scheduling application. In a later implementation, Karabuk & Wu, (2002) solved a decentralized resource capacity allocation problem on the semiconductor industry using an auction mechanism; the main contribution was the addition of a quadratic term to account for uncertainty in the problem.

Unfortunately, when developing approaches to coordinate the supply chain, implementing a mechanism is often insufficient, as agents may act strategically and compromise the efficiency of the system. Among few examples of research that explicitly address incentive compatibility we have Guo, Koehler, & Whinston (2007). They designed a mechanism where a centralized auctioneer facilitates bidding and resource exchanges to determine market clearing prices for multiple goods; in this research, a claim is made that the mechanism is robust to cheating by analyzing computational results. Likewise, Fan et al. (2003) designed an auction mechanism to allocate bundles of items through a double auction; in their research, analytical results are provided to argue the incentive compatibility of the proposed mechanism.

### 2.3 Mechanism Design and its Role on Coordination

It is our aim, by immersing ourselves in the mechanism design theory, to better understand the important design considerations required to create a mechanism for the coordination of agricultural production. Mainly, we seek to understand what a mechanism can achieve under this setting and what factors will determine a successful implementation.

We start by mentioning some of the most important results in mechanism design, followed by an analysis of the context in which we address our coordination problem.

### 2.3.1 Overview of Mechanism Design and Auctions

In mechanism design, we start from the seminal paper by Vickrey (1961), who proposed a sealed bid auction where the highest bidder gets the item but pays the price of the second highest bid; it results that this mechanism is both incentive compatible and maximizes revenue for the seller. Moreover, Vickrey generalized this result stating that for an auction where bidders state their demand schedules for all possible quantities, and where the winner pays the lowest possible winning bid, it is in the best interest of bidders to state their true valuations.

Thereafter, the results of Vickrey were further generalized by Clarke (1971) and Groves (1973), which gave birth to the “Vickrey-Clarke-Groves (VCG) mechanism.” In their generalization, they stated that for a mechanism in which bids are submitted for all possible combinations of goods and where the payments are as in the Vickrey auction, it is still a dominant strategy for bidders to state their true valuations. This gave birth to a theoretically interesting, yet highly impractical mechanism: The combinatorial auction. In brief, for small subsets of items, bidders would be able to place bids for all possible combinations; however, as the quantity of items grows, the combinatorial nature of the problem makes this computation prohibitively complex.

Mechanism design theory was advanced with contributions by Myerson (1981) who further characterized incentive compatibility in mechanisms, revenue equivalence of the four basic auctions and particularly, the Revelation Principle, which states that “Given any feasible auction mechanism, there exists an equivalent feasible direct revelation

mechanism which gives to the seller and all bidders the same expected utilities as in the given [indirect] mechanism” (Myerson, 1981). Thus, there is no loss of generality from considering only direct revelation mechanisms<sup>2</sup>.

The combination of the VCG mechanism and the revelation principle were thought to be a solution to the allocation problem, effectively reducing it to a computational, rather than an economic problem (Ausubel & Cramton, 2004). This gave rise to significant research on combinatorial auctions, their computational complications, the incentives created by the auctions and ways to design them to be effective. Further details for combinatorial auctions and their design can be found in the review by (De Vries & Vohra, 2003). However, among the problems of dealing with a VCG mechanism we have issues such as susceptibility to shill bidding<sup>3</sup>, collusion<sup>4</sup> and pathologies which can cause revenue to the seller to be zero (Ausubel & Milgrom, 2002); moreover, we also have the computational difficulties both for the bidders and the seller to determine values for packages as well as the winner determination respectively.

Because very often it is prohibitively difficult to have a valuation for all possible bundles of goods, it is desirable to opt for an indirect mechanism instead of a direct revelation mechanism. The benefit is that agents remain in a solution space which is relevant for their valuations, thus drastically reducing complexity (Mishra & Parkes, 2007; Parkes & Kalagnanam, 2005). If the idea of computing valuations for many bundles is

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<sup>2</sup> A direct revelation mechanism is one in which the bidders simultaneously and confidentially announce their value estimates to the seller; and the seller then determines who gets the object and how much each bidder must pay. This is done in a single bidding round.

An indirect mechanism in the other hand, will implement the outcome in several bidding rounds.

<sup>3</sup> To have a partner, acquaintance, friend or family bid on an item which is being sold in order to artificially raise the price of the item

<sup>4</sup> Working with other bidders to artificially lower the price of goods being purchased

taken to its extreme, we can relate the formulation of combinatorial auctions to that of auctioning infinitely divisible goods (Ausubel & Cramton, 2004).

### 2.3.2 Pragmatic Mechanism Design and the Coordination Problem

We find that applying a mechanism in an industrial setting is a task where multiple considerations must be taken into account. General theoretical solutions, albeit important, have to be translated into practice to achieve the greatest impact. In that sense, it is necessary for concepts from mechanism design to move from the theoretical to the practical without getting encumbered when basic assumptions are not met.

We must begin to see mechanisms as an engineering tool which can be applied in many situations, each with its own nuances and requirements (Roth, 2002). Moreover, we must not be dissuaded from using a mechanism when it fails to meet the stringent requirements of IC, BB, IR and efficiency; mechanism design can in many settings take an evolutionary approach, where the mechanism is refined and perfected as bidders simultaneously develop their sophistication (Phelps, McBurney, & Parsons, 2009). Thus, in this section we seek to build a framework for bridging the gap between the economic theory and the desired implementation of a coordination mechanism. We use this intuition to apply mechanism design to the agricultural horizontal coordination problem.

In the coordination problem, we can exploit the fact that we have self-interested individuals seeking to maximize some utility function. This means that a mechanism which efficiently allocates a set of continuous goods can be modeled as an optimization problem; and in particular, it may be modeled as a linear program (LP), which can be solved through primal or dual decomposition in an auction-like format (Albrecht, 2010; Vohra, 2011).

Therefore, we can rely on theoretical backing to appropriately design a mathematical model that implements the required coordination mechanism as an iterative auction.

Unfortunately, except on the most trivial cases, auctions are complex multi-agent systems which require extensive game-theoretical analysis; they may not be amenable to exact solutions nor guarantee efficiency (Tesauro & Bredin, 2002). In order to implement a mechanism successfully, we need to properly analyze it in its wider context and directly address the most relevant roadblocks. For the farm coordination problem specifically, we can deduce that an indirect mechanism is required (i.e. an iterative auction). This mechanism, if allowed to continue for sufficient bidding iterations, should converge to the optimum (Ausubel & Cramton, 2004); however, in most real world cases this is not possible as bidders are only willing to commit a limited amount of time and effort to reaching a solution. This requirement will cause the number of iterations to be generally fewer than needed; in turn, this may reduce efficiency both from a computational standpoint as well as induce gaming behavior on the bidding process (Ausubel & Cramton, 2004; Conen & Sandholm, 2001; Parkes & Ungar, 2000b). This strategic behavior from the bidders cannot be ignored, as its impact may be significant (Shen & Su, 2007); therefore, we must model and understand the strategic bidding problem independently.

#### 2.4 Conclusion and Recommendations for Research

From the review of the literature, we find that several models have been designed for supply chain coordination under multilateral information asymmetry; however, none have been proposed in agriculture; this is particularly true for auction mechanisms. Although auctions have been used in agriculture for purchasing goods and establishing market prices once the product is available, the use of auctions to coordinate agricultural planting and



harvesting of crops will be the first of its kind. As such, the implementation of these models would be highly valuable as a means to establish efficient production plans before the growing and harvesting season.

We also find that in agriculture the topic of supply chain coordination has been explored mostly from the perspective of contract driven vertical coordination. This perspective, although useful, grossly ignores a significant problem in agriculture: coordinating multiple small, heterogeneous and interdependent producers. Even when risk is reduced through contracted prices for crops, the coordination benefits may be insufficient. Thus, a mechanism which gives growers more flexibility to reach collaborative solutions will provide valuable improvements to the overall industry and in particular to the smaller producers. We argue that tools for horizontal rather than vertical coordination are of great importance, and their benefits can be numerous for producers and consumers alike.

We also note that little research has been done for coordination mechanisms which also account for incentive compatibility. In our literature review we only find two examples which analyze mechanisms which are effective even under strategic behavior of bidders. Therefore, this dissertation fills another gap in research by explicitly considering the possibility of bidders behaving strategically for their own advantage. We develop a mechanism which exploits the structure of the problem from the consolidation facility point of view; this mechanism minimizes the incentives for agents to misrepresent their information. Here, the decision process of bidders is modeled as a dynamic program and the optimal strategic bid is found; thereafter, the mechanism is designed to minimize the differences between the truthful and strategic bids placed by farmers. This simultaneous

analysis of efficiency and incentive compatibility is performed through the use of mathematical modeling and computational results alike.

Finally, the proposed research seeks to develop tools for risk reduction caused by the stochastic nature of yields. It was found that contract farming and supply chain coordination problems with stochastic yields are just beginning to take hold in agricultural planning. As a result, little research exists on the problem of coordination with stochastic yields. Furthermore, the results of this planning problem will be of great value for creating robust coordination mechanisms which can optimize contracts assignments as well as minimize yield risk for the consolidation facility and farmers alike.

### 3 METHODOLOGY

#### 3.1 Planning Process for Growers and Consolidation Facilities

The focus of our research is to improve the decision-making capabilities of farmers and the extended supply chain of which they are part of. In particular, we want to improve the competitiveness of agricultural cooperatives composed of farmers and a consolidation facility (CF) by working on the coordination aspects of these associations. These cooperatives require extensive planning and communication at the operational, tactical and strategic level. However, for the purposes of this research we focus on tactical planning, as season plans are the most likely to benefit from a coordinated approach.

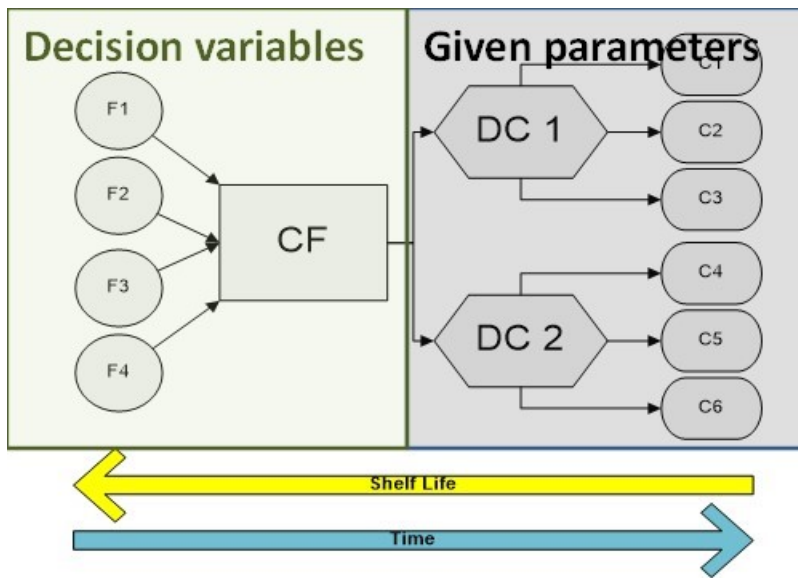


Figure 3.1 – Scope of the Proposed Supply Chain Model

We assume that there is a single consolidation facility, which sources product from a variety of growers. These growers have varying product offerings, production costs and resources available. The role of the consolidation facility is to observe downstream demand and to translate it into a procurement plan for the rest of the season. This procurement plan must be made in conjunction with growers such that an optimal outcome for the overall

system is obtained. The remainder of the supply chain is not considered, and its impact on the consolidation facility is reflected through a known and deterministic demand for the season (Figure 3.1).

In the following sections we briefly detail the planning process for growers, the CF and for the combined system attempting to reach an optimal allocation.

### 3.1.1 Grower

Production planning for the entire season is a critical activity for farmers of fresh produce. During the planning (pre-season) phase a blueprint for the expected harvest generally exists before any planting is done. These plans encompass tactical decisions on how much land to use, the varieties to plant and the timing of planting, and are of great importance as they dictate the outcomes of each subsequent stage in the season (Ahumada & Villalobos, 2009b). Furthermore, all subsequent stages (planting, growing and harvesting) require varying amounts of resources (such as labor, fertilizers, insecticides) and generate an expected amount of revenue, which must be accounted for when making the full season plan. Moreover, due to the long production lead times inherent to agriculture, the expectation of future crop yields and market prices plays a crucial role in making decisions before planting (Figure 3.2).

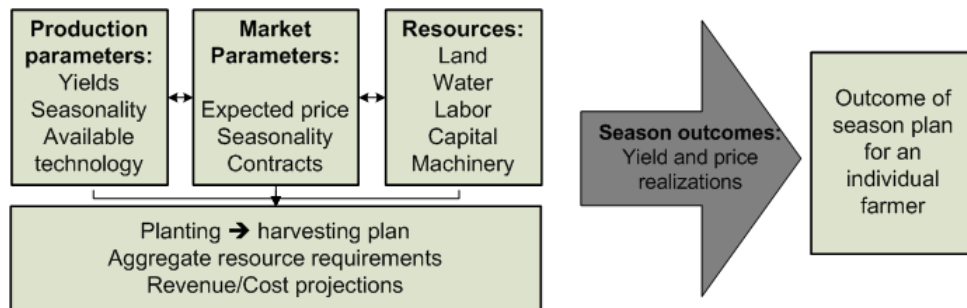


Figure 3.2 – Relevant Factors to the Farmers’ Planning Problem

To illustrate some of the information used by farmers to estimate their production quantities given their cost parameters and their goals, we present Table 3.1. Here we illustrate how the expected dates of harvest, the length of the harvest season and the expected yields vary as a function of the planting date. This is one of the central pieces of information used by farmers to plan for the season. With production and other market information, it is possible to make initial plans for the amount of each crop to plant and their planting dates in order to cover the market’s demand for the season.

Table 3.1 – Production Estimates of a Tomato Crop as a Function of Planting Periods

		Harvest by week																													
		November				December				January				February				March				April				May					
Date of Plant	Production	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4		
15-Aug	1,662			5	5	10	10	10	10	9	9	8	8	8	8																
30-Aug	1,828					5	5	10	10	10	10	9	9	8	8	8	8														
14-Sep	2,373					5	5	6	10	10	10	10	10	9	9	8	8														
29-Sep	2,564									5	5	10	10	10	10	9	9	8	8	8	8										
14-Oct	2,698											5	5	10	10	10	10	9	9	8	8	8	8								
29-Oct	2,684											5	5	10	10	10	10	9	9	8	8	8	8								
13-Nov	2,896													5	5	10	10	10	10	9	9	8	8	8	8						
28-Nov	2,837															5	5	10	10	10	10	10	9	9	8	8	8	8	8		
13-Dec	2,337															5	5	10	10	10	10	10	9	9	8	8	8	8	8		
28-Dec	2,183																	5	6	10	20	22	10	8	7	6	6				
12-Jan	1,794																					4	5	10	15	22	10	9	9	8	8

In the case of a single crop, planning for a full season may seem straightforward; however, note that the difficulty increases significantly if a farmer produces multiple crops. Depending on the expected yields and harvest dates, different amounts of land and labor are required throughout the season, making some planting schedules inherently better than others. To illustrate the impact of varying parameters on crop allocation, we show a sensitivity analysis for varying scenarios of labor availability (Figure 3.3). Here we observe that as labor becomes scarce, farmers seek to plant broccoli, cauliflower and iceberg lettuce as opposed to the more labor intensive romaine lettuce (Wishon et al., 2015). This shows the influence of external factors on the decisions of a single grower. As more factors add up, this multidimensional problem becomes exponentially hard for growers to solve.

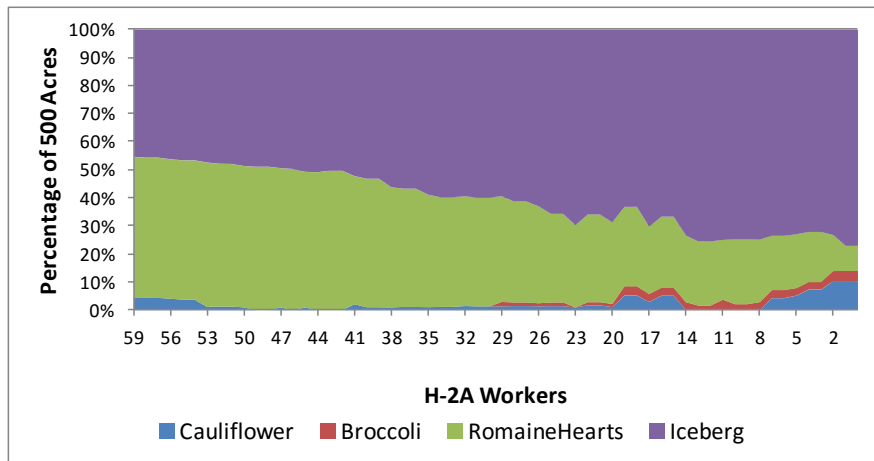


Figure 3.3 – Labor Sensitivity of Specialty Crops to Worker Availability

Ultimately, one of the main parameters which influences the decisions of farmers is price (or expected price) for its crops. In particular, if a price is negotiated through supply contracts or if a price is expected from the open market, farmers can use this information to make their plans for the upcoming season. This discussion on purchase prices leads us to our next section: the consolidation facility.

### 3.1.2 Consolidation Facility

The second concern of this research is a consolidation facility (CF), whose primary objective is to secure enough product to satisfy demand. This is usually accomplished by working with many firms through the use of supply contracts and purchasing commodities from the open market. At this level, observed demand and prices are less variable than those observed upstream since variability is pooled from various sources and inventories are held in cold storage. Figure 3.4 shows how individual supply from farmers, once pooled by the CF, appears significantly more stable. The primary concern for the CF then becomes that of securing contracts at the lowest cost to satisfy demand throughout the season, while utilizing available resources such as inventories and transportation infrastructure.

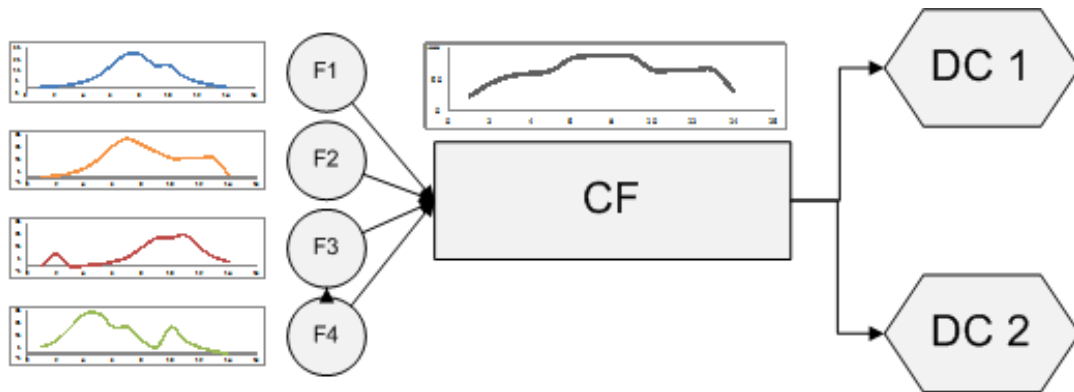


Figure 3.4 – Consolidation Facility’s Planning Problem

For the CF to accomplish its objectives, a stable and predictable delivery of products from the farmers to the CF is of great value; moreover, if the supply schedule is known before the harvest season starts, then the CF planning problem is greatly simplified. As a result, it is in the best interest of the CF to coordinate all farmers in the cooperative on the pre-season. Thereafter, once production assignments are made, the CF will be subject to the production outcomes from farmer contracts and from farmers honoring their commitments. Here, the CF may benefit from farmers overproducing, as this may prevent shortages; however, overproduction may also be in detriment of overall system coordination and therefore should be considered holistically.

### 3.1.3 Tactical Coordination on the Pre-Season

The above descriptions make no specific assumptions of cooperation or the lack of it. However, we can see that high transparency and availability of information would be of great benefit to the consolidation facility. Unfortunately, unless the entire enterprise (all growers and CF) were fully centralized and owned by a single individual, such detailed information is unrealistic. We have two main cases of collaboration in these supply chains:

On one hand, if we assume no collaboration, the consolidation facility can only make a limited amount of offers and negotiation rounds with each grower; this sequential negotiation approach is myopic in nature and presents multiple defects. Mainly, outcomes can be order dependent, with farmers at the different rounds having different treatment; likewise, from the farmer side, negotiation strategies may be restricted by pre-existing contracts, which reduce the requirements of the CF. Moreover, because on procurement the costs of one entity are the profits of the other, the incentives to collaborate and share information are hampered.

On the other hand, even under a collaborative approach greater transparency and an improved collaborative plan will not necessarily be reached. In fact, only under well designed collaborative approaches can these objectives be addressed and optimal solutions can be attained. A well designed coordination mechanism should be able to coordinate the chain in spite of competitive behavior among growers and in the grower-CF interface.

### 3.2 Envisioned Coordination Mechanism

As we have noted above, the farm planning problem involves a complex set of decisions that make planning challenging for farmers. If we combine several growers with varying production profiles and attempt to coordinate their actions, we expect this problem to grow significantly larger. Moreover, attempts for coordination must consider the game theoretic aspects of information sharing and the additional interactions which this entails.

In the supply chain literature, several approaches have been proposed for dealing with coordination when decisions span several echelons. These approaches show that using policies which align the incentives of suppliers and their customers (vertical coordination) the efficiency of the supply chain can be improved (Cachon & Lariviere, 2005; Simchi-



Levi et al., 2003). However, in the case of the farming cooperative problem, we encounter the objective is horizontal (among farmers) rather than vertical coordination. Precisely, it is a problem of horizontal coordination with multilateral information asymmetry (Albrecht, 2010), where no single player possesses all information for the full supply chain. For this coordination problem, a “marriage between an auction mechanism and a supply contract” is a viable research direction which can prove fruitful (F. Chen, 2003).

To illustrate the potential for coordination, take the hypothetical example of two growers that have different weather and soil conditions and can therefore produce two crops throughout the year as shown in Figure 3.5. If each grower acts independently, they would produce where the greatest return is expected. Suppose that in this example Crop 2 has the best margins for both farmers; the most likely scenario, under no coordination, would create oversupply of crop 2 in July-Dec, while being short in Crop 1. This option does not fare well in terms of supply stability and offering variety to downstream customers. Through a coordinated approach, a better solution which accommodates a more stable supply can be found; however, note that even with information sharing and goodwill, it is not always clear how a centralized planner should implement the best solution.

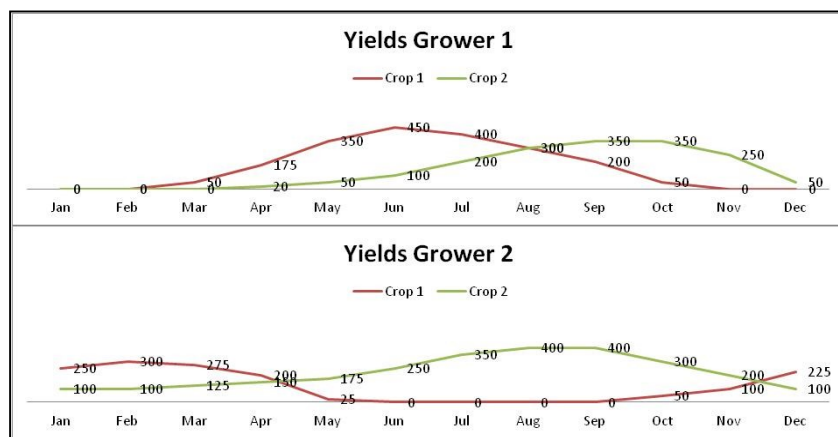


Figure 3.5 – Illustration of Differing Production Profiles

For the case above, plain information sharing can be thought of as a naive solution; however, remember that these agents are also competitors caring for their best interest, so why would they reveal their cost information? Furthermore, even if information is shared: can there be guaranteed accuracy? At this point, gaming behavior such as seeking convenient allocations and ex-ante compensation for future production will appear, and revealing information may not be on the best interest of each agent (F. Chen, 2003). The issue of coordination is further complicated when the stochastic nature of crops yields and the decay of products are accounted for; specifically, as storage is restricted, the timing and quantities of harvest become a central piece of the decision process. These factors must be accounted for by the cooperative when a production assignment is made.

Without a mechanism that elicits truthful information, any effort to make such an assignment from the side of the cooperative will be futile. Given this setting, we propose the use of a mechanism similar to an auction. The mechanism iteratively adjusts prices which are publicly announced by the CF; upon learning these prices, farmers respond with a public statement of their production plan. In this case, we create a new space of shared information which the cooperative can use to work towards a solution (Figure 3.6).

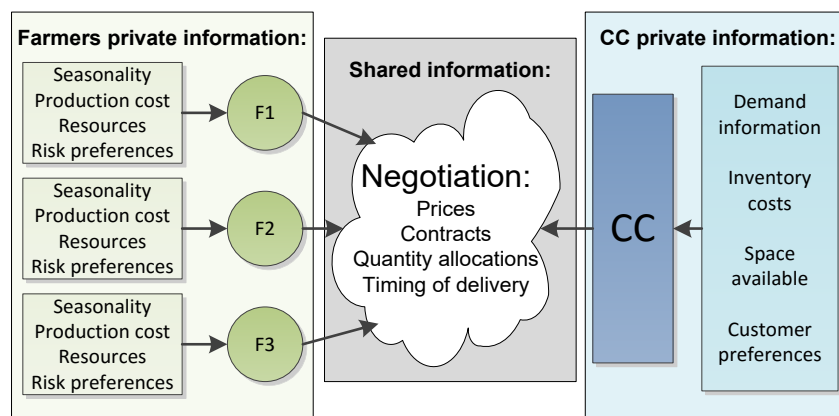


Figure 3.6 – Information Components of the Coordination Problem

To illustrate the use of an iterative auction to coordinate supply and demand, we use the following example illustrated in Figure 3.7 below (where the x-axis on each figure represents consecutive production periods). In *Iteration 1*, the CF announces a price schedule for multiple products throughout the season; however, the aggregate response of farmers to these prices yields an erratic supply, which the CF struggles to manage by using inventory alone. The auction can then in a subsequent iteration (*Iteration 2*) modify the prices of all items such that growers revise their plans and their new announcement translates into a better outcome for the CF. Performing this procedure iteratively will converge to a better solution that matches supply and demand; when prices don't change or when the desired allocation is reached, the auction terminates.

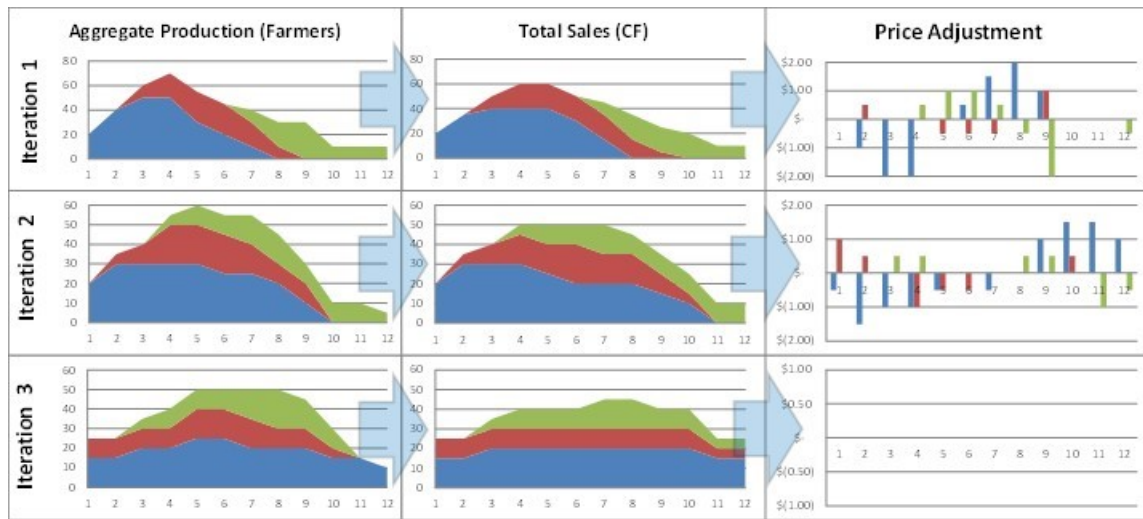


Figure 3.7 – Illustration of Auction Iterations (Farmers' and CF Perspective)

*This type of mechanism offers a structured approach to production planning, it's intuitive and simple to understand, and its fairness should not be contested as the allocation decisions are made by farmers rather than a dictatorial/centralized planner. Moreover, this mechanism can be translated into tractable mathematical models, as it is shown in the following sections.*

### 3.3 Objectives

The goal of the proposed research is to develop decision tools for small and medium-sized farmers to effectively coordinate their crop planning. In particular, we address the challenge of achieving coordination under incomplete/asymmetric information by developing an auction mechanism between retailer and suppliers. In this context, an optimal solution is obtained by allocating supply contracts to farmers while determining a fair compensation (based on internal prices) for their respective production. The auction mechanism is implemented by the consolidation facility, which acts as the institution in charge of consolidating demand information, negotiating with downstream customers and facilitating coordination; in other words, the CF is the global manager and auctioneer. To achieve this goal, we take the following steps:

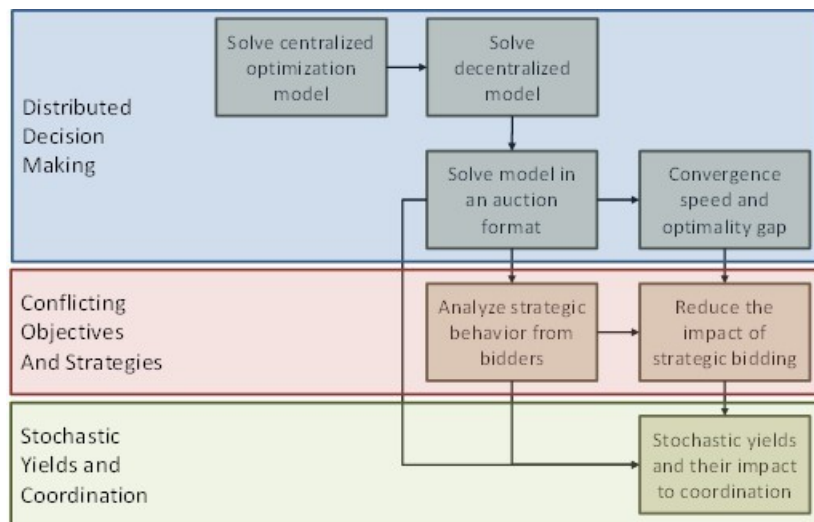


Figure 3.8 – Outline of Dissertation Objectives

1. We develop a mathematical model to assist farmers and cooperatives in making tactical production and consolidation decisions for the upcoming season. The designed model is centralized in nature and assumes that all relevant information is available. In this model we include all relevant factors affecting growers and the

- CF, such as production costs, resource availability and a known demand for the various products. Subsequently, the model is separated into various sub-problems representing the relevant players of the supply chain through the use of decomposition methods.
2. We formulate an auction mechanism that is compatible with the distributed structure of the coordination problem. The auction mechanism uses the solutions to farmer sub-problems to derive price variations which are then communicated to growers; farmers, in turn, adjust their production plans as a response to price changes. The purpose of the auction is to guide the allocation of contracts towards a global optimal solution in an efficient, quick and transparent manner.
  3. We recognize possible pathologies that can result from the implementation of the mechanism. Mainly, we focus on the possibilities created for bidders to strategically manipulate the outcome of the auction by misrepresenting their true preferences and the impact of their behavior on system efficiency. Later, we re-design the auction parameters such that the negative impact of this behavior is minimized and the overall profitability of the supply chain is maximized.
  4. We design an extension to the production problem for farmers seeking to honor their commitments with the CF after production assignments are determined from the auction. This formulation considers the variability in yields which is intrinsic to agricultural supply chains and the risks that it creates for farmers. Moreover, we seek to understand how farmers deviate from their production commitments (either by under-producing or over-producing) and how these risks are reduced through the use of option contracts.

5. We implement the developed tools using actual food supply chain information at the packing-house level as a case study for each of the research objectives.

To find a solution to this problem, we take a multidisciplinary approach, including agricultural science, operations research and mechanism design. Market mechanisms (such as auctions) have been historically utilized for discovering the value of an item when incomplete information and competitive behavior exist; furthermore, these mechanisms have a rich theoretical backing and a mathematical structure that is compatible with operations research. Thus, through these disciplines, the farming cooperative coordination problem can be modeled mathematically and solved in a decentralized manner despite incomplete information and self-interested agent behavior.

#### 3.4 Proposed Model for Centralized Supply Chain Optimization

The full, centralized, decision model will be refined and adapted to take the perspective of a centralized planner as done by (Ahumada & Villalobos, 2009b). This idealization of the system gives a starting point for capturing all relevant features of the system and quantifying a “centralized optimal solution”.

We begin by describing the problem as observed by a centralized planner (consolidation facility) which has control over the entire supply chain. The planner has the objective of maximizing supply chain profits for several farms, where each farm  $i \in I$  has its own characteristics such as production costs, available resources and size. Each farmer is able to produce a number of crops  $j \in J$  at multiple discrete time periods  $t \in T$  and is limited by his/her individual resources  $r \in R$ .

The constraints limiting the overall planning problem are: (3-1) Planting quantities should not exceed land owned by each farmer; (3-2) makes the amount harvested ( $H_{t(t^p)ji}$ ) in a given week dependent on the amount planted ( $P_{tji}$ ) and the expected yield for each associated crop, time period and farmer ( $Y_{t^p tji}$ ); (3-3) specifies the resource limitations to which each farmer is subjected (labor, water, capital); (3-4) ensures that the cooperatives' warehouse consolidates what has been harvested; and (3-5) specifies weekly demand, with the possibility of holding inventory at the warehouses.

$$\sum_t \sum_j P_{tji} \leq Land_i \quad \forall i \in I \quad (3-1)$$

$$H_{t(t^p)ji} = P_{t^p ji} * Y_{t^p tji} \quad \forall t, t^p \in T, j \in J, i \in I \quad (3-2)$$

$$\sum_j P_{tji} * RP_{rti} + \sum_j H_{tji} * RH_{rti} \leq Res_{rti} \quad \forall t \in T, r \in R, i \in I \quad (3-3)$$

$$W_{tj} \leq \sum_i H_{tji} \quad \forall t \in T, j \in J \quad (3-4)$$

$$W_{tj} + Inv_{tj} - Dem_{tj} = Inv_{t+1,j} \quad \forall t \in T, j \in J \quad (3-5)$$

In order to include critical quality and shelf life considerations we use the approach of Ahumada & Villalobos (2009a), where perishability is modeled through discrete quality (ripeness) states  $q \in Q$  and their respective shelf life  $sl_q$ . These quality states constrain inventory balance by tracking the harvest period  $h \in T$  and quality for items arriving to the warehouse  $W_{thjq}$ ; thereafter, constraints which use the additional information to construct a feasible space of perishable inventory balance are constructed in (3-6). We do not elaborate on this formulation as to keep the level of detail on the mathematical models at an appropriate scope for this section; however, for further detail we refer the reader to (Ahumada & Villalobos, 2009b; Mason & Villalobos, 2015; Rong, Akkerman, & Grunow, 2011) and to Chapter 4 of this dissertation.

$$\sum_h W_{thjq} + \sum_h Inv_{thjq} - Dem_{tj} = \sum_h Inv_{t+1,hjq} \quad \forall t, j, q; h \leq t - sl_q \quad (3-6)$$

Finally, the objective (3-7) of the cooperative is to maximize supply chain profits from selling the products (first term in the objective function) taking into account the resource costs of each grower to produce and deliver each crop to the warehouse.

$$\sum_{tj} W_{tj} Price_{tj} - \sum_{trji} P_{trji} RCP_{trji} - \sum_{trji} H_{trji} RCH_{rti} - \sum_{tj} W_{tj} RCW_{tj} \quad (3-7)$$

### 3.5 Proposed Model for Decentralized Coordination

Assuming that a centralized decision maker has control over the supply chain is seldom realistic. Therefore, we decompose the problem into two models in which the growers and the central buyer are modeled as separate entities with their own objectives and constraints. To show that the model can be decomposed effectively, we use Dantzig-Wolfe decomposition (Dantzig & Wolfe, 1960). This is a tool which has been analyzed in the mechanism design literature for its interpretation as dividing a centralized problem into one of multiple agents whose actions are aligned through communication of “prices” for resources (Albrecht, 2010; Davies, 2005; Vohra, 2011).

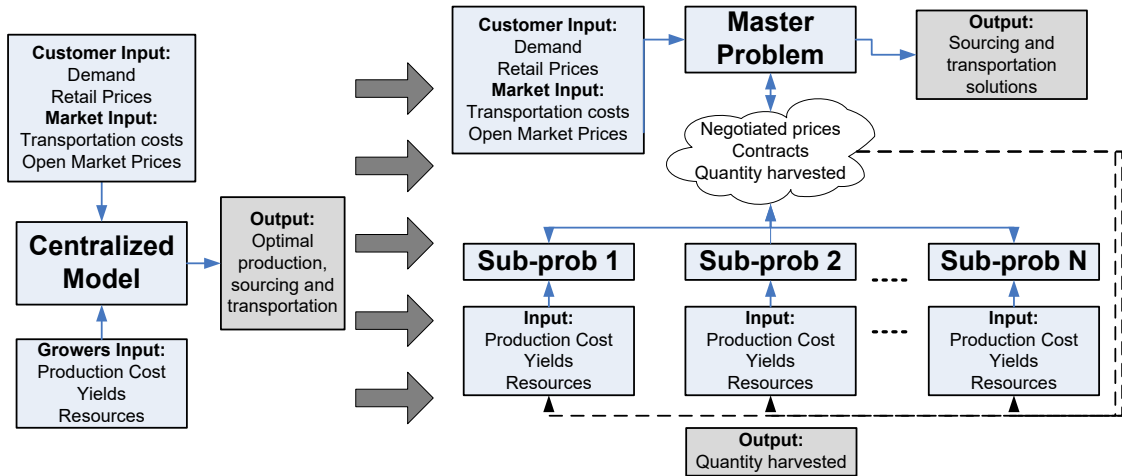


Figure 3.9 – Decomposition of Centralized Model

Before the decomposition we note that harvest quantities are directly proportional to planting decisions, which implies a linear equivalence between “planting” from the



growers' perspective and "product quantities" from the consolidation perspective (3-10). Moreover, we express the resource and land constraints as a single set of inequalities for simplicity.

The problem is now in a format which makes its applicability for decomposition readily apparent, with centralized demand constraints (3-10) and constraints applying to each farmer's usage of resources (3-9):

$$\text{Max} \quad \sum_{ri} (\sum_{tj} (\text{Price}'_{tj} - \text{RCP}'_{trji}) * P_{t^pji} ) \quad (3-8)$$

$$\text{St.} \quad \sum_j P_{t^pji} * \text{RP}'_{rt^pi} \leq \text{Res}_{rti} \quad \forall t, t^p \in T, r \in R, i \in I \quad (3-9)$$

$$\sum_{t^p} \sum_i P_{t^pji} * Y_{t^ptji} = \text{Dem}'_{tj} \quad \forall t \in T, j \in J \quad (3-10)$$

$$P_{t^pji} \geq 0 \quad \forall t, t^p \in T, r \in R$$

The above problem is decomposed into a master problem (MP) and a set of sub-problems (SP<sub>i</sub>), one for each farmer in the cooperative, where the master problem is given by the demand observed by the cooperative and the convex hull generated by the farmers planning problems; we use  $\lambda_{iv}$  to introduce columns into the master problem:

$$\text{Max} \quad \sum_v (\sum_{ri} \sum_{tj} (\text{Price}'_{tj} - \text{RCP}'_{trji}) * P_{t^pji} * \lambda_{iv}) \quad (\text{MP} - 3-11)$$

$$\text{St.} \quad \sum_v \sum_{it^p} P_{t^pji} * Y_{t^ptji} * \lambda_{iv} = \text{Dem}'_{tj} \quad \forall t \in T, j \in J$$

$$\sum_v \lambda_{iv} = 1 \quad \forall i \in I$$

$$P_{t^pji}^v \in Q_i, \lambda_{iv} \geq 0 \quad \forall i \in I$$

We obtain the extreme points of the feasible set of planting decisions through  $I$  sub-problems (SP<sub>i</sub>), which are used to generate columns in the master problem:

$$\text{Max} \quad \sum_{ri} \sum_{tj} (\text{Price}'_{tj} - \text{RCP}'_{trji}) * P_{t^pji} - (\sum_{t^p} \sum_i P_{t^pji} * Y_{t^ptji}) * \bar{y}_{tj} \quad (\text{SP}_i - 3-12)$$

$$\text{St.} \quad \sum_j P_{t^pji} * \text{RP}'_{rt^pi} \leq \text{Res}_{rti} \quad \forall t, t^p \in T, r \in R$$

$$P_{t^pji} \geq 0 \quad \forall t, t^p \in T, r \in R$$

Here,  $\bar{y}_{tj}$  are the values of the dual variables corresponding to the demand constraints derived from the master problem. The inclusion of this term into the farmers sub problem has a direct interpretation applicable to our application: *Announce the price vector  $\mathbf{p}$ , and then let each agent choose the planting schedule that maximizes his payoff*; where the inclusion of the dual variables implies that for some vector  $\mathbf{p}$  and for farmers seeking their own best interest, the system is at its optimal point (Vohra, 2011). Moreover, due to the structure of D-W decomposition, under a finite number of iterations for price announcements, we will converge to the optimal solution.

Unfortunately, by taking a closer look at the structure of the problem presented above, we find some implementation issues that may arise in practice.

1. The number of auction iterations required for convergence may be high
2. If the prices announced are allowed to both ascend and descend, the mechanism may be less attractive to the primary stakeholders
3. Despite the existence of a mechanism based on iterative price announcements and allocation responses, there is no guarantee that farmers will bid truthfully

The first issue can be addressed through fine tuning of parameters or a reasonable price initiation for the mechanism, while for the second issue Vohra (2011) provides an implementation procedure such that the algorithm can be implemented as an ascending price auction. Moreover, alternative formulations of the decomposition such as sub-gradient optimization can be used; for sub gradient optimization, although structurally similar to D-W and also based on dual decomposition, is more akin to an auction and easier to interpret. Unfortunately, there is no clear cut solution for the third issue; in fact, some analysis of dual decomposition shows that “cheating” may be possible and advantageous

for subunits (Jennergren & Müller, 1973). To avoid cheating, a more detailed analysis is required which uses the concept of incentive compatibility, described in Section 3.6.

### 3.6 Analysis of Incentive Compatibility

In the realm of mechanism design, “extracting information” for its use in coordination of a supply chain is a major contribution. For this reason it is indispensable to understand whether the mechanism does in fact provide the right information. A mechanism which elicits agents to reveal their true information by making bidding truthfully their best response has a formal name in economics: **Incentive compatibility (IC)**. In other words, if telling the truth is an ex-post Nash Equilibrium at each iteration of the game, then the mechanism is incentive compatible (Vohra, 2011).

If incentive compatibility is met, the model converges to the centralized solution. However, in practice incentive compatibility is rarely met, and neglecting to consider incentive compatibility may lead to sub-optimal results and, in a worst case, the mechanism may fail altogether. Therefore, it is key to design a simple mechanism which the various players can understand, but it is also indispensable to be aware of how users will react to the Bayesian game created. Not all mechanisms are incentive compatible, nor is it possible to prove incentive compatibility for all mechanisms; however, in this dissertation we analyze and analytically quantify the extent to which truthful disclosure is fulfilled.

To perform an analysis of incentive compatibility for any mechanism, one possible approach is to define and analyze the problem in a form similar to that of Myerson (1981). In his seminal work, which laid the foundations of mechanism design, Myerson characterizes incentive compatibility of a mechanism by using the concept of expected utility derived from a mechanism. Here he defines an incentive compatible mechanism as

one in which the utility obtained by any bidder from announcing his/her true valuation  $x^t$  is always greater than the utility of announcing any other valuation  $x^f$ . This, on its most simple terms is expressed as:

$$U(x^t) \geq U(x^f) \quad (3-13)$$

Where  $U_i$  is the expected utility for bidder  $i$  as a function of stating a given valuation  $x$ . In the case of an iterative auction, we can take the expected utility to be taken across all iterations as the utility obtained in each iteration multiplied by the probability of termination in each iteration.

$$U(x) = \sum_{k=1}^N u_k(x) p_k \quad (3-14)$$

In the formulation of Section 3.5 we deal with a mechanism for the procurement of goods by a centralized consolidation facility which will auction supply contracts for which farmers will be the bidders. Here, the sub-problem for any specific bidder given in (SPi – 3-12) is formulated as a mixed integer program which can be represented as:

$$\begin{aligned} \mathbf{Max} \quad & z^k = c^k x^k & (3-15) \\ \mathbf{St} \quad & Ax^k = b \\ & x^k \geq 0 \end{aligned}$$

In the context of mechanism design, we can take this formulation to be the decision of how much to bid in a given iteration of the auction. Here,  $z^k$  is the value for the truthful or incentive compatible objective function for bidder  $i$ , while  $x^k$  is the vector of actual production bids. These production bids and objective function occur for one of many auction iterations  $k \in 1..N$ , all of which may or may not be incentive compatible.

Suppose there is some other vector of feasible production bids  $\check{x}^k$  for some iteration  $k$  such that  $x^k \neq \check{x}^k$ ; furthermore, let  $\check{x}^k$  yield the objective function  $\check{z}^k = c^k \check{x}^k \neq z^k$ . The

total utility that the bidding farmer obtains from the auction is equal to the sum of the objective functions for all iterations. To put this formulation in the context of incentive compatibility, we should relate the formulation from (3-15) in the context of the incentive compatibility condition (3-12). We state the mechanism proposed in Section 3.5 is incentive compatible if the following inequality holds:

$$\sum_{k=1}^N z^k P_k \geq \sum_{k=1}^N \check{z}^k P_k \quad (3-16)$$

Where  $P_k$  is the probability that the auction terminates at a given iteration.

### 3.6.1 Solution Approach for the Assessing the Strategic Decision Problem

As the formulation above suggests, for the mechanism to be incentive compatible, the condition of (3-16) should hold across all iterations. To help us make the assessment of incentive compatibility, we need to take the perspective of the farmer participating in the mechanism and attempt to strategically optimize its bidding quantities.

Specifically, for the auction formulated in this dissertation, the price vector  $c^k$  for any of the auction iterations  $k$  will be affected by the bids announced in the previous iteration  $k - 1$ . As a result, this new price vector  $c_{(c^k, x^k, w^k)}^{k+1}$  can be calculated as a function of a farmer's own bids  $x^k$  and the random outcome of the bids from the other farmers  $w^k$ . If this decision problem is incorporated into the problem formulation detailed in (3-15) then we obtain an expanded problem given by (3-17) below:

$$\begin{aligned} \text{Max } z_i^{BR} &= c^i x^i + \sum_{k=i}^{K-1} c_{(c^k, x^k, w^k)}^{k+1} x^{k+1} & \forall i < K \\ \text{st: } & Ax^i = b \\ & x^i \geq 0 \end{aligned} \quad (3-17)$$

For the case of computing the Best Response (denoted above by BR), each bidder is still subject to the same constraints  $Ax^t = b$  during all iterations. However, since the announced price vector changes at each point, then the bidder must account for this and may attempt to anticipate/influence these changes; thus, the objective function changes significantly. This change results in the farmers bidding problem now having a new formulation as a dynamic problem where  $c^{k+1}$  represents the current state of the system and is a function of the current state  $c^k$ , the actions taken by the farmer  $x^k$  and a random component  $w^k$ .

It's trivial to show that for the final iteration, where for any price announcement the auction terminates, the game is reduced to a single stage mixed integer program; here, the problem is incentive compatible. However, this result is not clear for iterations which do not finalize the game. That is, in previous iterations, farmers may have no incentive to bid truthfully. Ultimately, to prove incentive compatibility, we must show  $z^* = z^{BR}$  for all iterations in accordance to (3-16). In the likely case of encountering a negative result, the focus of the research will be to minimize the negative impacts caused by the lack of incentive compatibility and formulate an effective (rather than optimal) mechanism.

The solution approach to this problem relies heavily on the use of dynamic programming, linear programming, quadratic programming, convex optimization and the use of heuristics. Moreover, due to the scope and difficulty of the problem we also have a heavy reliance on numerical methods and the intuition derived from computational results.

### 3.7 Coordination Problem under Stochastic Parameters

One of the greatest potentials of coordinated solutions for the agricultural supply chain lies in the possibility of reducing the exposure to risk of all the involved parties. This

implies that the farmers can be protected from the variability in yields and market prices, while the CF also protects itself from failing to meet its contracted demand. In order to do this, the random behavior of yields at each farming location and the behavior of market prices would have to be captured by the CF's objective function. However, this additional consideration creates a significant increase in the modeling complexity due to the incorporation of stochastic variables to an already complex decision model.

The consequence of stochastic yields means that production commitments made by the various farmers will not always hold. In fact, expected supply from each farm will vary around a mean, sometimes being higher and sometimes lower; however, the problem of variable yields is greatly aggravated if the farmer in question decides to overproduce or underproduce due to a misalignment of incentives. This problem can cause great conflict for the CF; in particular if the CF naively assumes that farmers will honor their production commitments after these are determined by the auction mechanism.

Although the mechanism proposed in Section 3.5 can be incentive compatible and viable (Section 3.6), there are still problems to be addressed for coordination. Specifically, the mechanism proposed ensures that farmers are given a guaranteed price for their crops as given by the auction. This reduces the exposure to risk that farmers observe; however, if farmers decide to dishonor their commitments and no consequence or penalty is stipulated in the contract, then a moral hazard problem is brought about. Furthermore, even if farmers honor their commitments and plan to match demand exactly, they are still exposed to yield variability which may cause them to take a hit to their profits.

As a result, we formulate a model for stochastic optimization of the planting quantities that a farmer must undertake in order to minimize the risks of undercutting the

CF with those of overproducing and wasting their product. Moreover, we also analyze this decision problem from the perspective of the CF and find conditions under which the supply chain remains coordinated in spite of stochastic yields.

Since the problem of stochastic optimization is complex, we limit the scope to the interaction between a single grower and the CF; we also limit the scope to planting a single crop for one production period. This simplification allows the sufficient level of detail to draw strong conclusions on the nature of the production problem and its implications for coordination; but it also provides the groundwork necessary to bring together the horizontal coordination problem with that of stochastic programming and mechanism design.

### 3.7.1 Solution Approach for the Stochastic Yields Coordination Problem

This model is formulated as a continuation to the tactical production planning problem and starts from the assumption that production contracts have been pre-established. Thereafter, the production problem for the farmer is how much to plant such that the costs of overage and underage are balanced in a newsvendor fashion; downstream in the supply chain, it is assumed that costs for the CF are minimized when the expected harvest quantities match the established supply contracts. With this expansion we place special emphasis on the conditions that coordinate the two players and the supply chain.

To solve this problem, we rely on two formulations: (1) A newsvendor problem with stochastic yields, and (2) an expansion with the possibility for the farmer to purchase option contracts as insurance to avoid the costs of overage and underage. For both formulations the conditions for optimality in the farmer's objective function are derived, and the conditions under which the supply chain is coordinated by matching expected production to contracted supply are identified.



A summary of all relevant parameters and decision variables for the farmer decision problem are described below:

**Decision variables and outcome functions:**

- $q$  = Quantity to plant for farmer (*Acres*)
- $q_u$  = Number of options for underage insurance to buy (*Units*)
- $q_o$  = Number of options for overage insurance to buy (*Units*)
- $\pi_F$  = Total profit obtained by farmer

**Parameters:**

- $S$  = Pre-established supply quantity (*Units*)
- $H$  = Amount harvested as a function of planting and random yield (*Units*)
- $x$  = Random variable for the stochastic yield (*Units per Acre*)
- $F(x)$  = CDF for the stochastic yield
- $f(x)$  = PDF for the stochastic yield
- $E[x]$  = Expected yield
- $p_F$  = Unit price offered to the farmer
- $c$  = Cost of harvesting realizes production (*Cost per unit*)
- $c_{pl}$  = Cost of planting (*Cost per acre*)
- $c_u$  = Unit cost of underage
- $c_o$  = Unit cost of overage
- $o_u$  = Cost of an option to under supply the CF
- $o_o$  = Cost of an option to sell above committed supply
- $s_u$  = Strike price for underage options ( $s_u < c_u$ )
- $s_o$  = Strike price for overage options ( $s_o < c_o$ )

For the newsvendor problem with options we define the following profit function for the farmer:

$$\begin{aligned} \pi_F = & p_F \min(H, S) - c_u(S - q_u - H)^+ - c_o(H - S - q_o)^+ - c_{pl}q - o_u q_u \\ & - o_o q_o - s_u(S - H)^+ - s_o(H - S)^+ \end{aligned} \tag{3-18}$$

Where  $p_F$  is the retail price for the crop, which is multiplied by the stochastic harvest quantity and is capped by the contracted supply. We subtract the costs of underage and

overage which begin taking place once farmers are no longer protected by the options which they purchased. These are followed by the costs of planting the crops, the underage and the overage options respectively. Finally, we have the special costs of underage and overage for which farmers are protected by the options purchased.

This formulation is sufficiently flexible to model the decision problem in many forms. For instance, for positive  $s_u, s_o$  we have a two cost system where farmers can avoid high penalty costs. However,  $s_u$  and  $s_o$  are allowed to take negative numbers, in which case these could act as yield insurance for  $s_u$ , or as a secondary purchase price for the case of  $s_o$ . The effectiveness of this method is tested through the use of computational results to gain intuition on the decision problem.

### 3.8 Validation and Case Study

The usefulness of the resulting decision support system is a critical outcome of the project. However, from previous experience, growers are not accustomed to using complicated planning models and avoid using them. Thus, a simple modeling approach and the use of case studies can go a long way in communicating the potential benefits of the coordination mechanism to the relevant stakeholders.

Therefore, our aim is not only to have a mathematical model and planning tools; but our aim is also to derive useful results that are well presented, easy to interpret and which relate to the intuition of stakeholders. In order to do this, we work with real agricultural data and models which are validated and proven to reflect the behavior of actual agricultural systems. These datasets contain information about the amount of labor, land and other resources used, as well as their associated costs. We primarily use mathematical models from (Ahumada & Villalobos, 2009b; Wishon et al., 2015), which use tactical

planning tools modeled through mixed integer programming; moreover, we will use real world data from (Villalobos et al., 2012) to perform the necessary case studies. The various results obtained from this study, both theoretical and case specific, can be shared with industry partners in their respective sectors of production and consolidation and will be published in academic journals, where the impact of the academic aspects of agricultural decision-making can be showcased.

## 4 COORDINATION MECHANISM DESIGN AND CONVERGENCE

### 4.1 Introduction

In Chapter 1 we established the importance for specialized tools which allow growers of fresh produce to better compete with larger operations. In recent years, farmers of fresh produce in the US have begun to form tighter relationships and expand their operations through the establishment of cooperatives and consolidation facilities (CFs). These cooperatives appear as a response to the decline of small and medium sized farms, which have difficulty competing with larger operations (James Matson et al., 2010). Moreover, farming cooperatives also provide farmers with economies of scale, a steady stream of local products and help reduce waste in the supply chain (James Barham & Debra Tropp, 2012). Yet coordinating a supply chain is not trivial, and failure to do so can cause cooperatives to fail (Karina et al., 2012).

It is clear that farmers operate in a complex and dynamic environment (Ahumada et al., 2012). Given this complexity, it is hard to expect a group of farmers to reach a joint solution and production plan through conventional methods; in particular, when we pose the following questions: How much should farmers get paid for their products? What should the CF charge for product handling and storage? How do we determine which farmer should produce which product and at what time? These questions are not trivial, as farmers will misrepresent their costs if they stand to gain from the outcomes of doing so.

This complexity and competitive behavior highlight the urgency of designing coordination policies that work under incomplete information. Unfortunately, as we see in Chapter 2, there is no evidence in the literature of structured planning mechanisms currently used for horizontal coordination of agricultural production. Nonetheless, in

Chapter 2 we also find that coordination mechanisms can be applied successfully in supply chain practice, and that there exists an ample theoretical backing to guide us on the design of a coordination mechanism.

In the remainder of this chapter we present the basic assumptions made and the proposed framework to build the coordination mechanism. Thereafter, we develop a model for agricultural planning which is representative of the farming cooperative and which can be solved through an auction mechanism. Finally, we provide computational results for the case of coordinating an agricultural cooperative; for this we use farming data from the region of Yuma, AZ which is representative of 4 crops in the region (broccoli, romaine lettuce, iceberg lettuce and cauliflower).

#### 4.2 Scope and Assumptions

The coordination mechanisms and planning tools to be developed in this research are tactical in nature, meaning that solutions are relevant for a few weeks to several months (Simchi-Levi et al., 2003). In agriculture, a typical season from planning to end of harvest spans between six months to one year and the decisions made for planting are relevant to the operations of the farm for the following months (Ahumada & Villalobos, 2009b). In ASCs, among the relevant decisions at a tactical level we have: The quantities to plant of each crop, timing of the planting, projections for the amount of labor required and the harvesting/marketing decisions for the crops.

Another assumption made to better reflect real world coordination problems is that farmers are different in their production profile, sophistication and quality of land. In practice, this is true as different individuals have different preferences and competitive advantages; moreover, even for farmland that is within close proximity, spatial variability

of soil properties may be significant (Nestor M. Cid-García, 2013). This variability causes yields, costs and risks observed in one farm to be different from other farms. To reflect farm heterogeneity, we assume that farmers have varying values for their most relevant parameters, including: Expected yields for each crop; size of their farmland; production costs (such as fertilizers, irrigation, access to capital, transportation costs, etc); likewise, it is also assumed that some farmers may have better access and management of resources such as water and hand labor.

In addition to all the assumptions relating to farmers as individuals, we assume that information availability is asymmetrical, meaning that no single player in the supply chain knows all the parameters of the other players. Mainly, any farmer can know with certainty its own production information; but cannot estimate any other farmers' costs or yields with complete accuracy. We also assume that the market prices and demand for crops are known for the upcoming season. Thus, even when production assignments have not been made to farmers, the CF knows the desired aggregate supply that is needed to satisfy demand.

Finally, for the purposes of this chapter, we assume that farmers do not act strategically or lie about their production decisions during the auction; moreover, farmers do not engage in arbitrage, meaning that farmers will not find it profitable to purchase crops in the external market and sell them to the CF for a profit as if they were their own production. We will later see in Chapter 5 that the non-strategic behavior assumption can be relaxed without sacrificing efficiency.

### 4.3 Model Structure

We use a mechanism akin to an iterative auction, where instead of tangible goods, the items being auctioned are production contracts/commitments for the upcoming

harvesting season. This mechanism iteratively adjusts prices which are publicly announced by the CF; upon learning these prices, farmers respond with a public statement of their production plan. The production information is aggregated by the CF as to conserve farmer’s information private and no individual production plans are revealed until the conclusion of the auction. In this case, we create a new space of shared information which the CF can use to move towards a solution; i.e. to obtain a supply schedule appropriate for meeting estimated customer demand. Figure 4.1 below illustrates the iterative nature of the coordination mechanism.

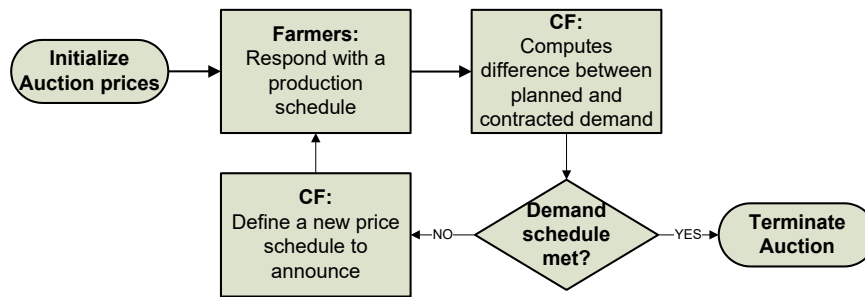


Figure 4.1 – Envisioned Coordination Mechanism Procedure

In order to formulate the overall coordination problem, as well as the mechanism required to coordinate production, we use a mixed integer programming (MIP) formulation of the farm planning problem. We begin by formulating the production problem as a centralized problem where all information is available and the CF has complete control over farming decisions (Section 4.4). This centralized formulation will serve as a tool to benchmark the efficiency of the coordination mechanism. In the following sections we illustrate how the centralized problem is equivalent and converges to the decentralized problem with asymmetric information (Section 4.5, 4.6). Finally, we quantify the efficiency of the mechanism through the computational results using the centralized solution as a benchmark (Section 4.7).

#### 4.4 Centralized Mathematical Model

For the centralized optimization problem we work on a variant of the model proposed by Ahumada, & Villalobos (2009), using a deterministic version of the tactical planning problem and limiting our focus on a single echelon. The mathematical formulation of the centralized model covers: The planting/harvesting decisions of growers, labor allocation, harvesting and consolidation of crops, inventory management, consolidation facility restrictions, costs of production and market prices. We also consider the perishability of crops using the formulation for discrete quality tracking provided by (Rong et al., 2011). The sets, parameters, variables, constraints and objective function are as follows:

##### **Indexes:**

- $t \in T$  : Planning **periods** (weeks)
- $p \in P, P(j, l) \subseteq T$  : Set of feasible **planting weeks** for crop **j** in location **l**
- $h \in H, H(j, l) \subseteq T$  : Set of feasible **harvesting weeks** for crop **j** in location **l**
- $j \in J$  : Potential **crops** to plant
- $q \in Q$  : **Quality states** of crops
- $l \in L$  : **Locations** (distinct farms) available for planting

##### **General Parameters (Farmer):**

- $Land_l$  : Land available at location  $l$  (in acres)
- $LaborP_{ptj}$  : Workers needed at period  $t$  for **cultivating** crop  $j$  planted period  $p$  (Men-week/Acre)
- $LaborH_j$  : Workers needed for **harvesting** crop  $j$  (Men-week/Acre)
- $MaxLab_l$  : Max number of workers that can be hired in location  $l$
- $Yield_{phj}$  : Expected yield of crop  $j$  at time  $p$  and harvested in week  $h$  (%/Week)



$Total_{jl}$  : Expected total production of crop  $j$  planted in location  $l$  (Cartons/Acre)  
 $MaxL_j$  : Maximum allowed amount to plant of crop  $j$  during one week (Acres)  
 $MinL_j$  : Minimum allowed amount to plant of crop  $j$  during one week (Acres)  
 $QualD_{jql}$  : Quality distribution  $q$  for crop  $j$  for farmer  $l$   
 $\Delta t_l$  : Travel time from location  $l$  to facility  
 $\Delta q_{lj}$  : Change in quality for product  $j$  traveling from location  $l$  to facility

**General Parameters (CF):**

$MaxDem_{hj}$  : Maximum demand of crop  $j$  at time  $h$  (Maximum open market)  
 $MinDem_{hj}$  : Minimum demand of crop  $j$  at time  $h$  (Contracted demand)  
 $qmin_j$  : Minimum quality accepted for crop  $j$   
 $WHCap$  : Total capacity of CF  
 $\Delta q_j$  : Change in quality for product  $j$  stored one week at CF

**Cost Parameters (Farmers):**

$Cplant_{jl}$  : Cost per acre of **planting** and cultivating for crop  $j$  (exclude labor)  
 $Charv_{jl}$  : Cost per acre of **harvesting** for crop  $j$  (exclude labor)  
 $Chire_t$  : Fixed cost to **hire** a seasonal worker at time  $t$   
 $Clab_t$  : Variable cost to **hire** a seasonal worker at time  $t$   
 $Ctrans_{jl}$  : Cost of transportation form location  $l$  to facility

**Cost Parameters (CF):**

$Cinv_j$  : Inventory cost for crop  $j$   
 $Cover_j$  : Cost of overage for product  $j$   
 $Cunder_j$  : Cost of underage for product  $j$

$Price_{hj}$  : Expected price for crop  $j$  at time  $h$

**Decision Variables (Farmers):**

$Vplant_{pjl}$  : Area to plant of crop  $j$  in period  $p$  at location  $l$

$Vharv_{hjl}$  : Harvest quantity of crop  $j$  in period  $h$  at location  $l$

$Vlab_{tl}$  : Seasonal laborers employed at location  $l$  at time  $t$

$VHire_{tl}$  : Seasonal laborers hired for location  $l$  at time  $t$

$VFire_{tl}$  : Seasonal laborers dismissed from location  $l$  at time  $t$

$Y_{jpl}$  (Binary) : **1** If crop  $j$  is planted at period  $p$  at location  $l$  **0** otherwise

$Vtrans_{hjq}$  : Amount to transport from location  $l$  of crop  $j$  with quality  $q$  at time  $h$

**Decision Variables (CF):**

$Vinv_{hjq}$  : Quantity to store of crop  $j$  with quality  $q$  at time  $h$

$Vsell_{hjq}$  : Quantity of crop  $j$  to sell with quality  $q$  at time  $h$

$Vover_{hj}$  : Overage of crop  $j$  at time  $h$

$Vunder_{hj}$  : Underage of crop  $j$  at time  $h$

**Objective Function:**

$$\begin{aligned} Max Z_{CP} = & \sum_{hj,q} V_{sell_{hjq}} Price_{hj} & (4-1) \\ & - \sum_{hj,q} V_{inv_{hjq}} C_{inv_j} - \sum_{hj,q} V_{over_{hj}} C_{over_j} - \sum_{hj,q} V_{under_{hj}} C_{under_j} \\ & - \sum_{ljqt} V_{trans_{hjq}} C_{trans_{jl}} - \sum_{tl} V_{Hire_{tl}} C_{hire_t} - \sum_{tl} V_{lab_{tl}} C_{lab_t} \\ & - \sum_{pjl} V_{plant_{pjl}} C_{plant_j} - \sum_{hjl} V_{harv_{hjl}} C_{harv_j} \end{aligned}$$

The objective function (4-1) states that we must maximize profit, which results from revenues from selling crops minus the costs of inventory, overage/underage penalties, transportation, labor and planting/harvesting respectively. Here, deviations from

committed demand are penalized, either through the costs of wasted product or the costs of shorting downstream customers at the CF level.

**Farming Constraints:**

$$\sum_j \sum_p V_{plant_{pjl}} \leq Land_l \quad \forall l \in L \quad (4-2)$$

$$Min_j Y_{jpl} \leq V_{plant_{pjl}} \leq Max_j Y_{jpl} \quad \forall j \in J, p \in P, l \in L \quad (4-3)$$

$$V_{harv_{hjl}} \leq \sum_p V_{plant_{pjl}} Yield_{phj} Total_{jl} \quad \forall h \in H, j \in J, l \in L \quad (4-4)$$

(4-2) Restricts the total amount of land that farmers have. Constraint (4-3) states that if farmers decide to plant a crop in a given time-period, the planting must be done within a maximum and minimum limit. (4-4) Sets an equivalence between harvesting with planting decisions and the yield of crops.

**Farming Labor Constraints:**

$$V_{lab_{tl}} \geq \sum_p \sum_j V_{plant_{pjl}} Labor_{ptj} + \sum_{h=t} \sum_j V_{harv_{hjl}} Labor_{Hj} \quad \forall t \in T, l \in L \quad (4-5)$$

$$V_{Hire_{tl}} - V_{Fire_{tl}} = V_{lab_{tl}} - V_{lab_{(t-1)l}} \quad \forall t \in T, l \in L \quad (4-6)$$

$$\sum_t V_{Hire_{tl}} \leq Max_{Lab}_l \quad \forall l \in L \quad (4-7)$$

(4-5) Ensures that during each time-period and for each location, there must be enough labor to cover all labor needs for harvesting and cultivating. Constraints (4-6) are the labor balance constraints for hiring and letting go of workers. Finally, (4-7) states that each location has a maximum amount of labor which can be hired during the season.

**Harvesting Quality Distribution:**

$$V_{harv_{hjl}} * Qual_{D_{hjq}} = V_{trans}_{lj(q-\Delta ql_j)(h+\Delta tl)} \quad \forall h, j, q, l \quad (4-8)$$

Equation (4-8) establishes an equivalence between what is harvested and the quality of the crop for each farming location throughout the season.

**Coupling Constraint:**

$$\sum_l Vtrans_{hljq} = PVarr_{h,j,q} \quad \forall j, q, h \quad (4-9)$$

Equation (4-9) creates an equivalence between goods transported from farming locations and arrivals to the CF. Although in the centralized formulation this constraint only serves the purpose of facilitating interpretation, in the decentralized formulation this constraint serves a key function as a coupling constraint for all sub-problems.

**Inventory Balance and Quality Tracking:**

$$PVarr_{h,j,q} + Vinv_{h-1,j,q+\Delta q_j} - Vsell_{hj,q} = Vinv_{h,j,q} \quad \forall j, q, h \quad (4-10)$$

Constraint (4-10) implements inventory balance at the CF from period to period with the addition of incorporating quality decay into the balance equation.

**Demand Constraints:**

$$MinDem_{hj} - Vunder_{hj} \leq \sum_{q_{max_j \geq q \geq q_{min_j}} Vsell_{hj,q} \quad \forall j, h \quad (4-11.a)$$

$$\sum_{q_{max_j \geq q \geq q_{min_j}} Vsell_{hj,q} \leq MaxDem_{hj} + Vover_{hj} \quad \forall j, h \quad (4-11.b)$$

(4-11) States the minimum and maximum demand that must be satisfied for each crop during each week, restricting the demand fulfillment to acceptable quality states.

**Warehouse Capacity Constraint:**

$$\sum_{jq} Vinv_{hj,q} \leq WHCap \quad \forall h \quad (4-12)$$

Finally, (4-12) limits the capacity of the warehouse.

This model provides a planting and harvesting schedule for all growers, which minimizes overall system costs and will be in sync with the operations of the CF, thus maximizing system wide profits. However, we have not yet addressed the concern of how to obtain a “centralized solution” without knowledge of all relevant parameters from each

section of the supply chain. To address this question, we reformulate the problem in a distributed manner and provide a framework to solve it in an auction like format.

#### 4.5 Decentralized Model Using WD Decomposition

The above centralized problem is conceptually useful and provides a measure for system optimality. Moreover, the model can be decomposed into a master problem (MP) and a set of sub-problems (SP<sub>*l*</sub>) (one for each farmer) by using Dantzig-Wolfe decomposition. Here the master problem is given by the demand observed by the CF and the convex hull generated by the farmers planning problems; meanwhile, each of the sub-problems is solved independently by only observing the parameters which are relevant locally for each farmer.

In this formulation we introduce the variable  $\lambda_l^k$ , where  $k$  is the iteration number, which is used to introduce local solutions from the farmers' planning problem into the CF master problem through a convex combination of the corresponding corner point solutions. If implemented through DW decomposition, the mechanism consists of the CF announcing different prices for crops; thereafter, farmers announce tentative production plans to the CF. Once a solution is provided by a farmer, the CF is able to keep this solution as part of a corner-point solution set; thereafter, these solutions are used to create a joint production plan dictated by the CF. Now we proceed to show the DW-reformulation of the problem and we define the new parameters and variables needed for implementation:

##### 4.5.1 Master Problem (MP):

**Parameters:**

$$Vharv_{hjl}^k, \quad VHire_{tl}^k, \quad VFire_{tl}^k, \quad Vlab_{tl}^k, \quad VPlant_{pjl}^k, \quad Vtrans_{hjl}^k,$$

**Variables:**

$$\lambda_l^k$$

**Master Objective Function:**

$$\begin{aligned}
Max Z_{MP} = & \sum_{hj,q,max_j \geq q \geq qmin_j} V_{sell_{hj,q}} * Price_{hj} & (4-13) \\
& - \sum_{hj,q} V_{inv_{hj,q}} C_{inv_j} - \sum_{hj,q} V_{over_{hj,q}} C_{over_j} - \sum_{hj,q} V_{under_{hj,q}} C_{under_j} \\
& - \sum_{lj,q,t} V_{trans_{hj,ql}^k} C_{trans_{jl}} \lambda_l^k - \sum_{tl} V_{hire_{tl}^k} C_{hire_t} \lambda_l^k - \sum_{tcl} V_{lab_{tl}^k} C_{lab_t} \lambda_l^k \\
& - \sum_{pjl} V_{plant_{pjl}^k} C_{plant_j} \lambda_l^k - \sum_{hjl} V_{harv_{hjl}^k} C_{harv_j} \lambda_l^k
\end{aligned}$$

**CF Constraints:**

$$\sum_l V_{trans_{hj,ql}^k} \lambda_l^k + V_{inv_{h-1,j,q+\Delta q_j}} - V_{sell_{hj,q}} = V_{inv_{h,j,q}} \quad \forall j, q, h \quad (4-14)$$

$$MinDem_{hj} - V_{under_{hj,q}} \leq \sum_{q,max_j \geq q \geq qmin_j} V_{sell_{hj,q}} \quad \forall j, h \quad (4-15)$$

$$\sum_{q,max_j \geq q \geq qmin_j} V_{sell_{hj,q}} \leq MaxDem_{hj} + V_{over_{hj,q}} \quad \forall j, h \quad (4-16)$$

$$\sum_{jq} V_{inv_{hj,q}} \leq WHCap \quad \forall h \quad (4-17)$$

$$\sum_k \lambda_l^k = 1 \quad \forall l \quad (4-18)$$

Note that equation (4-18) is added to the master problem to ensure convexity of the sub-problem solution space; moreover, the new parameters defined for the MP correspond to solutions to farmer sub-problems.

**4.5.2 Sub-Problems (SP<sub>l</sub>):**

We obtain the extreme points of the feasible set of planting decisions through  $L$  sub problems  $SP_l \forall l \in L$ , which are used to generate columns in the master problem. For the sub problems, the formulation of the constraints is the same as for the centralized problem; however, the objective function is augmented by the dual variables corresponding to the constraints of the master problem. Here, we use the dual variables  $\pi_{hj,q}^1$ , which is the dual for (4-14) and  $\mu_l$ , which is the dual for (4-18).

**Parameters:**

$$\pi_{jqt}^1, \mu_l$$

**Sub-Obj (for all locations "l"):**

$$\begin{aligned} \text{Max } Z_l = & - \sum_{jqt} Vtrans_{hjql} * Ctrans_{jl} & (4-19) \\ & - \sum_t (VHire_{tl} * Chire_t) - \sum_t (Vlab_{tl} * Clab_t) \\ & - \sum_{pj} (VPlant_{pjl} * Cplant_j) - \sum_{hj} (Vharv_{hjl} * Charv_j) \\ & - \sum_{hjq} \pi_{hjq}^1 * Vtrans_{hljq} - \mu_l \end{aligned}$$

**Subject to constraints:**

$$(4-2), (4-3), (4-4), (4-5), (4-6), (4-7), (4-8), (4-9)$$

The inclusion of the dual variables  $\pi_{ijqt}^1, \mu_l$  into the farmers sub problem have a direct interpretation: Announce the price vector corresponding the prices of the crops transported to the CF. Moreover, an encouraging result is that due to the structure of D-W decomposition, under a finite number of iterations for price announcements, the mechanism converges to the optimal solution.

Unfortunately, having a guarantee of convergence and optimality is not sufficient for this mechanism to be viable in practice. The main problem with this formulation is that once farmers announce a solution to the CF, they themselves lose control over the final determination that the CF can make for production assignments. Ultimately, the CF will recombine the solutions farmers to achieve a convex combination which is optimal for the overall system; however, this reduced transparency coupled with the difficulty of farmers interpreting the concept of convex combination of the solutions makes this mechanism undesirable.

In order to escape the fallbacks of a mechanism based on the DW-decomposition of the problem, we present a formulation of the problem which provides a more robust solution approach. Mainly, we continue using dual decomposition; however, in this case we implement a method of sub gradient optimization akin to an auction mechanism.

#### 4.6 Decentralized Model Using Sub-Gradient Optimization (Auction)

In this new formulation, instead of the CF recombining solutions, only the latest solutions for the sub-problems are used. In other words, the CF no longer combines solutions presented earlier and instead we limit the solution space to the latest bids placed by farmers. This mechanism is formulated through sub-gradient optimization by relaxing appropriate constraints and penalizing deviations in the objective function. The variables penalizing these deviations become prices for the shared resources. In our case, these prices become the auction prices which are announced by the CF in an iterative fashion. We now show the details on how to perform this decomposition and auction interpretation.

The lagrangian relaxation of the problem needed for subgradient optimization and the implementation of the problem as an iterative auction is formulated below.

##### **Variables:**

$\lambda_{hj q}$  : unconstrained

##### **Objective Function:**

$$\begin{aligned}
Max Z_{SG} = & \sum_{hj,q} \max_{j \geq q} \min_j V_{sell_{hj q}} * Price_{hj} & (4-20) \\
& - \sum_{hj q} V_{inv_{hj q}} * C_{inv_j} - \sum_{hj q} V_{over_{hj}} * Cover_j \\
& - \sum_{hj q} V_{under_{hj}} * C_{under_j} - \sum_{ljqt} V_{trans_{hjql}} * C_{trans_{jl}} \\
& - \sum_{tl} (V_{Hire_{tl}} * Chire_t) - \sum_{tl} (V_{lab_{tl}} * Clab_t) \\
& - \sum_{pjl} (V_{Plant_{pjl}} * C_{plant_j}) - \sum_{hjl} (V_{harv_{hjl}} * Charv_j) \\
& + \sum_{hj q} \lambda_{hj q} (PVarr_{h,j,q} - \sum_l V_{trans_{hljq}})
\end{aligned}$$



**Subject to:**

(4-2), (4-3), (4-4), (4-5), (4-6), (4-7), (4-8), (4-10), (4-11), (4-12), (4-13)

Note that for the above formulation (4-9) is relaxed and placed in the objective function being penalized by  $\lambda_{hjq}$ . Also note that with the relaxation of constraint (4-9), the mathematical model for the coordination problem becomes separable, and thus solving the full problem via sub gradient optimization becomes equivalent to solving the sub problems for all farming locations and the CF. We now present a formulation which is equivalent to solving the problem defined by the objective (4-20) and constraints (4-2 – 4-8) and (4-10 – 4-13). Here, the decentralized formulation is given by the following sub-problems:

**4.6.1 Farmer Sub-Problems:****Objective Function:**

$$\begin{aligned}
 Max Z_l = & - \sum_{ljqt} Vtrans_{hjq} Ctrans_{jl} & (4-21) \\
 & - \sum_{tl} (VHire_{tl} Chire_t) - \sum_{tl} (Vlab_{tl} Clab_t) \\
 & - \sum_{pjl} (VPlant_{pjl} Cplant_j) - \sum_{hjl} (Vharv_{hjl} Charv_j) \\
 & - \sum_{hjq} \lambda_{hjq} (\sum_l Vtrans_{hljq})
 \end{aligned}$$

**Subject to:**

(4-2), (4-3), (4-4), (4-5), (4-6), (4-7)

**4.6.2 Consolidation Facility Sub-Problem:****Objective:**

$$\begin{aligned}
 Max Z_{CF} = & \sum_{hj,qmax_j \geq q \geq qmin_j} Vsell_{hjq} Price_{hj} - \sum_{hjq} Vinv_{hjq} Cinv_j & (4-22) \\
 & - \sum_{hjq} Vover_{hj} Cover_j - \sum_{hjq} Vunder_{hj} Cunder_j \\
 & + \sum_{hjq} \lambda_{hjq} (PVarr_{h,j,q})
 \end{aligned}$$

**Subject to:**

(4-10), (4-11), (4-12), (4-13)

Note that the centralized problem is equivalent to that defined in Section 4.5. Here, the inclusion of the variables  $\lambda_{hjq}$  implies that there exist some vector  $\mathbf{p}$  corresponding to market clearing prices such that farmers seeking their own best interest will lead the system to an optimum (Vohra, 2011). Furthermore, in order to implement the coordination mechanism as an auction, we can use the constraint violation as a base for finding a “direction of improvement” such that  $\lambda_{hjq}^{k+1} = \lambda_{hjq}^k + \theta(\sum_l Vtrans_{hljq} - PVarr_{h,j,q})$ ; where  $\theta$  is an appropriately chosen parameter.

With this formulation we have a viable methodology to reach the centralized solution even under distributed and asymmetric information. The problem which we must address now relates to the implementation of the mechanism and understanding whether convergence can be achieved on few iterations. In the following section we provide this analysis through computational results and a case study.

#### 4.7 Practical Implementation of the Coordination Mechanism

In previous sections we have shown the theoretical formulations and expected convergence results for the proposed coordination mechanism; however, it is also desirable to understand how the mechanism will act in practice. In this section we present computational experiments to understand the expected behavior of the mechanism; we compare the quality of solutions that can be obtained for the WD-decomposition mechanism of Section 4.5 and the auction mechanism of section 4.6. These are benchmarked to the centralized solution as given by the centralized model of section 4.4.

For the data used in this case study, we use farming parameters drawn from a case study performed by (Wishon et al., 2015). In this study, Wishon et al. performed a study of the impact of labor availability on farming efficiency. The information used is

representative of a typical farm from the agricultural region of Yuma, AZ in the Southwestern United States.

#### 4.7.1 Definition of Parameters

For the case study, all parameters defined in Section 4.4 were assigned values from the original research study of Wishon et al. (2015). However, the original study did not capture relevant differences between the various farming locations and instead focused on modeling a “typical farm” from the region. This creates an issue since the mechanism has to be tested under the setting of multiple, heterogeneous farmers. Nonetheless, obtaining such information is not possible through the limited data; moreover, collecting additional data is a non-trivial task that requires an extensive amount of resources. This difficulty of obtaining information arises from the very structure of the problem we seek to address since specific farmers are unlikely to reveal true cost information.

Capturing additional cost information for multiple farms is an expensive and long process; therefore, the original data was modified to reflect a degree of variety of the various farmers. To do this, five parameters from the original dataset were adjusted: Land size, labor force, yield, spatial dispersion and planting costs. These parameters were modified within pertinent ranges to create various instances which correspond directly to having a number of different farmers. Moreover, in order to keep the generation of these “farmer-datasets” tractable and easily created, random variables were used to induce heterogeneity to the farming parameters. The random variables used for these parameters were as follows<sup>5</sup>:

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<sup>5</sup> Note that all variables are independent, except for Land/Labor which have a direct correlation ( $\rho=1$ ).

- Labor:  $[U\sim(18,52)]$  workers
- Land:  $[U\sim(150,250)]$  acres
- Yield:  $[U\sim(0.75, 1.35)]$ \* Base yield per crop
- Production costs:  $[U\sim(0.75, 1.35)]$ \* Base cost per crop
- Transportation costs:  $[U\sim(0.10, 0.30)]$ \* Base cost

Also note that in addition to the above parameters, the current model has the addition of shelf life for all four products through the constraint (4-10). This ensures that the products of broccoli and cauliflower can be stored for only one week, whereas romaine and iceberg lettuce can be stored for 2 weeks. No difference in value is accounted for in the objective function.

Upon generating  $N$  different dataset, where  $N$  is the number of farmers, test instances could be run. For this, five different test instances were solved, going from  $N=\{1, 5, 20, 50, 125\}$  farmers. Also note that even though the information for all farmers was generated jointly, for the implementation of the coordination mechanism, the “private” information for all farmers remains hidden from the CF and other farmers to complete the asymmetric information requirement. The computational results for all test instances are illustrated throughout the remainder of this section.

#### 4.7.2 Computational Results (Auction vs D-W Decomposition)

For the assessment of the computational results, there are three key metrics which are particularly relevant: (1) the optimality gap between the auction and the centralized solution, (2) the “centralized” optimal solution and the (3) speed of convergence. These metrics are relevant because a guaranty of efficiency is desired, but also to keep supplier effort at a reasonable level. We contrast the behavior of the D-W decomposition of the problem, which serves as an alternative to the auction mechanism.

Since the D-W decomposition of the problem treats the integer variables in the farmer sub-problem as continuous, we relax the integrality constraints in the farmer sub-problems for comparison purposes between the WD-decomposition and the sub-gradient optimization. We address these results in Figure 4.2 below.

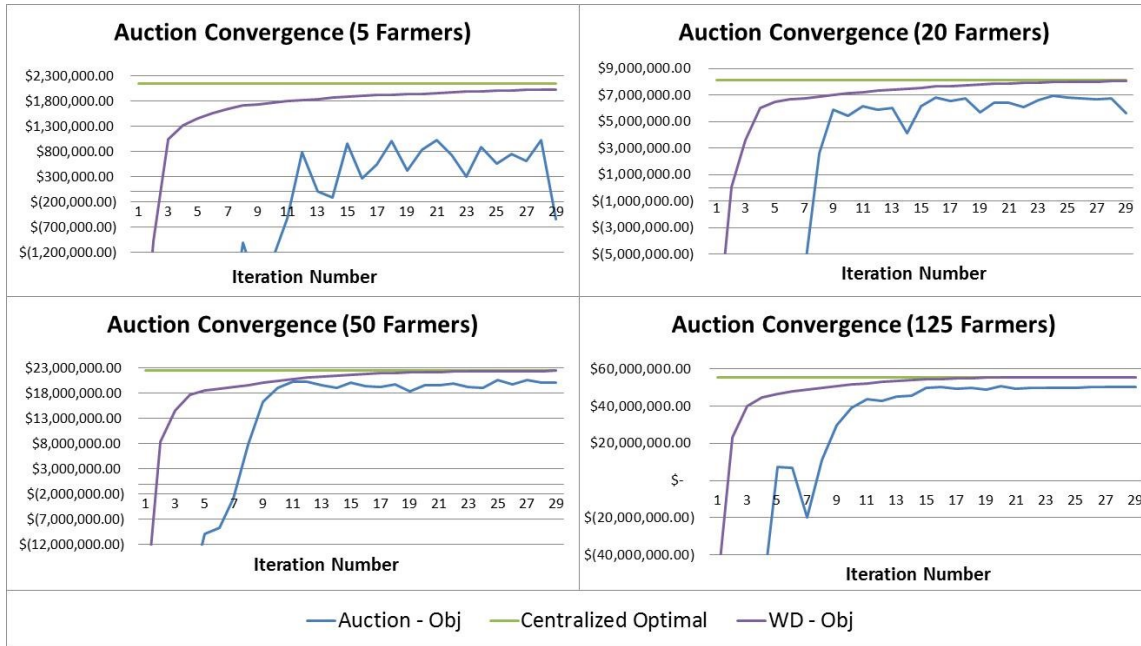


Figure 4.2 – Convergence and Optimality Gap for Various Problem Sizes

As it can be observed, as we iterate in both mechanisms, the optimality gap can be rapidly closed by the W-D decomposition of the problem; nonetheless, our primary focus is in the convergence of the auction mechanism which albeit doesn't converge as rapidly, it does approximate the optimal solution. On the other hand, we have the planning mismatch, which shows the difference between the desired supply by the CF and the aggregate deliveries planned by farmers; this metric also approximates zero as the auction converges. These results are further summarized in Table 4.1, which shows the optimal solution, the best solution achieved by the auction, the mismatch between desired supply

and the supply provided by farmers, optimality gap and the number of iterations required to reach a reasonable (80%) efficiency in the auction.

Table 4.1 – Results for Auction Convergence and Optimality

Number of participants	Optimal Solution	Best Auction Solution	% Supply-Demand Mismatch	% Optimality	Iterations to 80%
5 Farms	\$ 2,136,136	\$ 1,020,037	25%	48%	-
20 Farms	\$ 8,156,519	\$ 6,930,982	14%	85%	17
50 Farms	\$ 22,395,199	\$ 20,601,215	8%	92%	10
125 Farms	\$ 55,567,789	\$ 50,863,300	8%	92%	11

As it can be observed, the mechanism converges within a reasonable number of iterations up to a narrow optimality gap. This is an encouraging result for the practical implementation of the mechanism. Moreover, we see that the mechanism remains attractive for implementation even for organizations consisting of as few as 20 farmers. We also observe that the results obtained are consistent with economic theory, which states that fewer bidders will have a greater power to manipulate the market price; i.e. more elastic supply and less stable solutions.

#### 4.7.3 Computational Results (Integer Decision Variables)

After understanding the results and convergence properties of the mechanism for the LP case, we proceed to restrict some relevant variables to further quantify what can be expected of the mechanism in a mixed integer programming formulation. For this, we restrict the variables  $Vlab_{tl}$  and  $Y_{jpl}$  from the farmer sub problem back to integer and binary respectively in order to properly account for labor constraints and for the binary restriction of minimum planting quantities at each farming location. The results for convergence of the problem with integer variables are compared to the LP relaxation convergence in Figure 4.3 below. The figure shows the best integer solution, the

convergence of the auction in the LP relaxation and the more realistic convergence of the auction in the MIP case.

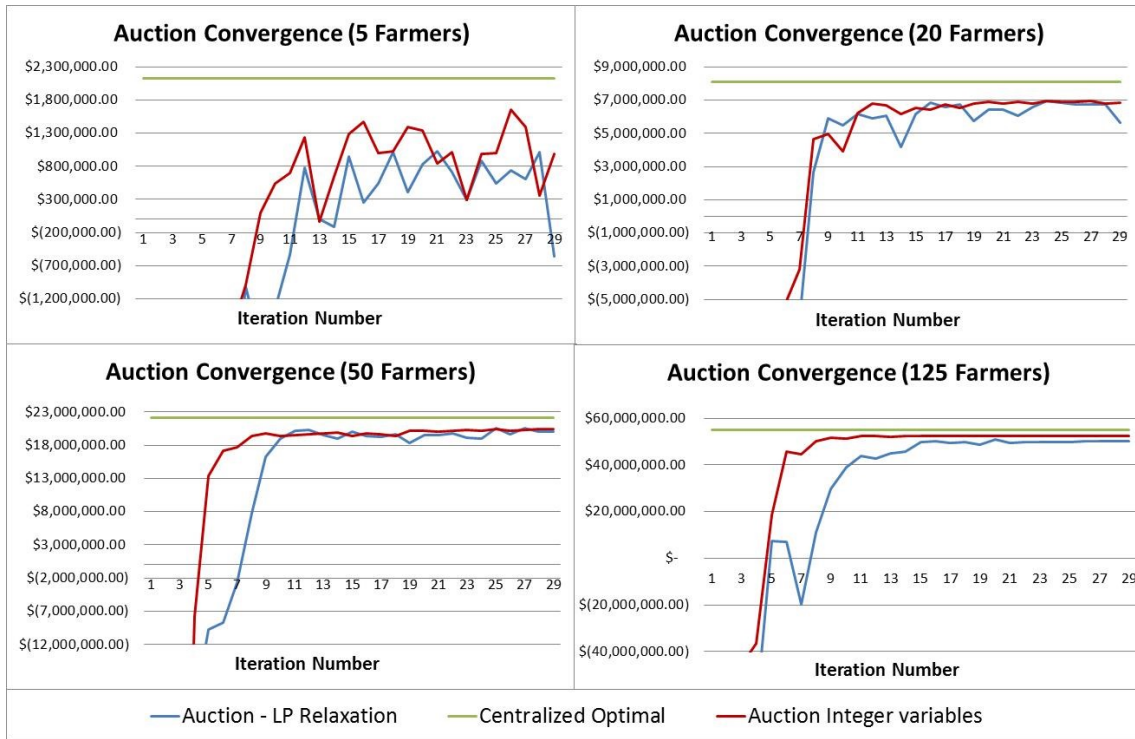


Figure 4.3 – Convergence for LP Relaxed Problem and Problem with Integer Variables

Surprisingly, the results obtained show that the auction converges faster and closer to the optimal solution for the case in which the farmer sub-problems use integer decision variables. The reason for this improvement is unclear, although it may be caused by removing flexibility from farmers, which in turn would limit the elasticity of supply. Nonetheless, this result provides further encouragement for the possibility of practical implementation of the mechanism, since the convergence properties of the mechanism appear to be strong despite assumptions or restrictions made at the farmer level.

#### 4.7.4 Additional Results

Now that we have shown the convergence in an aggregate level, we show the behavior of individual variables in more detail. This gives us further intuition for what to

expect of the mechanism in practice. For this we review the behavior of specific variables such as total aggregate production, share of production throughout several farms, the share of profits by farmers and the price dynamics throughout the auction. We focus on one specific problem instance: a 20 farmer cooperative problem.

In the previous section we observed how the total system profit progresses throughout the various auction iterations and showed that it converges rapidly towards the centralized optimum. Now analyze how total production behaves for each of the products under consideration (Figure 4.4). Here we observe that for the first two iterations it was unprofitable for farmers to produce given the announced prices; thereafter, in iteration 3, it was only profitable to produce reduced quantities of iceberg lettuce. Shortly after, production quantities rapidly increase and then stabilize to their long term optimal values.

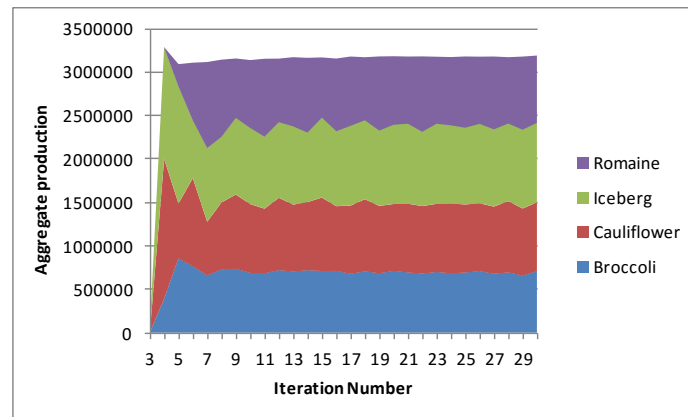


Figure 4.4 – Aggregate Production Commitments throughout the Auction

If we observe this from the perspective of the price actions as they occur in the background we have a dynamic system where prices will adjust to incentivize the production of some goods over others. This is illustrated by Figure 4.5 which shows the price dynamics for a single week (production period) of the production season, while Figure 4.6 shows the price for each crop averaged throughout the entire season.



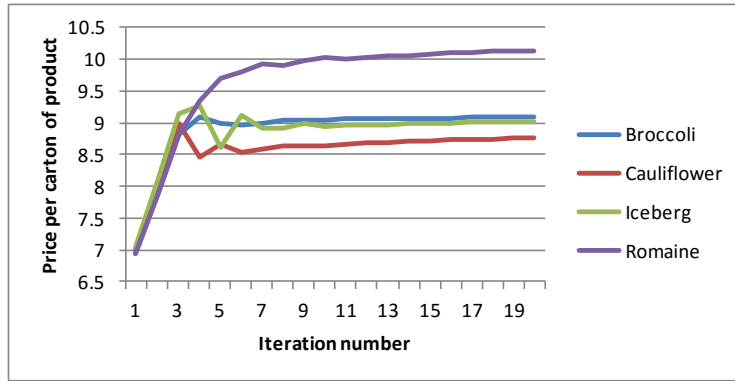


Figure 4.5 – Auction Prices for Week 27

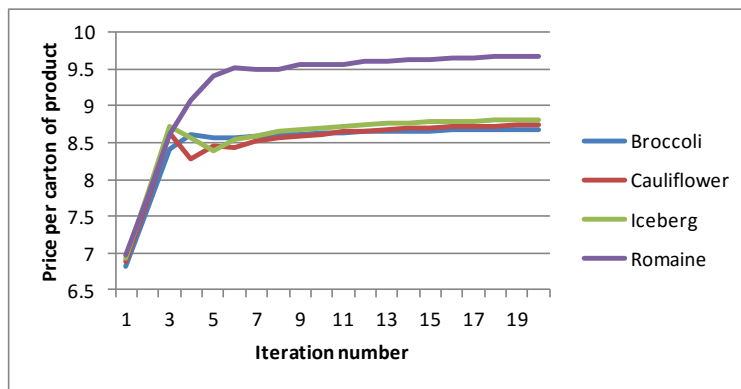


Figure 4.6 – Auction Price Averages for All Weeks during Harvest Season

It is worth noting that while aggregate prices may be increasing and prices for week 27 are also increasing, this does not mean that all prices behave similarly for all time-periods. In practice, the devised mechanism will adjust to oversupply in any given week by decreasing prices, while adjusting to overdemand by doing the opposite.

It is also worth noting that although average prices are increasing, this does not necessarily impact CF profits negatively; instead, by choosing how prices are raised in a scientific manner, overall supply chain profits are increased. We see this dynamic in Figure 4.7, which illustrates what the projected profits of the supply chain are after each auction

iteration takes place<sup>6</sup>. Here we note that the CF remains grossly unprofitable due to the penalties incurred for not meeting projected demand; this situation remains true up until the 8<sup>th</sup> auction iteration, where supply and demand become aligned. In contrast, farmers get profitable outcomes much earlier. We also observe that for this case farmers keep roughly 30% of the profits from the supply chain, with the rest going to the CF.

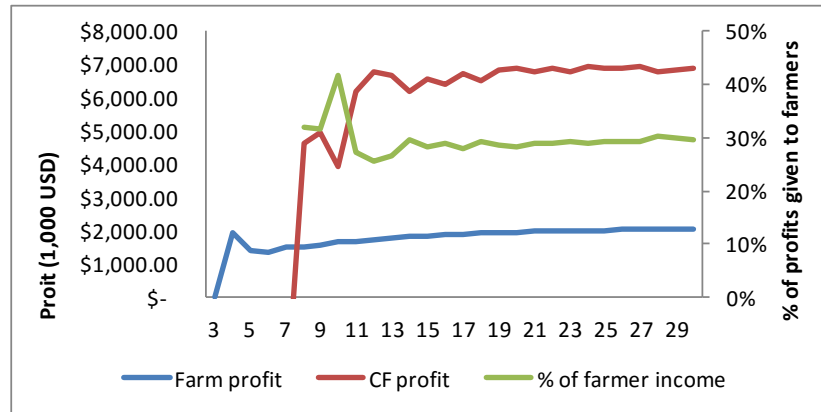


Figure 4.7 – Share of Supply Chains Profits for Farmers and Consolidation Facility

Here we also have an interest in what are the share of profits by farmers for different problem sizes; therefore, this information is provided in Figure 4.8 which gives an overview of farmer profits as a percentage of the entire system profits. We emphasize that these profits for farmers are in the form of direct transfers resulting from their individual production. If the mechanism were implemented a cooperative where farmers are also the owners of the CF, then the individual profits of farmers would be higher once the profits of the CF are redistributed or reinvested.

<sup>6</sup> In practice we will not be able to observe profits directly, since production costs remain private for all farmers; only projected revenues would be known.

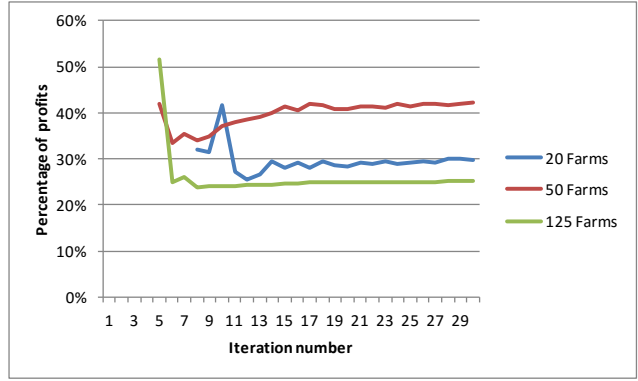


Figure 4.8 – Share of Supply Chain Profits Going to Farmers for Different Problem Sizes

Finally, another outcome that we are concerned about is the projected production for each farmer individually after the mechanism concludes. For this, we illustrate the total production that each farmer dedicates to each crop assuming that the mechanism shown above came to its conclusion at the 14<sup>th</sup> iteration (Figure 4.9). As we can see, for the case of 20 farmers at the 15<sup>th</sup> iteration, production schedules are highly heterogeneous, with most farmers specializing in one or two crops.

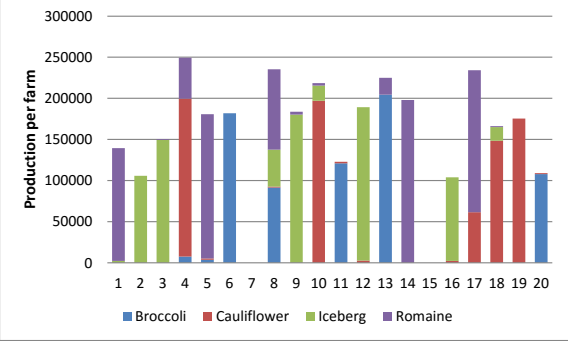


Figure 4.9 – Total Production Allocation per Farm (14<sup>th</sup> Iteration)

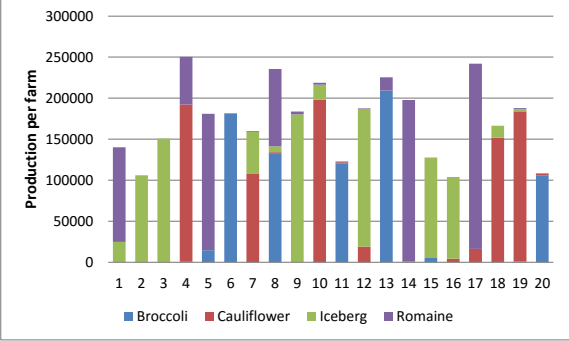


Figure 4.10 – Total Production Allocation per Farm (Optimal-Centralized Solution)

Unfortunately, we also find that in this solution for two farms (7 and 15) find it unprofitable to produce given current prices. This was not the case for the centralized-optimal solution (Figure 4.10), where all farms could produce for the profitability of the group to be maximized. Ideally all farmers should participate in the final solution if it is in

fact optimal to have them do so. We recognize this to be a problem, but sustain that as the mechanism is allowed to progress and prices to rise, the two outcomes should be identical.

#### 4.8 Conclusions

Throughout this research we have argued the importance of decentralized planning and coordination of the supply chain of fresh produce. Not only is this coordination desirable from an efficiency standpoint, but it is also indispensable for farmers which wish to thrive in a competitive environment. As a result, a model for coordinated production decisions among a group of farmers is formulated.

Nonetheless, this coordination is not easy to achieve, in particular when internal competition and strategic behavior hampers the sharing of information and the incentives to collaborate. As a result, a more robust approach which can be implemented in a decentralized manner despite the unavailability of information is developed. For this, an auction mechanism assigns production quantities for an upcoming season, thus creating a coordinated tactical plan for the CF which has a theoretical backing that guarantees convergence to an optimal outcome.

The proposed mechanism is shown to approximate the optimal solution within a reasonable number of iterations and to perform well for large problem instances. Moreover, the mechanism is shown to have good convergence properties under the common assumptions of integer labor numbers and the conditions of minimum required planting quantities on each period. These computational results show that this mechanism can be feasibly implemented in practice and that coupled with the appropriate planning tools for farmers and their consolidation facility the mechanism can provide a viable means for coordinated and efficient planning of agricultural production.

#### 4.9 Future Work

Although the mechanism has been shown to be feasible for implementation, there remain several questions which must be answered in order to make viable and improve this new framework. Mainly, the model developed makes the assumptions of a given customer demand which is known before the season, this assumption may not be true in practice. Furthermore, there is also the problem of defining a demand schedule which farmers agree to before the auction mechanism starts an iterative process to assign contracts. Also related to this is the problem of defining appropriate penalties for over/undersupply of a given product during the harvest season; such a problem may be addressed from the perspective of defining a cost for product wastage as well as the cost of demand not met with the next echelon of the supply chain.

Finally, the more interesting problem which was not addressed directly in this chapter is that of strategic bidding. That is, despite the implementation of a mechanism, farmers may find it advantageous to misrepresent their information to gain a strategic advantage. In this research we present a mechanism which converges to the optimal solution under the assumption of farmers stating their production quantities truthfully. However, if such a mechanism is to be implemented, an in depth analysis of incentives and deterrents for strategic bidding must be performed in order to understand and minimize the negative impacts of such behavior. Thus, we emphasize the importance of quantifying the prevalence of strategic bidding and understanding its impact (if any) on the quality of solutions obtained by this framework.

## 5 STRATEGIC FARMER BIDDING AND ITS IMPACT ON EFFICIENCY

### 5.1 Introduction

In Chapter 4 we presented a tactical planning model for a cooperative composed of multiple farmers who have expanded vertically through the establishment of a consolidation facility (CF). We show the viability of creating a mechanism in the form of an iterative auction; this mechanism assigns contracts for production quantities ahead of the growing season, ensuring that supply is matched to demand. through this mechanism we also ensure that farmers produce according to their comparative advantages and that the overall production plan is cost effective and profitable for farmers.

However, as we have stated earlier, a mechanism can exhibit severe flaws when implemented in practice. Mainly, if bidders deviate from truthful behavior or engage on strategies such as collusion, shill bidding or underbidding, then the efficiency of the mechanism is compromised. For this reason it is important that economic incentives are such that participants state their bids as close as possible to their true valuations and, if possible, to formulate the mechanism such that stating their true valuations is their best strategy. Not only does this help the efficiency of the mechanism, but it also reduces the computational burden on bidders.

In Chapter 2, we formally define what a mechanism is intended to achieve. We stated that a mechanism implements a Bayesian game for which the Nash Equilibrium coordinates the system. Here, four properties are of great importance for any mechanism: **Individual rationality (IR)**, defined as allowing agents to act freely and without obligation to participate (Sandholm, 1999); **budget balance (BB)**, meaning that the mechanism requires no external subsidies to be implemented (Chu & Shen, 2006); **incentive**

**compatibility (IC)**, or the property of mechanisms eliciting truthful revelation of information from participating agents (Myerson, 1981); and finally **efficiency**, or the allocation of goods such that the overall utility for all parties involved is maximized.

Unfortunately, a mechanism that fully implements all four requirements is generally not attainable, even for simple cases; for instance, for the case of bilateral trade, it is shown that no mechanism exists which implements all four requirements (Myerson & Satterthwaite, 1983). For multilateral trade, practical implementation may show that at least one of these characteristics was not attained. As a result, a compromise between efficiency, IR, IC and BB may be necessary; for instance, efficiency may be purposefully forfeited in order to achieve IC. One example of this is (Babaioff & Walsh, 2005), where a mechanism is deliberately made inefficient (to a reasonable extent) in order to secure BB, IC and IR.

Some mechanisms can be formulated to be viable for the allocation of goods while also obeying to the four properties mentioned above; one such mechanism is the Vickrey-Clarke-Groves (VCG) mechanism. However, although Clarke and Groves were able to formalize the conditions for an efficient, IC, BB and IR mechanism, we find that implementing this is generally not feasible in practice (Rothkopf, 2007). Mainly, a VCG-mechanism creates a momentous computational burden for calculating valuations as well as being highly susceptible other pathologies (Ausubel & Milgrom, 2002). Even under the positive results of the VCG-mechanism, in practice implementation isn't always practical.

Despite the difficulties detailed above, researchers have not shied away from proposing mechanisms to coordinate the supply chain. This problem does, however, highlight the importance of considering BB, IC and IR explicitly in order to minimize the

impact of deviations from the ideal assumptions of the mechanism. In particular, we place a strong emphasis on incentive compatibility, as it is the most elusive requirement and it is particularly important to the problem formulated in this thesis.

Since the VCG mechanism is impractical, the coordination mechanism detailed in Chapter 4 is formulated as an iterative auction. The result is an iterative, multiunit, multiple-product auction which must terminate within a reasonable number of iterations. This however, creates many questions for the behavior of the mechanism; chief among them is to understand the bidding strategies that surface from the few discrete iterations in this mechanism (Ausubel & Cramton, 2004; Conen & Sandholm, 2001; Parkes & Ungar, 2000b).

It is our objective to understand the conditions under which strategic bidding occurs, as well as its prevalence and severity. For this, in the current chapter the characteristics of our proposed mechanism are analyzed by formulating the strategic bidding problem as a dynamic program. We look at the bidding problem from the perspective of a farmer whose objective is to maximize his/her own profit. Once a suitable strategy for each farmer as an individual is found, the impact of strategic bidding on the overall system is quantified and appropriate measures are taken to address the problem. This problem is assessed through theoretical, as well as computational results in a case study similar to that of Section 4.7.

## 5.2 General Formulation of the Bidding Problem

The algorithmic behavior of the mechanism is straightforward. Simply stated, a price vector is announced for all possible items under consideration; then bidders state their production plans for the prices announced. This process is carried out until demand is matched to supply, or until a pre-established stopping condition is attained (Section 4.3)



The mechanism is limited to a reduced number of iterations  $N$ . Here, we also have  $L$  bidders and one seller who takes the role of the auctioneer. The role of the auctioneer is to aggregate production announcements, evaluate them in the context of the CF, and then compute a new set of prices. Each bidder has its own private valuation and cost functions determined directly by their local constraints and production costs; moreover, no bidder knows the private production information held by others. Likewise, the CF has no knowledge of the private information of the participating farmers.

We assume that price updates are given by the sub-gradient algorithm used to solve the decentralized problem (Section 4.6). Specifically, price adjustments on each iteration are given by:  $\lambda_{hjq}^{k+1} = \lambda_{hjq}^k + \theta(\sum_l Vtrans_{hljq} - PVarr_{h,j,q})$  where  $\theta$  is a suitable scalar which defines the scale of price adjustments. We assume that the use of this function and the parameter  $\theta$  are common knowledge for all bidders. Finally, we assume that although the auctioneer (CF) may be aware of strategic bidding by farmers, there is no counterspeculation from this player. By this we mean that the CF does not deviate from the stated pricing algorithm.

The reason for limiting the ability of the CF to counterspeculate is twofold: First, we want to simplify the bidding process for farmers in order to limit the computational burden of strategic bidding. The second reason is that counterspeculation becomes a self-defeating measure, as farmers can account for this behavior and model it on their own decision problems.

### 5.3 Theoretical Analysis and Intuition

As it can be seen, the iterative auction is simple and easily implemented; however, it leaves room for manipulation of prices by sophisticated bidders. In particular, if a bidder

finds no risk (or little risk) on misrepresenting its production quantities, then he/she can announce production quantities which are deflated and increase the magnitude of price adjustments in subsequent iterations. As a result, understanding the decision process of bidders is the first step towards refining the mechanism.

In order to analyze the above problem, we reformulate as a simplified version of the Chapter 4 decentralized problem in its generic form. In Section 4.6, the coordination problem has the form of a block angular matrix with a lagrangian relaxation on the binding constraints. By relaxing these constraints, the problem is decomposed to  $L + 1$  sub problems, where we have  $L$  bidders and one seller.

We illustrate the decomposition of the problem below, where  $c_y, A_y, b_y, y$  are the cost vector, constraint matrix, constraint vector and decision variables respectively for the seller; likewise, for each bidder  $l$  we have:  $c_l, A_l, b_l, x_l$  corresponding to the cost vector, constraint matrix, constraint vector and decision variables respectively.

$$\mathbf{Max} \quad c_y y + \sum_l c_l x_l \quad (5-1)$$

$$\mathbf{St} \quad A_y y = b_y \quad (5-2)$$

$$y = \sum_l x_l \quad (5-3)$$

$$A_l x_l = b_l \quad \forall l \in L \quad (5-4)$$

$$x_l \geq 0 \quad \forall l \in L ; y \geq 0 \quad (5-5)$$

By relaxing constraint (5-3), we obtain the seller sub problem and the bidder sub problems. These are augmented by the price vector  $\lambda$  as seen below. These problems can be solved to optimality by sub-gradient optimization. Here, the update of the price vectors  $\lambda$  is given by:  $\lambda^{k+1} = \lambda^k + \theta(y - \sum_l x_l^k)$ , where  $\theta$  is a suitable step size.

Seller sub problem

$$\begin{aligned} \text{Max} \quad & (c_y - \lambda)y & (5-6) \\ \text{St} \quad & A_y * y = b_y \\ & y \geq 0 \end{aligned}$$

Bidder sub problems

$$\begin{aligned} \text{Max} \quad & \sum_l (c_l + \lambda) x_l \quad \forall l \in L & (5-7) \\ \text{St} \quad & A_l * x_l \leq b_l \\ & x_l \geq 0 \end{aligned}$$

In order to better understand strategic bidding, we pick one specific bidder's sub-problem for any given iteration  $k$  in the auction. Let  $\mathbf{z}_l^*$  be the cost of the optimal planting plan for a given price announcement. For simplicity, from this point forward we refer to only one specific bidder as bidder  $l'$ . We also state the cost vectors simply as:  $\mathbf{c}_y$  and  $\mathbf{c}_l$  instead of  $(\mathbf{c}_y - \lambda)$  and  $(\mathbf{c}_l + \lambda)$  under the assumption that the price update is implicit in the price vector at any iteration. The simplified bidders sub problem in a given iteration  $k$  is given by:

$$\begin{aligned} \text{Max} \quad & \mathbf{z}_{l'}^* = \mathbf{c}_{l'}^k x_{l'}^k & (5-8) \\ \text{St} \quad & A_{l'} x_{l'}^k = b_{l'} \\ & x_{l'}^k \geq 0 \end{aligned}$$

If we take the individual bidder sub-problem (5-8) and assume that the solution being provided is truthful, then the solution to the coordination problem is trivial; however, we don't know that this will be generally true. More critically, the above representation of the bidder's sub-problem is incomplete, since at each iteration the maximum utility that can be obtained by a bidder is affected by the expectation of future prices. Thus, the more complete representation for the bidding problem in iteration  $k$  can be stated as:

$$\begin{aligned} \text{Max} \quad & \mathbf{z}^{BR} = \alpha^k \mathbf{c}^k x_{l'}^k + E \left[ \sum_{i=k}^{N-1} \alpha^{i+1} \mathbf{c}_{(c^i, x_{l'}^i)}^{i+1} x_{l'}^{i+1} \right] & \text{for } k < N & (5-9) \\ \text{St} \quad & A_{x_{l'}} x_{l'}^i = b_{l'} \quad \forall i \leq N \\ & x_{l'}^i \geq 0 \quad \forall i \leq N \end{aligned}$$

Here,  $c^{i+1}$  is the expected price for the following iterations,  $\alpha^i$  is a discount rate<sup>7</sup> and  $z^{BR}$  is the best response objective function of a bidder. In this reformulation we note that the bidder's problem becomes much larger; specifically, the number of variables in the problem grows by a factor of  $(N - k)$ . Furthermore, the objective function is no longer linear since the price vector  $c^{i+1}$  is a function of  $x_{l'}^i$ ; in fact, we have a relationship for prices from one iteration to the next given by:  $c^{i+1} = c^i + \theta(y^i - \sum_l x_{l'}^i)$ .

To simplify this expression, we assume that the variables  $y^i$  for the CF and  $x_l^i$  for all other bidders  $l \neq l'$  are random variables, and from the perspective of bidder  $l'$  these variables are and independent of the local bidding problem. As a result, we can decompose the price adjustment as in equation 5.10 below:

$$c^{i+1} = c^i + \theta(y^i - \sum_{l \neq l'} x_l^i - x_{l'}^i) \quad (5-10)$$

In this expression, let  $(y^i - \sum_{l \neq l'} x_l^i) = w^i$  where we can define  $w^i$  as the **outstanding balance** for any given product being auctioned. Therefore, if the remainder of bidders create an oversupply of a product, then a price decrease can be expected for the following iteration; otherwise, a price increase proportional to the difference can be expected. Moreover, during each iteration the quantity  $w^i$  will become known at the same time as  $x_{l'}^i$ , so  $w^i$  can be taken as a random disturbance from the perspective of bidder  $l'$ . With this change we have:

$$z^{BR} = \alpha^k c^k x_{l'}^k + E[\sum_k^{N-1} \alpha^{i+1} (c^i + \theta w^i - \theta x_{l'}^i) x_{l'}^{i+1}] \quad \forall k < N \quad (5-11)$$

---

<sup>7</sup> This discount rate can be interpreted as a probability for early termination of the auction; then  $\alpha^k$  can be interpreted as the appropriate weight used by a bidder to determine the expected cost of the overall problem

Unfortunately, this objective function becomes a stochastic, nonlinear, multi-period optimization problem, which cannot be solved through mixed integer programming as the preceding (Chapter 4) problem was. Therefore, we resort to using dynamic programming instead to derive some analytical results and intuition for the behavior of the mechanism, as well as an approximate solution methodology.

#### 5.4 DP Formulation of the Bidder's Sub-Problem

We observe the problem can be analyzed in the context of dynamic program with little modification. From this perspective, we declare the components and variables as:

$c^i$ : Is the **state vector** for the system in iteration  $i$

$x_{l'}^i$ : Is the **control vector** in iteration  $i$

$w^i$ : Is a random disturbance

In this system, we define the state transition (5-12) and cost function (5-13) as:

$$c^{i+1} = c^i - \theta x_{l'}^i + \theta w^i \quad (5-12)$$

$$g(c^k) = \alpha^k c^k x_{l'}^k \quad \forall k \leq N \quad (5-13)$$

Under this context, the objective is to choose the appropriate control vectors  $x_{l'}^i$ , which maximize the overall profit in all iterations. We restrict the set of controls  $x_{l'}^i$  to the convex space  $X$  defined by the system of equations  $A_{x_{l'}} x_{l'}^k = b_{l'}$ ;  $x_{l'}^k \geq 0$ . Finally, we define the terminal cost function  $J_N$  and the cost at stage  $N - 1$  as:

$$J_N(c^N) = \max_{x_{l'}^N \in X} c^N x_{l'}^N \quad (5-14)$$

$$J_{N-1}(c^{N-1}) = \max_{x_{l'}^{N-1} \in X} \alpha^{N-1} c^{N-1} x_{l'}^{N-1} + (1 - \alpha^{N-1}) E[J_N] \quad (5-15)$$

More generally, we may represent the cost to go as:

$$J_k(c^k) = \max_{x_{l'}^k \in X} \alpha^k c^k x_{l'}^k + (1 - \alpha^k) E[J_{k+1}] \quad \text{for } k < N \quad (5-16)$$

From this formulation, we can derive two valuable outcomes:

**Lemma 1:** If the probability of termination is  $\alpha^N = 1$ , which signals with certainty the final iteration in the auction, then the best response is to bid ones true valuation.

**Proof:** As it can be seen from problem definition in equation (5-14), the final stage problem is identical to the farmer sub-problem with non-strategic bidding. Since the profit of the bidder depends only on the current prices offered, then the objective function is linear and the best response is to bid the true optimal production schedule. ■

The outcome of this lemma is not surprising; in fact, a similar outcome was derived by Parkes & Ungar (2000b) who analyzed a limited set of bidding strategies for iterative auctions which they called “Myopic bidding strategies” (Parkes & Ungar, 2000a). In essence, they state that if a bidder were to calculate its best response by only looking at the outcome for the current operation, then the best response is to be truthful. Our first lemma is a special case of this, since in the final iteration there are no more iterations to contemplate and the solution is inherently myopic.

**Lemma 2:** If iteration  $N - 1$  has a zero probability of terminating the auction, the best response of any bidder is to state his/her production plan as zero for all products in iteration  $N - 1$ . Furthermore, if  $k < N$  consecutive iterations have a zero probability of termination, then the best response is to state a production plan of zero for all products in all  $k$  iterations.

**Proof:** Take the cost to go function for iteration  $N - 1$ : equation (5-15); note that if the probability of termination  $\alpha^{N-1} = 0$ , then it would be expected for the bidder to assign a value for the iteration  $N - 1$  down to zero. Thus the cost function becomes only the terminal cost:

$$\begin{aligned}
J_{N-1}(c^{N-1}) &= \max_{x_i^{N-1}, x_i^N \in X} \alpha^{N-1} c^{N-1} x_i^{N-1} + (1 - \alpha^{N-1}) E[J_N] \\
&= \max_{x_i^{N-1}, x_i^N \in X} 0 + E[c^N] x_i^N \\
&= \max_{x_i^{N-1}, x_i^N \in X} E[(c^{N-1} + \theta w^{N-1} - \theta x_i^{N-1})] x_i^N
\end{aligned}$$

Since  $x_i^N \geq 0$ , it is optimal to declare any variable being multiplied to  $x_i^N$  equal to zero ( $x_i^{N-1} = 0$ ) for all values of the state variable  $c^{N-1}$ . More formally, the sub-gradient obtained by taking the derivative on  $x_i^{N-1}$  is always negative and finding improvement on the objective function with decreasing values of  $x_i^{N-1}$ . Now we analyze the cost function for  $N - 2$  where  $\alpha^{N-2} = \alpha^{N-1} = 0$ .

$$\begin{aligned}
J_{N-2}(c^{N-2}) &= \max_{x_i^{N-2} \in X} \alpha^{N-2} c^{N-2} x_i^{N-2} + (1 - \alpha^{N-2}) E[J_{N-1}] \\
&= \max_{x_i^{N-2}, x_i^{N-1}, x_i^N} \alpha^{N-1} c^{N-1} x_i^{N-1} + (1 - \alpha^{N-1}) E[J_N] \\
&= \max_{x_i^{N-2}, x_i^{N-1}, x_i^N} E[(c^{N-1} + \theta w^{N-1} - \theta x_i^{N-1})] x_i^N \\
&= \max_{x_i^{N-2}, x_i^{N-1}, x_i^N} \alpha^N E \left[ \left( (c^{N-2} + \theta w^{N-2} - \theta x_i^{N-2}) + \theta w^{N-1} \right) \right] x_i^N
\end{aligned}$$

By the same analysis, it can be seen that it is optimal to state  $x_i^{N-2} = 0$  for all values of the state variable  $c^{N-2}$ . It can be shown by induction that the case will generalize for all  $x_i^{N-k}$ . ■

This result gives us some limited intuition for how to implement a mechanism while avoiding the most relevant pathologies of the formulation. Mainly, we can observe that in order for the mechanism to be incentive compatible and practically feasible, there must be some positive probability of termination before the final iteration. Unfortunately, gaining intuition for the case where iterations with a zero probability of termination precede some iteration  $N - k$ , becomes more elusive. In order to better address this problem, we

elaborate a generic form of the problem that expands the expectation of future iterations cost functions.

#### 5.4.1 Deriving a More Generic Cost-to-Go Function

For the reformulation of the bidding problem, we first assume the price adjustments for each iteration are known and given by  $\theta^k$ . Given this change, we expand the terms for the cost functions in all iterations such that the overall decision problem considers multiple stage decisions in a single iteration with expectation of the random shocks to the system.

We expand the expectation of  $E[J_N(c^N)]$  in the expression for  $J_{N-1}(c^{N-1})$ .

$$J_{N-1}(c^{N-1}) = \max_{x_i^{N-1} \in X} \alpha^{N-1} c^{N-1} x_i^{N-1} + (1 - \alpha^{N-1}) E[J_N(c^N)]$$

$$J_{N-1}(c^{N-1}) = \max_{x_i^{N-1}, x_i^N \in X} \alpha^{N-1} c^{N-1} x_i^{N-1} \\ + (1 - \alpha^{N-1})(c^{N-1} + \theta^{N-1} E[w^{N-1}] - \theta^{N-1} x_i^{N-1}) x_i^N$$

If we continue the recursive expansion for state  $J_{N-2}(c^{N-2})$ , we obtain:

$$J_{N-2}(c^{N-2}) = \max_{x_i^{N-2} \in X} \alpha^{N-2} c^{N-2} x_i^{N-2} + (1 - \alpha^{N-2}) E[J_{N-1}(c^{N-1})]$$

$$J_{N-2}(c^{N-2}) = \max_{x_i^{N-2}, x_i^{N-1}, x_i^N} \alpha^{N-2} c^{N-2} x_i^{N-2} \\ + \alpha^{N-1} (1 - \alpha^{N-2})(c^{N-2} + \theta^{N-2} E[w^{N-2}] - \theta^{N-2} x_i^{N-2}) x_i^{N-1} \\ + (1 - \alpha^{N-1})(1 - \alpha^{N-2})(c^{N-2} + \theta^{N-2} E[w^{N-2}] - \theta^{N-2} x_i^{N-2} + \theta^{N-1} E[w^{N-1}] \\ - \theta^{N-1} x_i^{N-1}) x_i^N$$

However, this problem notation can be greatly simplified by redefining some parameters. First, rather than looking at the  $k^{\text{th}}$  iteration, we change notation to see iteration  $N - k$  instead, meaning that we have  $k$  iterations left before the cutoff of the auction. This will simplify the notation as we expand relevant terms in the problem description. We also simplify notation and represent  $J_{N-k}(c^{N-k})$  simply as  $J_{N-k}$ . Finally, we let  $p_i^{N-k}$  be the



conditional probability of advancing exactly  $i$  iterations given that we are currently in iteration  $N - k$ , where  $0 \leq i \leq k < N$ ; here  $p_i^{N-k}$  is given by:

$$p_i^{N-k} = \begin{cases} \alpha^{N-k+i} \prod_{j=1}^i (1 - \alpha^{N-k+j-1}) & \forall i > 0, \quad i \leq k \\ \alpha^{N-k} & \forall i = 0 \end{cases} \quad (5-17)$$

We note that in this normalized notation  $\sum_{i=0}^k p_i^{N-k} = 1$ . Now we can proceed to express the cost for iteration  $N - 2$  as:

$$J_{N-2} = \max_{x_{i'}^{N-2}, x_{i'}^{N-1}, x_{i'}^N} p_0^{N-2} c^{N-2} x_{i'}^{N-2} + p_1^{N-2} (c^{N-2} + \theta^{N-2} E[w^{N-2}] - \theta^{N-2} x_{i'}^{N-2}) x_{i'}^{N-1} \\ + p_2^{N-2} (c^{N-2} + \theta^{N-2} E[w^{N-2}] - \theta^{N-2} x_{i'}^{N-2} + \theta^{N-1} E[w^{N-1}] - \theta^{N-1} x_{i'}^{N-1}) x_{i'}^N$$

By looking at this pattern, we can generalize the cost for any iteration  $N - k$  as:

$$J_{N-k} = \max_{x_{i'}^{N-k}, \dots, x_{i'}^N} p_0^{N-k} c^{N-k} x_{i'}^{N-k} + \sum_{i=1}^k p_i^{N-k} \left( c^{N-k} + \sum_{j=N-k}^{N-k+i-1} \theta^j (E[w^j] - x_{i'}^j) \right) x_{i'}^{N-k+i} \quad (5-18)$$

From this formulation, we can see two important outcomes: (1) The magnitude of multipliers for the linear terms of all future iterations are solely determined by  $\theta^j$ ,  $c^{N-k}$  and by  $E[w^j]$ ; and (2) the quadratic terms in the objective function (those resulting from the multiplication of  $x_{i'}^j$  and  $x_{i'}^{N-k+i}$ ) are always negative; therefore the quadratic components act as penalizing terms for the objective function, weighted down by the vectors  $\theta^j$  and  $p_i^{N-k}$ . More importantly, from the second outcome we can infer that the variables  $x_{i'}$  of greater and most consistent size will be most significantly penalized in the objective function.

Now that we have a compact representation of the decision problem, from equation (5-18), we derive one more lemma and a theorem:

**Lemma 3:** For any iteration which has a zero probability of terminating the auction, the best response of any bidder is to state his/her production plan as zero for all products.

**Proof:** This lemma can be regarded as a more generic form of *Lemma 2*; the result is directly derived from the cost to go function for iteration  $N - k$ . Here we can see that if  $p_i^{N-k} = 0$  for some  $i < k$ , then the linear component vanishes to zero; moreover, the first derivative on  $x_{i'}^{N-k+i}$  will always be negative, signaling a direction of improvement decreasing on  $x_{i'}^{N-k+i}$ . Therefore, the optimal bid for production on iteration  $N - k + i$  is zero. If it is the current iteration which has a zero probability of termination  $p_0^{N-k} = 0$ , then the solution degenerates to announcing a bid of zero. ■

**Theorem 1:** The mechanism proposed is not incentive compatible. Furthermore, the best response for any iteration other than the last will involve underbidding.

**Proof:** The result is directly derived from the cost to go function where all quadratic components can be seen to have a negative sign, and thus penalize the objective function. Thus, for those products which are most likely to be produced by any bidder, the penalty will be correspondingly higher. ■

This theorem simply reflects the intuition provided by (Ausubel & Cramton, 2004). In brief, for an iterative auction with a limited number of iterations, some bidders will engage in a “snake in the grass” strategy, which consists of keeping lower bids only to rapidly raise their production quantities once higher prices are observed.

The outcomes found from *Theorem 1* and *Lemmas 1, 2, 3* give us some intuition for how to design the final mechanism; however, they do not give us the full answer for the exact design we ought to use, nor will they give an estimate for the final efficiency of the mechanism. For a better understanding of this formulation, we must rely on computational

results and further expand the bidder's sub-problem. For this, we formulate a solution methodology which can be used by bidders to determine their best response in practice. Once the problem is solved computationally from the bidder's perspective, we can quantify the efficiency of the mechanism being implemented.

The approach in the remainder of the section is consistent with the ideas of evolutionary mechanism design (Phelps et al., 2009), where instead of seeking a mechanism which is perfectly IC, BB, IR and efficient (an arguably impossible outcome), we seek to design a simple mechanism. With this simple mechanism we can anticipate strategic behavior by solving the bidding problem computationally and then refine the mechanism's properties.

### 5.5 Computationally Solving the Bidder Sub-Problem

Note that given the significant size of the problem, any bidder seeking to act strategically will be faced with a decision problem of high complexity only to present what should otherwise be a straightforward bid. This is on itself a non-trivial decision problem, and must be carefully formulated to better understand strategic bidding behavior. Specifically, we anticipate the following rationale for each bidder:

1. A bidder wishes to present a proposal  $x_{l'}^k$  at time  $k$ . Clearly it is of importance for the bidder to know what the impact of his/her response will be on future prices  $c^{k+1}$ , in order to exert influence without compromising the profitability of the current iteration.
2. However, it is also of interest to have a plan for what the bids of upcoming iterations  $x_{l'}^{k+1}, x_{l'}^{k+2}, x_{l'}^{k+3}$  could be. Nonetheless, the more iterations a bidder seeks to plan ahead for, the bigger and more complex the decision problem becomes.

3. Most bidders weigh the gain that they obtain from making long term estimations; if this gain is small, they may resort to a simplified decision problem formulated through a *limited look ahead policy*.

To give bidders the flexibility to consider a subset of all the upcoming bidding rounds in the current iteration, we formulate the decision problem as one in which the bidder looks ahead  $S$  iterations into the future. The lookahead  $S$  can be as small as planning one iteration ahead, or large enough to account for all iterations until the auction terminates.

For strategic planning, we follow two approaches for optimizing the bidder sub-problem: (1) A quadratic optimization limited look ahead approach, and (2) a heuristic to solve the quadratic programming formulation.

### 5.5.1 Approximate Quadratic Programming Formulation

We proceed with the quadratic cost expansion from equation (5-18). Under this framework, we create the quadratic cost expansion for all upcoming iterations or for a subset of all upcoming iterations (a limited lookahead approach). For a robust formulation of the limited lookahead approach, we redefine the quadratic cost function as:

$$J_{N-k} = \max_{x_l^{N-k} \dots x_l^{N-k+S}} p_0^{N-k} c^{N-k} x_{l'}^{N-k} + \sum_{i=1}^S p_i^{N-k} \left( c^{N-k} + \sum_{j=N-k}^{N-k+i-1} \theta^j (E[w^j] - x_{l'}^j) \right) x_{l'}^{N-k+i} \quad (5-19)$$

$$+ \sum_{i=S+1}^k p_i^{N-k} \tilde{E}[J_{N-k+S+1}]$$

Where the parameter  $S$ , is the number of lookahead periods used. We also define  $\tilde{E}[J_{N-k+S}]$  as an approximation to the cost-to-go function after the limited look ahead.

The quadratic program is still constrained on each iteration to the solution space defined by  $A_{x_{l'}} x_{l'}^i = b_{l'}$ . If the objective function is convex, then the overall problem is

convex and can be solved with ease. Therefore, we begin our analysis by determining whether the objective function is convex/concave. In order to make the structure of the objective function more apparent, we reorganize the terms as seen in equation (5-20) below.

$$\begin{aligned}
J_{N-k} = & \max_{x_{i'}^{N-k} \dots x_{i'}^{N-k+S}} p_0^{N-k} c^{N-k} x_{i'}^{N-k} + \sum_{i=1}^s p_i^{N-k} \left( c^{N-k} + \sum_{j=N-k}^{N-k+i-1} \theta^j E[w^j] \right) x_{i'}^{N-k+i} \\
& - \sum_{i=1}^s p_i^{N-k} \left( \sum_{j=N-k}^{N-k+i-1} \theta^j x_{i'}^j \right) x_{i'}^{N-k+i} + \left( \sum_{i=S+1}^k p_i^{N-k} \right) \tilde{E}[J_{N-k+S+1}]
\end{aligned} \tag{5-20}$$

From the rearranging of terms in the objective function we see that the problem is non-linear and non-separable; however, the problem conforms to the format of a quadratic program, with a linear and a quadratic section corresponding to the production problem and the bidding penalties respectively. However, from this equation we have one additional term which poses a problem:  $\tilde{E}[J_{N-k+S+1}]$ , which does not have a tractable definition.

To take care of this problem and remove the term  $\tilde{E}[J_{N-k+S+1}]$ , we assume that the final iteration  $N - k + S$  is representative of upcoming iterations in the value of the objective function such that  $\tilde{E}[J_{N-k+S}] \sim \tilde{E}[J_{N-k+S+1}] \sim \tilde{E}[J_{N-k+S+2}] \sim \dots$  With this assumption in place, the decision variables for  $x_{i'}^{N-k+S}$  dictate the expected cost to go beyond  $N - k + S$  such that  $x_{i'}^{N-k+S} \sim x_{i'}^{N-k+S+1} \sim x_{i'}^{N-k+S+2}$ . Moreover, with this assumption we can also redefine the probabilities of termination at the lookahead  $S$  as  $p_S^{N-k} = \sum_{j=S}^N p_j^{N-k}$ , meaning that the probabilities of termination for all iterations beyond the lookahead period are collapsed into the last period being considered. With this assumption and correction in the objective function in place, the term  $\tilde{E}[J_{N-k+S+1}]$  can be dropped to yield the new cost-to-go quadratic function (5-21) below:

$$\begin{aligned}
J_{N-k} = & \max_{x_{l'}^{N-k}, \dots, x_{l'}^{N-k+s}} p_0^{N-k} c^{N-k} x_{l'}^{N-k} + \sum_{i=1}^s p_i^{N-k} \left( c^{N-k} + \sum_{j=N-k}^{N-k+i-1} \theta^j E[w^j] \right) x_{l'}^{N-k+i} \\
& - \sum_{i=1}^s p_i^{N-k} \left( \sum_{j=N-k}^{N-k+i-1} \theta^j x_{l'}^j \right) x_{l'}^{N-k+i}
\end{aligned} \tag{5-21}$$

Unfortunately, the objective function is not convex. This can be shown by expanding the quadratic terms of equation (5-21) in matrix form as:

$$= \frac{1}{2} \begin{bmatrix} x_{l'}^{N-k} \\ \vdots \\ x_{l'}^{N-k+s} \end{bmatrix}' \begin{bmatrix} 0 & P_1^{N-k} & P_2^{N-k} & \dots & P_s^{N-k} \\ P_1^{N-k} & 0 & P_2^{N-k+1} & \dots & P_s^{N-k+1} \\ P_2^{N-k} & P_2^{N-k+1} & 0 & \dots & \vdots \\ \vdots & \vdots & \vdots & \ddots & P_s^{N-k+s-1} \\ P_s^{N-k} & P_s^{N-k+1} & \dots & P_s^{N-k+s-1} & 0 \end{bmatrix} \begin{bmatrix} x_{l'}^{N-k} \\ \vdots \\ x_{l'}^{N-k+s} \end{bmatrix} \tag{5-22}$$

Where we define the probabilities of termination in matrix form as:

$$\begin{aligned}
P_1^{N-k} &= p_1^{N-k} \theta^{N-k} \mathbf{I}, & P_2^{N-k} &= p_2^{N-k} \theta^{N-k} \mathbf{I}, & P_2^{N-k+1} &= p_2^{N-k} \theta^{N-k+1} \mathbf{I}, & \dots \\
P_i^{N-k+j} &= p_i^{N-k} \theta^{N-k+j} \mathbf{I} & \forall i \leq s; j < s
\end{aligned}$$

Here,  $\mathbf{I}$  is the identity matrix, which is used in order to make the price adjustments in future iterations solely dependent on the decision variables for the same product in accordance to the structure of the subgradient algorithm and with equation (5-22). From the representation of the quadratic components of the objective function, we can easily extract the hessian matrix.

**Lemma 4:** The bidding problem for any farmer is quadratic and non-convex in the objective function.

**Proof:** The Hessian matrix on (5-22) has a distinct structure with a diagonal composed of only zeroes, making it fall into the category of "hollow matrices." We can disqualify the Hessian matrix from being positive semi-definite (PSD) or negative semi-definite (NSD) by noting that for any matrix, the sum of the eigenvalues will always be

equal to the trace of the matrix. For the matrix in (5-22) to be PSD/NSD, we would need all the eigenvalues to be zero; yet, we find that for any hollow matrix of size  $n > 2$  with all non-diagonal elements being strictly positive, there are always at least two non-positive eigenvalues (Charles, Farber, Johnson, & Kennedy-Shaffer, 2013) thus forcing the existence of at least one positive/negative eigenvalue and by consequence causing the Hessian matrix to always be indefinite. ■

Solving non-convex quadratic optimization problems creates an added level of complexity; nonetheless, obtaining near-optimal solutions is usually possible in practice through the use of commercial solvers. We find two problems with solving a non-convex optimization problem:

1. Because of this structure, it is usually impossible to guarantee if a given solution found by a commercial solver is globally optimal or simply locally optimal.
2. A solution can be grossly sub-optimal, yet it may conform to KKT conditions for local optimality; this causes difficulty for the solver on distinguishing the globally optimal solution.

In fact, it will be shown in section 5.7.2 that these problems are highly prevalent when using commercial solvers, and can cause difficulties in finding an optimal solution.

### 5.5.2 Heuristic DP Formulation

In order to reformulate the optimization problem in a way that makes the solutions easily attainable, we develop a heuristic approximation to obtain the solution to the quadratic problem. For this, we take the quadratic programming expansion and refer back to dynamic programming and the structural characteristics of the strategic bidding problem.

In order to define a sound heuristic for the bidding problem we refer back to equation (5-21), and take the case of the last iteration, which yields the cost  $J_N$ ; we know this iteration is the only incentive compatible iteration of the mechanism; moreover, the objective function is linear and convex on  $x_{l'}^N$  and its optimal solution is given by:

$$J_N = \max_{x_{l'}^N} c^N x_{l'}^N$$

Unfortunately, we cannot know with certainty the price vector  $c^N$  as it depends on the mismatch for all previous iterations. Nonetheless, assuming that we are at iteration  $k$ , the final price vector is given by:

$$E[c^N] = c^{N-k} + \sum_{i=k}^{N-1} (\theta^i E[w^i] - \theta^i x_{l'}^i) \quad (5-23)$$

As in previous formulations, the vector  $w$  is an independent random variable which can be estimated at any iteration through  $E[w^j]$ . Moreover, let's assume for now that a solution to all previous iterations  $i < N$  has been estimated and is represented by  $\hat{x}_{l'}^i$ ; under this assumption,  $c^N$  is estimated and a solution to the final iteration can be found. Furthermore, since we assume that all previous solutions have been initialized at some arbitrary feasible value  $\hat{x}_{l'}^i, \forall i \in [N-k, N-1]$ . Then the parameter  $c^N$  as well as any other  $c^i$  are known in expectation and the solution to the last stage of the dynamic program is a simple linear programming problem. The solution to the last stage is then used to update the solution estimate  $\hat{x}_{l'}^N$ .

Knowing that the solution to the last iteration complies with IC and using Bellman's principle of optimality, we can reformulate the one iteration lookahead for  $J_{N-1}$  as a linear program using similar assumptions, where  $J_{N-1}$  is given by:



$$J_{N-1} = \max_{x_l^{N-1}} p_0^{N-1} E[c^{N-1}] x_l^{N-1} + p_1^{N-1} (E[c^{N-1}] + \theta^{N-1} E[w^{N-1}] - \theta^{N-1} x_l^{N-1}) \hat{x}_l^N$$

$$J_{N-1} = \max_{x_l^{N-1}} p_0^{N-1} E[c^{N-1}] x_l^{N-1} + p_1^{N-1} (E[c^{N-1}] + \theta^{N-1} E[w^{N-1}]) \hat{x}_l^N - p_1^{N-1} (\theta^{N-1} x_l^{N-1}) \hat{x}_l^N$$

In this formulation,  $\hat{x}_l^N$  is treated as a constant, making the second term  $p_1^{N-1} (c^{N-1} + \theta^{N-1} E[w^{N-1}]) \hat{x}_l^N$  a constant as well. This term is now removed from the objective function, leaving a simple linear program.

To differentiate the heuristic objective functions from those of the quadratic program, we use the notation  $H_{N-k}$  for the cost-to go heuristic approximation objective functions.

With this change of notation, we show the heuristic cost-to-go for iteration  $N - 1$ :

$$H_{N-1} = \max_{x_l^{N-1}} p_0^{N-1} c^{N-1} x_l^{N-1} - p_1^{N-1} (\theta^{N-1} x_l^{N-1}) \hat{x}_l^N$$

Rearranging some terms, the result for stage  $N - 1$  now becomes:

$$H_{N-1} = \max_{x_l^{N-1}} (p_0^{N-1} c^{N-1} - p_1^{N-1} \theta^{N-1} \hat{x}_l^N) x_l^{N-1}$$

Where  $c^{N-1}$  can also be estimated on expectation from the solution estimations for  $\hat{x}_l^i, \forall i \in [N - k, N - 2]$ ; this allows a better estimate of  $\hat{x}_l^{N-1}$  to be obtained recursively in the same form as  $\hat{x}_l^N$ ; a process that can be generalized for all  $\hat{x}_l^i$ .

More generally, we now perform this procedure of linear estimations for any iteration  $i \in [N - k, \min(N, N - k + S)]$  and keeping the assumption that bidders may limit their lookahead policy to  $S$  iterations, the expression for the linear approximation for any iteration is given by equation (5-24) below:

$$H_i = \max_{x_l^i} \left( p_0^i c^i - \theta^i \sum_{g=1}^S p_g^i \hat{x}_l^{i+g} \right) x_l^i \quad (5-24)$$

Where  $c^i = c^{N-k} + \sum_{j=k}^{i-1} (\theta^j E[w^j] - \theta^j \hat{x}_{l'}^j)$  and where  $\hat{x}_{l'}^{i+g}$  are the solution estimates obtained recursively using the Bellman's principle of optimality. Furthermore, if we sum across all the objective functions from the heuristic, we obtain an approximation to the objective function of the quadratic programming approximation to the problem.

Note that we have assumed that  $\hat{x}_{l'}^i$  were arbitrary starting solutions. For this reason we will continue to perform this procedure using better, updated, estimates for all variables  $\hat{x}_{l'}^i \forall i < N$  to calculate the price vector  $c^{N-i}$  until no further refinement is needed. With this change, the recursion has a higher degree of accuracy; from this point, the optimal bid can be refined using better estimates for the anticipated auction prices. The final structure of the heuristic is as in Table 5.1 below.

Table 5.1 – Heuristic Pseudocode for the Quadratic Problem Approximation

<p><b>Heuristic pseudocode for iteration <math>N - k</math>:</b></p> <ol style="list-style-type: none"> <li>1. Initialize <math>\hat{x}_{l'}^i, \forall i \in [N - k, N]</math> at some arbitrary feasible solution</li> <li>2. For all <math>i \in [N - k, \min(N, N - k + S)]</math> recursively do: <ol style="list-style-type: none"> <li>a. Solve: <math>H_i</math></li> <li>b. Obtain optimal solution <math>x_{l'}^{i,*}</math></li> <li>c. Let <math>\hat{x}_{l'}^i = x_{l'}^{i,*}</math></li> </ol> </li> <li>3. If <math>(abs(\hat{x}_{l'}^i - x_{l'}^{i,*}) &lt; \delta \forall i)</math> then stop. Otherwise, return to Step 2</li> </ol>
--

Unfortunately, we cannot guarantee optimality for the final solution obtained once the heuristic terminates; nonetheless, the heuristic method has been shown to have good convergence properties and to have characteristics that make it more desirable than the quadratic programming formulation as it will be shown in Section 5.7.2 through computational results.

## 5.6 Farm Coordination Optimization Model

In the remainder of this chapter we explore the application of the derived models to the farm coordination problem of Section 4.6. We now provide a formulation of strategic bidding in accordance to the models of (5-21) and (5-24) above. For this, we first define the additional parameters and decision variables required for the expanded formulation. Thereafter, we define the constraints and objective function, as well as a redefinition of the consolidation facility and farmer sub-problems.

### 5.6.1 Farmer Strategic Sub-Problem Quadratic Approximation

#### **Indexes:**

$i \in I = (1 \dots N)$  : Auction iterations

#### **Parameters:**

$N$  : Maximum allowed number of iterations for the auction

$S$  : Number of look ahead steps for farmer planning  $S \leq N - k$

$K$  : Current iteration

$\alpha^k$  : Probability of terminating at any particular iteration  $k$

$p_i^{N-k}$  : Probability of terminating in  $i$  iterations given that are at iteration  $N - k$

$\theta^i$  : Price adjustment parameter declared for iteration  $i$

$w_{hjq}^i$  : Expected total mismatch between supply and demand for iteration  $i$

$\lambda_{hjq}^i$  : Current auction prices for iteration  $i$

#### **Decision variables (Farmers):**

$Vplant_{pjl}^i$  : Area to plant of crop  $j$  in period  $p$  at location  $l$

$Vharv_{hjl}^i$  : Harvest quantity of crop  $j$  in period  $h$  at location  $l$

$Vlab_{tl}^i$  : Seasonal laborers employed at location  $l$  at time  $t$

$VHire_{tl}^i$  : Seasonal laborers **hired** for location  $l$  at time  $t$

$VFire_{tl}^i$  : Seasonal laborers **dismissed** from location  $l$  at time  $t$

$Vtrans_{hjl}^i$  : Amount to transport from location  $l$  of crop  $j$  with quality  $q$  at time  $h$

**Subject to:**

**Farming Constraints**  $\forall l \in L, i \in [N - k, N]$  :

$$\sum_j \sum_p Vplant_{pjl}^i \leq Land_l \quad \forall i \in I \quad (5-25)$$

$$Min_j * Y_{jpl} \leq Vplant_{pjl}^i \leq Max_j * Y_{jpl} \quad \forall j \in J, p \in P, i \in I \quad (5-26)$$

$$Vharv_{hjl}^i \leq \sum_p Vplant_{pjl}^i * Yield_{phj} * Total_{jl} \quad \forall h \in H, j \in J, i \in I \quad (5-27)$$

**Farming Labor Constraints:**

$$Vlab_{tl}^i \geq \sum_p \sum_j Vplant_{pjl}^i LaborP_{ptj} + \sum_{h=t} \sum_j Vharv_{hjl}^i LaborH_j \quad \forall t, i \in I \quad (5-28)$$

$$VHire_{tl}^i - VFire_{tl}^i = Vlab_{tl}^i - Vlab_{(t-1)l}^i \quad \forall t \in T, i \in I \quad (5-29)$$

$$\sum_t VHire_{tl}^i \leq MaxLab_l \quad \forall i \in I \quad (5-30)$$

**Harvesting quality distribution:**

$$Vharv_{hjl}^i * QualD_{hjq} = Vtrans_{lj(q-\Delta ql_j)(h+\Delta tl)}^i \quad \forall h, j, q, i \quad (5-31)$$

Note that all the constraints for the new, strategic formulation are identical to those of the original formulation, with the distinction that we have expanded our constraint space to all iterations  $i$  rather than a single one. The greatest distinction in the strategic reformulation lies on the objective function and the solution methodology for each problem. We now detail the objective function (5-32) for the quadratic formulation:

$$\begin{aligned}
Max Z_l = & \sum_{i=N-k}^{N-k+S} p_i^{N-k} \left[ - \sum_{jq} Vtrans_{hjq}^i * Ctrans_{jl} - \sum_t (VHire_t^i * Chire_t) \right. \\
& - \sum_t (Vlab_t^i * Clab_t) - \sum_{pj} (Vplant_{pj}^i * Cplant_j) - \sum_{hj} (Vharv_{hj}^i * Charv_j) \left. \right] \quad (5-32) \\
& + \sum_{hjq} \left( \lambda_{hjq}^{N-k} p_0^{N-k} (Vtrans_{hjq}^{N-k}) + \sum_{i=1}^S p_i^{N-k} \left( \lambda_{hjq}^{N-k} + \sum_{g=N-k}^{N-k+i-1} \theta^g E[w_{hjq}^g] \right) Vtrans_{hjq}^{N-k+i} \right) \\
& - \sum_{hjq} \sum_{i=1}^S p_i^{N-k} \sum_{g=N-k}^{N-k+i-1} \theta^g Vtrans_{hjq}^g Vtrans_{hjq}^{N-k+i}
\end{aligned}$$

The above objective function is non-convex, as shown in *lemma 4*, and for this reason it will be hard to solve. In fact, computational results detailed in upcoming Section 5.7 show that solving the quadratic approximation directly by using commercial solvers generally yields solutions which are highly variable and can be grossly sub-optimal. For this reason, we also provide a formulation of the strategic problem which is solved through a heuristic method.

### 5.6.2 Farmer Strategic Sub-Problem Heuristic Approximation

In order to implement this heuristic, we reformulate the objective function as detailed in equation (5-24), where we formulate the decision problem for the current iteration  $i$ , but where the projected solution to all upcoming iterations are found iteratively. As a result, the LP approximation for iteration  $i$  is given by the following objective function (5-33). Where,  $\lambda_{hjq}^i = \lambda_{hjq}^{N-k} + \sum_{g=N-k}^{i-1} (\theta^g E[w_{hjq}^g] - \theta^g Vtrans_{hjq}^g)$  and  $Vtrans_{hjq}^i$  are the current best estimates for previous and upcoming iterations. The feasible space for this problem is given by (5-25 - 5-31).

$$\begin{aligned}
Max Z_l^i = p_0^i & \left[ - \sum_{jq} Vtrans_{hjq}^i Ctrans_{jl} - \sum_t (VHire_{tl}^i Chire_t) - \sum_t (Vlab_{tl}^i Clab_t) \right. \\
& - \sum_{pj} (Vplant_{pjl}^i * Cplant_j) - \sum_{hj} (Vharv_{hjl}^i * Charv_j) \left. \right] + p_0^i \sum_{hjq} \lambda_{hjq}^i Vtrans_{hjq}^i \quad (5-33) \\
& - \sum_{hjq} \theta^i * Vtrans_{hjq}^i \sum_{g=i}^S p_g^i \widehat{Vtrans}_{hjq}^{i+g}
\end{aligned}$$

Note that if we sum across the objective function of all iterations in the heuristic approximation from  $[N - k, N - k + S]$  through the formula  $\sum_{v=N-k}^{N-k+S} Z_l^v$ , then we obtain an approximation to the quadratic approximation's objective function.

### 5.6.3 Consolidation Facility Sub-Problem

For the case of the consolidation facility, the reformulation of the sub-problem is not necessary as we have assumed no counter speculation from the auctioneer. Moreover, since the CF only observes the bids for the current iteration, the formulation remains limited to one iteration at a time. In this case, the CF can only observe part of the solution space for each farmer  $Vtrans_{hjq}^{N-k}$ ; where,  $N - k$  is the current auction iteration. The constraints, objective function and price adjustments are as in Section 4.6. We restate the CF objective function and constraints to facilitate reference to the reader:

**Objective:**

$$\begin{aligned}
Max Z_{CF} = & \sum_{hj, qmax_j \geq q \geq qmin_j} Vsell_{hjq} Price_{hj} - \sum_{hjq} Vinv_{hjq} Cinv_j \\
& - \sum_{hjq} Vover_{hj} Cover_j - \sum_{hjq} Vunder_{hj} Cunder_j + \sum_{hjq} \lambda_{hjq} (PVarr_{h,j,q}) \quad (5-34)
\end{aligned}$$

**Subject to:**

**Coupling constraint:**

$$\sum_l Vtrans_{hjql}^{N-k} = PVarr_{h,j,q} \quad \forall j, q, h \quad (5-35)$$

**Inventory balance and quality tracking:**

$$PVarr_{h,j,q} + Vinv_{h-1,jq+\Delta q_j} - Vsell_{hj,q} = Vinv_{h,j,q} \quad \forall j, q, h \quad (5-36)$$

**Demand Constraints:**

$$MinDem_{hj} - Vunder_{hj} \leq \sum_{qmax_j \geq q \geq qmin_j} Vsell_{hj,q} \quad \forall j, h \quad (5-37)$$

$$\sum_{qmax_j \geq q \geq qmin_j} Vsell_{hj,q} \leq MaxDem_{hj} + Vover_{hj} \quad \forall j, h \quad (5-37)$$

**Warehouse Capacity Constraint:**

$$\sum_{jq} Vinv_{hj,q} \leq WHCap \quad \forall h \quad (5-38)$$

## 5.7 Farm Coordination Case Study Computational Results

As stated before, due to the high complexity of the proposed mechanism, the analytical results that we can obtain are limited. Therefore, if we need to understand the efficiency that we can expect in practice, we have to rely on computational results. These results build on top of the analytical findings of Section 5.3 and give us further intuition for practical design and implementation of the coordination tool.

### 5.7.1 Definition of Parameters and Assumptions

We perform a case study similar to that of Chapter 4, where data from an agricultural supply chain is used to test the coordination capabilities of a horizontally integrated cooperative. In practice, it is expected that bidders will speculate and will thus have a decision model for this purpose; therefore, we assume that the models of Section 5.6 are representative decision models for both the farmers and the consolidation facility.

The parameters for costs, yields and the production capabilities of each farmer used are the same as those of Chapter 4. One adjustment was made to the dataset, which consists of an upward adjustment of the prices paid by external customers to the CF; this is done to make these prices more representative processed products<sup>8</sup>, rather than point of first sale prices<sup>9</sup> (USDA, 2014). A test instance with 20 farmers is used and a comparative analysis with larger problem instances is performed in the later sections.

In addition to the parameters used in Chapter 4, four other parameters are required: the estimation of mismatch between supply and demand  $\omega_{hjq}^i$ , the probabilities of termination  $\alpha^{N-k}$ , the magnitude of price adjustments  $\theta^i$  and the starting prices for the first iteration  $\lambda_{hjq}^1$ . It is assumed that the parameters  $\lambda_{hjq}^1$ ,  $\theta^i$  and  $\alpha^{N-k}$  are known a-priory and are common knowledge. For the probabilities of termination  $\alpha^{N-k}$ : we make this assumption since they can be estimated from past history or made available from consensus. We chose to make the parameter  $\alpha^{N-k}$  explicitly stated by the auctioneer.

For the parameter  $\omega_{hjq}^i$ , it is also assumed that the general behavior of the auction can be predicted by bidders based on previous experience. In our case, the predicted behavior is based on the results of the non-strategic auction for the same parameters  $\lambda_{hjq}^1$  and  $\theta^i$  (Section 4.7). From the Section 4.7 output, the mismatch between supply and demand  $\omega_{hjq}^i$  is modeled/predicted through regression<sup>10</sup>. For simplicity, our case study

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<sup>8</sup> Products at the consolidation center which have been sorted, washed and packaged

<sup>9</sup> Prices paid to farmers for recently harvested goods “at the field”

<sup>10</sup> Note that the mismatch starts at a point which is higher than 100%. This occurs because of the sub-gradient formulation of the decentralized problem; here, given low prices, the CF will demand more products that farmers are capable of providing in the first iterations. This behavior is later corrected as prices are adjusted to be higher.



uses a simple regression line for the aggregate mismatch between supply and demand (Figure 5.1). Thus, the estimation of mismatch is given by:  $\omega_{hjq}^i = 0.9601 * \omega_{hjq}^0 i^{-0.325}$ .

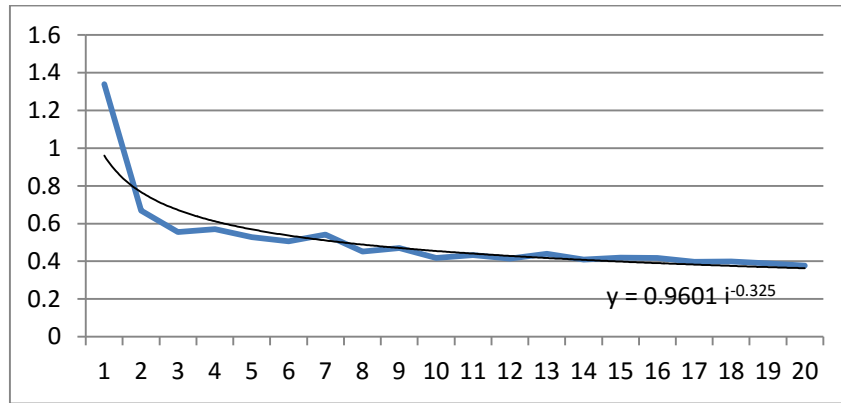


Figure 5.1 – Aggregate Mismatch between Supply and Demand

The parameters stated above allow us to limit our scope and to experiment with the mechanism under a simplified framework. Given this framework, we can better modify specific parameters to develop an intuition on the likely behavior of this coordination scheme. In the following sections we describe the computational results obtained.

### 5.7.2 Algorithms, Heuristics and Solvers Used

As it was stated earlier on this chapter, due to the non-convex nature of the bidding sub-problem there is a possibility that the decision problem, under its quadratic formulation, fails to find a good quality solution. More critically, it is possible that the solution encountered by the commercial solvers greatly underperforms by finding a local optimum. In order to account for this possibility and to ensure good quality solutions, test instances were run to benchmark the capabilities of a commercial solver, as well as the capabilities of finding a solution through the heuristic developed.

In this research, three algorithms from a commercial solver were utilized. The solver used was KNITRO 9.0 (Ziena Optimization LLC, 2014), which is benchmarked as the best

commercial solver for nonlinear programming problems (Mittelman, 2015). Three algorithms provided by KNITRO to solve non-linear optimization problems were used: Interior/Direct algorithm, Interior/CG algorithm and Active Set Algorithm<sup>11</sup>. Together with the heuristic proposed, a total of 4 algorithms are tested for each test instance of the auction with speculating bidders<sup>12</sup>. The results for the four algorithms are benchmarked with regard to two performance measures: (1) The objective function for the bidding sub-problem in Table 5.2<sup>13</sup> and (2) the percent underbidding as compared to the truthful solution ( $S = 0$ ) at each iteration in Table 5.3.

Table 5.2 – % Relative Optimality of Various Algorithms

Lookahead	Algorithm			
	Direct	CG	Active Set	Heuristic
<b>S</b>				
<b>0</b>	100.0%	100.0%	100.0%	100.0%
<b>1</b>	90.6%	33.8%	99.6%	100.0%
<b>2</b>	82.8%	32.6%	99.8%	99.9%
<b>5</b>	66.7%	54.7%	93.4%	99.7%
<b>10</b>	55.1%	73.2%	99.8%	99.2%
<b>14</b>	53.4%	71.8%	96.6%	98.8%

Table 5.3 – Percent Underbidding of Algorithms Compared to Truthful Solution

Lookahead	Algorithm			
	Direct	CG	Active Set	Heuristic
<b>S</b>				
<b>0</b>	0.0%	0.0%	0.0%	0.0%
<b>1</b>	100.0%	53.3%	0.4%	0.3%
<b>2</b>	100.0%	31.1%	0.2%	0.4%
<b>5</b>	100.0%	13.2%	0.2%	1.1%
<b>10</b>	100.0%	9.7%	0.2%	1.9%
<b>14</b>	100.0%	10.1%	0.2%	2.3%

<sup>11</sup> The Active Set Algorithm relies on a starting solution being provided. For our implementation, the best results were obtained when the provided solution was the solution to the non-strategic bidding problem.

<sup>12</sup> Note that the heuristic developed solves the quadratic optimization problem, and its final solution is directly comparable to the other algorithms.

<sup>13</sup> All four algorithms are run simultaneously for every combination of: Auction iteration  $k$ ; lookahead parameter  $S$ ; and farmer index  $l$ . The best solution from all four algorithms is taken and announced as a bid, and the mechanism continues. For every combination of  $S, k, l$  the best solution is given a value of 100% and the remaining solutions are scaled according to their gap.

The results are averaged across a subset of the auction iterations (2 to 14)<sup>14</sup> and detailed for six different values of the lookahead parameter  $S$ . Note that for Table 5.2, on average, the heuristic outperforms all other algorithms. Moreover, note that from Table 5.3 we observe that the heuristic is more aggressive than the Active Set method in underbidding; this is likely because the Active Set method relies heavily on being given an initial solution which, throughout the experiment, was the truthful bid.

As it can be observed, the heuristic developed in Section 5.5.2 has a superior performance. We can also see that for a lookahead of zero iterations all solutions are equivalent; this is an intuitive solution, as for  $S = 0$  the problem becomes a LP which implicitly assumes that the auction is immediately terminating. This result provides a generalization of *lemma 2*, showing that for any iteration with a probability of termination  $\alpha^{N-k} = 1$ , the solution is the same as the incentive compatible solution. This is also supported by Parkes & Ungar (2000a) on their analysis of myopic bidding strategies.

As for the Direct and CG methods, their poor performance is attributed to the non-convex nature of the problem. By further exploring the solutions to these algorithms we note that their objective functions are positive despite them having large amounts of underbidding; however, the cause of this apparent contradiction is that the solution places all the bidding weights in the variables corresponding to upcoming iterations, making the current iteration zero. This strategy minimizes the quadratic penalty component in the objective function; however, it fails to give sufficient weight to the linear component, thus leading to pathologies in the solution.

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<sup>14</sup> Iterations 1 and 15 are removed because in iteration 15 all bids are identical due to incentive compatibility and in iteration 1 most bids are of zero due to the low initial price

This pathology is further exemplified in Table 5.3 which shows the allocation of production for an instance of the mechanism using the CG method with  $S = 5$ . In this depiction, the main diagonal corresponds to the aggregate bid being placed in a given iteration, while the cells below the main diagonal are the strategic projections for future iterations.

Table 5.4 – Pathological Solution Returned by CG Method in KNitro

		Auction Iteration														
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Lookahead Iteration	1	0														
	2	0	0													
	3	0	163	2292												
	4	0	1485	890	2833											
	5	41.4	1205	179	534	2068										
	6	3318	436	0	12.8	1287	2878									
	7		56.2	0	0	1.46	481	3035								
	8			0	0	0	0	329	2716							
	9				0	0	0	0	647	3071						
	10					0	0	0	0	289	3364					
	11						0	0	0	0	0.26	0				
	12							0	0	0	0	0	0			
	13								0	0	0	0	0	0		
	14									0	0	0	0	0	0	
	15										0	3368	3365	3364	3359	3359

Finally, we summarize some of the main advantages of the developed heuristic:

- On average, it has both a higher objective function and is more aggressive in underbidding than the Active Set Algorithm
- Has a greater simplicity derived from solving a series of linear programs rather than a quadratic program
- From a computational standpoint, the heuristic has a rapid convergence which takes on average only 3 (and no more than 7) revisions to the solutions before stabilizing (Figure 5.2)

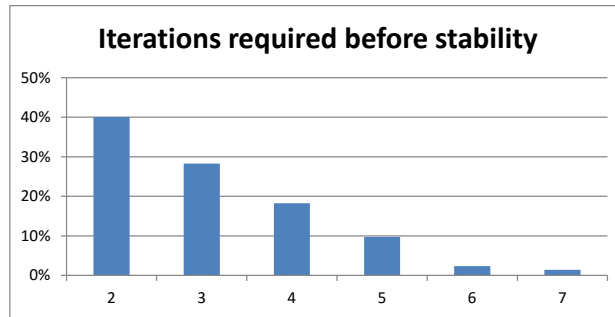


Figure 5.2 – Convergence Speed of Heuristic

- The heuristic can find a solution from any arbitrary starting point; in contrast, the Active Set Algorithm relies on being provided a good starting solution
- The proposed heuristic does not exhibit significant pathologies of underbidding or improperly weighting the importance of components of the objective function

### 5.7.3 Impact on Farmers Profits

Finally, in order to verify that the heuristic solution method is up to desired standards, we test whether the incorporation of speculation to the farmer’s sub-problem improves the profits observed by farmers. In other words, failure to speculate correctly can create more harm than good if it is incorrectly formulated, so we must verify that on expectation, farmers obtain a greater profit if they speculate.

For this, we ran an instance of the mechanism where all farmers engage in speculative behavior to test its impact computationally. The experiment was performed using a parameter  $\alpha^i = 0.1$  for all iterations and  $\alpha^{15} = 1.0$ , meaning that there is a cutoff at the 15<sup>th</sup> iteration. In order to obtain the expected value of the mechanism, unbiased by the quadratic penalty terms, we compute an indirect measure of farmer profits for each iteration, which is the profit that each farmer would realize if the auction were to terminate immediately; we call this the un-penalized profit  $Z_{N-k}^I$ , which is given for each farmer by:

$$\begin{aligned}
Z_{N-k,l}^I = & - \sum_{ljqt} Vtrans_{hjql}^{N-k} Ctrans_{jl} - \sum_{tl} (VHire_{tl}^{N-k} Chire_t - Vlab_{tl}^{N-k} Clab_t) \\
& - \sum_{pjl} Vplant_{pjl}^{N-k} Cplant_j - \sum_{hjl} Vharv_{hjl}^{N-k} Charv_j + \sum_{hjq} \lambda_{hjq}^k \sum_l Vtrans_{hjql}^{N-k}
\end{aligned} \tag{5-39}$$

In Figure 5.3 below, we graph the difference in aggregate farmers' profits between the truthful solution and the speculative solution at each iteration  $i \in [1, 15]$ . Here, we can see the difference in profits between instances in which the farmers speculate with a different time horizon  $S$ .

As it can be seen, the decision problem with the greatest lookahead capabilities ( $S = 14$ ) outperforms other lookahead policies, as well as the non-strategic bidding; in particular, we note that speculating with a longer time horizon allows bidders to make sacrifices in their objective function in the first iterations in exchange for a better outcome for the overall mechanism.

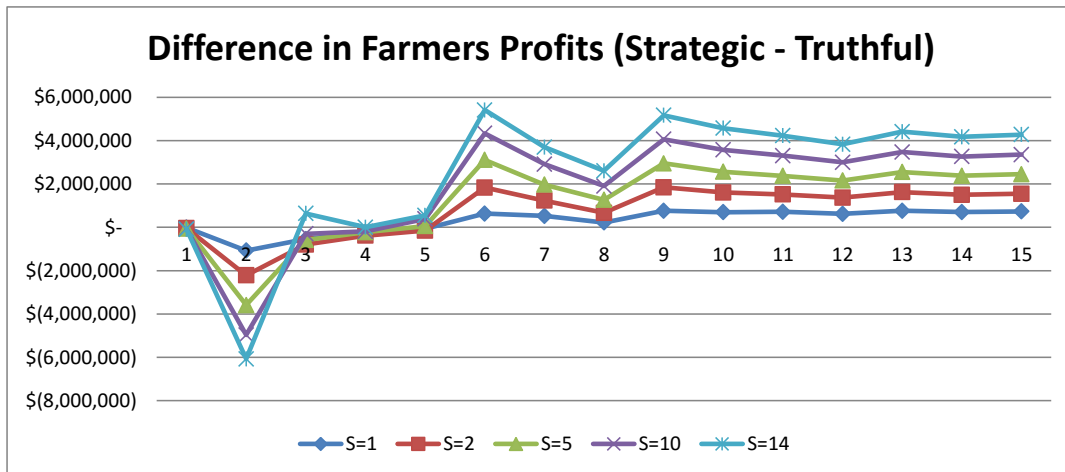


Figure 5.3 – Difference in Profit vs. Non-Strategic Solution for Various  $S$  Values

If we take a closer look at this speculative behavior, we see that farmers also tend to shift their production quantities between crops, rather than simply under-producing. This behavior reduces the risk of losing contracted production, while increasing the price of

more profitable crops. This behavior is better illustrated by Figure 5.4 below, which plots the aggregate difference between the strategic and truthful production bids for iterations one through nine (in X-axis); therefore, a higher value implies that farmers are overbidding, while negative implies underbidding.

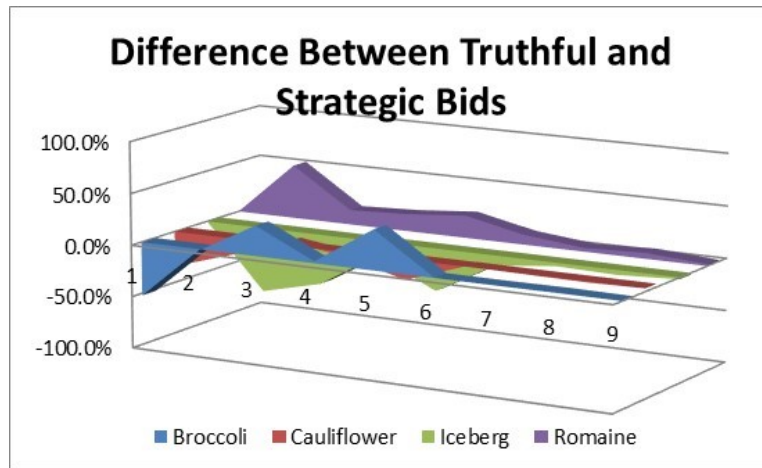


Figure 5.4 – Truthful vs Strategic Bids Difference (Iterations 1-9)

It can be observed that in aggregate farmers tend to underbid in each iteration, and favor specific crops. Moreover, it can also be seen that as the auction progresses, the difference between the strategic and truthful solutions is reduced, converging to the incentive compatible solution at termination.

The dynamic shown by the underbidding on certain crops in combination with the positive difference in profits observed shows that farmers are attempting to obtain higher profits through strategic manipulation of their bids; moreover, it shows that the mechanism is not incentive compatible and creates avenues for personal gain. However, this behavior does not show the complete picture nor the significance of the expected increase in farmers profits; in order to verify that the mechanism does benefit farmers and to what scale, we refer to the expected profit for the entire auction rather than the profit for each iteration.

To calculate the expected profit for the entire auction, we note that we have already calculated  $Z_{N-k}^l$  (the profit at each iteration if the auction were terminated immediately). By computing this value, we can also compute the total expected profit for the entire auction for each farmer as given by the following equation:

$$\sum_{i=0}^{N-1} p_i^1 * Z_{i+1,l}^l \quad \forall l \in L \quad (5-40)$$

Assuming that an instance of the mechanism has been run and that all relevant information has been recorded, equation (5-40) allows us to numerically calculate the expected profits for any given mechanism configuration. Also note that the same principle behind equation (5-40) can be applied to calculating the expected profits for the entire system; the expected objective functions off all farmers and the CF are given by:

$$\sum_l \sum_{i=0}^{N-1} p_i^1 * Z_{i+1,l}^l + \sum_{i=0}^{N-1} p_i^1 * Z_{i+1,CF} \quad (5-41)$$

Having defined the expected farmer profits (5-40) and the expected system profits (5-41), and having observed the solutions at each iteration, we proceed to assess the performance of the optimization model. The aggregate expected profits for all farmers and for the system for each lookahead case can be seen in Table 5.5 below, where speculation is built into the decision problem of each participating farmer. Clearly, speculating has a benefit for farmers as a group, who capture a higher percentage of supply chain profits through speculative bidding. Moreover, a larger speculation time horizon  $S$  appears to increase expected profits for farmers. We also observe that farmers capture a higher percentage of supply chain profits at the expense of system-wide efficiency.



Table 5.5 – Expected Aggregate Farmer Profits (All Farmers Speculating)

Lookahead	Expected Farm Profit	% Change	Expected System Profit	% Change
S=0	\$ 8,019,867		\$ 30,363,253	
S=1	\$ 8,244,187	2.8%	\$ 30,422,610	0.2%
S=2	\$ 8,370,202	4.4%	\$ 29,430,174	-3.1%
S=5	\$ 8,473,268	5.7%	\$ 29,499,614	-2.8%
S=10	\$ 8,496,337	5.9%	\$ 28,927,619	-4.7%
S=14	\$ 8,563,302	6.8%	\$ 29,052,975	-4.3%

The previous example assumes that all farmers are speculating simultaneously and following the same strategy; however, if we test the algorithm for the case where one single bidder engages in speculation, the results can be much different. In the case where a single bidder speculates we observe that speculation may have a negative impact on the strategic bidder as seen in Table 5.6 below, which shows the expected profits for a single farmer who speculates and the other 19 farmers taking part on the auction for varying time horizons. As it can be seen, the expected profits are decreased significantly for the single speculator, but more critically, the expected profits of all other farmers are also affected negatively.

Table 5.6 – Expected Profits (Single Farmer Speculating)

Lookahead	Speculating Farmer		Remaining (non-speculating) Farmers		Overall System Profits	
	Expected Profit	% Change	Expected Profit	% Change	Expected Profit	% Change
S=0	\$ 395,153		\$ 7,624,714		\$ 30,363,253	
S=1	\$ 377,172	-4.6%	\$ 7,581,386	-0.6%	\$ 30,695,454	1.1%
S=2	\$ 378,477	-4.2%	\$ 7,594,551	-0.4%	\$ 30,632,438	0.9%
S=5	\$ 380,136	-3.8%	\$ 7,589,282	-0.5%	\$ 30,503,616	0.5%
S=10	\$ 380,221	-3.8%	\$ 7,592,873	-0.4%	\$ 30,499,323	0.4%
S=14	\$ 380,883	-3.6%	\$ 7,597,575	-0.4%	\$ 30,656,137	1.0%

This result highlights the risk take by a farmer who speculates, where despite having a well formulated decision problem, the final outcome of the auction could be inferior.

The reason for the behavior observed in Table 5.6 can have multiple explanations. For instance, the decision problem for a single farmer may fail to capture the expected behavior of all other bidders. Likewise, recall that the parameter  $\omega_{hjq}^i$  was calculated using a simple linear model and is a generalized formula for all crops; it is likely that by having each farmer calculate this parameter with greater accuracy the outcome of the speculation problem could be enhanced. Finally, despite having a well-developed decision problem, the bidding problem developed optimizes profits for farmers, on expectation, leaving the possibility for bad outcomes open.

#### 5.7.4 Sensitivity of Speculation to Auction Design Parameters

Now that we have developed a viable model for speculative behavior on the side of bidders we can test the impact of various mechanism configurations to the expected efficiency of the system. We are concerned about this issue due to the iterative nature of the mechanism, which presents the risk of terminating at a sub-optimal solution. Nonetheless, as we have noted in *Lemma 3*, there must be a positive probability of termination in all iterations to ensure that bidding does not exhibit pathological behavior. This presents a *tradeoff between (1) early termination with sub-performing solutions, and (2) late termination with pathological bids at the start of the mechanism*. For this reason, a more detailed analysis is performed to determine which are the most effective mechanism configurations.

##### 5.7.4.1 Mechanism Benchmarking through Varying Termination Probabilities

When designing a mechanism, many parameters can be changed including the allocation rules, probabilities of termination, starting auction prices and the directions of price changes. Different combinations of these parameters make instances of the

mechanism with varying properties. In our formulation, we have made explicit assumptions about allocation rules; however, we have not made explicit decisions for starting prices, probabilities of termination, magnitude of price adjustments or direction of price changes, all of which are left as open parameters. In order to facilitate experimentation and gain a better understanding we focus on the impact of the probabilities of termination, leaving all other parameters fixed.

The initial price  $\lambda_{hjq}^1$  and the magnitude of adjustment  $\theta^i \forall i < N$ , will be kept unchanged across all trials. We also chose to focus only the case of the 20 farmer cooperative as this was the smallest problem which showed a stable behavior (Chapter 4). Thereafter, while these parameters are held constant, the probabilities of auction termination  $\alpha^{N-k} \forall k < N$  are modified. The rationale for using the probabilities of termination as a means for coordination is in hope that they induce sufficient risk aversion in bidders to entice truthful bidding; at the same time, a mechanism which is likely to terminate later (when prices are likely to be closer to the market clearing price) is more desirable, as the objective function is likely to be higher at the end of the auction.

In order to have a structured approach to understanding the effect of  $\alpha$  on the efficiency and behavior of the mechanism, we define six vectors for  $\alpha$ . The instances for the vector  $\alpha$  which are of interest to us are detailed in Table 5.7 below. These are labeled as “constant” where the probability of termination is the same at each iteration but is abruptly terminated at iteration 15. Likewise, we have instances where the probabilities of termination are increasing linearly and terminating at iteration 15; finally, we test geometrically and exponentially increasing probabilities of termination.

Table 5.7 – Probabilities of Termination for Experimental Trials

Iteration	Constant 1	Constant 2	Arithmetic 1	Arithmetic 2	Geometric	Exponential
1	10%	5%	10%	2%	1%	1%
2	10%	5%	14%	4%	1%	1%
3	10%	5%	18%	8%	2%	2%
4	10%	5%	22%	13%	3%	3%
5	10%	5%	26%	18%	4%	4%
6	10%	5%	30%	23%	6%	5%
7	10%	5%	34%	28%	8%	7%
8	10%	5%	38%	33%	12%	10%
9	10%	5%	42%	38%	17%	14%
10	10%	5%	46%	43%	23%	19%
11	10%	5%	50%	48%	33%	26%
12	10%	5%	54%	53%	47%	37%
13	10%	5%	58%	58%	67%	51%
14	10%	5%	62%	63%	95%	72%
15	100%	100%	100%	100%	100%	100%

Note that the table above details the probabilities  $\alpha^{N-k}$ , or probability of terminating once the iteration has been reached. On the other hand, the probability of terminating the auction exactly  $i$  iterations ahead given that we are already at iteration  $N - k$  is given by  $p_i^{N-k}$  as defined by equation (5-17). To illustrate the behavior of  $p_i^{N-k}$  as opposed to  $\alpha^{N-k}$ , we use the parameters from the second column in Table 5.7 and calculate the corresponding parameter  $p_i^{N-k}$  in Table 5.8 below.

Now that we have outlined the test instances we seek to illustrate, we proceed with the computational results. We focus on the impact of the mechanism configuration on aggregate farmer profits and system wide-profits as given by equations (5-40) and (5-41) respectively. We initially illustrate the mechanism behavior and thereafter compare the various probabilities of termination as given in Table 5.7.

Table 5.8 – Conditional Probabilities of Termination for Constant  $\alpha_i = 0.1$  for  $i < 15$

Current iteration (N-k)	$\alpha$	$P_i^{N-k}$														
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	0.1	0.100														
2	0.1	0.090	0.100													
3	0.1	0.081	0.090	0.100												
4	0.1	0.073	0.081	0.090	0.100											
5	0.1	0.066	0.073	0.081	0.090	0.100										
6	0.1	0.059	0.066	0.073	0.081	0.090	0.100									
7	0.1	0.053	0.059	0.066	0.073	0.081	0.090	0.100								
8	0.1	0.048	0.053	0.059	0.066	0.073	0.081	0.090	0.100							
9	0.1	0.043	0.048	0.053	0.059	0.066	0.073	0.081	0.090	0.100						
10	0.1	0.039	0.043	0.048	0.053	0.059	0.066	0.073	0.081	0.090	0.100					
11	0.1	0.035	0.039	0.043	0.048	0.053	0.059	0.066	0.073	0.081	0.090	0.100				
12	0.1	0.031	0.035	0.039	0.043	0.048	0.053	0.059	0.066	0.073	0.081	0.090	0.100			
13	0.1	0.028	0.031	0.035	0.039	0.043	0.048	0.053	0.059	0.066	0.073	0.081	0.090	0.100		
14	0.1	0.025	0.028	0.031	0.035	0.039	0.043	0.048	0.053	0.059	0.066	0.073	0.081	0.090	0.100	
15	1	0.229	0.254	0.282	0.314	0.349	0.387	0.430	0.478	0.531	0.590	0.656	0.729	0.810	0.900	1.000

In Figure 5.5 below we provide a graphical representation of system-wide profits at each iteration for a mechanism with probabilities of termination corresponding to the constant 1 case. As it can be observed, the total allocation of contracts converges towards a centralized optimal solution. Moreover, we observe that the rate of convergence towards the optimal remains attractive and very close to that of the non-strategic solution ( $S = 0$ ). Nonetheless, we also observe that on expectation, this mechanism has an expected objective function much below the centralized optima, which occurs due to the risk of early termination; and has an optimality gap of roughly 31%.

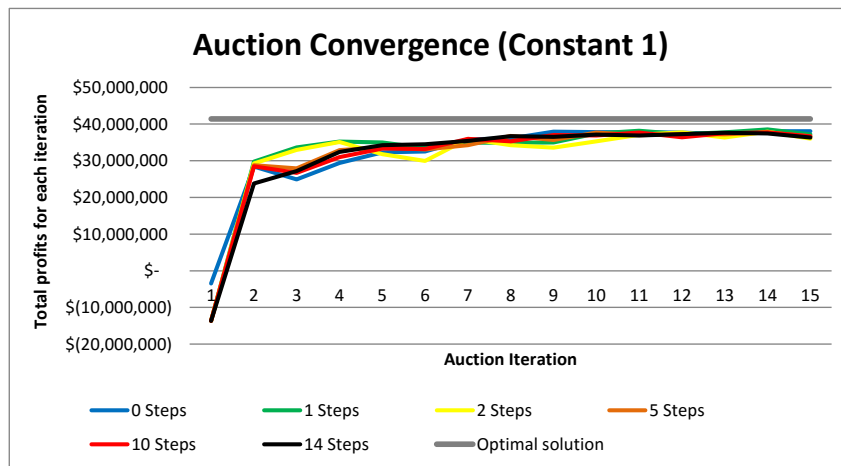


Figure 5.5 – System Profits per Iteration for  $\alpha^i = 0.1$

Fortunately, the CF has indirect control over this gap through appropriate design of the coordination mechanism. This can be done by balancing the risk of termination and the induced level of underbidding by controlling the *probability of termination*. This parameter can be stated explicitly by the CF, just as it can be left for bidders to estimate individually; nonetheless, if we assume that  $\alpha^i$  is explicitly stated, then we can use the scenarios detailed in Table 5.7 to computationally assess the expected efficiency.

We present the results corresponding to the overall behavior of the auction in Figure 5.6 below, where we detail the expected value of the mechanism (given by equation 5.41) as a function of the mechanism design and the number of lookahead iterations considered. Note that the non-strategic solution is kept as an “ideal” solution for benchmarking, keeping in mind that it is unlikely to be achieved in practice.

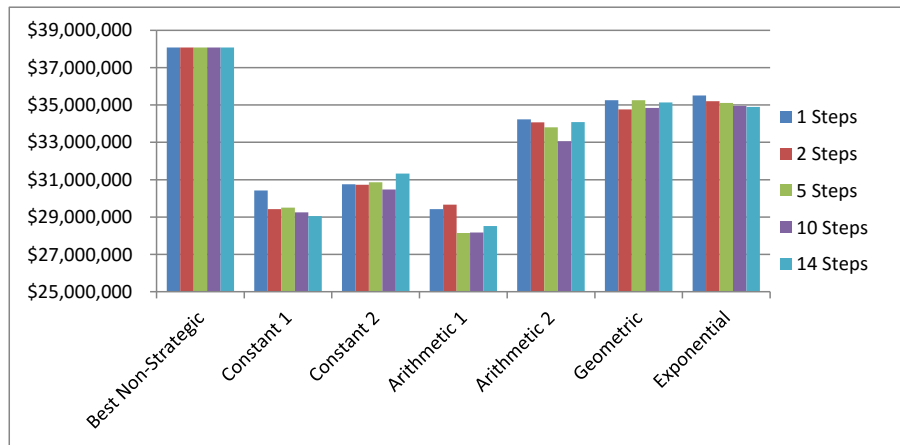


Figure 5.6 – Expected System Profits for Different Probabilities of Termination

The best solutions correspond to the geometric and exponential probabilities of termination. The defining feature of these two cases is that the probabilities of early termination are low, leading the initial and most undesirable iterations to be weighted down significantly. The end result is having a mechanism configuration for which the system

wide efficiency is significantly improved. It can be seen from Figure 5.6 that the optimality gap is reduced from 31% to 10%.

As an additional result, we also show the effect of probabilities of termination on the share of system profits which farmers obtain from engaging on the mechanism. These are shown in Figure 5.7 below.

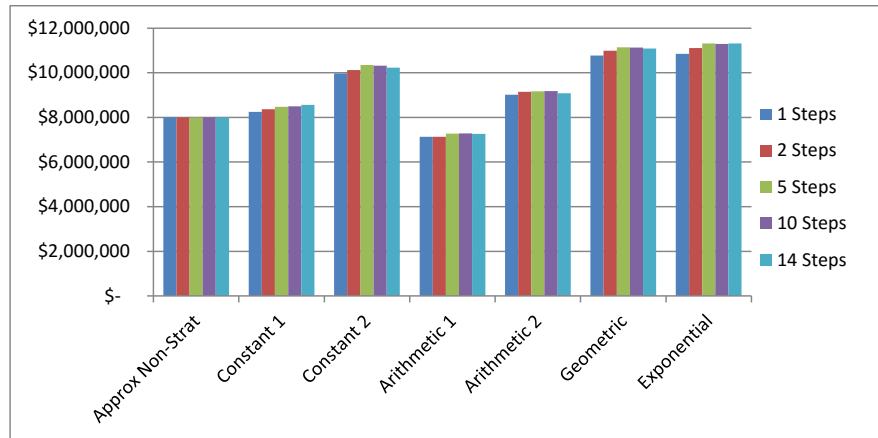


Figure 5.7 – Expected Farmer Profits for Different Probabilities of Termination

From these results, we infer that the probabilities of termination have an impact on system and farmer profits alike; moreover, engaging in speculation also has a positive impact on farmer’s profits for most mechanism configurations. Similarly, profits tend to increase with the number of lookahead periods considered  $S$ .

The results depicted above give us good intuition for what factors cause a coordination mechanism to operate successfully in practice. Moreover, through this research we have also shown that the mechanism is both effective and desirable for achieving coordinated outcomes.

Nonetheless, the results of this section focus only on changing one parameter: Probabilities/risk of termination. This is one of many parameters which could improve efficiency. Among other parameters that could be changed, we have: starting prices,

magnitude of price changes, number of iterations and restrictions on the direction of price changes. The combination of these parameters will yield mechanisms of varying effectiveness, which opens a new research question: What parameters values yield an “optimal mechanism”? Where we can define the optimal mechanism as one which maximizes system-wide profits when bidders use optimal bidding strategies.

### 5.7.5 Applying a Robust Mechanism to Cooperatives of Varying Sizes

From Section 5.7.4, we have learned of an effective mechanism configuration which yields desirable results for a cooperative of 20 farmers. However, it is of interest to know whether this mechanism has a similar effectiveness if applied to other problem sizes. In particular, if we have a cooperative composed of fewer farmers: Would the increased leverage of each individual be detrimental to the profitability of the group? And, if we have a cooperative with more farmers, will speculation become unattractive to farmers?

To address these two questions, we use the mechanism which was shown to have a positive effect on both farmers’ profits and system wide efficiency: Geometrically increasing probabilities of termination. In this mechanism the magnitude of price adjustments  $\theta$  is scaled accordingly to each problem size and the initial prices for the auction are kept unchanged. We test the behavior of the mechanism for problem sizes of 5, 20, 50 and 125 farmers. Moreover, since the lookahead speculation of 5 iterations was shown to give good results we only focus on the case where  $S = 5$ .

In order to illustrate the differences between each case, we observe four different measures of interest as they progress throughout the auction: (1) Total system profits, (2) farmer profits, (3) average prices per crop, and (4) the gap between truthful and strategic bids. Each of these are analyzed below.



### 5.7.5.1 System Profits

In Figure 5.8 below, we see the behavior of system profits as they progress on each iteration. Here the optimal centralized solution, system profits for the non-strategic case and system profits for the speculation case are plotted in each iteration.

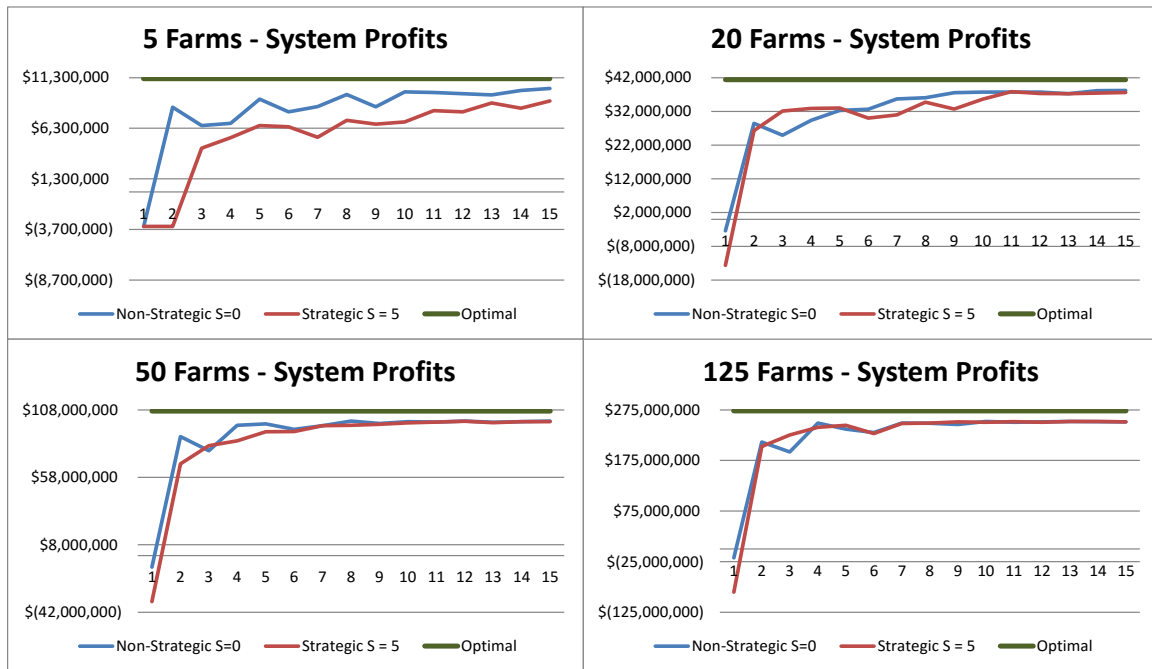


Figure 5.8 – Total System Profit for Various Problem Sizes

As it can be observed, the behavior of the mechanism is as expected, where less bidders have an increased power on the cooperative, which in turn compromises system efficiency. This can be observed by the convergence properties of the solution, where convergence is slower and less stable for the case of 5 farmers. Furthermore, this result is further exemplified by looking at the expected values of the mechanism as shown in Table 5.9 below. Note that as the number of bidders increases, the optimality gap decreases.

Table 5.9 – Total System Profits for Various Problem Sizes

Farms	Optimal Solution	Best Non-Strategic	Expected Strategic (S = 5)	Gap (VS Optimal)	Gap (VS Non-Strategic)
5	\$ 11,206,796	\$ 10,232,257	\$ 6,992,191	38%	32%
20	\$ 41,401,132	\$ 38,227,615	\$ 34,569,592	17%	10%
50	\$ 107,128,179	\$ 99,745,887	\$ 95,251,869	11%	5%
125	\$ 273,262,249	\$ 252,029,020	\$ 244,605,522	10%	3%

5.7.5.2 Farmer’s Profits

The behavior of the mechanism is further exemplified by farmer’s profits. These show the leverage that bidders can achieve, as higher profits throughout the auction reflect a better bargaining position. These are shown in Figure 5.9 below, where for cooperatives of a smaller size, the increase in farmer’s profits for the strategic case outperforms that of the non-strategic formulation; here the impact is greatest for the smaller cooperatives.

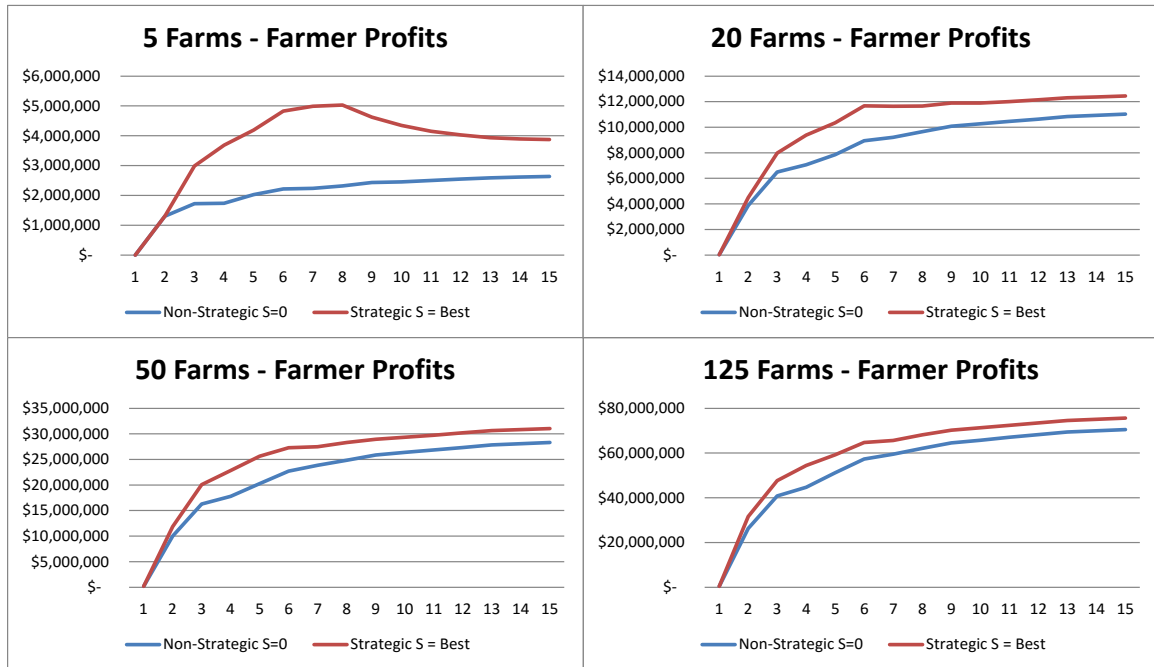


Figure 5.9 – Total Farmers Profits for Various Problem Sizes

This behavior is further exemplified by observing the behavior of the expected farmer’s profits. As expected, it can be observed that the smaller cooperative has the

greatest leverage by farmers, whereas the largest shows the least benefit from speculation. Nonetheless, in all problem instances, farmers benefit from speculating (Table 5.10).

Table 5.10 – Farmer’s Aggregate Expected Profits for Various Problem Sizes

Size	Non-Strategic	Strategic (S = 5)	% Increase
5	\$ 2,362,654	\$ 3,845,071	63%
20	\$ 9,775,419	\$ 11,121,138	14%
50	\$ 25,105,010	\$ 27,752,802	11%
125	\$ 62,722,793	\$ 67,869,651	8%

### 5.7.5.3 Behavior of Prices and Bidding Gaps

Finally, the bids placed by farmers and the behavior of the prices of crops throughout the auction are illustrated. The average prices of each crop in the mechanism are observed in Figure 5.10 below.

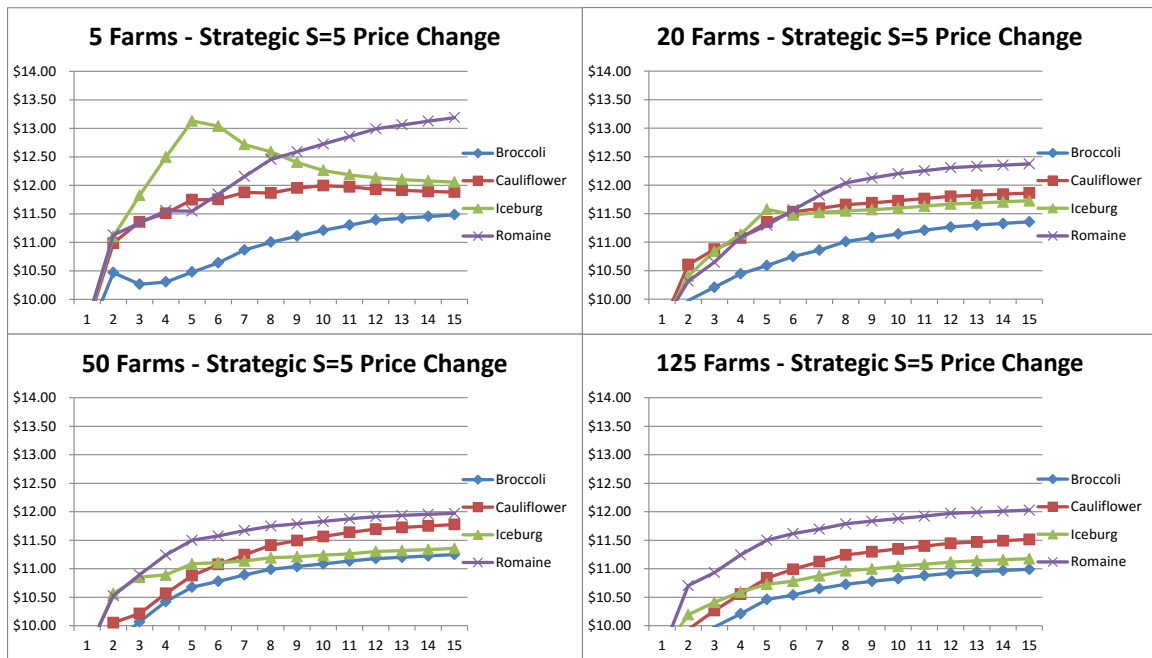


Figure 5.10 – Average Prices of Crops for Various Problem Sizes

In all cases we see that as the auction progresses, prices tend to converge towards the market clearing prices. Here we can observe that the average prices also tend to be much

higher for the smaller cooperative sizes, where farmers have most leverage on the changes. Moreover, we also observe that prices changes are greatest in the smaller problem sizes.

This increased strategic behavior is also illustrated by Figure 5.11, which shows the aggregate difference between truthful and strategic bids for each problem size<sup>15</sup>.

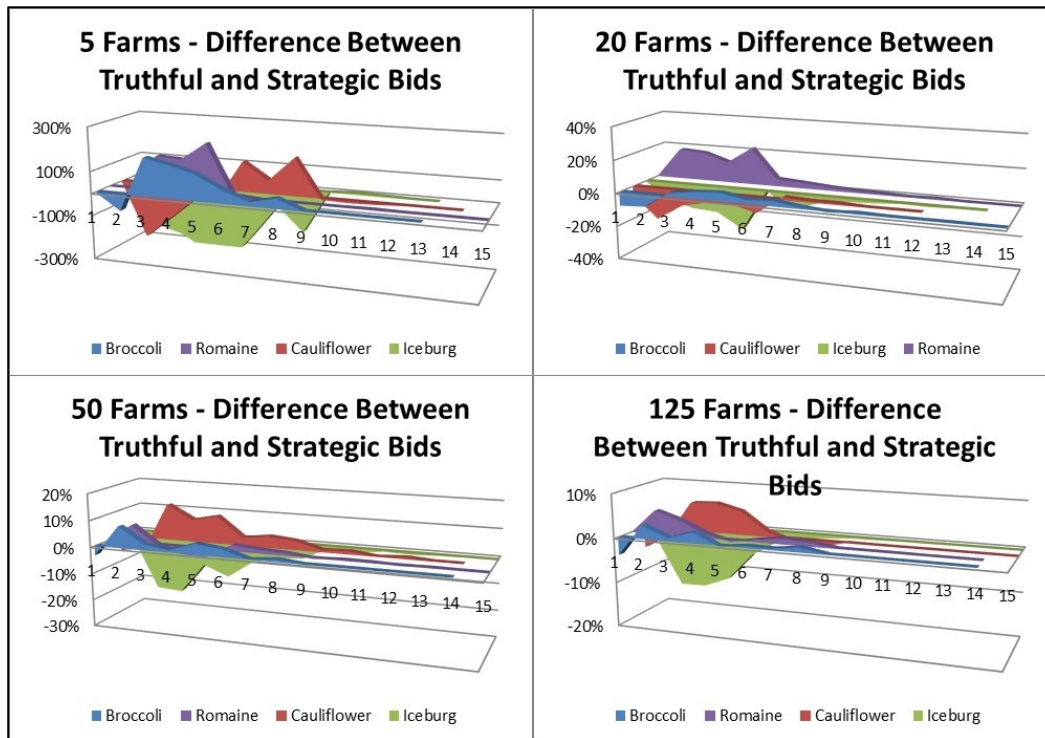


Figure 5.11 – Difference in Strategic to Truthful Bids for Various Problem Sizes

We observe that, as the auction progresses, farmers respond to risk by stabilizing their bids which are closer to their true valuations. Moreover, we also observe by looking at the scale of the graphs, that speculation is much greater for smaller problem sizes, reaching values close to 200% for romaine lettuce. This arises from cases in which it is best to not produce romaine lettuce, but where production is sought in order to some keep

<sup>15</sup> Note that the way in which the percentages are calculated is by taking the difference between the truthful and strategic solutions and then dividing the difference by the target demand set by the cooperative. Because the bidding difference is divided by a constant, the % mismatch can be greater than 100%

revenue while bringing up the prices of other crops. Specifically, by looking at the case of five farmers, it can be seen that significant underbidding occurs for iceberg lettuce, which also correlates with significant price increases for that same crop.

## 5.8 Conclusion and Discussion

Throughout this chapter, we have explored the practical feasibility of implementing a coordination mechanism in an agricultural cooperative. In this research, the coordination mechanism is formulated as an iterative auction where farmers place bids for production and standing bids at the iteration where the auction terminates become supply contracts. Farmers are free to bid any quantities throughout the auction and cannot be prevented from speculating or misrepresenting their bids. The objective of the chapter is to better understand speculative behavior, its impact on the efficiency of the overall system and to seek ways in which speculation can be minimized while maximizing profits.

It was shown through a dynamic programming formulation of the bidder speculation problem that the mechanism is not incentive compatible and that misrepresenting bids has a positive impact on farmers' profits. Pathologies of the mechanism were identified and forms to avoid them were detailed. Additionally, it was shown that the bidder speculation problem can be solved efficiently and in reasonable time. Finally, throughout the chapter, the impact of speculation on efficiency is illustrated computationally for a variety of mechanism configurations and for a variety of cooperative sizes. These results show that coordination mechanisms in agricultural cooperatives can be effective forms of coordination and that they have a high potential for obtaining good outcomes for farmers and the agricultural cooperative as a whole.

The research performed throughout this chapter provides a solid foundation for coordination of agricultural supply chains. Moreover, it also provides a foundation for mathematical analysis of coordination mechanisms. Nonetheless, these results also highlight the need for additional work regarding coordination in agricultural supply chains; two main avenues of research are devised: (1) We must compare this coordination mechanism with current contracting and coordination schemes used in agricultural supply chains; mainly, it is of great interest to benchmark this scheme against current contract farming practices and against production assignment based on pure negotiation. And (2) the design of the mechanism (as given by starting prices, probabilities of termination and magnitude of price changes) is also an optimization problem on itself. It is therefore necessary to explore the problem of maximizing system profits, using the mechanism parameters as the variables being optimized.

Further avenues of research of great interest exist on this research. Some of these include the analysis of the mechanism for non-perishable crops or even looking at perishable crops with technological investments in production and storage. Likewise, it would be interesting to refine the data used for the case study to better reflect the changing costs of production that farmers observe depending on their size; this could shed some light on the profitability of the mechanism on cooperatives where the size of farmers is more heterogeneous.

## 6 ADDRESSING BIAS FROM STOCHASTIC YIELDS

### 6.1 Introduction

In the previous chapters we have shown that production in the supply chain for fresh produce can be coordinated in spite of its decentralized nature and conflicting objectives. Furthermore, it was shown that through careful implementation of coordination mechanisms, coordinated outcomes can be achieved robustly, even when agents misbehave or act strategically. However, for these results, the coordination problem is assumed to be deterministic in yields. Therefore, although this dissertation has addressed the solving of large scale problems through auction mechanisms, it has so far failed to capture the greatest difficulties brought about by the stochastic yields prominent in agriculture.

Among the greatest problems of random yields are the difficulties created for matching the supply to the demand of agricultural goods. In particular, since agricultural goods have a long lead time, hedging supply or demand uncertainty cannot be done through the use of excess capacity, nor in many cases higher inventories as many of these products are perishable. This is particularly true for fresh produce, for which variability is greatly amplified (Fleisher, 1990). The stochastic nature of yields in fresh produce creates two main problems in the context of this research:

1. Because of yield variability farmers find themselves in a delicate decision for how much to produce. They have to balance the risks of overproducing and risking product loss against the risk of shorting their customers (Cook, 2011). This is a problem akin to the newsvendor problem.
2. Under the assumptions of Chapter 5, the cooperative under which farmers operate will guarantee a price and quantity purchase from each farmer as part of the

contract. However, having such strong guarantees has game theoretic implications leading to a Moral Hazard Problem. Under this framework, it would be possible for farmers to dishonor their production commitments with the CF to their own benefit. For instance, they could hold back their bids in the auction in hope to raise prices and then expect the CF to purchase the balance at a good price.

These two issues create risk for the CF, which should be aware of the implications of existing contractual agreements. From a coordination perspective, these agreements cannot be too stringent as they may harm farmers, but they cannot be too lax, as risk will be transferred disproportionately to the CF. For these reasons we choose to address the supply chain coordination problem with an emphasis on the gap between what is required from farmers and the expected value of their production. For the remainder of this chapter we use the term *production bias* to refer to the difference between production commitments (as made with the CF) and the expected value of production plans (as accounted for privately by farmers). Moreover, we bring to the reader's attention that, by addressing production bias we are coming back to the familiar concept of Incentive Compatibility, which was strongly emphasized in Chapter 5.

We formulate the farmer decision problem with stochastic yields and then determine the optimal production quantities which maximize farmer's profits. Thereafter we analyze the implications of these production quantities in terms of the expected production bias which they induce. For this, we formulate the decision problem as a newsvendor model with stochastic yields and with the use of options contracts for farmers to hedge their yield uncertainty. Furthermore, we seek to use the options contracts as an indicator of variance for the CF and also as a tool to reduce bias in the production process.



## 6.2 Literature Review

The problem of supply chain coordination using contracts has been extensively explored, showing that revenue sharing, quantity flexibility, buybacks or other arrangements can help coordinate the supply chain (Cachon & Netessine, 2004; Simchi-Levi et al., 2003). These models many times rely on the familiar formulation of the production problem as a newsvendor model where the quantity of production is chosen to balance the risks of over/underproduction. From this model, several extensions have been proposed including the inclusion of pricing, stochastic demand, stochastic yields and the inclusion of multiple periods to the planning problem (Bollapragada & Morton, 1999; Petruzzi & Dada, 1999; Yao, Chen, & Yan, 2006).

The newsvendor problem is a well-researched and developed topic, for which multiple reviews of the literature exist. For the newsvendor problem with stochastic yields, we refer the reader to Yano & Lee (1995), who take the closest look at planning with yield uncertainty. They show some of the earlier continuous and discrete time models for production planning as well as multiple period extensions. Nonetheless, in recent years newsvendor problem formulations have placed a much lower emphasis on yield uncertainty. These efforts have placed an increased emphasis on risk profiles, pricing decisions, marketing effort and supply chain coordination (Qin, Wang, Vakharia, Chen, & Seref, 2011); although Qin et al. also mention that coordination problems with stochastic supply and demand are now gaining traction. More recently, Inderfurth (2009) provides a compilation of studies geared towards addressing demand and yield uncertainty; although the focus is on inventory control rather than supply chain coordination. Overall, yield uncertainty has been addressed in many contexts; however, from the perspective of supply

chain coordination still little focus has been placed on quality and yield uncertainty (C. H. Lee, Rhee, & Cheng, 2013).

We mention some of the research which is most relevant to our problem. The problem of unreliable supply quantities has been explored by Agrawal & Nahmias (1997), who look at stochastic supply from the perspective of supplier selection where the objective is to select a subset of suppliers and assign them production quantities. The supplier selection problem was then expanded by Burke et al. (2009). Likewise, for the problem of stochastic yields, responsive and dynamic pricing is explored by (Tang & Yin, 2007; Tang & Li, 2012); however, supply chain coordination is not addressed. Nonetheless, from the perspective of supply chain coordination, recent advances for modeling stochastic yields were made by Lee et al. (2013) who penalize quality uncertainty from the manufacturer from returned or unsold units. More recently, Xu & Lu (2013) explore the impact of yield uncertainty on price setting newsvendors for procurement and in house manufacturing.

On the topic of supply chain coordination with stochastic yields, which is most relevant to us, we mention some of the most relevant and recent publications. For traditional manufacturing supply chains, Xu (2010) looks at supply chain coordination with uncertain yields and how the supply chain can be coordinated through the use of option contracts; in this research, the buyer has the option to exercise the options when demand materializes. Li, Li, & Cai (2012) model a distributor who faces random demand and stochastic supply; here they determine whether order quantities should be inflated or deflated in order to account for the stochastic supply. In a later publication, Li, Li, & Cai (2013) also explore the case of double marginalization with uncertain supply and sustain that supply shortages result from a lack of coordination; they propose a supply contract

with shortage penalties to coordinate the supply chain. More recently Güler & Keskin (2013) explore the use of various contract arrangements with stochastic supply; however, they don't explore the use of options contracts. Finally, Luo & Chen (2015) consider a supplier-manufacturer supply chain with stochastic supply and options contracts where the options are exercised by the manufacturer who also has access to a spot market.

From the previous compilation we see that newsvendor problems with supply uncertainty are being considered under multiple variations of the problem. In many cases, these formulations include the use of supply contracts and the use of options for supply chain coordination. However, in all of the aforementioned research, the party exercising the options is the downstream echelon on the supply chain (manufacturer/buyer); furthermore, all of these formulations are made considering the traditional manufacturing supply chain model.

In some cases it may be most appropriate to formulate the options contract such that it is the supplier, rather than the manufacturer, who has the capacity to exercise the options. This can be the case of a grower of fresh produce who commits to a given supply quantity; yet, due to yield uncertainty the supply quantity may not be met. Under this framework, it can be the supplier who exercises the option rather than the manufacturer. Moreover, the framework used to model the exercise of options contracts from the supplier side can also be used to capture more general decision problems, such as purchasing insurance or committing to additional supply under a variable price framework.

Among the decision problems in agriculture, Huh, Athanassoglou, & Lall (2012) consider the case of supply chain coordination using contract farming and possible supplier reneging; likewise Wang & Chen (2013) consider the case coordination with options

contracts but with deterministic yields. To our knowledge, no research has been done on the case of using options contracts from the perspective of the supplier with uncertain yields.

From the review of the literature we see that there is an opportunity to fill a gap in research for decision problems with stochastic yields. This gap occurs in the space of supply chain coordination, where options contracts have not been studied as a tool for coordination exercised by the supplier and sold by the manufacturer. In particular, for the case of agriculture, no research exists for supply chain coordination with stochastic yields using option contracts.

### 6.3 Model Formulation

To model the decision problem we first provide the notation to be used throughout this paper. Thereafter the model is formulated for the case where no options are used, and for the use of options contracts. From these results we derive additional intuition which can be used from the perspective of supply chain coordination; we analyze the conditions for which production bias is reduced.

We make some underlying assumptions. Firstly, we look at the decision process of a single farmer engaging in a contract with a CF. The demand for the consolidation facility is known and has been pre-determined. Moreover, this demand is communicated to the farmer through a negotiated supply quantity  $S$ , which can be the result of previous contract assignments such as those discussed in Chapters 4 and 5; moreover, the wholesale price  $p_F$  is also pre-established through similar mechanisms. Here, the farmer must honor his/her commitment with the CF. Likewise, we also assume that the agreed upon “supply quantity” coordinates the chain and minimizes the costs of the CF.

From the perspective of the farmer, we assume that the variance of production yields is constant and does not depend on the quantities planted; moreover, we assume that the farmer has spare capacity to plant more land if necessary and is not constrained by his/her land. Finally, in practice farmers may be able to sell or purchase produce from the open market; however, for this formulation we assume that farmers have a single buyer for its produce, prices are deterministic and arbitrage is not allowed. For the stochastic yields, the following assumptions apply: The quantity harvested  $H$  is stochastic and directly proportional to the quantity planted by the farmer  $q$ ; the realization of the harvest quantity is scaled by the stochastic yield random variable  $X$ .

A summary of all relevant parameters and decision variables for the farmer are described below:

**Decision variables:**

- $q$  = Quantity to plant for farmer (*Acres*)
- $q_u$  = Number of options for underage insurance to buy (*Units*)
- $q_o$  = Number of options for overage insurance to buy (*Units*)

**Parameters:**

- $S$  = Pre-established supply quantity (*Units*)
- $H$  = Amount harvested as a function of planting and random yield (*Units*)
- $x$  = Random variable for the stochastic yield (*Units per Acre*)
- $F(x)$  = CDF for the stochastic yield
- $f(x)$  = PDF for the stochastic yield
- $E[x]$  = Expected yield
- $p_F$  = Unit price offered to the farmer
- $c$  = Cost of harvesting realizes production (*Cost per unit*)
- $c_{pl}$  = Cost of planting (*Cost per acre*)

- $c_u$  = Unit cost of underage
- $c_o$  = Unit cost of overage
- $o_u$  = Cost of an option to under supply the CF
- $o_o$  = Cost of an option to sell above committed supply
- $s_u$  = Strike price for underage options ( $s_u < c_u$ )
- $s_o$  = Strike price for overage options ( $s_o < c_o$ )

We state the following additional assumptions on the parameters: For the farmer to have an incentive to purchase and use options, these should provide a form of insurance for under-overage; therefore we have that  $c_u > s_u + o_u$  and  $c_o > s_o + o_o$ . Moreover, for farmers to have an incentive to produce we must also have  $p_F > \frac{c_{plant}}{E[x]} + c$ . Finally production quantity and purchase of options contracts must be positive  $q, q_u, q_o \geq 0$ .

### 6.3.1 Farmer Decision Problem without Option Contracts

We formulate the problem as a special case of the newsvendor problem with stochastic yields. It is assumed that the consolidation facility has a strict acceptance policy, for which production above committed supply is not accepted and becomes lost revenue for farmers. For this, we define farmer's profits as the revenue obtained from selling crops minus the costs of underage, costs of overage and costs of planting respectively as seen in equation (7-1) below.

$$\pi_F = p_F \min(H, S) - c_u(S - H)^+ - c_o(H - S)^+ - q c_{pl} \quad (6-1)$$

Since  $\pi_F$  is a function of stochastic yields, we take expectation with respect to  $x$ :

$$\begin{aligned} E[\pi_F] &= E[p_F \min(H, S) - c_u(S - H)^+ - c_o(H - S)^+ - q c_{pl}] \\ &= p_F \int_{-\infty}^{\infty} \min(qx, S) f(x) dx - c_u \int_{-\infty}^{\infty} (S - qx)^+ f(x) dx - c_o \int_{-\infty}^{\infty} (qx - S)^+ f(x) dx - q c_{pl} \end{aligned}$$

After taking some integrals and rearranging terms, the expected profits are:

$$\begin{aligned}
E[\pi_F] &= (p_F + c_u)E[x]q - c_u S + (p_F + c_u + c_o) S \left(1 - F\left(\frac{S}{q}\right)\right) \\
&\quad - (p_F + c_u + c_o) \int_{\frac{S}{q}}^{\infty} qx f(x) dx - qc_{pl}
\end{aligned} \tag{6-2}$$

If we take derivatives and optimize with respect to  $q$ , we obtain the following:

$$\frac{dE[\pi_F]}{dq} = (p_F + c_u)E[x] - (p_F + c_u + c_o) \left( \int_{\frac{S}{q}}^{\infty} x f(x) dx \right) - c_{pl} = 0$$

$$\frac{d^2E[\pi_F]}{dq^2} = -(p_F + c_u + c_o) \left(\frac{S^2}{q^3}\right) f\left(\frac{S}{q}\right) \leq 0$$

Therefore, the profit function is convex on  $q \geq 0$  and an optimal solution  $q^*$  can be found by the farmer which will obey the following equality.

$$(p_F + c_u)E[x] - c_{pl} = (p_F + c_u + c_o) \int_{\frac{S}{q}}^{\infty} x f(x) dx \tag{6-3}$$

This result resembles one illustrated in a review of newsvendor problems with stochastic yields by Yano & Lee (1995).

### 6.3.2 Farmer Decision Problem with Option Contracts

The previous formulation, although useful for the most common decision problem faced by a farmer, does not capture the general requirements of this research. For our purposes, we include the costs of option contracts and cost of exercising options to the above equations. For this, we define the profit function as the sum of (1) expected revenues, (2) expected penalty costs, including underage and overage costs, (3) fixed costs, which include the cost of planting and of purchasing options, and (4) option exercise costs.

$$E[\pi_F] = E[R] + E[CP] + E[CT] + E[CO] \tag{6-4}$$

Each of these costs is expanded below, where expected revenues reflect the strict acceptance policy of the CF. However, unlike the formulation of (6-1), the penalty costs

are deferred by the quantities chosen by the option contracts. As a result, a relationship can be formed between the cost of exercising the options and the regular costs of underage and overage. Here, the strike price of the options will be less than the penalty costs; however, once the options purchased run out, then farmers are faced with the higher penalty costs. In this formulation we note that  $c_u, c_o$  must be positive and greater than zero; however,  $s_u, s_o$  need not be strictly positive; instead,  $s_u, s_o$  can act as a form of insurance which will allow farmers to gain income despite yield risk.

$$E[\pi_F] = E[p_F \min(H, S)] - E[c_u(S - q_u - H)^+ + c_o(H - S - q_o)^+] - E[c_{pl}q + o_u q_u + o_o q_o] - E[s_u(S - H)^+ + s_o(H - S)^+] \quad (6-5)$$

**Lemma 1:** The farmer decision problem to determine optimal production and option contract quantities is concave on  $q, q_u, q_o \geq 0$ ; moreover, since we have a maximization problem, any point satisfying the first order optimality conditions is guaranteed to be a global optimum.

**Proof.**

By taking expectation on yields, we obtain the following expression:

$$\begin{aligned} E[\pi_F] &= (p_F + s_u)E[x]q - s_u S + (p_F + s_u + s_o) S \left(1 - F\left(\frac{S}{q}\right)\right) \\ &\quad - (p_F + s_u + s_o) \int_{\frac{S}{q}}^{\infty} q x f(x) dx - c_u(S - q_u) F\left(\frac{S - q_u}{q}\right) \\ &\quad + c_u \int_{-\infty}^{\frac{S - q_u}{q}} q x f(x) dx - c_o \int_{\frac{S + q_o}{q}}^{\infty} q x f(x) dx + c_o(S + q_o) \left(1 - F\left(\frac{S + q_o}{q}\right)\right) \\ &\quad - c_{pl}q - o_u q_u - o_o q_o \end{aligned}$$

From this equation, we can take derivatives with respect to the planning quantity  $q$  and the unit option purchases  $q_u, q_o$  to obtain the first order optimality conditions given by the following first order optimality conditions:



$$(p_F + s_u)E[x] - (p_F + s_u + s_o) \int_{\frac{S}{q}}^{\infty} xf(x) dx + c_u \int_{-\infty}^{\frac{S-q_u}{q}} xf(x) dx - c_o \int_{\frac{S+q_o}{q}}^{\infty} xf(x) dx - c_{pl} = 0 \quad (6-6)$$

$$c_u F\left(\frac{S-q_u}{q}\right) - o_u = 0 \quad (6-7)$$

$$c_o \left(1 - F\left(\frac{S+q_o}{q}\right)\right) - o_o = 0 \quad (6-8)$$

And similarly, we take the second derivatives to verify the concavity of the formulated decision problem.

$$\frac{d^2 E[\pi_F]}{dq^2} = -(p_F + s_u + s_o) \left(\frac{S^2}{q^3} f\left(\frac{S}{q}\right)\right) - c_u \left(\frac{(S-q_u)^2}{q^3} f\left(\frac{S-q_u}{q}\right)\right) - c_o \left(\frac{(S+q_o)^2}{q^3} f\left(\frac{S+q_o}{q}\right)\right)$$

$$\frac{d^2 E[\pi_F]}{dq_u^2} = -\frac{c_u}{q} f\left(\frac{S-q_u}{q}\right); \quad \frac{d^2 E[\pi_F]}{dq_o^2} = -\frac{c_o}{q} f\left(\frac{S+q_o}{q}\right)$$

$$\frac{d^2 E[\pi_F]}{dq_o dq} = c_o \frac{S+q_o}{q^2} f\left(\frac{S+q_o}{q}\right); \quad \frac{d^2 E[\pi_F]}{dq_u dq} = -c_u \frac{S-q_u}{q^2} f\left(\frac{S-q_u}{q}\right); \quad \frac{d^2 E[\pi_F]}{dq_u dq_o} = 0$$

We will have concavity of the profit function if the hessian matrix is negative definite. This holds if the determinant of the hessian is negative for all values of  $q$ ,  $q_u$ ,  $q_o$ .

The determinant of hessian matrix is:

$$\begin{aligned} &= - \left[ \frac{(p_F + s_u + s_o)S^2}{q^3} f\left(\frac{S}{q}\right) + \frac{c_u(S-q_u)^2}{q^3} f\left(\frac{S-q_u}{q}\right) + \frac{c_o(S+q_o)^2}{q^3} f\left(\frac{S+q_o}{q}\right) \right] \frac{c_u c_o}{q^2} f\left(\frac{S-q_u}{q}\right) f\left(\frac{S+q_o}{q}\right) \\ &+ \frac{c_u}{q} f\left(\frac{S-q_u}{q}\right) \left[ c_o \frac{S+q_o}{q^2} f\left(\frac{S+q_o}{q}\right) \right]^2 + \frac{c_o}{q} f\left(\frac{S+q_o}{q}\right) \left[ c_u \frac{S-q_u}{q^2} f\left(\frac{S-q_u}{q}\right) \right]^2 \end{aligned}$$

Which will be negative as long as the following condition is satisfied:

$$\begin{aligned} &\left[ \frac{(p_F + s_u + s_o)S^2}{q^3} f\left(\frac{S}{q}\right) + \frac{c_u(S-q_u)^2}{q^3} f\left(\frac{S-q_u}{q}\right) + \frac{c_o(S+q_o)^2}{q^3} f\left(\frac{S+q_o}{q}\right) \right] \frac{c_u c_o}{q^2} f\left(\frac{S-q_u}{q}\right) f\left(\frac{S+q_o}{q}\right) \\ &\geq \frac{c_u}{q} f\left(\frac{S-q_u}{q}\right) \left[ c_o \frac{S+q_o}{q^2} f\left(\frac{S+q_o}{q}\right) \right]^2 + \frac{c_o}{q} f\left(\frac{S+q_o}{q}\right) \left[ c_u \frac{S-q_u}{q^2} f\left(\frac{S-q_u}{q}\right) \right]^2 \end{aligned}$$

By factorizing and eliminating some terms we obtain the following:

$$\begin{aligned} (p_F + s_u + s_o)S^2 f\left(\frac{S}{q}\right) + c_u(S - q_u)^2 f\left(\frac{S - q_u}{q}\right) + c_o(S + q_o)^2 f\left(\frac{S + q_o}{q}\right) \\ \geq c_o(S + q_o)^2 f\left(\frac{S + q_o}{q}\right) + c_u(S - q_u)^2 f\left(\frac{S - q_u}{q}\right) \end{aligned}$$

And simplifying further we obtain the following condition:

$$p_F + s_u + s_o > 0$$

This implies that the Hessian is negative definite and the decision problem is concave as long as the above condition is satisfied. ■

Thus, if the unit returns from option contracts are larger than the revenue per unit, then the problem will cease to be concave. Throughout the remainder of this chapter we assume that the above condition is satisfied.

### 6.3.3 Minimizing Production Bias

From the perspective of supply chain coordination and in order to maintain incentive compatibility, it is desired that the planned production by farmers is as close as possible to the supply required by the CF. In other words, the right incentives should be put in place such that the planned harvest quantities match required supply; in expectation this means that  $q = \frac{S}{E[x]}$ . This, is possible both with and without using option contracts and applies to any arbitrary distribution; however, we recognize that some distributions may be different in terms of risk, which goes beyond expected value which is not captured by this formulation. In this section we derive the necessary conditions to facilitate the reduction of production bias with and without options for any general distribution.

### 6.3.3.1 Unbiased Solutions without Options

From equation (6-3) we obtain a form in which the optimal planting quantity for farmers can be determined. However, to obtain a solution which is unbiased we may require a very particular combination of costs and incentives. The conditions can be derived from equation (6-3) by imposing the requirement that  $q = \frac{S}{E[x]}$ . This implies:

$$\frac{(p_F + c_u)E[x] - c_{pl}}{(p_F + c_u + c_o)} = \int_{E[x]}^{\infty} x f(x) dx$$

For illustration purposes, we assume that yields are normally distributed with  $X \sim N(\mu, \sigma)$ . With this assumption we have the following equality<sup>16</sup>:

$$\frac{(p_F + c_u)\mu - c_{pl}}{(p_F + c_u + c_o)} = \frac{\mu}{2} + \frac{1}{\sqrt{2\pi}}\sigma$$

Moreover, we can use the difference between the two sides of this equality as a bias indicator we label  $\Gamma_b$  for the base case without options.

$$\Gamma_b = \frac{(p_F + c_u)\mu - c_{pl}}{(p_F + c_u + c_o)} - \frac{\mu}{2} + \frac{1}{\sqrt{2\pi}}\sigma \quad (6-9)$$

As a result it is optimal for farmers to state their production quantities truthfully only for a small subset of all possible combinations of  $c_{pl}, c_o, c_u, c_o$ . We explore instances in which this condition is satisfied in Section 6.4 through computational results.

### 6.3.3.2 Obtaining Unbiased Solutions with Options

In a similar way in which we derive conditions under which production bias is eliminated for the case of production contracts with options. To do this, we refer back to

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<sup>16</sup>Note that we have used the conditional expectation formula:  $E[X|a < X < b] = \mu + \frac{\phi(\frac{a-\mu}{\sigma}) - \phi(\frac{b-\mu}{\sigma})}{\Phi(\frac{b-\mu}{\sigma}) - \Phi(\frac{a-\mu}{\sigma})}\sigma$ , where  $\phi()$  is the standard normal probability density function and  $\Phi()$  is its cumulative distribution function

the first order optimality conditions derived in section 6.3.2 and imposing the requirement that  $q = \frac{S}{E[x]}$ . This yields the following equations:

$$(p_F + s_u)E[x] - (p_F + s_u + s_o) \int_{E[x]}^{\infty} x f(x) dx + c_u \int_{-\infty}^{E[x] - \frac{q_u}{q}} x f(x) dx - c_o \int_{E[x] + \frac{q_o}{q}}^{\infty} x f(x) dx - c_{pl} = 0$$

$$c_u F\left(E[x] - \frac{q_u}{q}\right) - o_u = 0$$

$$c_o \left(1 - F\left(E[x] + \frac{q_o}{q}\right)\right) - o_o = 0$$

These conditions can be applied to any general distribution; however, assuming that yields are normally distributed with  $X \sim N(\mu, \sigma)$  we may simplify the expressions to:

$$\Gamma_o = \left(\frac{p_F + s_u - s_o}{2} + o_u - o_o\right)\mu - \frac{(p_F + s_u + s_o)}{\sqrt{2\pi}}\sigma - c_u \Phi\left(\frac{\mu q_u}{\sigma S}\right)\sigma - c_o \Phi\left(\frac{\mu q_o}{\sigma S}\right)\sigma - c_{pl} \quad (6-10)$$

$$\Phi\left(-\frac{\mu q_u}{\sigma S}\right) = \frac{o_u}{c_u} \quad (6-11)$$

$$1 - \Phi\left(\frac{\mu q_o}{\sigma S}\right) = \frac{o_o}{c_o} \quad (6-12)$$

Here,  $\Gamma_o$  is the bias indicator for the production bias in the case where option contracts are made available. Unfortunately, without knowing the values of  $q_u$  and  $q_o$ , there is no closed form solution for  $\Gamma_o$  and therefore the value must be solved numerically, using  $q_u$  and  $q_o$  given by equations (6-11) and (6-12); thereafter using their values to determine if equality can hold for the above expression. Note that equation (6-9), is a special case of equation (6-10), where  $q_u, q_o, s_u, s_o = 0$ .

## 6.4 Computational Results

To illustrate the results of the case study, we utilize a combination of input/output data obtained from Chapter 5. From the results of this previous case study, we have necessary information such as committed supply, wholesale prices, farmer costs and yields.

From the Chapter 5 results, we select the output from the 20-farmer cooperative with geometric prices of termination as seen in Section 5.7.4. From this output, we selected one specific farmer (Farmer 9) and the production of broccoli. The average weekly supply quantity and average production costs for that crop were used, as well as the average weekly wholesale price. These parameters were rounded to the nearest integer and the values which will be used from this study are:

- Supply Quantity,  $S = 9,000$  *Cartons*
- Random Yield,  $X = N\sim(920, 50)$  *Cartons per acre*
- Wholesale price,  $w = 12$
- Cost of planting,  $c_{pl} = 2,730$  *Per acre*
- Cost of harvesting,  $c' = 5$
- Effective price,  $p_F = w - c' = 7$

The parameters above are held constant throughout the computational results, while  $c_u, c_o, o_u, o_o, s_u, s_o$  are varied according to the requirements of the analysis being performed. Two responses are primarily observed: the impact to farmer's profits and the the impact to the expected production bias.

In the remainder of this section we analyze the following test instances: In Section 6.4.1 we run a base case for the decision problem without using options; thereafter, in section 6.4.2 a similar scenario is tested for the production problem using options and direct comparisons are made. In Section 6.4.3 we perform sensitivity analysis on the purchase cost of the options; this analysis is later expanded in Section 6.4.4 to include sensitivity analysis on the cost of options and the strike price of the options. Finally, in Section 6.4.5 we perform a sensitivity analysis on the variance of the yields.

### 6.4.1 Sensitivity to Underage and Overage Costs Without Options

In order to begin our analysis of the farmer decision process, we illustrate the impact of the quantity planted when the farmer has no access to options. For this, we graph the general behavior of the expected farmers costs and revenues as a function of the quantity planted ( $q$ ) (where  $c_o = 3$ ,  $c_u = 1$  and other parameters are as stated above). As it can be observed, the behavior of each component of the profit, as well as the final profits, have an expected convex behavior with one optimal value for the planting decision (Figure 6.1).

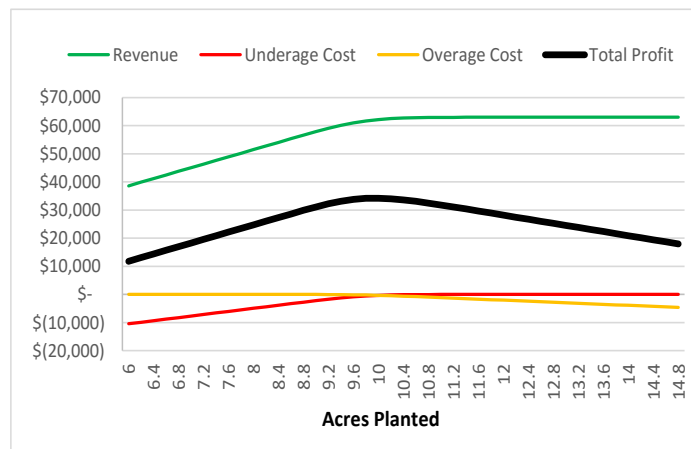


Figure 6.1 – Expected Profit and Components Sensitivity to Planting Quantity

For the following results, we use make a sensitivity analysis on the costs of overage ( $c_o$ ) and underage ( $c_u$ ) on the ranges of (-1, 5) and (0, 9) respectively.

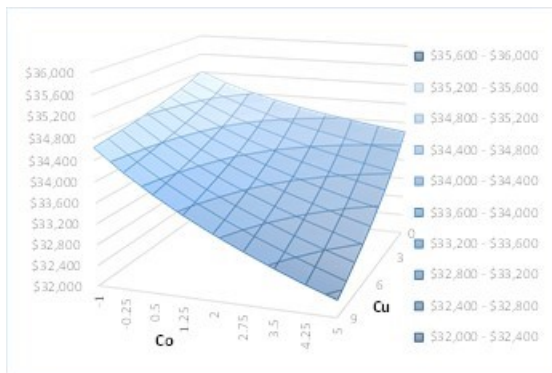


Figure 6.2 – Farmers Profits vs. Costs of Underage and Overage (No Options)

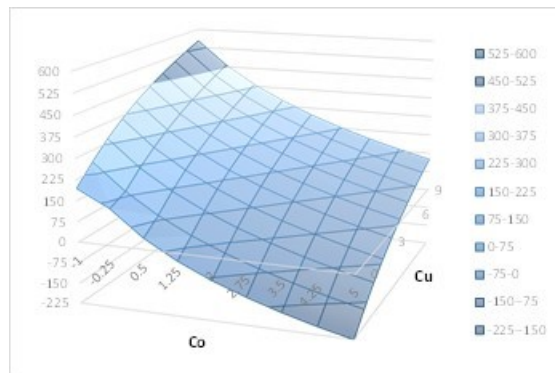


Figure 6.3 – Production Bias vs. Costs of Underage and Overage (No Options)

In Figure 6.2 above we can observe the expected farmer profits and bias respectively. It can be appreciated that profits behave as expected, monotonically decreasing on costs. Moreover, in Figure 6.3 we also observe that bias appears to decrease on both  $c_u$  and  $c_o$ ; however, its behavior is not convex. Furthermore, we observe that bias will be equal to zero for a small subset of all combinations of  $c_u$  and  $c_o$ , thereafter becoming negative. This behavior is consistent to that predicted by equation (6-9), which sustains that for some values of  $c_u$  and  $c_o$ , the expected production bias of farmers should be zero. This behavior is further illustrated in Figure 6.4 below, where we detail the observed bias given by computational results against the bias conditions of equation (6-9). As it can be observed, both values intercept at the origin, signaling that the behavior of bias is consistent to our findings.

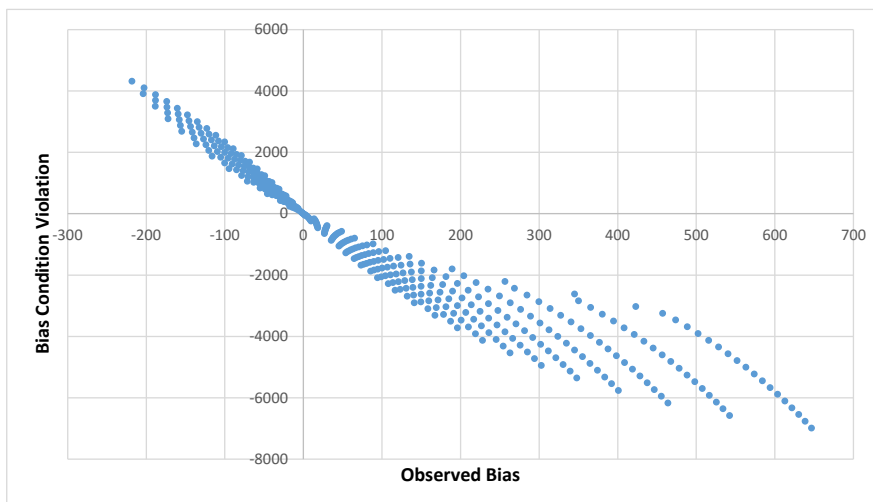


Figure 6.4 – Behavior of Production Bias

The results illustrated in this section provide a good overview for the base case without option contracts; however, they must be complemented with the results for the decision problem when options are present.

### 6.4.2 Sensitivity to Underage and Overage Costs With Options

As a continuation to the previous section, we provide an analysis on the same range of values for  $c_u$  and  $c_o$  in order to better understand what the impact of options on the farmer decision problem are. For this we include the added decision variables of  $q_o$  and  $q_u$ , as well as the parameters for the cost of options and the strike price of the options. These parameters are:  $s_o, s_u = 0$  and  $o_o, o_u = 0.2$ . With this expanded formulation we illustrate the modeled for the option contract case and make a simple comparison with the results of Section 6.4.1.

For the case of expected farmer profit, we detail the total profits when the farmer has access to options in Figure 6.5 below; likewise, we compare these expected profits to those detailed in Section 6.4.1 in Figure 6.6. As it can be observed, the expected profits for the case where option contracts are available are strongly better than those of the no option case.

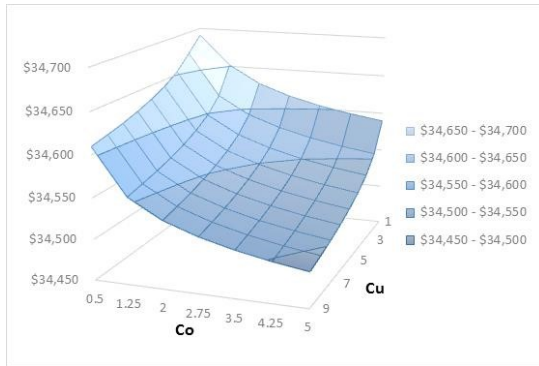


Figure 6.5 – Farmers Profits vs. Costs of Underage and Overage (With Options)

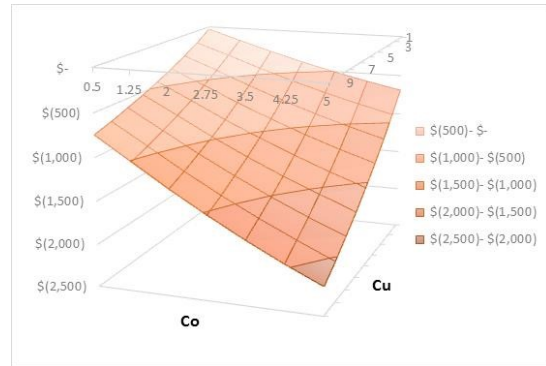


Figure 6.6 – Difference between Farmers Profits without Options - with Options

For the case of production bias, the difference of the behavior with and without options is much different, and making inferences is difficult. As it can be observed from Figure 6.7 below, the production bias for the farmer decision problem when options are



available is mostly flat on  $c_u$  and  $c_o$ . This indicates that the overall policy is more robust to bias; however, if we compare the production bias for this instance to that of Section 6.4.1 we observe that bias may not always be minimized when options are used. For this, we take the difference between the absolute bias values of Section 6.4.1 and the current section, which are illustrated in Figure 6.8 below. As it can be seen, there are instances in which using options may yield a higher expected bias than its simpler counterpart without options.

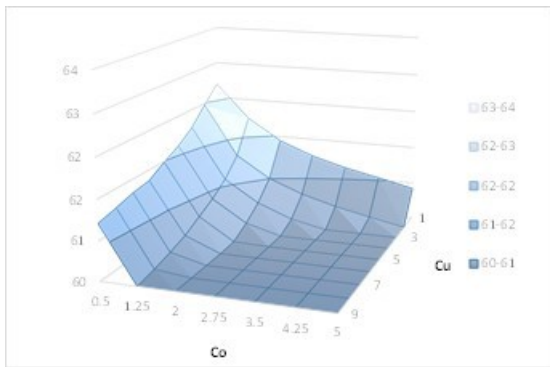


Figure 6.7 – Production Bias vs. Overage/Underage Costs (With Options)

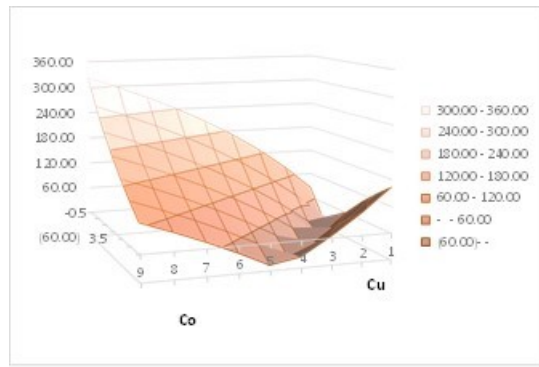


Figure 6.8 – Difference in Absolute Bias without Options - with Options

This result is further complemented by observing the behavior of the underage options  $q_u$  and overage options  $q_o$  as seen in Figure 6.9 and Figure 6.10.

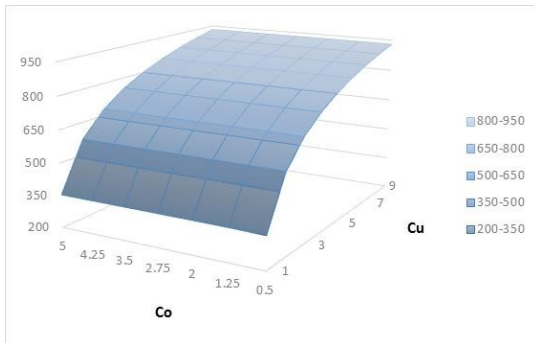


Figure 6.9 – Underage Options Sensitivity to Overage/Underage Costs (With Options)

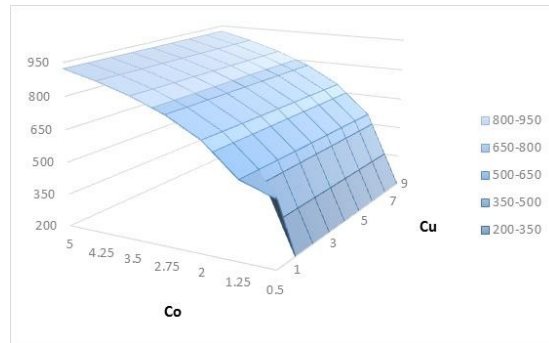


Figure 6.10 – Overage Options Sensitivity to Overage/Underage Costs (With Options)

The above result suggests that the greatest impact to this variable will come from other contract parameters such as the cost of the options or the strike prices of the options. It appears that with a good choice of these parameters, profits can be increased, while production bias can also be decreased. In the remaining sections we make the necessary sensitivity analysis to understand these differences.

### 6.4.3 Sensitivity to the Cost of Options

As a continuation to our analysis, we provide a sensitivity analysis on the parameters  $o_o$  and  $o_u$ , which are varied in the range of (0.1, 1.15). For this result, the values of other parameters are kept as  $s_o, s_u = 0$  while the values of  $c_o$  and  $c_u$  are varied in the ranges of (2, 5) and (3, 6) respectively.

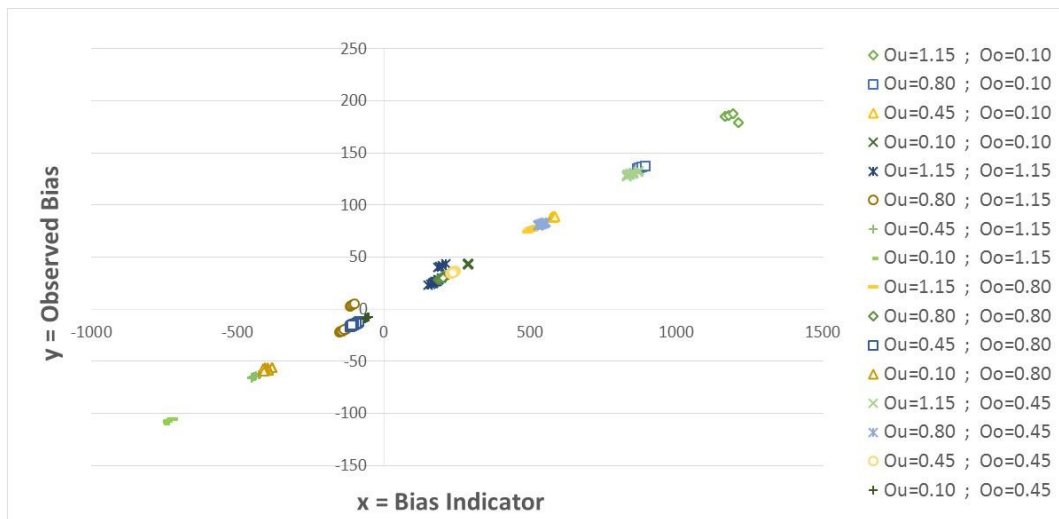


Figure 6.11 – Production Bias Sensitivity to Various Option and Penalty Costs

As it can be seen in Figure 6.11 above, the variation caused by the cost of the options is large and by far outweighs the variation caused by the costs of overage and underage. This observation is facilitated by allowing each combination of option costs to be represented by a different marker in the scatterplot. Note that, within each category for option costs, there is a degree of variation in the observed values; this occurs because of

the different costs of underage and overage being tested for, which contribute to the smaller variations in the data.

From Figure 6.11, it appears like the cost of options which minimizes the absolute production bias are given at the following combinations:  $o_u = 0.8, o_o = 1.15$ ;  $o_u = 0.45, o_o = 0.8$ ;  $o_u = 0.1, o_o = 0.45$  for the parameter values of this experiment. Moreover, the values of other parameters being manipulated do not appear to have a great bearing on the sensitivity of the results.

While Figure 6.11 gives us a general overview for what is the relative impact and importance of some cost parameters (mainly  $o_u, o_o, c_u, c_o$ ), it does not show a complete picture for the behavior of bias and expected profits as we vary the costs of the option contracts. Because of this, we show additional for the sensitivity to changes in option costs. For the following Figures (6.12 through 6.15) we show a sensitivity analysis for  $o_o$  and  $o_u$  on the range (0.1, 2.2) while we keep all other parameters constant. Note that for illustration purposes, the main axes on these figures have been sorted differently in each case.

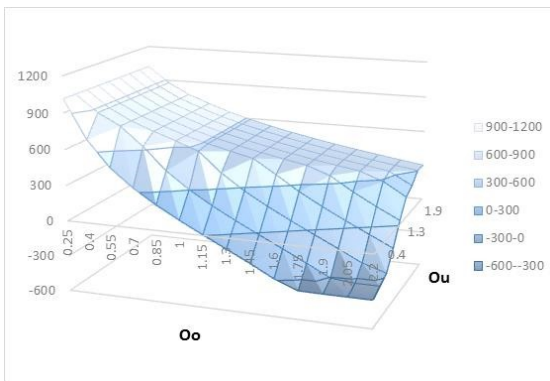


Figure 6.12 – Production Bias Sensitivity to Option Contract Costs

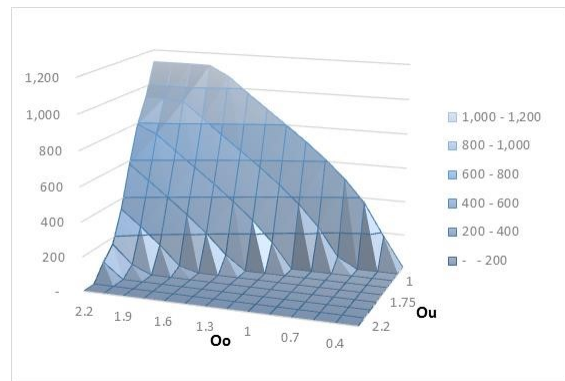


Figure 6.13 – Underage Option Quantity Sensitivity to Option Contract Costs

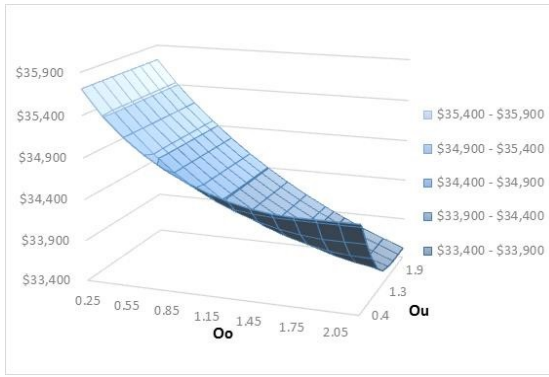


Figure 6.14 – Farmer Profits Sensitivity to Option Contract Costs

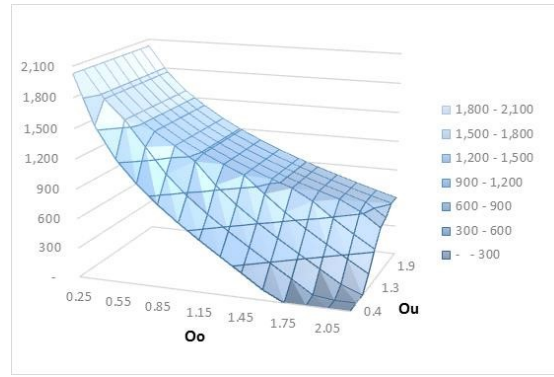


Figure 6.15 – Overage Option Quantity Sensitivity to Option Contract Costs

As it can be seen in Figure 6.12, once again we can observe that there will be a subset of option price combinations for which production bias will be zero; however, we also note that the behavior of production bias changes together with the parameter ranges upon which the analysis is being performed, making this behavior harder to model that system profits (Figure 6.14). Likewise, we can also see that the behavior of option contract quantities also acts according to expectations, with more options being demanded when their respective prices are lowered.

#### 6.4.4 Sensitivity to the Cost and Strike Price of Options

This analysis would not be complete without assessing the simultaneous impact of the strike price for the option contracts ( $s_u, s_o$ ) and their purchase cost ( $o_u, o_o$ ). In order to carry out this analysis, we perform a sensitivity analysis on all four variables simultaneously, with their corresponding ranges. The sensitivity analysis is performed on the range of (0.2, 2.7) for  $o_u$  and  $o_o$ ; at the same time we vary  $s_u$  and  $s_o$  on the (-2, 0) range. The negative values can be interpreted as the selling of insurance to farmers, who may still obtain revenue from failed or unsold crops; meanwhile, a strike price of zero would let farmers avoid penalty overage and underage costs.

The results are shown in Figure 6.16 below. Here we can observe that both option cost and strike price appear to have an impact on the magnitude and the location of the bias. However, it appears that strike prices will have the greatest effect on the magnitude, causing a greater dispersion when the subsidies are greatest; on the other hand, option costs have the same effect that was observed earlier, defining the location of the bias free zone on each graph.

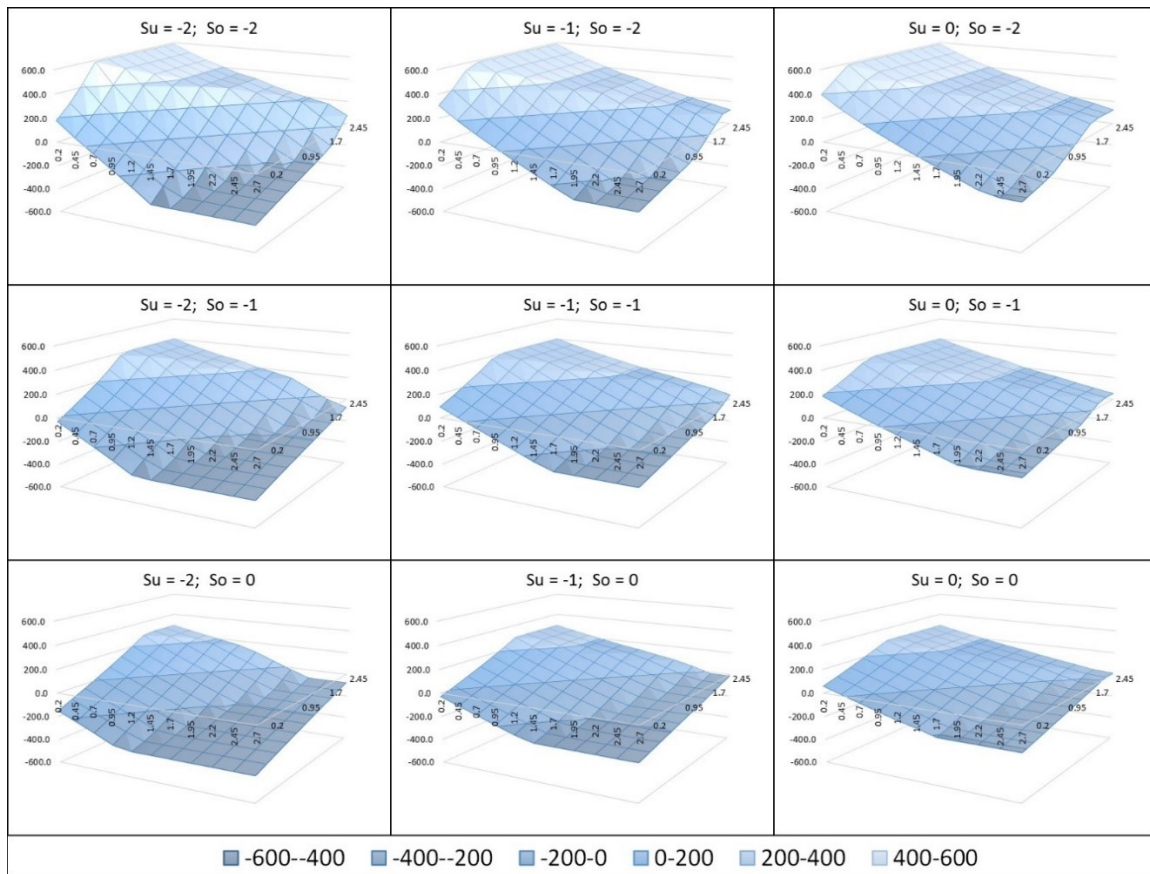


Figure 6.16 – Sensitivity of Production Bias to Option Cost and Strike Prices

The results in this section are those which are most relevant from a practical standpoint. This is because the buyer (Consolidation Facility) usually has little control over the costs of overage and underage observed by suppliers (Farmers). Usually, these costs are given by economic conditions and can be manipulated only through penalties and

subsidies. On the other hand, the costs of options and the strike prices of these options can be defined by the CF with more liberty.

#### 6.4.5 Sensitivity to the Variability in Yields

The last part of the analysis remaining is that of understanding the impact of yield variability to the decision of farmers. Unlike raising costs, whose impact can be predicted to some extent, the impact of variability is harder to predict and may depend on other cost parameters. Nonetheless, we expect to see the quantity of options for both overage and underage increasing with variability. This is the case demonstrated by Figure 6.17 below, which plots the expected harvest quantity, and the expected harvest within the range of the options purchased. Here we also show the target production required by the consolidation facility.

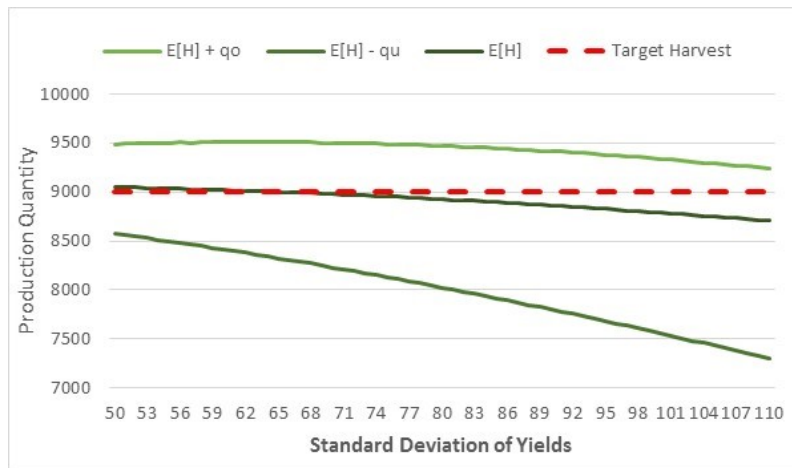


Figure 6.17 – Production Quantities Sensitivity to Variance

#### 6.5 Discussion and Conclusions

Throughout this chapter we analyzed the decision model of a farmer who has already committed to a given production quantity and needs to decide how much to plant in order to honor his/her commitment. As part of this decision, the farmer must balance the risks of

shorting his/her customer to those of overproducing. Thereafter, we include the possibility of allowing the producer to purchase option contracts which allow him/her to protect itself against the risk created by yield variability. Here, the options contracts serve as a flexible tool which establishes a secondary price for overproduction or as a form of insurance to the downside risk of lower yields.

The problem is modeled in the same fashion as a newsvendor problem with stochastic yields, but unlike previous research, the option contracts are sold to the producer (farmer) rather than the manufacturer (the consolidation center). This is a formulation which is unique to agriculture, where lead times are too high for option contracts to lower risk for buyers. Nonetheless, the buyer can still use option contracts as a tool for supply chain coordination which aligns the incentives of farmers to those of the CF. In this respect, it was shown via computational results that using options can reduce the magnitude of production bias as observed by the CF; this is a useful outcome which can help improve the planning process of the CF.

More important are the implications on future research opportunities. One of the simplest expansions to the problem could include the inclusion of external markets which farmers or the CF can buy/sell produce to. This problem would become of great interest if we consider stochastic prices realized at the time that harvest takes place. To make the decision model more accurate, one more expansion to this research can include the incorporation of risk preferences on the farmer decision problem. On this chapter we have assumed that farmers are risk neutral and thus we have not placed much emphasis on the shape of the pdf for the yield random variable. However, if bidders are assumed to be risk averse and to weigh losses from low yields more heavily, then the outcomes may differ.

Another possible expansion to this model comes from the fact that, in practice, the CF will work with a group of farmers rather than a single one. As a result, the CF can effectively reduce the variance of the aggregate supply from all farmers. However, having multiple suppliers, each with its own particular production costs, increases the difficulty of determining costs for options and strike prices. Even more important, we recall that the CF generally cannot observe the production parameters of farmers and therefore determining the best parameters that coordinate the chain proves elusive. On this context, we encounter the problem of designing a robust set of prices which minimize overall bias rather than the bias of a single supplier.

Finally, for one of the most interesting research directions, we have set the foundation for developing coordination mechanisms that go beyond planning production deterministically. With the formulation developed in this chapter, we can think of an auction mechanism which coordinates the planning process of multiple growers in an agricultural cooperative. Such a mechanism would build on the results of Chapters 4 and 5 by incorporating option contracts to the decision process of farmers. By awarding production contracts as well as selling options simultaneously, it would be possible for the CF to maximize profits while simultaneously minimizing risks; all this could be accomplished while preserving a good degree of efficiency and remaining nearly-incentive compatible. We propose that upcoming research in coordination mechanisms in agriculture can build on the results of this and previous chapters to create a robust, stochastic formulation of the horizontal coordination problem in agriculture.



## 7 A TOOL FOR FARMER GROUPING BY SIMILARITY

### 7.1 Introduction

In previous chapters we have established the difficulties of horizontal coordination focusing specifically on the implications of collaborating when internal competition is present. Among the greatest challenges of coordination, is the difficulty of obtaining relevant production information from the associated parties in order to make production decisions. Specifically, even if relevant data is requested from the collaborating parties, the veracity of the information may be questionable. In order to elicit truthful information and to better allocate resources, market mechanisms have been proposed as a solution.

In Chapter 4 it was shown that coordination mechanisms structured as auctions can generate sufficient information to coordinate the cooperative and lead towards optimal outcomes. Thereafter, in Chapter 5 it was shown that these mechanisms, can elicit sufficient information to coordinate the supply chain with little loss of efficiency. The results of this dissertation are a step forward on ensuring the financial viability of an agricultural cooperative and its member farmers. The mechanism discussed both leads towards optimal outcomes and also simplifies the negotiation process.

However, the managerial implications of running an agricultural cooperative go beyond the tactical production assignment and compensation from established contracts. Even if coordination problems are addressed, multiple issues persist, such as:

- Forecasting future demand and production
- Detecting and aiding underperforming farmers
- Strategically deploying new technologies
- Exploring new potential crops to be grown
- Disbursement of emergency funds

In order to ensure the long term viability of a cooperative it is necessary to provide other services to member farmers (a practice which is already common in most cooperatives); but it is also necessary to prioritize the need for these services. Like any other institution, agricultural cooperatives need to use their limited resources and reinvest them internally on its members. To ensure the success of each partner it is paramount to understand which farm or groups of farms are struggling. More generally, understanding what farms are similar to each other, creating well defined groups of farms and understanding each group can be beneficial to the cooperative.

Unfortunately, as the size of an agricultural cooperative grows, *understanding the specific situation of each member becomes impractical*. If surveys and measurements were taken on each farm, obtaining such information could become costly. Moreover, if the cooperatives leadership were to ask each member for their specific needs we newly encounter the longstanding problem of incentive compatibility. As a result, it is infeasible to rely on surveys to allocate resources. Thus, in order to reduce managerial complexity and overhead, an alternative way to make inferences about farmers must be devised.

We recognize that at its core, assigning resources to farmers is a coordination problem akin to assigning contracts; however, in this Chapter we chose to follow a different approach for coordination. That is, instead of designing a mechanism for assigning resources, we use data that is readily available from contract assignments given by the auction of Chapters 4 and 5.

In this Chapter we propose a novel framework for segmenting farmers into distinct groups such that the business problem of dealing with  $M$  farmers can be reduced to dealing with  $C$  farmer types, where  $C \ll M$ . Under this framework, the  $C$  groups of farmers will be

sufficiently different from one another, while the members of each group will be sufficiently similar. In order to achieve this, a clustering approach is used in conjunction with linear regression methods to assess the quality of the clusters formed. Moreover, we perform this analysis using data which has already been generated from the auction mechanism, thus eliminating the need for additional data collection.

## 7.2 Problem Definition

The core problem is one of unsupervised classification. In this problem we have a group of entities whose *primary characteristics* are hidden and cannot be independently measured or verified; nonetheless, each of these entities can be subjected to alternative measurements to reveal a set of *secondary characteristics*. The secondary characteristics are not of direct interest; nonetheless, they can be measured consistently and also serve as an indicator of the primary characteristics. Within this problem, secondary characteristics can be measured by subjecting each entity to a specific environment or set of *measurement parameters*. In the context of the agricultural cooperative case study, these characteristics are:

- *Primary characteristics* are core attributes of each farmer such as the production costs, yields, labor requirements, labor efficiency, profitability and others. These characteristics are critical for the success of individual farmers and also the cooperative at large. Moreover, these characteristics can be of use for determining which farmers get aid, technical assessment, emergency funds or even which farmers can be relied on to perform exploratory trials of new crops. For these primary characteristics, farmers cannot be asked directly as they will give subjective responses or misrepresent their information.

- **Secondary characteristics** are a reflection of each farmer's technical expertise and skill. For this case study, these characteristics are the bids placed during each auction iteration. Since the measurements are quantitative, and approximate production preferences under similar circumstances (i.e. same price vector), then these can be compared directly.
- **Measurement parameters** are the circumstances in which secondary characteristics are measured. In the problem at hand, these characteristics are the parameters of the mechanism as defined in each iteration. These are: The iteration number, the production period (week), the crop and the price offered for crops.

### 7.2.1 Objective

The problem objective consists on utilizing the secondary characteristics (bids of each farmer) to create clusters of farmers which consistently reflect the technical expertise within the cluster. Moreover, it is desirable that these clusters work as viable predictors of the yields, costs and even profitability of each farming operation. Within this framework, an assessment of the quality of the clusters is of great importance. Therefore an unbiased and quantitative assessment of cluster quality must be performed to determine the best solution for grouping farmers which balances complexity and misclassification error.

## 7.3 Methodology

### 7.3.1 Data structure:

The data structure used consists of three main components: (1) Primary characteristics; (2) secondary characteristics and (3) measurement parameters. These three components of the data structure are closely interrelated and are better exemplified in Table 7.1 below. As it can be seen, in Table 7.1 we are interested in measuring the primary

characteristics of farmers (shown on the horizontal labels); however, this is not directly measurable and thus we must measure the secondary characteristics which are the data populating the inner matrix (which is the data in the center of the matrix). Note also that primary characteristics have no direct relationship to the measurement parameters; but rather, secondary characteristics can be thought of as a function of the characteristics of the farmer and the measurement characteristics.

Table 7.1 – Data Structure for Clustering Problem

				Iteration	1					...	K						
				Week	1				...	W	...	1				...	W
				Crop	L	R	C	B	...	L	R	C	B	...	L	R	C
Entity	Labor	Yields	Costs	-	-	-	-	-	-	-	-	-	-	-	-	-	
Farm 1	XX /.. / XX	YY /.. / YY	ZZ /.. / ZZ	-	#	#	#	#	...	#	#	#	#	...	#	#	#
Farm 2	XX /.. / XX	YY /.. / YY	ZZ /.. / ZZ	-	#	#	#	#	...	#	#	#	#	...	#	#	#
Farm 3	XX /.. / XX	YY /.. / YY	ZZ /.. / ZZ	-	#	#	#	#	...	#	#	#	#	...	#	#	#
Farm 4	XX /.. / XX	YY /.. / YY	ZZ /.. / ZZ	-	#	#	#	#	...	#	#	#	#	...	#	#	#

This description of the data also falls within the framework of the auction mechanism described in Chapters 4 and 5, where secondary characteristics consist of bids. Also note that, in practice, the primary attributes are privately held information; however, for this case study the primary attributes are known to us as researchers and are used for validation. These values were retrieved from the input data, which is simulated to create a variety of farmers as described in Section 4.7.1 and include: Size of the farm, labor, crop yields, production costs, transportation costs and also profitability.

### 7.3.2 Performing Agglomerative Hierarchical Clustering

In order to group the various farms, hierarchical clustering was utilized. This method of unsupervised clustering was chosen because it creates a taxonomy or dendrogram, where those farmers which are most similar to each other will be closer together, while those who are most dissimilar are clustered further apart. This methodology has two main advantages:

- From a managerial perspective, it is an intuitive way of looking at the grouping of farms. This allows managers to choose the number of clusters which are best suited to their objectives (for instance, assigning resources to a group no larger than 20% of the instances); moreover, this also allows for some flexible interpretation of the variety of groups observed.
- From a validation standpoint, having a continuous spectrum of clusters allows for an assessment of error which is well behaved as the number of clusters is varied. More specifically, hierarchical clustering is deterministic and the clusters resulting from the algorithm remain consistent as we move through the taxonomy; this is not true for, other methods such as k-means clustering. This continuity will be important when we validate the clusters using quantitative methods, which are covered below.

### 7.3.3 Validation Using Prediction Error

In order to objectively and qualitatively determine the right amount of clusters to be used we formulate a method based on regression and prediction. Since all the values being clustered on (secondary attributes) are continuous and functions of the measurement parameters, a prediction model can be created; moreover, since all measurements are given, a measure of prediction error is calculated.

Since the objective is to assess the prediction capabilities of each cluster, we resort to a method of Ordinary Least Squares (OLS) through which the secondary characteristics within the data matrix can be estimated as a function of the measurement parameters. For the case in which we start with  $M$  farmers and  $C = M$  clusters, this implies that each farm will have its own least squares model. As for the case where  $C < M$ , for a cluster that

contains  $k$  farms, the measurements are concatenated without tracking which farm the measurements come from; this is equivalent to having  $k$  replicates, and a single set of predicted values applicable to all farms.

In mathematical form, for  $Y_i$  and  $X$  having a length of length  $N$ ; if each farm were a cluster in itself we have the regression model for a single farm  $i$ :

$$Y_i = X\beta_i \tag{7-1}$$

However, suppose we have  $k$  farms in some cluster  $c$ , then the model data resembles the concatenated vector and model below:

$$\begin{matrix} Y_1 & X \\ Y_2 & X \\ \vdots & \vdots \\ Y_k & X \end{matrix} = \begin{matrix} X \\ X \\ \vdots \\ X \end{matrix} \beta_c \tag{7-2}$$

This methodology could potentially require extensive calculations, recalculating a complete OLS model using the input data for each case; however, under some simplifying assumptions, we can make the complexity of the calculations significantly lower. The main assumption that we make is that for any entity and for any cluster, **all parameters in the regression vector  $\beta$  are relevant**. This assumption yields models with a higher variance than is desirable; however, as our interest is on a rapid and consistent estimation of error and because we seek to assess the quality of the clusters rather than to make direct use of OLS model equations, we let this increase in variance be justified.

Below we show that under the assumption detailed above, creating a predictive model for any arbitrary cluster is reduced to taking the simple average of the parameters from the OLS models of the cluster components.

**Proof:**

For simplicity, we use the following notation, where:

$$\begin{matrix} Y_1 \\ Y_2 \\ \vdots \\ Y_k \end{matrix} = Y_K \quad \text{and} \quad \begin{matrix} X \\ X \\ \vdots \\ X \end{matrix} = X_K \quad (7-3)$$

Then we have from (7-2) and definition (7-3) the following notation for the regression equation:

$$Y_K = X_K \beta_c \quad (7-4)$$

Here, we can perform the corresponding matrix operations:

$$X'_K Y_K = X'_K X_K \beta_c$$

$$(X'_K X_K)^{-1} X'_K Y_K = \beta_c$$

Note here that  $X'_K X_K = k X' X$  and  $X'_K Y_K = \sum_{i=1}^k X' Y_i$  where  $k$  is a scalar; thus:

$$(X' X)^{-1} (\sum_{i=1}^k X' Y_i) = k * \beta_c$$

$$\sum_{i=1}^k (X' X)^{-1} (X' Y_i) = k * \beta_c$$

$$\sum_{i=1}^k \frac{\beta_i}{k} = \beta_c \quad (7-5)$$

And the prediction equation for cluster  $c$  is:

$$\hat{Y}_c = X \hat{\beta}_c \quad (7-6)$$

Where the regression coefficient  $\beta_c$  is the average of the regression coefficients from the components of the cluster. ■

Therefore, the structure of the data allows for an easy aggregation of clusters and regression models which remains valid as long as the entities on each cluster are comparable. For our clustering application, as long as the entities being clustered together share enough similarity to one another, then aggregating linear models in this will be a



viable form of obtaining good prediction capabilities. However, we would also expect prediction error to increase if we have a cluster in which the various components are significantly different from each other.

If we are interested in measuring the goodness of fit for a particular farm  $i$  in cluster  $c$ , we can compare the actual measurements of the bids from farm  $i$  to the predicted values from the cluster  $c$ . The resulting comparison is expressed in a familiar form:

$$e_i = Y_i - \hat{Y}_c \quad (7-7)$$

As a result, this methodology provides a viable way to assess the goodness of hierarchical clustering at various levels of clustering and to determine the number of clusters which is desirable using an objective measure of error. Moreover, due to the simplifying assumptions on the model structure for each farm, calculating a prediction model for each cluster is greatly simplified and consists only of simple arithmetic operations using the parameters of each independent farm  $\beta_i$  as in formula (7-5). With this we can now calculate the error of prediction for each farm and for any number of clusters. Finally, we are able to quantify for any outcome of the hierarchical clustering algorithm the error of prediction for all farms; this can be done for any number of clusters ranging from 1 to  $M$ , where  $M$  is the number of farmers.

## 7.4 Results of Case Study

### 7.4.1 Description and Pre-Processing of Data

In this case study, we utilize data from Chapter 5 of the dissertation. Specifically, we use data obtained from running an instance of the coordination mechanism for a cooperative of 125 farmers across  $N = 15$  iterations, where the mechanism is tuned to perform close to its optimal behavior. We utilize the bids from each farm  $l \in L$ . The bids

that are used for clustering are for  $J$  crops,  $H$  time-periods and for  $N$  auction iterations and correspond to the vector  $Vtrans_{hjl}^i$  as announced by bidders during each iteration.

Although the data used for this case study is readily available, it has two main issues: Varying scales and high dimensionality. We discuss two ways in which we address these problems below.

#### 7.4.1.1 Data Scaling

In order to make the data from all farms comparable, each farm bid vector is normalized by dividing all of the values by the size of the farm in acres<sup>17</sup>. Thereafter, in order to prevent distortions on the distance calculations from the clustering algorithm, range scaling is performed on each column according to the following formula:

$$X_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \quad (7-8)$$

#### 7.4.1.2 Dimensionality reduction

Given that each farm will place a bid for multiple products and multiple time-periods, the length of the feature vector used to cluster farms can grow significantly. This problem is aggravated if we utilize multiple iterations of the auction. For the case study under consideration, we have a feature vector ( $Vtrans$ ) of size  $|H||J||N| = 20 * 4 * 15 = 1200$ , which is excessively large for hierarchical clustering using traditional distance based measured of similarity (Tan, Steinbach, & Kumar, 2006); therefore we explore methods to reduce the size of this vector. For this problem, we rely on the use of principal component analysis (PCA). Using the PCA approach, the total size of the feature vectors is reduced

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<sup>17</sup> Note that we can use farm size under the assumption that this is an easily verifiable or public information

from 1275 columns to 24 while preserving 95% of the variance. With this transformation on the data, we proceed to create the required clusters.

#### 7.4.2 Predictive Model for Farmer Bid Placement

As described in Section 7.3.3, a predictive model for farmer bids is made for each individual farm, and through the use of equation (7-5), a predictive model for farmer bids can also be made for every cluster. Nonetheless, making predictive models for farmer's bids is a challenging problem even when information is readily available (as is the case in this case study). Mainly, if OLS is used to create a model for bid prediction, creating a model for each of the 125 farms in this study can be expensive and thus simplifying assumptions are made.

To understand the structure of the model we first analyze the characteristics of the data; for the independent variables we have:

- **Iteration number ( $i$ ):** From the auction output, the bids placed throughout the full mechanism are of interest, thus all 15 iterations of the mechanism are used. This is a discrete categorical variable.
- **Crop type ( $j \in J$ ):** Includes four crops (broccoli, cauliflower, iceberg lettuce and romaine lettuce). Since these are four distinct products, then they are used as categorical variables.
- **Production period ( $h \in H$ ):** For each farmer and crop, these periods have an ordinal or categorical nature. Their numerical value is on itself of little relevance to the model and as a result these are treated as categorical variables.
- **Price of Crop ( $price \in J \times H$ ):** Is the only continuous variable that is used for prediction.

Due to the characteristics of this data, the prediction is performed by using indicator variables for all combinations of crop and production periods. Moreover, in order to simplify the model building process, we assume independence between each of these categories; as a result, for each farmer we create the equivalent of 80 prediction models ( $|H||J| = 20 * 4$ ). Each of these 80 models is fitted to a regression equation of the same general form, where only the  $\beta$  parameters change. By performing the necessary analysis it was found that the regression equation which best reflects the behavior of bids uses a transformation on the iteration number; the final form of the regression equation used is given in (7-8) below:

$$\beta_0 + \beta_1 * i^{-1.8} + \beta_2 * price_{j,h} = Vtrans_{hj}^i \quad \forall j \in J; h \in H \quad (7-8)$$

Moreover, because of the structural assumptions which we have made, the fitting of all 80 models can be done simultaneously through the use of a single design matrix  $X$  which preserves the independence between crop and time period combinations. By making these assumptions, the problem of creating multiple prediction models at one time is simplified. For this, we let  $I_{jh}$  be an indicator variable for each combination of crop and time period, where:

$$I_{j'h'} = \begin{cases} 0, & j' \neq j \text{ and } h' \neq h \\ 1, & j' = j \text{ and } h' = h \end{cases}$$

The resulting regression equation for each farm has the form:

$$\sum_j \sum_h (\beta_{0jh} + \beta_{1jh} * i^{-1.8} + \beta_{2jh} * price_{jh}) * I_{j'h'} = Vtrans_{hj}^i \quad \forall j' \in J; h' \in H \quad (7-9)$$

### 7.4.3 Clustering and Model Building

Upon reducing the dimensionality of the data through PCA and after creating a predictive model for the bids of each farmer, we proceeded to cluster the data using

standard agglomerative hierarchical clustering. For this, the similarity between farms is measured using Euclidean distance and three major variants of hierarchical clustering were used: Single Link, Average Link and Complete Link (Tan et al., 2006). This approach yields a full spectrum of clusters ranging from  $M$  clusters (where each farm is a cluster in itself) and 1 cluster (where all farms are clustered together). With this approach, we have information for the member farms for any number of clusters in the hierarchical clustering algorithm; moreover, due to the nested arrangement of clusters, this result can be assessed as a continuum through the results of each hierarchical clustering output.

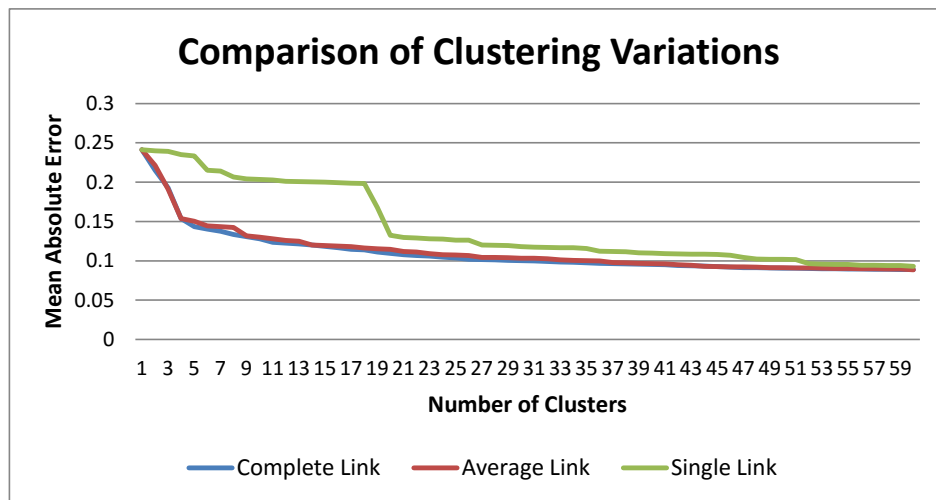


Figure 7.1 – Performance Comparison of Clustering For Three Algorithms

With the predictive models for each farm as given by equation (7-9) and with the use of equation (7-5) for, we now predict the values of  $Vtrans_{hjl}^i$ , for each farmer, iteration, crop and week combination; moreover, with these predictions, we assess the error of prediction for any cluster by comparing the measured values of  $Vtrans_{hjl}^i$  to the predicted values  $\widehat{Vtrans}_{hjl}^c$ . Now using a measure of prediction error for any number of clusters on each of the clustering methods we assess which variation of the hierarchical clustering algorithm is best suited for this problem. The comparison of prediction error for each of

these clustering results and throughout the continuum of the clusters is illustrated in Figure 7.1 above.

As it can be observed, the behavior of prediction error follows an expected pattern. On one extreme, when each farm is a cluster in itself prediction error is minimized as each model is fine tuned to each farmer; however, as we aggregate these farms into clusters predictive performance starts to degrade. Moreover, the loss in predictive performance is initially low, as farms of greater similarity are being clustered together; thus it is expected that the formula for the cluster can be extrapolated to its members. Nonetheless, as we continue to agglomerate clusters we find that predictive performance degrades, having a rapid decline once the number of clusters is small.

From these results we conclude that using complete link provides the best overall prediction performance regardless of the number of clusters being chosen. Moreover, we can also observe that predictive performance remains relatively flat, starting to pick up significantly at the 25 cluster mark, but also having a dramatic decrease in performance at the 4-5 cluster range. This result leads us to believe that from a managerial standpoint, the area of most interest lies between aggregating farmers in 5 clusters and ends at an aggregation of 25 clusters.

#### 7.4.4 Analysis of Clusters

As it was noted in Section 7.2, the main interest in clustering farmers is to make inferences about farmers without needing to engage on additional data collection. For this case study, the objective is to catalogue farmers based on their “unobservable” primary characteristics (yields, costs, management skills), using the “observable” secondary characteristics (production bids). In this section we detail a visualization of these

characteristics for the clusters formed using the Complete Link implementation of the hierarchical clustering algorithm.

#### 7.4.4.1 Visualizing primary characteristics

For the purpose of this case study, the primary characteristics are known to the investigator. As a result, it is possible to visualize this information and how it differs across various clusters. The primary characteristics of each farmer are scaled to the range [0-1] to reflect the relative competence of each farmer on each of these characteristics; (where zero corresponds to least competent). Thereafter, each of these characteristics is averaged across its cluster to reflect to collective competency of the farmers in that cluster. For the characteristics illustrated we use the Yields and Fixed Costs of the four crops modeled, as well as the size of their Land and Labor available.

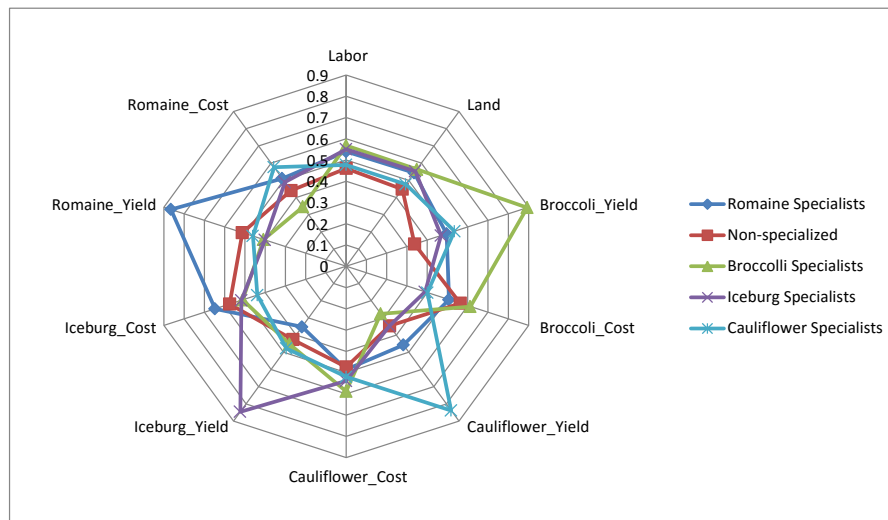


Figure 7.2 – Relative Competency of Farmers in 5 Clusters

For the breakdown of farmers in 5 clusters, we observe the variation of these characteristics in Figure 7.2 above. On this level, farmers are roughly catalogued on five groups; one specialized group for each crop and one unspecialized group of farmers.

In order to gain further information, these groups are further expanded using the hierarchy given by the algorithm. The most appropriate level on which to expand was also identified from Figure 7.1 and was determined to be 25 clusters. To better illustrate the differences between the sub-clusters at each of these groups, we show the expansion of the 25 main clusters by segmenting them according to their place in the hierarchy from Figure 7.2. This are illustrated in Figure 7.3 - Figure 7.7 below.

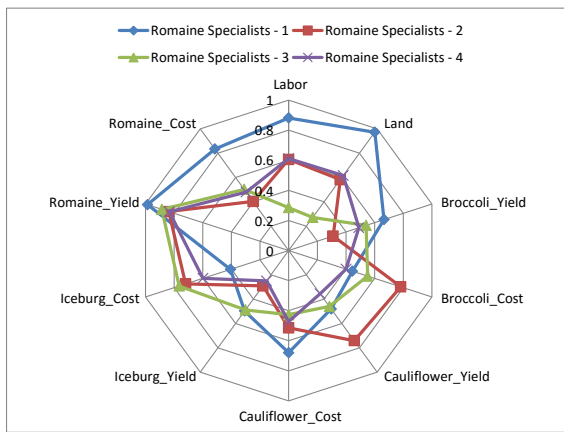


Figure 7.3 – Romaine Specialists

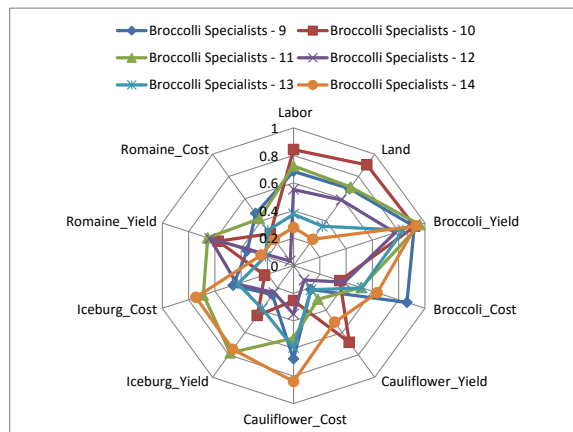


Figure 7.4 – Broccoli Specialists

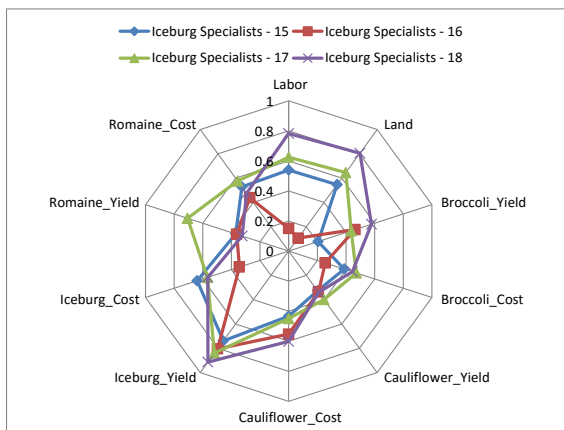


Figure 7.5 – Iceberg Specialists

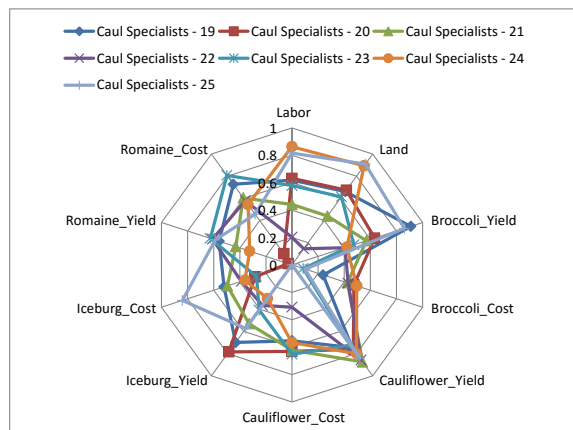


Figure 7.6 – Cauliflower Specialists



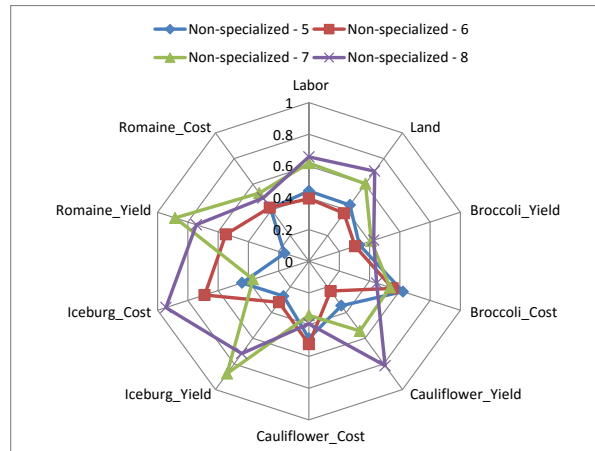


Figure 7.7 – Non-Specialized

As it can be seen from these figures, the components of each of the main clusters have significant differences between each other; nonetheless, they intra cluster similarity is greater than the inter-cluster similarity. Moreover, the defining characteristic which makes farmers cluster together appears to be the yields of the crops rather than the fixed costs associated with planting these crops.

Finally, for Figure 7.7, note that for the Non-Specialized farmers, making a clear distinctions becomes difficult. Nonetheless, clusters 5 and 6 appear to be the least competent overall in all crops and would be expected to be the least profitable operations. As a matter of fact, it turns out that some of the least profitable operations on this case study are concentrated in clusters 5 and 6.

To better illustrate this, we show the cluster assignments of the 20% least profitable farming operations in Figure 7.8. Here we show the total number of farms belonging to each of the 5<sup>th</sup>-level clusters as well as the 25<sup>th</sup>-level clusters. As it can be seen, most of these lower percentile cases are concentrated in only two clusters, while the remaining cases are scattered in other clusters.

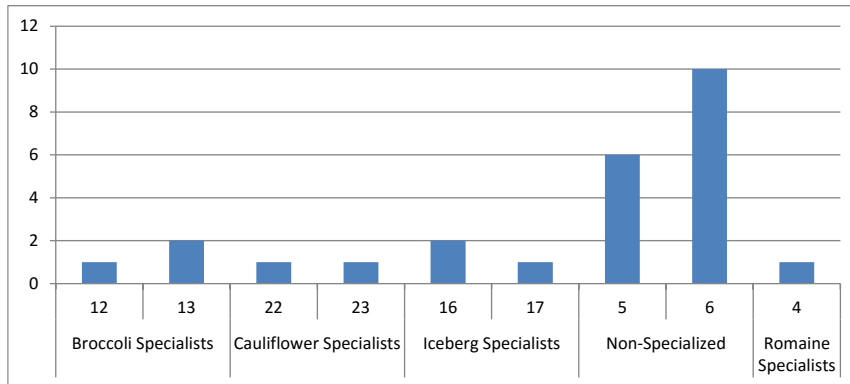


Figure 7.8 – 25 Least Profitable Farming Operations by Cluster

#### 7.4.4.2 Visualizing secondary characteristics

In the previous chapter we note that the clustering framework provides useful information and behaves in a way that can be validated through the primary characteristics. However, in practice these primary characteristics may not be observable and thus we must rely on the secondary characteristics to make inferences about the composition of the clusters. In this section we illustrate the information conveyed by the bids placed by farmers once these are visualized in a cluster by cluster basis.

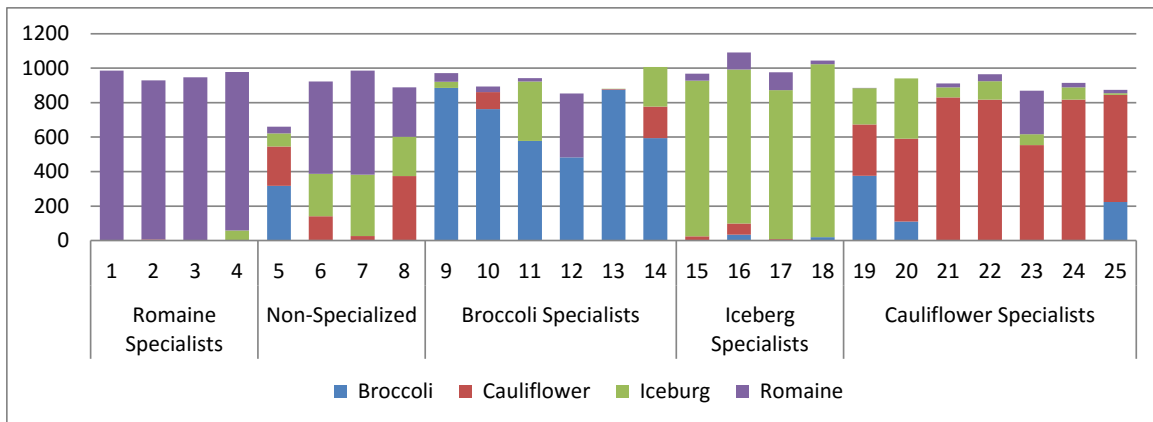


Figure 7.9 – Average Production per Acre by Cluster

To illustrate the qualities of the clustering algorithm, we first visualize the production commitments on each cluster. To do this, we follow the same approach as Section 7.4.1.1 and split the clusters in two levels (5 and 25 clusters); thereafter, we present the production

commitments of each group of farmers as the average committed production per acre of land (Figure 7.9) and the total committed production (Figure 7.10).

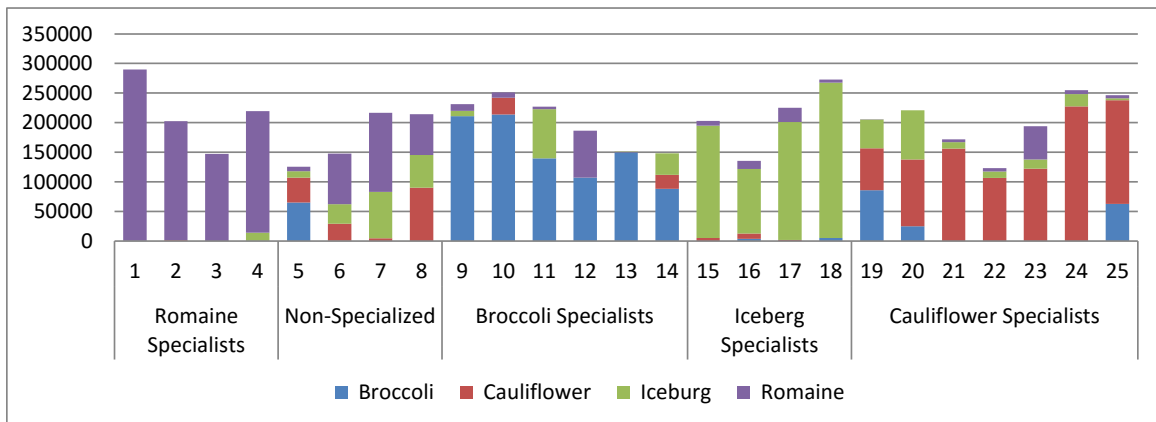


Figure 7.10 – Total Production per Acre by Cluster

As it can be seen, the general behavior of each cluster can be inferred from the secondary characteristics when they are visualized by their corresponding cluster segmentation. Furthermore, clusters 5 and 6 which were identified as the least competent in terms of their primary characteristics also reflect this fact by looking at their secondary characteristics.

## 7.5 Discussion

As it was argued throughout this chapter, many times in agricultural cooperatives it may be necessary to make decisions regarding the assignment of resources; for instance, resources can be allocated to the least competent farmers in order to raise the competitiveness of the cooperative as a whole. Unfortunately the assignment of resources can also be hampered by the difficulties of asymmetric information and competitive behavior. This presents a challenge, as additional information would have to be elicited from farmers or significant investigation may be required.

To address the problem of identifying groups of farmers for managerial purposes, we have formulated a methodology based on a clustering algorithm which utilizes existing information to make grouping inferences. In this chapter we show that the bidding information derived from the mechanism of Chapter 5 can be applied to problems that go beyond the assignment of production contracts; in this case, the information is used to segment farmers into different groups. Moreover, it was shown that these groups have structural properties which can convey significant information and are representative of production profiles of interest.

The segmenting of farmers into groups will also have implications that go beyond the assignment of resources and tactical level decisions. By having this information, the cooperative can also make better informed long term decisions such as determining the long term goals of the cooperative, exploring new crops to plant and revising production targets for upcoming seasons. Furthermore, these results can also be tied back to the auction mechanism, giving the auctioneer better control on the magnitude of price changes or design of the mechanism as well as identifying significant deviations from the expected behavior of farmers during the course of the auction.

From a methodological perspective, we also show that predictive models such as ordinary least squares can be utilized in combination with unsupervised clustering algorithms to better assess the quality of the clustering results. This combination of OLS and clustering was shown to be computationally efficient and to be easily implemented in practice, thus making it attractive for applications to problems of the size being analyzed in this dissertation.

## 8 CONCLUSIONS AND FUTURE RESEARCH

In this chapter we present a summary of the analysis and results obtained throughout this dissertation. We provide conclusions and comment on the contribution of the dissertation to the advance of knowledge in supply chain coordination and the management of agricultural systems. Finally, we provide recommendations for future research taking a high level perspective on the various contributions of this dissertation.

### 8.1 Dissertation Summary and Conclusions

Throughout this dissertation, we addressed the pressing issue of supply chain coordination in agricultural supply chains. Increased coordination has great potential to tackle the environmental shortcomings of food waste and socioeconomic issues which stem from the decline of small and medium farms. Yet, despite its promise, academic research has paid little attention to this growing concern. We found no coordination mechanisms for tactical production planning of multiple growers in agriculture; furthermore, little research has been done on coordination between fresh produce growers and buyers, with an emphasis on coordination.

Horizontal coordination in agricultural cooperatives reveals a pressing problem: difficulties arise when information asymmetry is present and internal competition hampers information sharing. Under this environment, coordination efforts may be compromised. As a result, not only should optimal solutions be attainable in a distributed manner, but a mechanism should elicit truthful production information; moreover, the mechanism must remain viable when participants deviate from the ideal assumptions of truthful communication. Finally, we also analyze additional shortcomings which stem from the nature of stochastic crop yields and their impact on planting decisions.

We successfully address the greatest challenges for coordination stated above. First, we formulated a model for tactical production planning, which coordinates production for various farms and a consolidation facility. We solved the coordination problem in a distributed fashion, despite the difficulties posed by information asymmetry, by using an auction mechanism. The auction iteratively varies prices for multiple crops throughout the growing season, allowing farmers to choose their own production quantities. Computational results show that the mechanism formulated converges rapidly towards the optimal solution, is simple and is an effective form of coordination.

Secondly, we address coordination in the presence of strategic behavior by farmers. We acknowledge that, despite being part of the same cooperative, farmers seek their own best interest and may benefit from misrepresenting their information. We developed a decision model for the farmer sub-problem, which strategically considers bid placement to maximize profits throughout the entire auction. The aforementioned decision model effectively increases farmer's profits and better represents optimal bidding strategies (from the farmer's perspective). Thereafter, we highlight the main pathologies of the coordination mechanism and how they can be avoided. We show, through computational results, that the mechanism is robust against strategic bidding and it provides solutions with a high system-wide efficiency.

Our third outcome concentrates on the stochastic nature of crop yields. Specifically, we tackle the problem of stochastic yields as they pertain to the coordination mechanism put forth in this dissertation. We take the perspective of a farmer who has already committed to a given supply quantity at the conclusion of the auction. Farmers, who commit to a specified supply quantity, face the decision of how much to plant in order to

honor their commitments. This decision problem is formulated as a newsvendor model with stochastic yields, which balances the risks of over/underproduction from farmers. Furthermore, an expansion to the model allows farmers to buy options contracts. It is shown theoretically and computationally that the supply chain can be coordinated through an appropriate choice of cost parameters from the CF, and that using option contracts benefits coordination.

Finally, we perform a case study as an expansion and follow-up to the auction mechanism. This shows that the auction generates a wealth of information, which can be used for purposes beyond coordinated tactical planning. Specifically, we note that the data structure arising from production bids is well suited for clustering methods, and that farmers can be segmented in groups consistent with their cost structures. Moreover, predictive measures verify the appropriateness of the clusters. This approach demonstrates great managerial value, as it reveals additional information for the assignment of resources, making competitiveness assessments or preparing strategic plans for the cooperative.

## 8.2 Dissertation Contribution

Throughout this dissertation, each chapter presented brought forth a variety of relevant academic contributions. Below, we describe some of the most important contributions.

We develop a mechanism, through which the necessary information is elicited from farmers, in the form of an auction. This method relieves the cooperative from the burden of negotiation, and allows contracts to be assigned in a fair, transparent and efficient manner. To the best of our knowledge, this area of research had not been explored and agricultural decision problems of this scale were not previously available.

We followed this first contribution with research considering the game-theoretic aspects of the agricultural coordination mechanism. We explore the practical implementation of an auction mechanism that allocates contracts for production of multiple interdependent and divisible goods. This is a novel approach in a field which has historically placed its attention in discrete goods and the combinatorial auctions required to allocate them. Our research is among the few supply chain coordination mechanisms which consider incentive compatibility explicitly; moreover, we found no other auctions, used for supply chain coordination, which consider bidder speculation as a formal optimization problem, through the use of dynamic programming, to derive analytical and computational results.

Most important, by analyzing the strategic implications of the coordination mechanism, we show that the auction developed is a simple and effective way to coordinate agricultural supply chains. This is a major contribution to the field of agricultural operations management, since we provide a mechanism which coordinates the supply chain and is robust to sophisticated agents misbehaving. This outcome should provide strong assurances to cooperatives seeking to implement coordination mechanisms; not only can these cooperatives rest assured that the mechanism converges, but they can also implement it without concern for pathological bidding problems at implementation.

As an additional contribution, we develop a newsvendor model with stochastic yields for determining planting quantities. We find that the problem of production with stochastic yields and with option contracts made available to the supplier (rather than the manufacturer) has not been researched. We modeled the farmer decision as a newsvendor problem, which is convex in planting quantities and option contracts. We show that option



contracts facilitate coordinated outcomes by making the difference between expected production and committed supply smaller and less sensitive to the costs of underage and overage seen by farmers.

Finally, we contribute to the managerial insights obtained by analyzing bid data acquired throughout the course of the auction. We show that, by using clustering methods, farmers can be segmented in homogeneous groups that reflect the true characteristics of their cost structures. Moreover, we achieve this through a combination of hierarchical clustering and prediction models to quantify the error of a given clustering outcome.

Nonetheless, the greatest contribution comes from looking at the dissertation as a whole. Throughout this dissertation, we developed a coordination mechanism which addresses one of the greatest challenges of agricultural cooperatives--determining tactical plans for the upcoming season which are efficient, fair and which provide a transparent method of contract assignment. Moreover, we address two great concerns for coordination: (1) Strategic bidding from farmers, and (2) failure to meet production targets due to stochastic yields. By developing this framework, as a whole, and connecting each of its components clearly in a single dissertation, we provide a solid foundation for future research and for practical implementation of the mechanisms developed. Not only are the models developed complete and mathematically rigorous; but they also reflect the behavior of agricultural systems more accurately by considering asymmetric information, strategic behavior and stochastic yields.

### 8.3 Recommendations for Future Research

Detailed throughout each chapter some potential expansions and avenues of research are detailed. However, two main avenues of research surface by taking the dissertation as

a whole: (1) The development of new tactical coordination models which incorporate stochastic optimization in the auction itself, and (2) a case study where the models developed are implemented in an actual agricultural cooperative.

For the development of tactical planning models, we argue that the foundation for this already exists in this dissertation. Stochastic planning can be incorporated to the expanded bidder's sub-problem. Moreover, a connection between farm planning and the CF problem can be made by continuing to use options as tools for coordination. The quantities of options purchased carry implicit risk assessments made by producers; as a result, the CF can estimate the variance of yields for each farmer. Ultimately, if the CF is able to extract information on yield risk from the purchase of option contracts, we can envision a coordinated outcome which is not only efficient in expectation, but one that also minimizes risk for the overall cooperative. We believe that this is the next logical step in developing coordination mechanisms which are more realistic and which provide even greater benefits to farmers.

Finally, although the research developed in this dissertation is promising and of strong theoretical value, farmers seldom use decision tools and optimization models to plan their production. Moreover, for farmers to use decision tools, these must be consistent with farmers' intuition and have results which they can relate to. Performing a detailed implementation and case study, involving a real agricultural cooperative, would facilitate the adoption of these models. For this, we endorse the idea of seeking a small agricultural cooperative where these tools can be implemented. Not only will this create interest in the agricultural community, but it will also surface academic insights in the coordination problem, leading to further refinement of the models developed in this dissertation.

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APPENDIX A

DATA FILES FOR DECENTRALIZED, NON-STRATEGIC MODEL

(See Attached CD)

APPENDIX B

RESULTS FOR DECENTRALIZED, NON-STRATEGIC MODEL

(See Attached CD)

APPENDIX C

AMPL CODE FOR CENTRALIZED MODEL

(See Attached CD)



APPENDIX D

AMPL CODE FOR DECENTRALIZED WD-MODEL

(See Attached CD)

APPENDIX E

AMPL CODE FOR DECENTRALIZED AUCTION MODEL

(See Attached CD)

APPENDIX F  
DATA FILES FOR DECENTRALIZED, STRATEGIC MODEL  
COMPARISON OF SOLVERS AND HEURISTIC

(See Attached CD)

APPENDIX G  
RESULTS FOR DECENTRALIZED, STRATEGIC MODEL  
COMPARISON OF SOLVERS AND HEURISTIC

(See Attached CD)

APPENDIX H

AMPL CODE FOR DECENTRALIZED, STRATEGIC MODEL

COMPARISON OF SOLVERS AND HEURISTIC

(See Attached CD)

APPENDIX I  
DATA FILES FOR DECENTRALIZED, STRATEGIC MODEL  
COMPARISON OF MULTIPLE FARM SIZES

(See Attached CD)

APPENDIX J  
RESULTS FOR DECENTRALIZED, STRATEGIC MODEL  
COMPARISON OF MULTIPLE FARM SIZES

(See Attached CD)

APPENDIX K

AMPL CODE FOR DECENTRALIZED, STRATEGIC MODEL

COMPARISON OF MULTIPLE FARM SIZES

(See Attached CD)



APPENDIX L  
INTEGRATED DATA, CODE AND RESULTS .XLSM FILE  
STOCHASTIC YIELD PROBLEM

(See Attached CD)

APPENDIX M  
DATA FILES FOR DECENTRALIZED, STRATEGIC MODEL  
COMPARISON OF MULTIPLE FARM SIZES

(See Attached CD)